

**GOVERNMENT OF PUERTO RICO
PUBLIC SERVICE REGULATORY BOARD
PUERTO RICO ENERGY BUREAU**

NEPR

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**IN RE: PUERTO RICO ELECTRIC
POWER AUTHORITY RATE REVIEW**

CASE NO.: NEPR-AP-2023-0003

**SUBJECT: Motion Submitting Spanish
Language Summaries and Notarizations of
Surrebuttal Testimonies filed on October
30, 2025**

**MOTION SUBMITTING SPANISH LANGUAGE SUMMARIES AND
NOTARIZATIONS OF SURREBUTTAL TESTIMONIES FILED ON OCTOBER 30,
2025**

TO THE HONORABLE PUERTO RICO ENERGY BUREAU:

COME NOW LUMA Energy, LLC (“ManagementCo”), and **LUMA Energy ServCo, LLC** (“ServCo”), (jointly referred to as “LUMA”), and respectfully state and request the following:

1. On October 30, 2025, LUMA submitted a *Motion Submitting LUMA’s Surrebuttal Testimonies (LUMA Ex. 70-72)*, as well as a *Motion Submitting Alejandro Figueroa’s Surrebuttal Testimony (LUMA Ex. 73)*.

2. Therein, LUMA filed the surrebuttal testimonies of Mr. Sam Shannon, Mr. Branko Terzic, Ms. Joseline Estrada and Mr. Alejandro Figueroa, all on behalf of LUMA. *See* LUMA Exhibits 70 through 73. LUMA informed the Energy Bureau, however, that it’d be submitting the corresponding Spanish-language summaries of LUMA Exhibits 70 through 73 on or before November 4, 2025.

3. LUMA also informed the Energy Bureau that Ms. Joseline Estrada and Mr. Alejandro Figueroa were not able to appear before a public notary to execute sworn attestations,

and that notarized versions of their surrebuttal testimonies would be filed on or before November 4, 2025.

4. In compliance with the Energy Bureau's May 9, 2025 Order, which established a requirement that all substantive English-language filings be accompanied by concise Spanish summaries to enhance public accessibility and participation, as well as the June 4, 2025 Order, which clarified that full translations are optional but summaries are mandatory, LUMA hereby submits Spanish-language summaries of the four aforementioned surrebuttal testimonies. *See* Annexes 1 through 4 of this Motion.

5. For clarity purposes of clarity of the record, LUMA is also hereby re-submitting Ms. Joseline Estrada's (LUMA Ex. 72) and Mr. Alejandro Figueroa's (LUMA Ex. 73) surrebuttal testimonies having been duly sworn under oath. *See Annexes 5 and 6.* In the coming days, LUMA will be uploading the final executed versions of these testimonios into the evidentiary record, by way of the Accion Platform.

WHEREFORE, LUMA respectfully requests that the Energy Bureau **take notice** of the aforementioned; **accept** the Spanish summaries and notarizations filed herewith; and **deem** LUMA in compliance with the Energy Bureau's May 9th Order, as modified by the June 4th Order.

RESPECTFULLY SUBMITTED.

In San Juan, Puerto Rico, this 4th day of November, 2025.

WE HEREBY CERTIFY that this Motion was filed using was filed using the electronic filing system of this Energy Bureau and that electronic copies of this Notice will be notified to Hearing Examiner, Scott Hempling, shempling@scotthemplinglaw.com; and to the attorneys of the parties of record. To wit, to the *Puerto Rico Electric Power Authority*, through: Mirelis Valle-Cancel, mvalle@gmlex.net; Juan González, jgonzalez@gmlex.net; Alexis G. Rivera Medina, arivera@gmlex.net; Juan Martínez, jmartinez@gmlex.net; and Natalia Zayas Godoy, nzayas@gmlex.net; and to *Genera PR, LLC*, through: Jorge Fernández-Reboredo, jfr@sbgblaw.com; Giuliano Vilanova-Feliberti, gvilanova@vvlawpr.com; Maraliz Vázquez-Marrero, mvazquez@vvlawpr.com; ratecase@genera-pr.com; regulatory@genera-pr.com; and legal@genera-pr.com; *Co-counsel for Oficina Independiente de Protección al Consumidor*, hrivera@jrsp.pr.gov; contratistas@jrsp.pr.gov; pvazquez.oipc@avlawpr.com; *Co-counsel for Instituto de Competitividad y Sustentabilidad Económica*, jpouroman@outlook.com; agraitfe@agraitlawpr.com; *Co-*

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**Resumen del testimonio de
contrarefutación de SAM SHANNON
EN NOMBRE DE
LUMA ENERGY LLC Y LUMA ENERGY SERVC, LLC**

El Sr. Sam Shannon presenta este testimonio de contrarefutación en nombre de LUMA Energy LLC y LUMA Energy ServCo, LLC (colectivamente, “LUMA”). El propósito del testimonio de contrarefutación del Sr. Shannon es abordar algunos problemas y diferencias de opinión de partes de los testimonios de respuesta del Sr. E. Kyle Datta en nombre de Solar and Energy Storage Association of Puerto Rico (“SESA”) y del Sr. Zachary Ming, consultor de Negociado de Energía, y del Sr. Steve Chriss en nombre de Walmart, presentados el 8 de septiembre de 2025 en el Caso Núm. NEPR-AP-2023-0003, *In Re: Revisión de Tarifas de la Autoridad de Energía Eléctrica de Puerto Rico*.

En primer lugar, el Sr. Shannon refuta la afirmación del Sr. Datta de que, para ser razonables, los costos clasificados por cliente deben variar total o casi totalmente en función del número de clientes. En lo que respecta a la red de distribución, explica que una parte de los activos debe existir para proporcionar servicio independientemente de la energía que fluya por la red de distribución, y otra parte existe para atender la demanda máxima. El Sr. Shannon demuestra que su propuesta de cobro al cliente es útil al implementar un mecanismo de desacoplamiento porque, en la medida en que se fijen más ingresos, habrá menos volatilidad basada en el aumento y la disminución del consumo por parte de los clientes. En este sentido, refuta las afirmaciones del Sr. Datta de que el aumento de los cargos a los clientes tiene un efecto “punitivo” en la medición neta y en los clientes de bajos ingresos. Coincide en que el aumento de las tarifas para los clientes tiene un mayor impacto en los clientes con bajo consumo. Sin embargo, afirma que esto es justo y razonable porque el cargo refleja con mayor precisión los costos y se aplica a todos los clientes de la clase GRS. El señor Shannon también señala que los clientes de bajos ingresos tienen su propia categoría que recibe un descuento.

En segundo lugar, el Sr. Shannon no está de acuerdo con la propuesta del consultor del Negociado de Energía, el Sr. Ming, de establecer un cargo mensual de 25 dólares para los clientes de GSS. Si bien coincide en que la amplia variación en el consumo de energía representa un desafío para establecer tarifas para la clase GSS, explica que los aumentos propuestos en los cargos a los clientes de GSS reflejarían mejor los costos clasificados por cliente. Aunque sostiene que su propuesta de cargo mensual de 75 dólares por cliente es razonable, señala que el Negociado de Energía, puede decidir adoptar una tarifa intermedia entre las dos recomendaciones.

En tercer lugar, el Sr. Shannon responde a la recomendación del Sr. Ming de mantener el trato actual de los descuentos para personas de bajos ingresos. Señala que el tratamiento actual de los descuentos resulta difícil de comprender para los consumidores y que su enfoque ofrece una solución más sencilla. Coincide con el Sr. Ming en que es injusto que los clientes de bajos ingresos paguen el SUBA-HH tal como funciona actualmente, con descuentos incorporados para personas de bajos ingresos, y explica que incorporar los descuentos en la asignación de ingresos es una forma sencilla de brindar alivio a los clientes de bajos ingresos, lo que garantiza que reciban descuentos que se transfieren inmediatamente a otros clientes y elimina la necesidad de incluir los descuentos en el recargo del SUBA-HH, lo que significa que los clientes de bajos ingresos no pagarían por sus descuentos.

En cuarto lugar, el Sr. Shannon responde a la propuesta del Sr. Ming de cambiar el diseño tarifario para los clientes de GRS de una tarifa escalonada a una tarifa fija. Indica que, si bien no se opone a las tarifas fijas, las tarifas escalonadas fomentan el ahorro de energía porque las tarifas aumentan con el consumo. El Sr. Shannon también responde a los cambios propuestos por el Sr. Ming en las tasas de GSP y GST. Justifica el actual diseño de tarifas escalonadas, en el que los clientes con factores de carga más

altos pagan un costo efectivo de energía menor que los clientes con factores de carga bajos, porque proporciona las señales de precio adecuadas para animar a los clientes a operar con factores de carga altos, de modo que la compañía eléctrica pueda recurrir a una generación de carga base menos costosa. Proporciona su análisis para demostrar que el diseño tarifario del Sr. Ming impone un mayor incremento a los clientes con un bajo factor de carga. Afirma que el diseño tarifario actual es preferible porque mantiene una distribución más precisa del impacto en las facturas, lo cual es importante dado el gran aumento en la clase. La propuesta del Sr. Ming también aumentaría los cargos por demanda de forma sustancial y permite pocas maneras de reducir sus cargos por demanda. Sin embargo, respaldaría la propuesta del Sr. Ming bajo una estructura tarifaria de Tiempo de Uso (TOU, por sus siglas en inglés).

En quinto lugar, el Sr. Shannon aborda cuestiones de diseño de tarifas a largo plazo y recomendaciones de las partes y los consultores del Negociado de Energía para cambios en el diseño de tarifas para casos futuros y recomienda que el Negociado de Energía inicie un procedimiento separado para gestionar las diversas formas de propuestas de modernización de tarifas. Apoya la ampliación de las tarifas por tiempo de uso en Puerto Rico porque incentiva a los clientes a trasladar su consumo a los períodos de menor consumo. También coincide con el testimonio del Sr. Chriss y del Sr. Ming respecto a la necesidad de nuevas tarifas para la infraestructura de carga rápida de corriente continua (DCFC, por sus siglas en inglés). También está de acuerdo con las propuestas para estudiar la posibilidad de cambiar las clases de clientes no residenciales para que se dividan según la demanda, en lugar de según el voltaje de servicio.

Finalmente, el Sr. Shannon responde al informe de los consultores del Negociado de Energía, los Sres. Smith y Dady, sobre el ajuste provisional de la tasa. Explica que el objetivo del ajuste de la tasa provisional es conciliar las tasas cobradas bajo las tasas provisionales con las tasas permanentes finalmente autorizadas, ya que se basan en diferentes requisitos de ingresos para el año fiscal 2026. Explica que las tarifas aplicadas en el año fiscal 2026 se basan en diferentes necesidades de ingresos durante tres partes diferentes del año. Específicamente, el requerimiento de ingresos para julio-agosto de 2025 se basa en el requerimiento de ingresos presupuestado autorizado para el año fiscal 2026. Para el período comprendido entre septiembre de 2025 y el final de las tasas provisionales en la primavera de 2026, el requerimiento de ingresos se basa en las tasas presupuestadas autorizadas para el año fiscal 2026, ajustadas según las tasas provisionales. Durante el período que comienza cuando las tasas permanentes entren en vigor en algún momento de la primavera de 2026 y finaliza el año de prueba del año fiscal 2026 en julio de 2026, se aplicarán los requisitos de ingresos permanentes autorizados para el año fiscal 2026. El Sr. Shannon no está de acuerdo con las recomendaciones de Smith y Dady de tener en cuenta las variaciones entre las ventas facturadas y las previstas, el número de clientes por clase y el presupuesto frente a los resultados reales. Explica que las variaciones entre la previsión de ventas autorizada y la propuesta son importantes para el cálculo de la tasa, pero no tienen nada que ver con conciliar la diferencia entre los requisitos de ingresos provisionales y permanentes. También explica que las variaciones entre el gasto y la recaudación de ingresos previstos y reales son habituales en la fijación de tarifas de los años de prueba y que no son relevantes para el ajuste de las tarifas provisionales y permanentes. Finalmente, proporciona un cálculo ilustrativo del ajuste provisional de la tasa.

**Resumen del testimonio de contrarefutación
de BRANKO TERZIC
EN NOMBRE DE
LUMA ENERGY LLC Y LUMA ENERGY SERVCO, LLC**

El Sr. Branko Terzic, consultor reconocido internacionalmente en materia de regulación y ex Comisionado de la Comisión Federal Reguladora de Energía y de la Comisión de Servicios Públicos de Wisconsin, presenta este Testimonio de ContraRefutación en nombre de LUMA Energy LLC y LUMA Energy ServCo, LLC (colectivamente, “LUMA”). El propósito del testimonio de contrarefutación del Sr. Terzic es abordar algunos problemas y diferencias de opinión de partes de los testimonios de respuesta del Dr. Ahmad Faruqui, el Sr. E. Kyle Datta y el Dr. Ramón J. Cao García, todos presentados el 8 de septiembre de 2025 en el Caso Núm. NEPR-AP-2023-0003, *In Re: Revisión de tarifas de la Autoridad de Energía Eléctrica de Puerto Rico*, en nombre de Solar United Neighbors (“SUN”), Solar and Energy Storage Association of Puerto Rico (“SESA”) y el Instituto de Competitividad y Sostenibilidad Económica (“ICSE”), respectivamente.

En primer lugar, el Sr. Terzic refuta las críticas del Dr. Faruqui sobre el cargo fijo al cliente propuesto por LUMA y su dependencia de los índices de referencia de las empresas de servicios públicos propiedad de inversionistas. El Sr. Terzic explica que los cargos fijos, mínimos o por instalaciones son componentes de larga data de la fijación de tarifas eléctricas que se utilizan para recuperar los costos fijos de los clientes y otros costos fijos inherentes a la prestación de un servicio continuo y a demanda. El Sr. Terzic argumenta además que la Autoridad de Energía Eléctrica de Puerto Rico (“AEE”) no debe compararse con empresas de servicios públicos propiedad de inversionistas saludables y rentables, sino más bien con entidades públicas de energía similares de escala comparable. Además, en respuesta a la invocación del Dr. Faruqui sobre el “gradualismo”, el Sr. Terzic fundamenta el diseño de tarifas en los criterios multifactoriales de Bonbright, enfatizando que el “gradualismo” no es un principio rector que supere a otros como la recuperación de costos, la equidad y la estabilidad.

En segundo lugar, respondiendo al Sr. Datta, el Sr. Terzic rechaza la premisa de que “no usar” el servicio de energía de una empresa de servicios públicos no puede generar costos recuperables, y aclara la definición de “servicio público” como la obligación continua de estar preparado con capacidad, reservas, conexión, medición, facturación e infraestructura de distribución suficientes para cada cliente conectado. El Sr. Terzic explica que un cliente recibe servicio de agua, luz o gas porque conserva el derecho a exigir servicio instantáneo en cualquier momento, lo que requiere la recuperación de costos mediante cargos fijos, facturas mínimas o cargos por demanda. El Sr. Terzic también discrepa de la propuesta del Sr. Datta de adaptar los principios de Bonbright para tener en cuenta los recursos energéticos distribuidos priorizando su rentabilidad o economía, y reitera que el papel de un regulador es fijar tarifas que recuperen los costos prudentes de la empresa de servicios públicos sobre una base justa y razonable, no asegurar u optimizar los rendimientos de las inversiones en recursos energéticos distribuidos propiedad de los clientes.

Finalmente, en respuesta a la afirmación del Dr. Cao de que AEE enfrenta un riesgo de “decadencia en espiral”, el Sr. Terzic argumenta que dicha afirmación es exagerada y depende de supuestos que no están presentes en el contexto de Puerto Rico. El Sr. Terzic señala que las pérdidas de clientes en la historia de las empresas de servicios públicos de EE.UU. no siempre han llevado al colapso y que, cuando la demanda cae, los reguladores pueden abordar los activos no utilizados a través de principios de “uso y utilidad”. El Sr. Terzic explica además que una mayor adopción de sistemas fotovoltaicos (“FV”) en los tejados no genera decadencia en espiral siempre que los clientes de FV permanezcan conectados y conserven la capacidad de generar demanda en el sistema de AEE. Según

el Sr. Terzic, el problema central de la fijación de tarifas radica en la antigua política de incorporar los costos fijos a las tarifas volumétricas, ya que ese diseño ahora desalinea la recuperación de costos cuando disminuyen las ventas de kWh. El Sr. Terzic explica que los cargos fijos calibrados adecuadamente son una respuesta prudente que mitiga, en lugar de acelerar, cualquier supuesta dinámica de “decadencia en espiral”.

**Resumen del testimonio de
contrarefutación de
JOSELINE N. ESTRADA RIVERA
EN NOMBRE DE
LUMA ENERGY LLC Y LUMA ENERGY SERVCO, LLC**

La Sra. Joseline N. Estrada Rivera (“Sra. Estrada”) es la directora de Tarifas y Presupuestos, Previsión de Carga e Investigación en LUMA Energy ServCo, LLC. En su testimonio de contrarefutación, la Sra. Estrada presenta la respuesta de LUMA a las críticas del Dr. Ramón J. Cao García, el Sr. E. Kyle Datta, el Dr. Asa Hopkins y el Sr. Zachary Ming con respecto a la metodología de previsión de carga de LUMA, las consideraciones de diseño de tarifas y las implicaciones económicas de los cambios de tarifas propuestos.

La metodología de previsión de LUMA se basa en modelos econométricos que incorporan cambios estructurales y de comportamiento en el panorama energético de Puerto Rico. Las variables explicativas centrales utilizadas en los modelos de regresión incluyen los grados día de enfriamiento (CDD, por sus siglas en inglés) para capturar la sensibilidad a la temperatura, variables binarias estacionales mensuales para tener en cuenta la variación intra-anual, el producto nacional bruto (PNB) como principal insumo macroeconómico y la población. Si bien los modificadores de carga como la eficiencia energética (EE), los vehículos eléctricos (EV, por sus siglas en inglés), la generación distribuida (DG, por sus siglas en inglés) y los sistemas de cogeneración (CHP, por sus siglas en inglés) no se incluyen como variables explícitas en las ecuaciones de regresión, sus efectos históricos están incorporados en los datos de consumo observados utilizados para estimar los modelos. Para evitar el doble conteo, LUMA aplica ajustes incrementales para estos modificadores en el período de previsión, utilizando el año fiscal 2025 como base para el desplazamiento de generación distribuida y un enfoque similar para la cogeneración en el sector industrial.

LUMA defiende la exclusión del precio de la electricidad del modelo de regresión residencial basándose tanto en evidencia empírica como en consideraciones prácticas de previsión. Los datos históricos muestran que el consumo de electricidad en Puerto Rico es relativamente inelástico al precio. A principios de 2023, Guidehouse y el equipo LUMA LFR exploraron la posibilidad de incluir el precio de la electricidad como variable explicativa en el modelo de pronóstico. Sin embargo, el análisis reveló correlaciones contraintuitivas entre el consumo histórico y los precios promedio, lo que sugiere que el precio no fue un predictor fiable en el contexto de Puerto Rico. Además, muchas empresas de servicios públicos estadounidenses, incluidas las reguladas por comisiones estatales, no incluyen el precio de la electricidad en sus modelos de previsión de carga a largo plazo. Un estudio de 2016 del Laboratorio Nacional Lawrence Berkeley descubrió que solo alrededor de la mitad de las entidades de suministro de carga modelaban explícitamente la elasticidad de los precios. Empresas de servicios públicos como Portland General Electric, ISO New England y DTE Electric publicaron metodologías que excluyen el precio como insumo directo, pero sus previsiones son aceptadas por los reguladores y se utilizan para la planificación integrada de recursos. En este contexto, la decisión de LUMA de excluir el precio de la electricidad se basa en pruebas empíricas, rigor estadístico y alineación con las mejores prácticas de la industria. El modelo sigue siendo sólido, transparente y adecuado para

su propósito de apoyar la planificación a largo plazo y la revisión regulatoria.

Un aspecto que a menudo se pasa por alto en el análisis de tarifas es la composición de la factura de electricidad. Desde 1996, la tarifa base ha representado solo entre el 21 % y el 35 % de la factura total, y el resto se debe a ajustes por combustible y energía comprada. Estos componentes son más volátiles y están influenciados por factores externos como los precios del petróleo y la disponibilidad de generación. La tasa base no se había actualizado desde 1989 hasta que se implementó un aumento provisional en 2016. A pesar de esto, indicadores económicos como el PNB y la renta disponible no mostraron impactos negativos, lo que sugiere que los aumentos de la tasa base por sí solos no desencadenan crisis económicas. LUMA destaca que se espera que el Plan Integrado de Recursos (PIR), que incluye recursos despachables de menor costo, reduzca los costos a largo plazo y ayude a compensar cualquier aumento de la tarifa base aprobado por la Oficina de Energía.

Las preocupaciones sobre la asequibilidad planteadas por el Dr. Cao se abordan con datos actualizados de 2024 que muestran que las facturas residenciales promedio se mantienen dentro del umbral del 6 % de la Junta de Control Fiscal en la mayoría de los escenarios. Los clientes de bajos ingresos se benefician de programas de tarifa fija, y los participantes de la medición neta (NEM, por sus siglas en inglés) están protegidos de los aumentos de tarifas a través de un crédito minorista 1:1. LUMA refuta la afirmación de que los aumentos de las tarifas eléctricas provocarán una desconexión generalizada de la red, señalando que la desconexión total es económicamente inviable y que la fiabilidad, no el precio, es el principal factor que impulsa la adopción de recursos energéticos distribuidos (DER, por sus siglas en inglés). Los programas CBES y ASAP de LUMA tienen como objetivo mejorar la fiabilidad y gestionar la integración de DER.

LUMA cuestiona las proyecciones de inflación del Dr. Cao, haciendo hincapié en el escaso peso de la electricidad en el Índice de Precios al Consumidor (IPC) y en el papel dominante de las perturbaciones en la cadena de suministro mundial y los precios de las materias primas en las recientes tendencias inflacionistas. Los datos históricos muestran que la inflación se mantuvo baja o negativa en los años en que aumentaron los tipos de interés básicos, y que los recientes repuntes de la inflación fueron impulsados por factores externos. LUMA sostiene que atribuir la inflación o el declive económico principalmente a las tarifas eléctricas simplifica en exceso el contexto macroeconómico de Puerto Rico.

La compañía también refuta la narrativa de la “decadencia en espiral”, explicando que la desconexión de la red es limitada y que la mayoría de los grandes clientes permanecen conectados como respaldo y para mayor flexibilidad. La adopción de sistemas de cogeneración entre los usuarios industriales viene impulsada por preocupaciones sobre la fiabilidad, no por el ahorro de costos. Un análisis de Guidehouse de 2023 reveló que, si bien 43 grandes clientes desplazaron aproximadamente 34 GWh/mes a través de la cogeneración, menos de cinco se desconectaron completamente de la red. Estos clientes siguen dependiendo de la energía centralizada como respaldo y para lograr flexibilidad operativa. LUMA destaca que la adopción de DER está aumentando, pero la red eléctrica sigue siendo esencial para la mayoría de los clientes.

LUMA reconoce errores en sus previsiones anteriores, particularmente en los años fiscales 2023 y 2024, y desde entonces ha revisado sus modelos residenciales e industriales. El modelo

residencial ahora considera los aumentos de consumo posteriores a 2020 como un cambio estructural permanente, impulsado por cambios de comportamiento y calor sin precedentes. El modelo industrial se actualizó con un enfoque de reconstitución que añade la autogeneración histórica para aislar la demanda subyacente. Estos cambios mejoran la precisión del modelo y reflejan la evolución de los patrones de consumo. Por el contrario, el modelo comercial ha demostrado un sólido rendimiento y permanece sin cambios.

El proyecto de mejora de la previsión de carga, lanzado en 2023, está dirigido principalmente a la evaluación sistemática de los factores que generan variaciones significativas entre las diferentes clases de clientes. Este esfuerzo se centra particularmente en identificar y analizar las variables emergentes que comenzaron a impactar sustancialmente la demanda de electricidad en los últimos años. El objetivo final es mejorar la precisión de los modelos de previsión.

En respuesta al testimonio del Sr. Datta, LUMA defiende sus preocupaciones sobre la pérdida de ingresos y el traslado de costos bajo estructuras tarifarias volumétricas. Los clientes de NEM pueden pagar menos por los servicios de la red que todavía utilizan, lo que crea problemas de subvención cruzada. Si bien las herramientas modernas de diseño de tarifas, como las tarifas TOU, pueden ser útiles, LUMA destaca la necesidad de modernizar las tarifas para que reflejen la causalidad de los costos y la equidad. La empresa también destaca los costos marginales reales asociados a la integración de DER, incluyendo la regulación de voltaje, la protección contra el reflujo y las mejoras de los transformadores.

LUMA reconoce la necesidad de datos empíricos y está llevando a cabo un estudio exhaustivo del perfil de carga para cuantificar mejor los impactos de DER. La empresa coincide con el Dr. Hopkins en que no se necesitan ajustes adicionales para la EE no programática, ya que estos efectos ya están incorporados en los datos históricos. LUMA también defiende su uso de variables binarias y la exclusión de interceptos en los modelos de regresión como práctica econométrica estándar. La decisión de utilizar el escenario del percentil 73 de CDD para las previsiones residenciales está respaldada por las recientes tendencias de calor y se ajusta mejor al consumo observado.

La baja sensibilidad del modelo comercial a la CDD y su sólido rendimiento de previsión justifican el mantenimiento de su especificación actual. LUMA coincide parcialmente con la crítica del Sr. Ming sobre los modificadores de carga y está evaluando un modelo residencial revisado que excluye el desplazamiento de la generación distribuida de los datos históricos. La empresa destaca que su enfoque de previsión está basado en datos empíricos, es transparente y se perfecciona continuamente. En general, el testimonio de LUMA respalda la validez de sus modelos y la razonabilidad de sus supuestos en el contexto del sistema energético en evolución de Puerto Rico.

**Resumen del testimonio de contrarefutación de
ALEJANDRO FIGUEROA
EN NOMBRE DE
LUMA ENERGY LLC Y LUMA ENERGY SERVCO, LLC**

El Sr. Alejandro Figueroa-Ramírez presenta este Testimonio de ContraRefutación en nombre de LUMA Energy LLC y LUMA Energy ServCo, LLC (colectivamente, “LUMA”). El testimonio de contarefutación del Sr. Figueroa tiene como objetivo abordar algunos problemas y diferencias de opinión con respecto a partes de los testimonios de respuesta del Sr. E. Kyle Datta en nombre de la Solar and Energy Storage Association of Puerto Rico (“SESA”) y el informe pericial de la Sra. Melissa Whited de Synapse Energy Economics, Inc., consultora del Negociado de Energía, presentados el 8 de septiembre de 2025 y el 6 de octubre de 2025, respectivamente, en el caso Núm. NEPR-AP-2023-0003, *In Re: Revisión de tarifas de la Autoridad de Energía Eléctrica de Puerto Rico*.

En primer lugar, el Sr. Figueroa refuta la conclusión a la que llegó el Sr. Datta en su testimonio de respuesta de que LUMA no debería necesitar aumentar el cargo fijo al cliente si se implementa un mecanismo de desacoplamiento de ingresos. El Sr. Figueroa aclara que aumentar el cargo al cliente logra un objetivo diferente al desacoplar los ingresos y confirma que ambos son necesarios.

A partir de ahí, el Sr. Figueroa aborda las recomendaciones formuladas por la Sra. Whited en sus informes. El Sr. Figueroa responde a la recomendación de la Sra. Whited de que LUMA base el objetivo de ingresos por desacoplamiento en el requisito total de ingresos de servicios públicos en todas las clases de clientes. LUMA establece el objetivo de ingresos en función de los ingresos por clase, pero acepta que la tasa de desacoplamiento se calcule en función de una comparación entre la recaudación excesiva o insuficiente del total de ingresos permitidos en todas las clases. Como explicó el Sr. Figueroa, él está de acuerdo con la recomendación de la Sra. Whited de que LUMA excluya los costos variables, como el combustible y la energía comprada, de la fórmula de desacoplamiento porque existen cláusulas adicionales que ya contemplan esos costos. El Sr. Figueroa no está de acuerdo con la recomendación de la Sra. Whited de implementar *el desacoplamiento total* sin normalización climática para mejorar la transparencia y reducir la complejidad, ya que el pronóstico de ventas de LUMA incorpora unidades de ventas normalizadas por clima, por lo que es apropiado comparar las ventas facturadas normalizadas por clima para garantizar una comparación verdadera. El Sr. Figueroa también está de acuerdo con la recomendación de la Sra. Whited de que LUMA incluya las ventas perdidas debido a interrupciones en el cálculo de desacoplamiento. El Negociado de Energía debería abordar la fiabilidad y la rendición de cuentas sobre el desempeño mediante mecanismos de incentivos separados.

El Sr. Figueroa está de acuerdo con la recomendación de la Sra. Whited de que el mecanismo funcione en ambos sentidos, y aplicar recargos cuando los ingresos sean inferiores a la cantidad autorizada y reembolsos cuando los ingresos la superen. El Sr. Figueroa señala que la propuesta de LUMA es la misma que la recomendación de la Sra. Whited de exigir ajustes anuales de desacoplamiento para limitar la carga administrativa y minimizar la volatilidad de las tarifas, al

tiempo que se garantiza una recuperación oportuna de los ingresos. El Sr. Figueroa indica que LUMA también está de acuerdo con su recomendación de establecer un límite máximo flexible para los ajustes al alza equivalente al 3 por ciento de los ingresos anuales sujetos al mecanismo de desacoplamiento, pero sostiene que debería establecerse un límite máximo similar para los ajustes a la baja (reembolsos en forma de créditos en la factura). En la medida en que LUMA recupere más allá del límite del 3 por ciento, el Sr. Figueroa afirma que la empresa de servicios públicos debería poder reinvertir los ingresos adicionales. LUMA no es una empresa de servicios públicos propiedad de inversores, por lo que los fondos pertenecen en última instancia a los ciudadanos de Puerto Rico. Cualquier financiación adicional disponible para apoyar proyectos adicionales, más allá de los solicitados en el caso de tarifas, redundaría en beneficio de los clientes de electricidad. El Sr. Figueroa también está de acuerdo con la recomendación de la Sra. Whited de que LUMA implemente el mecanismo de desacoplamiento a través de una cláusula adicional en lugar de a través de la contabilidad diferida para promover una conciliación oportuna y transparente de los ingresos por desacoplamiento, respaldar un flujo de efectivo estable para los servicios públicos y evitar grandes saldos acumulados de cobros insuficientes o excesivos por desacoplamiento.

Finalmente, el Sr. Figueroa está de acuerdo con la recomendación de la Sra. Whited de que LUMA presente una descripción completa del mecanismo de desacoplamiento antes de su implementación, incluyendo fórmulas, insumos, fuentes de datos y documentos de trabajo. En lo que respecta a las actualizaciones anuales, el Sr. Figueroa recomienda que el Negociado de Energía trate la actualización de esta cláusula adicional de forma similar a otras actualizaciones periódicas de cláusulas adicionales. También indica que LUMA está de acuerdo con que el Negociado de Energía revise el mecanismo de desacoplamiento durante un futuro caso de tarifas base, pero sugiere que el próximo caso de tarifas se llevará a cabo antes de cualquier experiencia real con la cláusula adicional y recomienda que la revisión se realice en un caso de tarifas posterior cuando haya algunos años de información sobre cómo funcionó dicha cláusula.

Annex 5

LUMA Exhibit 72 - Ms. Joseline Estrada's Surrebuttal Testimony (Notarized)

**GOVERNMENT OF PUERTO RICO
PUERTO RICO PUBLIC SERVICE REGULATORY BOARD
PUERTO RICO ENERGY BUREAU**

IN RE:

**PUERTO RICO ELECTRIC POWER
AUTHORITY RATE REVIEW**

CASE NO.: NEPR-AP-2023-0003

Surrebuttal Testimony of

Joseline N. Estrada Rivera

Director, Tariff & Budgets, Load Forecasting and Research, LUMA Energy ServCo, LLC

October 30, 2025

**Summary of Surrebuttal Testimony of
JOSELINE N. ESTRADA RIVERA
ON BEHALF OF
LUMA ENERGY LLC AND LUMA ENERGY SERVCO, LLC**

Ms. Joseline N. Estrada Rivera (“Ms. Estrada”) is Director of Tariff & Budgets, Load Forecasting and Research at LUMA Energy ServCo, LLC. In her prepared Surrebuttal Testimony, Ms. Estrada presents LUMA’s response to critiques by Dr. Ramón J. Cao García, Mr. E. Kyle Datta, Dr. Asa Hopkins, and Mr. Zachary Ming regarding LUMA’s load forecasting methodology, rate design considerations, and the economic implications of proposed rate changes.

LUMA’s forecasting methodology is built on econometric models that incorporate structural and behavioral changes in Puerto Rico’s energy landscape. The core explanatory variables used in the regression models include Cooling Degree Days (CDD) to capture temperature sensitivity, monthly seasonal binary variables to account for intra-annual variation, Gross National Product (GNP) as the primary macroeconomic input, and population. While load modifiers such as energy efficiency (EE), electric vehicles (EVs), distributed generation (DG), and combined heat and power (CHP) systems are not included as explicit variables in the regression equations, their historical effects are embedded in the observed consumption data used to estimate the models. To avoid double counting, LUMA applies incremental adjustments for these modifiers in the forecast period, using FY2025 as the baseline for DG displacement and a similar approach for CHP in the industrial sector.

LUMA defends its exclusion of electricity price from the residential regression model based on both empirical evidence and practical forecasting considerations. Historical data show that electricity consumption in Puerto Rico is relatively price inelastic. In early 2023, Guidehouse and the LUMA LFR team explored the possibility of including electricity price as an explanatory variable in the forecast model. However, the analysis revealed counterintuitive correlations between historical consumption and average prices, suggesting that price was not a reliable predictor in Puerto Rico’s context. Furthermore, many U.S. utilities, including those regulated by state commissions, do not include electricity price in their long-term load forecasting models. A 2016 study by Lawrence Berkeley National Laboratory found that only about half of load-serving entities explicitly modeled price elasticity. Utilities such as Portland General Electric, ISO New England, and DTE Electric have published methodologies that exclude price as a direct input, yet their forecasts are accepted by regulators and used for integrated resource planning. In this context, LUMA’s decision to exclude electricity price is grounded in empirical testing, statistical rigor, and alignment with industry best practices. The model remains robust, transparent, and fit for purpose in supporting long-term planning and regulatory review.

An often-overlooked aspect of rate analysis is the composition of the electricity bill. Since 1996, the base rate has accounted for only 21% to 35% of the total bill, with the remainder driven by fuel and purchased power adjustments. These components are more volatile and influenced by external factors such as oil prices and generation availability. The base rate had not been updated since 1989 until a provisional increase was implemented in 2016. Despite this, economic indicators like GNP and disposable income did not show negative impacts, suggesting that base rate increases alone do not trigger economic crises. LUMA emphasizes that the Integrated Resource Plan (IRP),

which includes lower-cost dispatchable resources, is expected to reduce long-term costs and help offset any base rate increases approved by the Energy Bureau.

Affordability concerns raised by Dr. Cao are addressed with updated 2024 data showing that average residential bills remain within the FOMB's 6% threshold under most scenarios. Low-income customers benefit from fixed-rate programs, and NEM participants are shielded from rate increases through a 1:1 retail credit. LUMA disputes the claim that electricity rate hikes will cause widespread grid defection, noting that full disconnection is economically impractical and that reliability, not price, is the primary driver of DER adoption. The company's CBES and ASAP programs aim to enhance reliability and manage DER integration.

LUMA challenges Dr. Cao's inflation projections, emphasizing electricity's small CPI weight and the dominant role of global supply chain and commodity price shocks in recent inflation trends. Historical data show that inflation remained low or negative in years when base rates increased, and recent inflation spikes were driven by external factors. LUMA argues that attributing inflation or economic decline primarily to electricity rates oversimplifies Puerto Rico's macroeconomic context.

The company also disputes the "death spiral" narrative, explaining that grid defection is limited and that most large customers remain connected for backup and flexibility. CHP adoption among industrial users is driven by reliability concerns, not cost avoidance. A 2023 Guidehouse analysis found that while 43 large customers displaced about 34 GWh/month through CHP, fewer than five fully disconnected from the grid. These customers continue to rely on centralized power for backup and operational flexibility. LUMA emphasizes that DER adoption is increasing, but the grid remains essential for most customers.

LUMA acknowledges past forecast errors, particularly in FY2023 and FY2024, and LUMA has since revised its residential and industrial models. The residential model now treats post-2020 consumption increases as a permanent structural change, driven by behavioral shifts and record-breaking heat. The industrial model was updated using a reconstitution approach that adds back historical self-generation to isolate underlying demand. These changes improve model accuracy and reflect evolving consumption patterns. The commercial model, by contrast, has demonstrated strong performance and remains unchanged.

The load forecasting improvement project, launched in 2023, is primarily aimed at the systematic evaluation of the factors driving significant variances across different customer classes. This effort focuses particularly on identifying and analyzing emerging variables that have begun to substantially impact electricity demand in recent years. The ultimate goal is to enhance the accuracy of forecasting models.

In response to Mr. Datta's testimony, LUMA defends its concerns about lost revenue and cost shifting under volumetric rate structures. NEM customers may underpay for grid services they still use, creating cross-subsidization issues. While modern rate design tools like TOU rates can help, LUMA stresses the need to modernize tariffs to reflect cost causation and fairness. The company also highlights real marginal costs associated with DER integration, including voltage regulation, backflow protection, and transformer upgrades.

LUMA acknowledges the need for empirical data and is conducting a comprehensive load profile study to better quantify DER impacts. The company agrees with Dr. Hopkins that no additional adjustments are needed for non-programmatic EE, as these effects are already embedded in historical data. LUMA also defends its use of binary variables and exclusion of intercepts in regression models as standard econometric practice. The decision to use the 73rd percentile CDD scenario for residential forecasts is supported by recent heat trends and is better aligned with observed consumption.

The commercial model's low sensitivity to CDD and strong forecast performance justify maintaining its current specification. LUMA partially agrees with Mr. Ming's critique on load modifiers and is evaluating a revised residential model that excludes DG displacement from historical data. The company emphasizes that its forecasting approach is empirically grounded, transparent, and continuously refined. Overall, LUMA's testimony supports the validity of its models and the reasonableness of its assumptions in the context of Puerto Rico's evolving energy system.

TABLE OF CONTENTS

	Page
I. INTRODUCTION	6
II. SURREBUTTAL TO CAO REPORT.....	8
III. REBUTTAL TO DATTA TESTIMONY.....	57
IV. REBUTTAL TO HOPKINS REPORT.....	66
V. REBUTTAL TO MING REPORT	70

I. INTRODUCTION

Q. 1 Please state your name, business address, title, and employer.

A. My name is Joseline N. Estrada Rivera. My business address is LUMA Energy, PO Box 363508, San Juan, Puerto Rico 00936-3508. I am the Director of Tariff & Budgets, Load Forecasting and Research for LUMA Energy ServCo, LLC (“LUMA ServCo”).

Q. 2 On whose behalf are you submitting this Surrebuttal Testimony?

A. My surrebuttal testimony is provided on behalf of LUMA Energy, LLC and LUMA Energy ServCo, LLC (jointly referred to as “LUMA”).

Q. 3 What is the purpose of your surrebuttal testimony?

A. To respond to several portions of the report of Dr. Ramón J. Cao García (“Cao Report”) filed in this proceeding on September 8, 2025 by the Institute of Competitiveness and Economic Sustainability (“ICSE”); pre-filed testimony of Mr. E. Kyle Datta (“Datta Testimony”) filed in this proceeding on September 8, 2025 on behalf of Solar & Energy Storage Association; the report of Dr. Asa Hopkins (“Hopkins Report”), consultant to the Puerto Rico Energy Bureau (“PREB”), dated October 2, 2025; and the report of Zachary Ming (“Ming Report”), consultant to PREB, dated October 6, 2025. The main purpose of my surrebuttal testimony is to respond to criticisms and mischaracterizations of my testimony, responses for information, and the load forecast used by LUMA. I will also respond to reports and statements made by others that I believe are inaccurate or provide incomplete information.

Q. 4 Are there any exhibits attached to your testimony?

A. Yes

23 **Q. 5 Please identify and enumerate those exhibits.**

24 A. I am sponsoring the following exhibits:

- 25 • LUMA Ex. 72.01 (Appendix 1 to my Surrebuttal Testimony)
- 26 • LUMA Ex. 72.02 (*An Analysis of the Economic Impact of Increasing the Price of*
27 *Electricity in Puerto Rico*, prepared by Navigant Economics, August 19, 2016)
- 28 • LUMA Ex. 72.03 (Improvement 5 CHP Report 2024-05-23)
- 29 • LUMA Ex. 72.04 (Improvement 5 Report - Solar PV 2024-04-29)
- 30 • LUMA Ex. 72.05 (Attachment 1 to LUMA's Response to SESA-of-LUMA-DIST-26).

31 **Q. 6 Did you consider any documents for your rebuttal testimony?**

32 A. Yes, I did.

33 **Q. 7 Which documents did you consider for your rebuttal testimony?**

34 A. In preparing this testimony, I reviewed the following documents:

- 35 • LUMA Ex. 4.0 (7.03.25) Direct Testimony Joseline N. Estrada-Rivera-Load
36 Forecasting
- 37 • LUMA Ex. 4.03 (7.03.25) Load Forecast Modifiers FY 2025 (Excel)
- 38 • LUMA Exhibit 4.02 (7.03.25) Load Forecast 2025 Update
- 39 • PC Exhibit 58.03 – My response to PC-of-LUMA-LOAD_FOR-5
- 40 • My response to SESA-of LUMA-LOAD_FOR-3
- 41 • All documents referenced in Appendix 1, attached to this testimony as Ex. 72.01.

42 **Q. 8 Did you provide a response to a request for information regarding the calculations on**
43 **Table 9 in your direct testimony?**

44 A. Yes.

Q. 9 Please state and explain that response.

A. In the previous estimate included in my testimony, load displacement due to Net Metering (NM) was applied uniformly across all rate classes. The methodology has been updated to more accurately reflect customer participation in the NM program. Net Metering (NM) load displacement was applied exclusively to the rate classes with customers actively enrolled in the program. Revised Table 9, inserted below, reflects this update. (Also refer to Ex. 72.05 derivation file SESA-of-LUMA-DIST-26_Attachment 1 with intact formulas for traceability.)

Table 9. NEM Program Base Revenues Reduction (Revised)

FY	Base Load \$ (only rates with enrolled customers)	Base load-NM (M\$) (only rates with enrolled customers)	Base Load (GWh)	Base load-NM (GWh) (only rates with enrolled customers)	NM Displacement (GWh)
2026	821.7	722.4	99.2	14,507.3	1,907.5
2027	823.5	705.3	118.2	14,165.1	2,294.0
2028	830.0	694.5	135.5	13,951.1	2,646.8

The reductions in load account for all displacements from the NM system, including both self-consumption and exported energy.

I was also asked to “explain why LUMA revenues, which only represent T&D costs, would be reduced by more than the reduction in NEM self-consumption [KWh x the rate (\$/Kwh)] for the specific rate class.” The reason why LUMA revenues would be reduced by more than the reduction due to NM displacement is because total revenues cover not only transmission and distribution expenses but also expenses associated to the Puerto Rico Energy Power Authority (PREPA), Genera, and Title III.

II. SURREBUTTAL TO CAO REPORT

Q. 10 On page 3 of the Cao Report, Dr. Cao stated that the equations used in his analysis

65 **did not take into account important recent developments in Puerto Rico, including**
66 **the rapid growth of photovoltaic (“PV”) electricity generation by resident consumers,**
67 **post-COVID social trends, the adoption of combined heat and power systems**
68 **(“CHP”) by institutional consumers, the rise in temperatures, and other variables.**

69 **Does LUMA have a response?**

70 A. Yes.

71 **Q. 11 Please state and explain LUMA’s response.**

72 A. Dr. Cao’s acknowledgment that his analysis did not incorporate several key developments
73 in Puerto Rico, such as the rapid growth of distributed photovoltaic (“PV”) generation,
74 post-COVID behavioral shifts, increased adoption of combined heat and power (“CHP”)
75 systems, and rising temperatures, raises a significant methodological concern: the potential
76 for Omitted Variable Bias (“OVB”).

77 In econometric analysis, OVB arises when a model excludes variables that are both
78 relevant to the outcome being studied and correlated with included explanatory variables.
79 This can lead to biased and inconsistent estimates, ultimately distorting the conclusions
80 drawn from the analysis.

81 For example, failing to control seasonal temperature variation, as captured by
82 Cooling Degree Days (“CDD”), can misrepresent electricity demand patterns. In Puerto
83 Rico, electricity consumption, particularly for cooling, is highly sensitive to temperature
84 fluctuations. If a model omits CDD, it may incorrectly attribute seasonal peaks in demand
85 to other factors, such as economic activity or customer behavior, leading to flawed policy
86 or planning conclusions.

87 LUMA emphasizes the importance of incorporating these evolving structural and
88 behavioral factors into a forecast modelling of Puerto Rico's energy system. As explained
89 later in this testimony, LUMA currently incorporates the historical impact of these
90 variables into the development of its forecasting models for the residential and commercial
91 customer classes. The models demonstrate strong statistical performance, with exogenous
92 variables effectively explaining the trends in the endogenous variable (consumption). For
93 the industrial class, this year we excluded from the historical data the load displaced by
94 customers with CHP systems, in an effort to correct the deviation and improve the
95 correlation with Gross National Product ("GNP").

96 The load forecast LUMA used to determine revenues incorporated the impact of
97 weather and distributed generation sources, such as rooftop PV systems and CHP systems.
98 Lines 85 to 176 of my direct testimony provide a detailed explanation of how both the
99 distributed generation adjustments and the CDD variable were incorporated.

100 As a first step, LUMA developed a base load forecast using regression models,
101 selecting CDD as an exogenous variable. CDD is a weather-related metric that estimates
102 the energy required to maintain a comfortable indoor temperature. In other words, CDD
103 reflects how hot it is and how much people are likely to use air conditioning, which is a
104 major driver of electricity use in Puerto Rico. For further details, please refer to lines 160
105 to 176 of my direct testimony.

106 Then, the impact of distributed generation was applied to this base load.
107 Additionally, a dummy variable was included in the residential model to capture the
108 increase in residential consumption observed after the COVID-19 period. This variable
109 represents lasting changes in how people use electricity at home, such as more time spent

indoors or working remotely. This phenomenon is discussed in lines 179 to 196 of my direct testimony.

Including variables like CDD and a COVID-19-related adjustment makes LUMA's electricity demand forecast more accurate and reliable.

Additionally, households have increasingly transitioned to high-efficiency appliances, while others have integrated emerging end-use technologies such as electric vehicles, remote work infrastructure, and enhanced space cooling systems. These behavioral and technological shifts exert upward or downward trends on electricity consumption patterns. Although the model does not explicitly quantify the marginal impact of each individual driver, the inclusion of a structural dummy variable serves as a proxy to capture the aggregate effect of these exogenous changes. This adjustment improves the model's specification, enhances its alignment with observed consumption trends, and mitigates the risk of structural forecasting errors.

Q. 12 On page 3 of the Cao Report, Dr. Cao argues that Appendix 1 to his report shows that that LUMA's "load forecasts are not valid" due to lack of information and methodological pitfalls. Does LUMA agree?

A. No, LUMA respectfully disagrees with Dr. Cao's assertion.

Q. 13 Please state and explain LUMA's response.

A. LUMA applies an empirical methodology aligned with best practices used across many U.S. jurisdictions. Since 2023, as part of our forecast improvement project, LUMA, together with our consultant Guidehouse, has systematically evaluated each model to ensure that all relevant variables influencing demand are considered, leveraging the most advanced techniques in the industry.

As evidence for his assertion, Dr. Cao references “large forecasting errors resulting from LUMA’s forecast equations” and “a serious lack of information and methodological pitfalls in these forecasting models.” Dr. Cao provides no further evidence in his introduction supporting his assertion that LUMA’s load forecasts are invalid. In the testimony that follows, LUMA will demonstrate that there is no evidence of a methodological pitfall.

Q. 14 On page 12 of the Cao Report, Dr. Cao wrote that a “demand equation is essential to estimate how much is going to be the quantity demanded or consumed of a good or service when there are changes in the price of the merchandise, the income of the consumer, or the price of substitute or complementary goods or services.” He argues that LUMA did not include “any information about estimated demand functions of electricity by customer categories,” further arguing that if LUMA does not know the relevant demand equations then it cannot know what will happen to expected quantities of electricity to be consumed if requested increases in the fixed tariff rate are granted. Does LUMA have a response?

A. Yes.

Q. 15 Please state and explain LUMA’s response.

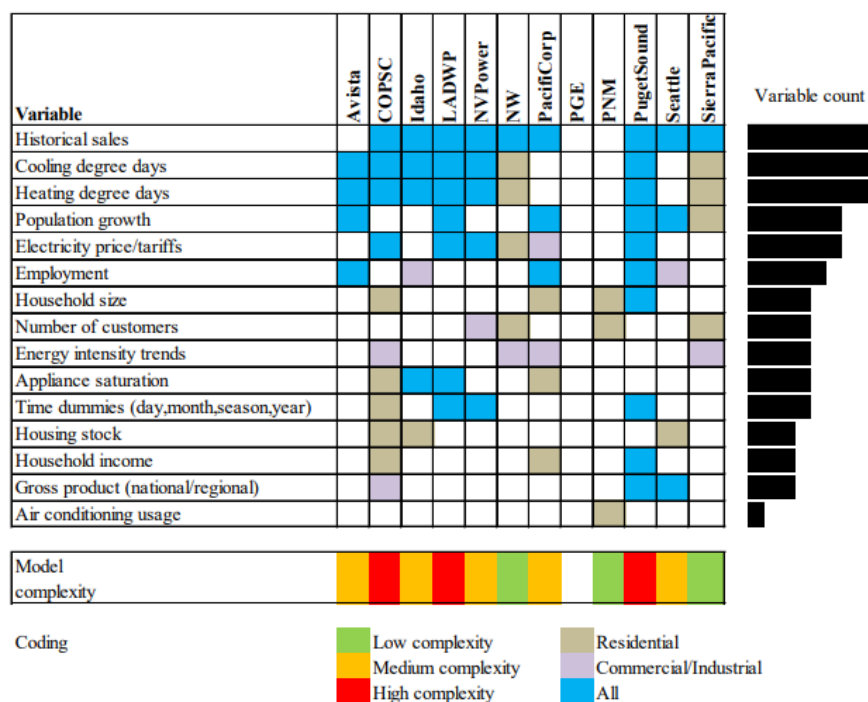
A. To start, other jurisdictions have accepted a similar approach to forecasts. Many mainland US utilities that use econometric methods to forecast customer energy consumption do not model electricity consumption directly as a function of its price, and these forecasts continue to be accepted by their regulators.

While Puerto Rico is indeed different from the mainland U.S. in many ways, this does not necessarily invalidate the use of similar forecasting methodologies. In fact, Puerto

Rico's electricity market structure, characterized by a single transmission and distribution operator (LUMA) and a fully interconnected island-wide grid, supports the assumption of price inelasticity in the short run, as consumers have limited alternatives and remain highly dependent on grid-supplied electricity. While demand may become somewhat more elastic in the long run due to factors like increased adoption of distributed energy resources or changes in the current regulation related to the net metering program, structural constraints such as limited provider choice and continued grid reliance suggest that demand is likely to remain inelastic overall, even over longer time horizons. Unlike competitive markets where customers can switch providers or adopt alternative energy sources more freely, Puerto Rico's centralized service provision limits consumer responsiveness to price changes.

A 2016 study of IRP long-run load forecast performance documented what types of variables were included in the load forecasting methods of different utilities. *See* Carvallo, Juan Pablo; Larsen, Peter H.; Sanstad, Alan H. and Charles A. Goldman, *Load Forecasting in Electric Utility Integrated Resource Planning*, Ernest Orlando Lawrence Berkeley National Laboratory, October 2016 (Refer to Exhibit 72.01, at ¶ 1) <https://eta-publications.lbl.gov/sites/default/files/lbnl-1006395.pdf>. Figure 1 from that study, reproduced below, provides a visual summary from that paper identifying that: "About half of the LSEs [load serving entities] in our sample reported specific information about price elasticities..."

Figure 1. LBNL Study of Model Variables



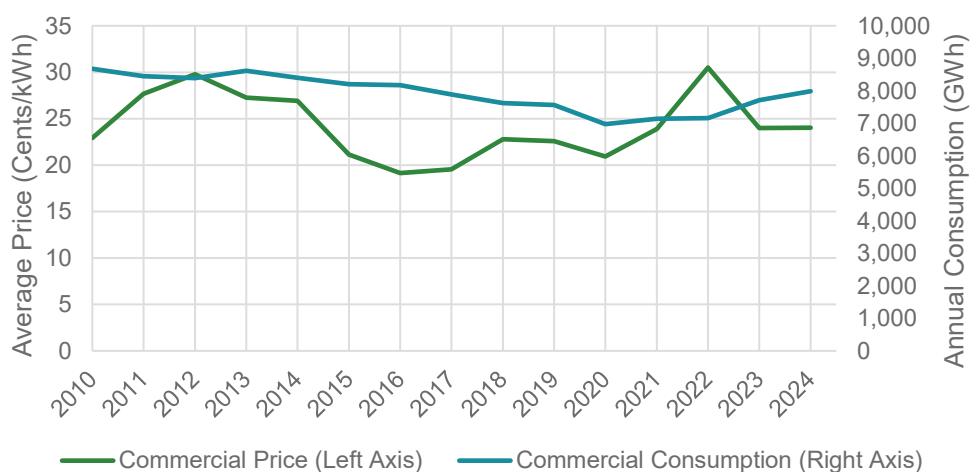
Other load forecast methodologies that were recently published and that do not model energy consumption as a direct function of prices include:

- **Portland General Electric (PGE).** Refer to Exhibit 72.01, at ¶ 2.
- **ISO New England.** See Section 3 (“Energy Forecasts”) of the May 2024 Forecast Modeling Procedure for the 2024 CELT Report: ISO New England Long-Run Energy and Seasonal Peak Demand Forecasts (Refer to Exhibit 72.01, at ¶ 3).
- **DTE Electric Company.** See, for example, Q20 (PDF page 12 of 556): “How was the Residential forecast developed?” of the direct testimony of DTE’s lead forecaster for Case No. U-21534 (Refer to Exhibit 72.01, at ¶ 4).

One example of a utility that does include some proxy for electricity prices in its forecasting model is ComEd. (Commonwealth Edison Company-Refer to Exhibit 72.01, at ¶ 5 - Appendix A of the document Load Forecast for Five-Year Planning Period June 2025

190 – May 2030). This utility includes (for the Residential class only) a variable for average
191 monthly billed amounts.

192 In early 2023, Guidehouse and the LUMA LFR team explored the possibility of
193 implementing something similar as part of LUMA's load forecast. Specifically, we
194 assessed whether we should include price as an explanatory variable in the analysis.
195 Following further analysis, the Guidehouse team determined that doing so would be
196 inappropriate given the counter-intuitive correlation between historical consumption and
197 average prices (see, for example, a comparison of average price (cents per kWh) and annual
198 consumption for Commercial customers in Figure 2 below). Despite a steady decline in the
199 average commercial class price between 2012 and 2017, there is also a decline in total
200 commercial consumption. The consumption data was remediated and did not count atypical
201 events such as Hurricane María.

Figure 2. Comparison of Commercial Average Price and Annual Consumption**Previous Studies on Elasticity in Puerto Rico & Empirical Data**

Dr. Cao's concerns about the importance of understanding how customers respond to rate changes are valid. However, existing research, such as the study *An Analysis of the Economic Impact of Increasing the Electricity Rates in Puerto Rico* conducted for the 2017 Rate Case (refer to LUMA Ex. 72.02), provided quantitative estimates of electricity demand elasticity by customer class. While it is true that no agreement with bondholders (RSA) has been finalized and that Puerto Rico's macroeconomic conditions have evolved significantly since the study (as reflected in rising employment, wages, and business activity), these changes warrant further study rather than invalidate the original findings.

The core insight remains electricity demand in Puerto Rico is relatively inelastic. That is, while rate increases may lead to modest reductions in consumption, the overall effect is small in percentage terms. Revenue trends also do not exhibit a corresponding pattern, suggesting that electricity remains a necessary good with limited short-term responsiveness to price changes.

An often-overlooked analysis is the composition of the electricity bill. The tariff

structure consists of several components. Initially, it included a base charge and a fuel charge. In 2000, with the entry of one of the independent power producers, energy purchases were incorporated. Later, in the 2017 rate case, CELI charges and government-mandated subsidies were added. Most of these subsidies, required by Puerto Rico's laws, had previously represented revenue losses.

As the recession began, oil prices rose, and energy purchases and new charges such as CELI and subsidies were introduced, the base rate component began to decline, becoming increasingly dependent on fuel and purchased power adjustments. Since fiscal year 1996, the base rate has accounted for approximately 21% to 35% of the total amount billed to customers. This component had not been updated since 1989, until the approval of a base rate increases in the 2017 rate case, which was implemented through a provisional tariff in August 2016.

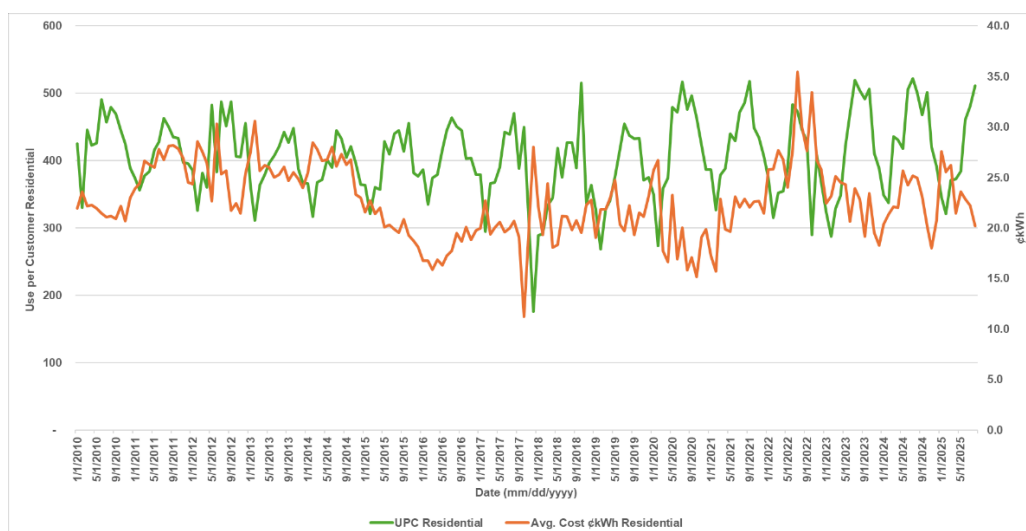
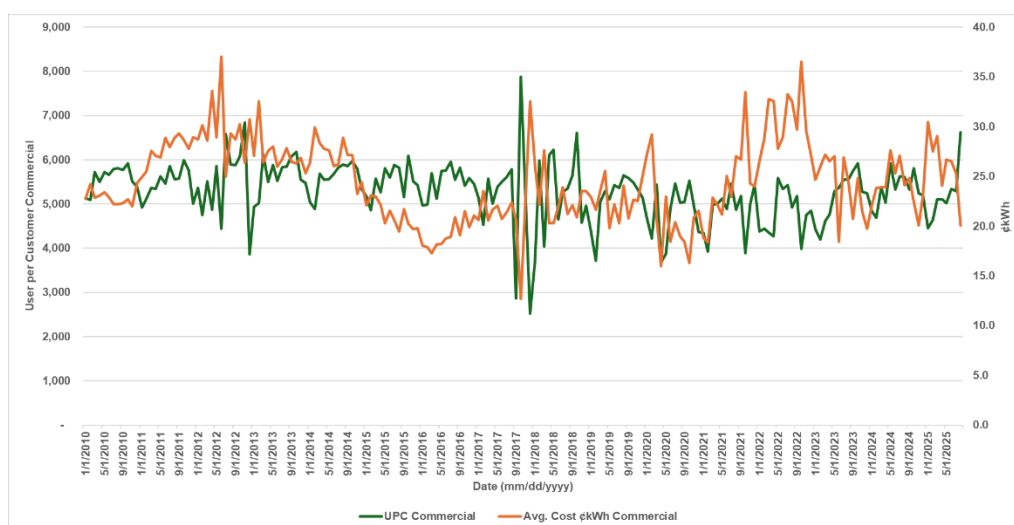
Despite this increase, data from the Puerto Rico Planning Board show that key economic indicators such as GNP and real disposable personal income ("YPD") did not reflect negative impacts on the economy. Past trends indicate that an increase in the base rate alone has not led to an economic crisis in Puerto Rico. It is important to recognize that other exogenous factors, such as geopolitical events affecting fuel prices and the availability of the generation fleet, have a greater influence on major tariff components. These factors directly impact the fuel and purchased power adjustments, which are recovered through the FCA and PPCA mechanisms on the bill.

LUMA believes that, in the long term, any savings in these components resulting from the implementation of the Integrated Resource Plan ("IRP"), which includes lower-

241 cost dispatchable resources, should help offset any rate increases approved by the Energy
242 Bureau in this proceeding.

243 The dataset, as shown in Figure 3 through 5 below, spans from January 2010 to
244 August 2025, covering over 15 years of monthly electricity pricing and consumption data
245 across Puerto Rico’s three main customer classes: residential, commercial, and industrial.
246 It includes average electricity costs (in ¢/kWh) and average usage per customer (“UPC”)
247 for each class, offering a rich time series to examine how consumption patterns have
248 evolved in response to price changes, economic shocks, and broader structural shifts in the
249 energy sector.

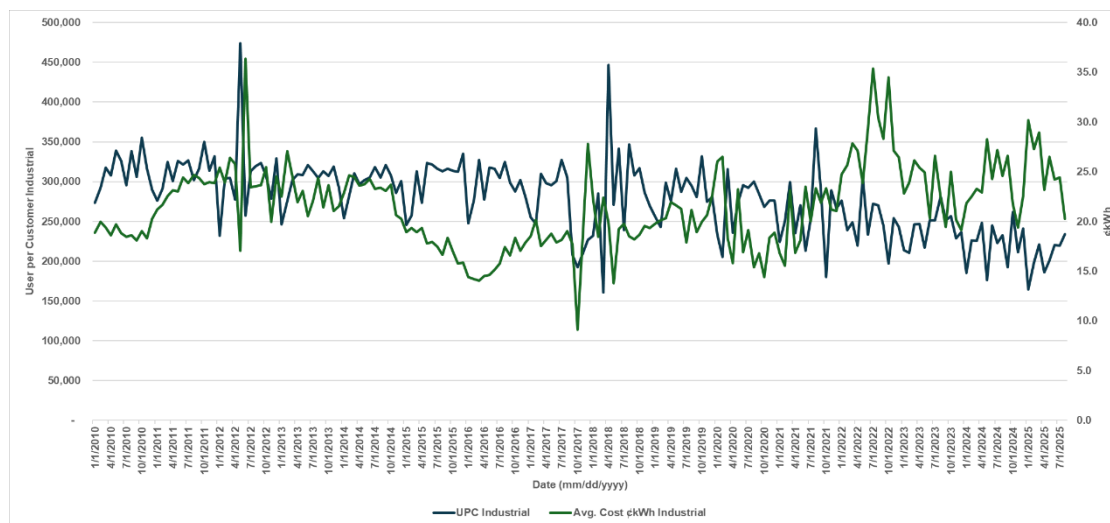
250 The following figure, Figure 3, illustrates the overall impact of the cost per kWh on
251 consumption per customer. Prior to 2020, residential electricity usage per customer in
252 Puerto Rico was remarkably stable, showing little variation despite fluctuations in average
253 prices. Starting in 2020, however, there is a noticeable upward shift in consumption, while
254 average prices remained relatively stable. This suggests a structural change in household
255 electricity use, possibly linked to lifestyle adjustments during and after the pandemic.
256 Overall, the data supports the conclusion that residential electricity demand is price
257 inelastic, with consumption largely unresponsive to price changes.

Figure 3: User per Customer Residential Consumption vs Residential Average Cost c/kWh**Figure 4: User per Customer Commercial Consumption vs Commercial Average Cost c/kWh**

Based on Figure 4, commercial electricity use per customer (UPC) exhibits relatively modest fluctuations compared to the more pronounced changes in average commercial electricity prices, indicating inelastic demand. During periods of price increases, such as 2012, 2017, and 2022, commercial usage did not decline proportionally, suggesting that electricity remains an essential input for business operations. Likewise, when prices fell, consumption did not rise significantly, reinforcing the notion that demand is not highly sensitive to cost. Overall, the data implies that commercial electricity

consumption in Puerto Rico is price-inelastic, with usage patterns shaped more by operational needs than by price signals.

Figure 5: User per Customer Industrial Consumption vs Residential Average Cost c/kWh



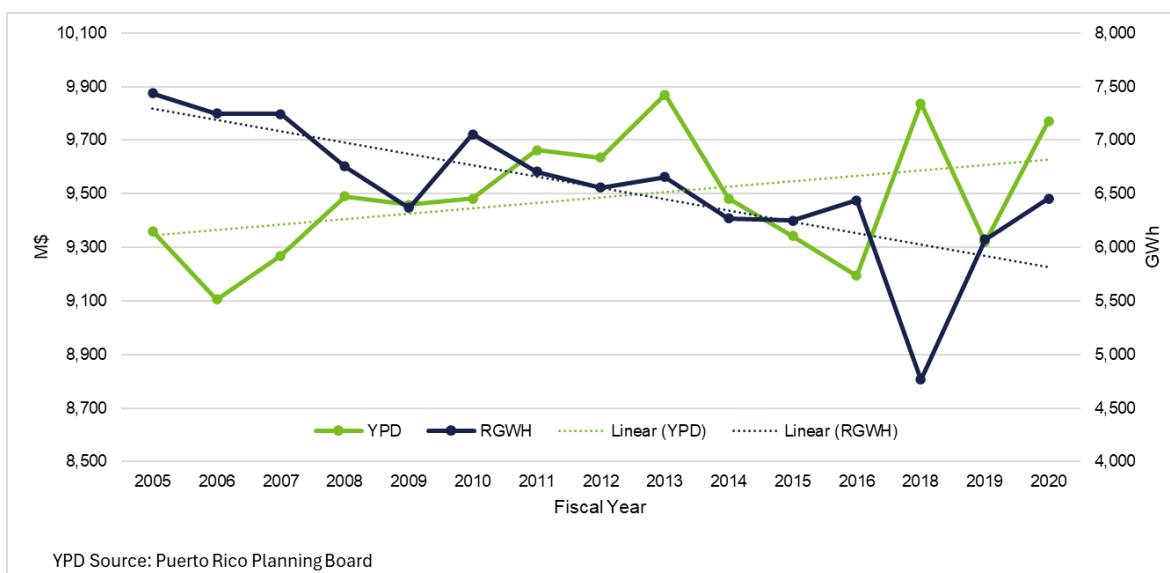
While industrial electricity demand, Figure 5, in Puerto Rico historically appeared price-inelastic, recent trends suggest a structural shift. Since 2021, average prices have increased while usage per customer has declined, breaking the earlier pattern of stable consumption. This divergence is likely not due to price responsiveness alone, but rather reflects a substitution effect: industrial customers are increasingly adopting on-site generation through PV systems and cogeneration to secure more reliable and cost-predictable energy during critical production periods.

This behavior represents a form of load displacement, where firms reduce their reliance on the utility by sourcing part of their electricity needs independently. Although these customers still rely on the grid, the observed reduction in metered consumption points to a changing relationship with the utility, one that will be explored further in the context of grid defection and distributed energy strategies.

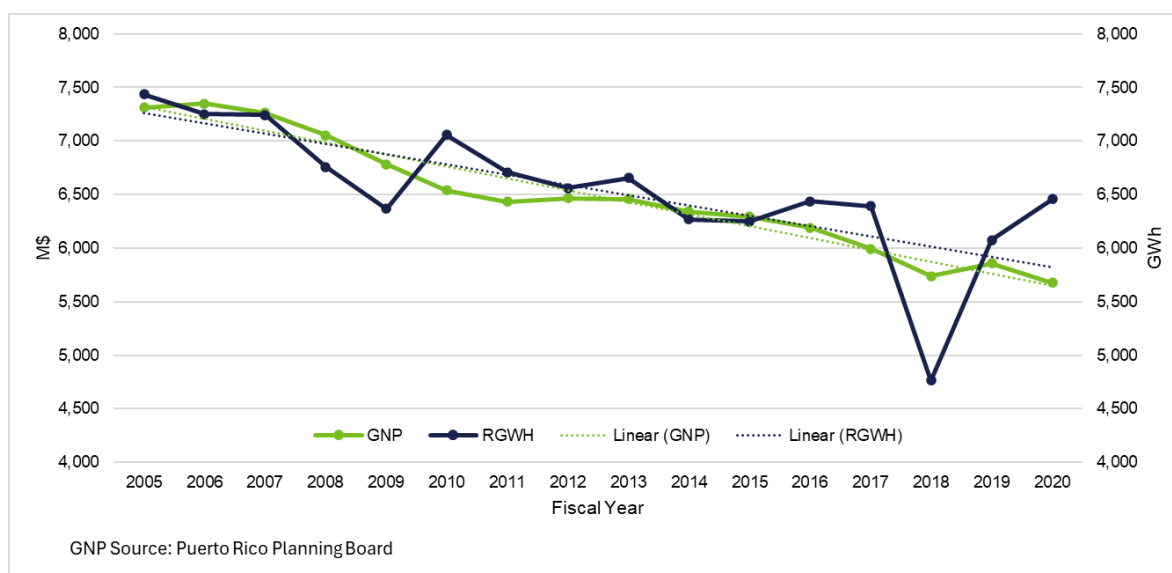
Macroeconomic Inputs Considerations

Annual historical data indicates that, beginning with the recession in 2007 and the subsequent financial assistance received by the population, particularly through President Obama's ARRA program, the correlation between residential energy consumption and real disposable personal income (YPD) began to weaken—at times even showing an inverse relationship. Although the aid was intended to alleviate the effects of the economic downturn, it did not result in increased residential electricity consumption. In contrast, the data shows a stronger and more consistent correlation with Gross National Product (GNP) during the same period, even beyond the recession. Figures 6 and 7 illustrate the trends between consumption and both macroeconomic indicators.

Figure 6: Residential Consumption (RGWH) and Personal Disposable Income (YPD) Constant 1954=100



297 **Figure 7: Residential Consumption (RGWH) and Gross National Product (GNP) Constant 1954=100**



298
 299 Figures 6 and 7 illustrate the trends between consumption and both macroeconomic
 300 indicators. While residential electricity consumption has historically shown a stronger
 301 correlation with GNP than with YPD, this relationship also aligns with the practical
 302 constraints of the forecasting process.

303 LUMA's forecasting methods are required to use only macroeconomic projections
 304 provided by the Financial Oversight and Management Board (FOMB), which does not
 305 publish forecasts for disposable personal income or net income. As a result, GNP is used
 306 in the regression equations as the primary macroeconomic driver.

307 However, while GNP may offer explanatory value in understanding historical
 308 consumption patterns, in our forecasting models it has a relatively lower impact on
 309 projected commercial and industrial consumption compared to other variables, such as
 310 sector-specific indicators or weather-related factors.

311 **Q.16 On page 20 of the Cao Report, Dr. Cao wrote, "When more than two or three**
 312 **dummies are used in an equation, it is necessary to test for the independence of the**

313 independent variables.” Do you agree?

314 A. No.

315 **Q. 17 Please state and explain your response.**

316 A. All binary variables included in the models identify discrete periods of time. A binary
317 variable is included, for example, for each month of the calendar year, to capture the
318 conditional mean of class-level consumption specific to that month. This is standard
319 practice in time-series forecasting. (Refer to Exhibit 72.01, at 70.01, at ¶ 6). No test of
320 independence is required. It is fundamentally true that monthly binaries are dependent:
321 February must always follow January.

322 **Q. 18 On page 20 of the Cao Report, Dr. Cao also admits that the use of dummy variables**
323 **is an acceptable and useful practice in econometrics, but that their use “involves the**
324 **risk of dummy variables trap,” referring to the use of binary variables that are**
325 **perfectly colinear with the intercept term. Does LUMA have a response?**

326 A. Yes.

327 **Q. 19 Please state and explain LUMA’s response.**

328 A. As further explained in connection with the issue of intercepts below, LUMA’s load
329 forecasting equations excluded the intercept term for this reason and Dr. Cao’s concern is
330 unfounded. Dr. Cao also admits that not including intercepts is not unusual in forecasting
331 models.

332 **Q. 20 On page 20 of the Cao Report, Dr. Cao noted that LUMA’s load forecasting**
333 **equations do not include intercepts. Does LUMA have a response?**

334 A. Yes.

Q. 21 Please state and explain LUMA’s response.

A. Dr. Cao’s report on this issue references the regression equations used by the LUMA load forecast. For convenience, the Residential model is reproduced here:

$$y_t = \sum_{m=1}^{M=12} \beta_{1,m} month_{m,t} + \beta_2 CDD_t + \beta_3 Pop_t + \beta_4 COVIDwin_t \\ + \sum_{m=6}^{M=9} \beta_{5,m} month_{m,t} \cdot post2019_t \cdot CDD500_t + \beta_6 month_{m \in (5,10),t} \cdot post2019_t \cdot CDD500_t + \varepsilon_t$$

The first term in this equation is (as it is in all of the equations) this:

$$\sum_{m=1}^{M=12} \beta_{1,m} month_{m,t}$$

In this term, the “month_{m,t}” variable is defined as a set of twelve binary variables capturing monthly seasonality. This variable is equal to 1 when month of sample t is the m-th month of the calendar year, and zero otherwise. For example, variable month_{1,t} is equal to one when month of sample t is January and zero otherwise.

The inclusion of 12 binary variables (one for each month) means that also including an intercept term would result in perfect multicollinearity, meaning that the moment matrix cannot be inverted, and that the parameter estimates would not be well-defined. This is the “dummy trap” that Dr. Cao himself cautions against. Put another way, the regression equations do not have a single intercept, but rather they have 12—a different one for each month of the year.

Q. 22 On page 20 of the Cao Report, Dr. Cao states that LUMA’s load forecasting equations “[d]o not provide estimated values for regression coefficients, not their standard deviations” and that the equations “[d]o not provide the standard goodness of fit

354 **statistics.” Does LUMA have a response?**

355 A. Yes.

356 **Q. 23 Please state and explain LUMA’s response.**

357 A. Regression outputs, including parameter estimates, standard errors, and goodness-of-fit
358 statistics are reproduced below. Notably, in Dr. Cao’s report, estimated parameter standard
359 errors are called “standard deviations.” The standard deviation is a measure of the
360 variability of a set of observed values, while the standard error is an estimate of the
361 precision of an estimated value. They are two different statistical concepts.

362 Parameter estimates for all customer classes were also included in the supporting
363 documentation filed on July 3, 2025, under the file titled 'LUMA Exhibit 4.02 (7.03.25) –
364 Load Forecast 2025 Update.xlsx'. The coefficients used to derive the base (unadjusted)
365 forecast can be found in row 3 of the 'Residential 73rd Percentile', 'Commercial', and
366 'Industrial' tabs.

367 Guidehouse has included the standard summary output of each linear regression
368 model, as produced by RStudio, the statistical computing environment used for model
369 estimation. Figures 8 through 10 below illustrate the output.

370 **Figure 8. Residential Model Output.**

Coefficients:				
	Estimate	Std. Error	t value	Pr(> t)
cdd	0.0568	0.0903	0.63	0.53081
cal_month_f8	332.6355	84.8448	3.92	0.00015 ***
cal_month_f1	231.5035	73.4917	3.15	0.00209 **
cal_month_f2	166.5224	71.9912	2.31	0.02253 *
cal_month_f3	224.0828	74.2429	3.02	0.00314 **
cal_month_f4	232.9181	76.4253	3.05	0.00287 **
cal_month_f5	274.6342	80.3916	3.42	0.00088 ***
cal_month_f6	294.3413	81.8764	3.59	0.00048 ***
cal_month_f7	327.5653	84.0690	3.90	0.00017 ***
cal_month_f9	316.5475	84.0350	3.77	0.00026 ***
cal_month_f10	303.1315	84.9352	3.57	0.00053 ***
cal_month_f11	269.8583	77.8186	3.47	0.00074 ***
cal_month_f12	245.9428	75.9469	3.24	0.00158 **
res_covid_winter_20_21	37.0617	11.5619	3.21	0.00175 **
population_thousands	0.0683	0.0157	4.36	0.0000290487 ***
post_2019_may_oct:cdd_over_500	0.9884	0.1538	6.43	0.0000000032 ***
cdd_over_500:post_2019_jun	0.9412	0.1875	5.02	0.0000019551 ***
cdd_over_500:post_2019_jul	1.0765	0.1729	6.23	0.0000000084 ***
cdd_over_500:post_2019_aug	0.5669	0.1404	4.04	0.0000991635 ***
cdd_over_500:post_2019_sep	0.9872	0.1644	6.00	0.0000000238 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Residual standard error: 26.3 on 113 degrees of freedom				
(41 observations deleted due to missingness)				
Multiple R-squared: 0.998, Adjusted R-squared: 0.998				
F-statistic: 2.94e+03 on 20 and 113 DF, p-value: <0.000000000000002				

371
372 **Figure 9. Commercial Model Output**

Coefficients:				
	Estimate	Std. Error	t value	Pr(> t)
gnp_1954_millions_dollars	0.15181	0.00879	17.27	< 0.0000000000000002 ***
cdd	0.14685	0.32732	0.45	0.65458
cal_month_f8	-318.36301	209.50720	-1.52	0.13157
cal_month_f1	-347.33590	141.08866	-2.46	0.01542 *
cal_month_f2	-251.54998	148.07793	-1.70	0.09227 .
cal_month_f3	-546.87020	175.02445	-3.12	0.00229 **
cal_month_f4	-477.46097	130.98154	-3.65	0.00041 ***
cal_month_f5	-271.78230	166.74333	-1.63	0.10605
cal_month_f6	-410.39730	139.89798	-2.93	0.00410 **
cal_month_f7	-255.06044	179.36192	-1.42	0.15792
cal_month_f9	-328.87768	174.37485	-1.89	0.06200 .
cal_month_f10	-357.07807	180.28905	-1.98	0.05020 .
cal_month_f11	-333.96129	191.28311	-1.75	0.08370 .
cal_month_f12	-498.82792	116.70211	-4.27	0.000042 ***
com_covid_binary_transitory	-158.80259	34.40539	-4.62	0.000011 ***
cdd:cal_month_f1	-0.09563	0.45736	-0.21	0.83478
cdd:cal_month_f2	-0.40632	0.48929	-0.83	0.40815
cdd:cal_month_f3	0.48678	0.50320	0.97	0.33554
cdd:cal_month_f4	0.25853	0.42725	0.61	0.54639
cdd:cal_month_f5	-0.08704	0.43066	-0.20	0.84021
cdd:cal_month_f6	0.13229	0.39692	0.33	0.73957
cdd:cal_month_f7	-0.08365	0.43249	-0.19	0.84701
cdd:cal_month_f9	0.03009	0.42317	0.07	0.94345
cdd:cal_month_f10	0.10751	0.43093	0.25	0.80346
cdd:cal_month_f11	-0.00565	0.47268	-0.01	0.99049
cdd:cal_month_f12	0.31842	0.38481	0.83	0.40982

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Residual standard error: 26.4 on 107 degrees of freedom				
(41 observations deleted due to missingness)				
Multiple R-squared: 0.999, Adjusted R-squared: 0.998				
F-statistic: 3.28e+03 on 26 and 107 DF, p-value: <0.000000000000002				

Figure 10. Industrial Model Output

Coefficients:				
	Estimate	Std. Error	t value	Pr(> t)
gnp_1954_millions_dollars	0.05799	0.00498	11.65	< 0.0000000000000002 ***
cal_month_f8	-139.96199	30.67937	-4.56	0.000012315 ***
cal_month_f1	-184.71584	30.87188	-5.98	0.000000023 ***
cal_month_f2	-176.58714	31.18083	-5.66	0.000000103 ***
cal_month_f3	-152.61644	30.85959	-4.95	0.000002497 ***
cal_month_f4	-168.78662	30.85275	-5.47	0.000000249 ***
cal_month_f5	-154.12112	30.61952	-5.03	0.000001713 ***
cal_month_f6	-155.45521	30.43673	-5.11	0.000001244 ***
cal_month_f7	-151.75411	30.58185	-4.96	0.000002325 ***
cal_month_f9	-149.95601	30.87594	-4.86	0.000003639 ***
cal_month_f10	-146.40652	31.28277	-4.68	0.000007600 ***
cal_month_f11	-152.33489	30.61981	-4.98	0.000002201 ***
cal_month_f12	-155.94387	30.77470	-5.07	0.000001481 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Residual standard error: 16.2 on 120 degrees of freedom (41 observations deleted due to missingness) Multiple R-squared: 0.994, Adjusted R-squared: 0.993 F-statistic: 1.55e+03 on 13 and 120 DF, p-value: <0.0000000000000002				

Q. 24 In Appendix 1 to the Cao Report, Dr. Cao reproduced Tables 2 to 7 from your direct testimony and compared LUMA's load forecasts with actual load values over time. Dr. Cao claims that this comparison demonstrates load forecasting errors ranging from -12.2% to 18.7%, and that such a margin of error is usually not acceptable in forecasting. Do you have a response?

A. Yes. LUMA agrees with Dr. Cao's statement regarding the significant variance between the projections developed for fiscal years 2023 and 2024, which fall outside the acceptable margins of +3% or -3%. Precisely as part of the ongoing initiative to improve forecast accuracy, we proceeded to revise both the residential and industrial models for the rate review, as we will explain below.

Q. 25 Please explain your response.

A. The data included in my testimony, which compares actual load with the forecast, aims to demonstrate how, in recent years, the traditional exogenous variables that typically influence load have begun to lose their explanatory power relative to the evolving behavior of the load itself.

391 As a result, during the fiscal year, LUMA initiated an improvement project that is
392 still ongoing, with the goal of enhancing forecast accuracy. Historically, exogenous
393 variables have effectively explained trends in the commercial class. However, this has not
394 been the case for the residential and industrial classes. To address this, LUMA revised the
395 residential and industrial load forecasting models used in the rate review process.

396 Recently, the residential class has been significantly affected by weather
397 conditions. Beginning in FY 2020, the impact became more pronounced due to the
398 COVID-19 restrictions, which led many residential customers to work from home.
399 Additionally, relief funds were used to purchase air conditioning units, which customers
400 continue to use, especially during the current heat wave. As noted in my direct testimony
401 (lines 409 and 469), following FY 2024, Puerto Rico experienced the highest number of
402 cooling degree days in its recorded history. This extreme weather not only affected regular
403 residential customers but also Net Metering customers, who increased their electricity
404 consumption from both the grid and their self-generation systems.

405 Given that there have been five summers (as of February 2025) in which residential
406 consumption has been materially higher than in pre-2020 summers, the LUMA-LFR team
407 believes that it is now more prudent to treat this step-change not as a temporary shock, but
408 as a permanent structural change.

409 This change does not impact the regression model specification. This remains the
410 same as that provided for the 2024 PREPA fiscal plan and budget. Only the definition of
411 one input variable, the $post2019_t$ variable, changes. This is shown below in the variable
412 definitions. For reference, the regression model can be described in the following equation:

$$y_t = \sum_{m=1}^{M=12} \beta_{1,m} month_{m,t} + \beta_2 CDD_t + \beta_3 Pop_t + \beta_4 COVIDwin_t + \sum_{m=6}^{M=9} \beta_{5,m} month_{m,t} \cdot post2019_t \cdot CDD500_t + \beta_6 month_{m \in \{5,10\},t} \cdot post2019_t \cdot CDD500_t + \varepsilon_t$$

y_t = Class-level billed consumption (GWh) of residential customers in month of sample t .

$month_{m,t}$ = A set of twelve binary variables capturing monthly seasonality. This variable is equal to 1 when month of sample t is the m -th month of the calendar year and zero otherwise. For example, variable $month_{1,t}$ is equal to one when month of sample t is January, and zero otherwise.

CDD_t = Monthly cooling degree days (base 65 degrees Fahrenheit) observed in month of sample t . These are drawn from the National Weather Service as a monthly series for the San Juan Area.

Pop_t = Estimated total population by month, derived from annual values obtained by LUMA from the U.S. Census.

$COVIDwin_t$ = A binary variable capturing the impact of COVID on consumption in the winter after the emergence of COVID to account for forecast over-prediction during the winter months. This variable is equal to one in the period beginning November of calendar year 2020 running through to the end of April of calendar year 2021, and zero otherwise.

$post2019_t$ = A binary variable capturing the step-change in Residential consumption starting in calendar year 2020. This variable is equal to one in calendar years 2020 and later, and zero otherwise. This variable is always multiplied by $CDD500_t$ and a monthly binary variable in the equation above. It controls for the observation by Guidehouse and the LUMA LFR team that after 2019, Residential customers appear to be

more sensitive to higher temperatures. In combination with the monthly binary and CDD500_t, it acts as a spline, meaning it lets the model treat very hot months differently. When monthly CDD are higher than 500 in the month identified by the monthly binary, then there is an incremental increase in consumption.

$CDD500_t$ = The number of monthly cooling degree days observed in month of sample t higher than 500. This variable takes a zero in months with cooling degree days under 500. These are drawn from the National Weather Service as a monthly series for the San Juan Area. This variable captures the observation that the relationship between consumption and CDD changes at higher values of CDD, and that (for example) an increase of one CDD from 450 to 451 will result in a smaller consumption increase than an increase of one CDD from 550 to 551.

$month_{m \in (5,10),t}$ = A binary variable to account for differences in consumption in May or October after the start of COVID. This variable is equal to one if month of sample t is either the fifth or the 10th month of the calendar year (May or October), and zero otherwise. That is, the parameter associated with the group of variables that begins with this one captures the post-2019 temperature-sensitive “bump” to residential consumption for the months of May and October. The model assumes that this relationship is the same for both May and October.

$\beta_{1,m}, \beta_2, \beta_3, \beta_4, \beta_{5,m}, \beta_6$ = Regression-estimated parameters (coefficients).

The result of the climatic change when incorporated in the regression model is that forecast monthly consumption no longer declines between the summers of calendar years 2024 and 2028 to revert to the pre-2020 pattern but instead remains at its post 2020 level.

Industrial customers, as discussed in my direct testimony, have been affected by the adoption of CHP systems. For the rate review, LUMA updated the industrial model to account for this factor and to produce a more accurate forecast. Some changes were applied to control for the rapid growth in self-generation from the CHP. The approach developed by Guidehouse estimated historical self-generation volumes to modify the historical industrial consumption used to estimate the industrial regression model. Including self-generation directly within the regression model will help to generate a projection of industrial consumption as if no self-generation was being used. This creates a cleaner baseline that reflects total underlying demand, allowing the model to isolate the true relationship between electricity use and its drivers without distortion from self-generation. This forecast would then be adjusted using an estimate of the self-generation associated with the cumulative installed self-generating capacity instead of (as previously) the incremental capacity.

Previously, when historical self-generation was relatively modest, it was not explicitly controlled either in the data or in the regression specification. The effects of such generation (when they are small) would be reflected in the estimated parameters, and any incremental generation in the forecast period would be controlled for by applying the forecast load modifiers. Because the volume of self-generation has grown so rapidly, the volume of the estimated load that has been displaced (historically) by self-generation is added back in to the consumption before the regression is estimated. This means that the load modifiers that are applied must be based on the total accumulation of self-generation, and not just the incremental adoption.

479 This methodology is consistent with how many jurisdictions in North America
480 account for energy efficiency (EE) and demand side management (DSM) programs within
481 load forecasting. For example, Independent System Operator for New England (ISO-NE)
482 modifies observed loads, adding back in historical estimates of EE, demand response (DR),
483 and photovoltaic (PV) self-generation in a process referred to as “reconstitution.”
484 Regressions are estimated using these reconstituted data, providing the “gross” forecast,
485 which is subsequently adjusted (similar to LUMA’s procedure) by applying forecast EE,
486 DR, and PV to the gross forecast. See ISO New England Inc., *Forecast Modeling*
487 *Procedure for the 2024 CELT Report: ISO New England Long-Run Energy and Seasonal*
488 *Peak Forecast*, May 2024 (available at [https://www.iso-ne.com/system-planning/system-](https://www.iso-ne.com/system-planning/system-forecasting/load-forecast)
489 forecasting/load-forecast).

490 The Pennsylvania-New Jersey-Maryland Interconnection (PJM) also reconstitutes
491 loads served by PV self-generation or offset by demand response prior to estimating its
492 regression models. See Itron, prepared for PJM, *2022 Model Review: Final Report*, 2022
493 (available at [https://www.pjm.com/-/media/DotCom/planning/res-adeq/load-forecast/pjm-](https://www.pjm.com/-/media/DotCom/planning/res-adeq/load-forecast/pjm-model-review-final-report-from-itron.pdf)
494 model-review-final-report-from-itron.pdf).

495 Using the inputs for the LUMA self-generation load modifier forecast, Guidehouse
496 developed a “backcast” of estimated historical self-generation-displaced load. The
497 backcast is the set of values applied to historical observed consumption to reconstitute
498 gross load. The backcast approach is used rather than the empirical estimates of displaced
499 load, developed previously by Guidehouse, to ensure consistency between backward and
500 forward-looking assumptions regarding customer self-generation.

501 The backcast is estimated using the following three inputs:

Self-generation capacity (kW). The LUMA LFR team maintains a set of estimated values for the installed capacity of individual industrial customers' generation.

Capacity Factor (%). The LUMA LFR team's load modifier workflow applied a capacity factor of 72% for its forecast of FY2025 self-generation. Guidehouse understands this value was provided to LUMA by Siemens and has used this value for the backcast. For the budget forecast to be developed in early 2025, the Load Forecasting and Rates (LFR) team has elected to apply a 72% capacity factor through FY2025. For FY2026 through FY2028, capacity factors were derived based on current consumption patterns observed among CHP customers. The methodology is detailed in my direct testimony at lines 230 and 246, with supporting documentation provided in the response to PC Exhibit 58.03, PC-of-LUMA-LOAD_FOR-12, and the complete set of formulas available in LUMA Exhibit 4.03 (7.03.25) – *Load Forecast Modifiers FY2025*, specifically in the 'CHP CF customer' tab, cells B3 to G190.

Self-Generation Install Date. Guidehouse used one of three sources to determine the self-generation install date for each customer.

In each month the displaced load for each self-generating customer was estimated using the following equation:

Equation 1. Backcast Calculation

$$z_{i,t} = capacity_i \cdot capFactor \cdot hours_t$$

$z_{i,t}$ = The estimated displaced load from self-generation for customer i in month t .

$capacity_i$ = The installed generation capacity for customer i .

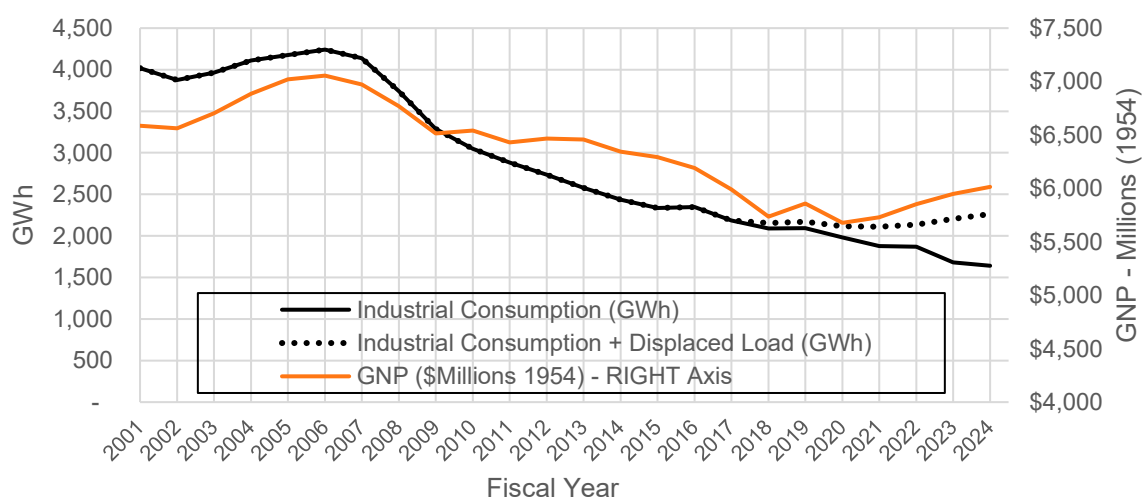
$capFactor$ = Assumed capacity factor (72%).

$hours_t$ = The number of hours in month t (if the generation was installed in month t then the number of hours in the month after the installation date).

Figure 11, reproduced below, compares observed historical consumption (solid black line) with historical reconstituted consumption (i.e., with historical displaced load added back in), the dotted black line, and with historical GNP (orange line, right axis).

Once the backcast is added to historical industrial consumption to create the reconstituted industrial load, it is once more closely correlated with GNP (i.e., both are increasing in the period since FY2021).

Figure 11. Industrial Consumption, GNP, and Industrial Consumption + Displaced Load



After adding the backcast of historical self-generation back into historical industrial loads (i.e., creating a “reconstituted” gross industrial load), Guidehouse re-estimated the industrial forecast regression model. Re-estimating the Industrial forecast model included two updates:

1. Adding the backcast historical self-generation to historical industrial consumption, as described above.

2. Removing the Industrial binary from the regression model, as described above.

Because historical Industrial consumption controls for historical self-generation, there is no longer a need for the Industrial binary within the regression model. The Industrial binary was included within the Industrial forecast as a temporary solution to account for the step-change in Industrial consumption starting in March of 2022. The correction applied by the inclusion of the backcast displaced load renders the binary variable obsolete. Additional information regarding the Industrial binary is included in Appendix A. Industrial Forecast Context.

Due to an unintentional error, the industrial equation included in my direct testimony was the one used in previous years. The following equation is the current one that was used to derive the industrial consumption forecast:

$$y_t = \sum_{m=1}^{M=12} \beta_m month_{m,t} + \beta_2 GNP_t + \beta_3 indBinary_t + \varepsilon_t$$

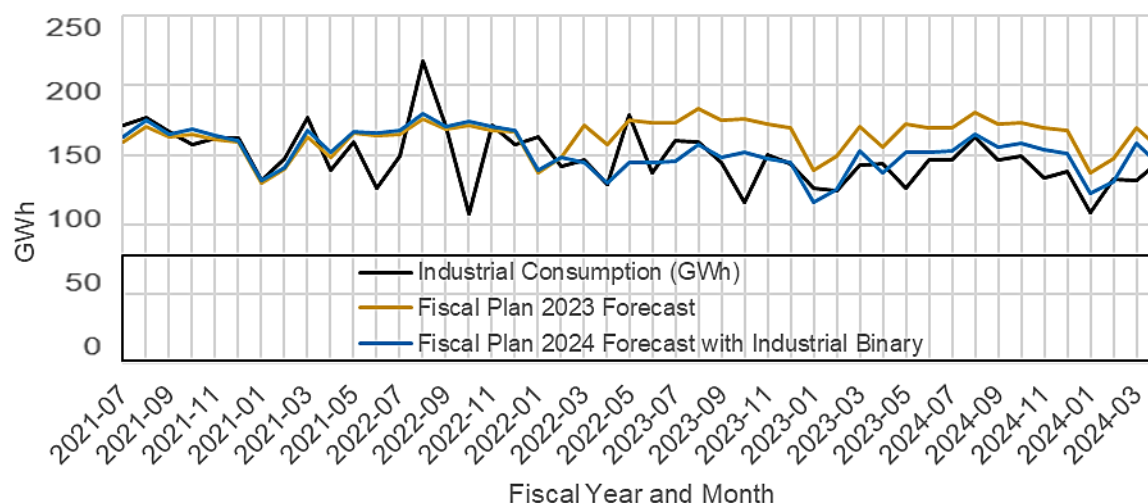
$indBinary_t$ = A binary variable capturing the step-change in Industrial consumption starting in March of 2022. This variable is equal to one if month t is March of calendar year 2022 or later, and zero otherwise.

β_3 = Regression-estimated parameter (coefficients).

And all other variables are as defined above.

The outcome of this model is shown in Figure 12 below. In this diagram, the black line represents actual observed industrial consumption, the yellow line represents the forecast using the previous model, and the blue line represents the forecast using the current model.

Figure 12. Industrial Consumption, Fiscal Plan 2023 and 2024 Forecast



Q. 26 On page 7 of the Cao Report, Dr. Cao concludes that the proposed electricity rate increases in Puerto Rico would significantly exceed the affordability threshold set by the FOMB, which recommends that electricity costs not surpass 6% of household income. Using 2023 data, though, Dr. Cao concludes the average residential bill already exceeds this threshold on average and posits that the proposed rate increases would cause the burden to rise to 10.1% of median income under the “optimal” approach and 8.7% under the “constrained” approach. Dr. Cao argues this would disproportionately harm low-income households, encourage grid defection, and accelerate a financial “death spiral.” Does LUMA have a response?

A. Yes.

Q. 27 Please state and explain LUMA’s response.

A. Dr. Cao raises valid concerns about affordability, but his conclusion that proposed rate increases would significantly exceed the FOMB’s 6% affordability threshold does not fully reflect Puerto Rico’s residential rate structure or the protections in place for low-income

households. Using updated 2024 data, the average residential customer under current FY25 rates pays about \$1,175 annually, roughly 4.3% of the median household income of \$27,213, well below the 6% threshold. Even under the constrained scenario (\$0.32/kWh), the average burden rises only to 5.9%, remaining within the recommended limit. Only under the optimal scenario (\$0.37/kWh) does the average burden reach 6.9%, slightly exceeding the threshold.

These averages also overstate the impact on the most vulnerable customers. Many low-income households are enrolled in fixed-base or subsidized rate programs that cap monthly bills, often between \$30 and \$50, regardless of consumption. As a result, their electricity burden as a share of income is typically lower than the overall average and is largely insulated from the full effect of rate increases. Dr. Cao himself acknowledges that his affordability calculations do not account for these subsidies, which means his estimate of the burden on low-income customers is overstated.

Moreover, Dr. Cao's analysis does not account for net energy metering ("NEM") customers, who are credited at a 1:1 retail rate for energy exported to the grid. These customers are less exposed to rate increases and, in some cases, may even benefit from higher rates through increased credit value. This undermines the claim that rate hikes uniformly harm all customers or inevitably accelerate grid defection.

Finally, Dr. Cao uses 2023 income data, whereas LUMA's analysis relies on 2024 median household income, which better reflects current conditions. Even modest income growth can materially improve affordability ratios. Taken together, these factors show that under most scenarios average residential customers remain within or near the FOMB's

affordability threshold, and that low-income protections and NEM policies significantly reduce the impact of rate increases on the most vulnerable and on solar-adopting customers.

Q. 28 On page 8 of the Cao Report, Dr. Cao asserts that proposed electricity rate increases in Puerto Rico would significantly raise the cost of intermediate inputs across key industrial sectors, with the most pronounced impacts on wholesale and retail trade, government, manufacturing, mining and construction, and other services. Dr. Cao believes that, as a result, the costs are likely to be passed on to customers, claiming it could result in emigration, worsen fiscal strain on the government, erode competitiveness in the export market, and exacerbate the housing deficit. Does LUMA have a response?

A. Yes.

Q. 29 Please state and explain LUMA's response.

A. Dr. Cao's concerns about rising electricity costs in key sectors such as manufacturing, construction, and commerce are understandable, but they overstate the risk of widespread grid abandonment or an economic collapse.

The evidence to date shows that commercial and industrial customers (Figures 13 and 14) are responding primarily through partial load displacement rather than full defection. For commercial customers, the 1:1 NEM credit structure creates a strong economic incentive to remain grid-connected, since it allows them to offset usage at the full retail rate and substantially lower their bills while still benefiting from grid reliability.

Figure 13. Commercial consumption and cost per kWh

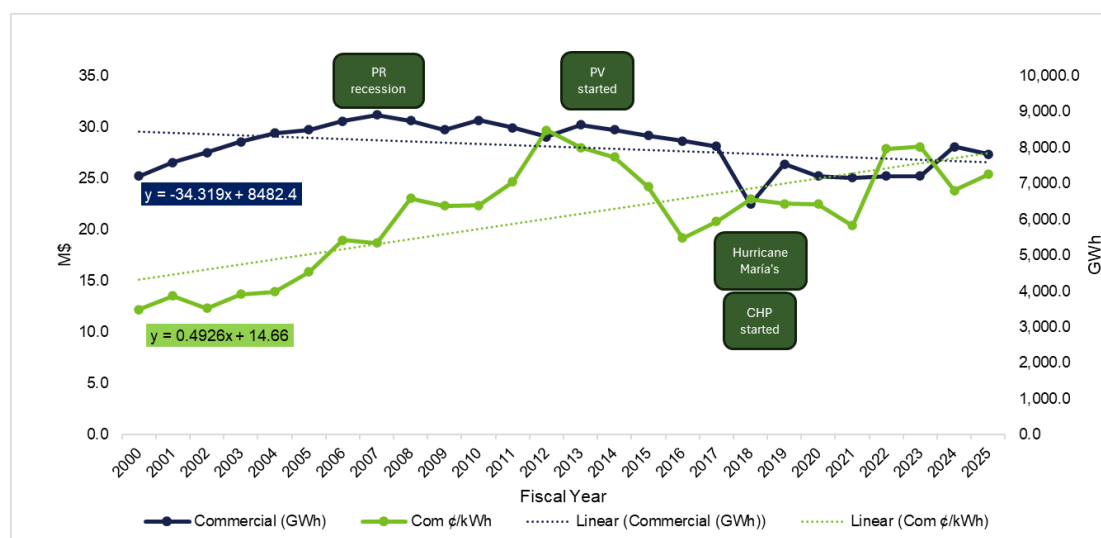
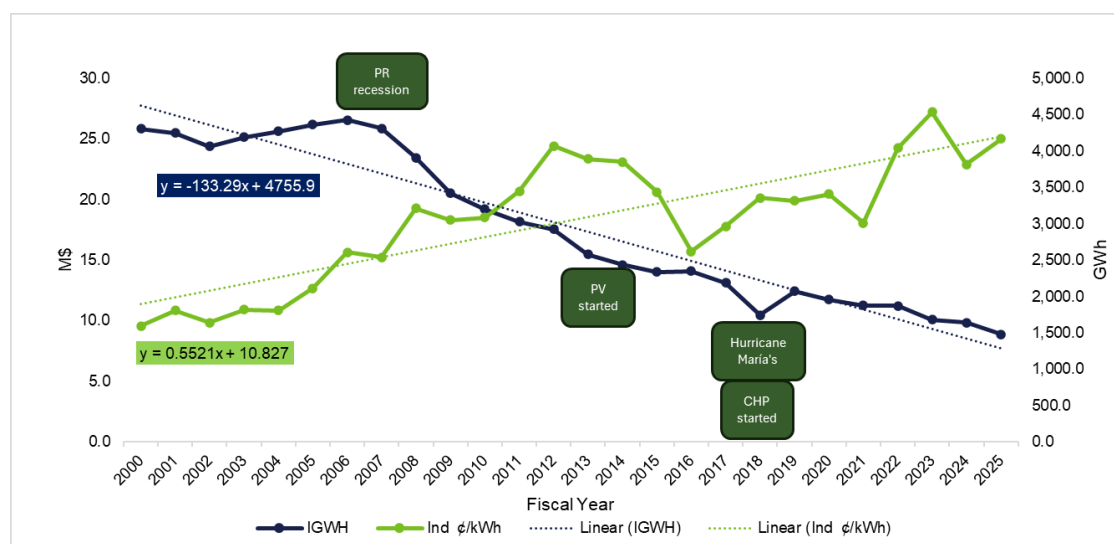


Figure 14. Industrial consumption and cost per kWh



On the industrial side, a 2023 Guidehouse analysis found that 43 large customers displaced about 34 GWh per month through combined heat and power (CHP) systems, yet fewer than five fully disconnected from the grid (please refer to LUMA Ex. 72.03). Most continue to rely on centralized power for backup and operational flexibility, underscoring the grid's ongoing importance even for heavy self-generators. These patterns indicate that

628 although DER adoption is increasing, Puerto Rico's grid remains an essential part of the
629 energy distribution.

630 Dr. Cao raises important concerns about the potential for electricity rate increases
631 to contribute to broader economic challenges such as emigration, housing shortages, and
632 fiscal strain. While higher electricity rates may increase operating costs for some sectors,
633 the evidence suggests that many commercial and industrial customers are adapting through
634 energy efficiency improvements and by leveraging rate design mechanisms, such as NEM
635 and behind-the-meter generation, not only to maintain operational reliability, but also to
636 reduce electricity costs or even generate new revenue streams. These adaptive strategies
637 reduce the likelihood of full cost pass-through to consumers. Moreover, structural
638 challenges like housing deficits, migration trends, and fiscal pressures are shaped by a
639 complex mix of factors, including demographic shifts, state and federal policy,
640 macroeconomic conditions, limited construction activity, and rising input costs (e.g.,
641 pharmaceutical raw materials, cement, equipment). Migration, for example, is more closely
642 tied to long-term economic opportunity and industrial development than to utility rates
643 alone. Attributing these systemic issues primarily to electricity prices overstates their role
644 and overlooks the broader economic context in which they occur.

645 Dr. Cao based his conclusion on Input-Output (I-O) model which is a widely used
646 tool for estimating the total economic impact, direct, indirect, and induced, of a change in
647 demand. The I-O model is a quantitative economic analysis tool that represents the supply-
648 chain dynamics between different sectors of an economy. It uses a matrix format to show
649 how the output from one industry (e.g., steel) becomes an input for another (e.g.,
650 construction), allowing them to trace how changes in one sector ripple through others.

651 However, the methodology is inherently static, relying on fixed technical
652 coefficients derived from historical data. In this case, the Input-Output matrix being used
653 was last updated in 2013, meaning it does not reflect over a decade of economic,
654 technological, and structural changes. While this version is outdated, it is important to note
655 that a more recent I-O matrix from 2017 is available.

656 Although still not fully up to date, the 2017 matrix may offer a more accurate
657 reflection of Puerto Rico's evolving economic landscape, including industrial composition,
658 labor market dynamics, or other macroeconomic shifts occurring within the island.
659 Choosing to rely on an even older version, such as the 2013 matrix, increases the likelihood
660 of producing biased or less representative results, particularly when evaluating the
661 economic impacts.

662 These coefficients assume that the structure of production remains unchanged over
663 time, holding consumer preferences, government policies, technologies, and relative prices
664 constant. The model also assumes no substitution between inputs in production and
665 excludes broader general equilibrium effects, such as offsetting gains or losses in other
666 sectors or regions.

667 In today's rapidly evolving economic environment, these assumptions are
668 increasingly unrealistic and can lead to misleading conclusions.

669 When the underlying I-O data is outdated, the resulting analysis can be significantly
670 flawed. Key risks include:

- 671 1. Flawed multiplier estimates: multipliers derived from obsolete economic
672 relationships may overstate the impact of expansionary policies or

investments. For example, they may not reflect modern production processes that are more efficient and require fewer inputs.

2. Distorted investment assessments: economic impact assessments for projects such as infrastructure development may be inflated if based on an outdated industrial structure. This can lead to misallocation of resources and poor policy outcomes.

3. Rigid production functions: outdated I-O models assume that industries use the same combination of inputs to produce outputs, regardless of technological change. This assumption fails to reflect the evolving nature of production processes.

Technological progress continuously reshapes the structure of production (Refer to Exhibit 72.01, at ¶ 15). When I-O matrices are not updated to reflect these changes:

1. Production coefficients become inaccurate, as they assume constant input proportions across sectors.

2. Emerging industries and products are excluded, leading to underrepresentation of dynamic sectors. For example, despite acknowledging significant changes in Puerto Rico's energy landscape, including solar adoption, remote work, and combined heat and power (CHP) systems, these developments are not captured in decades-old I-O tables.

3. Technological stagnation is implied, as the same production technology is assumed across all outputs of an industry (Refer to Exhibit 72.01, at ¶ 16).

- 695 4. Production functions become outdated, representing a weighted average of
696 inputs for primary and secondary products that no longer reflect current
697 practices.

698 Even when inflation adjustments are applied, the relative weights used, such as
699 those from the Consumer Price Index, may be based on benchmarks as old as 2006, further
700 compounding inaccuracies.

701 Over time, the structure of the economy changes significantly (Refer to Exhibit
702 72.01, at ¶ 17):

- 703 1. Sectoral shifts occur, with services often gaining prominence over manufacturing.
704 An older Input-Output table may overemphasize manufacturing while understating
705 the economic impact of the modern service industry. The same quantity of inputs
706 is needed per unit of output, regardless of the level of production (Refer to Exhibit
707 72.01, at ¶ 18).
- 708 2. Consumption patterns change, and fixed household spending assumptions may no
709 longer reflect reality, leading to poor estimations of induced effects.

710 Finally, I-O models assume unlimited availability of inputs, raw materials, and
711 labor (Refer to Exhibit 72.01, at ¶ 15). This assumption may not be held in real-world
712 scenarios, particularly when analyzing large-scale impacts or supply-constrained
713 environments.

714 In conclusion, while I-O models remain a valuable analytical tool, their
715 effectiveness is severely compromised when based on outdated data. Policymakers and
716 analysts must exercise caution and ensure that the data used reflects the current economic
717 structure, technological landscape, and consumption behavior.

Q. 30 On pages 10 and 11 of the Cao Report, Dr. Cao argues that increasing electricity rates will directly raise intermediate costs across all industrial sectors, leading to higher consumer prices and contributing to cost-push inflation in Puerto Rico. Dr. Cao describes the disruptive effects of inflation, such as distorted resource allocation, reduced investment and savings, increased income inequality (especially harming those on fixed incomes), and greater social and labor instability. Using official expenditure weights, Dr. Cao estimates that the Consumer Price Index (CPI) would rise by 3.0% under the “optimal” rate increase scenario and by 1.8% under the “constrained” scenario, both significantly above Puerto Rico’s recent average inflation rate of 1.5%. Dr. Cao believes that even the lower scenario would more than double the typical inflation rate, and the higher scenario would triple it, noting that these electricity-driven price increases would coincide with recent federal import tariff hikes, further compounding inflationary pressures in an economy heavily reliant on imports. Does LUMA have a response?

A. Yes.

Q. 31 Please state and explain LUMA’s response.

A. Although increases in electricity rates can contribute to cost-push inflation, the evidence contained in the appendices cited by Dr. Cao suggests that the direct impact on Puerto Rico’s CPI is far smaller than Dr. Cao estimates. According to Appendix 5, electricity accounts for only 2.84% of the CPI basket, one of the smallest weights among all categories, while housing, transportation, and food dominate the index. Even a very large electricity price increase would therefore translate into a relatively modest direct effect on the CPI. To reach a 3% increase in the index from electricity alone would require either

implausibly large rate hikes or unsubstantiated assumptions about economy-wide multiplier effects.

Historical data for Puerto Rico suggests that while electricity rate increases can contribute to cost-push inflation, the relationship is not straightforward or consistently observed. Notably, in 2017, a year in which the electricity base rate increased, inflation remained subdued or even declined in the following fiscal and calendar years. For instance, fiscal year inflation was just 0.6% in 2017 and 0.0% in 2020, while calendar year inflation was 1.8% and -0.5%, respectively.

Inflation Rate (y-o-y)	2017	2018	2019	2020	2021	2022	2023	2024
Fiscal Year	0.6%	1.6%	0.5%	0.0%	0.2%	4.6%	5.4%	2.4%
Natural Year	1.8%	1.2%	0.1%	-0.5%	2.4%	6.1%	3.4%	2.0%

Source: Puerto Rico Department of Labor (2025)

The more pronounced inflationary pressures observed in 2022 and 2023, with calendar year inflation reaching 6.1% and 3.4%, coincided with global supply chain disruptions, pandemic-related fiscal stimuli, and commodity price shocks, rather than being driven solely or primarily by local electricity rate adjustments. These dynamics reflect broad-based demand and supply shocks, not isolated cost-push effects from electricity prices.

Therefore, attributing recent inflation trends in Puerto Rico directly to electricity rate increases oversimplifies a complex macroeconomic environment. The data suggests that while electricity prices may play a role, they are not the dominant driver of inflationary outcomes.

We must not lose sight of the fact that the PREB is evaluating an increase in the base rate, a component that, as previously mentioned, has historically represented less than

35% of the total electricity bill in Puerto Rico. In contrast, the Integrated Resource Plan (IRP) can more accurately define the future costs of fuel and purchased power, which together account for approximately 60% to 70% of the total bill. Therefore, future lower-cost dispatch scenarios could help offset any base rate increases approved by the PREB.

In addition, firms rarely pass input cost changes straight through to final prices at a one-for-one rate. They typically adjust production methods, improve efficiency, substitute inputs, or absorb part of the cost in margins, especially in competitive markets. This elasticity and substitution dampen the transmission of electricity cost changes into consumer prices and makes simple proportional calculations misleading.

Puerto Rico's inflation is also multi-causal and overwhelmingly shaped by factors beyond local electricity rates. Because the island imports most goods and raw materials, global commodity prices, shipping costs, supply-chain dynamics, and U.S. tariff policy exert a far stronger and more volatile influence on the general price level than electricity does. Singling out electricity as the primary driver of future inflation oversimplifies the issue and overstates its contribution.

Dr. Cao's analysis also appears to treat all customers as fully exposed to the tariff increase, yet in practice a rapidly growing share of residential, commercial, industrial, and agricultural customers participates in Puerto Rico's NEM program or have behind-the-meter solar and storage systems. These customers experience much lower effective electricity rates, sometimes approaching zero at the margin, which dilutes the average cost shock across the economy and further weakens the pass-through to the CPI.

Finally, the very instability in U.S. tariff and commodity prices cited in Dr. Cao's analysis underscores how multiple external factors already produce larger swings in

intermediate costs for Puerto Rico's industrial sector than electricity does. Against this backdrop, projecting a CPI increase of 3.0% from electricity alone, more than double Puerto Rico's recent average inflation of 1.5%, appears to overstate the true inflationary impact. A more balanced view would treat electricity as one of several cost drivers, acknowledge the small direct weight of electricity in the CPI, incorporate realistic substitution and efficiency responses, and account for the mitigating effect of distributed generation. Under such assumptions, the inflationary effect of electricity rate increases would be far more limited than Dr. Cao suggests.

Q. 32 On page 11 of the Cao Report, Dr. Cao asserts that increases in electricity prices are likely to negatively impact Puerto Rico's economic activity and employment, since electricity is a fundamental input for the production of goods and services. Dr. Cao argues that the existing Gross National Product ("GNP") models are outdated and so cannot provide reliable quantitative forecasts. Based on this, Dr. Cao concludes that the effects of electricity rate increase on GNP and employment cannot be responsibly estimated with current tools, yet concludes there would be an adverse impact. Does LUMA agree?

A. No.

Q. 33 Please state and explain LUMA's response.

A. Dr. Cao argues that electricity price increases are likely to depress Puerto Rico's economic activity and employment because electricity is a fundamental production input, but he maintains that reliable quantitative estimates cannot be produced with current GNP models, which he says are outdated and fail to capture factors such as large federal disaster and

808 pandemic relief funds, the economy's structural contraction, and the rapid adoption of
809 distributed generation and remote work.

810 While these concerns about model limitations are valid, GNP still functions as a
811 relevant, though no longer dominant, indicator in forecasting commercial and industrial
812 electricity demand, since aggregate economic output remains tied to energy use in these
813 sectors. It is not used for residential load, where consumption depends more on weather
814 and behavioral factors.

815 Recent internal analyses show that although GNP has continued to rise, commercial
816 and industrial electricity consumption has stagnated or declined, indicating a weakened
817 historical relationship due to distributed generation, efficiency improvements, and
818 structural shifts such as remote work. Updated forecasting models for the rate review
819 reflect this decoupling. For example, data after FY 2020 shows that commercial and
820 industrial loads are now less sensitive to estimated GNP. In the case of the commercial
821 class, demand is also influenced by weather. Although GNP has exhibited sustained
822 growth, electricity consumption from the grid by the Industrial customer class has declined,
823 largely attributable to the adoption of on-site CHP systems. Figures 15 and 16 below depict
824 the relationship between GNP and electricity consumption (not remediated) across
825 customer classes:

826 **Figure 15. Commercial consumption and Gross National Product**

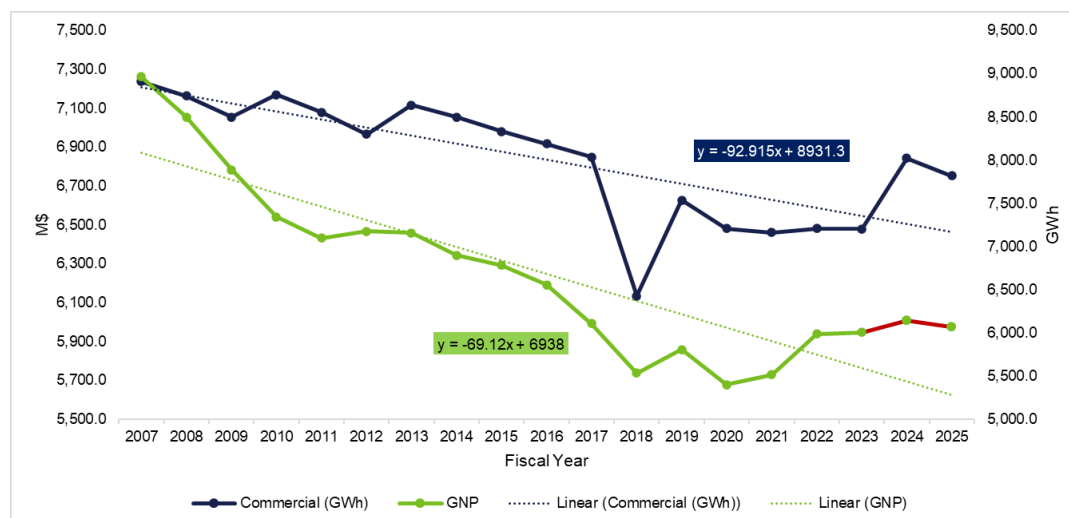
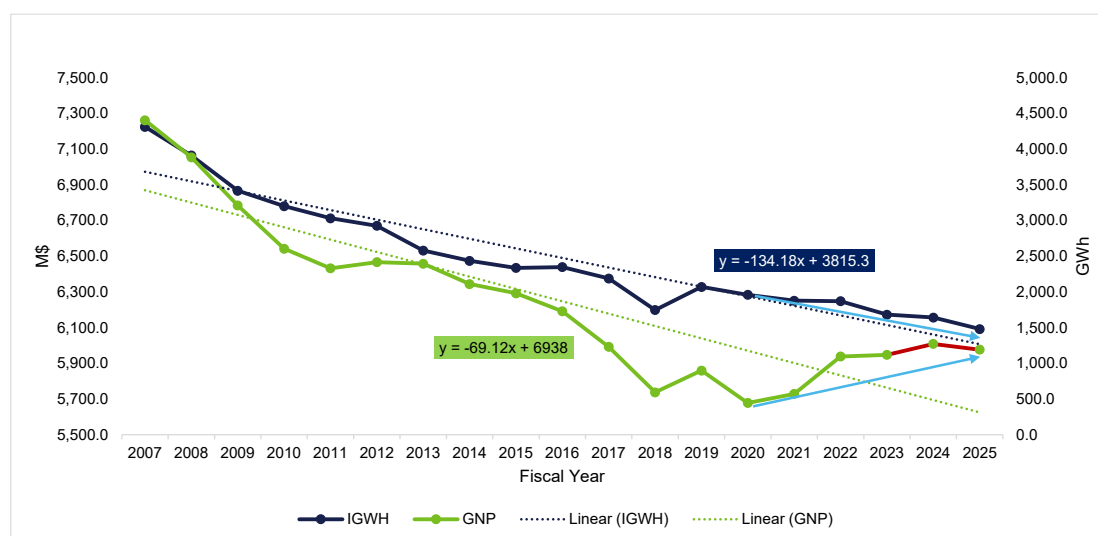


Figure 16. Commercial consumption and Gross National Product



Moreover, the GNP forecasts used in these models are not produced internally but supplied by the Fiscal Oversight and Management Board (FOMB), whose projections are expected to incorporate the very structural changes Dr. Cao highlights. Thus, the forecasting framework already adjusts for these limitations rather than ignoring them. GNP remains a useful macroeconomic anchor when combined with other variables in an adaptive modeling framework and should not be discarded outright.

Q. 34 On page 13 of the Cao Report, Dr. Cao states that the “death spiral” is a phenomenon

that occurs when a utility “increases the price charged to its customers and some of them drop out from the service of the utility. A reduced number of customers and diminished levels of consumption by remaining customers given the large fixed costs characteristic of electric power utilities, induces the utility to further raise price, fueling a spiral of increasing price, reduced quantity demanded, rising prices again and so on, until the utility goes bankrupt.” Does LUMA have a response?

A. Yes.

Q. 35 Please state and explain LUMA’s response.

A. Dr. Cao’s concern is most appropriately addressed not through the base consumption forecast, but through the forecast adoption of load modifiers (e.g., distributed solar generation supported by battery storage, or large customer fossil fuel-based self-generation).

Dr. Cao characterizes a “death spiral” as the dynamic where rising utility prices cause customers to leave, which in turn forces further price increases and ultimately threatens the utility’s viability. In Puerto Rico, however, the current adoption of distributed energy systems is driven less by rising electricity rates and more by concerns over grid reliability, particularly its resilience during and after severe weather events or widespread outages caused by failures in the electric system. This concern is more appropriately addressed through the forecast of load modifiers such as distributed solar with battery storage or large-scale fossil-fuel self-generation rather than through the base consumption forecast. LUMA estimates that, in 2023, an average residential NEM customer displaced about 278 kWh per month, roughly 4% of total residential consumption, based on an engineering comparison of simulated PV generation with actual export data. Although this

860 represents modest load displacement today, continued NEM growth will increase its
861 system-wide impact. (Refer to LUMA Ex. 72.04).

862 Full grid defection remains economically and technically impractical for most
863 households due to the storage needed for reliability during low-solar periods. For example,
864 an 800 kWh/month household would need about five 13.5 kWh batteries and sixteen 400-
865 W panels to cover two cloudy days, at an estimated lease cost of \$535/month (\$0.73/kWh),
866 compared with roughly \$200/month at current grid rates (\$0.25/kWh). A hybrid approach,
867 solar plus storage while staying grid-connected, typically costs about \$248/month
868 (\$0.31/kWh), a price that customers are willing to pay in exchange for greater energy
869 autonomy.

870 The PREPA Fiscal Plan projects an average rate around \$0.31/kWh by FY2026,
871 closing the cost gap between grid power and partial self-sufficiency. NEM customers also
872 benefit from a 1:1 retail credit that offsets usage, reducing bills to the basic service fee of
873 about \$4/month (projected to \$8/month by FY2027), maintaining a strong incentive to
874 remain connected. Even with rates projected to rise to ~\$0.45/kWh by FY2040 and
875 ~\$0.55/kWh with debt recovery, NEM customers can continue offsetting most increases,
876 making partial grid defection, not full disconnection, the likely path for most residential
877 users in the near and medium term. Affordability constraints and future changes in
878 financing, interest rates, and technology costs will influence adoption, underscoring the
879 importance of sensitivity analyses to assess consumer response, determine key economic
880 thresholds, and forecast grid defection. These insights are critical to evaluating the long-
881 term viability of Puerto Rico's NEM program and guiding policy and infrastructure
882 planning. While these insights are valuable for informing key assumptions in forecasting

consumption and long-term planning, they do not support the overstated conclusions advanced by Dr. Cao and the ICSE, which appear to significantly overestimate the likelihood of widespread grid defection or a collapse in electricity demand.

A parallel trend is emerging among large industrial and commercial customers adopting CHP systems. Most remain grid-connected for backup during outages but are generating most of their own electricity, significantly reducing volumetric consumption. Guidehouse's 2024 analysis identified 43 such customers displacing about 34 GWh/month (over 400 GWh annually) in 2023, with an average installed capacity of ~3.95 MW, sufficient to meet full onsite needs (please refer to LUMA Ex. 72.03). While fewer than five have completely ceased volumetric purchases, the resulting revenue loss from large-load customers is material and has implications for cost recovery, rate design, and long-term planning. The analysis, based on monthly billing data, would benefit from higher-resolution metering for more precise impact assessment. Reliability, rather than economics, is cited as the primary motivation for CHP adoption: LUMA's 2023 survey found all CHP-equipped industrial clients ranked reliability first. This aligns with broader island trends, including expanded LNG infrastructure and manufacturers' declarations of energy independence, signaling a shift toward self-sufficiency and resilience among Puerto Rico's largest energy users.

Caution should be exercised when relying on Dr. Cao's estimates of potential price impacts resulting from base rate increases, as the analysis likely overstates the dollar effects due to its reliance on outdated economic data that no longer reflects Puerto Rico's current economic structure. The following information is based on data published by the Puerto Rico Planning Board.

Between 2000 and 2025, Puerto Rico underwent a significant structural transformation in its economy, particularly in terms of GDP composition, price levels, and employment patterns. The island's economic profile in 2025 differs markedly from that of 2008.

Historically, Puerto Rico's industrial model was centered on manufacturing for U.S. markets, evolving from textiles to chemicals, electronics, and ultimately pharmaceuticals. By the late 1990s and early 2000s, Puerto Rico had become a leading U.S. exporter of pharmaceutical and medical products. Benchmarking with U.S. trade data confirms this trend, with pharmaceutical exports exceeding \$30 to \$40 billion in 2019, and the sector accounting for a substantial share of both output and manufacturing employment.

Between 2000 and 2025, Puerto Rico underwent a qualitative transformation in its industrial composition. While the island preserved, and in some respects deepened, its high-value, export-oriented manufacturing base, particularly in pharmaceuticals and medical devices, employment patterns shifted markedly toward the service and government sectors, and away from traditional manufacturing and other tradable goods industries.

This transformation reflects the combined effects of multinational corporate behavior, including tax-driven relocation of capital and intangible assets; a prolonged economic contraction and demographic decline, particularly between 2006 and 2017; institutional restructuring under the PROMESA framework; and major natural disasters, most notably Hurricane María.

Given these profound changes, any economic impact analysis that relies on outdated structural data risks misrepresenting the true magnitude and distribution of price

929 effects. Updated, sector-specific data and a modern understanding of Puerto Rico's
930 economic dynamics are essential for accurate modeling.

931 The phase-out of the federal tax benefit known as Section 936 (and related
932 corporate tax changes) is widely identified in the empirical literature as a major structural
933 inflection: firms reorganized, some production relocated, and the island's earlier catch-up
934 model weakened. Econometric and working-paper studies find the repeal had measurable
935 negative effects on manufacturing establishments and investment. That policy change set
936 in motion a long reallocation of firms and assets that continued to affect composition after
937 2000 (Refer to Exhibit 72.01, at ¶ 20). The following describes the economic structure shift
938 between 2008 to 2024:

939 1. Structural change in GDP composition profits:

- 940 a. In 2008, Puerto Rico's Gross Domestic Product (GDP) was primarily driven
941 by the manufacturing sector, which accounted for approximately 46% of total
942 output. Real Estate and Rental and Leasing contributed around 14%, while
943 agriculture, construction, and government represented 1%, 3%, and 5%,
944 respectively. By 2024, manufacturing's share had increased slightly to 47%,
945 while Real Estate and Rental and Leasing declined marginally to 13%.
946 Agriculture and construction also experienced modest declines. These shifts
947 reflect a gradual transformation in the island's economic structure,
948 characterized by a move toward high-value manufacturing, notably in
949 pharmaceuticals and biotechnology, alongside the emergence of a more robust
950 service sector, including finance, healthcare, and professional services. This
951 evolution signals a broader trend of economic modernization and

diversification, as documented by the Puerto Rico Planning Board and the Financial Oversight and Management Board for Puerto Rico (2020).

2. Structural change in employment composition

a. Between 2008 and 2023, Puerto Rico experienced a notable shift in employment patterns. The share of employment in manufacturing declined from approximately 18.4% to 12.1%, while employment in the service sector increased significantly, from 55% to 65%. Meanwhile, agriculture and government employment shares declined, and construction saw a modest increase. This trend underscores a key structural dynamic: although manufacturing continues to contribute substantially to GDP, it now employs fewer workers, reflecting its evolution into a more capital-intensive and technologically advanced sector. In contrast, the service sector has become the dominant source of employment, driven by demographic shifts, fiscal restructuring, and changing labor market demands industry (Refer to Exhibit 72.01, at ¶ 21).

3. Economic and Social Context

a. From the early 2000s through 2008, Puerto Rico's economy was heavily reliant on tax incentives, most notably Section 936, which supported the island's manufacturing dominance. However, the economic structure began to shift significantly following a series of major shocks: the phase-out of Section 936 by 2006, the global financial crisis in 2008, Hurricane María in 2017, the 2020 earthquake sequence, and the COVID-19 pandemic. These events intensified long-standing recessionary trends, contributed to a shrinking labor

975 force, and deepened fiscal instability. In response, Puerto Rico initiated
976 structural reforms aimed at diversifying the economy, enhancing productivity,
977 and expanding the service sector to build greater economic resilience.

978 4. Demographic Challenge

- 979 a. Puerto Rico has experienced a notable shift in its birth trends, closely tied to
980 the island's broader economic transformation, from a predominantly
981 agricultural economy to an industrialized one. These demographic patterns
982 remained relatively stable until the early 2000s, when the expiration of key tax
983 incentives for foreign corporations, including Section 936, triggered the
984 closure of many manufacturing enclaves. The 1990s marked the beginning of
985 a period of economic instability, driven by a series of exogenous shocks and
986 the onset of deindustrialization. These developments disrupted long-standing
987 economic and demographic trends, contributing to structural changes that
988 continue to shape Puerto Rico's economic and social landscape today (Refer
989 to Exhibit 72.01, at ¶ 22).

990 The post-María period represents a phase of temporary structural distortion, driven
991 by reconstruction-related spending, superimposed on longer-term shifts in economic
992 composition. These structural changes, particularly in dollar terms, are not captured in
993 traditional "pass-through" I-O analyses.

994 Puerto Rico underwent significant demographic and economic changes between
995 approximately 2006 and 2017. During this period, the island experienced a prolonged
996 economic contraction, GDP declined cumulatively (with estimates varying by baseline),
997 and population loss accelerated due to sustained out-migration to the U.S. mainland.

998 This combination of weak aggregate demand, mounting fiscal pressures (including
999 rising public debt), and population decline led to a structural reduction in both domestic
1000 employment and labor force participation. The impact was particularly pronounced
1001 in routine manufacturing, retail, and construction sectors, which are more sensitive to
1002 cyclical and structural downturns.

1003 In contrast, employment in the pharmaceutical sector, a capital and knowledge-
1004 intensive industry, did not decline in proportion to manufacturing's overall share of GDP
1005 (Refer to Exhibit 72.01, at ¶ 23). This reflects the sector's reliance on automation,
1006 specialized labor, and export-driven production, which insulated it to some extent from
1007 broader labor market contractions.

1008 Puerto Rico's trajectory reflects a hybrid model that combines an externally
1009 mediated industrialization, led by multinational corporations, premature
1010 deindustrialization, where manufacturing employment declines before full industrial
1011 maturity is reached and a domestic economic retrenchment, with a shift toward public-
1012 sector and service-based employment, as migration and fiscal constraints limit private-
1013 sector job creation.

1014 III. REBUTTAL TO DATTA TESTIMONY

1015 **Q. 36 On page 8, lines 12–13, and page 9, lines 1–24 of the Datta Testimony, Mr. Datta**
1016 **argues that LUMA's concern about "lost revenues" relating to NEM customers'**
1017 **reduced consumption despite the grid update costs needed to accommodate those**
1018 **customers is flawed because, he argues, the reduced consumption cannot create**
1019 **recoverable costs and would be economically inefficient. Does LUMA have a**

1020 response?

1021 A. Yes.

1022 **Q. 37 Please state and explain LUMA's response.**

1023 A. Revenue adequacy is often misunderstood, but it is a cornerstone of sound utility
1024 regulation, not a euphemism for guaranteed profits (Refer to Exhibit 72.01, at ¶ 7).
1025 Regulatory frameworks are designed to ensure that utilities can recover the costs necessary
1026 to maintain a safe and reliable electric grid. When a large share of fixed costs, such as grid
1027 maintenance, vegetation management, and system operations, is recovered through
1028 volumetric rates, NEM customers who reduce their net consumption may inadvertently
1029 cause the utility to under-recover these essential costs.

1030 This isn't about protecting utility profits (Refer to Exhibit 72.01, at ¶ 8); it's about
1031 ensuring that the infrastructure everyone relies on is adequately funded. Although we have
1032 seen that the use of NEM customers with batteries installed could have applications for the
1033 grid, even when NEM customers export excess energy during the day and import at night,
1034 effectively using the grid as its substitute, they still depend on the system but may not
1035 contribute proportionally to its upkeep.

1036 While it's true, as Datta points out, that "lost revenue" is not a cost, it serves as a
1037 useful proxy for identifying imbalances in cost allocation. From an economic perspective,
1038 it signals a disconnect between who causes costs and who pays for them (Refer to Exhibit
1039 72.01, at ¶ 8). If NEM customers avoid paying for grid services they continue to use, the
1040 financial burden shifts to non-NEM customers. This creates a cross-subsidization issue,
1041 which is particularly concerning in Puerto Rico, where the grid is both fragile and

underfunded, rooftop solar adoption is high, and the utility is navigating bankruptcy. In such a context, ensuring fair cost recovery becomes even more critical.

Mr. Datta is right to highlight that modern rate design tools, such as minimum bills or time-of-use (“TOU”) rates, can address these issues. However, acknowledging the availability of solutions does not negate the existence of the problem. LUMA’s concerns about lost revenue are not unfounded; they are symptoms of outdated rate structures that have not kept pace with the growth of distributed energy resources (“DERs”). The appropriate economic response is not to dismiss these concerns, but to modernize tariffs in a way that reflects cost causation, grid usage, and fairness across all customer classes.

Finally, unrecovered grid upgrade costs deserve serious consideration. As NEM penetration increases, it can trigger the need for additional investments in voltage regulation, backflow protection, and transformer upgrades. These are real marginal costs associated with integrating DERs into the grid. While it is incumbent upon LUMA to quantify these costs transparently, dismissing them outright overlooks the physical and operational realities of grid management in a high-DER environment.

Q. 38 On page 8, line 14; page 11, lines 3–30; and page 12, lines 1–7 of the Datta Testimony, Mr. Datta argues that LUMA’s concern about NEM customers “cost-shifting” to non-NEM ratepayers is flawed because, he argues, the assertion relies on incomplete data, ignores potential benefits to the grid, and lacks empirical evidence. Does LUMA have a response?

A. Yes.

Q. 39 Please state and explain LUMA's response.

A. Cost shifting is a legitimate concern under volumetric rate structures, particularly from a regulatory economics standpoint (Refer to Exhibit 72.01, at ¶ 8). It occurs when one group of customers pays less than their actual cost to serve, and the resulting shortfall is recovered from others. In Puerto Rico, this issue is especially relevant because most grid costs are recovered through per-kilowatt-hour charges. As NEM customers significantly reduce their net consumption, the financial burden of maintaining the grid shifts to non-NEM customers. This is not a political argument, it is a mechanical outcome of how rates are currently designed in the face of growing DER adoption.

While Mr. Datta is right to emphasize the importance of a comprehensive cost-benefit analysis, it is critical to recognize that the absence of quantified benefits does not negate the presence of measurable costs. NEM customers may avoid paying for grid services they continue to rely on, such as backup capacity, frequency control, and voltage regulation (Refer to Exhibit 72.01, at ¶ 9). Additionally, their participation can trigger local grid upgrades, and they often export energy during periods of low marginal value, such as midday solar surpluses (Refer to Exhibit 72.01, at ¶ 10). These are real marginal costs that must be acknowledged and fairly allocated. Ignoring them simply because benefits have not yet been quantified introduces analytical bias; both sides must be measured to ensure sound policy.

Empirical evidence from other jurisdictions with high DER penetration supports the concern about cost shifting, such as studies from California (Refer to Exhibit 72.01, at ¶ 11). The state's experience illustrates how cost shifting can persist and even intensify as DER adoption grows. California initially transitioned from NEM 1.0 to NEM 2.0 due to

1086 concerns that full retail rate compensation for exported solar energy allowed participating
1087 customers to avoid paying their share of fixed grid and public program costs, shifting those
1088 burdens onto non-participating ratepayers. However, subsequent evaluations of NEM 2.0
1089 revealed that the cost shift remained significant and disproportionately impacted low-
1090 income customers. In response, the California Public Utilities Commission adopted a
1091 successor tariff that replaces retail export compensation with values derived from the
1092 Avoided Cost Calculator and introduces high differential import rates to better reflect grid
1093 conditions and encourage solar-plus-storage adoption. These reforms aim to reduce the cost
1094 shift, promote equity, and ensure that DER compensation aligns more closely with the
1095 value provided to the grid.

1096 Mr. Datta's critique regarding the lack of customer load data is valid, as historical
1097 data limitations have made it difficult to precisely measure the extent of cost shifting.
1098 However, this gap is being addressed through a comprehensive load profile study currently
1099 underway (Refer to Response to Request for Information SESA-of-LUMA-LOAD_FOR-
1100 3: Permanent Rates – Load Forecasting (NEPR-AP-2023-0003)). This study covers
1101 customers with and without CHP and PV systems across Puerto Rico. It will provide
1102 empirical insights into consumption patterns, export behavior, and system impacts under
1103 real operating conditions. These findings will directly inform cost allocation, benefit
1104 quantification, and future tariff design.

1105 In this context, it is premature to dismiss cost shifting as a mere "narrative." The
1106 prudent approach is to acknowledge the theoretical basis for concern while relying on
1107 empirical studies, such as the ongoing load profile analysis, to determine the actual

magnitude of the issue. Only then can Puerto Rico move toward a rate design that is both equitable and economically sustainable.

Q. 40 On page 12, lines 8–28, and page 13, lines 1–24, Mr. Datta argues that LUMA’s concerns about NEM customers creating additional costs to LUMA that are not offset by benefits to non-NEM ratepayers is flawed because, he argues, LUMA has not adequately considered or analyzed avoided energy and capacity costs, reduced line losses, deferred infrastructure investments, and resilience. Does LUMA have a response?

A. Yes.

Q. 41 Please state and explain LUMA’s response.

A. From an economic and regulatory standpoint, the burden of proof applies equally to claims of both net benefits and net costs. While Mr. Datta rightly points out that LUMA has not yet quantified all the potential benefits of DERs, he simultaneously assumes significant benefits without empirical support. In regulatory proceedings, potential value is not equivalent to realized value.

DERs may offer theoretical system benefits, but these must be demonstrated with data rather than inferred. If NEM customers are imposing measurable costs, such as those related to voltage regulation (Refer to Exhibit 72.01, at ¶ 8), transformer upgrades, or protections for bidirectional power flow, those costs are real and immediate. Unless they are offset by quantified and attributable benefits, they represent a net burden that must be addressed through appropriate cost recovery mechanisms.

It is also important to recognize that the benefits of DERs are highly context dependent (Refer to Exhibit 72.01, at ¶ 8). Their value hinges on three key factors: location

(whether DERs are installed on constrained versus unconstrained feeders), timing (whether exports align with peak demand periods), and penetration level (whether the system is approaching diminishing returns). In Puerto Rico, the grid peaks in the evening, while most rooftop solar is non-dispatchable and lacks storage. Consequently, NEM exports often occur when the marginal value of energy is low, and the grid already has surplus capacity. This means that the most valuable avoided costs, such as capacity deferral during evening peaks, are largely unrealized or minimal under current conditions. While DERs can indeed provide benefits, their magnitude in Puerto Rico's present configuration is likely modest.

Mr. Datta's critique hinges on the absence of a comprehensive cost-benefit study. LUMA is currently conducting a NEM economics study, along with load profile analyses that include customers with and without PV and CHP systems across Puerto Rico. These efforts are intended to provide the empirical foundation necessary for future rate design and policy decisions.

LUMA's testimony appropriately highlights the incremental grid costs associated with NEM growth, including voltage regulation and protection equipment, reverse power flow upgrades, and transformer replacements or reconfigurations. These are not hypothetical concerns, they are observed consequences of increased distributed generation. When these costs are not recovered from NEM customers, they are effectively socialized across non-participants, creating a cross-subsidy and undermining cost causation principles.

Q. 42 On page 14, lines 1–24, and page 15, lines 1–9, Mr. Datta argues that LUMA does not adequately credit NEM customers with providing system wide reliability benefits.

1153 **Does LUMA have a response?**

1154 A. Yes.

1155 **Q. 43 Please state and explain LUMA's response.**

1156 A. While many NEM customers now pair PV systems with batteries, the mere presence of
1157 storage does not guarantee reliability value. Most behind-the-meter batteries are operated
1158 for self-consumption or backup power, not for coordinated grid support. As such, they
1159 function more as private resilience devices than as dispatchable system resources.

1160 To provide measurable reliability benefits, these batteries must be aggregated,
1161 scheduled, and dispatched in alignment with system needs, particularly during evening
1162 peaks when solar output is negligible and system stress is highest. This is the operational
1163 gap that LUMA's Customer Battery Energy Sharing (CBES) program seeks to address.

1164 LUMA's CBES program is a demand-side grid service designed to shave peak
1165 demand and facilitate smoother generation ramping during Puerto Rico's evening peak
1166 hours. The program operates on an opt-out basis, meaning customers are enrolled by
1167 default and must actively choose to opt out. This design has enabled high enrollment and
1168 participation rates, particularly under the enhanced CBES+ platform.

1169 Recent dispatch data from summer 2025 demonstrates the program's operational
1170 maturity:

Month	Average Enrollment	Average Participation Rate
June	12,225	86%
July	67,165	69%
August	73,188	82%

1171
1172 These figures indicate that CBES+ is not merely a pilot or theoretical construct, it
1173 is a functioning, large-scale DER program. However, seasonal variation in customer

behavior remains a constraint. During the summer, many customers prioritize battery use for personal reliability, which can reduce the volume of energy available for grid dispatch. This behavioral dynamic introduces variability in the program's effective contribution to system reliability.

From an economic standpoint, CBES dispatch currently carries a fixed cost of approximately \$1.25 per kWh, based on the incentive paid to participating customers. In contrast, the short-run marginal cost of dispatching a conventional peaker plant is estimated at around \$0.23 per kWh. While CBES may offer environmental or resilience co-benefits, these are not yet monetized or formally evaluated. As such, CBES is currently more expensive on a per-kWh basis, and its economic competitiveness relative to centralized alternatives remains uncertain without a comprehensive economic impact study.

To that end, LUMA is also pursuing the Accelerated Storage Addition Program (ASAP), which aims to deploy utility-scale battery energy storage systems (BESS) across the island. These installations are expected to provide firm, centrally dispatched capacity that can complement or substitute for distributed programs like CBES. In parallel, the Integrated Resource Plan (IRP) process is underway to evaluate a portfolio of generation and storage options that can meet Puerto Rico's reliability needs while minimizing long-term costs to consumers.

Finally, while Mr. Datta's use of Loss of Load Hours (LOLH) and Value of Lost Load (VoLL) to estimate avoided outage costs is theoretically valid, it assumes that DERs consistently discharge during forecasted load-shedding events. The CBES+ data shows meaningful dispatch activity, but not all enrolled customers discharge fully or consistently, and seasonal opt-out behavior can reduce available capacity. As such, the implied \$2–\$5

1197 billion per year in avoided outage costs likely overstates the realized reliability benefits
 1198 under current operational conditions.

1199 **IV. REBUTTAL TO HOPKINS REPORT**

1200 **Q. 44 In Section 3.2 of the Hopkins Report, Dr. Hopkins concludes that no “additional**
 1201 **corrective factor” or “adjustments” to LUMA’s forecast model are necessary to**
 1202 **account for non-programmatic efficiency. Does LUMA agree with this conclusion?**

1203 A. Yes.

1204 **Q. 45 In Section 3.2 of the Hopkins Report, Dr. Hopkins states that LUMA “does not**
 1205 **include an exogenous variable (a driver of the regression load forecast) that reflects”**
 1206 **the expected impact of “contributing entities” other than LUMA on Puerto Rico’s**
 1207 **energy efficiency goal, nor “similar changes in energy efficiency (such as an exogenous**
 1208 **variable reflecting decreasing energy intensity of the economy over time).” The**
 1209 **premise for Dr. Hopkins’ analysis is that “LUMA should incorporate the impact of**
 1210 **[broader energy efficiency policies and programs] in its load forecast.” Does LUMA**
 1211 **have a response?**

1212 A. Yes.

1213 **Q. 46 Please state and explain LUMA’s response.**

1214 A. LUMA’s base load forecast (unadjusted model) incorporates reductions in energy
 1215 consumption due to EE measures already embedded in historical consumption data. These
 1216 include:

- 1217 1. Government Sector Reductions Mandated by Act 57-2014
- 1218 a. Municipalities – As per Regulation 8818.

b. Local Government Entities – Required to reduce consumption by 40% by FY2022, using FY2013 as the baseline

c. Legislature – Targeted 12% reduction based on 2013 consumption levels.

2. Lighting Efficiency Programs

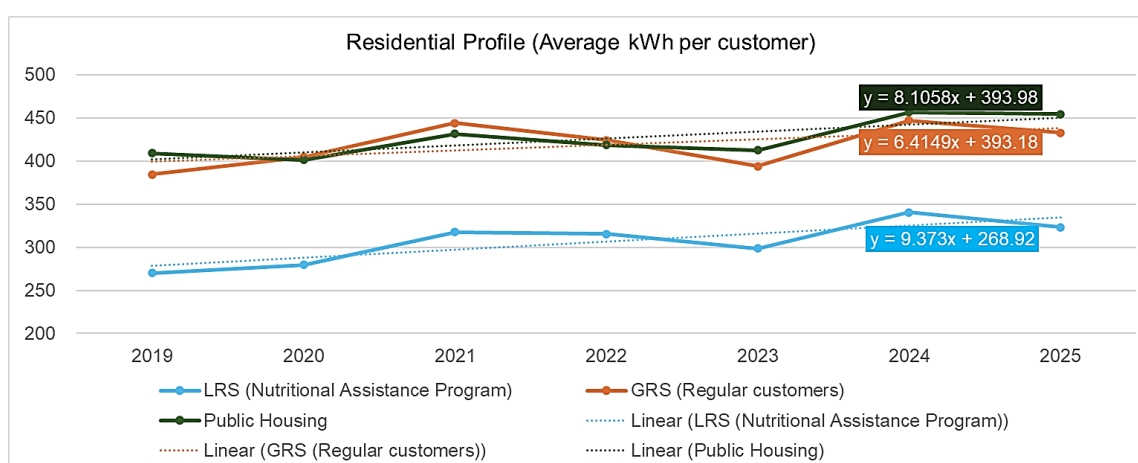
a. Replacement of incandescent bulbs with LED lighting across residential, commercial, and industrial sectors, initiated by PREPA in 2008.

3. Customer-Initiated Energy Efficiency Measures

a. Residential Sector: Replacement of window or standard mini-split A/C units with inverter mini-splits; Adoption of solar water heaters, incentivized by government tax credits in the 2000s; Replacement of household appliances with more energy-efficient models.

Historical data shows that average consumption by residential customers increased, particularly the low-income customers, even with some federal and local EE programs deployed in or after 2023:

Figure 17: Residential Consumption Profile 2019-2025



b. Commercial and Industrial Sectors: Implementation of various EE measures contributing to observed consumption reductions, particularly customers

1237 with substantial consumption in transmission voltage level (Refer to Exhibit
1238 72.01, at ¶¶ 13 & 14).

1239 However, the major contributor to the reduction is the distributed generation. The
1240 following figures depict the trends of those classes by voltage level:

Figure 18: Commercial and Industrial Transmission Voltage Level 2019-2025

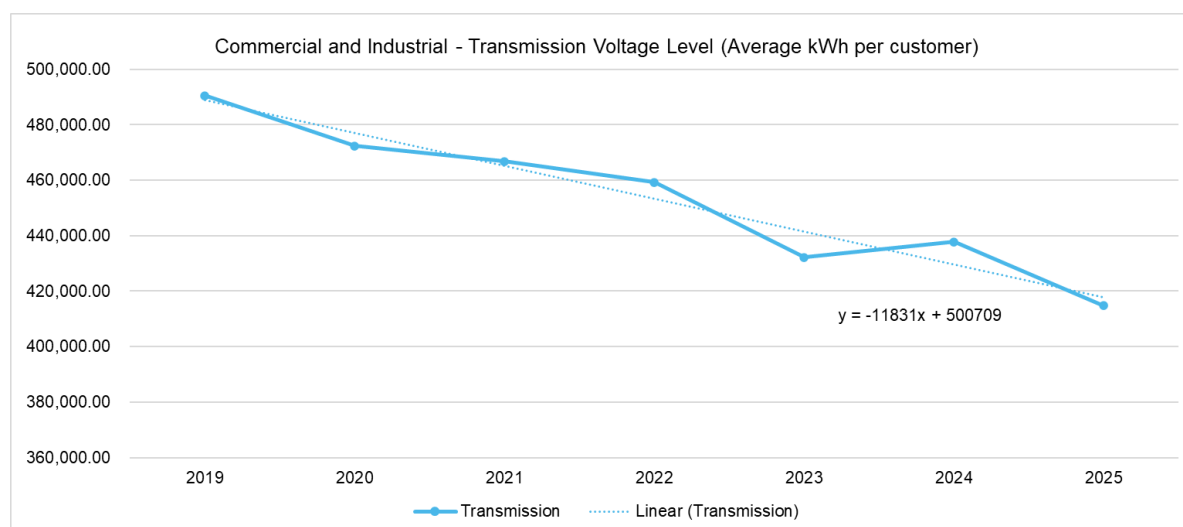
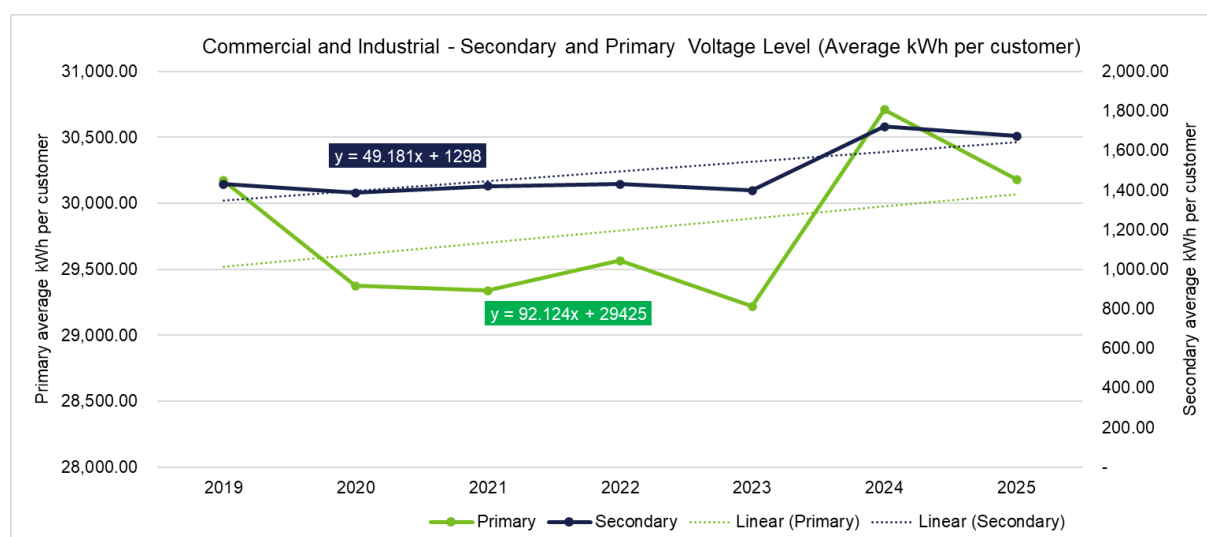


Figure 19: Commercial and Industrial Secondary and Primary Voltage Level 2019-2025



c. Streetlighting Adjustments

Post-Hurricane María, most streetlights were replaced with LED fixtures. In April 2019, the Puerto Rico Energy Bureau (PREB) ordered PREPA to manually adjust streetlighting consumption to reflect the gradual restoration of the system. This manual adjustment continued until October 2023, when operational data confirmed full restoration. Despite the LED replacements, the billing system continued to reflect sodium and mercury

vapor bulb consumption until PREB approves a new rate design for LED lighting. This manual offset significantly reduced the apparent consumption savings from LED adoption. Since 2023, LUMA has been measuring sodium and mercury consumption, and a further reduction in the public lighting class is expected once the new LED rate structure is approved.

In short, most of the reductions described above are already embedded in the historical consumption data used to calibrate the load forecast models by customer class. The adjusted forecast used in the rate review includes reductions mandated by PREB for specific years. These adjustments account not only for LUMA's EE programs but also for broader government-mandated initiatives.

Finally, the EE Market and Potential Study (Puerto Rico Energy Efficiency Market Baseline and Potential Study – September 24, 2025) was completed after the development of these projections. Currently, LUMA technical staff are reviewing and preparing comments related to the study, as we have preliminarily identified certain deficiencies. Once the Energy Bureau confirms the results of the study, LUMA can proceed to incorporate its impact into future forecasts in alignment with the study's findings.

V. REBUTTAL TO MING REPORT

Q. 47 On page 21 of the Ming Report, Mr. Ming states that binary variables, which LUMA used in its regression analysis to reflect key impacts on the rate forecast, are standard for capturing categorical factors and Dr. Cao's concern over their use is "not persuasive." Does LUMA agree?

A. Yes.

Q. 48 On page 21 of the Ming Report, Mr. Ming states that LUMA's decision to use the 73rd

percentile of median monthly CDD data for the residential model is inconsistent with the assumption used for other customer classes, like the 50th percentile for CDD used for the commercial model. Mr. Ming argues that the higher sensitivity of residential load regarding CDD data should be accounted for using a different coefficient for CDD, not using a higher percentile for CDD data. Later, on Page 23, Dr. Ming argues that “it is not reasonable for LUMA to use different CDD scenarios in the residential and commercial regression models” and LUMA should use the same percentile scenario for CDD in both the commercial and residential models. Do you have a response?

A. Yes.

Q. 49 Please state and explain your response.

A. LUMA respectfully disagrees with Mr. Ming’s recommendation to apply the 50th percentile approach to the residential model, as was done for the commercial sector. The 50th percentile scenario results in an unsupported reduction in the FY 2026 forecast.

Adjusting the CDD coefficient is not deemed an appropriate solution, as the regression model is based on a monthly time series beginning in 2010.

Residential customers tend to exhibit a distinct pattern of electricity use in response to high temperatures. Many households turn off their cooling systems when they leave for work, allowing their homes to heat up throughout the day. Upon returning in the late afternoon or evening—often during peak demand hours—they ramp up usage by turning on air conditioning and other appliances simultaneously. This behavior leads to sharp spikes in residential load during hot days, particularly when extreme weather events occur. Using a higher percentile of CDD in the residential model helps capture this sensitivity and

better reflects the upper-bound demand that utilities must be prepared to serve. It also aligns with recent years' weather trends, which show more frequent and intense heat events that amplify this load pattern.

The historical period used in the regression model primarily reflects average weather conditions, which skews the model's weighting toward typical climate patterns. As a result, it does not sufficiently account for the more extreme climate variability observed in several of the past five fiscal years.

BASLINE FORECAST ASSUMPTIONS

Over the past several forecast periods, LUMA has utilized the Guidehouse-developed 50th percentile CDD forecast as the baseline scenario. This scenario was considered for the rate review load forecast. However, the resulting 9.5% reduction in FY 2026 (after applying modifiers) was not supported, especially when compared to the 3.1% estimated reduction in FY 2025.

ALTERNATIVE SCENARIOS EVALUATED

To improve forecast accuracy, LUMA analyzed two additional CDD scenarios:

1. 73rd percentile CDD forecast: FY 2026 load reduction = 7.2%
2. 80th percentile CDD forecast: FY 2026 load reduction = 6.2%

The interannual variance across all evaluated scenarios for fiscal years 2027 and 2028 appears consistent. LUMA calculated the 10-year Average Growth Rate (AGR) based on observed data. The AGR for the 73rd percentile scenario is positive in FY 2026 and aligns with the observed AGR in fiscal years 2024 and 2025. Moreover, the average AGR for the 73rd percentile scenario over fiscal years 2026–2028 (-0.3%, the average of 0.22%, -0.31%, and -0.77%) is closer to the average observed AGR over the past three years (0.8%, the average of 0.52%, 1.56%, and 1.27%) than the 50th percentile scenario (-0.5%, the

average of -0.03%, -0.52%, and -0.98%), supporting the selection of the 73rd percentile scenario. Even when compared to the unadjusted models, the 73rd percentile scenario demonstrates a better fit, with an average growth rate (AGR) of 0.8% (average of 0.79%, 0.84%, and 0.78%) across the three forecast years. In contrast, the 50th percentile scenario yields a lower AGR of 0.6% (see tables below).

Figure 20: Comparison of CDD Modifiers to Adjusted Load Forecast

Adjusted Load Forecast - Modifiers applied %

FY	Actual	Interannual CDD 50th percentile	Interannual CDD 73th Percentile	Interannual 80th Scenario	AGR 10-year Actual	AGR 10-year CDD 50th percentile	AGR 10-year CDD 73th Percentile	AGR 10-year 80th Scenario
2020	6.3				(0.88)			
2021	6.9				0.29			
2022	(0.4)				0.47			
2023	(8.1)				(0.52)			
2024	15.9				1.56			
2025 e	(3.1)				1.27			
2026		(9.5)	(7.2)	(6.2)		(0.03)	0.22	0.32
2027		(5.4)	(5.8)	(5.2)		(0.52)	(0.31)	(0.14)
2028		(5.4)	(5.3)	(5.2)		(0.98)	(0.77)	(0.61)

* AGR FY 2028 compared with FY 2017 to avoid impact hurricane María to the load.

e=estimate: observed data up to February 2025

Figure 21: Comparison of CDD Modifiers to Unadjusted Load Forecast

Unadjusted Load Forecast								
Date	FY	Interannual CDD 50th percentile	Interannual CDD 73th Percentile	Interannual 80th Scenario	AGR 10- year Actual	AGR 10- year CDD 50th percentile	AGR 10-year CDD 73th Percentile	AGR 10- year 80th Scenario
2020	6.3				(0.88)			
2021	7.3				0.32			
2022	(0.7)				0.47			
2023	(8.1)				(0.52)			
2024	15.9				1.56			
2025 e	(3.1)				1.27			
2026		(4.1)	(1.8)	(0.8)		0.55	0.79	0.89
2027		0.3	(0.2)	0.3		0.65	0.84	0.99
2028		0.2	0.2	0.3		0.61	0.78	0.92

* AGR FY 2028 compared with FY 2017 to avoid impact hurricane María to the load.

e=estimate: observed data up to February 2025

The selected scenario provided a more reasonable outlook and aligned better with observed trends. Final residential consumption in FY 2025 decreased 4.3%, a little deeper than the estimated, and in FY 2026 as of September 2025 (preliminary), the data reflects an approximate 2% reduction, which substantiates LUMA's decision for a scenario with a less pronounced decline, aligned with the 73rd percentile forecasted decrease.

OBSERVED CDD TRENDS AND HISTORICAL CONTEXT

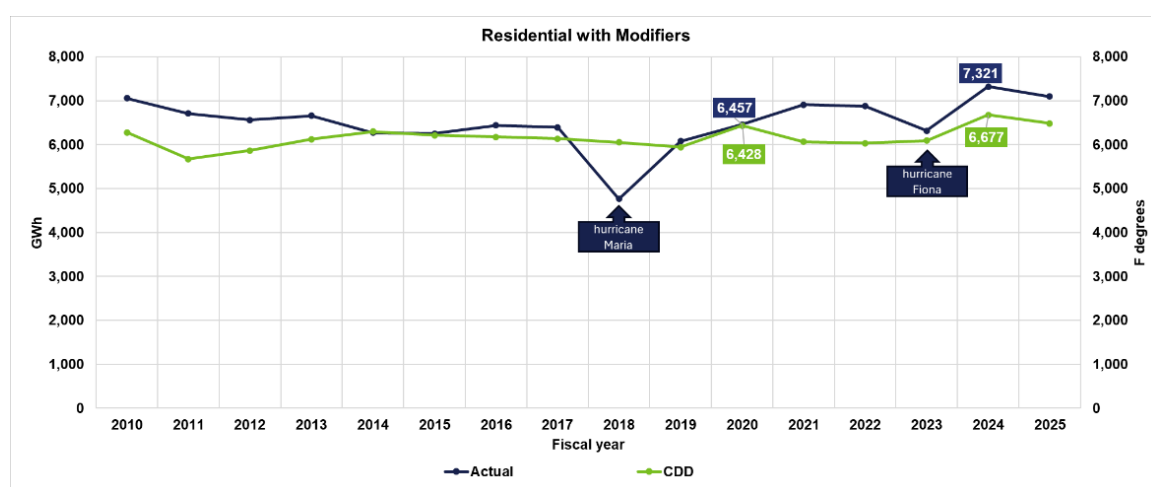
Historically, a spike in CDD was followed by a decline the next year. This trend did not hold in FY 2020 and 2024, indicating a shift in climate patterns and sustaining warmer conditions.

Since May 2023, Puerto Rico has experienced a prolonged heat wave, with record-breaking temperatures through at least March 2025. June 2023 recorded 625°F CDD, surpassing the previous high in June 2014. Each month following ranked among the top three historically in terms of CDD. FY 2024 recorded the highest fiscal year CDD on record: 9.6% (585°F) higher than FY 2023, and 3.9% (249°F) higher than FY 2020 (previous record).

IMPACT ON RESIDENTIAL CONSUMPTION

Residential energy consumption increased significantly in FY 2024, consistent with elevated CDD. The following figure illustrates the correlation between observed consumption and CDD. While an apparent decoupling between the two variables is evident during fiscal years 2021 and 2022, the correlation strengthens notably beginning in FY 2023, coinciding with rising temperatures.

Figure 22: Residential Consumption and CDD Comparison



COMMERCIAL LOAD FORECAST PERFORMANCE

The commercial model has demonstrated strong performance, with a FY 2025 variance of only 0.75% relative to the forecast. This high level of accuracy provides no justification for modifying its current specification. Furthermore, the model exhibits lower sensitivity to CDD fluctuations compared to the residential model.

Q. 50 On page 22, Mr. Ming states that LUMA “failed to adjust the residential regression to account for historical effects of load modifiers such as DG, EE, and EV’s. As a result, the final consumption forecast risks overcounting the effect of load modifiers. LUMA designed its regression model using the historical between consumption and the independent variables. DG, EE, and EV affect historical consumption data that

the regression relationship is based on. Therefore, the regression results already implicitly include potential future of these load modifiers.” As a result, Mr. Ming believes PREB should “update its regression model so it takes into account the historical impact of these load modifiers in future load forecast efforts.” Does LUMA agree?

A. Partially.

Q. 51 Please state and explain LUMA’s response.

A. As stated in this testimony, since 2023, LUMA has been engaged in a continuous improvement process to enhance the accuracy of its demand forecasts. In 2024, the industrial model was modified with this objective. As explained in this testimony (see rebuttal to Dr. Cao’s Report), the load displaced by CHP systems was estimated from historical data, added to the actual consumption, and then added back into the forecasts. In the case of the industrial model, the displacement associated with net metering systems was deemed insignificant, and therefore, this load was not removed from the model.

The residential model, on the other hand, exhibited significant variance in previous years, as discussed in this testimony (refer to rebuttal to Dr. Cao’s Report). In response, we adjusted the model components related to temperature, which have been identified as the primary factor influencing this behavior. In 2025, LUMA, in collaboration with Guidehouse, initiated a new phase of model evaluation for the residential class, similar to the approach taken with the industrial class. This phase began in October 2025, and it involves assessing a residential model that excludes distributed generation (“DG”) displacement from historical data. Based on the results of this evaluation, LUMA may adopt this revised model in the next forecasting cycle.

1386 Finally, the commercial model has demonstrated high accuracy to date, and as such,
1387 no changes are currently recommended.

1388 Empirical evidence also supports the validity of LUMA methodology. For example,
1389 the significant under-forecast of residential consumption in FY2024 was not due to
1390 unmodeled DG, EE, or EV effects, but rather to record-high temperatures and a persistent
1391 post-2020 behavioral shift in residential electricity use. Similarly, the FY2025 industrial
1392 forecast error was primarily driven by unmodeled self-generation, which has since been
1393 addressed through explicit adjustments. Notably, the commercial forecast errors in both
1394 FY2024 and FY2025 were within 2%, further demonstrating that the exclusion of explicit
1395 price or load modifier variables does not inherently compromise forecast accuracy.

1396 Currently, load reduction or increase associated with the modifiers is already
1397 embedded in the consumption data used in the regression models for the main customer
1398 classes. In other words, LUMA accounts for the historical impact of these load modifiers
1399 in the development of the regression model. However, future integration (in terms of net
1400 metering capacity and customers) is considered an incremental impact of the displaced
1401 load, which is applied incrementally to the unadjusted forecast to avoid double counting.
1402 As a result, the historical impact informs the baseline, while the incremental count of load
1403 modifiers appropriately accounts for future impacts.

1404 **DISTRIBUTED GENERATION AND NET METERING**

1405 The forecasted load displacement is explained in my direct testimony, notably at
1406 lines 197 to 228. As explained, the observed data already includes the load displacement
1407 from customers participating in the net metering program. LUMA is aware of the need to
1408 avoid double counting this modifier. For the forecasted years, LUMA applies the

1409 incremental load reduction as the DG modifier, using the difference in displaced load from
 1410 fiscal year 2025 as the baseline to avoid the double counting. (See following table.)

Residential DG-NM (GWh)

Fiscal Year	Total Load Displacement	Reduction applied (FY-FY2025)
2025	1,319.0	
2026	1,709.6	390.6
2027	2,074.1	755.1
2028	2,405.2	1,086.2

1411
 1412 In the future, once more robust tools are available to isolate and quantify the actual
 1413 impact of EE programs, LUMA will be able to refine and update the methodology
 1414 accordingly

1415 Aware of recent changes in the drivers influencing load trends, in 2023 LUMA
 1416 launched the Load Forecasting Improvement Project. Recently, as part of this project and
 1417 due to the significant deviation between industrial observed data and the forecast, the
 1418 methodology for the industrial model was updated. Specifically, the impact of CHP
 1419 systems was excluded from historical data, and after estimating the model coefficients, the
 1420 CHP impact was reintroduced as a modifier. LUMA does not rule out updating the
 1421 residential model in a similar manner in the future, excluding the impact of distributed
 1422 energy displacement from historical consumption, as the Net Metering program continues
 1423 to significantly affect the load.

1424 ENERGY EFFICIENCY

1425 With respect to energy efficiency (EE), LUMA acknowledges that, at the time the
 1426 load forecast was developed, the most appropriate approach was to apply the percentage

adjustment as directed by PREB. EE forecast used in the rate review includes reductions mandated by PREB for the rate review period. These adjustments account not only for LUMA's EE programs but also for broader government-mandated initiatives.

Historical data indicates that average customer consumption has increased, particularly among low-income customers and those served at the low-voltage level, despite the implementation of certain federal and local EE programs after 2023.

ELECTRIC VEHICLES

Finally, due to the lack of localized data to quantify the impact of EVs in Puerto Rico, LUMA relied on information from the PR100 study. Forecasting EV adoption remains a challenge—not only for LUMA, but for jurisdictions across the United States.

In conclusion, the regression model does not overcount the effects of DG, EE, or EVs. It reflects the net historical relationship between consumption and its drivers, and any future adjustments are applied cautiously and only when warranted by external data. This ensures that the forecast remains both empirically grounded and methodologically sound.

Q. 52 On page 22, Mr. Ming “agree[d] with Dr. Cao’s argument that LUMA should include electricity price in the residential regression.” Mr. Ming opined that electricity price “impacts a customer’s consumption” and impacts “the customer’s adoption of DG or EE, later arguing on page 27 that the “consumption forecast should investigate customer price elasticity” by including electricity price as a regression variable. Does LUMA have a response?

A. Yes.

1448 **Q. 53 Please state and explain LUMA's response.**

1449 A. Mr. Ming adopted Dr. Cao's idea that electricity price should be included as a regression
1450 variable because it can influence both electricity consumption and customer adoption of
1451 DG or EE measures. While these assumptions are theoretically sound in the context of
1452 microeconomic demand modeling, the empirical evidence and practical forecasting
1453 considerations in Puerto Rico suggest that including electricity price in the residential
1454 regression would not improve forecast performance. In fact, it may introduce statistical
1455 complications. One such complication lies in how the projected price per kWh would be
1456 derived, as it is directly related to the projected load, creating a circular dependency in the
1457 forecast.

1458 Moreover, all studies reviewed indicate that electricity consumption is price
1459 inelastic. For example, between FY2021 and FY2022, the average residential electricity
1460 price increased by approximately 30%, yet total residential consumption declined by only
1461 0.4%. This weak relationship indicates that price is not a strong explanatory variable for
1462 short- to medium-term consumption behavior in this context.

1463 Furthermore, out-of-sample testing conducted in 2023 showed that including
1464 electricity price in the regression did not improve forecast accuracy. In fact, the inclusion
1465 of price introduced concerns related to endogeneity and multicollinearity with other
1466 macroeconomic variables, such as income and economic activity, which can bias
1467 coefficient estimates and reduce model reliability.

1468 It is also important to note that many U.S. utilities, including those regulated by
1469 state commissions, do not include electricity price in their long-term load forecasting
1470 models. A 2016 study by Lawrence Berkeley National Laboratory (Refer to Exhibit 72.01,

at ¶ 1) found that only about half of load-serving entities explicitly modeled price elasticity in their forecasts. Utilities such as Portland General Electric (Refer to Exhibit 72.01, at ¶ 2), ISO New England, and DTE Electric (Refer to Exhibit 72.01, at ¶ 3) have published methodologies that exclude price as a direct input, yet their forecasts are accepted by regulators and used for integrated resource planning.

In conclusion, while electricity price is conceptually relevant, its empirical contribution to forecast accuracy in Puerto Rico's residential sector is minimal. LUMA's decision to exclude price from the base case regression model is grounded in empirical testing, statistical rigor, and alignment with industry best practices. The model remains robust, transparent, and fit for purpose in supporting long-term planning and regulatory review.

Q. 54 On page 22, Mr. Ming disagreed with Dr. Cao about including disposable personal income in the regression and instead supports "LUMA's decision to use GNP as the key economic variable" as a reasonable choice. Does LUMA agree.

A. Yes.

Q. 55 On page 25, Mr. Ming states, "LUMA forecasted annual peak demand applying historical load factors to the consumption of each customer class. LUMA's approach inappropriately ignores the load shape of load modifiers. Load modifiers affect usage at different times of day; therefore, a simple load factor without a more detailed load shape cannot capture their impact on peak demand. In particular, DG likely produces some energy during peak hours that potentially shifts the system peak demand later in the day." Does LUMA agree?

A. No.

1494 **Q. 56 Please state and explain LUMA's response.**

1495 A. LUMA respectfully disagrees with Mr. Ming's statement. However, regarding his
1496 recommendation, once the load profile study is completed, LUMA intends to update the
1497 load factors by rate category, incorporating a more refined customer segmentation (for
1498 example, between GRS Regular and GRS Net Metering customers).

1499 **DETERMINATION OF ANNUAL MAXIMUM LOAD**

1500 To estimate the annual maximum load, LUMA allocated energy consumption by
1501 customer class and rate category based on the most recent 12-month proportional
1502 distribution of consumption by rate. Once the consumption was distributed, load factors by
1503 rate (the same used in the approved 2020 IRP) were applied. Finally, the non-coincident
1504 load by rate was totaled for each fiscal year. To determine the forecasted annual peak load,
1505 the annual variance of the total non-coincident load is applied to the most recently observed
1506 peak demand, usually from the fiscal year in which the projection is made.

1507 It is also important to consider Puerto Rico's load profile. While DG systems,
1508 particularly solar PV, typically generate electricity during daylight hours and may reduce
1509 peak demand in some jurisdictions, this is not the case in Puerto Rico. The island's system
1510 peak occurs between 6:00 PM and 9:00 PM, after solar generation has largely ceased. As
1511 a result, DG does not reduce peak demand during these critical hours. In fact, by lowering
1512 mid-day load and leaving evening demand unchanged, DG may inadvertently increase the
1513 relative height of the peak. This is precisely why LUMA relies on historical load factors,
1514 which already reflect the net impact of DG on peak demand under local conditions.

1515 LUMA initiated a load profile study in March 2024, selecting a sample of
1516 approximately 60 customers from different rates (different customer characterization) with

1517 hourly meter readings. Preliminary load profile data from this study were incorporated into
1518 the forecasting procedure. However, due to ongoing data collection challenges, the dataset
1519 remains incomplete. At the time the forecast was developed, there was insufficient data to
1520 update the load profiles for each rate category. In particular, LUMA has not yet been able
1521 to collect hourly data for certain critical rate classes, most notably primary voltage
1522 customers. These data limitations have also delayed the imputation process needed to
1523 address missing values across several months, further constraining the completeness and
1524 accuracy of the load profiles.

1525 **Q. 57 Does this complete your testimony?**

1526 A. Yes

ATTESTATION

Affiant, Joseline N. Estrada Rivera, being first duly sworn, states the following:

The foregoing prepared Surrebuttal Testimony and exhibits attached thereto constitute testimony filed in rebuttal to the report of Dr. Ramón J. Cao García ("Cao Report") filed in this proceeding on September 8, 2025 by the Institute of Competitiveness and Economic Sustainability ("ICSE"); pre-filed testimony of Mr. E. Kyle Datta ("Datta Testimony") filed in this proceeding on September 8, 2025 on behalf of Solar & Energy Storage Association; the report of Dr. Asa Hopkins ("Hopkins Report"), consultant to the Puerto Rico Energy Bureau ("PREB"), dated October 2, 2025; and the report of Zachary Ming ("Ming Report"), consultant to PREB, dated October 6, 2025. If asked the questions included in the Surrebuttal Testimony, I would give the answers set forth in the Surrebuttal Testimony. I further state that the facts and statements provided herein are true and correct to the best of my knowledge.

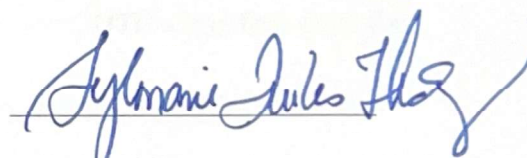

 Joseline N. Estrada Rivera

Affidavit No. 490

Acknowledged and subscribed before me by Joseline N. Estrada Rivera, in her capacity as Director of Tariff & Budgets, Load Forecasting of LUMA, of legal age, married, and resident of San Juan, Puerto Rico, who has been identified by drivers license (1748940)

In San Juan, Puerto Rico, this 4 day of November 2025.




 Notary Public

LUMA Ex. 72.01

**APPENDIX 1 TO SURREBUTTAL TESTIMONY OF
JOSELINE N. ESTRADA RIVERA**

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LUMA Ex. 72.02 (*An Analysis of the Economic Impact of Increasing the Price of Electricity in Puerto Rico*, prepared by Navigant Economics, August 19, 2016)

An Analysis of the Economic Impact of Increasing the Price of Electricity in Puerto Rico¹

By

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Navigant Economics

and

Justin Lenzo, Ph.D.
Navigant Economics

August 19, 2016

I. Introduction**A. Purpose of Analysis**

The Puerto Rico Electric Power Authority (PREPA) is, for all practical purposes, a monopoly supplier of electricity in Puerto Rico.² PREPA has undertaken an initiative to address its mounting debt and required capital investments by restructuring its debt service terms and increasing revenues. As part of this initiative, PREPA is analyzing the necessity of changing electricity rates charged to its customers.

As an economic matter, it appears to us inevitable that, in order for PREPA to return to sound economic footing, address its debt, cover its operating costs, and make necessary capital investments, PREPA will have to increase electricity rates over the next several years. These increases will, however, affect the Puerto Rican economy as a whole. Because electricity is an essential commodity for households and businesses, increases in PREPA's rates are likely to reduce residents' disposable income and therefore have a contractionary effect on the regional economy. In part to mitigate the magnitude of necessary rate increases, PREPA has negotiated an agreement with creditors (herein, the "Restructuring Support Agreement" or "RSA") that effectively attenuates the amount of revenue that PREPA will be required to raise through its operations over the next several years in order to service and pay off its debt. To the extent that the necessary price increases will be lower as a result of the RSA than they would otherwise be, the Puerto Rican economy will benefit.

¹ This research was funded by the Puerto Rico Electric Power Authority (PREPA). The views expressed in this paper are those of the authors and do not necessarily reflect the views of PREPA. Any errors are the sole responsibility of the authors.

² See "PREPA IS...", PREPA, accessed August 10, 2016, at http://www.prepa.com/aeees_eng.asp.

The purpose of our analysis is to quantify the likely economic benefits, in terms of key macroeconomic variables, of the rate changes necessary under the terms of the RSA to meet revenue requirements, in comparison to the economic effects of price increases that would be necessary in the absence of the negotiated RSA.³ Specifically, we apply economic analysis and regional data to simulate what the effects will be on employment, gross domestic product (GDP), and per capita disposable personal income in the Commonwealth of Puerto Rico over the next several years as a result of the price increases necessary to restore solvency to PREPA and finance investments required for environmental compliance, assuming that the RSA is effectuated, relative to the effects of the price increases that would be necessary in its absence.

We account in our analysis for the demand responses resulting from the increased rates using price elasticities that we have estimated from historical data on electricity demand in Puerto Rico over recent years. We then simulate the effects of the anticipated rate increases on the overall economy using a sophisticated regional macroeconomic model. We quantify substantial benefits to the economy of Puerto Rico over the next five years attributable to the RSA.

B. Summary of Paper and Conclusions

The rest of the paper is organized as follows. In Section II, we provide relevant background on PREPA's fiscal challenges in the context of the broader stagnation and decline that has characterized Puerto Rico's economy in recent years. In Section III, we describe the methodology by which we estimated the price elasticity of demand for electricity in Puerto Rico by customer segment, and present the results. In Section IV, we apply these elasticity estimates alongside other financial and economic modelling to simulate the regional macroeconomic effects on employment, GDP, and disposable income of raising electricity rates to cover PREPA's revenue requirements under select policy scenarios. Section IV also describes the macroeconomic model we apply, its application to Puerto Rico, and the results of our simulations. Section V offers concluding comments.

Our main findings are as follows. First, PREPA operates within a challenging economic context characterized by a prolonged and ongoing recession, a significant drop in energy sales, a declining population, and low per capita income. In addition, PREPA must come into compliance with existing EPA requirements, compliance with which will necessitate capital investments. PREPA cannot rely on—or wait for—a natural recovery of the local economy to put the utility on a sounder fiscal footing. As an economic matter, any realistic approach to addressing PREPA's fiscal problems involves increasing the rates that PREPA charges its customers.

³ These alternative policy scenarios without the RSA will be discussed in more detail in Section IV.C.

Second, consistent with the findings of economic research on electricity demand in other geographic areas, we find that electricity demand by PREPA's customers is relatively price inelastic, but not perfectly so. In response to increases in electricity rates, customers of all classes—consumer, commercial, and industrial—will, on average, decrease their usage of electricity. However, in percentage terms, these reductions in usage will be small in proportion to the increase in rates. Therefore, increasing electricity rates is an effective way of increasing revenues. The additional revenues come, however, with a loss in disposable income for households and an increase in production costs for businesses.⁴

Third, the key benefit of the RSA to residents of Puerto Rico, and to the Puerto Rican economy as a whole, is that it moderates the degree of rate increases necessary to meet revenue requirements, especially over the next few years, relative to alternative policy scenarios. Our regional economic simulations show that the economic benefits of the terms of the RSA, relative to other scenarios, amount to thousands of jobs saved and a difference in GDP of more than \$1 billion over the next five fiscal years.

II. Relevant Background on Puerto Rico and PREPA

A. What is PREPA?

Founded in 1941, the Puerto Rico Electric Power Authority (“PREPA”) is a public corporation that supplies almost all of the electric power used in Puerto Rico.⁵ PREPA serves nearly 1.5 million customers on the islands of Puerto Rico, Vieques, and Culebra.⁶

PREPA provides electricity through a combination of self-generation and purchased power. As of FY 2013, PREPA generated approximately two-thirds of Puerto Rico's electricity production through power plants at Aguirre, Costa Sur,

⁴ To be clear, there are other economic and policy factors that are changing contemporaneously in Puerto Rico and that affect disposable income and production costs. It is beyond the scope and purpose of our analysis to forecast the total effect of all of these factors on disposable income and production costs in the coming years.

⁵ Public corporations are organizations owned by the Commonwealth government; however, they are not formally considered government agencies (or funded as such). PREPA is one of about 50 public corporations in Puerto Rico. The Puerto Rico Water Resources Authority became the first public corporation in Puerto Rico in 1941. This agency was renamed PREPA in 1979. PREPA consolidated virtually all electricity supply on the island by 1981. See “PREPA IS...,” The Puerto Rico Electric Power Authority, accessed August 10, 2016, at http://www.prepa.com/aeees_eng.asp, and “A Sketch of Our History,” The Puerto Rico Electric Power Authority, accessed August 10, 2016 at http://www.prepa.com/historia_eng.asp for a history of the corporation.

⁶ PREPA defines its mission as “To provide electric services to our clients in the most efficient, economical and reliable way, without harming the environment.” See “Investors and Financial Community Portal,” Puerto Rico Electric Power Authority, accessed August 10, 2016, at <http://www.aeepr.com/INVESTORS>.

Palo Seco, San Juan, and Cambalache.⁷ Private cogenerators EcoEléctrica L.P., at Peñuelas, and AES-PR, at Guayama, produced most of the remainder.⁸ In 2015, petroleum powered about 51 percent of Puerto Rico's electricity generation, almost entirely through PREPA-owned power plants, whereas natural gas powered 31 percent, coal powered 16 percent, and renewable energy powered 2 percent.⁹

PREPA operates and maintains a transmission network of over 2,400 miles of transmission lines and 175 transmission centers.¹⁰ Its distribution network comprises approximately 29,000 miles of aerial lines, approximately 1,700 miles of underground lines, 334 substations, and 27 technical offices.¹¹ As of the end of FY 2015, PREPA had 6,975 employees.¹²

As a public corporation, PREPA is ultimately required to finance itself through its operations and its own borrowing. Traditionally, the Government Development Bank (GDB) of Puerto Rico has acted as the main source of short-term financing for PREPA and other public corporations. However, the GDB's own insolvency impedes its ability to provide this financing going forward.¹³ PREPA is ultimately responsible for repaying its own debt, which has accumulated to \$9 billion.¹⁴

⁷ See "PREPA IS...", The Puerto Rico Electric Power Authority, accessed August 10, 2016, at http://www.prepa.com/aees2_eng.asp, and "Fortieth Annual Report, On the Electric Property of the Puerto Rico Electric Power Authority, under Terms of Trust Agreement, Dated as of January 1, 1974, as amended, to U.S. Bank Trust National Association Trustee," URS, June 2013, accessed at <http://www.aeepr.com/INVESTORS/DOCS/Financial%20Information/Annual%20Reports/Consulting%20Engs%20Annual%20Report%20FY2013.pdf> (hereafter, *2013 URS*), pp. 2-3.

⁸ See *2013 URS*, pp. 2-3. PREPA has supplied a portion of its electricity through purchased power starting in FY 2000, when it contracted with EcoEléctrica. See "Plant Report: EcoEléctrica LP, Leadership, skill, attitude, community key to vital plant's success in delicate ecosystem," *Combine Cycle Journal*, accessed August 10, 2016, at <http://www.ccj-online.com/4q-2012/plant-reports-ecoelectrica-lp>.

⁹ See "Puerto Rico Territory Energy Profile," U.S. Energy Information Administration, available at <https://www.eia.gov/state/print.cfm?sid=RQ>.

¹⁰ See "PREPA IS...", The Puerto Rico Electric Power Authority, accessed August 10, 2016, at http://www.prepa.com/aees2_eng.asp.

¹¹ See "PREPA IS...", The Puerto Rico Electric Power Authority, accessed August 10, 2016, at http://www.prepa.com/aees2_eng.asp.

¹² PREPA's workforce declined from 7,822 in FY 2014 and 8,465 in FY 2013. See "Monthly Report to the Governing Board," The Puerto Rico Electric Power Authority, June 2015, p. 3, available at <http://www.aeepr.com/INVESTORS/DOCS/Financial%20Information/Monthly%20Reports/2015/June%202015.pdf>. See also *2013 URS*, p. 92.

¹³ D. Andrew Austin, "Puerto Rico's Current Fiscal Challenges," Congressional Research Service Report 7-5700, R44095, April 11, 2016 (hereafter, *CRS R44095*), pp. 12-15. See also Michael Corkery, "Puerto Rico's Indebted Power Utility Adds to Island's Problems," *The New York Times*, July 1, 2014.

¹⁴ See *CRS R44095*, p. 13. The Commonwealth legislature is not obligated to allocate funds to guarantee the debts of PREPA or other public corporations. See, for example, "673,145,000 Puerto Rico Electric Power Authority Power Revenue Bonds, Series 2013A," accessed on August 10, 2016, at <http://www.gdb->

Due to its mounting debt obligations, PREPA's bond ratings have declined in recent years.¹⁵ PREPA currently lacks an investment grade bond rating from any of the three major ratings agencies.¹⁶ With its rising debt level and the ratings downgrades it has experienced over the last several years, PREPA executives and consultants expect that the agency will have very limited access to credit markets for at least the next few years.¹⁷

As these facts suggest, PREPA currently faces a dire fiscal situation, exacerbated by the economic conditions of Puerto Rico. In addition to its mounting debt obligations, moreover, PREPA must invest in capital improvement projects to comply with the Mercury and Air Toxics Standards (MATS) set by the EPA in 2011.¹⁸ PREPA recently underwent a regulatory rate case in which it provided information and sworn testimony regarding its financial situation and investment plans.¹⁹ As filed in the rate case, the total planned capital expenditure for investment in and maintenance of the electric system—including but not limited to the environmental compliance projects—amounts to approximately \$1.4 billion

pur.com/investors_resources/documents/2013-08-19-OSSeries2013-A-Agosto2013-FINAL.pdf. The GDB has traditionally played a role as a guarantor of the debt of public corporations; however, its own debt problems make this role untenable going forward. See *CRS R44095*, pp. 14-15.

¹⁵ For example, see Moody's listing of PREPA's actions over the last few years with respect to PREPA's Power Revenue Bonds, "Puerto Rico Electric Power Authority Credit Rating," Moody's Investors Service, Inc., available at <https://www.moody.com/credit-ratings/Puerto-Rico-Electric-Power-Authority-credit-rating-600028250>. Moody's issued downgrades of PREPA's Power Revenue Bonds in at least December 2012, June 2013, February 2014, June 2014, and September 2014. On July 13, 2016, Moody's upgraded its outlook for PREPA from "negative" to "developing," specifically citing the approval of a temporary rate increase by the Energy Commission in June 2016. The ratings agency left PREPA's Caa3 bond rating unchanged. See "Moody's revises PREPA's outlook to developing from negative," Moody's Investor Service, Inc., July 13, 2016, accessed at https://www.moody.com/research/Moodys-revises-PREPAs-outlook-to-developing-from-negative--PR_903459476.

¹⁶ Moody's currently rates PREPA bonds at Caa3, Fitch Ratings at C, and Standard & Poor's at D. See "Investor Resources," Government Development Bank for Puerto Rico, accessed on August 10, 2016, at http://www.gdb-pur.com/investors_resources/prepa.html. Moody's and Fitch's ratings put PREPA in "speculative grade," whereas S&P's rating means it views PREPA as being in default. For definitions of the agencies' ratings, see Moody's Investor Service: Ratings Symbols and Definitions, July 2016, "Global Long-Term Rating Scale," at <https://www.moody.com/sites/products/AboutMoodyRatingsAttachments/MoodysRatingSymbolsandDefinitions.pdf>; Fitch Ratings, "Definitions of Ratings and Other Forms of Opinion," December 2014, at https://www.fitchratings.com/web_content/ratings/fitch_ratings_definitions_and_scales.pdf; and S&P Global Ratings, "S&P Global Ratings Definitions," June 29, 2016, at https://www.standardandpoors.com/en_US/web/guest/article/-/view/sourceId/504352.

¹⁷ "An Update on the Competitiveness of Puerto Rico's Economy," Federal Reserve Bank of New York, July 31, 2014 (hereafter, *NY Fed 2014 Report*), pp. 9,20 and See Order Establishing Provisional Rates, *In Re: Review of Rates of the Puerto Rico Power Authority*, Commonwealth of Puerto Rico, Puerto Rico Energy Commission, No.: CEPR-AP-2015-0001, Matter: Provisional Rates, June 2016, p. 5, available at <http://energia.pr.gov/wp-content/uploads/2016/06/24-junio-2016-Order-Establishing-Provisional-Rates.pdf> (hereafter, *Provisional Rates Order 2016*).

¹⁸ 2013 URS, pp. 32-34.

¹⁹ *Provisional Rates Order 2016*, pp.1, 4-6. PREPA filed its petition for the rate case on May 27, 2016.

for the three—year period from fiscal year 2017 to 2019.²⁰ PREPA must fund these investments in addition to covering operations and routine maintenance.

Because of limitations on its access to credit, PREPA must fund operations and investment through revenue; however, the revenue earned at current rates is insufficient to meet its debt service, capital investment costs, and operating costs.²¹ In fact, PREPA’s Chief Restructuring Officer testified before Congress in January of 2016 that, absent rate increases, PREPA could be unable to make cash payments to cover operations and pay debt as early as the summer of 2016.²² The Chief Restructuring Officer reiterated the need to raise immediate revenues in the recent rate procedure, stating that PREPA faced a funding gap of over \$700 million as of July 1, 2016.²³

Furthermore, as discussed in Sections II.A and II.B, PREPA cannot rely on future growth in electricity demand to provide a means of increasing revenues without raising rates, because economic growth in Puerto Rico has been negative in recent years and does not appear poised to turn positive in the foreseeable future. Increases in rates that PREPA charges for electricity are a necessary component of its plans to address debt repayment and operational and capital improvements going forward.

The insufficiency of PREPA’s revenue streams to meet its debt service obligations came to a crisis point in 2015 when it became clear that PREPA would be unable to make the required payments on its bonds in the coming years. Through a series of negotiations, PREPA and its bondholders reached an agreement by which PREPA would repay its debt under a defined schedule, and the debt holders agreed to a reduction in the owed amount. This arrangement is referred to as the Restructuring Agreement (RSA), which was first reached in December 2015 and amended in the months following. Because the bondholders agreed to a reduction in the amount owed to them, the agreement reduces the amount of revenues that PREPA must generate in order to remain solvent. At the same time, as noted above, because of the debt crisis that PREPA, other public corporations, and the government of Puerto Rico has undergone, PREPA

²⁰ PREPA Ex. 5.0 (Testimony of Francis X. Pampush, Lucas D. Porter, and Dan T. Stathos, Subject: Testimony in Support of Petition), Commonwealth of Puerto Rico Puerto Rico Energy Commission, No. CEPR-AP-2015-0001, May 26, 2016, lines 851-859.

²¹ *Provisional Rates Order 2016*, p. 5.

²² Statement of Lisa J. Donahue, Chief Restructuring Officer of Puerto Rico Electric Power Authority, Before the Committee on Natural Resources, Subcommittee On Energy And Mineral Resources, U.S. House of Representatives, “Exploring Energy Challenges and Opportunities Facing Puerto Rico,” January 12, 2016, available at http://naturalresources.house.gov/uploadedfiles/testimony_donahue.pdf.

²³ *Provisional Rates Order 2016*, p. 5. Ms. Donahue reiterated in her May 27, 2016 testimony that PREPA revenues and cash balances were insufficient to cover debt service and operational costs in the near term, even without considering the additional costs related to capital investments.

executives and consultants do not expect that PREPA will have normal access to capital markets for the next several years. Hence, all costs, investments, and other obligations PREPA incurs to supply electricity to its customers will have to be financed essentially contemporaneously from its revenues from customers, and not via capital markets. This requirement imposes a strict necessity for PREPA's prices to be adequate to cover current operations and necessary investments.

B. Economic Conditions in the Commonwealth of Puerto Rico

PREPA's current fiscal challenges are exacerbated by overall economic stagnation and decline in Puerto Rico since 2005.²⁴ As is well documented in a 2014 report by the Federal Reserve Bank of New York ("New York Fed"),²⁵ key economic indicators such as GNP, per capita GNP,²⁶ employment, population, and Puerto Rico's Economic Activity Index have all been either declining in recent years or lack a stable, upward trend.²⁷ Indeed, Puerto Rico has a median household income lower than that of every state—and, in fact, barely more than half of the lowest-income state.²⁸ The poor economic performance and lack of economic growth in the Commonwealth means that PREPA cannot rely on electricity demand growth to increase revenues at current rates.

A number of factors are understood to have contributed to the economic slump in Puerto Rico. First, the island's manufacturing base has declined substantially over the last twenty-five years. Data from the BLS on manufacturing employment indicates that the Commonwealth lost about 90,000 manufacturing jobs over the 26 years between February 1990 and February 2016, a decline of 55 percent.²⁹ The manufacturing decline is partially attributable to the 1996-2006

²⁴ See Anne O. Krueger, Ranjit Teja, and Andrew Wolfe, "Puerto Rico – A Way Forward" June 29, 2015 (hereafter, *Krueger et al.*), p. 4, especially the graphs of Real GNP and Economic Activity. The New York Fed states that the Puerto Rican has been stagnant since the 1970s. See *Report on the Competitiveness of Puerto Rico's Economy*, Federal Reserve Bank of New York, June 29, 2012, available at <https://www.newyorkfed.org/regional/puertorico/index.html> (hereafter, *NY Fed 2012 Report*), p. 4. As the graphs in the Krueger et al. report show, the Puerto Rican economy experienced a period of growth in the first half of the aughts, but then entered a decline mid-decade, from which it has not yet recovered.

²⁵ Puerto Rico is assigned to the 2nd District of the Federal Reserve, served by the New York Fed. See *NY Fed 2014 Report*, p. i.

²⁶ GDP measures the economic region's total income and the total expenditure on its output of goods and services. While GDP measures economic activity within the region, GNP measures the economic activity of the region's residents, whether or not the activity occurred within the region or externally. See Gregory N. Mankiw, *MACROECONOMICS*, 4th ed. (New York: Worth Publishers, 2000), pp. 15, 27.

²⁷ See Figures 1-6 of *NY Fed 2014 Report*, pp. 3-5.

²⁸ Amanda Noss, "Household Income: 2013," American Community Survey Briefs, U.S. Department of Commerce, Economics and Statistics Administration, U.S. Census Bureau, September 2014, p. 3. See Table 1 for a listing of median household income for each state and Puerto Rico based on 2012 and 2013 data gathered by the US Census Bureau. Puerto Rico had a median household income of \$19,183 in 2013, whereas the lowest ranked state, Mississippi, had a median income of \$37,963.

²⁹ See "State and Area Employment, Hours, and Earnings," Bureau of Labor Statistics Data Series SMS72000003000000001, available at <http://data.bls.gov/timeseries/SMS72000003000000001>. The BLS data

phase-out of tax incentives that had encouraged US-based multinationals to operate subsidiaries on the island.³⁰ The shrinking manufacturing base, of course, decreases job opportunities in Puerto Rico and diminishes the tax base.³¹

Second, Puerto Rico's population has declined in every year since 2004, when it peaked at 3.8 million.³² It declined at an accelerating rate to about 3.6 million in 2013 and 3.5 million in 2015.³³ New York Fed economists Jaison Abel and Richard Deitz attributed the decline to both a decline in the birth rate and net out-migration from the island.³⁴ They also found that out-migrants tended to be disproportionately from the younger and less educated population segments.³⁵ In addition to the overall decline of resources that accompanies population loss, the lower birth rate and disproportionate out-migration of younger, working-age people result in an aging of the remaining population. This shift in the age distribution of the population puts a greater fiscal burden on the Commonwealth, which must fund retirement and health care programs with a diminished tax base.

Consistent with these demographic and economic shifts, labor force participation has declined since at least 2006. The labor force participation rate—the percent of the population working or actively seeking work—declined each year from 49

records manufacturing employment for Puerto Rico in February 1990 as 161,500 and in February 2016 as 72,200.

³⁰ The tax-incentives, known as “possessions tax credits” or “Section 936” credits, were instituted by Congress as part of the Tax Reform Act of 1976. The details and effects of these tax incentives are beyond the scope of this report. It suffices to note that the incentives encouraged US-based multinationals with high-value intangible property, especially pharmaceutical firms, to set up subsidiaries in Puerto Rico to obtain tax credits on worldwide earnings from, for example, patents and trademarks. For more information, see *NY Fed 2012 Report*, p. 16, and also United States Government Accountability Office, *Puerto Rico Fiscal Relations with the Federal Government and Economic Trends during the Phaseout of the Possessions Tax Credit*, Report to the Chairman and Ranking Minority Member, Committee on Finance, U.S. Senate, GAO-06-541, May 2006, available at <http://www.gao.gov/new.items/d06541.pdf> (hereafter, *GAO-06-541*), pp. 5-6.

³¹ While the Section 936 credits allowed corporations to save on federal taxes, we understand that they generally paid taxes on their local operations to the Commonwealth.

³² See “Puerto Rico Intercensal Estimates (2000-2010),” United States Census Bureau, accessed at https://www.census.gov/popest/data/intercensal/puerto_rico/pr2010.html, and “Puerto Rico Commonwealth Characteristics: Vintage 2015,” United States Census Bureau, accessed at https://www.census.gov/popest/data/puerto_rico/asrh/2015/index.html. For a graph of the historical population from 1950 to 2013, see Jaison R. Abel and Richard Deitz, “The Causes and Consequences of Puerto Rico’s Declining Population,” Federal Reserve Bank of New York, *Current Issues in Economics and Finance* 20, no. 4 (2014) accessed at https://www.newyorkfed.org/medialibrary/media/research/current_issues/ci20-4.pdf (hereafter, *Abel and Deitz 2014*), Chart 1, p. 2.

³³ “Annual Estimates of the Resident Population: April 1, 2010 to July 1, 2015,” U.S. Census Bureau, Population Division, accessed on August 10, 2016, at http://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=PEP_2015_PEPANNRES&sr=c=pt. See also Chart 2 of *Abel and Deitz 2014*, p. 2. The US mainland continued to experience modest population growth during this time.

³⁴ *Abel and Deitz 2014*, pp. 2-3.

³⁵ *Abel and Deitz 2014*, p. 5.

percent in FY 2006 to 40 percent in FY 2015.³⁶ Economists Anne Krueger, Ranjit Teja, and Andrew Wolfe, in their 2015 report *Puerto Rico – A Way Forward*, remark that the 40 percent labor force participation rate, compared to the 63 percent mainland rate, is the “single most telling statistic in Puerto Rico.”³⁷ Furthermore, the unemployment rate—that is, the proportion of the labor force that is not employed—has been persistently higher than the mainland unemployment rate for decades.³⁸ Whereas the monthly overall US average unemployment rate ranged from 5.0 to 5.7 percent in 2015, Puerto Rico’s monthly unemployment rate ranged from 12.0 to 12.3 percent.³⁹ The higher unemployment rate may, in part, be driven by the fact that the island is subject to minimum wage laws that establish the same minimum wage in Puerto Rico as that in the rest of the US, despite a different economic environment.⁴⁰ According to Krueger et al, the current level of the minimum wage is harmful to the economy and to the employment rate in Puerto Rico because a significant portion of Puerto Rico’s economy today is tourism, in which it competes with other Caribbean nations that have no comparable minimum wage restriction and therefore have lower labor costs.⁴¹ The relatively low labor force participation and high unemployment demonstrate an underutilization of Puerto Rico’s human capital resources.⁴² The employment situation undoubtedly contributes to the out-migration of the younger working-age population as well.

Third, the housing crisis, credit crunch, and broader US recession from 2007 to 2009 had a severe, negative impact on Puerto Rico. Because the mainland US is

³⁶ Statistical Appendix of the Economic Report to the Governor and to the Legislative Assembly, Commonwealth of Puerto Rico Office of the Governor Planning Board, 2015 (hereafter, *Statistical Appendix 2015*), p. A-62, Table 32. The labor force participation rate is defined as the ratio of the number of people employed or looking for work to the population aged 16 years or older. The GDB uses data from the Bureau of Labor Statistics to calculate the rate.

³⁷ Krueger et al., p. 6.

³⁸ *NY Fed 2012 Report*, p. 4 and Figure 4.

³⁹ See “Local Area Unemployment Statistics,” Bureau of Labor Statistics Data Series LASST7200000000000006, available at <http://data.bls.gov/timeseries/LASST7200000000000006> and “Labor Force Statistics from the Current Population Survey,” Bureau of Labor Statistics Data Series LNS14000000, available at <http://data.bls.gov/timeseries/LNS14000000>.

⁴⁰ *NY Fed 2012 Report*, p. 7 and Krueger et al., p. 6. Economists generally agree that when a minimum wage is set significantly higher than wages that would arise under a market equilibrium for a particular job, the effect is to reduce employment in that job. The extent to which current minimum wage levels contribute to unemployment in Puerto Rico and elsewhere in the United States is the subject of debate in economics literature and in the policy arena. The NY Fed notes that the annual salary for a full-time minimum-wage worker, about \$15,000, is close to the median household income for the island, about \$19,000, and even closer to Puerto Rico’s income per capita. Krueger et al. remark that a full-time minimum-wage worker earns 77 percent of Puerto Rico’s per capita income, whereas such a worker earns only 28 percent of the mainland per capita income.

⁴¹ Krueger et al., pp. 8, 17-18.

⁴² *NY Fed 2014 Report*, p. 6.

Puerto Rico's largest trading partner and source of investment, Puerto Rico's economy has historically tracked the overall US economy.⁴³ It is therefore not surprising that Puerto Rico's GNP and GDP suffered their largest recent contractions during the time surrounding 2007-2009 nationwide recession, as shown in Exhibit 1.⁴⁴ The Puerto Rico economy has not kept pace, however, with the mild recovery experienced by the overall US economy after 2010. As Exhibit 1 shows, Puerto Rico's economy grew slightly in FY 2012, but declined again from FY 2013 to FY 2015.

Fourth, the Puerto Rican economy is constrained by relatively high costs for fuel, transportation, and energy.⁴⁵ Global oil prices more than doubled between 2005 and 2014.⁴⁶ This increase in oil costs, among other factors, generally increased the cost of doing business on the island and, in particular, increased the cost of electricity for PREPA, which (as noted earlier) produces a majority of its electricity using oil-fired plants.⁴⁷ As will be discussed further in Section II.C, fuel costs are, by design of the regulatory rates, largely passed through in a formulaic manner to PREPA's customers. Hence, when oil prices fall, as they did throughout most of FY 2016, PREPA's electricity prices fall. Conversely, of course, when oil prices rise, PREPA's electricity prices also increase.

Electricity prices in Puerto Rico have historically exceeded those in most other areas of the US.⁴⁸ Even in 2015, after oil price declines led to a reduction in PREPA's average rates, Puerto Rico continued to have higher electricity prices than all US states except for Hawaii.⁴⁹ The primary explanatory factor for these higher rates is most likely the continued dependence on high-cost oil inputs to fuel electricity generation, whereas most mainland utilities primarily use either natural gas or coal.⁵⁰ Furthermore, the isolation of the electrical system requires that the system maintain a higher margin of reserve energy (relative to the

⁴³ *Krueger et al.*, p. 5 and *NY Fed 2014 Report*, p. 3, Figure 1.

⁴⁴ Whereas the US-wide recession technically ended in 2009, the graphs of regional GNP and GDP make clear that in Puerto Rico, the recession continued through 2010 and into 2011.

⁴⁵ *Krueger et al.*, pp. 6, 8.

⁴⁶ *Krueger et al.*, p. 6.

⁴⁷ "Puerto Rico Territory Energy Profile," U.S. Energy Information Administration, accessed on August 10, 2016 at <https://www.eia.gov/state/print.cfm?sid=RQ>.

⁴⁸ "Puerto Rico Territory Energy Profile," U.S. Energy Information Administration, accessed on August 10, 2016 at <https://www.eia.gov/state/print.cfm?sid=RQ>. Also see, *Krueger et al.*, p. 8.

⁴⁹ "Puerto Rico Territory Energy Profile," U.S. Energy Information Administration, accessed on August 10, 2016 at <https://www.eia.gov/state/print.cfm?sid=RQ>.

⁵⁰ The US Energy Information Administration reports that only one percent of US electricity generation used petroleum-based fuel, whereas coal and natural gas each powered a third of generation. See "Frequently Asked Questions: What is U.S. electricity generation by energy source?" at <http://www.eia.gov/tools/faqs/faq.cfm?id=427&t=3>.

interconnected systems on the mainland), increasing operating costs.⁵¹ In addition, oil-fired generation plants produce more pollutants than natural gas plants and hence raise cleanup and compliance costs for PREPA relative to mainland utilities that rely less on oil-fired generation in favor of natural gas.⁵²

In addition to fuel and energy costs, transportation costs are higher for the island economy than for the mainland.⁵³ These higher transportation costs are likely driven, in part, by maritime shipping regulations under the Jones Act.⁵⁴

Because of these structural economic problems, the Puerto Rico's government, its municipalities, and especially its public corporations have accumulated public debt to levels that now exceed Puerto Rico's Gross National Product (GNP).⁵⁵ As discussed above, PREPA alone has debt of about \$9 billion, or about one-eighth of the total debt of the central government, municipalities, and public corporations.⁵⁶

To understand the analysis of the effect on the macroeconomy of PREPA's necessary rate changes, it is useful examine PREPA's rate structure, which provides the means by which PREPA generates revenue.

C. PREPA's Current Rate Structure

PREPA's customers are designated, for rate purposes, into one of four customer classes: Residential, Commercial, Industrial, and Other. The proportion of total revenues contributed by each class in fiscal year 2015 is shown in Exhibit 2.⁵⁷

⁵¹ José Fernando Prada, "The Value of Reliability in Power Systems -Pricing Operating Reserves-," Massachusetts Institute of Technology Energy Laboratory Working Paper, June 2009, p. 38, at <http://web.mit.edu/energylab/www/pubs/el99-005wp.pdf>.

⁵² US Energy Information Administration, "Frequently Asked Questions: How much carbon dioxide is produced per kilowatthour when generating electricity with fossil fuels?" at <https://www.eia.gov/tools/faqs/faq.cfm?id=74&t=11>.

⁵³ Krueger *et al.*, p. 8.

⁵⁴ The extent to which the Jones Act provisions increase transportation costs and contribute to Puerto Rico's economic problems is controversial. See United States Government Accountability Office, *Puerto Rico: Characteristics of the Island's Maritime Trade and Potential Effects of Modifying the Jones Act*, Report to Congressional Requesters, GAO-13-260, March 2013 (hereafter, *GAO-13-260*), for background and analysis on the Jones Act and its effects on Puerto Rico.

⁵⁵ See *CRS R44095*, p. 10. See also Figure 4 for an illustration of the debt accumulation over time by Puerto Rico's public corporations, the Commonwealth government, and municipalities.

⁵⁶ *CRS R44095*, p. 13.

⁵⁷ PREPA data on revenues, customer counts, and electricity usage (hereafter "PREPA Financial Data") was obtained from PREPA's Directorate of Planning and Environmental Protection. Our understanding from conversations with PREPA personnel is that the revenues recorded in the PREPA Financial Data are *billed* revenues, not *collected* revenues. Since these are billed revenues, we are accurately computing the average rates per kilowatt-hour even in the presence of non-paying customers.

Each customer class contains various subclasses and service categories that affect the applicable rates. The rate for any particular customer is determined mainly by the customer class, service voltage, and service application as described in PREPA's Rate Book.⁵⁸ At a high level, however, regardless of the customer class, each customer's overall rate can be decomposed into three components: a basic rate, a fuel purchase-cost adjustment, and a purchased-power-cost adjustment.⁵⁹

The fuel-cost adjustment is tied to the costs of fuel inputs, primarily oil, required for production by PREPA's generating facilities. The purchased power adjustment charge covers costs associated with PREPA's purchases of electricity from EcoEléctrica, AES-PR, and producers of energy from renewable sources like wind and solar. The adjustment charges for fuel and purchased power costs are based on moving averages, forecasts, and true-ups of input costs designed to "pass through" the costs of fuel and purchased power to customers, so that PREPA approximately breaks even (on average) on electricity provided using these inputs.⁶⁰ Exhibits 3.A and 3.B provide the average fuel-cost and purchased-power adjustments over the years 2010 to 2015 and indicate that the purchased power adjustment charge has generally been smaller than the fuel cost adjustment charge.⁶¹ The fuel cost adjustment charge averaged \$0.14 per kilowatt-hour over fiscal years 2010 through 2015, whereas the purchased power charge averaged about \$0.05.

The basic rate component is the only portion of overall tariffs that is designed to provide PREPA revenue from which it funds operations (other than the costs of fuel and purchased power described above), capital investment, and debt service. PREPA's basic rates require a rate case to change.⁶²

⁵⁸ PREPA's Rate Book describes the intricacies of how rates and total bills are computed for each customer class and subclass at any particular billing period. The official version of the Rate Book (August 2014 revision) is *Autoridad de Energía Eléctrica de Puerto Rico: Tarifas para el Servicio de Electricidad* (hereafter, *PREPA Rate Book*) available at <http://www.aeepr.com/DOCS/manuales/LibroTarifas02.pdf>. A draft English version, *Puerto Rico Electric Power Authority: Electric Service Rates*, is available at <http://www.aeepr.com/Documentos/Ley57/Electric%20Service%20Rates.pdf>.

⁵⁹ The basic rate is further broken down into various components that may apply based on the customer class and other circumstances. PREPA sets a minimum bill, which can influence the effective average rate that the customer pays. In the case of general residential customers, there is a fixed charge of \$3.00 that is also the minimum bill. PREPA charges some of its larger customers a monthly demand charge, which is based on the highest rate of electrical flow used by the customer.

⁶⁰ The adjustment rules and formulas are described in *PREPA Rate Book*, pp. 72-74.

⁶¹ PREPA's cost of purchased power, and ultimately the adjustment charged to consumers, is a function of the contracts that PREPA has with EcoEléctrica, AES-PR, and others, as well as a function of PREPA's capacity adjustments to its own generating facilities. See *2013 URS*, pp. 58-59 for a summary of these factors and how they affected costs in the FY2013-2014 timeframe.

⁶² *New Regulation on Rate Filing Requirements for the Puerto Rico Electric Power Authority's First Rate Case*, La Comisión de Energía de Puerto Rico (CEPR), March 28, 2016, pp. 4-5, 7, available at <http://energia.pr.gov/wp-content/uploads/2016/04/Reglamento-Regulation-on-Rate-Filing-8720.pdf>.

The basic rate terms vary considerably by the service category, usage quantity, and time of use.⁶³ The service category in turn may depend both on the type of customer and on the type of electrical service. Service categories within the Residential customer class are largely defined by whether the residential household qualifies for the federal Lifeline program and whether the household resides in public housing.⁶⁴ For customers in the Commercial or Industrial classes, the service category depends on the voltage (transmission, primary distribution, or secondary distribution), application, usage quantities, and other factors.⁶⁵ Most basic rate terms have remained unchanged since 1989.⁶⁶

Exhibit 4 reports the overall average rates by customer class for each fiscal year between 2010 and 2015.⁶⁷ For Residential customers, average rates fell from 26.1 cents per kilowatt-hour in FY 2014 to 23.5 cents in FY 2015. For Commercial customers, average rates fell from 27.1 cents per kilowatt-hour in FY 2014 to 24.2 cents in FY 2015. For Industrial customers, average rates fell from 23.1 cents per kilowatt-hour in FY 2014 to 20.6 cents in FY 2015.

When any business entity incurs debt financing, it is making a promise to pay back the providers of the financing. One way or another, it must do so out of the revenues it earns for providing its products and services. In addition, a business must ultimately pay for its labor, material inputs, capital investments, and other resources from its revenues. Hence, for a business to be viable in the long run, its revenues must be adequate to cover its operating costs, to repair, upgrade, and replace its equipment, to repay its debt investors, and, if applicable, to provide an adequate return to its equity investors. In the case of PREPA, while its total annual revenues have been between \$4 billion and \$5 billion in fiscal years 2010 through 2015, its annual basic rate revenues have been just over \$1 billion over this time period.⁶⁸ That PREPA's annual basic rate revenues—from which it must fund operations, capital expenditures, and debt service—are a fraction of

⁶³ Our understanding of PREPA's basic rate terms is based on our reading of the unofficial English version of the PREPA Rate Book. We intend this summary only as background and caution that the reader should consult official sources for details on PREPA's rate terms.

⁶⁴ *PREPA Rate Book*, pp. 2-8.

⁶⁵ The details of Commercial and Industrial basic rate terms are covered in pages 9 to 56 of the PREPA Rate Book. Service categories under the Other customer class are covered in pages 57-72.

⁶⁶ According to the *PREPA Rate Book*, the basic rate terms for the "Unmetered Service for Small Loads" service category, within the "Other" customer class, went into effect on January 19, 2008 (see p. 67). The basic rate terms for all other service categories have been effective since at least June 5, 2000, according to the *PREPA Rate Book*. PREPA management reports that most of these basic rates have not changed since 1989.

⁶⁷ Considerable variation exists among service categories within each class. See *2013 URS*, p. 70 for a table of rate averages by service category for FY 2013. The average rates in that table, as well as the rates in this paragraph and associated exhibits, include the adjustment charges.

⁶⁸ See Exhibit 5.

PREPA's current debt gives a sense of fiscal crisis in which PREPA finds itself. That is, current rate levels are aligned with overall costs faced by the utility.

One of the problems currently facing PREPA is a relatively high rate of customer non-payment.⁶⁹ Net accounts receivable totaled \$1.5 billion in FY 2013, or 31 percent of total billed charges in FY 2013.⁷⁰ Of these accounts receivable, \$603 million, or 40 percent, was owed by governmental customers at either the Commonwealth or municipal levels.⁷¹ As a 2014 report by FTI Capital Advisors remarked, non-payment by its governmental customers and PREPA's inability to take action against government customers effectively subsidizes these customers.⁷² The amount of electricity usage by non-paying customers is also likely insensitive to price changes. If a customer is not inclined to pay its electricity bill—and does not view enforcement of the charges as credible—then that customer is unlikely to react to price changes by adjusting consumption. We expect, therefore, that non-payment by governmental customers diminishes the average sensitivity to price changes among customers in the Commercial class, where government agencies comprised 18 percent of the customers in FY 2013 and consumed 32 percent of the electricity.⁷³

As discussed in Section II.A, the electricity rate increases needed to meet PREPA's revenue requirements will, despite the need for them, have some adverse effects on the macroeconomy of Puerto Rico. Electricity is a necessity for households and businesses, and consumers have limited ability to adjust their consumption of electricity in response to price changes. Taken together, these conditions imply that an increase in the price of electricity, all else equal, will cause a material loss in disposable income, meaning that households and businesses will have less ability to purchase other goods and services.

⁶⁹ Mary Williams Walsh, "How Free Electricity Helped Dig \$9 Billion Hole in Puerto Rico," DealBook, *The New York Times*, February 1, 2016, accessed at <http://www.nytimes.com/2016/02/02/business/dealbook/puerto-rico-power-authoritys-debt-is-rooted-in-free-electricity.html>.

⁷⁰ 2013 URS, p. 80. The Consulting Engineers report that FY 2013 net accounts receivable totaled to \$1.494 billion. From the PREPA Financial Data, we calculate total charges across the four customer classes (including adjustment charges) of \$4.821 billion for the same fiscal year. The ratio of these two figures is 0.31.

⁷¹ 2013 URS, p. 80.

⁷² Accounts Receivable and CILT Report, Presented to Puerto Rico Electric Power Authority, FTI Capital Advisors, November 15, 2014, p. 17.

⁷³ 2013 URS, p. 66. The Consulting Engineers report does not provide the proportion of customers that are government agencies or their share of overall consumption. We are not able to distinguish customer counts, usage, or rates for government customers from private commercial customers in the PREPA Financial Data, so we are unable to separately estimate the electricity demand from government customers.

However, as we noted earlier, the required electricity rate increases are lower under the terms of the RSA than they would be without such an agreement.⁷⁴ Hence, the restructuring agreement attenuates the loss in disposable income and generates benefits to the regional macroeconomy relative to the scenario without the agreement.

III. Demand Elasticity Estimation

A. What is a Price Elasticity of Demand and Why Does it Matter?

Our ultimate purpose, as noted, is to estimate the effects of the necessary price increases under the Restructuring Agreement on GDP, employment, and per capita income in Puerto Rico, relative to the effects on the economy of the price increases that would be necessary without such an agreement. Accurately evaluating the effects of any such rate changes requires taking into account whether and to what degree households and businesses adjust their consumption of electricity in response to these rate changes. The degree of sensitivity of consumption to price changes affects the total additional expenditure on electricity that households and businesses will make and, therefore, has implications for the macroeconomic effects of the price changes.

To see the importance of considering the sensitivity of consumption to price changes, consider the following example of a single household. Suppose that, without the price change, the household consumes 5,000 kilowatt-hours (kWh) of electricity in a year and that it pays an average overall rate of 25 cents per kWh. Without the price increase, this household would be charged \$1,250 for its total consumption for the year. Now suppose that the rate is increased to 30 cents per kWh. If the household does not adjust its consumption of electricity at all in response to the price increase, it will expend \$1,500 on electricity at the new price. The difference of \$250 will be additional revenue for PREPA and will also be a loss in disposable income for the household—that is, \$250 less that the household is able to spend on other goods and services, or save. If, instead, the household cuts its consumption of electricity by 10 percent, or 500 kWh, over the course of the year, then the household will pay \$1,350 at the new prices. The additional revenue for PREPA and loss of disposable income will be only \$100 in this case, less than half of the effect that arises if the household does not change its consumption.

As this example illustrates, the more sensitive the quantity demanded is to changes in price, the less additional revenue will result from a price increase. For

⁷⁴ As we will discuss Section IV.C, policy scenarios that leave electricity prices unchanged are not realistic options going forward. In any realistic policy case, PREPA will have to raise basic rates to cover revenue requirements generated by operating costs, debt service, and needed capital improvements.

many goods (but not for electricity, as explained below), the quantity demanded could be sensitive enough that a price increase results in a decrease in revenues because the additional revenue per unit is more than offset by the reduction in units sold.

Economists use the concept of the *price elasticity of demand* to characterize how sensitive a consumer's usage decision is to the changes in the price of that good.⁷⁵ Formally, the price elasticity of demand (often called simply the “demand elasticity”) is the (negative) percentage change in the quantity demanded for a good in response to a percentage change in the price of that good. The formula for calculating demand elasticity (denoted here as E_D) is often expressed:⁷⁶

$$E_D = \frac{\Delta Q}{\Delta P} \cdot \frac{P}{Q}$$

where P is the price (before the price change), Q is the quantity demanded (before the price change), ΔP is the change in price, ΔQ is the change in quantity that results from the change in price.⁷⁷

If the elasticity of demand is less than -1, demand is considered “elastic,” and if the elasticity is between -1 and 0, demand is considered “inelastic.” Demand for necessities such as electricity is usually price inelastic, so we would expect to find that households have demand elasticities between -1 and 0.

One important application of demand elasticity is to be able to predict or estimate the consumption response to a price change. Consider the above example again and suppose that through research and/or statistical analysis we have estimated the price elasticity of demand for households to be -0.2. Suppose again that without the price change, the household consumes 5,000 kWh at an average rate of 25 cents per kWh and suppose that the utility is considering raising the price to 30 cents per kWh. With an estimate of demand elasticity, we are able to predict the effect on quantity demanded and the household's expenditure on electricity by rearranging the formula above. We can compute the new quantity demanded (Q')

⁷⁵ Walter Nicholson, *MICROECONOMIC THEORY: BASIC PRINCIPLES AND EXTENSIONS*, 6th ed. (Fort Worth, TX: The Dryden Press, 1994) (hereafter, *Nicholson*), pp. 203-204.

⁷⁶ *Nicholson*, p. 203.

⁷⁷ The discussion simplifies certain aspects of how economists apply demand elasticity in practice. Demand elasticity is actually a *differential* concept in that it formalizes how quantity demanded responds to *small* changes in price (infinitesimally small, in fact). With very small changes in price, it does not matter whether the pre-change or post-change price and quantity are used for P and Q in the formula. When considering real-world price changes, however, one can arrive at a different value for elasticity depending on whether pre-change or post-change values are used. Some economists prefer to use the average of the pre-change and post-change values for P and Q in the elasticity formula. See, for example, Gregory N. Mankiw, *PRINCIPLES OF ECONOMICS*, 2nd ed. (Stamford, CT: Cengage Learning, 2000), pp. 96-97. My calculation in this section is only illustrative and my results would not materially change if we used the post-change prices or average prices.

in our example as:

$$Q' = (1 + E_D * (\Delta P/P)) * Q = (1 - 0.2 * 0.05/0.25) * 5,000 = 4,800 \text{ kWh}.$$

With the calculated quantity of 4,800 kWh, we can then compute the household's expenditure under the new price as \$1,440.

While demand elasticity in the example pertained to a single household, economists also apply the concept to populations of households and businesses, usually as an average. Estimating an average price elasticity of demand for electricity among a group of households allows us to predict the total change in consumption and expenditure by the group that would arise in response to a price change.⁷⁸ Likewise, estimating a demand elasticity for businesses—which could be different from that of households—allows us to predict the collective response of business customers to a price change. As with the case of a single household, the higher (in absolute value) is the average elasticity among the group, the less additional total expenditure is incurred from a given price increase.

B. What Drives Demand for Electricity?

According to the US Energy Information Administration (EIA), in 2013 approximately 36 percent of total US energy consumption was by the Residential sector, 35 percent was by the Commercial sector, 28 percent was by the Industrial sector, and 0.2 percent was by the Transportation sector.⁷⁹ According to PREPA data, the relative consumption patterns in Puerto Rico in 2013 were more heavily weighted toward the Commercial sector: 36 percent of total energy consumed in Puerto Rico was by Residential customers, 49 percent by Commercial customers, 14 percent by Industrial customers, and 2 percent by Other.⁸⁰ Some of the difference in the US overall versus Puerto Rico distribution between the Commercial and Industrial sectors may be due to differences in how PREPA and

⁷⁸ Clearly, using an average and applying it to a group might neglect important variation within the group. In practice, the level of aggregation is usually determined by the available data. As we will explain in Section III.D, the data we used to estimate demand elasticity is aggregated to the customer class level (Residential, Commercial, Industrial, and Other). One interesting source of variation that is hidden at this level of aggregation is the substantial presence of government clients in the Commercial class. As discussed in Section II.C, these clients tend not to pay their bills and therefore probably have less price elastic demand than clients that do pay their bills. Our estimates of average elasticity within the Commercial class will derive from a mixture of paying and non-paying Commercial clients. It is likely that the true elasticity of paying clients will be higher than our estimates of the class average.

⁷⁹ “The Annual Energy Outlook 2015 with Projections to 2040,” the U.S. Energy Information Administration, April 2015 (hereafter, *Annual Energy Outlook 2015*), pp. A-3 and A-4. The percentages are calculated from the 2013 data in Table A2. The table lists total 2013 US electricity consumption at 12.6 quadrillion Btu (“quads”). It lists Residential consumption at 4.75 quads, Commercial at 4.57 quads, Industrial at 3.26 quads, and Transportation at 0.02 quads. See Exhibits 6, 7.A, and 7.B.

⁸⁰ PREPA Financial Data. Aggregate total consumption across customer classes for calendar year 2013 is 17.8 billion kilowatt-hours. Aggregate consumption by customer class is 6.3 billion kilowatt-hours for Residential, 8.6 billion for Commercial, 2.5 billion for Industrial, and 0.3 billion for Other. See Exhibit 6.

the EIA define the two sectors. However, the fact that consumption in Puerto Rico is more heavily weighted toward Commercial users relative to Industrial than in the rest of the US is also likely a result of Puerto Rico's economy being weighted less toward manufacturing (which is considered "Industrial") and more toward services (which is considered "Commercial") relative to the US economy as a whole.⁸¹

Of residential consumption of purchased electricity in the US in 2013, the top ranked uses were space cooling (i.e., air conditioning) (13.9 percent), lighting (12.4 percent), water heating (9.3 percent), space heating (8.9 percent), refrigeration (7.6 percent), and televisions and related equipment (6.9 percent).⁸² While we have not found data on the relative weights for Puerto Rico specifically, it is likely for climate reasons that air conditioning represents a greater share of Residential electricity use than the national data indicate, whereas space heating likely represents a lower share.

Of commercial consumption of purchased electricity in the US in 2013, the top ranked uses were lighting (19.2 percent), ventilation (10.9 percent), space cooling (10.3 percent), and refrigeration (7.8 percent).⁸³ Lighting and air conditioning are therefore the top uses of purchased electricity nationwide, together accounting for over a quarter of total electricity consumption among both residential and commercial users. While we do not know the usage shares by category in Puerto Rico for Commercial customers, it is likely that lighting and air conditioning are also the top uses there, given that air conditioning likely accounts for a higher share of Commercial electricity use than it does nationwide.

The substantial share of electricity consumption that goes to air conditioning also implies that overall consumption varies seasonally, with higher consumption in warmer months. Exhibit 8 presents average consumption by month for PREPA customers overall and for Residential, Commercial, and Industrial customers. The graphs exhibit a clear seasonal pattern with March through October being the period of relatively high consumption. As we will discuss in more detail in Section III.D, the National Oceanic and Atmospheric Administration (NOAA) maintains a temperature measure known as cooling degree days (CLDD) that

⁸¹ As discussed in Section II.B, the industrial sector in Puerto Rico has experienced a marked decline since the phase-out of the Section 936 tax credits, which fully expired in 2006.

⁸² *Annual Energy Outlook 2015*, p. A-9. The percentages are calculated from the 2013 data, as presented in Exhibit 7.A.

⁸³ *Annual Energy Outlook 2015*, p. A-11. The percentages are calculated from the 2013 data, as presented in Exhibit 7.B.

purports to measure the climate's contribution to the demand for air conditioning.⁸⁴

For residential customers, at least with regard to air conditioning, water heating, refrigeration, and television equipment, the amount of electricity used depends on which appliances they own—and likely when those appliances were manufactured. As technology improves, the cost of producing more energy-efficient appliances tends to decrease, providing incentives to manufacturers to increase the energy efficiency of their designs. In addition to any direct value they attach to energy efficiency because of environmental concerns, consumers of these appliances value energy efficiency because it reduces the cost of ownership by reducing the cost of electricity needed to run the appliance over its lifetime. Hence, we expect energy efficient appliances, all else equal, to generate higher willingness-to-pay among consumers. In addition to market incentives, the US Department of Energy maintains and enforces energy efficiency standards that also impel appliance manufacturers to increase the energy-efficiency of their products over time.⁸⁵ The total effect of market and regulatory forces appears to be a long-run decline in energy usage by appliances such as refrigerators and air conditioners.⁸⁶

One implication of these trends is that a residential household's consumption of electricity is likely affected by the timing of its purchases of appliances. Another implication is that the price of electricity may affect the timing of such purchases, at least at the margin. Consider the following example of a consumer considering the purchase of new refrigerator. Suppose the consumer currently owns a refrigerator that uses 800 kWh per year and suppose that the consumers expects the refrigerator to last five more years before it needs to be replaced. Suppose that the consumer expects the price of electricity to be \$0.25/kWh on average over the next five years. The expected annual energy cost of the consumer's refrigerator at this electricity price is then \$200 and the cost of using the refrigerator over its remaining lifetime is \$1000. Suppose that the consumer has an opportunity to buy a new refrigerator for \$425 that is very similar to her current refrigerator, except that it uses only 500 kWh per year. If the consumer were to buy the new refrigerator, then the energy costs would be \$125 per year, or \$625 over the same five-year horizon that she expects to be able to maintain her

⁸⁴ See "Degree Day," NOAA's National Weather Service Glossary, accessed on August 10, 2016 at <http://forecast.weather.gov/glossary.php?word=degree%20day>.

⁸⁵ See, for example, the impact study by Steve Meyers, James E. McMahon, and Michael A. McNeil, "Impacts of US federal energy efficiency standards for residential appliances," *Energy* 28 (2003).

⁸⁶ "Saving Energy and Money with Appliance and Equipment Standards," U.S. Department of Energy, DOE/EE-1086, December 2015.

current unit.⁸⁷ While the consumer would save \$375 worth of energy costs over five years, this savings would not be enough to warrant the \$425 purchase price of the new unit.⁸⁸ However, if electricity prices were expected to be \$0.30/kWh, then the old refrigerator costs \$1,200 over its remaining lifetime, whereas the energy cost of the new unit over that time is \$750. The energy cost savings of \$450 is enough to warrant the \$425 purchase price, so the consumer would purchase the new refrigerator.

Among a large population of consumers, at any given time, a portion of consumers will be facing an upgrade decision, at which time the price of electricity can affect whether or not they upgrade. Furthermore, among consumers who have already decided to upgrade—perhaps because their refrigerators have failed—the price of electricity may affect their decision among models with different energy consumption rates. Through these mechanisms, appliance purchase decisions can be an important way—even the primary way—that consumers respond to electricity price changes in a manner that affects their electricity usage. Of course, it is likely that many customers will not be in a situation in which a modest change in the price of electricity would induce them to purchase new appliances in the time immediately after the price change goes into effect. Therefore, the response to an electricity price change—or at least the portion of the response driven by appliance upgrades—will likely not be observed in full effect immediately, but rather will unfold over time as consumers reach decision points at which past electricity price changes affect their actions.

Income levels in the population may also directly affect the apparent sensitivity of electricity usage to electricity prices. Durable goods such as refrigerators often require high upfront expenditures. Hence, the lack of disposable income or accumulated savings can impede consumers from upgrading appliances to more energy efficient models, or delay their ability to do so. This is particularly likely to be a relevant factor in Puerto Rico, given its low median income level. Even though we may expect lower-income consumers to be more price sensitive generally, they may appear to exhibit less price sensitivity to electricity because they are less able to incur the upfront costs of appliance upgrades, and hence their usage of electricity may not change as much as high-income consumers in response to a price change.

While the discussion in this section has been oriented toward household demand for electricity, commercial and industrial customers are also likely to experience

⁸⁷ It need not be the case that the expected lifetime of the new model is five years. Five years is the relevant horizon because it is the horizon over which costs of the new refrigerator are comparable to the old one. As long as the consumer expects the refrigerator to last *at least* five years, it does not matter precisely how long the expected duration of the new model is.

⁸⁸ We ignore time-discounting of future energy costs for simplicity, but such discounting would mean that the future energy cost savings would need to be greater to justify the upfront expenditure for the new appliance.

gradual adjustments to price changes. For applications such as ventilation and space cooling, a business would likely have to incur substantial capital investment to upgrade its existing systems. A business may therefore not replace its cooling systems immediately in response to electricity price changes, but may delay electricity conserving upgrades until it is time to replace the equipment in the normal course of business.

C. Econometric Framework

We estimate the elasticity of demand for electricity by customers in Puerto Rico using econometric techniques known as regression analysis. As we explain in this subsection, our regression specifications are motivated by features of electricity demand discussed in Section III.B above and tailored to the available data for Puerto Rico.

We estimate a separate regression equation for each of the Residential, Commercial, and Industrial customer classes.⁸⁹ For each of these customer classes, we specify a regression equation of the following form:⁹⁰

$$\ln q_t = \beta \ln p_t + \sum_{k=1}^K \alpha_k \ln q_{t-k} + \sum_{j=1}^{J_1} \gamma_j x_{jt} + \sum_{j=1}^{J_2} \zeta_j y_{jt} + \delta_t + \delta_0 + \epsilon_t$$

where the Latin letters denote variables, the Greek letters (except ϵ_t) denote coefficients to be estimated,⁹¹ “ln” denotes the natural logarithm of the variable it precedes, t indexes the month of the observation, and K , J_1 , and J_2 are counts of the variables they index. The variable q_t is average usage within the class in the month of the observation, measured in kilowatt-hours per customer. The variable q_{t-k} is average usage in k -th month prior to the observation month, and is referred to as the “auto regressive term of the k -th order.” The variable p_t is the average overall rate charged to customers in the class that month, in dollars per kilowatt-hour. The variables x_{jt} are climate-related demand shifters and the variables y_{jt} are regional macroeconomic demand shifters. We will discuss the details of both of these sets of variables below. The term δ_t is a parameter that captures seasonality and δ_0 is the constant term of the regression.⁹²

⁸⁹ We did not analyze demand of the Other customer class. The Other customer class, which consists of varied customer groups such as agricultural customers and public lighting, accounted for no more than 2.8 percent of electricity consumption in any year since 2010, based on PREPA Financial Data.

⁹⁰ For notational simplicity, we omit customer class subscripts on the variables and coefficients. The reader should note that three entirely separate regression equations of the form presented were estimated and three distinct sets of coefficient estimates were obtained.

⁹¹ The ϵ_t term is the unobserved error term in the regression.

⁹² Seasonality is in actuality captured using dummy variables for each month, so δ_t can be seen as the dot-product of these dummy variables and their associated regression coefficients.

The use of a log-demand specification follows the literature on electricity demand going back at least to Houthakker, Verleger, and Sheehan (1974).⁹³ The functional form assumes a constant elasticity of demand within the range of electricity prices observed in the data.

The inclusion of lagged usage in the regression is intended to capture the persistent influence of the existing stock of electricity-using equipment on average demand. The dynamics of appliance upgrades discussed in Section III.B has motivated a number studies of electricity demand to model the demand as a function not only of contemporaneous factors (including price), but also of past values of electricity consumption. The inclusion of lagged dependent variables in econometric models of electricity demand goes back to Houthakker, Verleger, and Sheehan (1974), who call the specification a “flow-adjustment model of demand.”⁹⁴ In surveys of the electricity demand literature by Taylor (1975) and Bohi and Zimmerman (1984), the dominant theoretical electricity demand model is one that views demand as a function of contemporaneous factors, such as the price of electricity, and the stock of electricity-using equipment.⁹⁵ Data limitations usually prevent researchers from including equipment stock directly in the econometric specification,⁹⁶ so the persistence of the equipment stock is captured by using lagged values of electricity consumption. In Bohi and Zimmerman’s (1984) survey of the literature, the few studies available of commercial or industrial electricity demand also tended to model electricity demand as responding to price changes over time rather than instantaneously, and employed lagged dependent variables accordingly.

To better understand the role of the lagged usage term, consider a simplified form of the underlying demand model:

⁹³ H. S. Houthakker, Philip K. Verleger, Jr. and Dennis P. Sheehan, “Dynamic Demand Analyses for Gasoline and Residential Electricity,” *American Journal of Agricultural Economics* 56, no. 2 (May 1974) (hereafter, *Houthakker et al.*), pp. 412-418. See also Yu Hsing, “Estimation of residential demand for electricity with the cross-sectionally correlated and time-wise autoregressive model,” *Resource and Energy Economics*, 16 (1994), pp. 255-263 and Jan Bentzen and Tom Engsted, “A revival of the autoregressive distributed lag model in estimating energy demand relationships,” *Energy* 26 (2001), pp. 45-55 for other examples of studies using the log demand form.

⁹⁴ *Houthakker et al.*, pp. 412-418. See also the following literature surveys: Lester D. Taylor, “The demand for electricity: a survey,” *The Bell Journal of Economics* 6, issue 1 (1975) (hereafter, *Taylor*), pp. 74-110 and Douglas R. Bohi and Mary Beth Zimmerman, “An Update on Econometric Studies of Energy Demand Behavior,” *Annual Review of Energy* 9 (1984) (hereafter, *Bohi and Zimmerman*), pp. 105-154. Most of the studies reviewed in these surveys employ the flow-adjustment form.

⁹⁵ *Taylor*, pp. 74-110 and *Bohi and Zimmerman*, pp. 105-154. Houthakker, Verleger, and Sheehan motivate the use of persistence terms in their econometric specification by consideration of consumer durables and also by habit formation. See *Houthakker et al.*, pp. 412-418.

⁹⁶ A notable exception is the Dubin and McFadden study in 1984. In the paper, the authors jointly estimate structural models of electricity demand and demand for consumer durables. See Jeffrey A. Dubin and Daniel L. McFadden, “An Econometric Analysis of Residential Electric Appliance Holdings and Consumption,” *Econometrica* 52, no. 2 (March 1984), pp. 345-362.

$$\ln q_t = (1 - \psi) \ln q_{t-1} + \psi \ln q^*(p_t, w_t)$$

where $q^*(p_t, w_t)$ can be interpreted as the optimal amount electricity usage that would arise if the population were to immediately adjust the entire equipment stock in response to the current price p_t and any other factors, w_t , that affect demand.⁹⁷ In this form, demand is a weighted average of the usage that would arise if the equipment stock was perfectly adjustable in the short term and the last period's usage, which is the usage that would arise if the equipment stock was not adjustable at all. The parameter ψ can be interpreted as the proportion of the population that is in a position to upgrade their appliances or otherwise adjust their electricity-using equipment. The rest of the population, the proportion $(1 - \psi)$, can be thought of as stuck with the equipment they had in the previous period and hence will consume the same amount of electricity as they did then.⁹⁸

While the first-order autoregressive term is included in our regression model primarily to capture persistence effects related to the equipment stock, higher-order lagged terms are included to address concerns related to serial correlation. Serial correlation is the correlation over time in the error term, ϵ_t , that arises from the correlation over time in unobserved factors that affect demand.⁹⁹ Serial correlation is common in regressions using time-series data. In models that include autoregressive terms, the presence of serial correlation can result in biased estimates of the coefficients.¹⁰⁰ One approach to overcoming serial correlation is to include lagged values of the dependent variable to absorb the effect of these unobserved correlated factors, and thereby eliminate the serial correlation. If serial correlation is eliminated through use of lagged terms, then the coefficient estimates are unbiased and the standard errors are correctly estimated.¹⁰¹ Through diagnostics on our regression results, we determined the appropriate set of lagged dependent variables to include in each regression.¹⁰² For Residential demand, we found that the first-order autoregressive term alone was sufficient. For the Commercial regression, we found it necessary to include lagged usage terms for

⁹⁷ The w_t variable could, for example, contain the x_t and y_t variables in the above equation for $\ln q_t$.

⁹⁸ The model can incorporate factors, such as seasonal demand shifters, that affect consumption month-to-month for the entire population without changing the qualitative insights of this simplified form.

⁹⁹ Damodar Gujarati, *ESSENTIALS OF ECONOMETRICS*, 2nd ed. (Boston: Irwin/McGraw-Hill, 1999), pp. 378-379.

¹⁰⁰ William H. Greene, *ECONOMETRIC ANALYSIS*, 5th ed. (Upper Saddle River, NJ: Prentice Hall, 2002) (hereafter, *Greene*), pp. 265-266. In models without autoregressive terms, serial correlation does not generate bias in the coefficient estimates; however, it can cause ordinary least squares estimation to result in incorrect standard errors.

¹⁰¹ This of course assumes there are no other econometric problems or departures from the conditions of the classical linear regression model. See *Greene*, pp. 42-47.

¹⁰² In particular, we iteratively ran each regression and examined the partial autocorrelation graphs of the residuals. If there appeared to be non-negligible remaining serial correlation, then we added the next higher-order lagged term and repeated the process.

the previous five months as well as a 12-month lagged term.¹⁰³ For the industrial regression, we found it necessary to include lagged usage terms for the previous eight months, as well as the 12-month lagged term.

As an alternative to including higher-order autoregressive terms, we also employ a Feasible Generalized Least Squares (FGLS) method developed by Hatanaka (1974) to obtain unbiased and efficient estimates in the presence of serial correlation.¹⁰⁴

Without the autoregressive terms, the estimated short-run and long-run price elasticities of demand would be equal to the estimated coefficient on price (β).¹⁰⁵ With the autoregressive terms included, β is equal the short-run (one-month) elasticity. The long-run elasticity is calculated from the price coefficient and the coefficients on the autoregressive terms. In regressions with only a first-order autoregressive term, the long-run elasticity is $\beta/(1 - \alpha)$, where α is the coefficient on lagged usage.¹⁰⁶ With higher-order autoregressive terms, the long-run elasticity is computed by solving a linear system of equations.¹⁰⁷

The climate variables and regional macroeconomic variables control for other factors that could affect demand in a given month. As discussed in Section III.B, the use of air conditioning is a primary contributor to overall electricity consumption. Since air conditioning is used more frequently under hotter and more humid weather conditions, we incorporate climate controls to account for such effects. Given that electricity is used as an input to a wide range of economic activity, we expect that more electricity is also used during periods with higher income levels and production activity. We incorporate standard economic indicators measured at the regional level to account for these effects. The data

¹⁰³ The need for a 12-month lag most likely arises because of the seasonality in the data that follows an annual cycle. We also tried alternative regressions where we included all twelve lagged terms. The sixth-order through 11th-order lags were not statistically significant, did not materially affect the other coefficient estimates, and were not necessary to eliminate correlation in the residuals, so they were dropped in the interest of parsimony.

¹⁰⁴ See Michio Hatanaka, “An Efficient Two-Step Estimator for the Dynamic Adjustment Model with Autoregressive Errors,” *Journal of Econometrics* 2, issue 3 (1974) (hereafter, *Hatanaka 1974*), pp. 199-220 and *Greene*, p. 277.

¹⁰⁵ This equivalence is a useful property of the log-demand model. The coefficient is the partial derivative of the log of quantity with respect to the log of price. Rules of calculus show that this partial derivative is equal to the partial derivative of (unlogged) quantity with respect to (unlogged) price times the ratio of price to quantity, or in other words the price elasticity of demand.

¹⁰⁶ The formula for the long-run elasticity in the first-order autoregressive case assumes that α is less than one in absolute value. Otherwise, the autoregressive process is not stable and the long-run elasticity is not well defined mathematically. All of our estimates discussed in Section III.E result in stable processes where the elasticity is well-defined.

¹⁰⁷ While the actual formulas for any order higher than two or three are intractable, the long-run elasticities can be computed by solving a linear system. We also used simulations to check our computation of these long-run responses. We omit the details of the computations in this paper, but they are available upon request.

subsection below provides more details on the selection and construction of the climate and macroeconomic variables included in the regressions.

D. Data Sources and Variable Definitions

1. Electricity Usage and Prices

Monthly historical data on customer counts, electricity usage, and revenues were obtained from PREPA's official financial data.¹⁰⁸ We used data for fiscal years 2010 to 2015 to estimate the price elasticity of demand for electricity in Puerto Rico.¹⁰⁹ We normalized aggregate usage and revenues to 30-day month equivalents to eliminate variation due solely to the number of days in the observation month.

Average consumption per customer was calculated in each month and for each customer class as the total usage for the class divided by the customer class count in that month. Average consumption per customer is defined in units of kilowatt-hours per customer.

The overall average rate for a class in each month is calculated as the total class revenues (that is, the sum of basic revenues for the customer class, fuel-oil adjustment revenues for the class, and purchased-power adjustment revenues for the class) divided by the aggregate usage of the class in that month. The overall rates are then adjusted for inflation using the GDP deflator discussed below. The unit of measurement for this variable is 1954 US dollars per kilowatt-hour.

Exhibits 9, 10, and 11 depict the monthly customer counts, average usage, and average rate for each class from July 2009 through December 2015.¹¹⁰

2. Puerto Rico Macroeconomic Indicators

We included regional Gross Domestic Product (GDP) as a control for the overall state of demand in Puerto Rico.¹¹¹ As GDP is related to both aggregate income and production activity, we expect that it controls for the effect of macroeconomic conditions on electricity usage. Regional GDP is taken from the Statistical Appendix of the Economic Report for the Governor and Legislative Assembly

¹⁰⁸ PREPA Financial Data.

¹⁰⁹ Fiscal years for Commonwealth government agencies and public corporations run from July 1 to June 30. For example, FY 2015 runs from July 1, 2014 to June 30, 2015.

¹¹⁰ As the exhibits show, there appears to be a period of measurement error or data noise in the calendar year 2012. From conversations with PREPA personnel, we have learned that PREPA underwent a change in billing systems and experienced migration problems during that process. Omitting the 2012 observations would leave us with too few data points to estimate the models precisely, especially when autoregressive terms are included.

¹¹¹ GDP is generally considered a better indicator of economic activity within a particular geographic region than GNP. See Gregory N. Mankiw, *MACROECONOMICS*, 4th ed. (New York: Worth Publishers, 2000), p. 16.

compiled by the Puerto Rico Planning Board.¹¹² We use the version of the GDP series deflated to 1954 USD.

The GDP series is available only at the annual, not monthly, level. For use in the monthly regressions, we use cubic spline interpolation to approximate a monthly series. To the extent that this approach fails to account for seasonal variation in regional production that could affect electricity usage, we expect that such variation is captured through the seasonal controls in the regression or through the monthly economic activity series discussed below.

In order to normalize average electricity rates for inflation in the same manner as GDP, we used the implicit GDP deflator calculated from the ratio of real (1954) GDP to nominal GDP as the deflator for PREPA revenues.

The Government Development Bank of Puerto Rico (GDB) maintains an Economic Activity Index for the Puerto Rican economy. This index is constructed from four economic indicators of the state of the island's economy: total payroll employment, cement sales, gasoline consumption, and electricity generation.¹¹³ The GDB views the EAI as a reliable indicator of general economic activity in Puerto Rico.¹¹⁴ The EAI and its components are also observed at the monthly level and therefore exhibit intra-year variation in regional economic activity that is lacking in data interpolated from annual series.

A concern regarding direct use of the EAI in the regression is that electricity generation is part of its construction, raising a potential endogeneity problem. That is, unobserved factors that are correlated with electricity demand (the dependent variable in our regressions) may be correlated with electricity generation as well, since electricity is typically produced to meet demand. These factors would generate correlation between the unobserved error term and the EAI, potential resulting in bias in our elasticity estimates. To avoid introducing endogeneity bias into the regression, we do not use the EAI itself in our regressions. Rather, we include the three components of the index other than electricity generation—payroll employment, gasoline consumption, and cement

¹¹² Selected Series of Income and Product, Total and Per Capita dataset, "T1_AE-2015.xlsx," from Statistical Appendix of the Economic Report for the Governor and Legislative Assembly, Government Development Bank for Puerto Rico, available at <http://www.gdb-pur.com/economy/statistical-appendix.html>.

¹¹³ Documentation from "Economic Activity Index," Commonwealth of Puerto Rico, Puerto Rico Fiscal Agency and Financial Advisory Authority, May 2016 (hereafter, *Economic Activity Index*), available at <http://www.gdb-pur.com/documents/2016-May-EconomicActivityIndex.pdf>, p. 12.

¹¹⁴ *Economic Activity Index*, p. 2 and 12. The GDB also shows that the EAI correlates highly with regional Gross National Product (GNP) when aggregated to the annual level (see pp. 2-4).

sales—to capture the effect of regional economic activity on electricity demand in the same manner that using the EAI would do.¹¹⁵

3. Climate Variables

As mentioned above, the National Oceanic and Atmospheric Administration (NOAA) maintains a temperature measure known as cooling degree days (CLDD) that is constructed to reflect conditions that likely stimulate the use of air conditioning.¹¹⁶ The NOAA defines a single day's CLDD value as the difference, in tenths of degrees Celsius, between the mean daily temperature for that day and a base of 18.33°C, or 65°F.¹¹⁷ If the mean daily temperature is below 65°F, then the day is assigned a CLDD contribution of zero. The CLDD value for a month is the sum of these daily contributions over the month.

In consultation with PREPA, we determined that 65°F was likely too low to reflect a threshold that tends to trigger the use of air conditioning in Puerto Rico and that 75°F was a better threshold temperature.¹¹⁸ Therefore, we constructed a CLDD metric using daily temperature data from the National Weather Service (NWS), employing the same methodology as is used in the NOAA-maintained version except for the higher threshold temperature. Because the CLDD is an accumulation of daily measurements, we normalize the values to 30-day equivalents for use in the regression.

The NWS maintains several dozen monitoring stations around Puerto Rico. We used measurements from four stations surrounding the dense population center of

¹¹⁵ We conducted a diagnostic regression of the log EAI on the logs of its components, with and without the electricity generation component. We found that employment, gasoline consumption, and cement sales can fit the EAI to a high degree. If we were directly interested in estimating the effect of the EAI on electricity demand, we could employ an instrumental variables technique, using these components as instruments. However, we are not directly interested in this effect and would only use the EAI to absorb the effect of regional economic conditions so that their omission would not generate bias in the coefficients of interest. Including the components of the index directly in the regression accomplishes the goal just as well.

¹¹⁶ Cooling degree days are compiled by the NOAA's National Centers for Environmental Information (NCEI) using data collected by the NOAA's National Weather Service (NWS). See also "Technical Documentation: Heating and Cooling Degree Days," U.S. Environmental Protection Agency, available at https://www3.epa.gov/climatechange/pdfs/heating-cooling_documentation.pdf.

¹¹⁷ For example, if the high temperature for a particular day was 90°F and the low temperature was 66°F, the mean temperature for that day would be 78°F. 78°F is 23.89°C and 65°F is 18.33°C. Converting the temperatures to tenths of degrees Celsius and taking their difference, we have $238.9 - 183.3 = 55.6$ CLDD. Hence, that day's CLDD contribution would be 55.6. See "Heating and Cooling Degree Days," National Weather Service Weather Forecast Office, available at http://www.srh.noaa.gov/key/?n=climate_heat_cool.

¹¹⁸ Because of the way that daily contributions to a month's CLDD are truncated at zero, it is not true that our redefinition of the metric amounts to a mere rescaling of the variable, so the redefinition of the variable is not extraneous. Having said that, whether we use the standard CLDD or our customized version appears to have little effect on our estimates of elasticity

San Juan, where the population of Puerto Rico is concentrated.¹¹⁹ We calculated the cooling degree days for each month for each station and then calculated the average of the CLDD across the four stations to form our regression variable. While the temperature measurements across the various stations are highly correlated, the use of the average reduces any effects of anomalous temperature measurements at individual stations.

Also in consultation with PREPA, we augmented the CLDD climate variable with other climate variables that PREPA collects and uses in its own forecasts of energy production needs. PREPA maintains its own set of 21 weather stations at facilities around Puerto Rico, Vieques, and Culebra and constructs averages from station readings to use in its forecast models. We included in our regressions monthly variables for the maximum daily temperature averaged over the month, the maximum daily heat index averaged over the month, the maximum daily relative humidity averaged over the month, and cumulative rainfall within the month.¹²⁰ Each of these variables is an average of the values for the 21 stations.

E. Results

The results of our regressions are shown in the tables in Appendix A. For each of the Residential, Commercial, and Industrial customer classes, we provide coefficient estimates for the model without autoregressive terms and with a first-order autoregressive term included. For the first-order autoregression, we provide estimates obtained from ordinary least squares (OLS) and from a feasible generalized least squares (FGLS) method that is robust to serial correlation. We also present estimates for Commercial and Industrial using higher-order autoregressive terms and estimated using OLS. As discussed in Section III.C, we found that the Commercial and Industrial demand regressions required inclusion of higher-order autoregressive terms—that is, lagged values beyond the immediately preceding month for each observation—to eliminate serial correlation in the estimated residuals.¹²¹

¹¹⁹ The four stations used are named in the NOAA data as RIO PIEDRAS EXPERIMENTAL STATION US, WEATHER FORECAST OFFICE SAN JUAN US, TOA BAJA LEVITOWN US, and SAN JUAN L M MARIN INTERNATIONAL AIRPORT US.

¹²⁰ Whereas maximum daily temperature is a measure of temperature, relative humidity is a measure of the amount of water vapor present in the air. The heat index combines temperature and humidity into a measure of discomfort typically felt by human beings in such atmospheric conditions.

¹²¹ In the Appendix A tables, the regressions without autoregressive terms are labeled “AR(0) OLS.” The regressions with first-order lagged dependent variables are labelled “AR(1) OLS” and “AR(1) FGLS” depending on the estimation method used. For the Commercial class, the “AR(1:5,12) OLS” column provides the coefficient estimates from the model with lagged values for months one through five and a one-year lag. Likewise, the model “AR(1:8,12)” in the Industrial class regressions provides estimates from the model with lags for months one through eight and a one-year lag.

For each customer class and each autoregressive structure considered, we present results with and without the inclusion of the interpolated GDP variable, in consideration of the possibility of interpolation introducing serial correlation.¹²² Combined with the autoregressive structure, serial correlation generated by the use of interpolated variables can introduce bias into the estimated coefficients. While we have tailored the autoregressive structure to eliminate serial correlation in the estimated residuals, we run alternative regressions without the interpolated variable as a robustness check. However, we find that the estimated elasticities are somewhat sensitive to whether or not GDP is included.

In addition to the estimated regression coefficients, each column in the Appendix A tables includes the long-run elasticity computed from the coefficients, as discussed in Section III.C. These long-run elasticity estimates from each regression are summarized in Exhibit 12. The long-run elasticity estimates range (in absolute value) from -0.223 to -0.151 for Residential demand, from -0.238 to -0.078 for Commercial demand, and from -0.306 to -0.121 for Industrial demand. For residential demand, even the top end of the range of estimates is below the nationwide long-run elasticity of 0.32 estimated by Bernstein and Griffin (2006), although the range is within the range of state-level elasticities they find.¹²³

The coefficient on price is estimated to be negative in all regressions, consistent with economic theory that demand curves are downward sloping. In all but two regressions, both relating to Commercial demand, the price coefficients estimated are statistically significant at the 95 percent confidence level.

The estimated coefficients on the autoregressive terms are more surprising. For the Residential customer class, the first-order autoregressive coefficient is positive when estimated using the FGLS method; however, its value is close to zero and is not statistically significant. In all other regressions, the coefficient on the prior month's usage is estimated to be negative, and almost always statistically significant. These results are at odds with the theoretical model of equipment stock effects that, in part, motivate the use of an autoregressive framework, as discussed in Section III.C. Furthermore, the estimates of long-run elasticity are somewhat sensitive to whether or not the autoregressive terms are included.

¹²² Hasem Dezhbakhsh and Daniel Levy, "Periodic properties of interpolated time series," *Economic Letters* 44 (1994), pp. 221-228. In addition, for Commercial demand, the coefficient on GDP is strongly negative and statistically significant, contrary to the expected relationship between overall economic activity and Commercial demand for electricity.

¹²³ M.A Bernstein and J. Griffin, "Regional Differences in the Price-Elasticity of Demand for Energy," National Renewable Energy Laboratory, Subcontract Report, NREL/SR-620-39512, February 2006, p. 17. Of the mainland states, 18 had estimated elasticities less than 0.25 in absolute value with negative sloping demand curves. Another 16 states were estimated to have positive sloping demand curves. See Figure 5.5 on p. 41 and/or the table on pp. 78-79.

To address the sensitivity of the results with respect to the autoregressive structure and the inclusion of GDP, we run the regional economic simulations using low-end and high-end estimates of elasticities. As we will show, even the differences between the extremes of our elasticity estimates generate only modest differences in the simulation results on the effects of electricity price increase on Puerto Rico's GDP, employment, and per capita income.

All of the regressions fit at least moderately well, with adjusted R^2 values ranging from 0.585 to 0.836.¹²⁴ The seasonality controls collectively have significant explanatory power in most regressions,¹²⁵ though the sign and significance of the effect in a particular month can differ across customer classes. While several of the control variables included in the regressions are not statistically significant, we believe it is nevertheless correct to include them given our understanding of electricity demand in Puerto Rico, as discussed in Section III.B. Furthermore, we have conducted several robustness checks with respect to the control variables. With the exceptions of the sensitivities discussed above, the inclusion or exclusion of these other control variables does not substantially affect our estimates of the elasticities.

Having computed a range of plausible estimates of the price elasticity of demand, we use these estimates to compute the likely effect of the proposed electricity rate increases on household disposable income, business costs, and key regional economic indicators in the Commonwealth. We explain our methodology for doing so and our results in the next section.

IV. Regional Economic Simulation of Effects of Basic Rate Increases

A. Background on Regional Economic Modeling with REMI

Economists and policy planners use regional macroeconomic models to study how economic shocks or changes in economic policies affect a regional economy overall. These models recognize that the economic interactions between sectors in a regional economy determine the effects of economic shocks and policy changes on the economy. For example, consider a construction project that renovates a generating facility in the region. The construction project will temporarily stimulate demand for local construction jobs and materials. The increase in employment and local incomes, in turn, will increase the demand for

¹²⁴ The regressions that fit less well are those that do not include lagged values of electricity usage. This result is not surprising. First, as discussed Section III.C, persistence of the equipment stock suggests that demand in previous periods affects demand in the observed period. Second, time-series regressions with autoregressive terms tend to exhibit higher fit than regressions without such terms.

¹²⁵ In particular, an F -test of joint significance on the seasonal dummies rejects the null hypothesis that they do not have an effect at the 95 percent confidence level for most of regressions presented. The exceptions are the Commercial demand regressions without the higher-order autoregressive terms.

other goods and services purchased in the region. Ultimately, the total increase in regional production, employment, and household income may be substantially greater than the direct effect of the construction of the facility because of the spillover in demand to other economic sectors. This phenomenon is called the “multiplier effect.”¹²⁶

The magnitude of multiplier effects depends on existing conditions for a regional economy such as the housing stock, the quality of roads and public transportation, the local prices for other goods and services, and other factors. Of course, the multiplier effect can also compound a negative change as much as a positive one. If a manufacturing plant closes or taxes are raised (without re-investment in public goods) or the price for an input good to other sectors of an economy goes up, then the regional economy will decline to an extent beyond the direct negative impact because of multiplier effects.

In any real-world regional economy, the relationships between economic sectors, as well as the structure of demand and supply within each sector, are complex. To handle this complexity, economists often rely on software models that approximate the economic structure of a region to analyze how changes in key parameters will affect the economy overall.

Regional Economic Models, Inc. (“REMI”) has developed a software model that estimates the direct effects and multiplier effects among many sectors of a regional economy and that is calibrated by measurements specific to a defined regional economy. REMI models are considered computed general equilibrium (CGE) macroeconomic models because they involve more extensive structural modeling of the regional economy than simpler Input/Output (I/O) matrix models. While CGE models like REMI utilize an I/O matrix for the region, they add structural equations that model dynamics within the regional economy that I/O models ignore. In particular, REMI models estimate linkages among output demand (including household consumption); labor and capital demand; labor supply and population; market shares of local industries relative to national and international industries; and production costs and compensation rates.

A REMI simulation measures dynamic changes relative to the baseline that it has established from its time-series calibrations. For example, if a REMI baseline model for a regional economy has established that the population in the region is steadily declining, then a major construction project may increase the demand for labor and have the impact of reducing the decline in population, at least

¹²⁶ Furthermore, if the renovation project modernizes the generating facility and increases its efficiency, then there may exist long-term economic benefits (e.g. lower electricity prices) that persist beyond the life of the construction project. These benefits could also be factored into the regional economic model and the benefits may also flow to other sectors. It is beyond the scope of our present analysis to model the modernization or efficiency benefits of PREPA’s planned capital investments—and we lack the data to do so. Therefore, these effects are omitted from our simulations.

temporarily, for the regional economy. The positive impact on population (due, for example, to changes in out-migration and in-migration) is thus measured as the population that can be expected in the region with the construction project relative to the population absent the project. The population may decline in both scenarios over time; however, the REMI simulation measures the positive impact on the population relative to the declining baseline.

REMI simulations have been applied to analyze a wide range of economic and policy topics, including the following:

- **Impact of increased electricity rates:** A study concerning electricity prices in areas served by electric cooperatives, which are primarily rural areas across 47 states, found that increased electricity prices would decrease employment and decrease GDP in both the directly affected areas and for the entire U.S. economy. Moreover, these price increases would increase migration to the urban areas of the United States.¹²⁷
- **Multiplier effect of construction:** A study concerning the construction of a new, wind-energy generation facility in Maine found that the construction would have two effects on local employment: direct and induced employment increases during the construction phase, and direct and induced employment increases during the operation phase.¹²⁸
- **Relative benefits of policy options:** A study concerning a policy objective of reducing air pollution caused by refineries, factories, and other stationary sources in California found that while two alternative options would both result in loss of employment, the magnitude of the loss would be approximately 63% greater for one option versus the other option on an annual basis to achieve the same reduction in air pollution.¹²⁹

We have adopted a REMI model, calibrated to Puerto Rico, for our analysis. This model was procured by license from REMI. The calibration of the REMI model for Puerto Rico is consistent with key aspects of the Puerto Rican economy. The default REMI model for Puerto Rico has a baseline trend of declining population for the next thirty years. It assumes that most energy consumption by industries other than electricity production itself is in the form of electricity, rather than direct use of oil, gas, or other natural sources. The REMI model also assumes that household consumption of energy is primarily in electricity rather than direct use

¹²⁷ “Affordable Electricity: Rural America’s Economic Lifeline,” National Rural Electric Cooperative Association, July 27, 2015, at <https://www.nreca.coop/wp-content/uploads/2015/07/FINAL-STUDY-7-24-15-Affordable-Electricity-Rural-Americas-Economic-Lifeline.pdf>.

¹²⁸ Order Approving Term Sheet, State of Maine Public Utilities Commission, Ocean Energy Long-Term Contracting, Docket No. 2010-00235, February 26, 2013, p. 9.

¹²⁹ *Alliance of Small Emitters/Metals Industry et al. v. South Coast Air Quality Management District*, 60 Cal. App. 4th 55 (1997), p. 7.

of other energy sources. Lastly, it also assumes that electricity is primarily generated from fuel-oil inputs rather than natural gas.

The REMI model's multiplier effects were calibrated by REMI for the economy of Puerto Rico in 2015 to the extent feasible from available public data sources. We understand from discussions with REMI personnel that some public data sources are released annually and with a lag, meaning that REMI's calibration generally relies on trends based on historical data through 2012. Furthermore, some data sources needed to calibrate REMI models are not released for Puerto Rico, so the calibrations relevant to those data sources relied on national trends. In particular, most of the elasticity parameters that govern how specific industries react to changes in input prices are set to values calibrated from national data.

The REMI software provides a great deal of flexibility to the user, with thousands of parameters and data points that can be used to model a particular economic shock or policy change. However, this flexibility is not limitless. For example, the REMI software does not provide a means of directly setting the price elasticity of demand for select goods like electricity.¹³⁰ Given the importance of the demand elasticity to our analysis, we devised a way to work around this limitation, as discussed in Section IV.E below. REMI consultants provided invaluable technical assistance throughout the course of our analysis in helping us to find the optimal ways to model the phenomena that we were studying.

REMI is most often used to simulate *changes* in economic variables that arise from a policy or economic shock, rather than to forecast absolute levels or trends in these variables. Our study follows this approach. We do not attempt to make forecasts about whether employment will be at particular levels in particular years or to make analogous predictions about the other variables of interest. Furthermore, as discussed in the next subsection, sensitivity analyses that we have performed indicate that the differential effects we estimate are robust to changes in the REMI Puerto Rico model's baseline assumptions.

B. Customization of the REMI Puerto Rico Model

REMI allows for further customization of its model beyond the regional economic baseline when future economic conditions are expected to prevail that are not reflected in the calibrated trends. For example, we recognized that PREPA must undertake new construction for electricity-generation to satisfy the environmental regulatory requirements discussed in Section II.A, as well as other maintenance and modernization needs, within our study period and that a scenario in which such investment did not occur was not a feasible or realistic baseline. We also recognized that updated forecasts of fuel costs had fallen below previous forecasts

¹³⁰ We understand from conversations with REMI personnel that a forthcoming version of the REMI software will have the ability to set commodity-specific elasticities.

expectations and that, by consequence, households and businesses would face lower electricity costs than are implied by trends calibrated to data through 2012. Neither of these factors depended on whether or not the RSA went forward and hence they are not considered components of one policy scenario or another. Rather, we assume that the capital expenditure and forecasted fuel cost adjustments will occur in all scenarios and therefore incorporate them into the REMI Puerto Rico model as an adjustment to the baseline.¹³¹

In applying the capital expenditures to the baseline, we did not assume the full amount of the forecast \$6.4 billion expenditure between 2016 and 2030 would flow to other sectors in the Puerto Rico economy.¹³² Most of PREPA's forecasted capital expenditure will be spent on equipment imported from the mainland United States and then installed at the facility in Puerto Rico. Capital expenditure that flows out of the region ("off-island" expenditure) does not generate multiplier benefits to the regional economy in the way that purchases from local suppliers ("on-island" expenditures) do. In consultation with PREPA and its consultants, we determined that a reasonable allocation between on-island and off-island capital expenditures followed the breakdown between labor expenditures and non-labor (mainly equipment) expenditures. This allocation has 15 percent of the forecast \$6.4 billion, or just under \$1 billion, in capital expenditures from 2016 to 2030 being spent on-island.¹³³

Additionally, in consultation with REMI, we developed a "custom industry" within the software to reflect the demand for services from other sectors generated by investments in electricity production. Within the default REMI Puerto Rico model, the economic sector that best approximates the target of these capital expenditures is the Construction sector. However, the custom industry alters the demand flows from other sectors to reflect characteristics of energy industry construction and investment. For example, the custom industry has relatively more demand for technical and scientific services and relatively less demand for finance and insurance services than the default Construction sector.

¹³¹ We only incorporated the capital expenditures associated with these projects into the REMI model. The investments may potentially increase the efficiency with which PREPA produces electricity and such efficiencies may have longer term economic benefits. However, we lacked the necessary data to model and forecast such benefits. Since incorporating such efficiencies would only change the REMI baseline and would not differ materially across the policy scenarios compared, we do not believe that the omission of these benefits has a material effect on our results.

¹³² Rate Case Financial Model, filed in Response to the ECs 1st Information Request, in support of PREPA Ex. 5.0 (Revenue Requirement Testimony), Puerto Rico Electric Power Authority's Verified Petition for Approval of Permanent Rates and Temporary Rates, No.: CEPR-AP-2015-0001, Commonwealth of Puerto Rico Puerto Rico Energy Commission, May 27, 2016 (hereafter *PREPA Financial Model*). The \$6.4 billion amount is the sum of the total capital expenditure for FY 2016 through FY 2030.

¹³³ Because some types of capital expenditure are more labor-intensive than others, the year-to-year percentages vary from 11 percent to 21 percent.

Because fuel costs are passed through to PREPA customers through the fuel cost adjustment charge, as discussed in Section II.C, a change in future forecasts of fuel costs affect forecasted electricity rates. As with the capital expenditures, these changes in fuel forecasts apply to all relevant policy scenarios and hence are appropriately incorporated into the REMI Puerto Rico model as an adjustment to the baseline. We implement the effects of these revised fuel cost forecasts in the same manner as the electricity rate adjustments discussed in Section IV.E.

With regard to both the capital expenditures and revised fuel forecasts, we conducted sensitivity analyses of our policy impact simulations to ensure that our results are not dependent on the assumptions and forecasts that go into these modifications of the baseline. In particular, we saw little difference in the results of our policy simulations even when scaling the capital expenditures or fuel cost changes up or down by factors even as large as 50 percent.

The historical trends used by REMI for its baseline model did not address PREPA's increasing insolvency and likelihood for bankruptcy within our study period. A weakness of the REMI model recognized by other researchers is that historical trends do not capture binary changes such as bankruptcies of a virtually an entire industry and the resulting economic effects on an economy. We did not customize the REMI baseline model to assume the bankruptcy of PREPA absent any actions being taken. Instead, we modeled alternative scenarios that involved price increases that provide sufficient revenues to maintain solvency and we present our results as comparisons among these non-bankruptcy scenarios.

C. Policy Scenarios Considered in Simulations

As discussed in Section IV.A, the purpose of our REMI analysis is not to make forecasts, in absolute terms, of Puerto Rico's key economic indicators under various policy scenarios. Rather, our purpose is to evaluate the likely differential effects of the policy embodied by the RSA relative to alternative scenarios.

The primary policy scenario of interest (the "Restructuring Scenario") assumes that PREPA is able to restructure its debt, attain efficiency improvements, and adjust rates according to the terms of the Restructuring Agreement. Relative to scenarios without the RSA, revenue requirements over the next few years are diminished somewhat under the RSA because total debt is reduced by about 15 percent, debt payments are spread over a longer repayment period than current terms, and investments in operational efficiency improvements are funded. Despite these cost savings, PREPA will still need to raise rates to meet revenue requirements under the Restructuring Scenario.

We identify three other policy scenarios that provide alternative "but-for" worlds in the case that the RSA does not go forward. Whether or not the RSA is

effectuated, we understand and assume that PREPA must still meet its revenue requirements, which are higher in the absence of the RSA, as discussed earlier.¹³⁴ If the RSA does not go forward, the estimated amount of short-term capital that would need to be raised through refinancing is about \$1.8 billion.¹³⁵ The three Non-Restructuring Scenarios we consider differ by the assumed amortization period over which PREPA would be required to repay the principal and interest on this refinancing.¹³⁶ The assumed amortization periods are 10 years (“Non-Restructuring, 10YA”), 5 years (“Non-Restructuring, 5YA Scenario”), and 3 years (“Non-Restructuring, 3YA Scenario”).¹³⁷ The shorter the amortization period, the more aggressively PREPA would have to raise electricity rates over the amortization period to cover its debt service obligations.

The refinancing assumed in these scenarios is hypothetical and PREPA management does not view these scenarios as reliable alternatives to restructuring because PREPA may not be able to raise the amount of capital required in each.¹³⁸ Nevertheless, these scenarios provide next-best alternatives to the Restructuring Scenario and are therefore appropriate benchmarks against which to evaluate the benefits of the restructuring terms.

For each policy scenario, we simulate the effects of the required rate increase twice: once using elasticities at the low end of our range of estimates and once using elasticities at the high end. As we discuss in Section IV.F, there are only relatively minor differences in the effects between the bounds of our range of elasticity estimates.

¹³⁴ In conversations with PREPA management, we have learned that the operational efficiency improvements planned as part of the Restructuring Scenario could not realistically be implemented outside of the terms of the Restructuring Agreement. Without the Restructuring Agreement, PREPA would lack the short-term resources necessary to invest in these improvements because of the debt service obligations that would arise.

¹³⁵ PREPA and its restructuring advisors estimates that this amount is needed to replenish PREPA’s debt service reserve and Self Insurance Fund, refinance the maturity of the legacy fuel lines, and refinance the automatic maturity of the Series 2016 Bonds upon termination of the Restructuring Agreement. See Schedule F-4, In Re: The Puerto Rico Electric Power Authority Initial Rate Review, Commonwealth of Puerto Rico Puerto Rico Energy Commission, No. CEPR-AP-2015-0001, May 27, 2016 (hereafter, *Schedule F-4*), p. 8.

¹³⁶ A “scenario” where PREPA does not borrow at all and simply raises rates sufficiently high to meet immediate revenue requirements is simply not realistic. PREPA managers and advisors do not believe that the immediate cash needs that would arise upon termination of the RSA could feasibly be funded through collected revenues, even with price increases more drastic than considered in any of the Non-Restructuring Scenarios described here.

¹³⁷ *Schedule F-4*, p. 8.

¹³⁸ *Schedule F-4*, p. 8.

D. Necessary Rate Increases to Meet Revenue Requirements under Policy Scenarios Considered

We rely on financial modeling performed as part of the recent rate case to obtain the size of the necessary rate increases under each of the policy scenarios discussed in Section IV.C.¹³⁹

As part of PREPA's restructuring efforts, a team from Navigant Consulting constructed a long-term financial model to forecast the magnitude of rate changes needed to cover PREPA's expected capital and operating expenditures (including debt service). The financial model and rate forecasts were submitted as part of the rate case to the Puerto Rico Energy Commission (PREC) on May 27, 2016.¹⁴⁰ The Energy Commission has since approved a provisional rate increase of 4.2 cents per kWh for the interim period while rate case proceedings continue.¹⁴¹ The financial model was constructed in close consultation with PREPA's management and the restructuring advisory team to obtain accurate and reasonable forecasts for capital expenditures, debt service, fuel and purchased power, labor and pension expenses, electricity needs, and other key inputs. That model was not created by the authors of this paper, and we do not take credit or responsibility for it. We rely on the financial model for its calculations of necessary price increases that serve as inputs to our macroeconomic analysis. The financial model's underlying assumptions and its methodologies and results were scrutinized by PREPA management, GDB staff, Energy Commission staff, and restructuring advisors as part of the rate case proceedings.

The financial model calculates revenue requirement, pro forma financial statements, and overall rates for each fiscal year through FY 2030 under the four policy scenarios.¹⁴² We rely specifically on the model's forecasted overall average rates from FY 2017 to FY 2030. Exhibits 14.A and 15.A present the forecasted overall average rates needed to meet the revenue requirements, according to the Navigant Consulting financial model. Exhibit 15.A also presents

¹³⁹ *PREPA Financial Model*.

¹⁴⁰ CEPR-AP-2015-0001, Completeness Determination of the PREPA Petition for Rate Review, Public Notice and Intervention Instructions, p. 1.

¹⁴¹ We understand that the 4.2 cent per kWh increase overall rate increase breaks down into a basic rate increase of 1.3 cents per kWh and a transitional debt service charge of 2.9 cents per kWh. See Order Establishing Provisional Rates, Matter: Provisional Rates, in Re: Review of Rates of the Puerto Rico Power Authority, Commonwealth of Puerto Rico Puerto Rico Energy Commission, No.: CEPR-AP-2015-0001, June 24, 2016, p. 6.

¹⁴² See Exhibit 13. In calculating revenue requirements and the needed overall rates, PREPA's customers were assumed to have perfectly inelastic demand for electricity. This assumption of no demand response to price changes is standard in electricity rate cases. To the extent that consumers respond to electricity rate increases by reducing usage, revenues under the new rates will not exactly match the revenue requirements. However, given that we have estimated PREPA customers to have relatively inelastic demand, the revenue shortfall is unlikely to be very large.

historical average annual rates back to fiscal year 2000. As Exhibit 15.A shows, the peak rates under the Restructuring Scenario are not outside the range of rates experienced in recent years. Exhibits 14.B and 15.B present the relative differences of the forecasted rates in each scenario, relative to the baseline rates.

E. Modeling the Effects of Rate Increases within REMI

One of the constraints of the Puerto Rico version of the REMI model is that it does not explicitly contain a variable for the price of electricity faced by households.¹⁴³ To overcome this limitation, we model the effect of electricity rate increases on Residential customers as an effect on household disposable income, which we then incorporate into REMI.¹⁴⁴ This approach also allows us to incorporate into the modeling the price elasticity of demand we estimated for Residential customers, because the elasticity of demand determines for any price increase, the change in expenditure caused by that price increase.¹⁴⁵

A limitation of our approach is that it does not take into account any economic effects that are generated by the reduction of electricity usage by households or businesses¹⁴⁶ or any substitution toward other energy sources. Estimating such effects would require additional data (for example, on sales of solar panels or energy efficient appliances) and we do not believe they would materially alter the simulated effects on the overall regional economy.

To model the effect of the rate increases on Commercial and Industrial customers, we employ a similar approach to the one used for Residential customers.¹⁴⁷ Specifically, we model the rate increases as changes in overall average production costs for businesses, using the same expenditure change formulas discussed above.

¹⁴³ A household electricity price parameter is available in other regional models, but has not been incorporated into the Puerto Rico model. Even regional models that have an electricity price parameter do not allow the user to set the price elasticity of demand for electricity. Rather, the price elasticity of demand for electricity is set the same as other “necessities” at 0.12. See “REMI Policy Insight 9.5 Model Documentation,” Regional Economic Consulting Models, 2007, p. 25.

¹⁴⁴ A loss in household disposable income is set in REMI as an increase in the “Total Consumer Price (amount)” variable. The REMI documentation and consultation with REMI personnel revealed this approach to be the best way of modeling a loss of disposable income to households.

¹⁴⁵ Our methodology for estimating the expenditure effect caused by price changes relies on those price changes not being too large. As shown in Exhibit 15.A, the rates considered under the scenarios we analyze are within the range of rates encountered by consumers in recent years, and hence within the range of the data used in our regressions. However, if PREPA were to consider drastic rate changes that put rates way outside the range of observed data, such rate changes might cause consumers to change their behaviors in ways that make our elasticity estimates inapplicable (for example, many customers that have tended to pay their bills may decide to stop doing so).

¹⁴⁶ For example, if retail stores reduced its operating hours in order to reduce electricity usage, then there could be an effect on sales and possibly employment. These effects would not be captured in our modeling of the effect of price increases.

¹⁴⁷ While the Puerto Rico model does contain an “Electricity Fuel Cost” parameter for commercial and industrial sectors, REMI does not allow the user to set the demand elasticity.

The Puerto Rico version of the REMI model allows the user to specify changes in production costs at the industry level.¹⁴⁸ We allocated the overall expenditure change for Commercial and Industrial customers (summed together)¹⁴⁹ across the model's sectors in proportion to their electricity expenditure in the REMI baseline. For example, the Real Estate sector in aggregate is projected to spend about twice as much on electricity in 2017 as the Primary Metal Manufacturing sector (probably due to the relative sizes of the two sectors) in REMI's Puerto Rico model. The increase in electricity expenditure by the Real Estate sector as a result of the price increase is therefore assumed to be twice as much as the additional expenditure on electricity by Primary Metal Manufacturing.

F. Simulation Results

We focus on three key macroeconomic indicators: employment, Gross Domestic Product (GDP), and per capita disposable personal income. Exhibits 16-18 present the differences, in natural units and in percentages, between the Restructuring Scenario and each Non-Restructuring Scenario. Exhibits 19-21 graphically present the differences in the respective indicators (in their natural units) between the Restructuring Scenario and the three Non-Restructuring Scenarios. Exhibits 22-23 organize this information differently, presenting the percentage differences in each indicator between the Restructuring Scenario and each Non-Restructuring Scenario in turn. There are versions of each simulation exhibit using the low-end and high-end of our elasticity estimates in Section III.E.

The simulation results consistently show that the Restructuring Scenario fares considerably better with respect to each of the macroeconomic indicators we studied. The benefits of restructuring invariably peak in FY 2018 according to these simulations.

With regard to total employment, the Restructuring Scenario results in between 4,800 and 7,600 more jobs (between 0.52 and 0.84 percent) under the low-end elasticity estimates and between 3,500 and 5,500 more jobs (between 0.39 and 0.60 percent) under the high-end elasticity estimates, relative to the Non-Restructuring Scenarios in FY 2018.

The Restructuring Scenario in the peak year (2018) results in between \$462 million and \$747 million more in regional GDP (0.45 percent and 0.73 percent respectively) in that year under the low-end elasticity estimates and between \$340 million and \$527 million more (0.33 percent and 0.51 percent respectively) under

¹⁴⁸ The Puerto Rico REMI model contains 46 sectors, including government, manufacturing, and service sectors.

¹⁴⁹ It does not appear to be possible to partition the REMI sectors into a group corresponding closely to Commercial and another corresponding to Industrial customers. We attempted such partitioning based on whether the sector had "manufacturing" in its name; however, the electricity expenditures in the REMI baseline were not at all in the same ballpark as we found in the PREPA data.

the high-end estimates. Over the five fiscal years from 2017 through 2021, the restructuring benefits amount to between \$1.3 billion and \$1.9 billion cumulatively using the low-end elasticities and between \$900 million and \$1.4 billion using the high-end elasticities.

The simulations indicate that the average resident of Puerto Rico would have between \$135 and \$211 more in annual disposable personal income under the Restructuring Scenario compared to the Non-Restructuring Scenarios, using the low-end elasticity estimates. These equate to percentage gains in average disposable income of between 0.77 percent and 1.21 percent. If the high-end estimates are used, the range of per capita disposable personal income gains is \$101 to \$152 (or 0.58 to 0.87 percent).

After the amortization period in each Non-Restructuring Scenario, the simulations suggest that the Restructuring Scenario does slightly worse than Non-Restructuring; however, the difference is never more than minor.¹⁵⁰ Furthermore, the simulations do not account for the increased riskiness of the Non-Restructuring Scenarios in that PREPA might not be able to raise enough revenues in the short-term to meet the terms of the refinancing.

V. Conclusion

As we discussed in Section II, increases in PREPA's basic tariffs for electricity service are necessary for PREPA to fund operating and capital expenditures, including debt service and environmental compliance costs. These rate increases are necessary whether or not the RSA goes forward. However, under the RSA, the required magnitude of rate increases will be less than they would be under scenarios without the RSA.

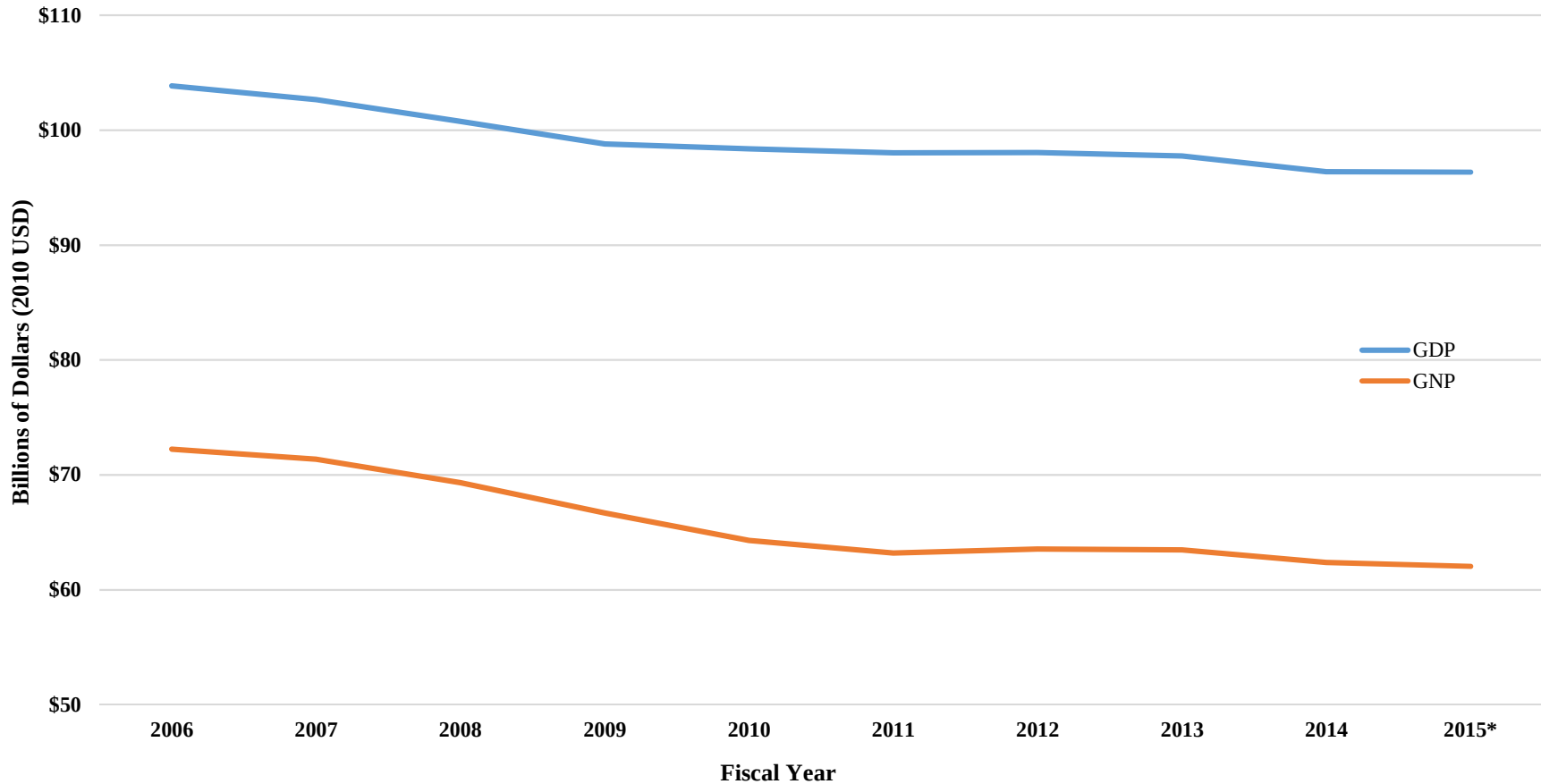
Our study of electricity demand among residents and businesses in Puerto Rico provides quantitative estimates of how PREPA's customers will adjust electricity consumption in response to rate increases. Our estimates are consistent with the generally held view that electricity demand is inelastic, but not perfectly inelastic. We find that electricity rate increases will likely lead to a slight decrease in electricity consumption; however, the net effect of the rate increases will be to increase PREPA revenues and its customers' total expenditures on electricity.

Because increased electricity expenditures will, all else equal, leave households with less disposable income and raise production costs for businesses, electricity rate increases are expected to have a contractionary effect on the economy of Puerto Rico. Since the electricity rate increases necessary under the RSA are less

¹⁵⁰ Per capita disposable personal income under Restructuring never falls more than 0.17 percent below the Non-Restructuring benchmark. Total employment never falls more than 0.08 percent below and GDP never falls more than 0.06 percent below.

than those necessary without the RSA, however the RSA effectively mitigates the contractionary effect, leaving the overall economy of Puerto Rico better off than if the RSA does not go forward. We have estimated these economic benefits of the RSA to include thousands of jobs saved and hundreds of dollars in disposable income per household per year saved over the next five years. Furthermore, we estimate GDP in Puerto Rico over the next five years to be \$900 million to \$1.9 billion higher with the RSA than without it.

Exhibit 1: Commonwealth of Puerto Rico Gross Domestic Product and Gross National Product: 2006-2015



Notes:

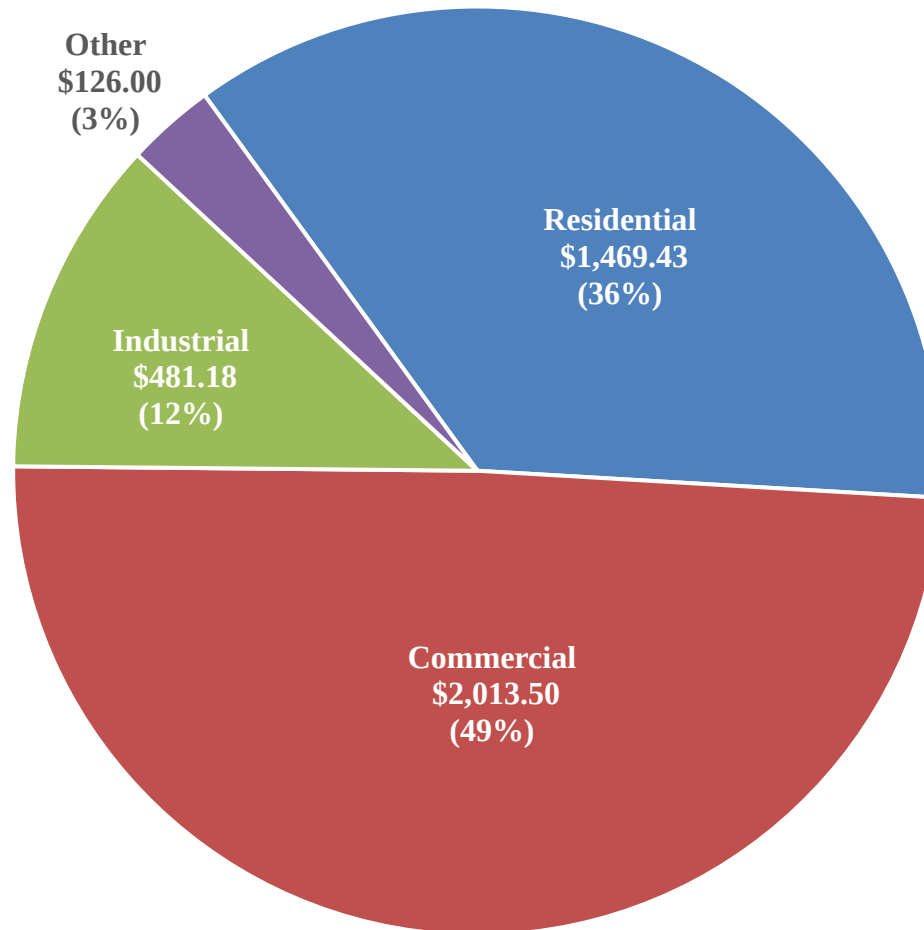
Fiscal Year (FY) runs from July of the previous year to June of the current year.

* Indicates preliminary figures.

Sources:

Commonwealth of Puerto Rico, Government of Development Bank for Puerto Rico, Statistical Appendix of the Economic Report for the Governor and Legislative Assembly, Selected Series of Income and Product, Total and Per Capita, TABLE 1, available at: <http://www.gdb-pur.com/economy/statistical-appendix.html>.

Exhibit 2: Total PREPA Revenue by Customer Class in 2015



Notes:

Revenues in millions of USD.

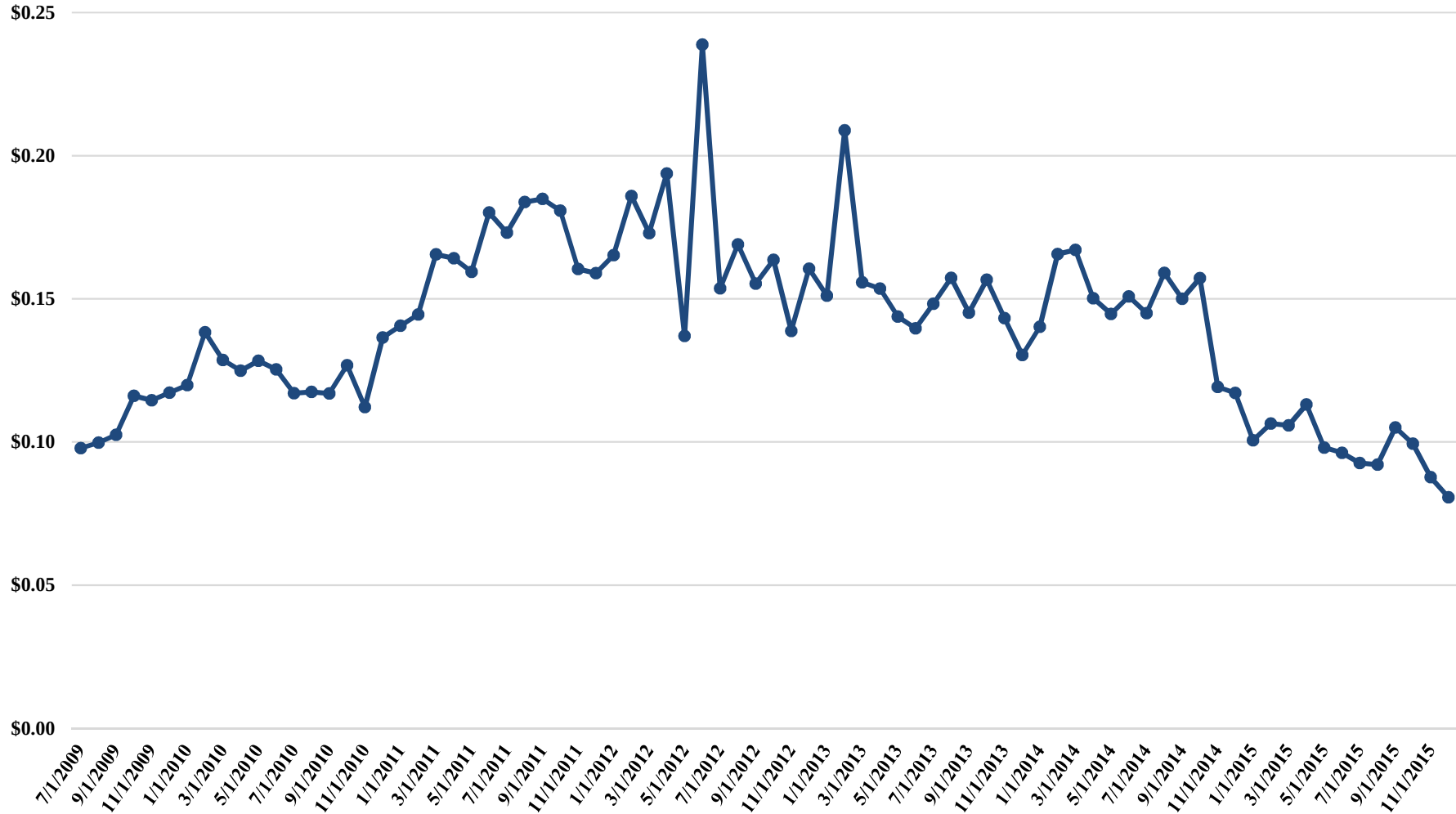
Total revenue in 2015 was \$4,090.10 million.

Percentages are the class shares of total revenue.

Sources:

PREPA Financial Data.

Exhibit 3.A: Average Fuel Cost Adjustment Charge Per Kilowatt-Hour: 2010-2015

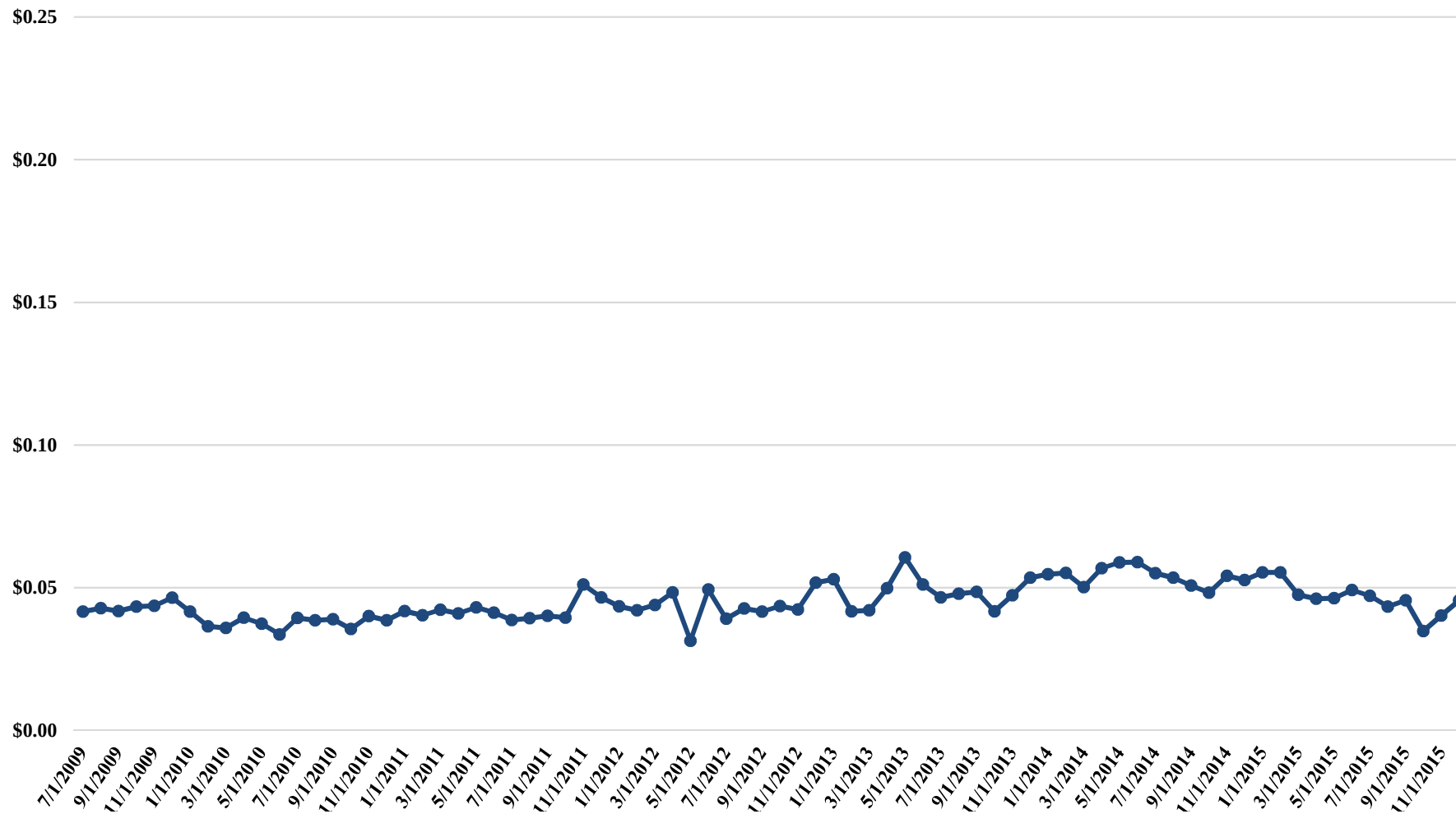
**Note:**

Average over all customer classes.

Sources:

PREPA Financial Data.

Exhibit 3.B: Average Purchased Power Adjustment Charge Per Kilowatt-Hour: 2010-2015

**Note:**

Average over all customer classes.

Sources:

PREPA Financial Data.

Exhibit 4: Overall Annual Average Rates By Customer Class: 2010-2015

Fiscal Year	Residential	Commercial	Industrial	Other	All Classes
2010	\$0.21	\$0.22	\$0.19	\$0.31	\$0.22
2011	\$0.24	\$0.25	\$0.21	\$0.34	\$0.24
2012	\$0.27	\$0.30	\$0.24	\$0.28	\$0.28
2013	\$0.25	\$0.28	\$0.23	\$0.38	\$0.26
2014	\$0.26	\$0.27	\$0.23	\$0.38	\$0.26
2015	\$0.24	\$0.24	\$0.21	\$0.35	\$0.24

Sources:
PREPA Financial Data.

Exhibit 5: Basic Rate Revenue and Total Revenue: 2010-2015

Fiscal Year	Basic Rate Revenue	Total Revenue
2010	\$1,120.89	\$4,154.40
2011	\$1,087.03	\$4,406.16
2012	\$1,079.77	\$5,031.43
2013	\$1,114.05	\$4,821.35
2014	\$1,097.28	\$4,634.52
2015	\$1,076.05	\$4,090.10

Notes:

In millions of USD.

Sources:

PREPA Financial Data.

Exhibit 6

US Energy Consumption by Economic Sector: 2013

	Residential	Commercial	Industrial	Transportation	Total
Consumption	4.75	4.57	3.26	0.02	12.6
Percentage Total	37.7%	36.3%	25.9%	0.2%	100.0%

Notes:

Unit of consumption is quadrillion Btu.

Sources:

U.S. Energy Information Administration (EIA), Annual Energy Outlook 2015 with projections to 2040, DOE/EIA-0383(2015), April 2015, Table A2.

Puerto Rico Energy Consumption by Economic Sector: 2013

	Residential	Commercial	Industrial	Other	Total
Consumption	6.3	8.6	2.5	0.3	17.8
Percentage Total	35.4%	48.3%	14.0%	1.7%	100.0%

Notes:

Unit of consumption is billion kilowatt-hours.

Sources:

PREPA Financial Data.

Exhibit 7.A: US Residential Energy Consumption by Application: 2013

Key Indicator	Consumption	Percentage
Space cooling	0.66	13.9%
Lighting	0.59	12.4%
Water heating	0.44	9.3%
Space heating	0.40	8.4%
Refrigeration	0.36	7.6%
Televisions and related equipment ¹	0.33	6.9%
Clothes dryers	0.20	4.2%
Furnace fans and boiler circulation pumps	0.13	2.7%
Computers and related equipment ²	0.12	2.5%
Cooking	0.11	2.3%
Dishwashers ³	0.09	1.9%
Freezers	0.08	1.7%
Clothes washers ³	0.03	0.6%
Other uses ⁴	1.19	25.1%
Total Purchased Electricity	4.75	100.0%

Notes:

Unit of consumption is quadrillion Btu.

1. Includes televisions, set-top boxes, home theater systems, DVD players, and video game consoles.
2. Includes desktop and laptop computers, monitors, and networking equipment.
3. Does not include water heating portion of load.
4. Includes small electric devices, heating elements, and motors not listed above. Electric vehicles are included in the transportation sector.

Sources:

U.S. Energy Information Administration (EIA), Annual Energy Outlook 2015 with projections to 2040, DOE/EIA-0383(2015), April 2015, Table A4.

Exhibit 7.B: US Commercial Energy Consumption by Application: 2013

Key Indicator	Consumption	Percentage
Lighting	0.91	19.9%
Ventilation	0.52	11.4%
Space cooling ¹	0.49	10.7%
Refrigeration	0.37	8.1%
Office equipment (non-PC)	0.22	4.8%
Space heating ¹	0.16	3.5%
Office equipment (PC)	0.11	2.4%
Water heating ¹	0.09	2.0%
Cooking	0.02	0.4%
Other uses ²	1.68	36.8%
Total Purchased Electricity	4.57	100.0%

Notes:

Unit of consumption is quadrillion Btu.

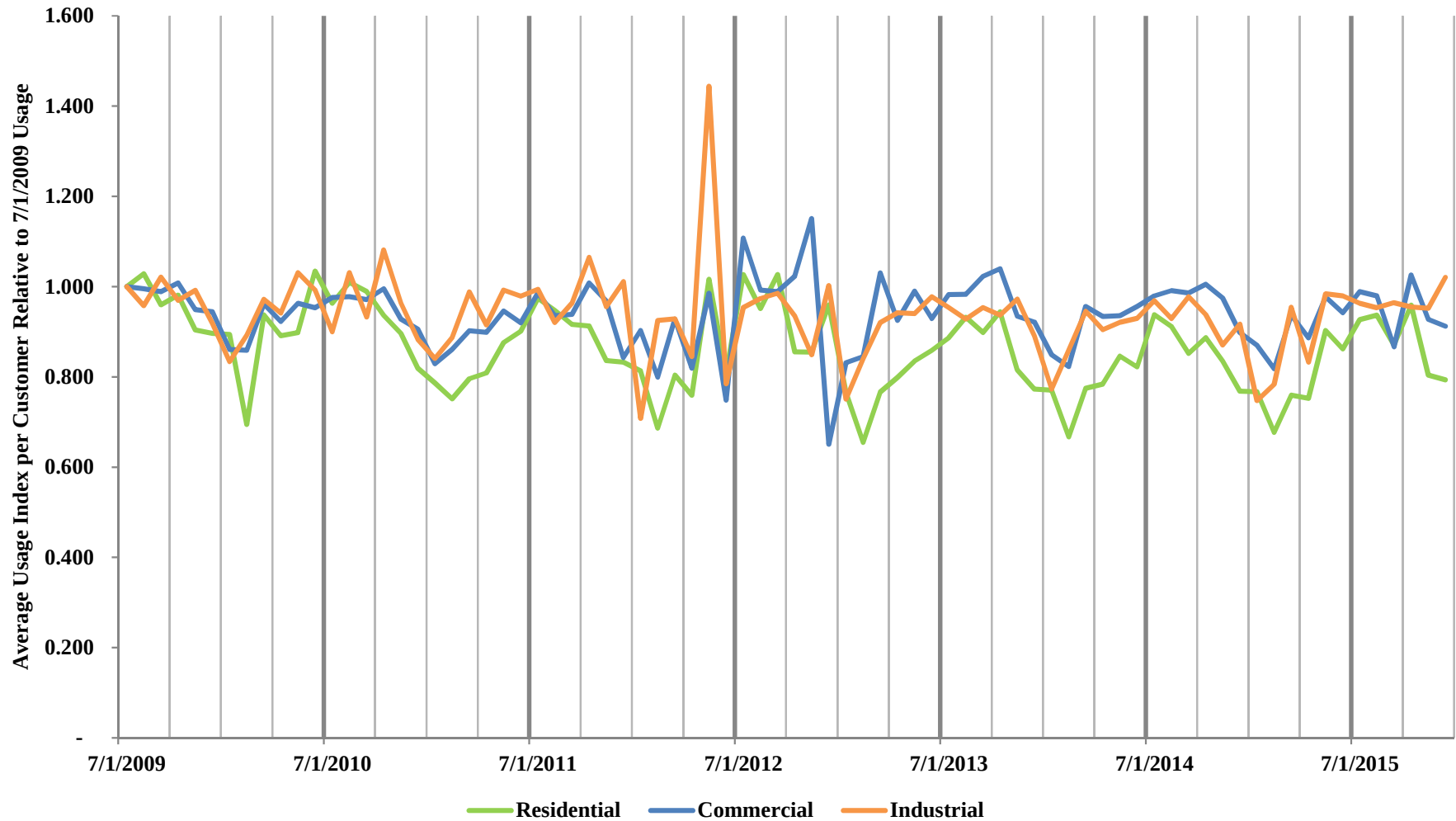
1. Includes fuel consumption for district services.

2. Includes (but is not limited to) miscellaneous uses such as transformers, medical imaging and other medical equipment, elevators, escalators, off-road electric vehicles, laboratory fume hoods, laundry equipment, coffee brewers, and water services.

Sources:

U.S. Energy Information Administration (EIA), Annual Energy Outlook 2015 with projections to 2040, DOE/EIA-0383(2015), April 2015, Table A5.

Exhibit 8: Seasonality Pattern in Average Usage per Customer by Customer Class: 2010-2015



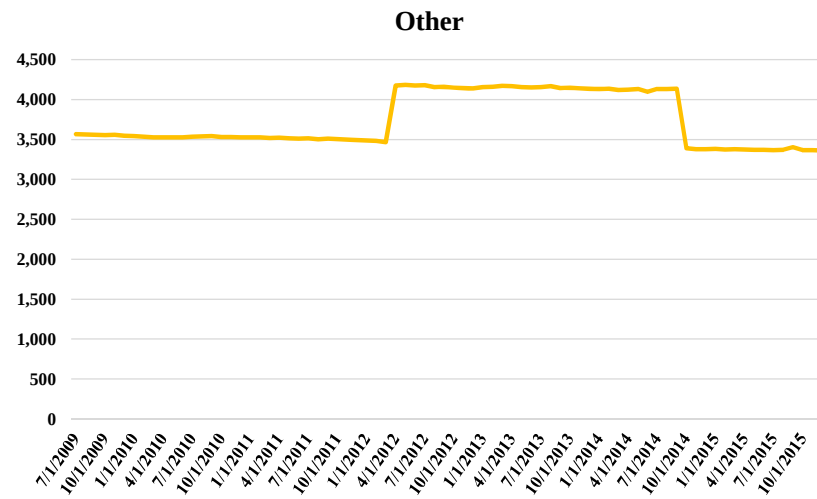
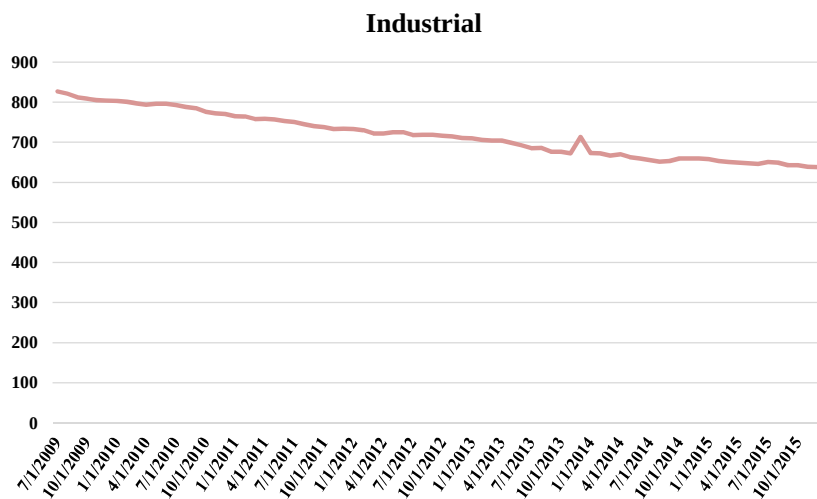
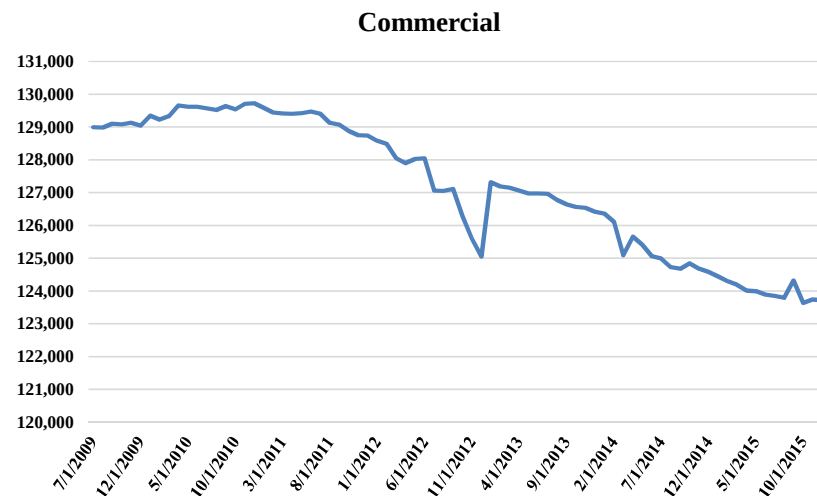
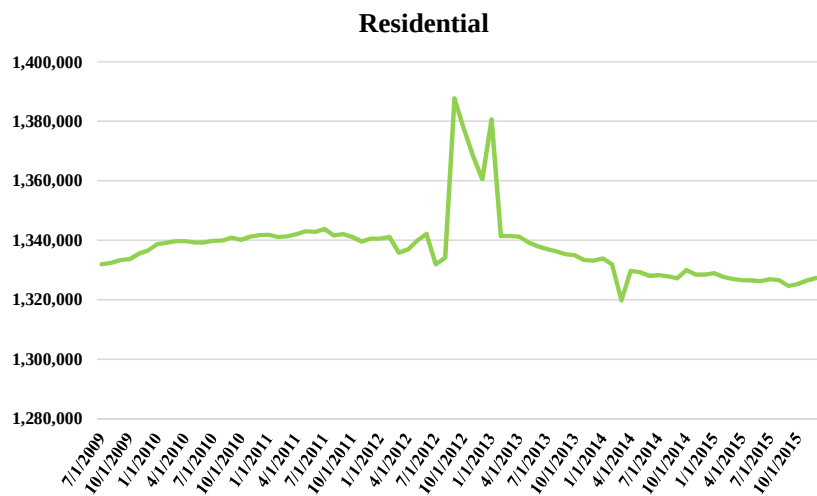
Note:

All usage data indexed to usage amount observed in July 2009.

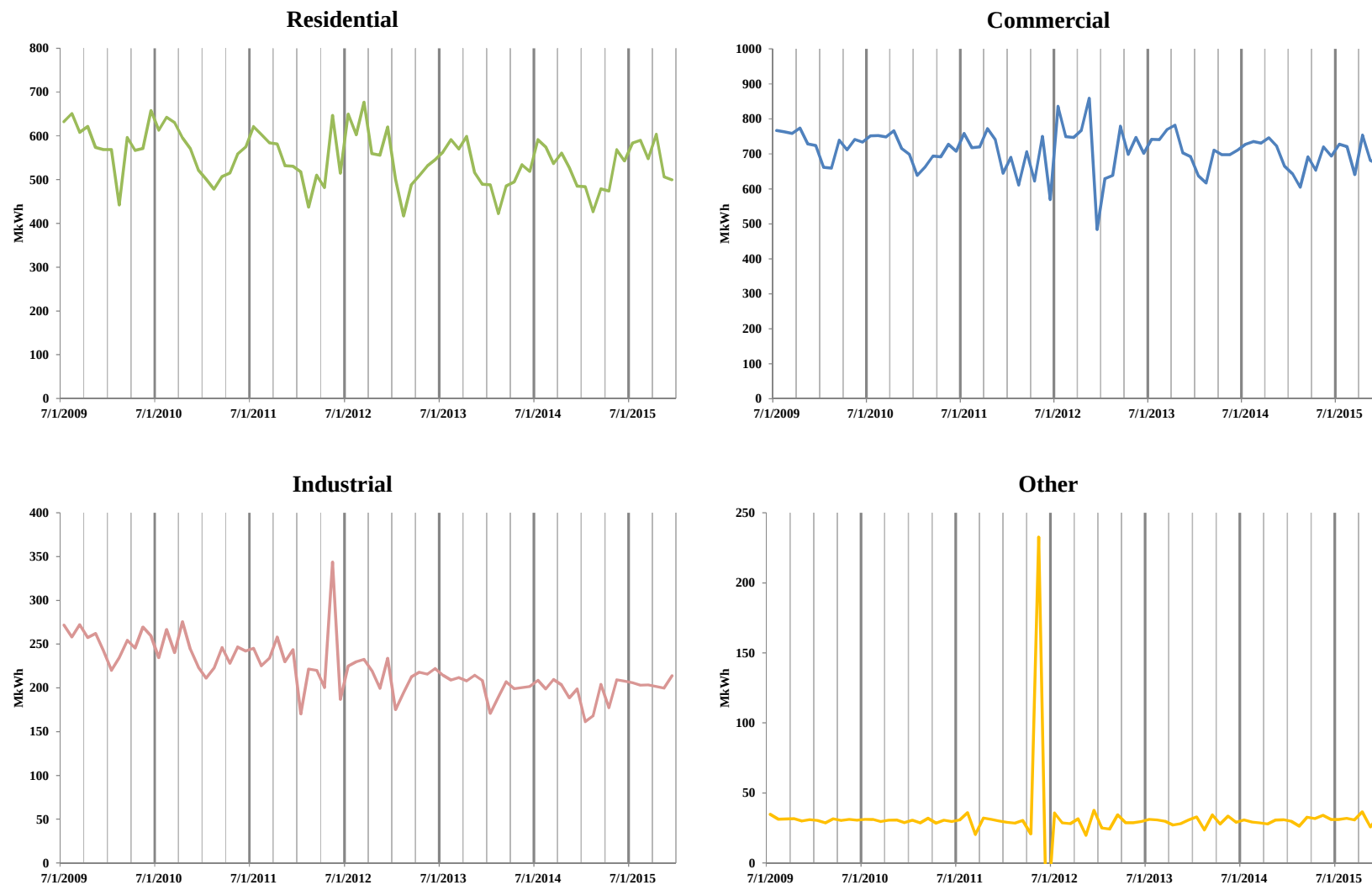
Sources:

PREPA Financial Data.

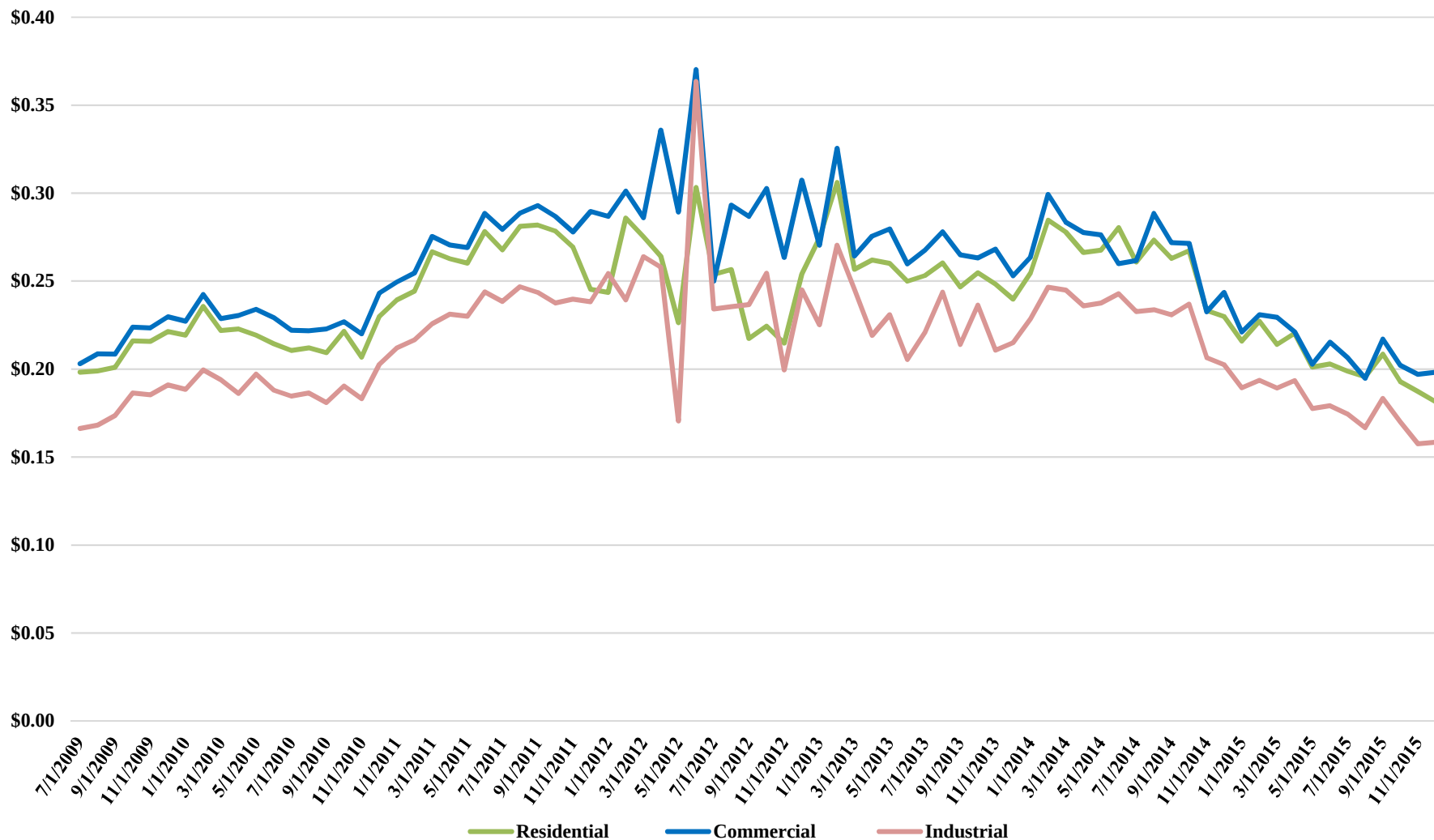
Exhibit 9: Customer Counts by Class: 2010-2015



Sources:
PREPA Financial Data.

Exhibit 10: Average Usage by Customer Class: 2010-2015

Sources:
PREPA Financial Data.

Exhibit 11: Average Rate per Kilowatt-Hour by Customer Class: 2010-2015**Sources:**

PREPA Financial Data.

Exhibit 12: Summary of Elasticity Estimates

	AR(0) OLS [1]	AR(1) OLS [2]	AR(1) FGLS [3]	AR(k) OLS [4]
<i>With GDP included as explanatory variable</i>				
Residential	-0.199	-0.151	-0.175	
Commercial	-0.238	-0.153	-0.215	-0.104
Industrial	-0.306	-0.121	-0.134	-0.170
<i>Without GDP included as explanatory variable</i>				
Residential	-0.223	-0.187	-0.201	
Commercial	-0.170	-0.103	-0.121	-0.078
Industrial	-0.305	-0.127	-0.136	-0.210

Notes:

[1] Ordinary least squares method without autoregressive terms.

[2] Ordinary least squares method with the first-order autoregression.

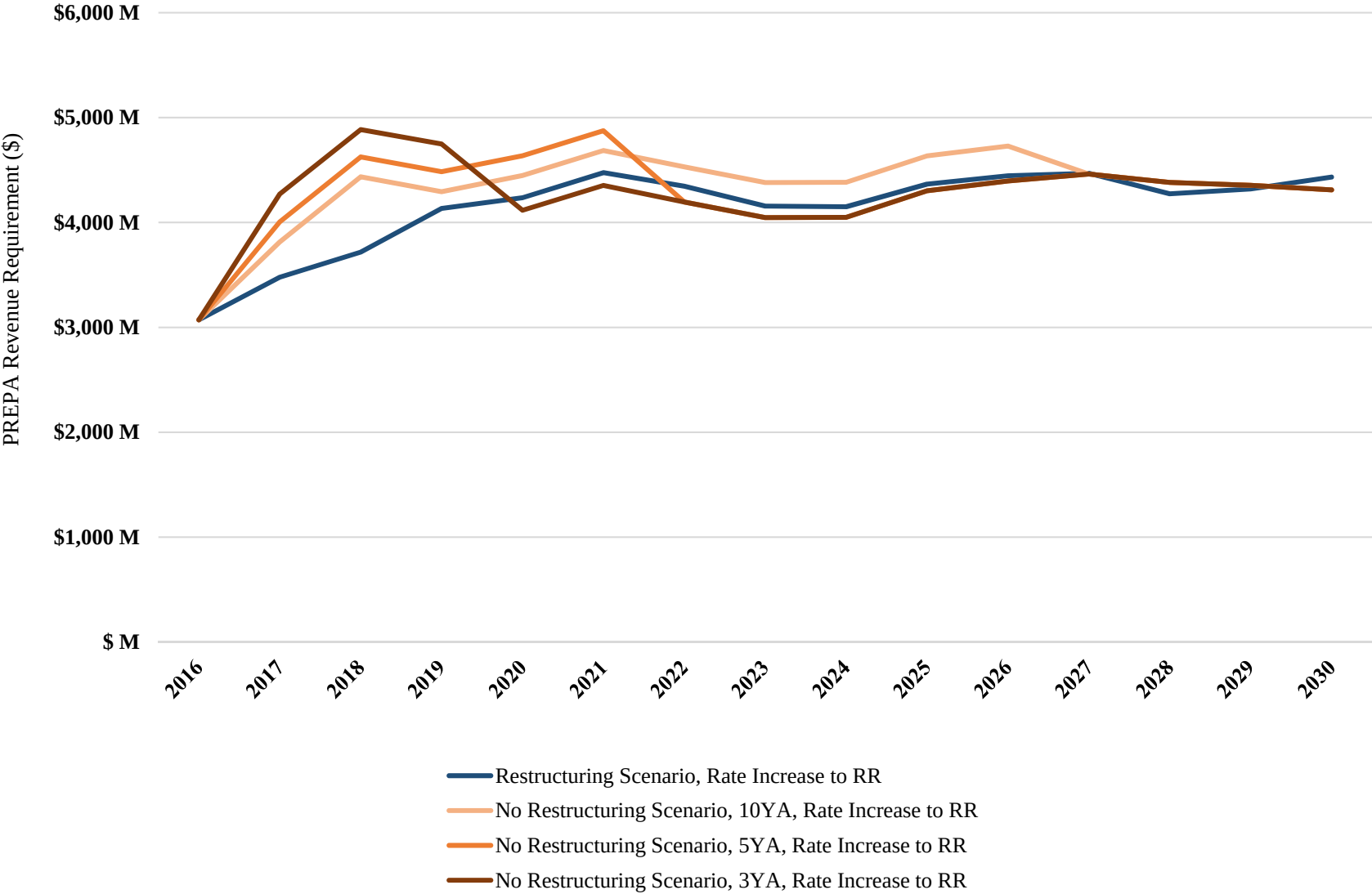
[3] Feasible generalized least squares method with the first-order autoregression.

[4] For the Commercial class, ordinary least squares method with lagged values for months one through five and a one-year lag.
For the Industrial class, ordinary least squares method with lagged values for months one through eight and a one-year lag.

Source:

Appendix A.

Exhibit 13: Revenue Requirements under Alternative Policy Scenarios: 2016-2030



Sources:
PREPA Financial Model.

Exhibit 14.A: Average Rates under Revenue Requirement Pricing in Alternative Policy Scenarios: 2016-2030

FY	Restructuring Scenario, Rate Increase to Revenue Requirement	No Restructuring Scenario, 10YA, Rate Increase to Revenue Requirement	No Restructuring Scenario, 5YA, Rate Increase to Revenue Requirement	No Restructuring Scenario, 3YA, Rate Increase to Revenue Requirement	Baseline
2016	\$0.1779	\$0.1779	\$0.1779	\$0.1779	\$0.1779
2017	\$0.2014	\$0.2208	\$0.2319	\$0.2474	\$0.1614
2018	\$0.2147	\$0.2561	\$0.2670	\$0.2821	\$0.1714
2019	\$0.2383	\$0.2476	\$0.2586	\$0.2738	\$0.1772
2020	\$0.2427	\$0.2548	\$0.2656	\$0.2358	\$0.1821
2021	\$0.2558	\$0.2679	\$0.2786	\$0.2488	\$0.1854
2022	\$0.2479	\$0.2584	\$0.2393	\$0.2393	\$0.1838
2023	\$0.2366	\$0.2494	\$0.2303	\$0.2303	\$0.1832
2024	\$0.2357	\$0.2490	\$0.2300	\$0.2300	\$0.1865
2025	\$0.2475	\$0.2627	\$0.2439	\$0.2439	\$0.1906
2026	\$0.2514	\$0.2674	\$0.2486	\$0.2486	\$0.1944
2027	\$0.2522	\$0.2518	\$0.2518	\$0.2518	\$0.1941
2028	\$0.2407	\$0.2468	\$0.2468	\$0.2468	\$0.1936
2029	\$0.2427	\$0.2447	\$0.2447	\$0.2447	\$0.1977
2030	\$0.2486	\$0.2417	\$0.2417	\$0.2417	\$0.2005

Sources:

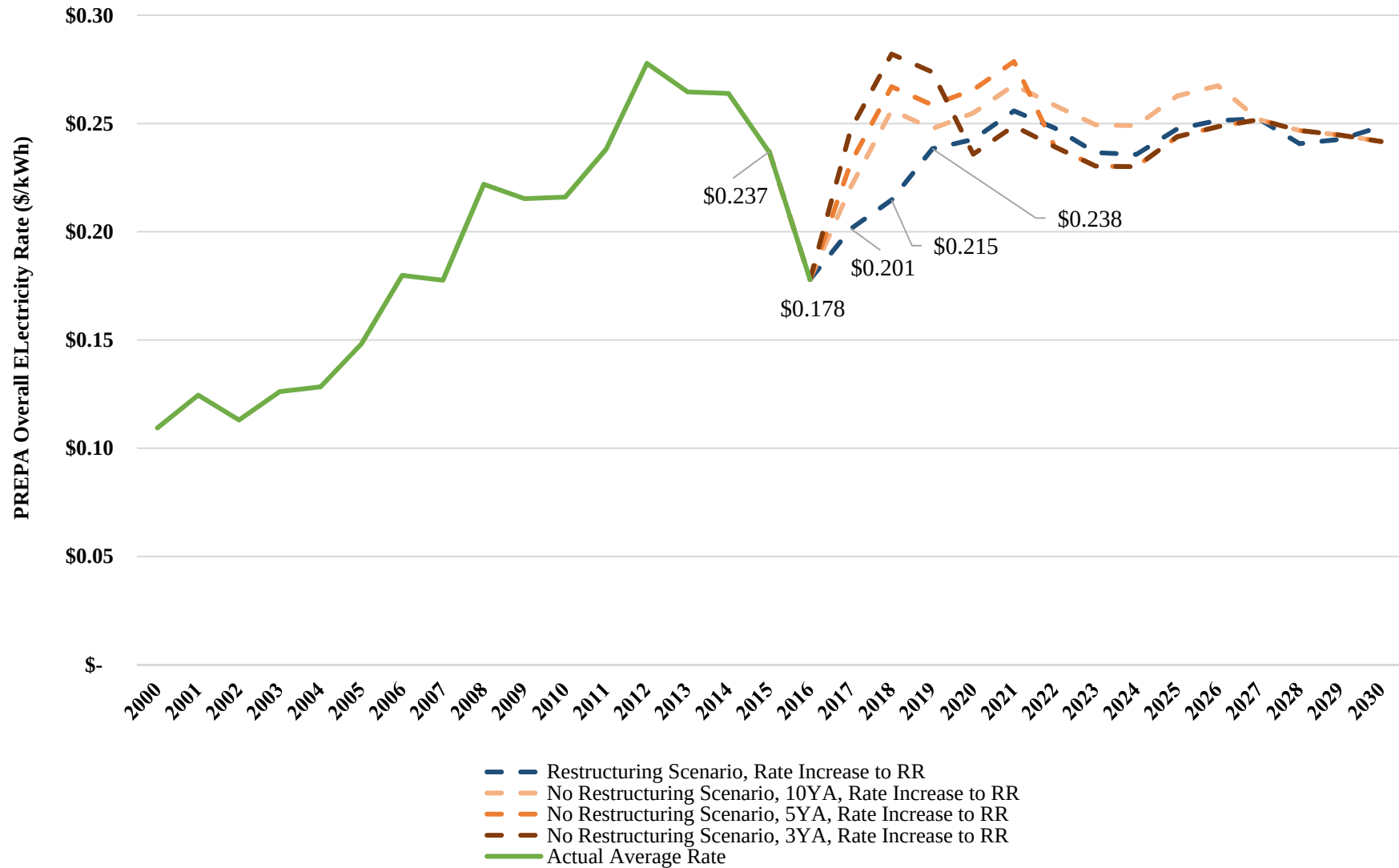
PREPA Financial Model.

Exhibit 14.B: Percentage Increases in Average Rates Relative to Baseline under Revenue Requirement Pricing in Alternative Policy Scenarios: 2016-2030

FY	Restructuring Scenario, Rate Increase to Revenue Requirement	No Restructuring Scenario, 10YA, Rate Increase to Revenue Requirement	No Restructuring Scenario, 5YA, Rate Increase to Revenue Requirement	No Restructuring Scenario, 3YA, Rate Increase to Revenue Requirement
2016	0.00%	0.00%	0.00%	0.00%
2017	24.78%	36.80%	43.70%	53.25%
2018	25.24%	49.42%	55.77%	64.55%
2019	34.50%	39.72%	45.92%	54.50%
2020	33.23%	39.90%	45.81%	29.48%
2021	38.00%	44.49%	50.31%	34.23%
2022	34.89%	40.61%	30.19%	30.19%
2023	29.11%	36.10%	25.72%	25.72%
2024	26.38%	33.48%	23.31%	23.31%
2025	29.83%	37.83%	27.94%	27.94%
2026	29.29%	37.54%	27.85%	27.85%
2027	29.91%	29.72%	29.72%	29.72%
2028	24.31%	27.46%	27.46%	27.46%
2029	22.76%	23.76%	23.76%	23.76%
2030	23.98%	20.57%	20.57%	20.57%

Sources:
PREPA Financial Model.

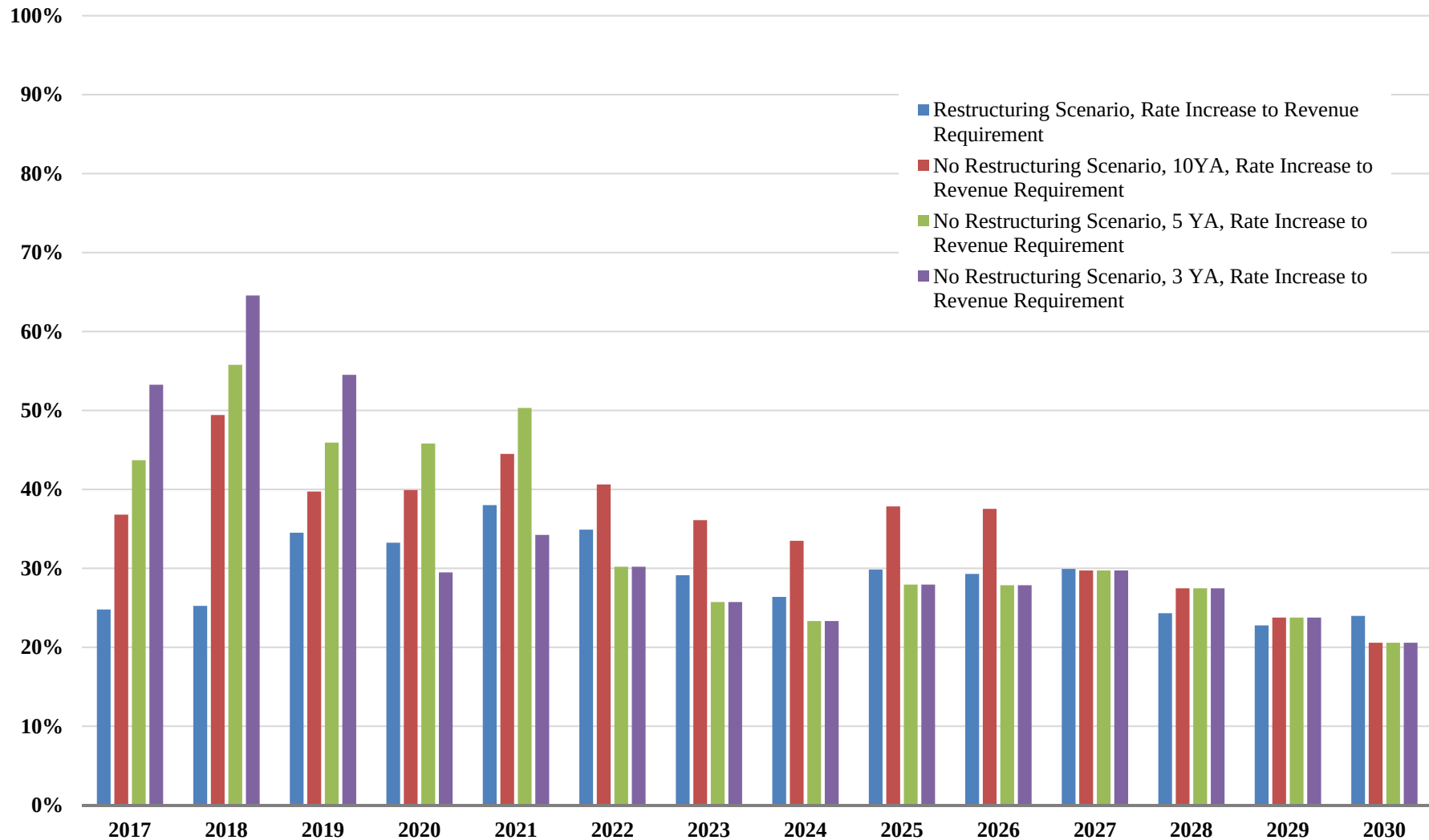
Exhibit 15.A: Historical Average Rates (2000-2016) and Forecast Average Rates under Revenue Requirement Pricing in Alternative Policy Scenarios (2017-2030)



Sources:

PREPA Financial Model.

**Exhibit 15.B: Percentage Increases in Average Rates Relative to Baseline under Revenue Requirement Pricing in Alternative Policy Scenarios:
2017-2030**



Sources:
PREPA Financial Model.

Exhibit 16.A: Summary of Differential Effects of Restructuring Scenario vs Non-Restructuring Scenario, Assuming 10-Year Refinancing Amortization and Low-End Elasticity Estimates: 2017-2030

Year	Total Employment Difference (Number of Jobs)	Total Employment Percentage Difference	GDP Difference (2015 USD)	GDP Percentage Difference	Per Capita Disposable Income Difference (2015 USD)	Per Capita Disposable Income Percentage Difference
2017	2,251	0.25%	\$210,926,269	0.21%	\$65.49	0.38%
2018	4,756	0.52%	\$461,791,000	0.45%	\$135.12	0.77%
2019	1,468	0.16%	\$167,956,051	0.16%	\$24.38	0.13%
2020	1,861	0.21%	\$213,504,253	0.20%	\$45.21	0.24%
2021	1,680	0.19%	\$201,672,791	0.19%	\$41.68	0.22%
2022	1,469	0.17%	\$185,522,145	0.17%	\$37.03	0.19%
2023	1,664	0.19%	\$209,205,883	0.19%	\$46.36	0.23%
2024	1,672	0.19%	\$214,813,150	0.19%	\$47.78	0.23%
2025	1,828	0.21%	\$236,213,658	0.21%	\$54.82	0.26%
2026	1,888	0.22%	\$248,401,524	0.21%	\$57.85	0.27%
2027	257	0.03%	\$77,588,287	0.07%	-\$5.17	-0.02%
2028	836	0.10%	\$136,466,988	0.11%	\$24.99	0.11%
2029	325	0.04%	\$78,403,493	0.06%	\$4.52	0.02%
2030	(577)	-0.07%	-\$27,677,741	-0.02%	-\$31.66	-0.13%

Sources:

REMI Simulations as described in Section IV of Report.

Exhibit 16.B: Summary of Differential Effects of Restructuring Scenario vs Non-Restructuring Scenario, Assuming 10-Year Refinancing Amortization and High-End Elasticity Estimates: 2017-2030

Year	Total Employment Difference (Number of Jobs)	Total Employment Percentage Difference	GDP Difference (2015 USD)	GDP Percentage Difference	Per Capita Disposable Income Difference (2015 USD)	Per Capita Disposable Income Percentage Difference
2017	1,732	0.19%	\$160,952,627	0.16%	\$50.71	0.30%
2018	3,539	0.39%	\$339,824,965	0.33%	\$101.27	0.58%
2019	1,064	0.12%	\$118,900,443	0.11%	\$18.00	0.10%
2020	1,364	0.15%	\$153,225,867	0.14%	\$33.77	0.18%
2021	1,206	0.14%	\$141,944,481	0.13%	\$30.40	0.16%
2022	1,064	0.12%	\$131,248,629	0.12%	\$27.48	0.14%
2023	1,235	0.14%	\$151,258,373	0.14%	\$35.30	0.18%
2024	1,257	0.14%	\$156,994,637	0.14%	\$36.82	0.18%
2025	1,361	0.16%	\$171,455,035	0.15%	\$41.55	0.20%
2026	1,410	0.16%	\$180,760,054	0.16%	\$44.03	0.21%
2027	164	0.02%	\$51,253,728	0.04%	-\$4.40	-0.02%
2028	632	0.07%	\$99,179,462	0.08%	\$19.53	0.09%
2029	236	0.03%	\$54,870,481	0.05%	\$3.44	0.01%
2030	(480)	-0.06%	-\$28,099,915	-0.02%	-\$25.61	-0.11%

Sources:

REMI Simulations as described in Section IV of Report.

Exhibit 17.A: Summary of Differential Effects of Restructuring Scenario vs Non-Restructuring Scenario, Assuming 5-Year Refinancing Amortization and Low-End Elasticity Estimates: 2017-2030

Year	Total Employment Difference (Number of Jobs)	Total Employment Percentage Difference	GDP Difference (2015 USD)	GDP Percentage Difference	Per Capita Disposable Income Difference (2015 USD)	Per Capita Disposable Income Percentage Difference
2017	3,501	0.38%	\$328,253,080	0.32%	\$101.87	0.60%
2018	5,981	0.66%	\$583,246,027	0.57%	\$167.38	0.96%
2019	2,820	0.31%	\$308,404,029	0.30%	\$60.01	0.33%
2020	3,220	0.36%	\$361,179,683	0.34%	\$80.92	0.44%
2021	3,030	0.34%	\$354,612,643	0.33%	\$77.59	0.41%
2022	(293)	-0.03%	\$28,998,629	0.03%	-\$32.57	-0.17%
2023	(245)	-0.03%	\$25,036,498	0.02%	-\$17.70	-0.09%
2024	(472)	-0.05%	-\$8,039,945	-0.01%	-\$20.84	-0.10%
2025	(380)	-0.04%	-\$7,540,965	-0.01%	-\$14.41	-0.07%
2026	(367)	-0.04%	-\$13,639,051	-0.01%	-\$13.24	-0.06%
2027	(143)	-0.02%	\$4,382,311	0.00%	-\$4.52	-0.02%
2028	509	0.06%	\$72,182,437	0.06%	\$20.63	0.09%
2029	146	0.02%	\$32,722,572	0.03%	\$2.48	0.01%
2030	(673)	-0.08%	-\$61,273,731	-0.05%	-\$32.66	-0.14%

Sources:

REMI Simulations as described in Section IV of Report.

Exhibit 17.B: Summary of Differential Effects of Restructuring Scenario vs Non-Restructuring Scenario, Assuming 5-Year Refinancing Amortization and High-End Elasticity Estimates: 2017-2030

Year	Total Employment Difference (Number of Jobs)	Total Employment Percentage Difference	GDP Difference (2015 USD)	GDP Percentage Difference	Per Capita Disposable Income Difference (2015 USD)	Per Capita Disposable Income Percentage Difference
2017	2,651	0.29%	\$246,372,648	0.24%	\$77.64	0.46%
2018	4,376	0.48%	\$421,628,712	0.41%	\$123.44	0.70%
2019	2,031	0.22%	\$217,304,490	0.21%	\$44.01	0.24%
2020	2,330	0.26%	\$255,938,591	0.24%	\$59.67	0.32%
2021	2,147	0.24%	\$246,094,124	0.23%	\$55.82	0.29%
2022	(296)	-0.03%	\$8,326,927	0.01%	-\$25.57	-0.13%
2023	(250)	-0.03%	\$7,362,884	0.01%	-\$14.61	-0.07%
2024	(411)	-0.05%	-\$15,586,998	-0.01%	-\$16.94	-0.08%
2025	(317)	-0.04%	-\$12,095,813	-0.01%	-\$11.46	-0.05%
2026	(298)	-0.03%	-\$15,208,490	-0.01%	-\$10.46	-0.05%
2027	(116)	-0.01%	\$28,709	0.00%	-\$3.53	-0.02%
2028	401	0.05%	\$53,822,457	0.04%	\$16.47	0.07%
2029	114	0.01%	\$23,065,253	0.02%	\$2.14	0.01%
2030	(541)	-0.06%	-\$51,248,438	-0.04%	-\$26.14	-0.11%

Sources:

REMI Simulations as described in Section IV of Report.

Exhibit 18.A: Summary of Differential Effects of Restructuring Scenario vs Non-Restructuring Scenario, Assuming 3-Year Refinancing Amortization and Low-End Elasticity Estimates: 2017-2030

Year	Total Employment Difference (Number of Jobs)	Total Employment Percentage Difference	GDP Difference (2015 USD)	GDP Percentage Difference	Per Capita Disposable Income Difference (2015 USD)	Per Capita Disposable Income Percentage Difference
2017	5,182	0.57%	\$486,037,722	0.48%	\$150.72	0.89%
2018	7,630	0.84%	\$747,016,375	0.73%	\$210.80	1.21%
2019	4,644	0.52%	\$498,024,895	0.48%	\$108.01	0.60%
2020	319	0.04%	\$94,176,482	0.09%	-\$23.60	-0.13%
2021	5	0.00%	\$57,477,986	0.05%	-\$16.32	-0.09%
2022	(582)	-0.07%	-\$10,629,014	-0.01%	-\$27.91	-0.14%
2023	(569)	-0.06%	-\$20,009,777	-0.02%	-\$21.71	-0.11%
2024	(658)	-0.07%	-\$38,672,030	-0.03%	-\$22.71	-0.11%
2025	(493)	-0.06%	-\$29,941,053	-0.03%	-\$15.65	-0.08%
2026	(432)	-0.05%	-\$29,975,925	-0.03%	-\$13.94	-0.07%
2027	(177)	-0.02%	-\$7,590,430	-0.01%	-\$4.85	-0.02%
2028	495	0.06%	\$63,394,325	0.05%	\$20.58	0.09%
2029	144	0.02%	\$26,288,245	0.02%	\$2.63	0.01%
2030	(667)	-0.08%	-\$65,960,419	-0.05%	-\$32.35	-0.14%

Sources:

REMI Simulations as described in Section IV of Report.

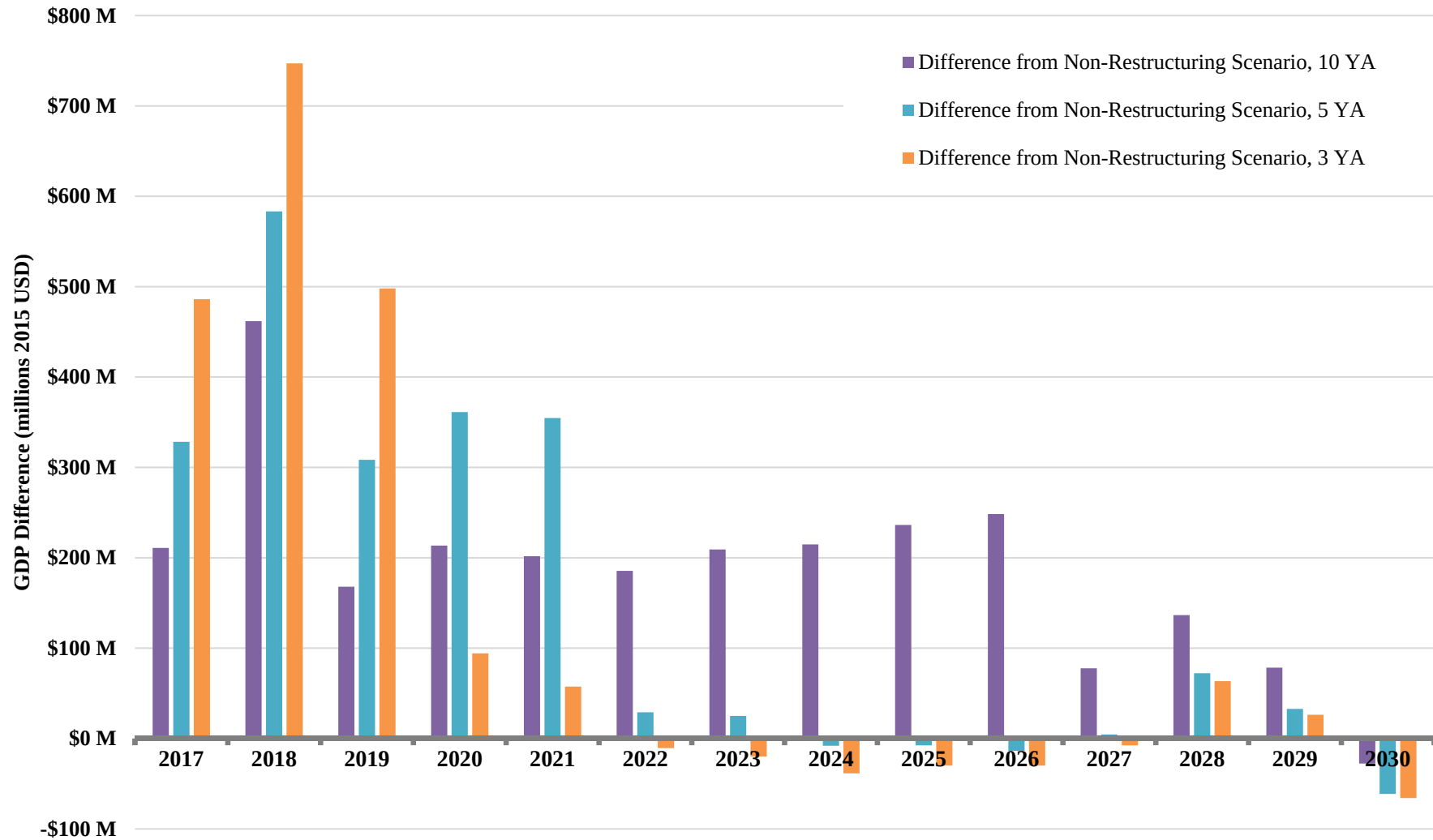
Exhibit 18.B: Summary of Differential Effects of Restructuring Scenario vs Non-Restructuring Scenario, Assuming 3-Year Refinancing Amortization and High-End Elasticity Estimates: 2017-2030

Year	Total Employment Difference (Number of Jobs)	Total Employment Percentage Difference	GDP Difference (2015 USD)	GDP Percentage Difference	Per Capita Disposable Income Difference (2015 USD)	Per Capita Disposable Income Percentage Difference
2017	3,833	0.42%	\$356,176,452	0.35%	\$112.30	0.66%
2018	5,451	0.60%	\$526,559,247	0.51%	\$151.92	0.87%
2019	3,280	0.36%	\$344,289,275	0.33%	\$77.68	0.43%
2020	122	0.01%	\$51,229,104	0.05%	-\$19.06	-0.10%
2021	(72)	-0.01%	\$29,162,638	0.03%	-\$13.11	-0.07%
2022	(500)	-0.06%	-\$19,345,942	-0.02%	-\$22.05	-0.11%
2023	(480)	-0.05%	-\$24,435,403	-0.02%	-\$17.44	-0.09%
2024	(539)	-0.06%	-\$36,945,951	-0.03%	-\$18.20	-0.09%
2025	(393)	-0.04%	-\$27,569,017	-0.02%	-\$12.25	-0.06%
2026	(340)	-0.04%	-\$26,380,168	-0.02%	-\$10.87	-0.05%
2027	(136)	-0.02%	-\$8,079,860	-0.01%	-\$3.66	-0.02%
2028	395	0.05%	\$47,925,599	0.04%	\$16.54	0.07%
2029	116	0.01%	\$18,783,296	0.02%	\$2.35	0.01%
2030	(534)	-0.06%	-\$54,347,751	-0.04%	-\$25.83	-0.11%

Sources:

REMI Simulations as described in Section IV of Report.

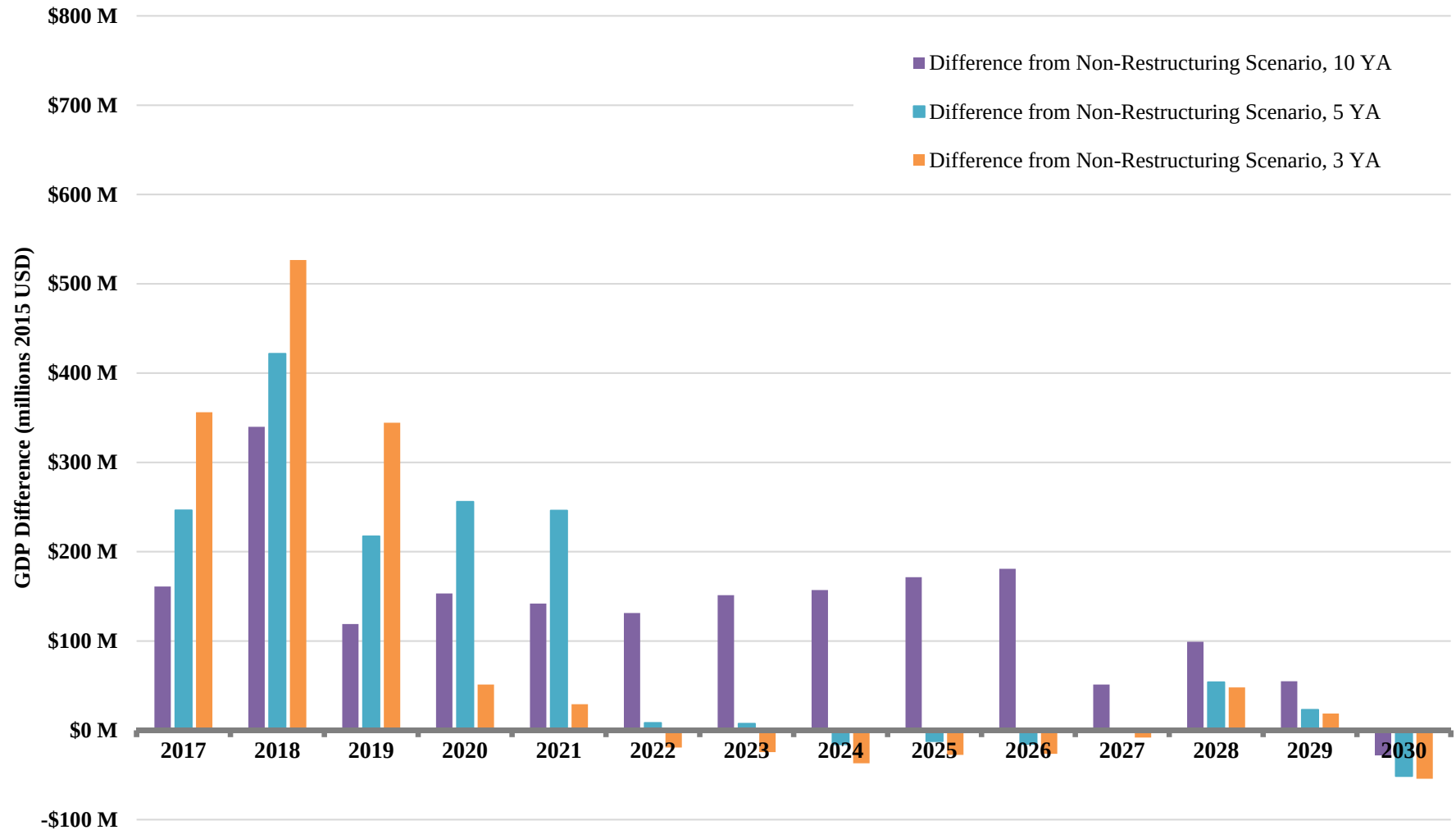
Exhibit 19.A: Summary of Differential GDP Effects of Restructuring Scenario vs Non-Restructuring Scenarios Using Low-End Elasticity Estimates: 2017-2030



Sources:

REMI Simulations as described in Section IV of Report.

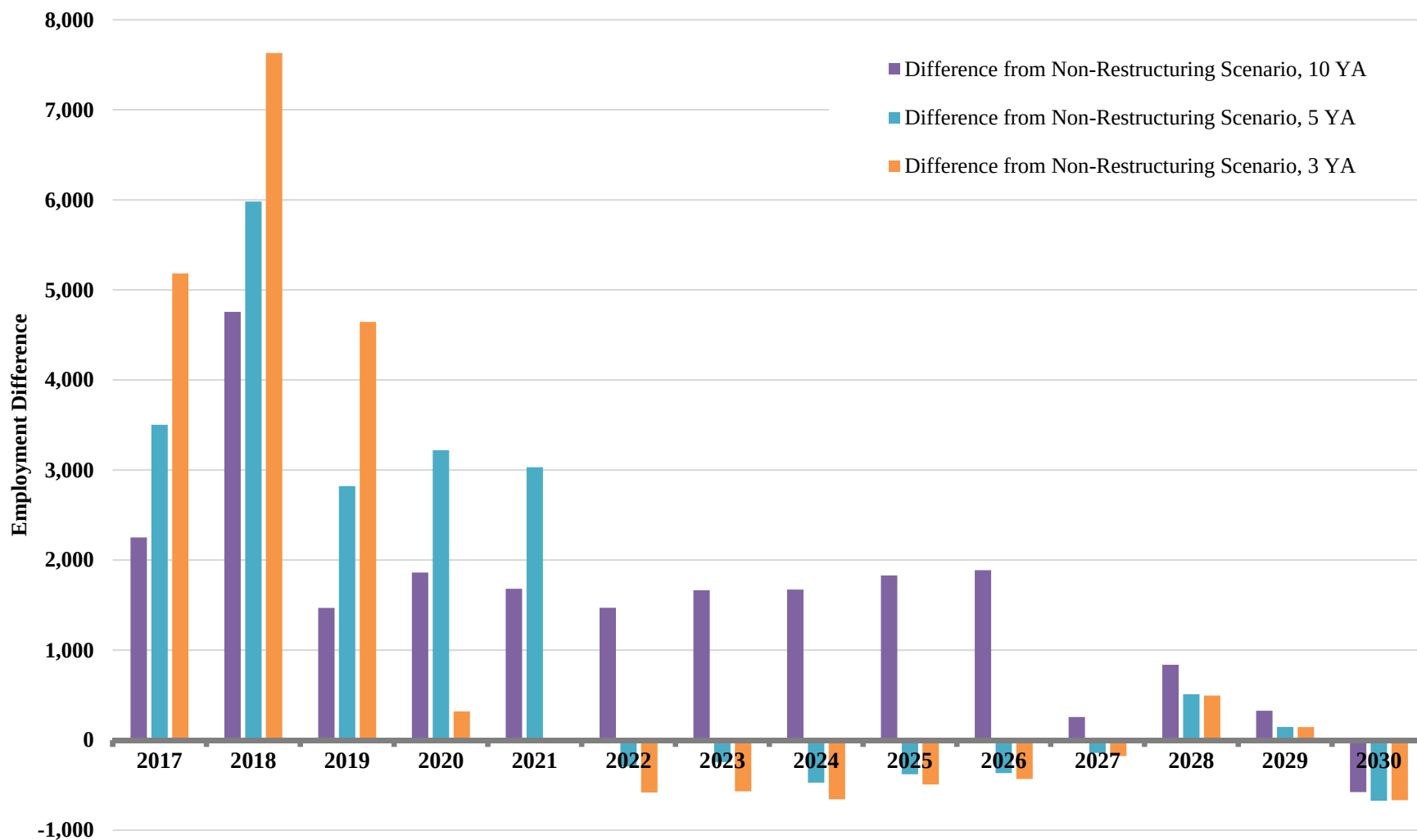
Exhibit 19.B: Summary of Differential GDP Effects of Restructuring Scenario vs Non-Restructuring Scenarios Using High-End Elasticity Estimates: 2017-2030



Sources:

REMI Simulations as described in Section IV of Report.

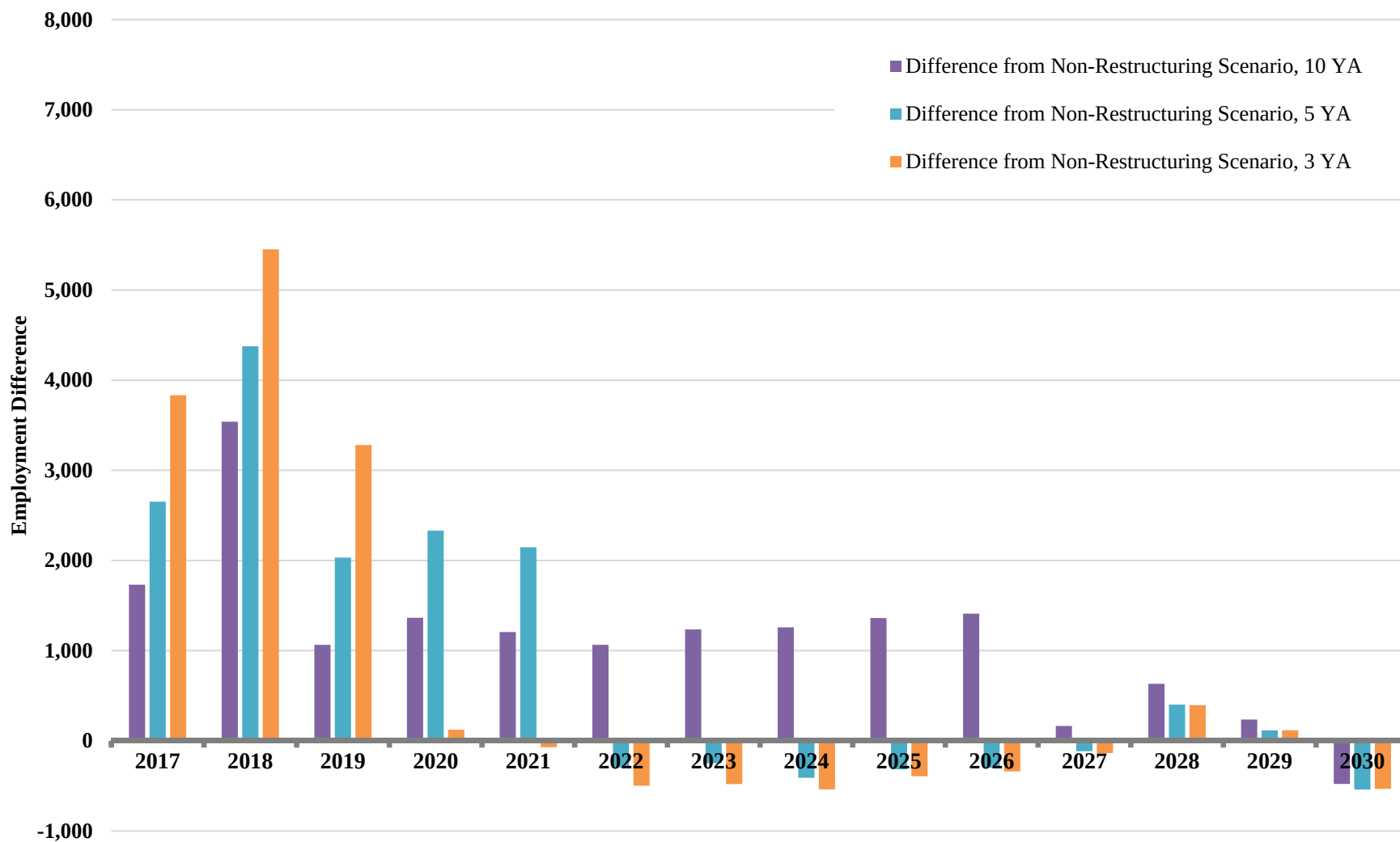
Exhibit 20.A: Summary of Differential Employment Effects of Restructuring Scenario vs Non-Restructuring Scenarios Using Low-End Elasticity Estimates: 2017-2030



Sources:

REMI Simulations as described in Section IV of Report.

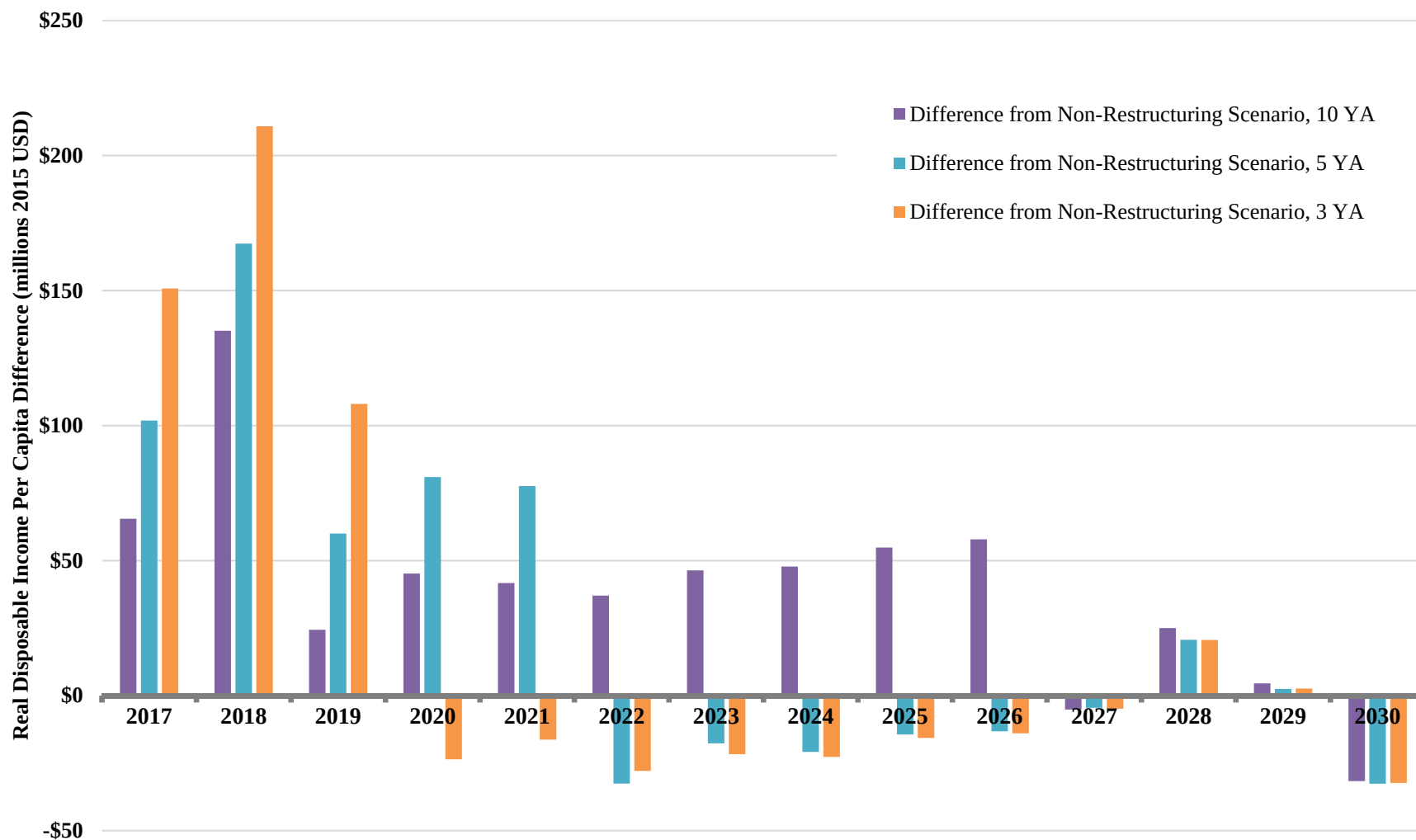
Exhibit 20.B: Summary of Differential Employment Effects of Restructuring Scenario vs Non-Restructuring Scenarios Using High-End Elasticity Estimates: 2017-2030



Sources:

REMI Simulations as described in Section IV of Report.

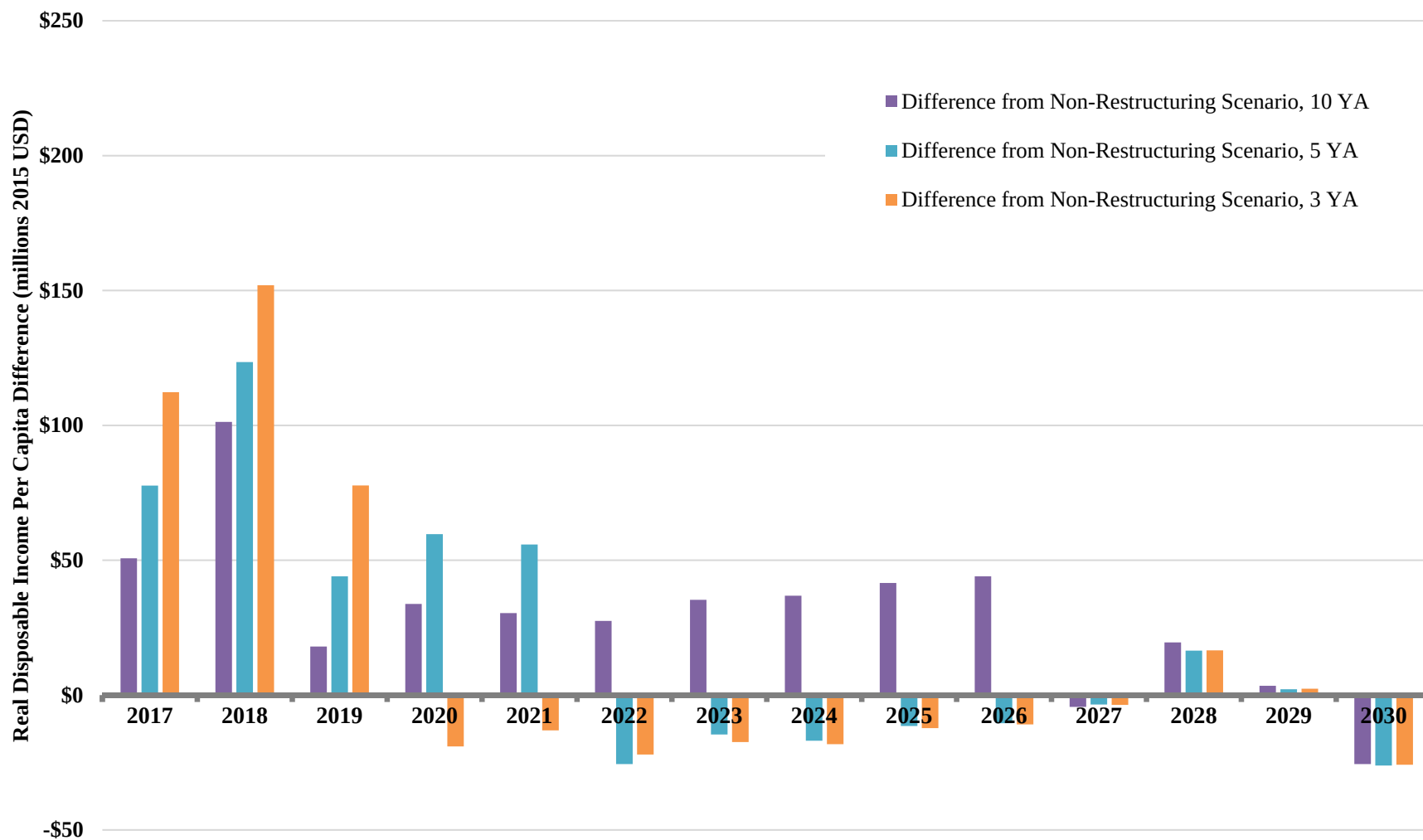
**Exhibit 21.A: Summary of Differential Effects on Per Capita Disposable Income of
Restructuring Scenario vs Non-Restructuring Scenarios
Using Low-End Elasticity Estimates: 2017-2030**



Sources:

REMI Simulations as described in Section IV of Report.

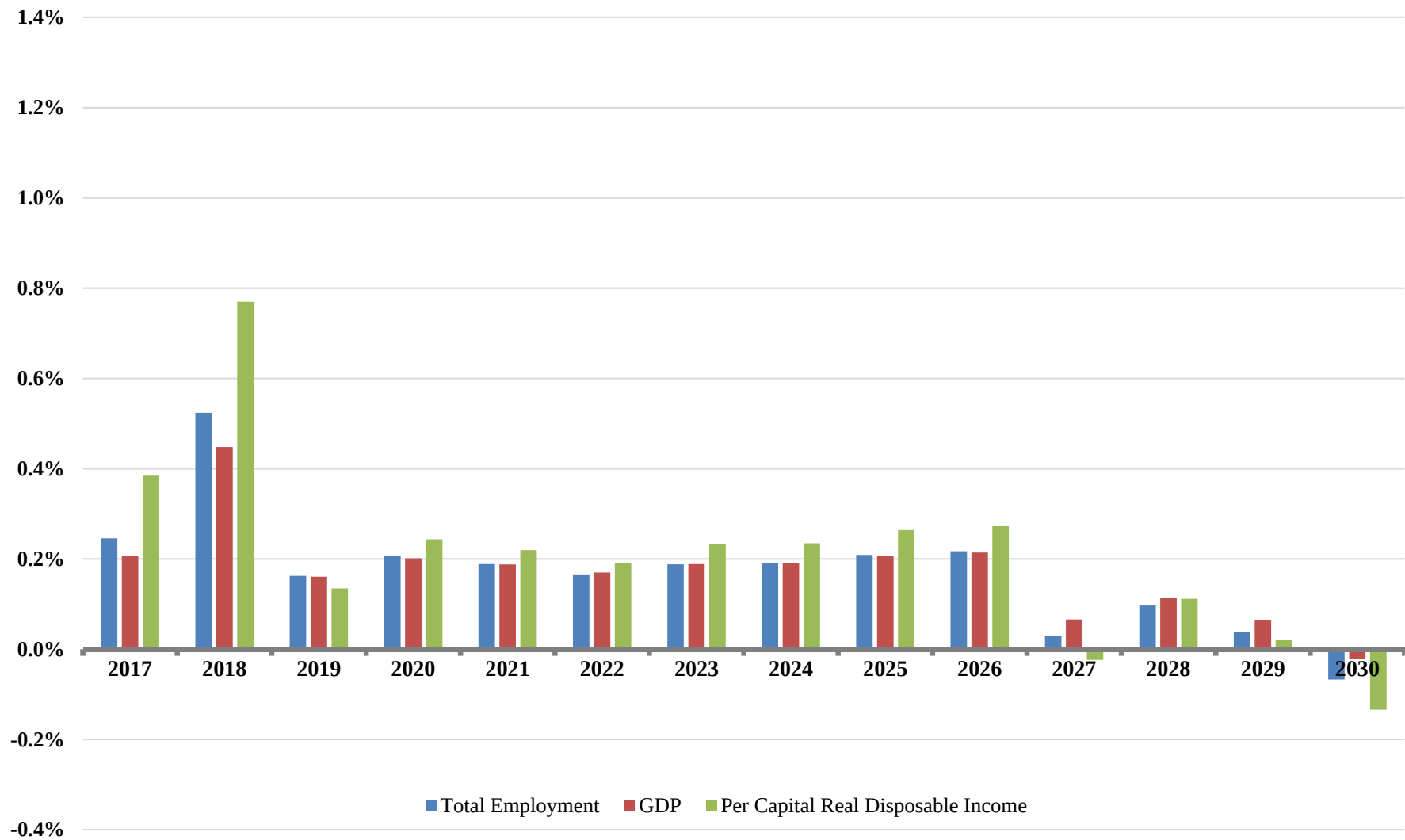
**Exhibit 21.B: Summary of Differential Effects on Per Capita Disposable Income of
Restructuring Scenario vs Non-Restructuring Scenarios
Using High-End Elasticity Estimates: 2017-2030**



Sources:

REMI Simulations as described in Section IV of Report.

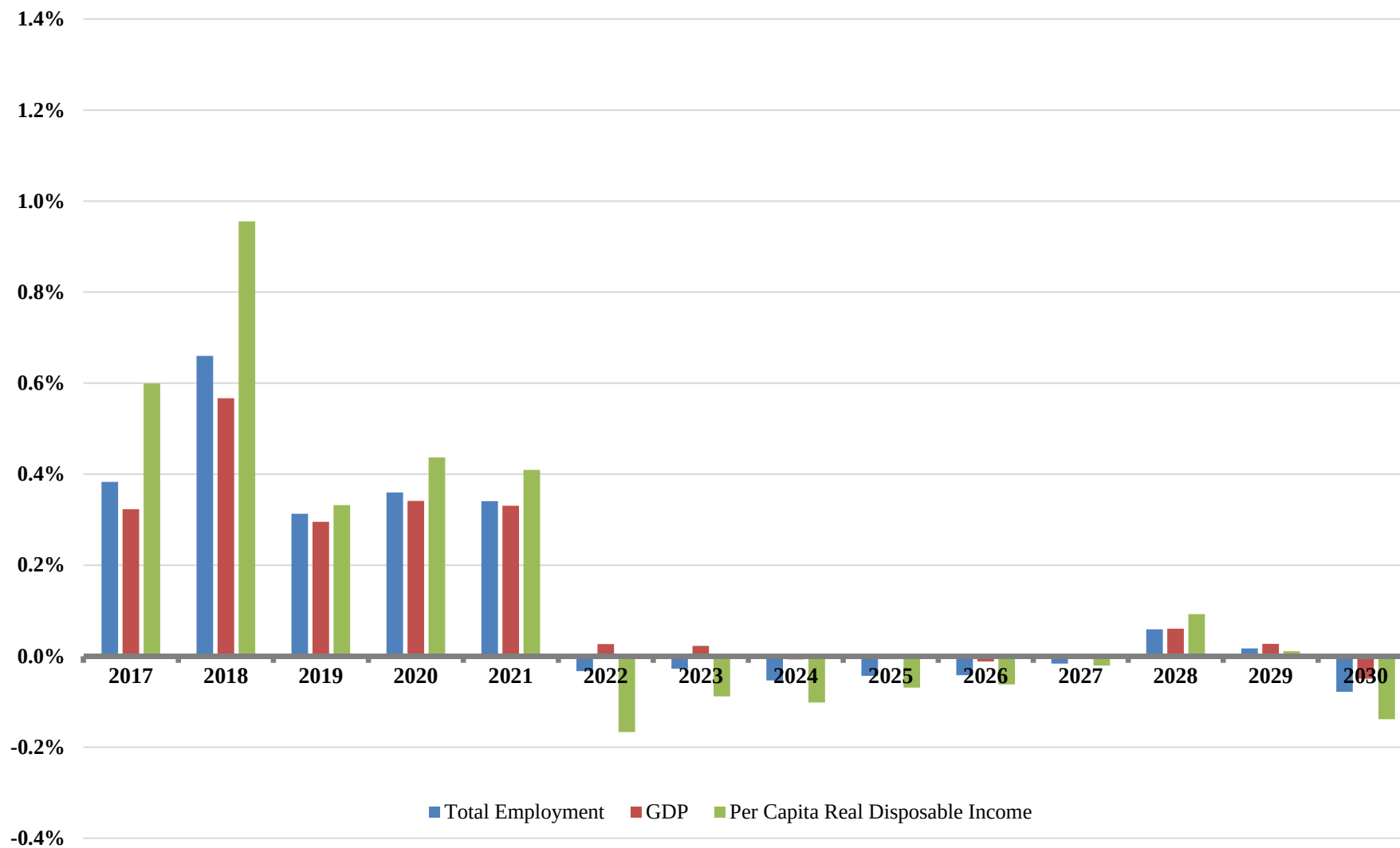
Exhibit 22.A: Summary of Differential Effects of Restructuring Scenario vs Non-Restructuring Scenario, Assuming 10-Year Refinancing Amortization and Low-End Elasticity Estimates: 2017-2030



Sources:

REMI Simulations as described in Section IV of Report.

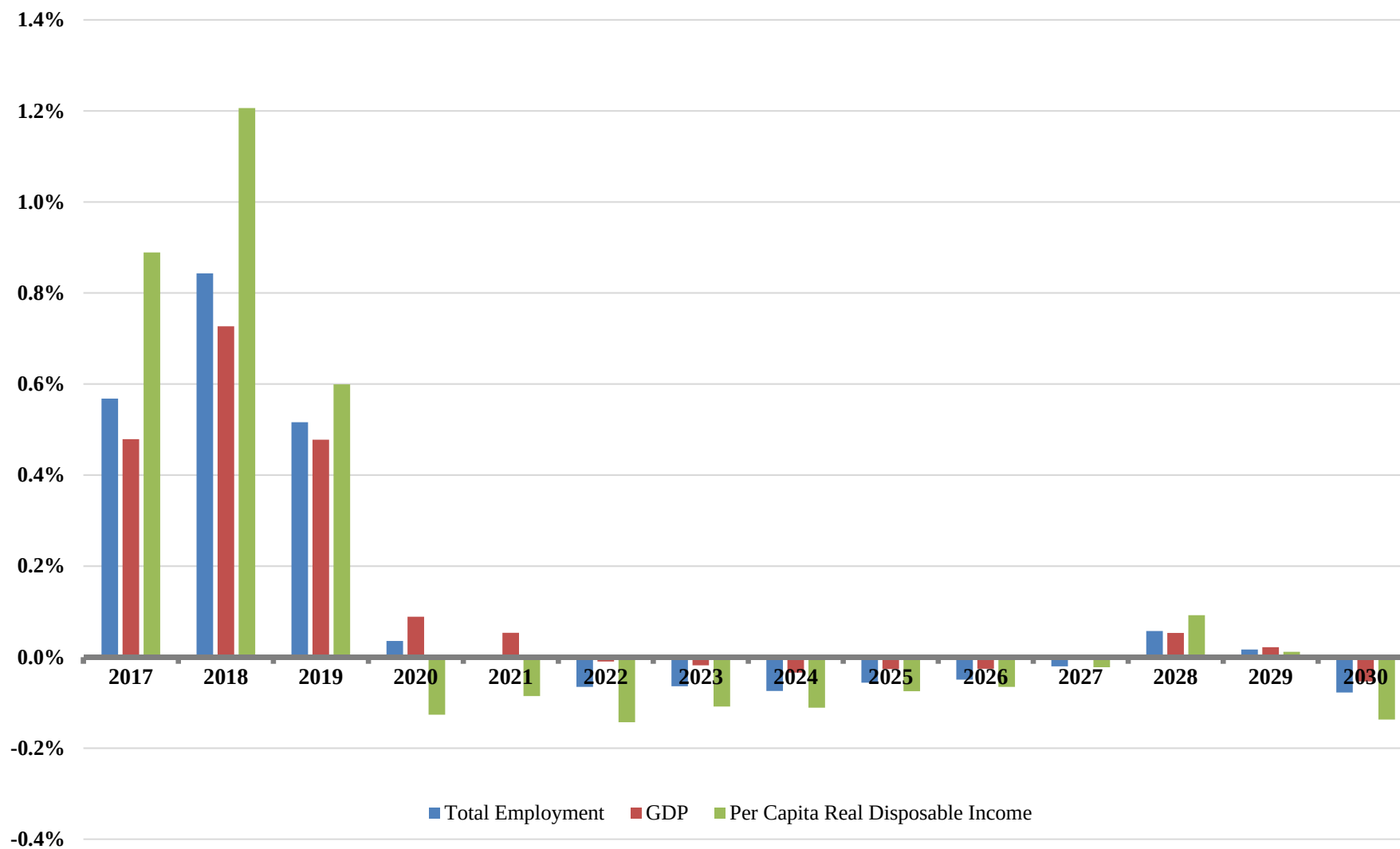
Exhibit 22.B: Summary of Differential Effects of Restructuring Scenario vs Non-Restructuring Scenario, Assuming 5-Year Refinancing Amortization and Low-End Elasticity Estimates: 2017-2030



Sources:

REMI Simulations as described in Section IV of Report.

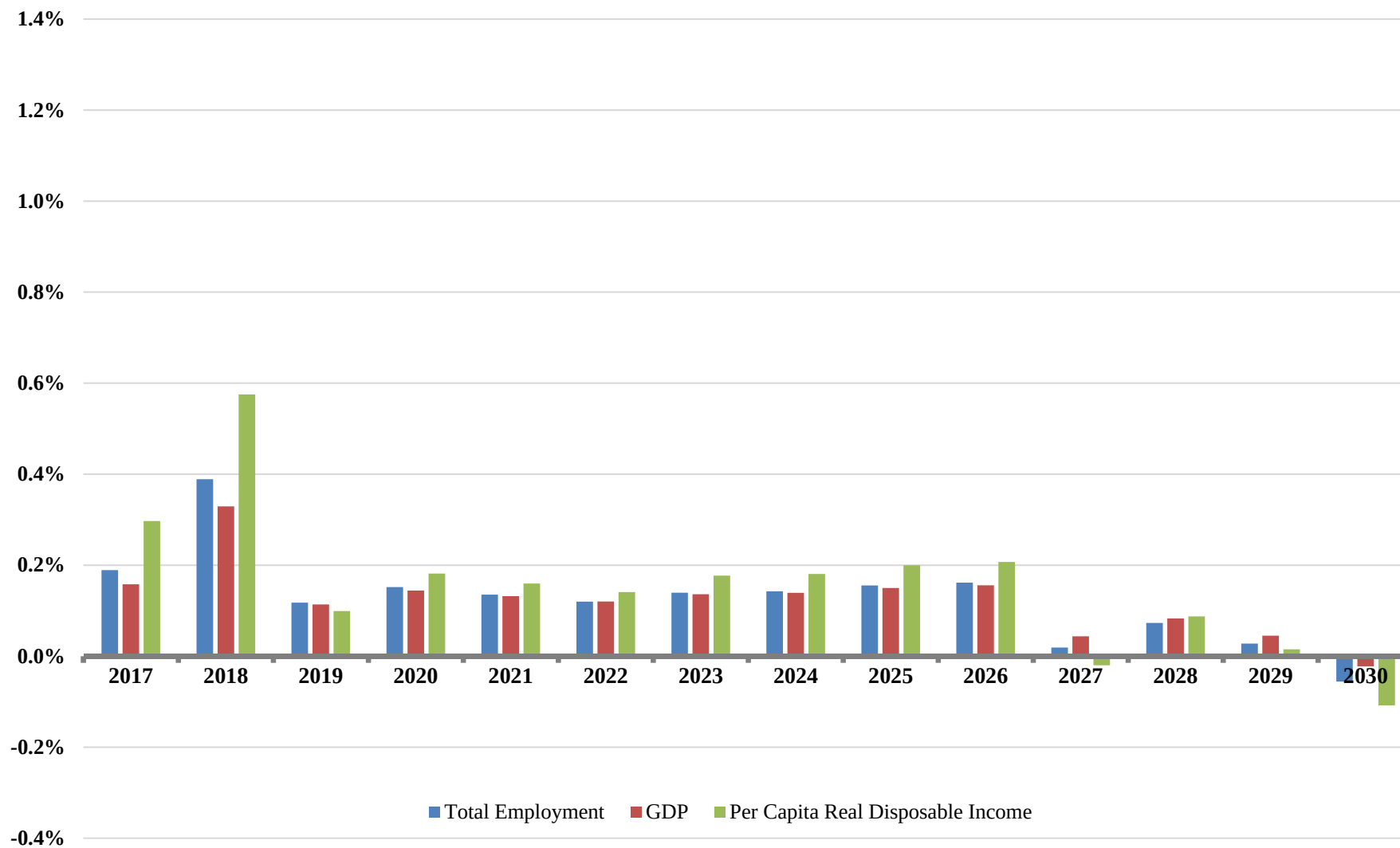
Exhibit 22.C: Summary of Differential Effects of Restructuring Scenario vs Non-Restructuring Scenario, Assuming 3-Year Refinancing Amortization and Low-End Elasticity Estimates: 2017-2030



Sources:

REMI Simulations as described in Section IV of Report.

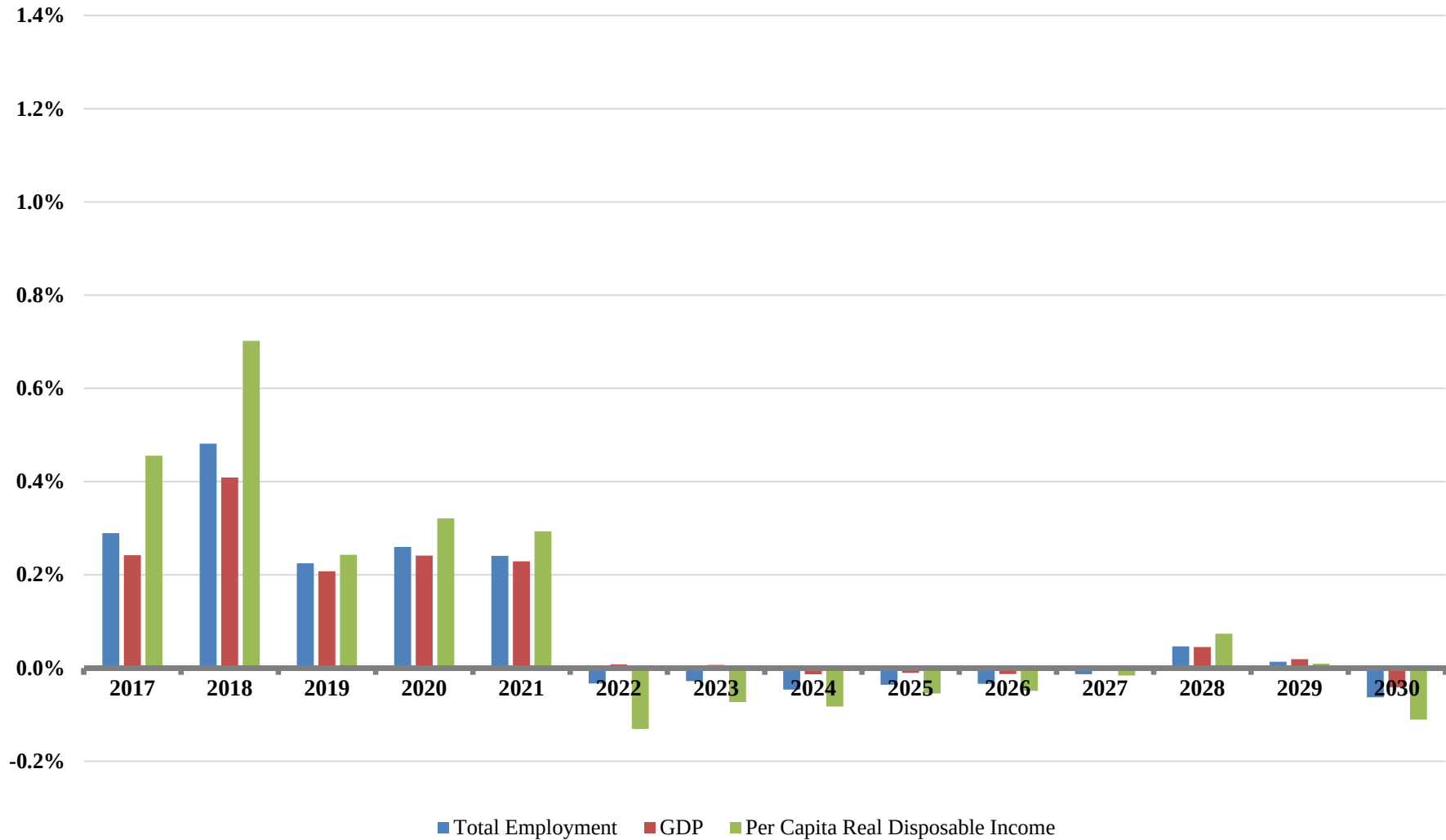
Exhibit 23.A: Summary of Differential Effects of Restructuring Scenario vs Non-Restructuring Scenario, Assuming 10-Year Refinancing Amortization and High-End Elasticity Estimates: 2017-2030



Sources:

REMI Simulations as described in Section IV of Report.

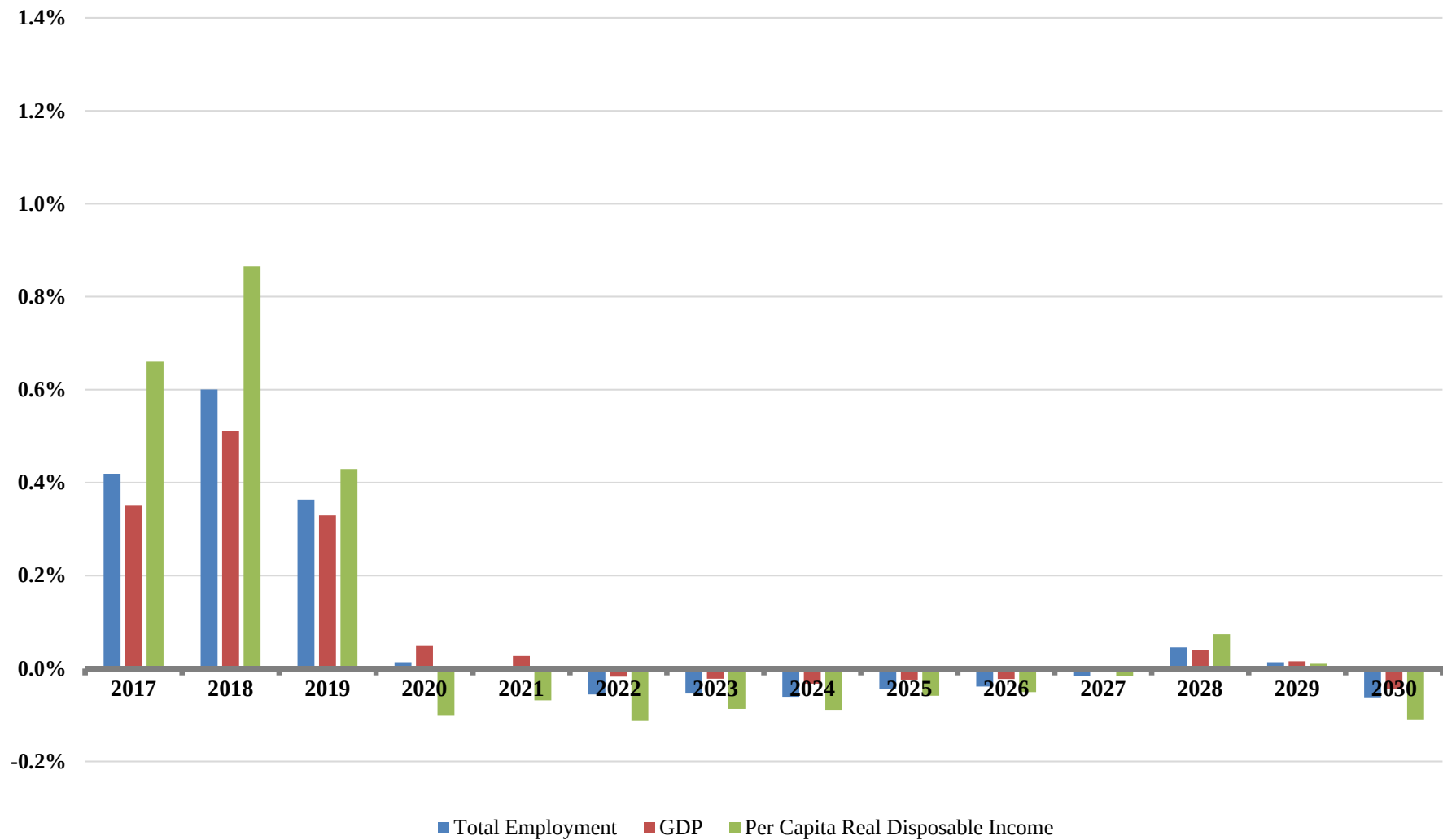
Exhibit 23.B: Summary of Differential Effects of Restructuring Scenario vs Non-Restructuring Scenario, Assuming 5-Year Refinancing Amortization and High-End Elasticity Estimates: 2017-2030



Sources:

REMI Simulations as described in Section IV of Report.

Exhibit 23.C: Summary of Differential Effects of Restructuring Scenario vs Non-Restructuring Scenario, Assuming 3-Year Refinancing Amortization and High-End Elasticity Estimates: 2017-2030



Sources:

REMI Simulations as described in Section IV of Report.

**Exhibit 24: Summary of Cumulative Benefits
Attributed to Differential Effects of Restructuring Scenario vs Non-Restructuring
Scenario: 2017-2030**

	Assuming 10-Year Refinancing Amortization	Assuming 5-Year Refinancing Amortization	Assuming 3-Year Refinancing Amortization
Total Employment (Job-Years)	15,784 to 21,376	11,821 to 16,635	10,204 to 14,840
GDP (2015 USD)	\$1.9 billion to \$2.6 billion	\$1.4 billion to \$2.0 billion	\$1.1 billion to \$1.8 billion
Per Capita Disposable Income (2015 USD)	\$412 to \$548	\$270 to \$375	\$218 to \$314

Sources:

REMI Simulations as described in Section IV of Report.

Appendix A:
Estimated Coefficients from Electricity Demand Regressions

LUMA Ex. 72.02

	Residential Electricity Demand, Measured as Mean Consumption (kwh/customer) in the Observed Month (log)		
	AR(0) OLS	AR(1) OLS	AR(1) FGLS
Mean Consumption 1 month prior (kwh/customer) (log)		-0.282** (0.127)	0.018 (0.283)
Price of Electricity (1954 USD/kwh) (log)	-0.199** (0.075)	-0.194** (0.073)	-0.172** (0.084)
Nav Cooling Degree Days w/ 75 deg F base (0.1 deg Celcius) (log)	0.094* (0.053)	0.080 (0.051)	0.073 (0.053)
Mean Max Daily Temperature (deg Fahrenheit) (log)	-0.026 (0.772)	0.316 (0.759)	0.810 (0.828)
Mean Max Daily Heat Index (deg Fahrenheit) (log)	-0.506 (0.433)	-0.467 (0.417)	-0.601 (0.436)
Mean Max Daily Relative Humidity (log)	-0.157 (0.468)	0.015 (0.457)	-0.235 (0.492)
Mean Daily Rainfall (inches) (log)	0.022 (0.018)	0.018 (0.017)	0.029 (0.018)
Payroll Employment (log)	-0.162 (1.073)	-0.115 (1.033)	0.133 (1.079)
Gasoline Consumption (log)	0.002 (0.077)	-0.023 (0.075)	-0.011 (0.081)
Cement Sales (log)	0.004 (0.089)	-0.007 (0.086)	0.027 (0.089)
Regional Gross Domestic Product (1954 USD) (log)	4.314* (2.330)	5.652** (2.323)	2.912 (2.821)
February	-0.054 (0.037)	-0.065* (0.036)	-0.065 (0.039)
March	-0.005 (0.042)	-0.034 (0.043)	-0.014 (0.050)
April	-0.020 (0.051)	-0.028 (0.049)	-0.032 (0.051)
May	0.040 (0.059)	0.038 (0.057)	0.029 (0.058)
June	0.062 (0.068)	0.080 (0.066)	0.047 (0.068)
July	0.098 (0.068)	0.118* (0.066)	0.091 (0.069)
August	0.100 (0.073)	0.134* (0.072)	0.074 (0.080)
September	0.109 (0.071)	0.145** (0.071)	0.095 (0.077)
October	0.065 (0.072)	0.104 (0.072)	0.040 (0.080)
November	0.039 (0.053)	0.064 (0.053)	0.025 (0.057)
December	0.021 (0.033)	0.038 (0.033)	0.015 (0.036)
ehat			-0.340 (0.340)
Constant	-20.388* (10.394)	-30.262*** (10.953)	-16.694 (14.247)
Long-run response	-0.199	-0.151	-0.175
Observations	72	72	69
R ²	0.823	0.839	0.846
Adjusted R ²	0.748	0.766	0.767
Residual Std. Error	0.050 (df = 50)	0.048 (df = 49)	0.048 (df = 45)
F Statistic	11.037*** (df = 21; 50)	11.586*** (df = 22; 49)	10.739*** (df = 23; 45)

Note:

*p<0.1; **p<0.05; ***p<0.01
Price of Electricity defined as the average per kilowatt-hour rate for the customer class in the observed month.

LUMA Ex. 72.02

	Residential Electricity Demand, Measured as Mean Consumption (kwh/customer) in the Observed Month (log)		
	AR(0) OLS	AR(1) OLS	AR(1) FGLS
Mean Consumption 1 month prior (kwh/customer) (log)		-0.202 (0.129)	0.121 (0.293)
Price of Electricity (1954 USD/kwh) (log)	-0.223*** (0.076)	-0.225*** (0.075)	-0.176* (0.090)
Nav Cooling Degree Days w/ 75 deg F base (0.1 deg Celcius) (log)	0.049 (0.048)	0.029 (0.049)	0.051 (0.048)
Mean Max Daily Temperature (deg Fahrenheit) (log)	0.533 (0.727)	0.901 (0.755)	1.175 (0.733)
Mean Max Daily Heat Index (deg Fahrenheit) (log)	-0.405 (0.439)	-0.354 (0.434)	-0.541 (0.438)
Mean Max Daily Relative Humidity (log)	0.248 (0.424)	0.461 (0.439)	-0.091 (0.476)
Mean Daily Rainfall (inches) (log)	0.031* (0.017)	0.031* (0.017)	0.036** (0.017)
Payroll Employment (log)	1.130 (0.834)	1.451* (0.847)	0.677 (0.928)
Gasoline Consumption (log)	0.009 (0.078)	-0.007 (0.078)	0.006 (0.082)
Cement Sales (log)	0.081 (0.080)	0.091 (0.079)	0.092 (0.078)
February	-0.066* (0.038)	-0.077** (0.038)	-0.074* (0.040)
March	-0.014 (0.043)	-0.037 (0.045)	-0.016 (0.051)
April	-0.017 (0.052)	-0.023 (0.052)	-0.037 (0.051)
May	0.041 (0.061)	0.040 (0.060)	0.021 (0.058)
June	0.073 (0.070)	0.089 (0.069)	0.035 (0.070)
July	0.101 (0.070)	0.116* (0.069)	0.078 (0.071)
August	0.105 (0.074)	0.132* (0.075)	0.052 (0.083)
September	0.105 (0.073)	0.131* (0.074)	0.067 (0.078)
October	0.061 (0.074)	0.088 (0.075)	0.009 (0.082)
November	0.033 (0.054)	0.050 (0.055)	0.005 (0.057)
December	0.022 (0.034)	0.034 (0.035)	0.006 (0.037)
ehat			-0.356 (0.347)
Constant	-5.240 (6.563)	-8.947 (6.888)	-3.799 (7.820)
Long-run response	-0.223	-0.187	-0.201
Observations	72	72	69
R ²	0.810	0.819	0.848
Adjusted R ²	0.736	0.743	0.775
Residual Std. Error	0.051 (df = 51)	0.050 (df = 50)	0.049 (df = 46)
F Statistic	10.898*** (df = 20; 51)	10.794*** (df = 21; 50)	11.648*** (df = 22; 46)

Note:

*p<0.1; **p<0.05; ***p<0.01
Price of Electricity defined as the average per kilowatt-hour rate for the customer class in the observed month.

LUMA Ex. 72.02

	Commercial Electricity Demand, Measured as Mean Consumption (kwh/customer) in the Observed Month (log)			
	AR(0) OLS	AR(1) OLS	AR(1) FGLS	AR(1;5,12) OLS
Mean Consumption 1 month prior (kwh/customer) (log)		-0.348*** (0.122)	-0.559** (0.256)	-0.393*** (0.125)
Mean Consumption 2 months prior (kwh/customer) (log)				-0.307** (0.142)
Mean Consumption 3 months prior (kwh/customer) (log)				-0.181 (0.122)
Mean Consumption 4 months prior (kwh/customer) (log)				-0.141 (0.136)
Mean Consumption 5 months prior (kwh/customer) (log)				-0.395*** (0.122)
Mean Consumption 12 months prior (kwh/customer) (log)				-0.043 (0.122)
Price of Electricity (1954 USD/kwh) (log)	-0.238** (0.097)	-0.206** (0.091)	-0.335*** (0.113)	-0.257*** (0.088)
Nav Cooling Degree Days w/ 75 deg F base (0.1 deg Celcius) (log)	-0.072 (0.063)	-0.075 (0.059)	-0.121* (0.062)	-0.011 (0.058)
Mean Max Daily Temperature (deg Fahrenheit) (log)	0.616 (0.939)	0.628 (0.878)	1.467 (0.956)	-0.099 (0.850)
Mean Max Daily Heat Index (deg Fahrenheit) (log)	0.318 (0.514)	0.528 (0.486)	0.419 (0.502)	0.430 (0.468)
Mean Max Daily Relative Humidity (log)	0.842 (0.574)	0.844 (0.537)	0.621 (0.556)	0.568 (0.498)
Mean Daily Rainfall (inches) (log)	0.011 (0.021)	0.011 (0.020)	0.016 (0.020)	0.023 (0.019)
Payroll Employment (log)	2.450 (1.467)	2.373* (1.372)	3.998** (1.526)	1.766 (1.371)
Gasoline Consumption (log)	0.002 (0.093)	0.004 (0.087)	0.022 (0.093)	-0.010 (0.083)
Cement Sales (log)	0.102 (0.107)	0.079 (0.101)	0.170 (0.108)	0.034 (0.098)
Regional Gross Domestic Product (1954 USD) (log)	-6.408** (2.914)	-6.324** (2.726)	-10.495*** (3.270)	-5.177* (2.586)
February	0.074 (0.045)	0.080* (0.042)	0.069 (0.043)	0.055 (0.044)
March	0.101* (0.051)	0.126** (0.048)	0.130** (0.050)	0.068 (0.054)
April	0.102 (0.063)	0.136** (0.060)	0.162** (0.067)	0.056 (0.067)
May	0.131* (0.074)	0.150** (0.069)	0.177** (0.073)	0.010 (0.082)
June	0.121 (0.085)	0.150* (0.080)	0.197** (0.088)	0.023 (0.084)
July	0.165* (0.084)	0.181** (0.078)	0.230*** (0.084)	0.088 (0.081)
August	0.155* (0.092)	0.192** (0.087)	0.261** (0.101)	0.106 (0.088)
September	0.176* (0.090)	0.203** (0.085)	0.248** (0.093)	0.140* (0.083)
October	0.175* (0.091)	0.216** (0.086)	0.255** (0.096)	0.171** (0.084)
November	0.157** (0.066)	0.203*** (0.064)	0.240*** (0.076)	0.165** (0.063)
December	0.009 (0.042)	0.062 (0.043)	0.102 (0.061)	0.064 (0.040)
chat			0.401 (0.339)	
Constant	25.883** (12.487)	28.086** (11.705)	45.528*** (14.172)	38.817*** (11.509)
Long-run response	-0.238	-0.153	-0.215	-0.104
Observations	72	72	69	72
R ²	0.622	0.676	0.703	0.756
Adjusted R ²	0.463	0.530	0.552	0.607
Residual Std. Error	0.060 (df = 50)	0.056 (df = 49)	0.056 (df = 45)	0.051 (df = 44)
F Statistic	3.914*** (df = 21; 50)	4.641*** (df = 22; 49)	4.642*** (df = 23; 45)	5.056*** (df = 27; 44)

Note:

*p<0.1; **p<0.05; ***p<0.01
Price of Electricity defined as the average per kilowatt-hour rate for the customer class in the observed month.

LUMA Ex. 72.02

	Commercial Electricity Demand, Measured as Mean Consumption (kwh/customer) in the Observed Month (log)			
	AR(0) OLS	AR(1) OLS	AR(1) FGLS	AR(1;5,12) OLS
Mean Consumption 1 month prior (kwh/customer) (log)		-0.352*** (0.127)	-0.652* (0.329)	-0.393*** (0.129)
Mean Consumption 2 months prior (kwh/customer) (log)				-0.291* (0.147)
Mean Consumption 3 months prior (kwh/customer) (log)				-0.188 (0.126)
Mean Consumption 4 months prior (kwh/customer) (log)				-0.192 (0.138)
Mean Consumption 5 months prior (kwh/customer) (log)				-0.439*** (0.124)
Mean Consumption 12 months prior (kwh/customer) (log)				-0.062 (0.126)
Price of Electricity (1954 USD/kwh) (log)	-0.170* (0.095)	-0.139 (0.090)	-0.199* (0.107)	-0.199** (0.086)
Nav Cooling Degree Days w/ 75 deg F base (0.1 deg Celcius) (log)	-0.007 (0.058)	-0.011 (0.055)	-0.025 (0.058)	0.042 (0.053)
Mean Max Daily Temperature (deg Fahrenheit) (log)	-0.080 (0.916)	-0.058 (0.862)	0.211 (0.959)	-0.664 (0.828)
Mean Max Daily Heat Index (deg Fahrenheit) (log)	0.226 (0.531)	0.439 (0.505)	0.427 (0.544)	0.386 (0.483)
Mean Max Daily Relative Humidity (log)	0.204 (0.514)	0.214 (0.483)	0.115 (0.585)	0.066 (0.444)
Mean Daily Rainfall (inches) (log)	-0.0003 (0.021)	-0.0002 (0.020)	-0.005 (0.021)	0.014 (0.019)
Payroll Employment (log)	0.259 (1.116)	0.210 (1.050)	0.231 (1.086)	-0.112 (1.033)
Gasoline Consumption (log)	-0.014 (0.096)	-0.012 (0.090)	-0.007 (0.099)	-0.022 (0.085)
Cement Sales (log)	-0.012 (0.098)	-0.034 (0.092)	-0.018 (0.096)	-0.057 (0.090)
February	0.089* (0.046)	0.095** (0.043)	0.097** (0.045)	0.072 (0.045)
March	0.111** (0.052)	0.136*** (0.050)	0.156*** (0.056)	0.079 (0.056)
April	0.091 (0.065)	0.125* (0.062)	0.161** (0.074)	0.039 (0.069)
May	0.119 (0.076)	0.138* (0.072)	0.169** (0.081)	-0.016 (0.083)
June	0.093 (0.087)	0.122 (0.082)	0.165* (0.095)	-0.013 (0.085)
July	0.149* (0.086)	0.166** (0.081)	0.202** (0.091)	0.070 (0.083)
August	0.131 (0.094)	0.168* (0.090)	0.233** (0.112)	0.079 (0.089)
September	0.164* (0.093)	0.191** (0.088)	0.240** (0.102)	0.123 (0.085)
October	0.165* (0.094)	0.206** (0.089)	0.262** (0.110)	0.157* (0.086)
November	0.156** (0.068)	0.202*** (0.067)	0.257*** (0.089)	0.161** (0.065)
December	0.001 (0.043)	0.055 (0.045)	0.110 (0.073)	0.056 (0.041)
chat			0.409 (0.403)	
Constant	4.701 (8.237)	7.201 (7.801)	8.623 (8.149)	23.171** (8.726)
Long-run response	-0.170	-0.103	-0.121	-0.078
Observations	72	72	69	72
R ²	0.585	0.640	0.642	0.734
Adjusted R ²	0.422	0.489	0.471	0.580
Residual Std. Error	0.062 (df = 51)	0.059 (df = 50)	0.060 (df = 46)	0.053 (df = 45)
F Statistic	3.597*** (df = 20; 51)	4.234*** (df = 21; 50)	3.757*** (df = 22; 46)	4.777*** (df = 26; 45)

Note:

*p<0.1; **p<0.05; ***p<0.01
Price of Electricity defined as the average per kilowatt-hour rate for the customer class in the observed month.

LUMA Ex. 72.02

	Industrial Electricity Demand, Measured as Mean Consumption (kwh/customer) in the Observed Month (log)			
	AR(0) OLS	AR(1) OLS	AR(1) FGLS	AR(1:8:12) OLS
Mean Consumption 1 month prior (kwh/customer) (log)		-0.457*** (0.117)	-0.403** (0.165)	-0.359** (0.146)
Mean Consumption 2 months prior (kwh/customer) (log)				-0.072 (0.145)
Mean Consumption 3 months prior (kwh/customer) (log)				0.103 (0.152)
Mean Consumption 4 months prior (kwh/customer) (log)				0.146 (0.154)
Mean Consumption 5 months prior (kwh/customer) (log)				0.249 (0.167)
Mean Consumption 6 months prior (kwh/customer) (log)				-0.063 (0.159)
Mean Consumption 7 months prior (kwh/customer) (log)				0.158 (0.141)
Mean Consumption 8 months prior (kwh/customer) (log)				-0.180 (0.130)
Mean Consumption 12 months prior (kwh/customer) (log)				-0.125 (0.095)
Price of Electricity (1954 USD/kwh) (log)	-0.306*** (0.077)	-0.176** (0.076)	-0.188** (0.083)	-0.195** (0.079)
Nav Cooling Degree Days w/ 75 deg F base (0.1 deg Celcius) (log)	0.037 (0.064)	0.048 (0.057)	0.038 (0.060)	0.058 (0.059)
Mean Max Daily Temperature (deg Fahrenheit) (log)	-0.278 (0.948)	0.356 (0.853)	0.403 (0.971)	-0.022 (0.865)
Mean Max Daily Heat Index (deg Fahrenheit) (log)	-0.770 (0.525)	-0.652 (0.465)	-0.533 (0.497)	-0.668 (0.463)
Mean Max Daily Relative Humidity (log)	0.235 (0.574)	0.251 (0.507)	0.073 (0.554)	0.030 (0.526)
Mean Daily Rainfall (inches) (log)	0.019 (0.021)	0.024 (0.019)	0.027 (0.021)	0.016 (0.020)
Payroll Employment (log)	0.734 (1.369)	-0.123 (1.229)	0.148 (1.359)	-0.173 (1.222)
Gasoline Consumption (log)	-0.145 (0.096)	-0.224** (0.087)	-0.258** (0.097)	-0.276*** (0.087)
Cement Sales (log)	0.154 (0.109)	0.205** (0.097)	0.226** (0.103)	0.151 (0.103)
Regional Gross Domestic Product (1954 USD) (log)	-0.256 (2.866)	1.133 (2.556)	0.272 (3.082)	1.992 (2.670)
February	0.177*** (0.045)	0.066 (0.049)	0.074 (0.055)	0.105* (0.061)
March	0.193*** (0.052)	0.160*** (0.046)	0.153*** (0.048)	0.172** (0.065)
April	0.167*** (0.062)	0.128** (0.056)	0.125** (0.058)	0.177** (0.076)
May	0.270*** (0.073)	0.215*** (0.066)	0.209*** (0.068)	0.303*** (0.086)
June	0.257*** (0.084)	0.229*** (0.075)	0.221*** (0.079)	0.312*** (0.094)
July	0.218** (0.084)	0.155** (0.076)	0.145* (0.080)	0.180* (0.092)
August	0.231** (0.090)	0.157* (0.082)	0.160* (0.086)	0.224** (0.097)
September	0.299*** (0.088)	0.232*** (0.080)	0.230*** (0.083)	0.239** (0.093)
October	0.271*** (0.090)	0.219*** (0.081)	0.203** (0.085)	0.246*** (0.084)
November	0.213*** (0.066)	0.190*** (0.059)	0.176*** (0.062)	0.230*** (0.065)
December	0.197*** (0.041)	0.193*** (0.037)	0.187*** (0.039)	0.195*** (0.041)
chat			-0.069 (0.235)	
Constant	10.918 (12.650)	10.128 (11.173)	14.054 (13.079)	3.949 (11.661)
Long-run response	-0.306	-0.121	-0.134	-0.170
Observations	72	72	69	72
R ²	0.713	0.781	0.783	0.836
Adjusted R ²	0.593	0.683	0.672	0.716
Residual Std. Error	0.061 (df = 50)	0.054 (df = 49)	0.055 (df = 45)	0.051 (df = 41)
F Statistic	5.924*** (df = 21; 50)	7.939*** (df = 22; 49)	7.051*** (df = 23; 45)	6.955*** (df = 30; 41)

Note:

Price of Electricity defined as the average per kilowatt-hour rate for the customer class in the observed month.

LUMA Ex. 72.02

	Industrial Electricity Demand, Measured as Mean Consumption (kwh/customer) in the Observed Month (log)			
	AR(0) OLS	AR(1) OLS	AR(1) FGLS	AR(1;8,12) OLS
Mean Consumption 1 month prior (kwh/customer) (log)		-0.449*** (0.115)	-0.403** (0.160)	-0.350** (0.145)
Mean Consumption 2 months prior (kwh/customer) (log)				-0.065 (0.144)
Mean Consumption 3 months prior (kwh/customer) (log)				0.117 (0.150)
Mean Consumption 4 months prior (kwh/customer) (log)				0.164 (0.151)
Mean Consumption 5 months prior (kwh/customer) (log)				0.252 (0.166)
Mean Consumption 6 months prior (kwh/customer) (log)				-0.045 (0.156)
Mean Consumption 7 months prior (kwh/customer) (log)				0.182 (0.136)
Mean Consumption 8 months prior (kwh/customer) (log)				-0.162 (0.127)
Mean Consumption 12 months prior (kwh/customer) (log)				-0.103 (0.090)
Price of Electricity (1954 USD/kwh) (log)	-0.305*** (0.075)	-0.184** (0.073)	-0.191** (0.078)	-0.213*** (0.075)
Nav Cooling Degree Days w/ 75 deg F base (0.1 deg Celcius) (log)	0.040 (0.057)	0.037 (0.050)	0.036 (0.051)	0.039 (0.052)
Mean Max Daily Temperature (deg Fahrenheit) (log)	-0.310 (0.868)	0.486 (0.795)	0.435 (0.823)	0.222 (0.796)
Mean Max Daily Heat Index (deg Fahrenheit) (log)	-0.776 (0.516)	-0.628 (0.458)	-0.531 (0.491)	-0.666 (0.461)
Mean Max Daily Relative Humidity (log)	0.210 (0.499)	0.357 (0.443)	0.081 (0.515)	0.188 (0.479)
Mean Daily Rainfall (inches) (log)	0.019 (0.021)	0.026 (0.018)	0.027 (0.019)	0.018 (0.020)
Payroll Employment (log)	0.655 (1.029)	0.236 (0.916)	0.227 (0.927)	0.440 (0.900)
Gasoline Consumption (log)	-0.146 (0.095)	-0.220** (0.086)	-0.256*** (0.095)	-0.268*** (0.086)
Cement Sales (log)	0.149 (0.095)	0.224** (0.086)	0.232** (0.089)	0.174* (0.098)
February	0.177*** (0.044)	0.065 (0.048)	0.073 (0.055)	0.100 (0.060)
March	0.194*** (0.051)	0.158*** (0.046)	0.153*** (0.047)	0.171** (0.065)
April	0.167*** (0.062)	0.130** (0.055)	0.125** (0.057)	0.182** (0.075)
May	0.270*** (0.072)	0.217*** (0.065)	0.209*** (0.067)	0.306*** (0.086)
June	0.257*** (0.083)	0.233*** (0.074)	0.222*** (0.078)	0.321*** (0.093)
July	0.217** (0.083)	0.158** (0.075)	0.145* (0.078)	0.190** (0.090)
August	0.230** (0.089)	0.160* (0.081)	0.160* (0.085)	0.235** (0.095)
September	0.299*** (0.087)	0.233*** (0.079)	0.230*** (0.082)	0.244** (0.092)
October	0.271*** (0.089)	0.220*** (0.080)	0.202** (0.084)	0.249*** (0.083)
November	0.213*** (0.065)	0.189*** (0.058)	0.176*** (0.061)	0.228*** (0.064)
December	0.197*** (0.041)	0.194*** (0.036)	0.187*** (0.038)	0.194*** (0.040)
ehat			-0.052 (0.226)	
Constant	10.038 (7.856)	13.960* (7.022)	15.395* (7.650)	9.563 (8.859)
Long-run response	-0.305	-0.127	-0.136	-0.210
Observations	72	72	69	72
R ²	0.713	0.780	0.782	0.834
Adjusted R ²	0.601	0.688	0.678	0.719
Residual Std. Error	0.060 (df = 51)	0.053 (df = 50)	0.055 (df = 46)	0.051 (df = 42)
F Statistic	6.343*** (df = 20; 51)	8.443*** (df = 21; 50)	7.508*** (df = 22; 46)	7.253*** (df = 29; 42)

Note:

Price of Electricity defined as the average per kilowatt-hour rate for the customer class in the observed month.

LUMA Ex. 72.03 (Improvement 5 CHP Report 2024-05-23)

Improvement 5: Historical Displaced Load – Combined Heat and Power

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Table of Contents

Executive Summary	4
1. Introduction	7
1.1 Improvement 5 Goals	7
1.2 LUMA Approvals	8
1.3 Structure of this Report.....	9
2. Methods	10
2.1 CHP Identification.....	10
2.1.1 CHP Identification Challenges	10
2.1.2 Identification Algorithm.....	13
2.2 Estimate Counterfactual Consumption	18
2.3 Quantify Displaced Load	19
2.4 Apply Methods to 213 and 313 Customers	20
3. Input Data.....	24
3.1 CHP Analysis	24
3.2 Rate 213 and 313 Analysis.....	27
4. Results	30
4.1 Displaced Load (CHP Suspected Customers)	30
4.2 Displaced Load (213 and 313 Customers).....	34
4.3 Total Displaced Load.....	37
4.4 Fiscal Plan Forecast Reconciliation	38

List of Tables

Table 1: Customer CHP Survey Data.....	11
Table 2: Review of customers with known CHP	17
Table 3: Customer Data Available for the Study.....	24
Table 4. Summary of Customers by Rate Class.....	26
Table 5. Summary of Customers with Potential CHP Installaion	27
Table 2. Summary of Customers by Rate Class.....	Error! Bookmark not defined.

List of Figures

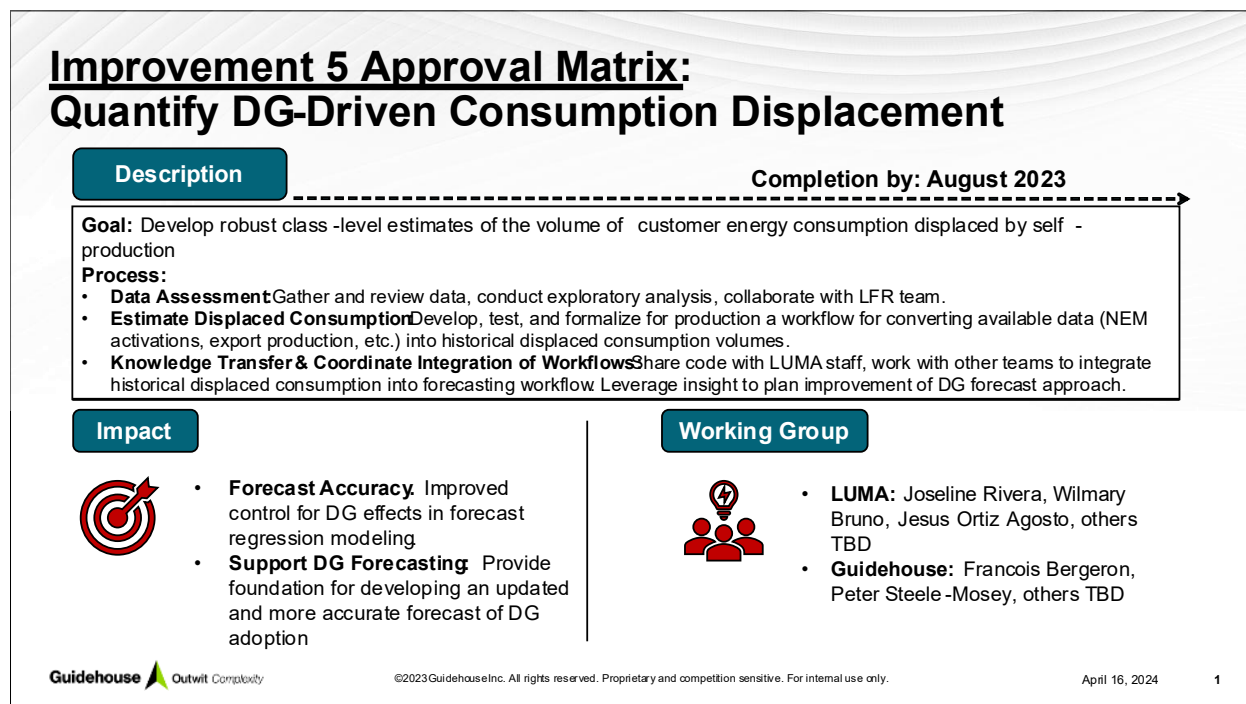
Figure 1. Improvement 5 Approval Matrix.....	4
Figure 2. Monthly Displaced Load and Billed Consumption.....	5
Figure 3. Improvement 5 Approval Matrix.....	8
Figure 4. Monthly Consumption, Customer 8478911612.....	11
Figure 5. Monthly Consumption Customer 4017071247.....	12
Figure 6. Monthly Consumption, Customer 5345157219.....	15
Figure 7. Monthly Consumption, Customer 5383761764.....	15

Figure 8. Counterfactual Consumption Example – Customer SAID 0834540182	19
Figure 9. Displaced Consumption Estimation Example – Customer SAID 0834540182	20
Figure 10. Manual Removal Example – Outlier Issue – SA-ID: 4424398701	21
Figure 11. Manual Removal Example – Temporary Reduction – SA-ID: 1369602757	22
Figure 12. Manual Removal Example – Unclear Trend – SA-ID: 2801502458	23
Figure 13. Max Monthly Consumption by CHP Detection Status	26
Figure 14. Average CHP Impacts Across All Detected Installations	31
Figure 15. Aggregate CHP-Displaced Monthly Consumption	32
Figure 16. Displaced Consumption per Customer, Sorted	33
Figure 17. CHP-Displaced Load by Rate Class	34
Figure 18. Average 213/313 Impacts Across All Detected Installations	35
Figure 19. Aggregate 213/313-Displaced Monthly Consumption	35
Figure 20. Displaced Consumption per 213/313 Customer, Sorted	36
Figure 21. 213/313 Displaced Load by Rate Class	37
Figure 22. Aggregated Displaced Monthly Consumption	37
Figure 23. Displaced Load and Billed Consumption	38
Figure 24. Monthly Industrial Consumption (GWh)	39
Figure 25. Industrial Rate Total Consumption (Large Volume Rates)	40
Figure 26. Industrial Rate Total Consumption (Smaller Volume Rates)	41

Executive Summary

At the April 20 meeting of LUMA's Load Forecast Governance Committee, Guidehouse presented a request for approval to develop a detailed workplan and budget for Improvement 5, a project to estimate the historical loads displaced by net-metered solar distributed generation (DG¹) and Industrial installations of combined heat and power (CHP) cogeneration. The approval matrix presented at that meeting is shown in Figure 1, below.

Figure 1. Improvement 5 Approval Matrix



Source: Guidehouse

Guidehouse submitted a formal workplan and budget on 2023-04-26. This was approved via email by the LUMA Load Forecast and Research (LFR) team lead on 2023-05-04.

The Improvement 5 analysis is divided into two parts: estimating load displaced by DG and estimating load displaced by CHP. This report provides Guidehouse's final reporting for CHP-displaced consumption.

For this analysis, the LUMA LFR team provided Guidehouse with the historical billing data of a set of customers that they believed had installed CHP generation. The Guidehouse team used these data, as well as other information about the customers provided by the results of a survey deployed by LUMA², and web research conducted by the Guidehouse team to develop and test an algorithm for detecting significant load drops with characteristics consistent with the use of

¹ Although "distributed generation" can refer to many types of electricity generation equipment and installations, for the purposes of this report, unless otherwise explicitly noted, "DG" refers only to solar generation enrolled in LUMA's net energy metering (NEM) program.

² To further identify customers with CHP, the LUMA LFR team coordinated with the Customer Experience and IRP teams to identify customers that are suspected to have CHP. LUMA sent out a survey to these customers to 1) confirm if these customers have CHP, and 2) identify the CHP installation date.

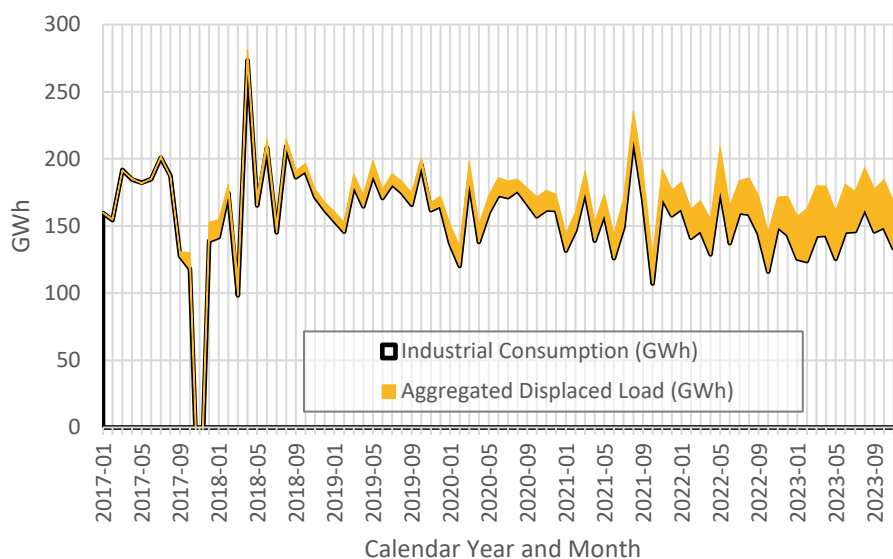
CHP. The Guidehouse team then applied the approach developed and tested on the customers with suspected CHP to identify rate 213 and 313 customers³ with potential CHP and estimate the displaced consumption from these customers.

Guidehouse's key finding of this analysis is that **self-generation by large customers reduced LUMA's sales by approximately 414 GWh in calendar year 2023, or nearly 35 GWh per month**. The analysis also suggests that this value is trending up, and it seems likely displaced consumption due to self-generation by large non-residential customers will continue to grow.

Because of the limits to the available data, there is some uncertainty regarding the attribution of the consumption reductions due to CHP. It is possible that some of what is identified as consumption displaced by CHP generation in this report may in fact be due to some other exogenous change in customers' consumption behavior (e.g., closure of a production line). The Guidehouse team deliberately (and conservatively) set the parameters of its algorithm to reduce the possibility of any misattribution. However, this possibility cannot be eliminated, and reviewers should bear this in mind when considering the results.

Figure 2, below shows aggregate estimated displaced consumption combined with the raw (un-remediated) Industrial class consumption data. The figure provides an illustration of what loads might have been, absent the estimated adoption of CHP by the customers included in this analysis. This plot shows aggregate actual monthly billed Industrial consumption (black line) and the estimated volume of CHP-displaced load (orange area) stacked on top of it.

Figure 2. Monthly Displaced Load and Billed Consumption



Source: Guidehouse analysis

Based on this analysis, Guidehouse has made three recommendations for the LUMA LFR team to consider:

- **Adjust Historical Consumption for Forecast Estimation.**
 - It is a standard practice by many utility load forecasting teams to adjust historical consumption values by “adding back in” energy efficiency savings prior to

³ Customers on rates 213 or 313 are Commercial and Industrial customers with high voltage service and, as a result, are potential candidates for CHP.

estimating the regression that provides forecast “gross” consumption. These utilities then adjust the forecast by applying forecast energy efficiency achievement.

- The LUMA LFR team should consider the value of a similar approach for addressing the impacts of CHP in its load forecast. This approach would address concerns related to possible omitted variable bias arising from the fact that at present the forecast does not include any explicit controls for historical CHP (i.e., the effects are “embedded” in the other regression parameters and double-counting future impacts is avoided by applying a load modifier of incremental CHP output).
- **Engage Directly with CHP-Equipped Customers.** The LUMA LFR team should consider working with Customer Experience and other LUMA teams to obtain more precise intelligence regarding the installed capacities of the systems operated by the 24 customers identified as having CHP-displaced load. This could allow for improved precision in the estimation of displaced load and enable improved forecasting of CHP load modifiers. Even in cases where the customers themselves will not share information with LUMA, LUMA staff in other teams may have sufficient experience observing these customers’ operations to provide useful insight to the LFR team for forecasting CHP output and electricity consumption.⁴

Develop Estimated Capacity Factors. If the LUMA LFR team can obtain better information about the nameplate capacities of the CHP installations used by the customers with displaced consumption, these can be applied to the estimated displaced consumption to develop (potentially) industry-specific capacity factors. These values could be used to allow for greater precision in the forecasting of load modifier growth. The capacity factors should include economic (e.g., CHP cheaper than the grid) and non-economic (e.g., outages, processes requiring heat, etc.) dispatching.

⁴ The LFR team may wish to consider meeting with Customer Experience staff (or other staff with experience observing LUMA’s largest customers) on a semi-regular basis (e.g., every six months) to discuss these largest customers and review their recent historical loads. This might provide valuable information about individual customer operations that could assist the LFR team in adjusting its forecast as needed.

1. Introduction

LUMA is currently experiencing unprecedented growth in the penetration of self-generation in its service territory. Growth in self-generation is most significant amongst Residential customers acquiring rooftop photovoltaic (PV) and participating in LUMA's net energy metering (NEM) program has significantly accelerated in recent years. A review of program registrations indicates that the number of Residential DG customers has, between July of calendar year⁵ 2022 and the end of December of calendar year 2023, grown by an estimated average of 4% *per month*.⁶

Self-generation outside the NEM program by large non-residential customers cannot be tracked as accurately as NEM program participation, and although the magnitude of growth in combined heat and power (CHP) cogeneration facilities is much less certain, there is evidence to suggest that there has been significant growth in its use in the last 3 – 5 years. When the Guidehouse load forecasting team updated the LUMA long-term load forecast model for the Industrial class in August of calendar year 2023, the team needed to include a new binary variable within the regression model to account for a significant step-change in Industrial consumption that appeared to originate in the early half of calendar 2022.

The LUMA Load Forecasting and Research (LFR) team has communicated to Guidehouse its suspicion that most of this drop in Industrial load may be attributable to the acquisition of CHP by a small group of large power consumers.

1.1 Improvement 5 Goals

LUMA's load forecasting process does not, at present, apply controls for historical distributed generation in its estimation of the key relationships between monthly consumption and its drivers.

The LUMA LFR team, assisted by Guidehouse, has been focused on putting in place a new set of workflows to allow the LFR team to move away from using the regression outputs previously estimated in 2018. Lacking data on historical CHP output, the LFR team has no straightforward option for addressing CHP output in its analysis of historical data. As a result, in the regression analysis to develop forecast models, the effects of CHP are attributed to other covariates that are correlated with the uptake of CHP. This misattribution is referred to in econometrics as "omitted variable bias".

Where changes to consumption due to CHP are relatively small, this is not a matter of great concern. As the adoption of CHP grows, however, failing to control for historical CHP output can bias the forecast. The LUMA LFR team has mitigated against this issue by applying "Load Modifiers" to the base (unadjusted) forecast. These modifiers (estimates of the impacts of future DG and CHP, among other effects) apply the *incremental* impacts of new load modifiers, and so avoid concerns of double-counting.

⁵ For clarity, when referring to years, Guidehouse has taken care to specify whether a year is a calendar year or a fiscal year (LUMA's fiscal year runs from July through June). If the convention is not explicitly specified, readers should assume a calendar year.

⁶ Commercial customer growth over the same period has also been very strong at approximately 4% per month, though Commercial DG customers only represent approximately 2% of all Commercial customers, as of the end of December of calendar year 2023.

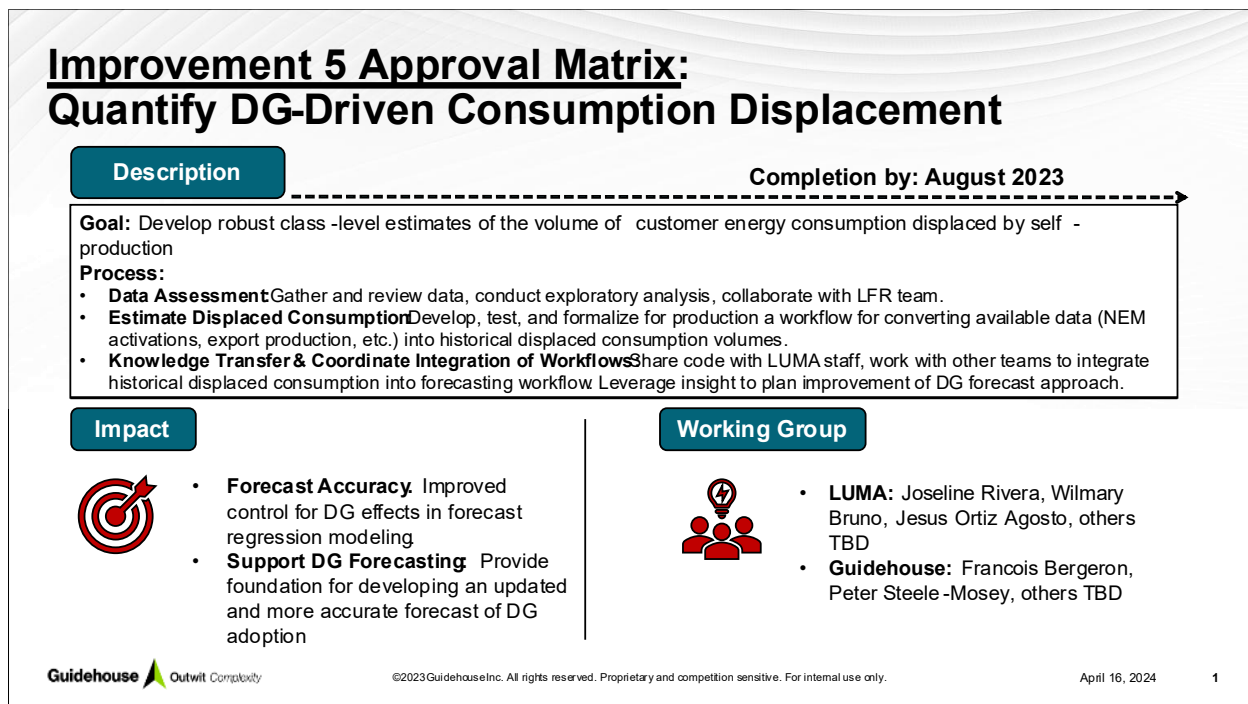
Guidehouse has likewise included a binary variable intended to control for the recent apparent growth in Industrial self-generation in the Industrial forecast regression model, but this should be regarded as a temporary measure. A more precise estimate of historical CHP impacts could replace this binary and, combined with the LUMA LFR team's projection of CHP (i.e., load modifier) growth, deliver a more accurate long-term forecast of Industrial consumption.

Accordingly, **the primary goal of Improvement 5 (and this report) is to develop a monthly estimate of historical Industrial class consumption displaced by CHP**. Historical consumption displaced by the NEM program across the Residential, Commercial, and Industrial classes ("DG customers") is addressed in a separate report⁷.

1.2 LUMA Approvals

At the April 20, 2023, during a meeting with LUMA's Load Forecast Governance Committee, Guidehouse presented a request for approval to develop a detailed workplan and budget for Improvement 5, a project to estimate the historical loads displaced by net-metered solar distributed generation (DG) and Industrial installations of CHP generation. The approval matrix presented at that meeting is shown in Figure 3, below.

Figure 3. Improvement 5 Approval Matrix



Source: Guidehouse

Guidehouse submitted a formal workplan and budget on 2023-04-26. This was approved via email by the LUMA Load Forecast and Research (LFR) team lead on 2023-05-04.

⁷ "Improvement 5 Report – Solar PV 2024-04-29.docx" was provided to the LUMA LFR Team on April 9th, 2024.

1.3 Structure of this Report

This report is divided into four sections, including this Introduction. The four main sections of the report are:

1. **Introduction.** This section.
2. **Methods.** A description of the analytic approach.
3. **Input Data.** A description of the data used to estimate monthly displaced loads.
4. **Results.** Graphical and tabular summaries of the key analysis outputs.

This report is accompanied by two Excel workbooks that include the summary data used to develop the tables and graphics provided in this report, and PDFs of diagnostic plots of monthly consumption for each of the customers considered in this analysis (one set for the CHP analysis and one for all rate 213 and 313 Industrial customers). These files are:



Customer-Level
Results 2024-04-01.p



213-313 Customer
Results 2024-05-15.p



Imp 5 CHP Memo



213_313 CHP
Analysis

These workbooks may be especially useful for readers interested in CHP impacts for a specific customer. The drop-down menu in the “OUT-07a Results by Customer” and “OUT-05 Results by Customer” tabs in the “Imp 5 CHP Memo.xlsx” and the “213_313 CHP Analysis.xlsx” workbooks above respectively, allow the user to display a monthly load plot for any of the customers considered in this analysis (i.e., the Excel-based equivalent of the plots included in the PDF).

2. Methods

The goal of Guidehouse's CHP analysis was to examine a set of customers identified by LUMA staff as possibly possessing behind-the-meter generation and the broader set of customers on rates 213 and 313, identify those with CHP, and estimate the impact of that CHP on the historical electricity consumption of customers.

Guidehouse's method for accomplishing this goal involved four steps:

1. **Identify CHP.** Examine historical consumption data to identify customers with substantial reductions in consumption in a pattern consistent with the use of CHP self-generation, comparing substantial drops against available information on customer CHP installations to develop an effective algorithm to identify these patterns.
2. **Estimate Counterfactual Consumption.** Use pre-CHP installation consumption to estimate a baseline level of counterfactual consumption (i.e., what would have been consumed absent CHP installation).
3. **Quantify Displaced Load.** Subtract observed loads from the estimated counterfactual baseline to quantify the displaced load.
4. **Quantify Displaced 213 and 313 Customer Load.** Apply the above steps (excluding the comparison to available CHP installation information) to the broader group of rate 213 Commercial customers and 313 Industrial customers to estimate the displaced load from this customer group.

2.1 CHP Identification

This section is divided in two subsections. The first describes some of the key challenges to the precise identification of CHP installations and limitations of the available data. The second describes the process by which Guidehouse developed the algorithm used to identify CHP installations.

2.1.1 CHP Identification Challenges

In prior research, LUMA identified the installed capacity of on-site generation for four customers, in the group of 38, that it believed might have on-site generation. LUMA determined installation dates and capacity values for these four customers based on prior research conducted by the LFR team, including a survey distributed to these customers in August and September of 2023. Information about CHP capacity is provided to LUMA when customers request an evaluation for the interconnection of their generator, and the LFR team receives an annual update from the LUMA evaluation team. Some customers may install and use self-generation without receiving an evaluation from LUMA, meaning the information the LFR team has is likely incomplete.

Four customers responded to the survey distributed in August and September 2023, confirming that they had CHP on-site. The information provided by these customers is summarized in Table 1 below.

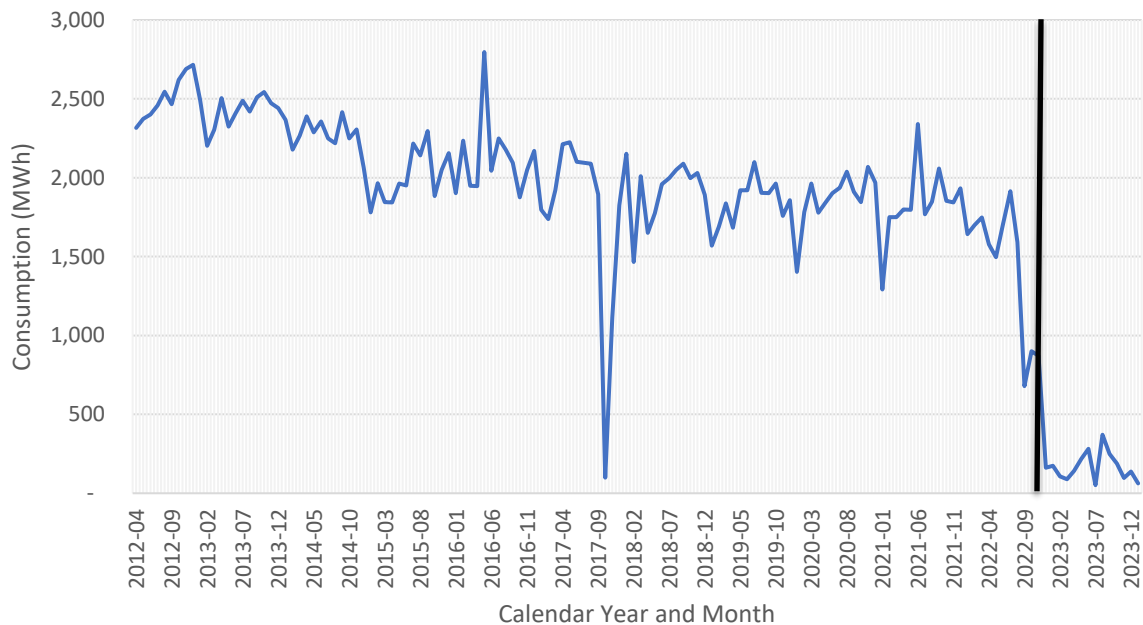
Table 1: Customer CHP Survey Data

SA ID	CHP Installation Date	CHP Capacity	Solar Capacity	Battery Capacity
7808781022	2018-02-25	3 MW	875 kW	1300 kW
4017071247	2020-01-07	5,280 kW	None	None
6829691944*	2022-06-30	9,400 kW	2 MW	240 kW
8478911612	2022-11-01	3,800 kW electric / 3,200 kW thermal	None	1.1 MW peak output

* Guidehouse was informed by LUMA that this customer has multiple sites, and the SA ID in the original survey data (2537555433) was incorrect. The SA ID associated with the correct site is actually 6289691944.

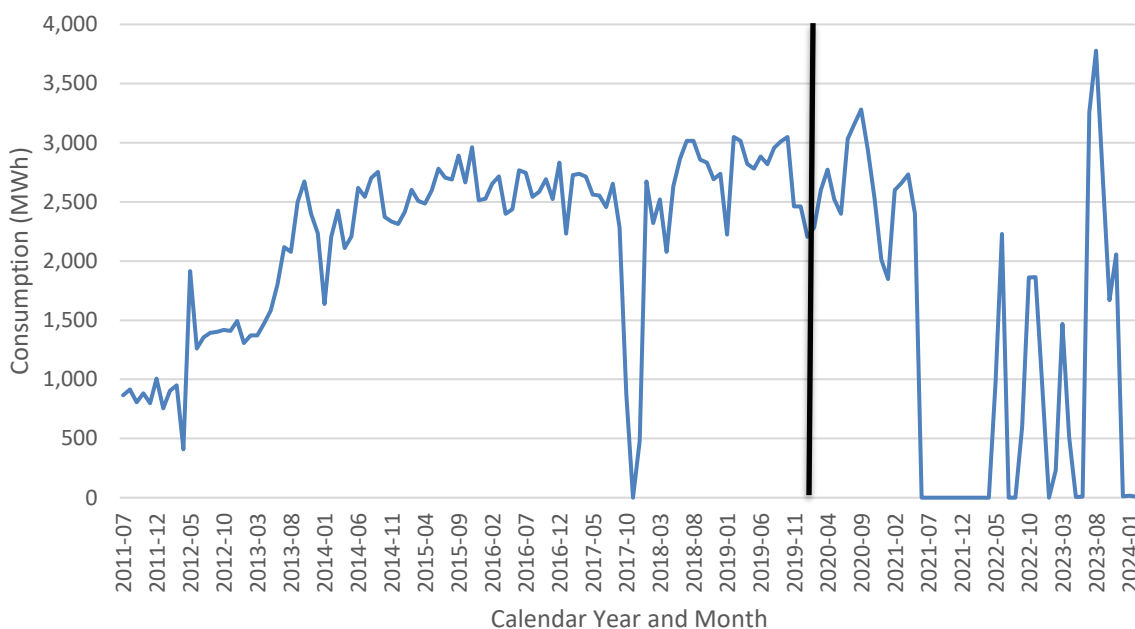
Source: LUMA LFR Team provided to Guidehouse on September 14th, 2023 (filename: Combined Heat and Power Survey(1-4).xlsx)

Of these four customers, three display significant changes in their monthly consumption patterns in months following the provided CHP installation date. These changes are consistent with the installation of CHP. For example, Figure 4 shows a decline in consumption for customer SA ID 8478911612, beginning in approximately November 2022 (indicated by the black vertical line).

Figure 4. Monthly Consumption, Customer 8478911612

Source: Guidehouse analysis

One of the four customers (SA ID 4017071247) showed a decrease in consumption consistent with installation but not until a year and a half after the indicated installation date (beginning of calendar year 2020), indicated in Figure 5 with the black vertical line.

Figure 5. Monthly Consumption Customer 4017071247

Source: Guidehouse analysis

These examples demonstrate two critical points for estimating displaced consumption: a) not all customers self-report the required data, and b) self-reporting may be imprecise.

Accordingly, the Guidehouse team determined that it would be beneficial to develop an independent estimate of displaced load based on an analysis of customer monthly billing data. It is possible to identify potential cases of CHP adoption and displaced load by identifying sustained load reductions on an individual customer basis, informed by qualitative inputs provided by the LUMA LFR team.

Although this was the best available approach with the limited available data, algorithmic detection of self-generation is subject to two crucial limitations:

1. **Alternative Causes.** Load reductions may be driven by causes other than self-generation. Algorithmic detection might inappropriately attribute CHP generation to simple changes in a commercial or industrial customer's production.
2. **Offsetting Production.** This approach may fail to detect CHP deployed to offset new production. CHP that comes online at approximately the same time as new production demand could result in only a modest net change in billed consumption and remain undetected.

The Guidehouse team determined that, for the ultimate use-case of the Improvement 5 outputs, the second limitation is not a major concern. The Guidehouse team believes it is unlikely, given historical Industrial load declines, that there has been significant load growth near-perfectly offset by self-generation. Any such cases are unlikely to materially impact the Industrial load forecast and so can be safely ignored.

The first limitation is critical to address however, to avoid confounding the effects of self-generation (the historical effects of which aren't explicitly controlled for in the forecasting

regression analysis) with the effects of macro-economic drivers (which are controlled for in the forecasting regression analysis) on Industrial load. Confounding self-generation impacts with standard economic impacts on load could result in “double-counting” load reductions.

Controlling for these “double-counted” load reductions in regression estimation could result in a biased forecast of Industrial consumption.

The Guidehouse team’s approach to this issue is described below.

2.1.2 Identification Algorithm

For the reasons noted above, the Guidehouse team determined that its approach to detecting CHP installations should be conservative. That is, the team determined that it would be more prudent to develop an estimate of CHP-displaced load that *underestimated* CHP than to develop an estimate that *overestimated* CHP-displaced load by attributing standard, economically driven load reductions to the use of self-generation.

This determination was an important motivation for some of the analytic choices identified below. The remainder of this section first describes the approach the Guidehouse team used to detect the use of CHP self-generation and is followed by a description of some of the exploratory analysis that informed the development of that approach.

Algorithm Description

The Guidehouse team determined that the most appropriate way to identify the use of self-generation was through a time-wise comparison of each customer’s load. When a customer shows a significant, sustained reduction in load, there is a high probability that self-generation is being used.

Consumption for industrial customers can be extremely variable. To smooth out this variation and identify drops in consumption likely to be associated with the installation of CHP, Guidehouse calculated a moving average of consumption using a centered 7-month window (i.e., three months prior and three months after each month included in the average) for all customers included in the CHP analysis.

The moving average consumption for month m (MAC_m) was calculated for each customer included in the analysis using Equation 1:

Equation 1. Moving Average of Consumption Equation

$$MAC_m = \frac{\sum_{i=m-3}^{m+3} Consumption_i}{7}$$

This moving average is used to detect potential cases of CHP-displaced load.

CHP is determined to be detected when both the following conditions hold:

- a. $MAC_m/MAC_{m-12} < 0.5$
 - A customer was flagged as potentially having installed a CHP system when the 7-month moving average dropped to less than half of the moving average 12 months prior.

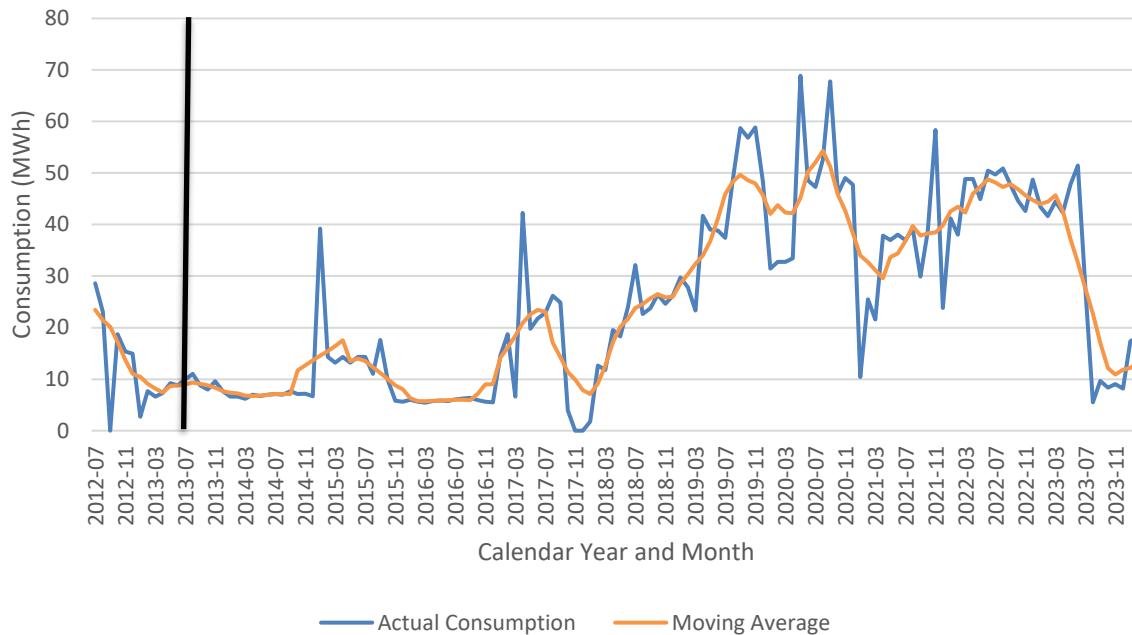
- The year/month pair in which the condition above holds is referred to as the CHP detection date, $MAC_{m=d}$, where the subscript “d” identifies the detection date month.
- b. $MAC_{m=d+12}/MAC_{m=d-12} < 0.5$
- If the moving average of customer consumption 12 months following the detection date ($m=d+12$) remains 50% or less than the moving average consumption 12 months *prior* to the detection date ($m=d-12$), then the load reduction is sustained, and more likely to be the result of self generation.
 - This condition is only applied when there are sufficient data available to check it. For example, in the case of SAID 0915232851, the detection date is March of 2023. The final month of available billing data for this customer is January of 2024. With less than 12 months of data following detection, this second condition cannot be evaluated, and so (following a visual inspection of historical consumption) this customer is counted as having displaced load with CHP as of the detection date.

In summary, when the moving average of consumption is less than half the value it was 12 months previous, there has been a significant drop in that customer’s consumption (condition a. is met). When the moving average remains less than half the pre-CHP value for a year after the detection date (condition b. is met), the drop in consumption is likely to be related to some systematic change in customer usage (e.g., acquisition of CHP) and not just random variation in load. Condition b. is required to exclude false detection of CHP caused by random variation in load.

The detection date is not assumed to be the date at which CHP begins to displace load. Guidehouse has assumed some ramp in output, with load assumed to be displaced for 8 months prior to the detection date (see Section 2.2 below for more details).

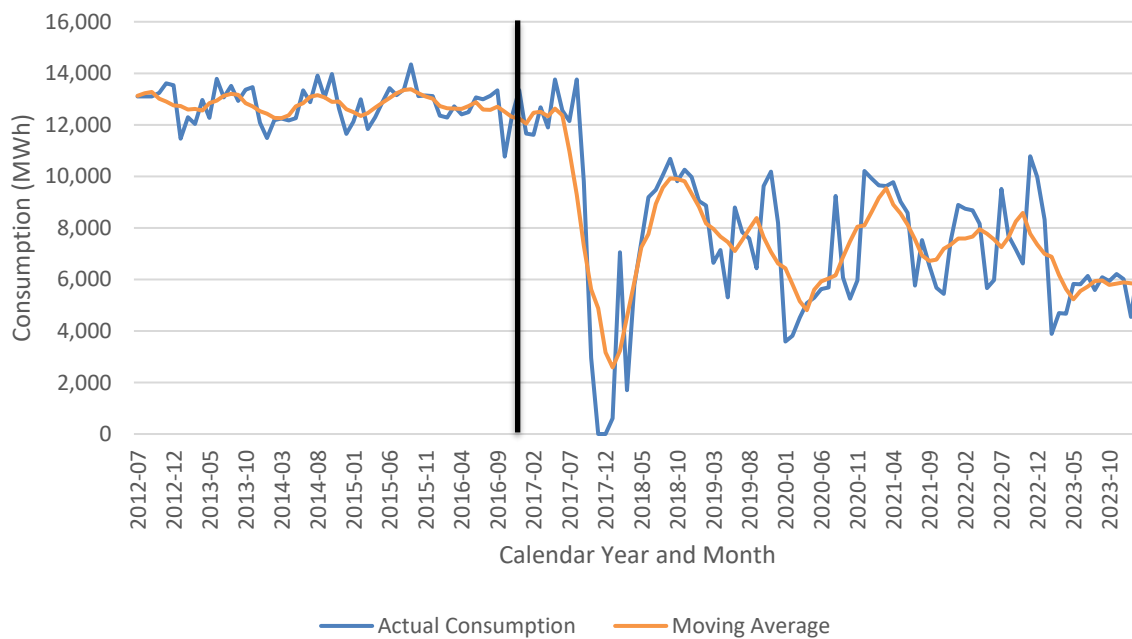
There are two exceptions to the detection conditions above for customers LUMA identified as potentially installing CHP. The customer with SAID 5345157219, and the customer with SAID 5383761764. The first SAID is a customer for which CHP was detected by the algorithm, but where Guidehouse overrode the algorithm and flagged the customer as one for which no CHP was detected. The second is a customer for which CHP was *not* detected but that Guidehouse flagged as one for which CHP was detected.

In the first case, the detection month was July of calendar year 2013 (indicated by the black vertical line in Figure 6). Based on a visual inspection of the data, this does not seem to be accurate. The detection occurs because of what appears to be a spike in consumption in the earliest months of data. The overall trend of the data in Figure 6 suggests this is likely an anomaly, not CHP installation.

Figure 6. Monthly Consumption, Customer 5345157219

Source: Guidehouse analysis

In the second case, the second condition was relaxed on the assumption that the LFR team (who identified for Guidehouse that this customer had installed CHP in 2017) had accurate information about this installation. On the basis of a visual inspection of the data (Figure 7), which aligned with the information provided by the LFR team, see below.

Figure 7. Monthly Consumption, Customer 5383761764

Source: Guidehouse analysis

Algorithm Development

The detection algorithm makes use of three parameters:

- Length of centered moving average window (final value – 7 months)
- Magnitude of delta to trigger detection (final value – 50%)
- Lookback period to compare against (final value – 12 months)

The Guidehouse team selected the final values for each of these parameters following an extensive period of testing.

Testing was applied across two criteria:

1. How well did the algorithm detect “known” CHP installations (see below for definition of “known”)?
2. Does a visual examination of each customer’s historical consumption profile intuitively support the detection date?

A “known” CHP installation is one in which some third-party evidence could be found that identified the customer as having a CHP installation. “Known” CHP installations, and the information source are identified in Table 2 below.

Table 2: Review of customers with known CHP

SA-ID	CHP Installation Date	CHP Installation Source*	Has Other DERs?
0138041105	Feb 2023	News Article	No
0915232851	2022	US DOE CHP Database	No
1904231632	2015	US DOE CHP Database	No
2045381904	2020	US DOE CHP Database	No
2367212053	Oct 2023	News Article	No
2834102127	2022	US DOE CHP Database	No
3153261921	Jun 2017	Case Study - CHP Provider (and US DOE)	No
4017071247	Jan 2020	LUMA's CHP Survey	No
4124231805	2022	US DOE CHP Database	No
4130471875	Sep 2020	News Article	No
5346702770	2020	US DOE CHP Database	No
5383761764	2017	LUMA's LRF Team	No
5925521746	Jul 2017	LUMA's LRF Team	No
6829691944	Jun 2022	LUMA's CHP Survey	Yes
7808781022	Feb 2018	LUMA's CHP Survey	Yes
8162141907	2022	US DOE CHP Database	No
8478911612	Nov 2022	LUMA's CHP Survey	Yes

*CHP installation date is a union of multiple sources: the US DOE Combined Heat and Power Installation Database (<https://doe.icfwebservices.com/chp>), the CHP survey (**Error! Reference source not found.**), a web scan by the Guidehouse team (new articles, company announcement, etc.), and any LUMA's LRF team information/knowledge. Note that web URL are not provided in this report to maintain customer anonymity, but are available to LUMA staff in supporting Excel documentation.

The testing procedure was iterative and qualitative, with the Guidehouse team adjusting the parameters, comparing detected dates with known installations⁸ and conducting extensive visual inspections of individual customer data plots.

Crucially, a significant driver of the final parameter selection was the motivation to avoid (as much as possible) identifying changes in production or other unrelated changes in consumption patterns as CHP use. Although the team took great care to avoid such misidentifications, it cannot guarantee that some instances of consumption changes identified as CHP use may not

⁸ Priority was given to visual inspection over calibration of detection with "known" dates, given the sometimes highly uncertain timing of "known" installation reported, for example, in the public news media.

in fact be the result of some other exogenous driver of customer load. Visual inspection of the average consumption of customers with detected CHP (see Figure 14 at the start of Section 4.1), however, provided the Guidehouse team with confidence in the outcome and accuracy of its analysis.

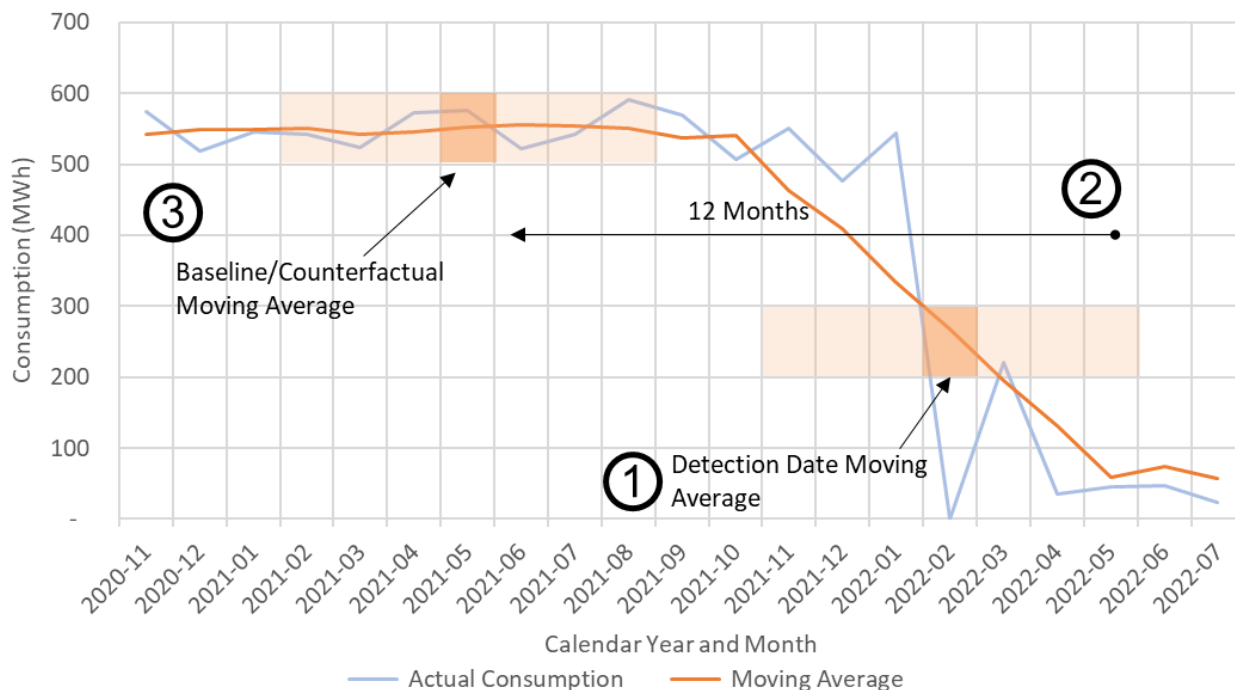
2.2 Estimate Counterfactual Consumption

Before estimating displaced consumption, it is necessary to establish a baseline. Guidehouse experimented with a variety of different baseline estimation methods, including the application of trends and seasonality. However, after review and testing, Guidehouse concluded that applying either trend or seasonal patterns to the baseline would impose inappropriately strong structural assumptions about the underlying customers' consumption patterns.

Instead, Guidehouse defined each customers' baseline as the centered 7-month moving average consumption value observed in the month preceding the 12-month period leading up to the end of the period covered by the moving average on the detection date.

Figure 8 illustrates an example of implementing this process in more detail (numbers in list below correspond to numbers in graphic):

1. Identify detection date per the steps identified in Section 2.1.2. In this case, the detection is February of calendar year 2022
2. Count back 12 months from the end of the detection date to set the range of the moving average window.
3. Select the 7-month centered moving average from the month before this 12-month span. This becomes the baseline or counterfactual consumption (i.e., what the Guidehouse team estimates consumption *would have been* absent CHP).

Figure 8. Counterfactual Consumption Example – Customer SAID 0834540182

Source: Guidehouse

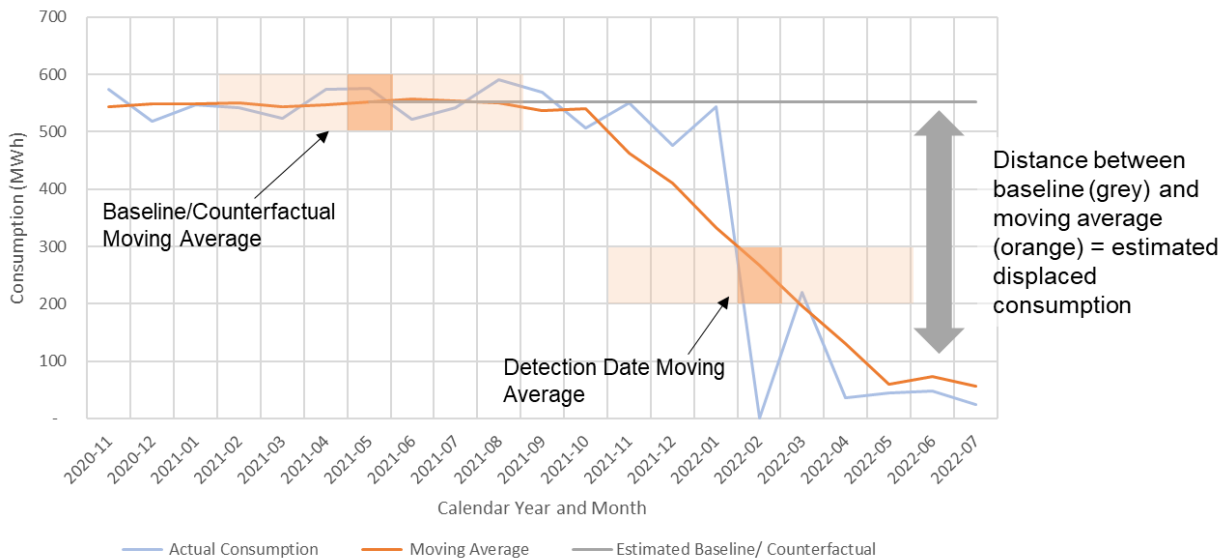
A specific numerical example is presented to assist the readers' understanding:

- The detection date for SAID 0834540182 is February of calendar year 2022 (see text on page 2 of the PDF that accompanies this report: "Customer-Level Results 2024-04-01.pdf" and graphic above)
- The 7-month moving average window centered on the detection date (February 2022) ends in May of 2022 (three months after the detection date).
- Twelve months (one year) prior to May 2022 is May 2021. The moving average consumption centered on May 2021 therefore becomes the estimated baseline.

12 months (from the end of the detection date moving average window) was selected after some testing, and is intended to capture the fact that many CHP installations undergo a period of "working up" prior to being deployed at expected capacity.

2.3 Quantify Displaced Load

Displaced load is estimated as the difference between the counterfactual estimated baseline (i.e., the 7-month centered moving average in the first month preceding the 12-month period that extends until the end of the moving average window for the detection date) and observed monthly consumption. Displaced load is estimated starting from the month after the month that provides the estimated baseline, as illustrated in Figure 9.

Figure 9. Displaced Consumption Estimation Example – Customer SAID 0834540182

Source: Guidehouse

Guidehouse experimented with starting the baseline period earlier and later (relative to the detection date) but determined (for the reasons noted in the section above) that starting from the period beginning 12 months prior to the end of the detection date moving average window was the most suitable.

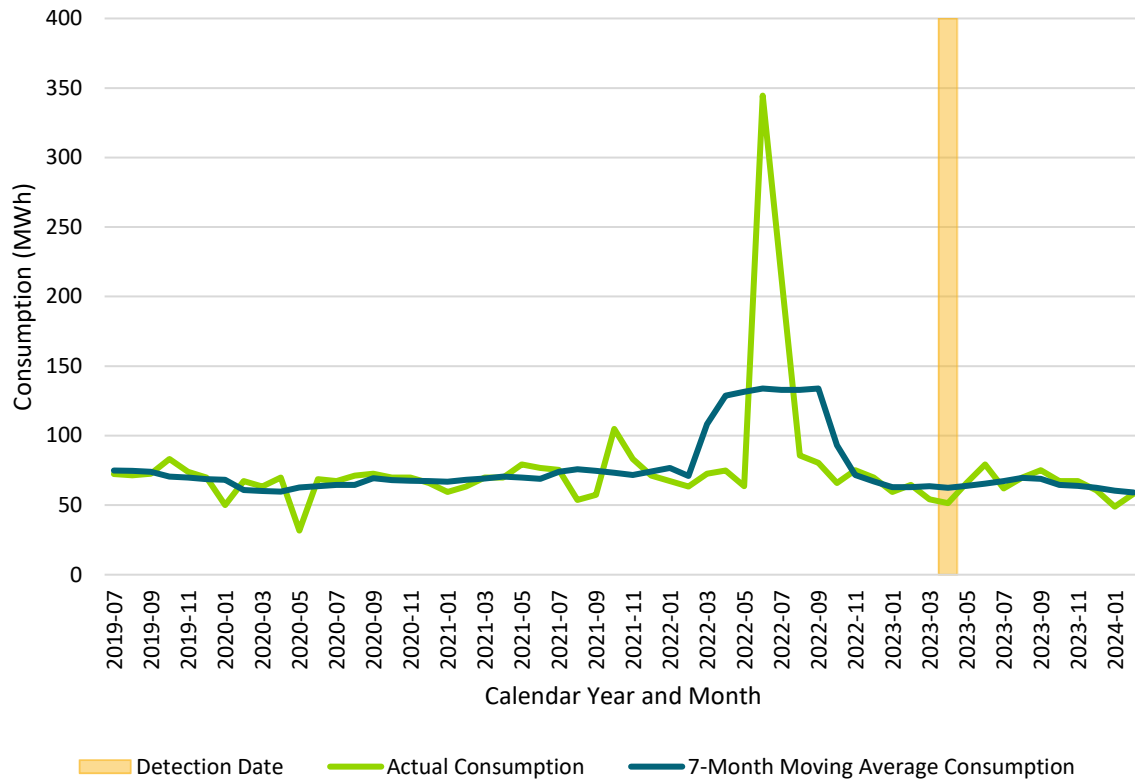
Because this period starts considerably before the detection date, there is the risk that “displaced consumption” will be estimated in months prior to CHP actually being in service. This appears to be the case in the example above. This risk has little cost, however, as the average “displaced consumption” where CHP is not actually yet in service typically equals zero (i.e., the baseline is above actuals in some months, but below in others).

2.4 Apply Methods to 213 and 313 Customers

Guidehouse applied the approach to all customers on rates 213 and 313, because the LUMA LFR team identified those rates as most likely to include additional customers with CHP.

There were no additional data sources to verify the results for the wider group of rate 213 and 313 customers, so Guidehouse relied on the algorithm to identify customers with potential CHP. Upon visual inspection of the results, Guidehouse found that, due to the limited timeframe of the data and data quality issues, the algorithm was producing a significant number of false positives. Guidehouse reviewed the consumption patterns of each identified customer to identify false positives and removed them manually (override). Manual overrides fell under the following categories:

1. **Outlier Issue.** The reduction is the result of an outlier artificially increasing the rolling average and triggering the algorithm. Figure 10 shows the monthly actual consumption, 7-month moving average consumption, and detection date for a customer with an outlier issue. You can see from inspection of the graph that the outlier observation caused enough of an increase in the moving average to falsely trigger the algorithm.

Figure 10. Manual Removal Example – Outlier Issue – SA-ID: 4424398701

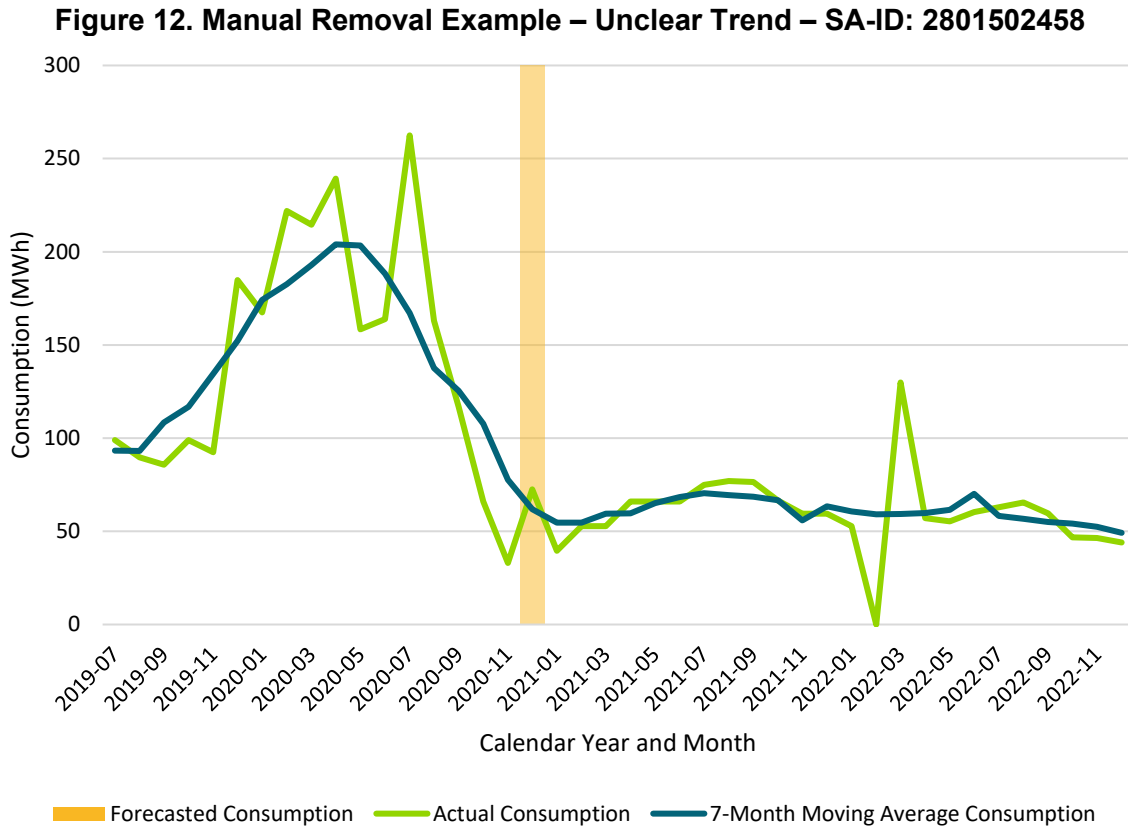
Source: Guidehouse analysis

2. **Temporary Reduction.** The reduction in consumption is temporary, rather than sustained, but lasts at least 12 months (condition b was satisfied). An example of this type of false positive is shown in Figure 11 below.

Figure 11. Manual Removal Example – Temporary Reduction – SA-ID: 1369602757

Source: Guidehouse analysis

3. **Unclear Trend.** The reduction is inconsistent with installation of CHP or DG (such as too gradual of a reduction or temporary increases in consumption) or there is not enough data around the detection date to be certain it is not an outlier issue. This is the least straightforward of the algorithm exceptions, but it is also the most prevalent in the 213 and 313 customer CHP detections. One example of a customer with an unclear trend that was removed from analysis is shown in Figure 12 below. Visual review of the consumption pattern shows that the identified consumption drop is just consumption returning to previous levels (i.e., consumption levels prior to a temporary increase in load).



Source: Guidehouse analysis

3. Input Data

The following sections describe the data inputs for the initial CHP analysis and the rate 213 and 313 analysis.

3.1 CHP Analysis

The LUMA LFR team provided Guidehouse with monthly consumption data for 38 Industrial customers that they had identified as potentially being equipped with CHP self-generation.⁹ A summary of the available data for each customer (and an indication as to whether the algorithm described in Section 2.1 identified that customer as being equipped with CHP) is provided in Table 3, below.

Table 3: Customer Data Available for the Study

#	SAID	Start Date	End Date	Number of Observations	Average Monthly Consumption (MWh)	CHP Detected?
1	0138041105	2011-07	2024-02	152	1,298	No
2	0834540182	2014-09	2024-02	114	438	Yes
3	0840871309	2012-07	2024-02	140	3,641	No
4	0915232851	2013-07	2024-02	128	2,139	Yes
5	0971911009	2011-07	2024-02	152	118	No
6	1531941287	2011-07	2024-02	152	325	No
7	1626722191	2011-07	2024-02	152	866	Yes
8	1904231632	2011-07	2024-02	152	774	Yes
9	2045381904	2011-07	2024-02	152	1,562	No*
10	2367212053	2012-04	2024-02	143	1,166	Yes
11	2834102127	2011-07	2024-02	152	1,124	Yes
12	3153261921	2011-07	2024-02	152	126	Yes
13	3367151766	2012-04	2024-02	143	985	Yes
14	3617071358	2012-07	2024-02	140	1,678	Yes
15	3620990315	2011-07	2024-02	152	1,756	Yes
16	3807261678	2011-07	2024-02	152	2,813	No
17	4017071247	2011-07	2024-02	152	1,925	Yes
18	4124231805	2012-07	2024-02	140	731	Yes
19	4130471875	2012-07	2024-02	140	791	Yes
20	4716722098	2012-02	2024-02	145	302	Yes
21	4842841385	2012-04	2024-02	143	2,644	Yes
22	4994064765	2014-09	2024-02	114	2,641	Yes
23	5345157219	2012-07	2024-02	140	24	No**

⁹ The LUMA LFR team also identified three new customers that it believed might be so equipped, but without any data history, displaced load could not be estimated. The three customers in question were SAID: 8393019734, 7612890207, 1759466476.

#	SAID	Start Date	End Date	Number of Observations	Average Monthly Consumption (MWh)	CHP Detected?
24	5346702770	2012-04	2024-02	143	3,138	Yes
25	5383761764	2012-07	2024-02	140	9,541	Yes***
26	5925521746	2012-07	2024-02	140	475	Yes
27	6829691944	2013-05	2024-02	130	6,692	Yes
28	7373761231	2011-07	2024-02	152	1,461	No
29	7648092040	2022-05	2024-02	22	293	No
30	7808781022	2011-07	2024-02	152	1,448	Yes
31	8162141907	2013-11	2024-02	124	3,489	No
32	8261063592	2023-03	2024-02	12	3,905	No
33	8393019734	2022-07	2024-02	20	1,082	Yes
34	8404801413	2012-04	2024-02	143	1,269	Yes
35	8478911612	2012-04	2024-02	143	1,814	Yes
36	9642361025	2011-07	2024-02	152	760	No
37	9714231764	2011-07	2024-02	152	255	Yes
38	9957151728	2012-07	2024-02	140	1,001	No

* LUMA LFR staff have identified for Guidehouse that they have some information to suggest that this customer put some CHP into service in approximately December of 2020. This is certainly consistent with this customer's load, which exhibits a substantial drop (~600 MWh per month) in that month. However, this customer does not demonstrate a *sustained* drop in load, with loads returning to baseline levels in approximately October of 2022. This might possibly be a case of CHP self-generation being used to offset increases in loads associated with changes in production, but Guidehouse does not have the data necessary to check this hypothesis.

** Although the algorithm did detect the presence of CHP for this customer, the Guidehouse team concluded that this detection was erroneous on the basis of a visual inspection of monthly customer loads.

*** Although the algorithm did **not** detect the presence of CHP for this customer, information from the LFR team, supported by a visual inspection of the monthly consumption indicated that customer load were being displaced due to self-generation.

Source: Guidehouse analysis

The average monthly consumption provided in the table above includes average consumption across all months, including (for those with CHP detected) those months in which loads may have been displaced by self-generation.

Table 4 provides a summary of customers with suspected CHP by rate class. Rates 212 and 213 are commercial rate classes, whereas rates 313, 333, and 363 are industrial rate classes.

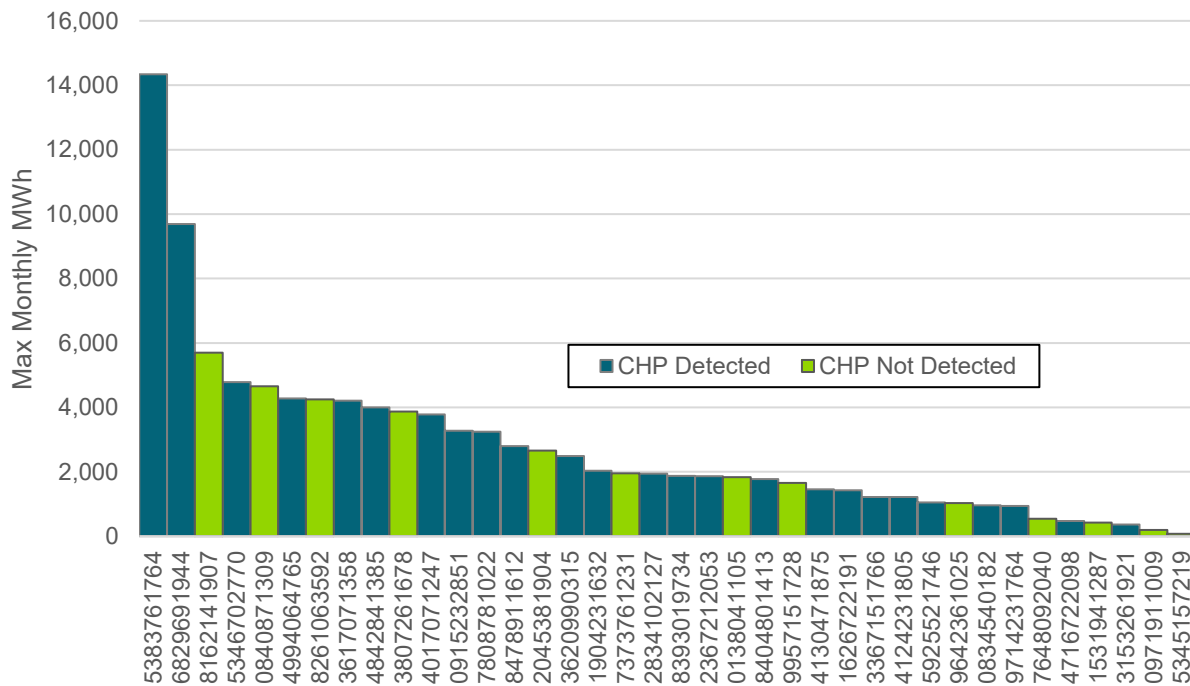
Table 4. Summary of Customers by Rate Class

Rate Class	Number of Customers	Average Consumption	Number with CHP Detected
212	2	75	1
213	7	646	5
313	19	1,213	12
333	1	9,541	1
363*	9	3,248	6

*One SAID, 6829691944, is identified in the data provided by LUMA to Guidehouse as belonging to Rate 393. Guidehouse has confirmed with the LUMA LFR team that in fact this customer should be considered a Rate 363 customer. Rate 393 was cancelled under the new rate structure, but this customer's rate information was not changed in the billing system because the 393 charges were the same as the current Rate 363 charges.

Source: Guidehouse analysis

Figure 13 provides a summary of the relative sizes of the customers for whom CHP was detected. This graph sorts customers from highest single monthly consumption value to lowest and color-codes them according to whether CHP was detected (green) or not (red). It should be noted here that although CHP was detected for SAID 3367151766, it was detected for this customer in February of 2024, the last month of data available for this analysis.

Figure 13. Max Monthly Consumption by CHP Detection Status

Source: Guidehouse analysis

3.2 Rate 213 and 313 Analysis

Guidehouse was also provided with historical billing data for all rate 213 and 313 customers. The LUMA LFR team provided Guidehouse with monthly consumption data for 844 rate 213 and 313 customers covering the period of July 2019 through February 2024.

It should be noted that the data provided for rate 213 and 313 customers was from a different source than the customers with suspected CHP and generally covered a shorter timeframe. Additionally, the data for customers in rates 213 and 313 had data completeness issues not found in the suspected-CHP consumption data. For the algorithm to function correctly, the consumption data must cover a significant time frame and be reasonably complete and accurate. The less input data provided to the algorithm, the less certain the outcome. Additionally, significant amounts of missing data may impact the algorithm's accuracy.

To address this, Guidehouse imposed a set of data completeness criteria on the data, removing any customers who did not meet these requirements. The requirements were as follows:

1. *Sufficient Timeframe.* Customers must have at least 2 years of monthly consumption data.
2. *Reasonably Complete.* Customers' data must be at least 90% complete over the timeframe of available data.

Applying these restrictions reduced the number of 213 and 313 customers from 844 customers to 623 customers. Additionally, to avoid double-counting displaced consumption, customers that were included in the analysis of suspected CHP customers were excluded from this analysis, reducing the total number of customers to 603.

As discussed in the methods section, the consumption data for customers in rates 213 and 313 contained significantly more outliers than the suspected-CHP customer consumption data. To reduce the number of false detections, Guidehouse removed extreme outliers before running the algorithm. The definition of an extreme outlier is any observation which is 4 times higher than the 7-month moving average of consumption in that month. Guidehouse was purposefully conservative in this definition to avoid removing true observations, as Industrial load is highly variable.

The algorithm identified 54 customers with potential CHP or DG installations. Out of these 54 customers, 35 were manually removed from analysis because visual inspection indicated it may be a false positive. A summary of the potential CHP or DG customers, along with the reason for overriding the detection (if applicable) is shown below.

Table 5. Summary of 213, 313 Customers with Potential CHP Installation

#	SA-ID	Rate	Total Estimated Displaced Consumption (MWh)	Detection Date	Override Reason
1	0713250827	313	34,301	2022-06-01	Outlier Issue
2	1247419429	313	8,423	2021-12-01	
3	1446731355	313	623	2022-01-01	Outlier Issue
4	1920007192	313	163	2022-07-01	
5	2610990810	313	548	2020-12-01	
6	4331941265	313	543	2023-09-01	Unclear Trend

#	SA-ID	Rate	Total Estimated Displaced Consumption (MWh)	Detection Date	Override Reason
7	4367151767	313	2,316	2024-02-01	
8	4424398701	313	1,205	2023-04-01	Outlier Issue
9	4648871912	313	18,752	2022-09-01	
10	5451498233	313	68	2023-11-01	Unclear Trend
11	5458441457	313	2,212	2020-07-01	Unclear Trend
12	5903064654	313	27,680	2023-04-01	Outlier Issue
13	6901502472	313	1,135	2020-07-01	Outlier Issue
14	6925581199	313	1,284	2021-06-01	Unclear Trend
15	7114231663	313	145	2023-06-01	
16	7142361939	313	333	2023-05-01	Unclear Trend
17	0105111343	213	5,737	2022-05-01	
18	0137790989	213	578	2021-10-01	Unclear Trend
19	0225751929	213	27,196	2022-06-01	Outlier Issue
20	0239142228	213	620	2020-07-01	Unclear Trend
21	0919142393	213	14,255	2022-02-01	Outlier Issue
22	0919142402	213	1,529	2020-07-01	
23	1053232470	213	8,231	2022-04-01	Outlier Issue
24	1137790103	213	967	2022-02-01	Unclear Trend
25	1298041660	213	1,069	2022-05-01	Unclear Trend
26	1369602757	213	940	2021-01-01	Temporary Reduction
27	1419142437	213	237	2022-03-01	Unclear Trend
28	1495570709	213	1,010	2020-11-01	
29	2627790275	213	2,563	2020-12-01	
30	2801502458	213	3,639	2020-12-01	Unclear Trend
31	2922291882	213	5,339	2021-10-01	
32	3718037118	213	1,070	2023-09-01	Unclear Trend
33	3877696342	213	3,329	2023-04-01	Outlier Issue
34	4632071854	213	3,194	2020-10-01	
35	4672733906	213	588	2024-03-01	Unclear Trend
36	4889862111	213	5,350	2020-07-01	
37	5365701058	213	1,179	2021-10-01	
38	5429142137	213	75	2022-02-01	
39	5517790520	213	-140	2022-11-01	Outlier Issue
40	5720990332	213	817	2020-12-01	
41	5983947678	213	15,922	2023-04-01	Unclear Trend
42	6029142472	213	117	2024-01-01	Unclear Trend

#	SA-ID	Rate	Total Estimated Displaced Consumption (MWh)	Detection Date	Override Reason
43	6078142918	213	1,253	2022-12-01	
44	6094232842	213	2,943	2022-07-01	Outlier Issue
45	6626041327	213	1,081	2022-08-01	Unclear Trend
46	6629142612	213	1,884	2023-08-01	Outlier Issue
47	7117790441	213	2,648	2022-03-01	Unclear Trend
48	8272316150	213	946	2023-12-01	
49	8276989526	213	1,755	2024-03-01	Unclear Trend
50	8538871442	213	1,047	2024-03-01	Outlier Issue
51	8696771701	213	25,094	2022-01-01	Outlier Issue
52	8696771707	213	10,385	2022-07-01	Outlier Issue
53	9363264956	213	120	2023-10-01	Unclear Trend
54	9655020397	213	2,148	2021-06-01	

Source: Guidehouse analysis

4. Results

The presentation of the results of the CHP analysis is split into four sections.

The first three sections present the results of the methods discussed in Section 2 applied to the data discussed in Section 3.

The final section reconciles these findings with the most recent (as of December of calendar year 2023) updates to the Industrial load forecast, specifically the inclusion of the new “Industrial binary” independent variable to control for the substantial decline in Industrial loads observed to begin in approximately the first six months of calendar year 2022.

4.1 Displaced Load (CHP Suspected Customers)

The 24 (out of 38 examined) Industrial customers¹⁰ on average displaced approximately 1.5 GWh per month each in the six months beginning from the detection date identified by Guidehouse’s algorithm.

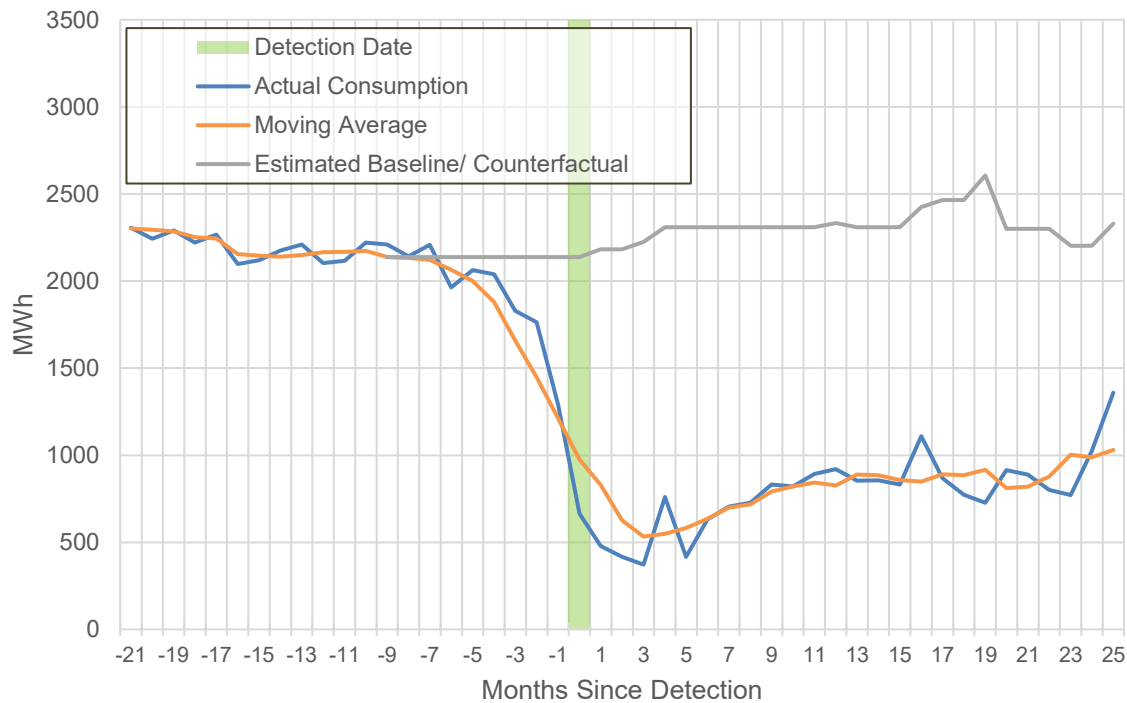
The average monthly observed consumption (blue line), centered 7-month moving average consumption (orange line), and estimated baseline consumption (grey line) across all 24 customers for whom CHP was detected are all illustrated in Figure 14, below.

This diagram was developed by aligning each customer’s time series on the basis of the month in which CHP was detected for each one, instead of calendar dates. So if month “0” is the month of CHP detection, month “-1” is one month prior to the month of detection, month “1” is one month after the month of detection, month “2” is two months after the month of detection, etc. So, for example, for

- SAID 0834540182 the month of detection is February, 2022, so
 - Month “0” is February, 2022
 - Month “1” is March, 2022
 - Month “2” is April, 2022
 - Etc.
- SAID 1626722191 the month of detection is April, 2021, so
 - Month “0” is April 2021
 - Month “1” is May 2021
 - Month “2” is June 2021
 - Etc.

The mechanics of this process can be observed by following the formulas in the “OUT-02a Average Plot” tab of the workbook that accompanies this report.

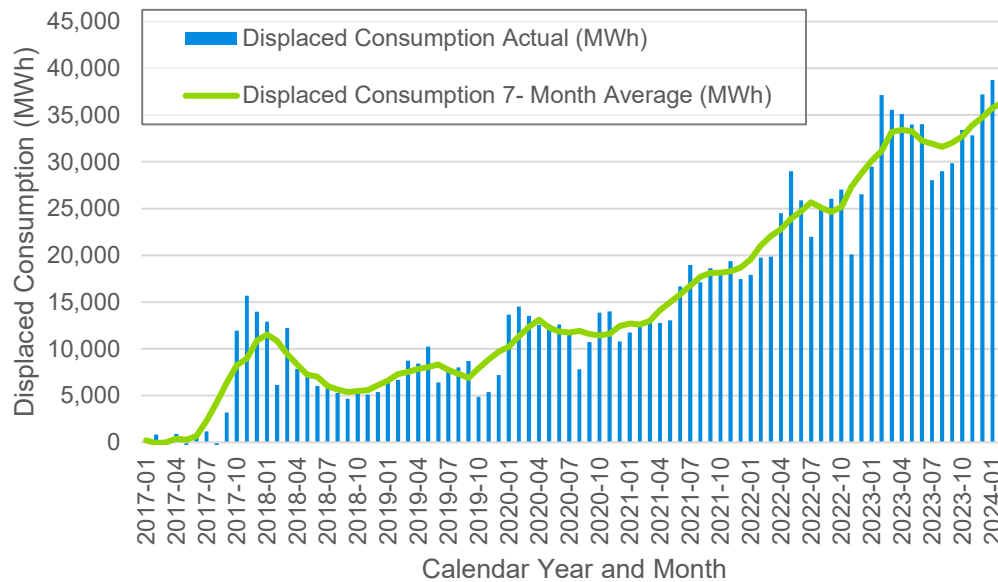
¹⁰ CHP was detected for 25 customers, but for one of these, SAID 3367151766, CHP was detected only in the final month of the available data, so the magnitude of the displaced load remains for the moment uncertain.

Figure 14. Average CHP Impacts Across All Detected Installations

Source: Guidehouse analysis

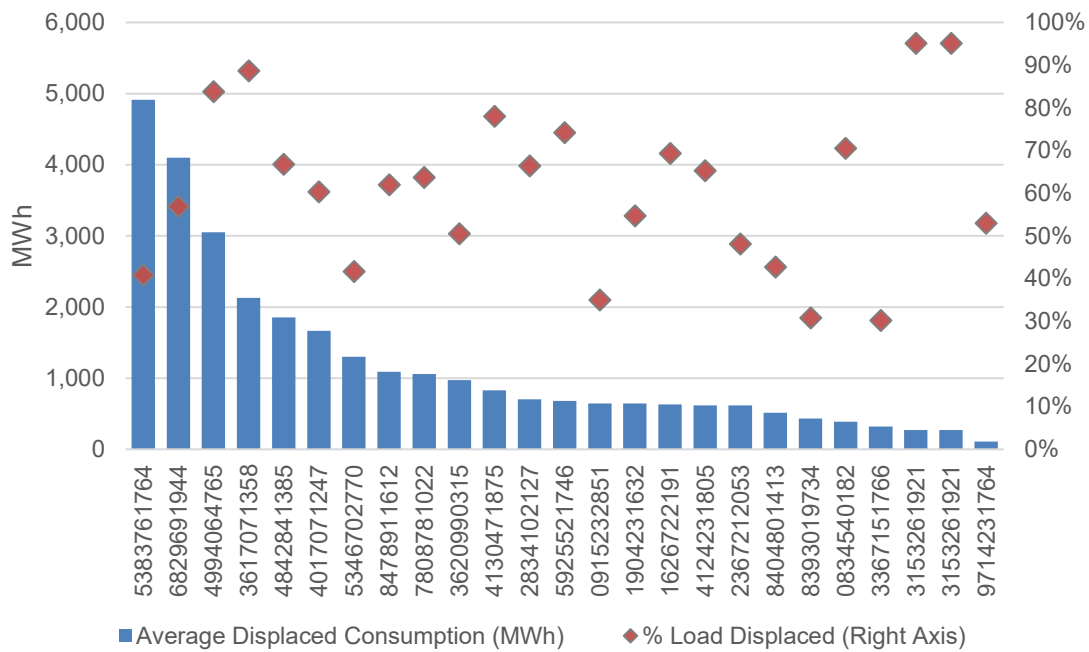
This is an average across all the included customers, based on the detection date of CHP. By using the detection date rather than the calendar date, values can be averaged across customers, and the robustness of the analysis demonstrated by the intuitive outcome plotted above.

In aggregate, there appears to be as much as 37 GWh of consumption per month displaced by CHP in the Industrial class, as may be seen in Figure 15, below.

Figure 15. Aggregate CHP-Displaced Monthly Consumption

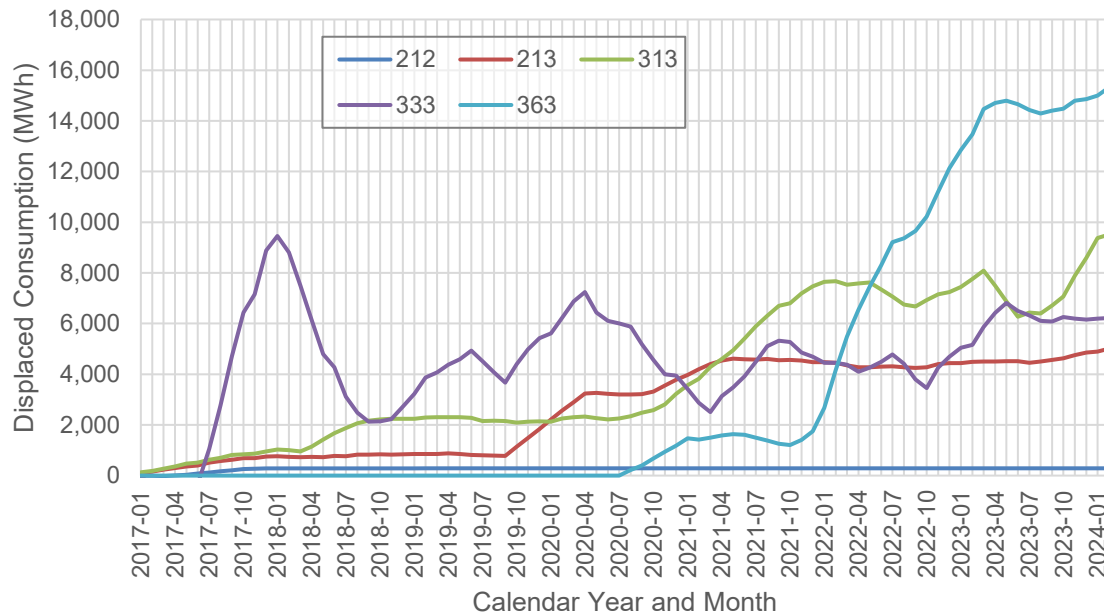
Source: Guidehouse analysis

The diversity of the average monthly magnitude of displaced consumption and of the share of baseline consumption that is displaced can be seen in Figure 16 below, which arranges the average displaced consumption values from largest to smallest (vertical columns), and also provides the displaced consumption as a percentage of the baseline (equivalent to the estimated percent reduction in load) as orange diamonds, read off the right-hand axis.

Figure 16. Displaced Consumption per Customer, Sorted

Source: Guidehouse analysis

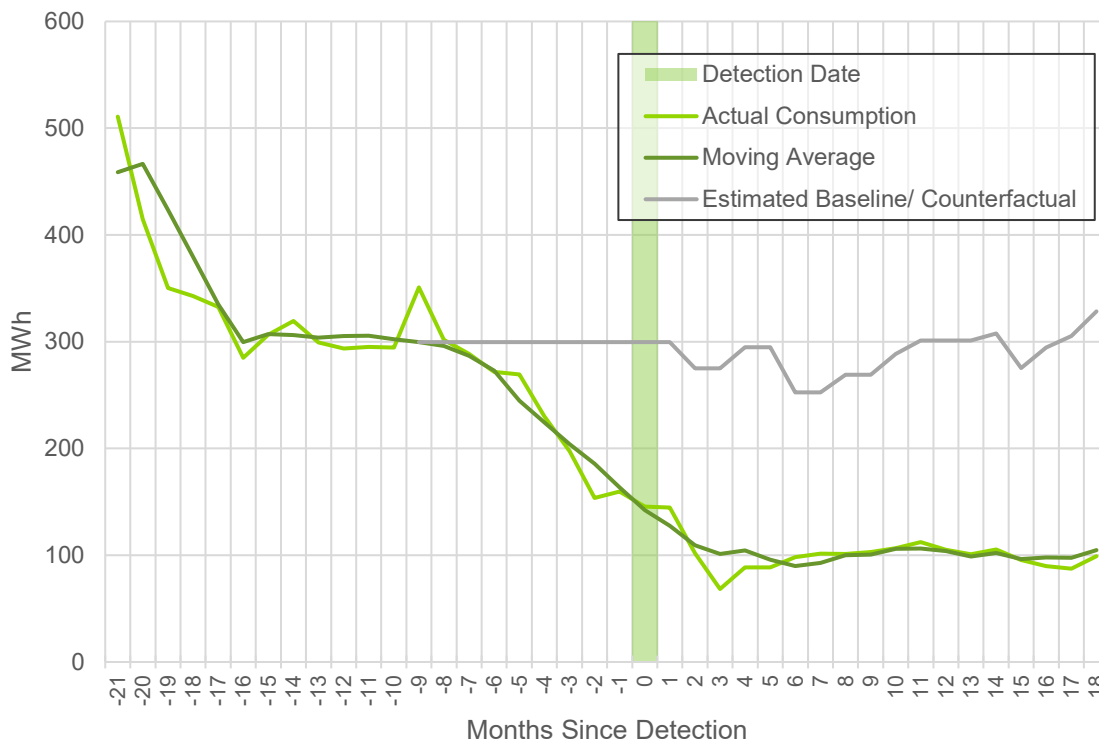
The total displaced load by rate class is provided in Figure 17. Consistent with the findings of the Improvement 7 use per customer (UPC) analysis, rate class 363 (light blue line) demonstrates a significant increase in the volume of displaced loads beginning at the start of calendar year 2022.

Figure 17. CHP-Displaced Load by Rate Class

Source: Guidehouse analysis

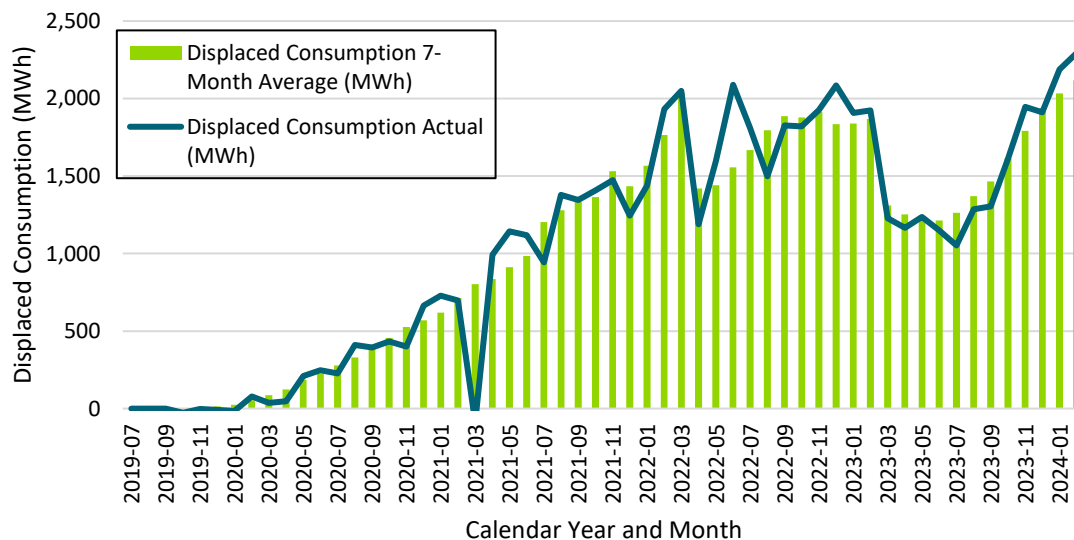
4.2 Displaced Load (213 and 313 Customers)

The 19 rate 213 and 313 customers on average displaced approximately 0.40 GWh per month, each in the six months beginning from the detection date identified by Guidehouse's algorithm, and less than a third of the average for CHP-suspected customers. The average displaced consumption by customer for rate 213 and 313 customers is shown in Figure 18 (same graph as Figure 14 for CHP-suspected customers).

Figure 18. Average 213/313 Impacts Across All Detected Installations

Source: Guidehouse analysis

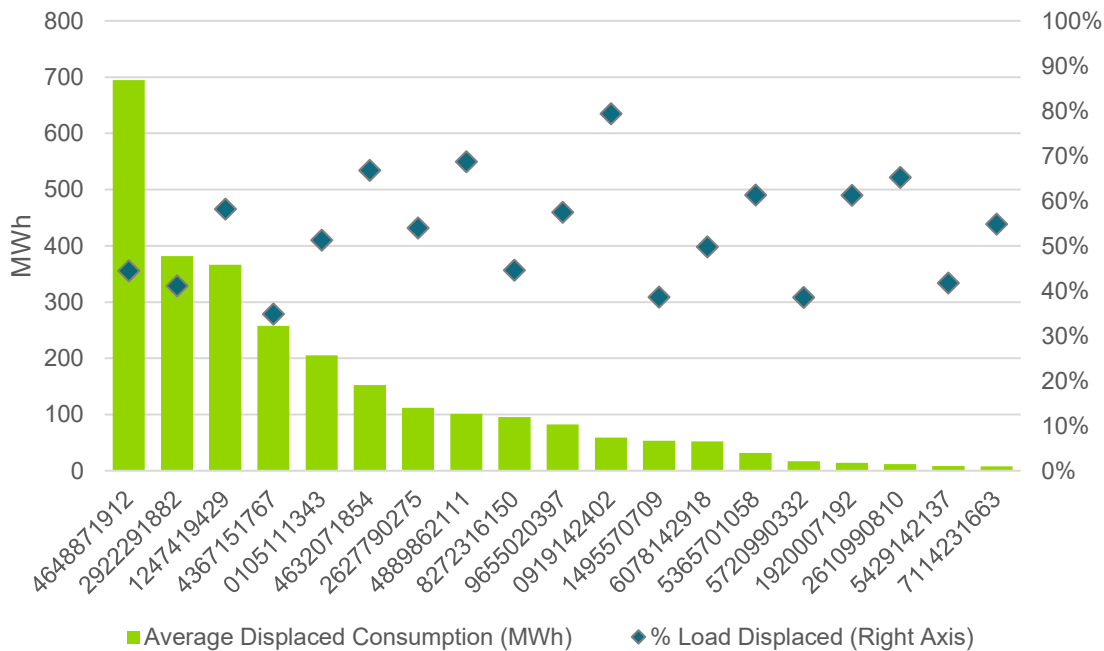
In aggregate, there appears to be as much as 2 GWh of consumption per month displaced by CHP and DG in the 213 and 313 rate classes (in addition to the displaced consumption from suspected CHP customers), as may be seen in Figure 19, below.

Figure 19. Aggregate 213/313-Displaced Monthly Consumption

Source: Guidehouse analysis

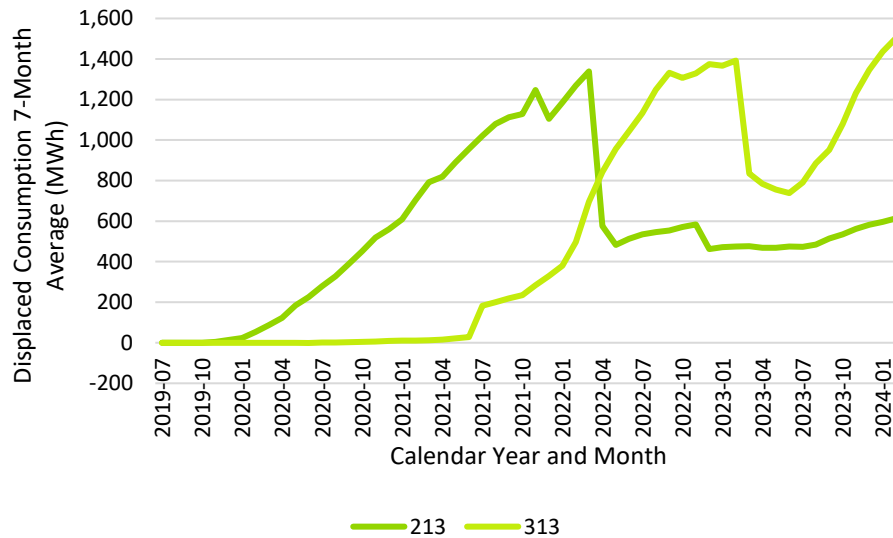
Similar to the CHP-suspected customers, the diversity of the average monthly magnitude of displaced consumption and of the share of baseline consumption that is displaced can be seen in Figure 20 below, which arranges the average displaced consumption values from largest to smallest (vertical columns), and also provides the displaced consumption as a percentage of the baseline (equivalent to the estimated percent reduction in load) as orange diamonds, read off the right-hand axis.

Figure 20. Displaced Consumption per 213/313 Customer, Sorted



Source: Guidehouse analysis

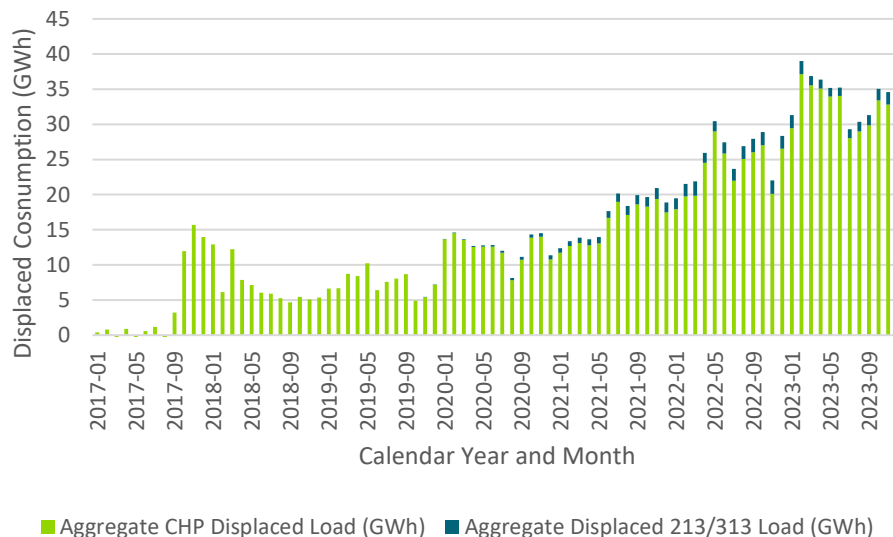
The total displaced load by rate class is provided in Figure 20. There were a number of customers' whose data only covered the period of July 2019 through early 2022, and a similar number of customers whose data started in early 2022 and covered through early 2024. Customers with detection dates whose data only covered through early 2022 are likely the cause of the steep decrease in rate 213 customers in April 2022. Guidehouse suspects these customers switched SA-IDs in early 2022, which would explain why there are complementary sets of incomplete data.

Figure 21. 213/313 Displaced Load by Rate Class

Source: Guidehouse analysis

4.3 Total Displaced Load

The 43 customers with identified CHP displaced an average of 34 GWh per month in calendar year 2023. Figure 22, which shows the total displaced load by month by analysis, demonstrates that the 213 and 313 customers represent a relatively small amount of this total.

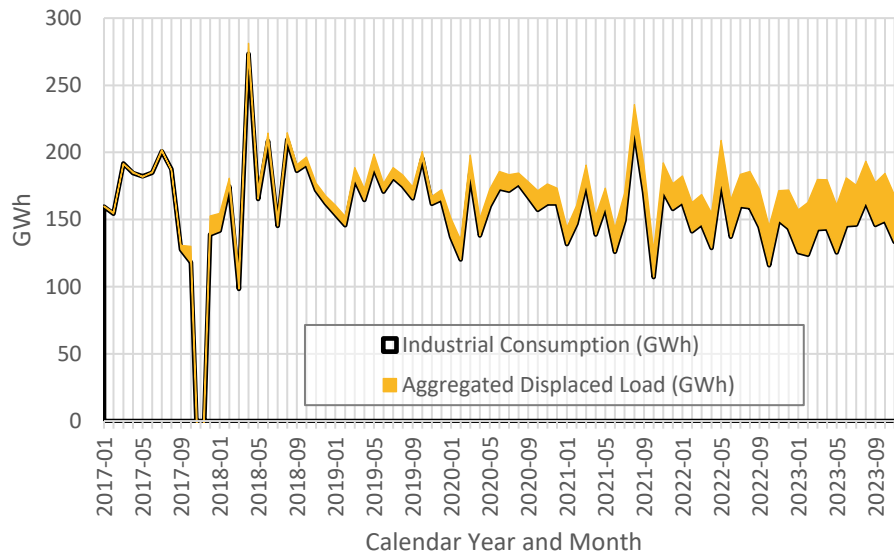
Figure 22. Aggregated Displaced Monthly Consumption

Source: Guidehouse analysis

Finally, the aggregate estimated displaced consumption across all analyzed customers can be combined with the raw (un-remediated) Industrial class consumption data to provide a visual illustration of what loads might have been, absent the adoption of CHP by the customers

included in this analysis. This is shown in Figure 23, which shows aggregate billed Industrial consumption (black line) and volume of CHP-displaced load (orange area).

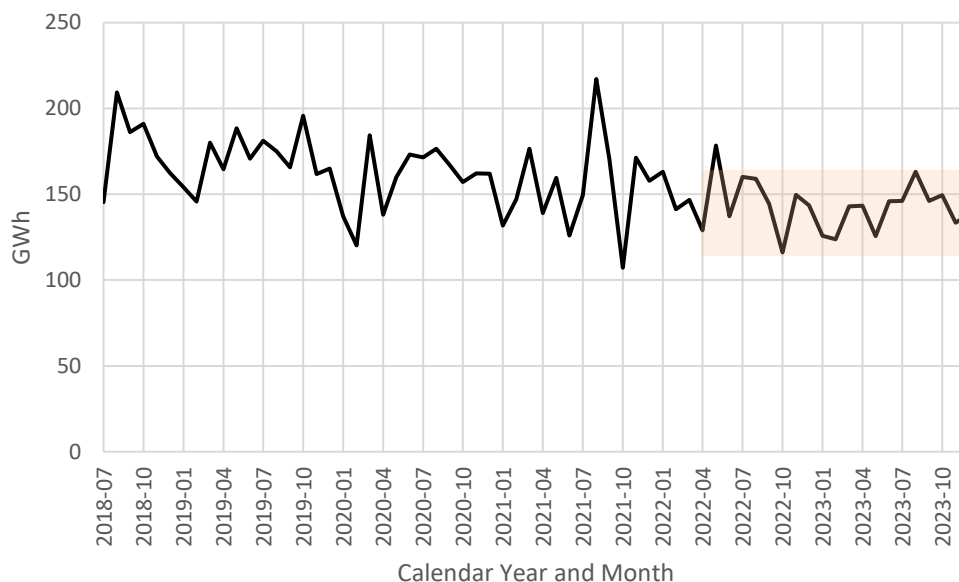
Figure 23. Displaced Load and Billed Consumption



Source: Guidehouse analysis

4.4 Fiscal Plan Forecast Reconciliation

As part of the December 2023 update to the long-term load forecast model initially developed as part of Guidehouse's Improvement 2, Guidehouse added a new term to the regression model used for the Industrial class. This new variable is a binary variable intended to capture the step-change reduction in Industrial consumption in the early part of calendar year 2022. This step-change in total Industrial monthly energy consumption is highlighted in Figure 24 below.

Figure 24. Monthly Industrial Consumption (GWh)

Source: Guidehouse analysis

The estimated parameter associated with this variable is approximately -24.4.¹¹ This indicates that, conditional on the macro-economic and seasonality effects controlled for by the other model variables, monthly industrial consumption is on average 24.4 GWh lower in the estimation period from March of calendar year 2022 through November of calendar year 2023 than in the period from July of calendar year 2010 through February of calendar year 2022.

Though this drop was only identified after work on Improvement 5 had begun, assessing to what degree this drop in Industrial consumption may be attributable to CHP (as opposed to a simple continuation of the years-long trend of Industrial load decay) was an important goal of this analysis.

The CHP analysis presented in this report detected CHP-displaced load in 25 of the 38 customers identified by the LUMA LFR team as potentially possessing CHP. Displaced load (as shown in Figure 15, above) was relatively steady at an average of approximately 8 GWh per month for the period from October of calendar year 2017 until the start of calendar year 2020. After this point displaced load increased through calendar year 2023 in which it reached approximately 39 GWh per month. This includes an increase of approximately 17 GWh per month since March of 2022 (i.e., since the industrial binary has been applied).

¹¹ This is the estimated parameter value based on the macro-economic inputs that were available up until March 6, 2024, when updated inputs were shared with Guidehouse. The updated GNP values – provided to LUMA by the FOMB – included upward revisions to both historical and forecast values. Guidehouse re-estimated the industrial model at this stage, and the resulting estimate of the industrial binary was -31.4. This larger negative value is estimated by the model to compensate for the increase in historical GNP and continue to allow it accurately predict industrial consumption in-sample. Put another way: based on history, a higher GNP would predict higher consumption. Because consumption decreases, the industrial binary needs to increase to align the backward-facing model predictions with observed consumption.

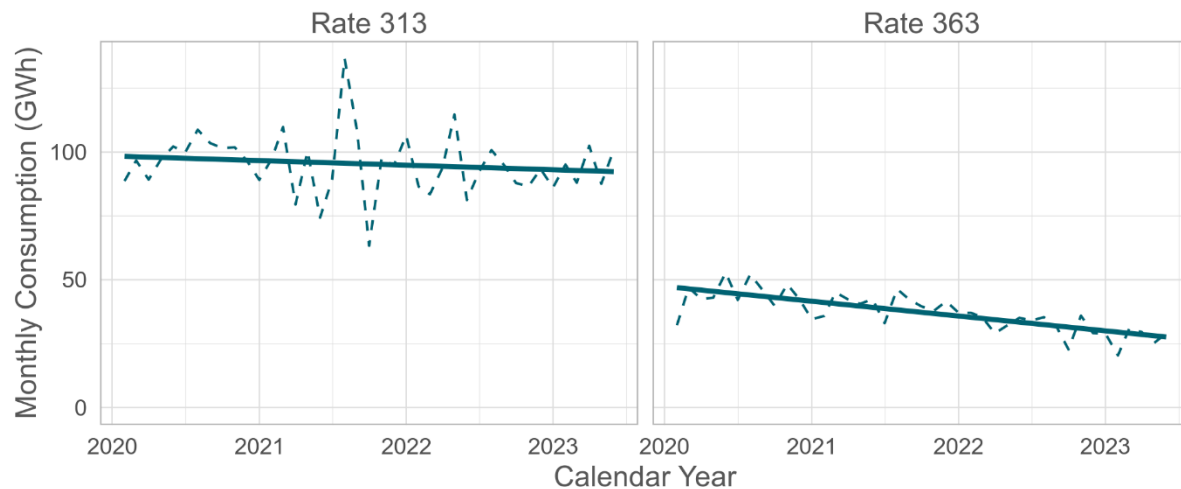
From July of 2023 through February of 2024 the approximate percentage of displaced load contributed by each rate class was¹²:

- 1% from rate class 212 (Commercial);
- 15% from rate class 213 (Commercial);
- 25% from rate class 313 (Industrial);
- 18% from rate class 333 (Industrial); and
- 42% from rate class 363 (Industrial)

To reconcile the CHP analysis results with the industrial dummy coefficient, Guidehouse reviewed total consumption on industrial rates including CHP and non-CHP customers. Guidehouse found that since CY 2020, industrial consumption has declined on two rates, 313 and 363, whereas industrial consumption on other rates remained relatively steady over that period.

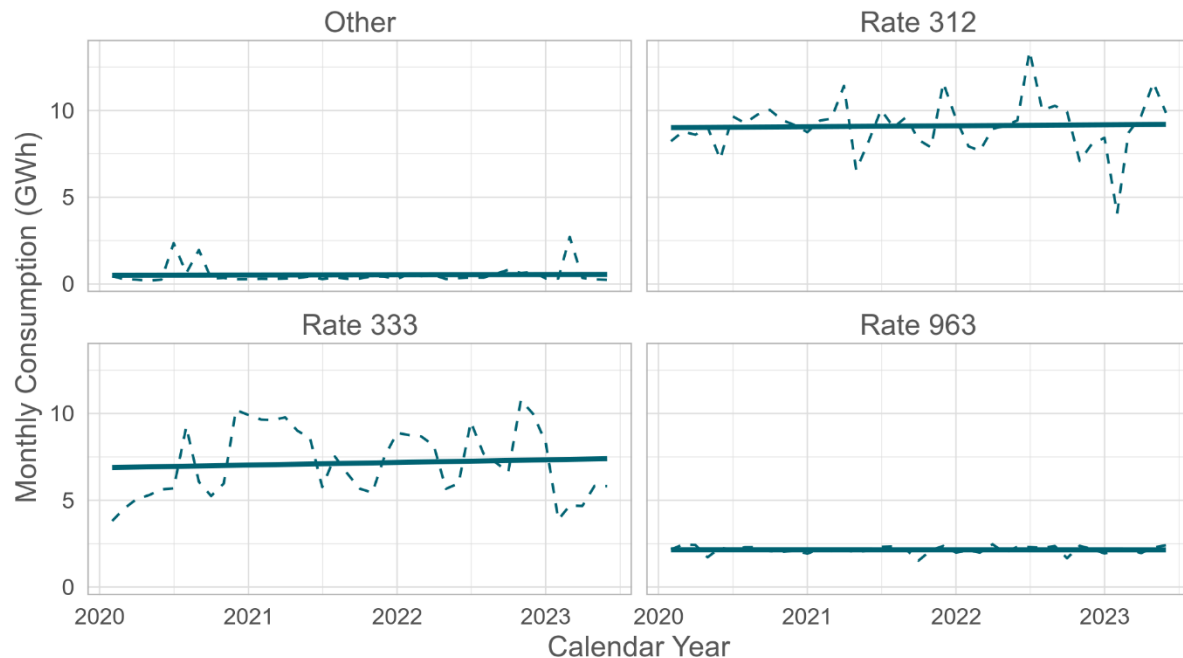
Figure 25 and Figure 26 depict monthly sales volume and a linear trend overlay for the rates with largest and with smaller volumes, respectively.

Figure 25. Industrial Rate Total Consumption (Large Volume Rates)



Source: Guidehouse analysis

¹² The percentage of CHP displacement across the rate classes sums to greater than 100% due to rounding.

Figure 26. Industrial Rate Total Consumption (Smaller Volume Rates)

Source: Guidehouse analysis

Separately, Guidehouse reviewed industrial customer counts on each rate and found that numbers were stable for all rates except 313, which declined only slightly between CY 2020 and 2023.

Comparison of the CHP analysis results against the trends in total consumption by rate produced the following findings:

- For rate 313, CHP likely a very high proportion of the decline in consumption between 2020 and 2023.
 - The CHP analysis detected growth in displaced consumption (compared to before 2020) with displaced loads in the post-2020 period being 1 GWh higher than in the 2020 and earlier period.
 - Total displaced load for this rate class varied considerably in this period; fluctuating between 4 and nearly 9 GWh per month. Displaced load in 2019 was an average of 2 GWh per month.
 - This approximately aligns with the magnitude of the decline in average monthly consumption for all customers on 313 between 2020 and 2023 (approximately 4.5 GWh)
- Rate 363 customers exhibited a decline of approximately 17 GWh per month between the start of 2020 and May of calendar year 2023.
 - In the same period, the estimated total incremental displaced load from rate 363 customers is approximately 15 GWh .
 - The difference of approximately 2 GWh between may be explained by reduced production among customers outside of the those included in the CHP analysis.

The LUMA LFR team identified that one customer on rate 363 reduced their cement production, accounting for a load reduction of approximately 4 GWh per month. This customer was not included in the Improvement 5 CHP analysis because it was not suspected to have CHP at the time of the analysis.

LUMA Ex. 72.04 (Improvement 5 Report - Solar PV 2024-04-29)

Improvement 5: Historic Displaced Load – Solar PV Estimated Displaced Consumption Distributed Generation Net Energy Metering Customers

Prepared for:



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2024-04-19

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Table of Contents

Executive Summary	4
1. Introduction	8
1.1 Improvement 5 Goals	9
1.2 LUMA Approvals	10
1.3 Structure of this Report.....	11
2. Methods	12
3. Input Data.....	17
3.1 Improvement 5 Customer Billing Data	17
3.1.1 Improvement 5 Billing Data Preparation	18
3.1.2 Installed PV Capacity Over Time	19
3.2 Hourly Historical Weather Data	22
4. Results	27
4.1 Estimated Solar Production	27
4.2 Estimated Displaced Load	32
5. Conclusions & Recommendations	35
5.1 Load Forecasting Recommendations	36
5.2 Data Collection Recommendations.....	38

List of Tables

Table 1. Average Displaced Consumption per Customer, kWh Per Month	5
Table 3: Parameters of the engineering approach.....	15
Table 4: Data Received by Guidehouse for Improvement 5	17
Table 5: Known Parameters Values	25
Table 6: Calculated Parameters Values	25
Table 7. Count of Customers in Data as of December of Each Calendar Year	29
Table 8: Average Solar Production, kWh Per Customer, per Year	30
Table 9: Average Capacity Factor per Month	32
Table 10. Average Solar PV Onsite and Displaced Consumption per Customer, ...	35

List of Figures

Figure 1. Improvement 5 Approval Matrix.....	4
Figure 20. Observed Consumption and Estimated Displaced Load, ...	6
Figure 1. Improvement 5 Approval Matrix.....	10
Figure 2: Installed Capacity by Month	19
Figure 3: Average Installed Capacity per Customer (all rate class) by Month	19
Figure 4: Residential System Size by Month	20
Figure 5: Commercial System Size by Month.....	21

Figure 6: Industrial System Size by Month	21
Figure 7: Distribution of Installed Capacity by Class.....	22
Figure 8: Monthly Global Horizontal Irradiance.....	23
Figure 9: Monthly Plane of Array Irradiance	24
Figure 10: Plane of Array Irradiance Per Hour (Summer and Winter).....	25
Figure 11: Estimated Solar PV Production by Month per Customer - Residential.....	28
Figure 12: Estimated Solar PV Production by Month per Customer - Commercial	28
Figure 13: Estimated Solar PV Production by Month per Customer - Industrial	28
Figure 14: Average Solar PV Production Per Hour (Summer and Winter) in 2022 (Calendar Year).....	29
Figure 15: Hourly Impact of Distributed Solar PV in 2022 (Calendar Year).....	31
Figure 16: Guidehouse's Approach vs. Fixed Capacity Factor	31
Figure 17: Monthly Residential Displaced Consumption and PV Generation Per Customer	33
Figure 18: Monthly Commercial Onsite Consumption and PV Generation Per Customer.....	33
Figure 19: Monthly Industrial Onsite Consumption and PV Generation Per Customer	34
Figure 20: Observed Consumption and Estimated Displaced Load,.....	36

This report is accompanied by an Excel workbook that includes the data used in the tables and figures presented below.

This workbook is called: *"Improvement 5 Solar Report 2024-04-29.xlsx"*

Important Note:

Guidehouse has developed the analysis above based on a number of different data sets provided by LUMA over a period from early 2023 to early 2024.

Guidehouse understands that over this time LUMA's internal processes and database queries have been evolving and improving, thus some of the aggregate counts, capacity measurements, or consumption volumes of customer groups discussed in this report may not reflect the latest data available to LUMA.

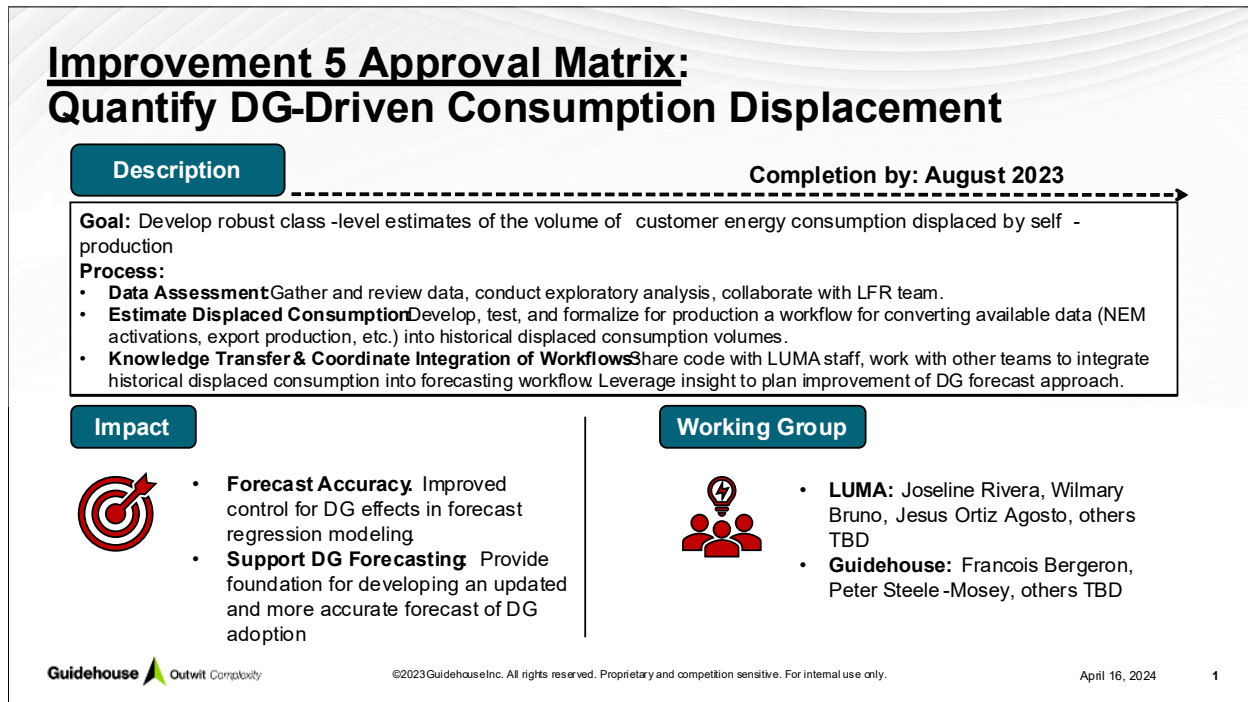
The core analysis covered by this report, however, is based principally on individual customer billing data. In the case of solar PV net energy metering customers ("DG customers") while this is not a complete census of all such customers, the data provided by LUMA cover a super-majority of these customers.

Guidehouse is confident therefore in the robustness of its analysis, in the representativeness of its results, and in the accuracy of its conclusions.

Executive Summary

At the April 20 meeting of LUMA's Load Forecast Governance Committee, Guidehouse presented a request for approval to develop a detailed workplan and budget for Improvement 5, a project to estimate the historic loads displaced by net-metered solar distributed generation (DG¹) and Industrial installations of combined heat and power (CHP) generation. The approval matrix presented at that meeting is shown in Figure 1, below.

Figure 1. Improvement 5 Approval Matrix



Guidehouse submitted a formal workplan and budget on 2023-04-26. This was approved via email by the LUMA Load Forecast and Research (LFR) team lead on 2023-05-04.

The Improvement 5 analysis is divided into two parts: estimating load displaced by DG and estimating load displaced by CHP. This report provides Guidehouse's final reporting for the analysis of consumption displaced by the DG customers² enrolled in LUMA's NEM program.

The purpose of this analysis is to assist the Load Forecasting and Research (LFR) team to understand the impact of the growth of customer self-generation on historic consumption. This outcome supports the path of continuous improvement in forecast methods mapped out in the Regulatory Long-Term Load Forecast Review report³ (the "Review report") and will help the LFR

¹ Although "distributed generation" can refer to many types of electricity generation equipment and installations, for the purposes of this report, unless otherwise explicitly noted, "DG" should be understood to refer only to solar generation enrolled in LUMA's net energy metering (NEM) program.

² Consistent with usage by LUMA staff, unless otherwise explicitly noted, "DG" in this report is used to identify only those customers with solar PV installations participating in LUMA's net energy metering program, and should not be understood to include customers with CHP.

³ Guidehouse, prepared for LUMA, *Regulatory Long-Term Load Forecast Review: Current State Assessment & Future Methods Recommendations*, June 2022

make forecast modeling improvements to deliver a more accurate long-term load forecast and annual Fiscal Plan.

Guidehouse has previously presented LUMA⁴ with a draft of its report estimating the historic volumes of large customer load displaced by CHP. This report is the companion to that, providing an Guidehouse's estimate of consumption displaced by solar PV customers enrolled in LUMA's net energy metering (NEM) program and subject to the **NM Rate rider**. This group is referred to in the reporting below as "DG customers".

Solar displaced consumption estimates are derived using an engineering analysis applied to observed individual customer-installed nameplate capacity values. Estimated solar production is compared with observed customer exports to the grid. The difference between these values is estimated displaced consumption.

The average monthly displaced consumption per customer, by class and calendar year is presented in Table 1, below.

Table 1. Average Displaced Consumption per Customer, kWh Per Month

Calendar Year	Residential	Commercial	Industrial
2015	293	3,710	28,334
2016	232	3,591	28,478
2017	194	4,479	42,259
2018	180	4,166	49,341
2019	236	4,489	49,840
2020	288	4,059	52,212
2021	290	3,120	73,415
2022	293	3,646	61,396
2023	278	2,915	58,715

These values can be applied to the total count of registered DG customers to obtain an estimate of the aggregate volume of displaced consumption in each month of 2023, and for the year as a whole.

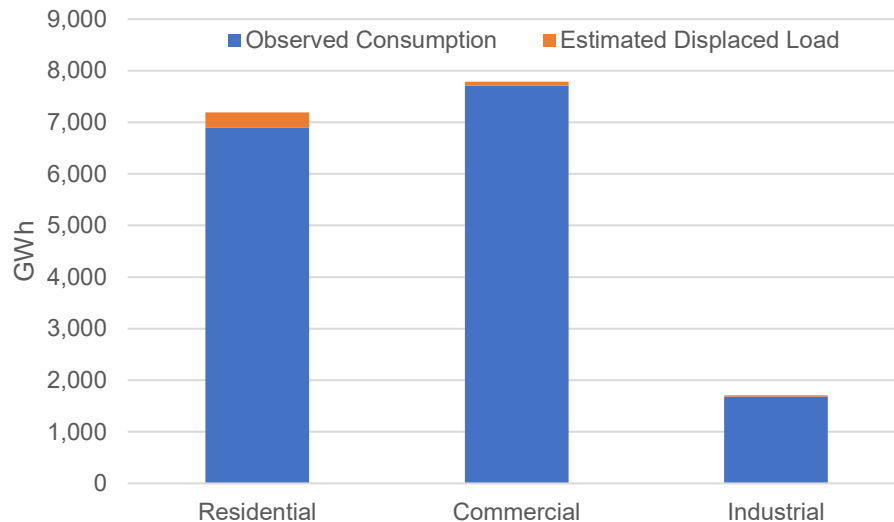
Total class-level observed consumption (blue) and estimated displaced load (orange) are presented in Figure 2.⁵

<https://energia.pr.gov/wp-content/uploads/sites/7/2022/07/Motion-Submitting-Regulatory-Long-Term-Load-Forecast-Review-NEPR-MI-2021-0001.pdf>

⁴ Second draft reflecting LUMA feedback of the report "Improvement 5: Historic Displaced Load – Combined Heat and Power" (filename "Improvement 5 CHP Report CLEAN 2024-04-17.docx" submitted 2024-04-17 by email.

⁵ The values and calculations for this graph may be found in the tab "OUT-10-DG Compared to Load" of the workbook that accompanies this report.

Figure 2. Observed Consumption and Estimated Displaced Load, Calendar Year 2023, by Class



Although the total volume of displaced consumption is relatively small at present (residential displaced consumption is approximately 4% of total residential consumption), the rapid growth of the number of DG customers suggests that the share of residential consumption that is self-supplied is likely to continue to grow rapidly for the near future.

This estimate of displaced consumption does not control for any solar “rebound” effect. Rebound is a documented outcome in many jurisdictions that offer customers net-metering. The rebound effect occurs when the availability of very low-cost self-generation results in customers equipped with that generation increasing their consumption. Guidehouse continues to work with LUMA to identify to what degree this effect is impacting LUMA customers, but has at present insufficient data to explicitly control for this effect as part of this analysis.

Based on the outcomes of this analysis, Guidehouse has proposed two sets of recommendations, the first set related directly to the consideration of DG customer displaced consumption in the load forecast, and the second set related to data collection considerations for DG customers.

A summary of these recommendations is provided below. Additional detail for all recommendations can be found in Section 5, below.

Load Forecasting Recommendations

Guidehouse’s findings suggest three important recommendations related directly to the Fiscal Plan load forecast for consideration by the LFR team:

- first, that the LFR team should consider either using displaced consumption to adjust historical loads prior to regression estimation or
- second, consider adopting a use-per-customer times customer count forecast approach, distinguishing between DG and non-DG customers; and,

- third, that the LFR team should continue to use the available data to understand DG customer characteristics to help to improve the accuracy of the LFR team's load modifier forecast.

Data Collection Recommendations

Access to complete and accurate data remains the LUMA LFR team's greatest challenge.

Guidehouse recommends that the LFR team continue to work with the IT team to establish an internally consistent robust database of DG customers' consumption (both before and after NEM program enrollment) and cross-sectional characteristics. Guidehouse further recommends that the LFR team work with other teams within LUMA to expand the types of data collected from these customers, and so to better support the load modifier forecast.

1. Introduction

LUMA is currently experiencing unprecedented growth in the penetration of self-generation in its service territory.

LUMA offers a net metering program with very generous terms, effectively allowing customers to use the grid as lossless storage, such that they are charged only for withdrawals from the grid in excess of their exports, and that excess credits can be carried forward to their subsequent bill.⁶ Combined with grid reliability challenges, this value proposition appears to have motivated significant growth in the acquisition of rooftop solar photo voltaics (PV) and participation in LUMA's net energy metering (NEM) program.

As of the end of December 2023⁷, these "DG customers"⁸ accounted for approximately 5% of Industrial customers and 8% of Residential customers. Though there has been little growth in Industrial DG adoption, the number of registered Residential DG customers has between July of calendar year⁹ 2022 and the end of December of calendar year 2023 grown by average of 4% - *per month*.¹⁰ There were twice as many registered Residential DG customers in December 2023 as there were in July 2022.

Self-generation outside the NEM program by large non-residential customers cannot be tracked as accurately NEM participation, and although for this reason the magnitude of growth in combined heat and power (CHP) cogeneration facilities is much less certain, there is evidence to suggest that there has been significant growth in its use in the last 3 – 5 years. When the Guidehouse load forecasting team updated the LUMA long-term load forecast model for the Industrial class in August of calendar year 2023 it needed to include a new binary variable to account for a significant step-change in Industrial consumption that appeared to originate in the early half of calendar 2022.

The LUMA Load Forecasting and Research (LFR) team has communicated to Guidehouse its suspicion that most of this drop may be attributable to the acquisition of CHP by a small group of large power consumers.

⁶ See sections 5.3 – 5.5 of

LUMA, *Agreement to Interconnect Generators with Capacity of 25 kW or less with the Electric Distribution System of the Electric Power Authority and Participate in Net Metering Programs – Terms and Conditions*, undated, accessed in February 2024

<https://lumapr.com/wp-content/uploads/2023/11/Interconnection-and-Net-Metering-Agreement-Individuals.pdf>

⁷ Per data provided by LUMA staff to Guidehouse 2024-01-29.

⁸ "DG" stands for distributed generation. Although "distributed generation" can refer to many types of electricity generation equipment and installations, for the purposes of this report, unless otherwise explicitly noted, "DG" should be understood to refer only to solar generation enrolled in LUMA's NEM program. This is a convention used internally by the LUMA LFR team and is adopted here to ensure the terminology of this report is consistent with internal conventions.

⁹ For clarity, when referring to years, Guidehouse has taken care to specify whether a year is a calendar year or a fiscal year (LUMA's fiscal year runs from July through June). If the convention is not explicitly specified, readers should assume a calendar year.

¹⁰ Commercial customer growth over the same period has also been very strong at approximately 4% per month, though Commercial DG customers only represent approximately 2% of all Commercial customers, as of the end of December of calendar year 2023.

1.1 Improvement 5 Goals

LUMA's load forecasting does not, at present, apply any historical controls in its estimation of the key relationships between monthly consumption and its drivers.

The LUMA LFR team, assisted by Guidehouse, has been focused on putting in place a new set of workflows to allow it to move away from using the regression outputs previously estimated in 2018 and, lacking precise data on DG and CHP output has not prioritized addressing these factors in its analysis of historical data. This means that the effects of DG and CHP are attributed by the regression analysis to other covariates that are approximately correlated with the uptake of these forms of generation. This is referred to in econometrics as “omitted variable bias”.

Where changes to consumption due to DG and CHP are relatively small, this is not a matter of great concern.

As the adoption of DG and CHP grow, however, failing to control for them historically may bias the forecast. The LUMA LFR team has mitigated against such effects to date in its application of “Load Modifiers” to the base (unadjusted) forecast. These modifiers (estimates of the impacts of future DG and CHP, among other effects) apply the *incremental* impacts of new load modifiers, and so avoid concerns of double-counting.

As the impacts of these historic load modifiers grow, however, the current approach may need to be revised to more explicitly control for historical DG and CHP and to appropriately carry forward the effects of forecast adoption.

Accordingly, **the primary goal of Improvement 5 (and this report) is to develop a monthly estimate of the historical consumption displaced by DG, by class.** Historical consumption displaced by the CHP amongst LUMA's larger customers is addressed in a separate report.

“Displaced load” or “displaced consumption” takes on a very specific definition in this work; displaced consumption is the reduction in consumption attributable to DG, compared to an estimated baseline in which no DG was deployed. This is not necessarily the same as the amount of electricity that DG customers self-supply, though for the purposes of this report these are assumed to be the same.

When customers enroll in the NEM program and begin to self-supply, they substantially reduce their variable cost of electricity consumption. Economic theory that when the price of a “normal” good falls, its consumption should increase, suggesting that there should be an expectation of some solar “rebound” effect with residential DG customers increasing their electricity consumption once equipped with self-generation. The solar rebound effect has previously been documented in the academic literature by Beppler et al (2021)¹¹, Nguyen et al (2024)¹², Aydin et

¹¹ Beppler, R.; Matisoff, D.; and M. Oliver, Electricity Consumption Changes Following Solar Adoption: Testing for a Solar Rebound, Economic Inquiry, July 2021

https://www.researchgate.net/publication/353582051_Electricity_Consumption_Changes_Following_Solar_Adoption_Testing_for_a_Solar_Rebound

¹² Nguyen, L. T.; Rathasiri, S.; Wagner, L.; Nguyen, D.T.; and Rohde, N. *Solar Rebound Effects: Short and Long Term Dynamics*, Renewable Energy 223 (2024)

<https://www.sciencedirect.com/science/article/pii/S0960148124001162>

al (2023)¹³ and others. Beppler et al estimated that solar adoption amongst the approximately 8,000 PJM residential customers included in the study led to these customers increasing their consumption by approximately 16%, equivalent to approximately 28% of production.¹⁴

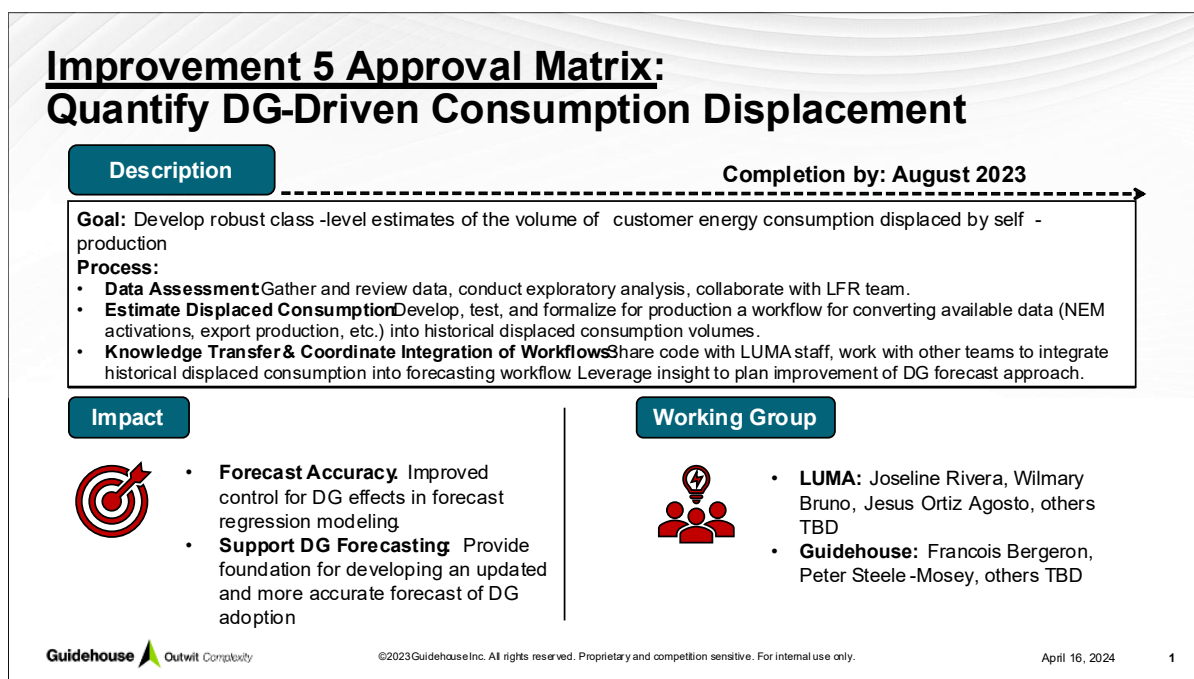
Guidehouse continues to work with LUMA to develop a better understanding of the degree to which residential DG customers may exhibit a rebound effect, but does not at present have sufficient data to explicitly control for this effect in this report.

This means therefore that implicitly the results reported in this document assume no rebound effect.

1.2 LUMA Approvals

At the April 20 meeting of LUMA's Load Forecast Governance Committee, Guidehouse presented a request for approval to develop a detailed workplan and budget for Improvement 5, a project to estimate the historic loads displaced by net-metered solar distributed generation (DG) and Industrial installations of CHP generation. The approval matrix presented at that meeting is shown in Figure 1, below.

Figure 3. Improvement 5 Approval Matrix



Guidehouse submitted a formal workplan and budget on 2023-04-26. This was approved via email by the LUMA Load Forecast and Research (LFR) team lead on 2023-05-04.

¹³ Aydin, E.; Brounen, D.; and A. Ergun, *The Rebound Effect of Solar Panel Adoption: Evidence from Dutch Households*, Energy Economics Volume 120, April 2023 106645

<https://doi.org/10.1016/j.eneco.2023.106645>

¹⁴ The paper's authors note that they were "*deliberately conservative in our imputation of household PV generation*", implying that their estimated rebound is understated.

1.3 Structure of this Report

This report is divided into five sections, including this Introduction. Each section is further subdivided, with a sub-section addressing DG (Distributed Solar Analysis). The five main sections of the report are:

1. **Introduction.** This section.
2. **Methods.** A description of the analytic approaches applied.
3. **Input Data.** A description of the data used to estimate the monthly displaced loads.
4. **Results.** Graphical and tabular summaries of the key outputs of the analysis.
5. **Conclusion.** A summary of the main findings of the analysis.

This report is accompanied by one Excel workbook that includes the summary data used to develop the tables and graphics provided in this report. This is:

- Improvement 5 Solar Report 2024-04-29.xlsx

2. Methods

This section describes the methods used to estimate the average loads displaced by DG. The Improvement 5 Solar Analysis provides an estimate of displaced consumption by:

- developing an estimate of solar production based on LUMA customer installation data and historical Puerto Rico climate conditions.
- calculating the difference between estimated production and observed customer exports to the grid.

This calculation delivers an estimate of the DG output consumed by the customer (“self-use”), which was assumed to be equivalent to the customer’s displaced load. This does not account for any solar rebound (see Section 1).

The methods below describe the approach used by the Guidehouse team to estimate the solar production required for the engineering analysis.

Individual customer solar energy output is calculated as a function of that customer’s nameplate installed solar capacity, historical hourly celestial and climatic conditions (angle of the sun, irradiance reaching ground, etc.) for Puerto Rico, and average system characteristics (tilt angle, etc.) for Puerto Rico as reported by the National Renewable Energy Laboratory (NREL).¹⁵

The Guidehouse team calculated the average solar irradiance reaching solar panels based on hourly historical weather data for Puerto Rico.¹⁶ This is applied to the assumed average installation characteristics of customers’ solar panels drawn from the NREL report cited above.

Although individually specific installation characteristics (e.g., panel tilt, panel azimuth, panel efficiency, etc.) are not available for LUMA customers at present, if LUMA were to expand the detail of the data collected as part of NEM program registration, it would be able to update the analysis below to estimate solar production more precisely for individuals and groups.

The approach to estimating hourly solar energy production can be broken into 7 equations.

- **Equation 1:** The first equation calculates the solar azimuth. The sun’s position is known, and its azimuth depends on the sun’s zenith, the Earth’s declination, and the latitude.
- **Equation 2:** The second equation calculates all the angles relative to the sun and the panels using Puerto Rico average assumptions. In future iterations of this analysis these values may be replaced by installation-specific values, should they become available.
- **Equation 3:** The third equation calculates the hourly plane of array irradiance, which defines solar output per square meter of panel surface area, in any given hour.
- **Equation 4:** The fourth equation applies the estimated output per square foot to the estimated panel area for the given customer’s installation. Panel area is estimated based on the Standard Test Conditions (STC) estimate of panel efficiency (see below for details)

¹⁵ National Renewable Energy Laboratory (NREL), *Puerto Rico Low-to-Moderate Income Rooftop PV and Solar Savings Potential*, December 2020.

Available at: <https://www.nrel.gov/docs/fy21osti/78756.pdf>

¹⁶ NREL NSRDB: National Solar Radiation Database.

Available at: <https://nsrdb.nrel.gov/>

- **Equation 5:** The fifth equation calculates losses due to panel degradation over time. The degradation factor reduces the energy output of a solar panel as it gets older.
- **Equation 6:** The sixth equation calculates the losses due to cell temperature. Standard Test Conditions are not always representative of on-site cell temperature; therefore, a correction is applied as solar cells produce less energy than STC if the cell is warmer (or more if it's colder).
- **Equation 7:** The last equation calculates add system losses. These include initial light-induced degradation, soiling, shading, mismatch, wiring & connections, availability, and nameplate rating variations.

Equation 1 calculates the solar azimuth. This is calculated using the Earth's declination (δ)¹⁷, the hour angle (h_a)¹⁸, the latitude (Φ), and the solar zenith angle (ϕ_z):

Equation 1. Solar Azimuth

$$\phi_A = \cos^{-1} \left(\frac{\sin \delta \cos \Phi - \cos h_a \cos \delta \sin \Phi}{\sin \phi_z} \right)$$

The angle of incidence (AOI) calculates the angle between the sun's location and the solar panel array. The panel azimuth and tilt used in Equation 2 are assumptions drawn from NREL's Puerto Rico solar potential study, while the solar zenith is from the NREL Solar Radiation Database data.

Equation 2. Angle of Incidence (AOI)

$$AOI = \cos^{-1}(\cos \phi_z \cos \theta_T + \sin \phi_z \sin(\sin \theta_T) \cos(\phi_A - \theta_A))$$

Where:

ϕ_z	=	the solar zenith angle
ϕ_A	=	the solar azimuth angle
θ_A	=	the panel azimuth angle
θ_T	=	the panel tilt angle

Equation 3 estimates the effective output capacity by area (i.e., W/m²) of the array. Once all the angles are calculated in the prior two equations, the solar irradiance hitting the plane of array (POA) can be calculated using this set of formulas:

Equation 3. Effective Output Capacity by Area of the Array

$$\begin{aligned}
 POA &= POA_B + POA_R + POA_D \\
 POA_B &= DNI \cdot \cos(AOI) \\
 POA_R &= GHI \cdot albedo \cdot \frac{(1 - \cos \theta_T)}{2} \\
 POA_D &= DHI \cdot \frac{(1 + \cos \theta_T)}{2}
 \end{aligned}$$

Where:

¹⁷ Sun declination is derived from the day of the year.

¹⁸ Hour angle is derived from the longitude, the local time, and the equation of time, which itself is derived from the day of the year. See: <https://pvpmc.sandia.gov/modeling-guide/1-weather-design-inputs/sun-position/basic-solar-position-models/> for a detailed breakdown on how to calculate the equation of time and the hour angle.

DNI	=	Direct Normal Irradiance (W/m^2)
GHI	=	Global Horizontal Irradiance (W/m^2)
$albedo$	=	Surface albedo
DHI	=	Diffuse Horizontal Irradiance (W/m^2)

Equation 4 calculates the solar PV generation using the outputs from the prior equations:

Equation 4. Ideal Solar PV Generation Without Losses

$$kW_{produced_{raw}} = \frac{W_{installed}}{STC} \cdot POA$$

Which can be simplified, since STC is a thousand to:

$$kW_{produced_{raw}} = A_{installed} \cdot POA$$

Where:

$kW_{produced_{raw}}$	=	Ideal solar PV generation with no losses (kW)
$W_{installed}$	=	Installed capacity (W)
STC	=	Standard Test Conditions ($1000 W/m^2$) ¹⁹
POA	=	Plane of array irradiance (kW/m^2)
$A_{installed}$	=	Installed area (m^2) based on STC (exactly equal to $kW_{installed}$) ²⁰

To refine the engineering approach, three forms of losses will be added: solar panel degradation (due to age), performance reduction due to cell temperature, and system wide losses. Equation 5 accounts for the degradation over time.

Equation 5. Solar PV Generation After Degradation

$$kW_{produced_{degr.}} = kW_{produced_{raw}} \cdot Age_{system} \cdot degradation$$

Where:

$kW_{produced_{degr.}}$	=	Solar PV generation after degradation (kW)
Age_{system}	=	Age (in years) of a solar system (W)
$degradation$	=	Average solar panel degradation factor (%/year)

In Equation 6 the impact of the solar irradiance and air temperature on the solar cell temperature is evaluated to estimate an adjusted generation.

Equation 6. Solar PV Generation After Temperature Losses, Including Degradation

$$T_{cell} = T_{air} + (INOCT - 20^{\circ}C) \cdot \frac{POA}{800 W/m^2}$$

¹⁹ Standard Test Conditions are the industry standards used to evaluate panel efficiency. This standard uses a POA irradiance of $1000 W/m^2$.

²⁰ By design of the STC ($1000 W/m^2$), the area (m^2) will be exactly equal to the installed capacity in kW since the installed capacity in watts is divided by a thousand.

$$kW_{produced_{temp}} = \frac{POA}{1000 \text{ W/m}^2} \cdot kW_{produced_{degr.}} \cdot (1 + \gamma(T_{cell} - T_{STC}))$$

Where:

T_{cell}	=	Solar PV cell temperature (°C)
T_{air}	=	Air temperature (°C)
$INOCT$	=	Installed nominal operating cell temperature (°C) ²¹
POA	=	Plane of array irradiance (W/m ²)
$kW_{produced_{degr.}}$	=	Solar PV generation after degradation (kW)
$kW_{produced_{temp}}$	=	Solar PV generation after temperature losses, including degradation (kW)
γ	=	Temperature coefficient (%/°C)
T_{STC}	=	Temperature at standard test conditions (25°C) ²²

Finally, general system losses are added at the end.

Equation 7. Solar PV Generation After All Losses

$$kW_{produced} = kW_{produced_{temp}} \cdot (1 - losses)$$

Where:

$kW_{produced}$	=	Solar PV generation after all losses: degradation, temperature, and system losses (kW)
$kW_{produced_{temp}}$	=	Solar PV generation after temperature losses, including degradation (kW)
$losses$	=	Average system losses (%)

The process outlined above is performed for every hour for every customer and then aggregated by month, to estimate monthly solar production per customer. In the approach above, some parameters are known, some are calculated, and some must be estimated. Table 2 provides the list of parameters, their source, and in which category they fall.

Table 2: Parameters of the engineering approach

Category	Symbol	Parameter	Source
Known	$kW_{installed}$	Installed Capacity	LUMA's Distributed Generation Billing Data
	GHI	GHI	NREL Solar Radiation Database ²³
	DHI	DHI	NREL Solar Radiation Database
	DNI	DNI	NREL Solar Radiation Database
	ϕ_z	Solar Zenith	NREL Solar Radiation Database
	ϕ	Latitude	Google Maps
	$albedo$	Albedo	NREL Solar Radiation Database
Calculated	δ	Earth's Declination	Derived from the day of the year
	ϕ_A	Solar Azimuth	Derived from solar zenith and Earth's declination

²¹ Nominal operating cell temperature is evaluated at 20°C and 800W/m² irradiance.

²² 25°C is the temperature for Standard Test Conditions (STC)

²³ NREL National Solar Radiation Database: <https://nsrdb.nrel.gov/>

Category	Symbol	Parameter	Source
	AOI	Angle of Incidence	Derived from solar and panel angles
	POA	Plane of Array Irradiance	Derived from AOI, irradiance, albedo, and panel tilt
Estimated	$losses$	System-Wide Losses	14% – NREL 2020's Puerto Rico Solar Study ^{24,25}
	$degradation$	Degradation Factor	0.5%/year – NREL 2020's Puerto Rico Solar Study
	$INOCT$	Installed Nominal Operating Cell Temperature	49°C – NREL 2020's Puerto Rico Solar Study
	γ	Temperature Coefficient	0.47%/°C – NREL 2020's Puerto Rico Solar Study
	θ_A	Panel Azimuth	180° (Full South) – Average angle from NREL 2020's Puerto Rico Solar Study
	θ_T	Panel Tilt	10° – Average angle from NREL 2020's Puerto Rico Solar Study

A limitation of this method is that the estimated parameters are not site-specific. This can be updated if LUMA is able to acquire site-specific data (e.g., panel azimuth and tilt, etc.). Such updates are possible as improved data become available because this method allows for sites to be modeled independently and at a timestep only limited by the weather data.

The output of this approach is a time series of monthly solar production values by individual net-metered customers. This can be applied to observed export and consumption data on an individual basis to deliver an estimate of onsite and displaced consumption by customer.

Self-use consumption electricity produced by distributed generation (also referred to as “onsite consumption”) can be derived by subtracting the observed exportations (energy delivered to the grid by the customer) from the solar production estimated by the engineering approach.

This report treats onsite consumption as equivalent to displaced consumption. This assumption may in future be updated, pending the results of Guidehouse's ongoing work to assess the presence or magnitude of any solar rebound effect amongst residential customers. No rebound effect is expected for any non-residential customers. This is a reflection of the underlying economic drivers of residential consumption (utility-maximizing) as compared with non-residential consumption (profit-maximizing).

²⁴ NREL 2020's Puerto Rico Solar Study: <https://www.nrel.gov/docs/fy21osti/78756.pdf>

NREL 2020's Puerto Rico Solar Study Code:
https://github.com/openEDI/documentation/blob/main/PVROOFTOPS_PR.md

²⁵ Aron P. Dobos - NREL, PVWatts Version 5 Manual: [pvwatts5.pdf](https://www.nrel.gov/pvwatts/pvwatts5.pdf) (nrel.gov)

3. Input Data

This section describes the primary sets of data used as inputs to the solar analysis.

This section is split into two sub-sections, each of which provides a description of data used in the engineering analysis, and a description of the steps taken to prepare these data for the analyses. The two sub-sections are:

1. **Improvement 5 Customer Billing Data.** This section describes the billing data from which:
 - installed capacity by customer values were obtained.
 - the monthly exports for each customer were obtained.
2. **Hourly Historical Weather Data.** This section describes the hourly weather data (the plane of array irradiance) that was used in the engineering analysis (data hosted by NREL). This section also identifies the average panel tilt and azimuth used in NREL 2020's Puerto Rico Solar Study, developed in the context of the PR 100 project.

This chapter presents the cleaning steps undertaken by Guidehouse in preparing the DG data (Section 3.1.1), an overview of the changes in installed customer DG capacity over time (Section 3.1.2), and a summary of the irradiance (Section 3.2) one of the principal drivers of solar output.

3.1 Improvement 5 Customer Billing Data

Table 3 presents the dataset provided by LUMA's Load Forecast and Research team. This data set, referred to as the "Improvement 5" dataset is drawn from LUMA's SUB006 report which provides monthly billing data for DG customers.

Table 3: Data Received by Guidehouse for Improvement 5

Distributed Generation Monthly Billing Data (2016 – 2023)²⁶:	
•	Month (Billing month)
•	Service Account (SA)
•	Rate
•	Installed Capacity
•	Exported Energy (kWh)
•	Net Consumption (kWh) – the energy that the customer is billed for.
•	Total Consumption ("Gross") (kWh) – the energy that the customer withdraws from the grid. This value minus exports equals Net Consumption (to a minimum value of zero)

Guidehouse prepared these data by addressing standard data quality issues, like missing data points, duplicated data, etc.

²⁶ Sent by the LFR team on June 13 & June 19.

Filenames: Data for DG Consumption FY17 to FY22.xlsx & Data for DG Consumption FY23.xlsx

3.1.1 Improvement 5 Billing Data Preparation

When reviewing LUMA's installed capacity and billing data, three types of data issues were found: duplicated rows, double billing in a period, and variable capacity billed per month. These are each described below, along with the approach used to resolve them:

- Duplicated rows – Same Month, SA, Rate, Installed Capacity, kWh exported billed, and kWh consumed billed:
 - 23,135 rows (out of 2,466,867) were found to be duplicates and were deleted.
- Double billing in a period – Same Month, SA, Rate, Installed Capacity, but different kWh exported billed, and kWh consumed billed:
 - 2,818 rows were added to other billing in that month, leading to more kWh exported billed, and kWh consumed billed.
- Variable Capacity:
 - Guidehouse assumed that customers installing solar are keeping the system in place. As soon as an SA is in the billing data for solar PV, the solar system is assumed to have been installed. The SA (and its installed capacity) stays in the total installed capacity, even if it is not billed for a month or two. However, to account for systems that could change SA (for example a house with solar PV being sold to a new owner), any SA that has not been billed in the last six months is dropped from the total installed capacity.

As shown in Figure 4, this approach smooths the peaks and troughs in the customer installed capacity data provided by LUMA; the green columns represent the aggregate capacity in each month drawn from the billing data. The blue line represents Guidehouse's estimate of the installed and generating capacity in each month, controlling for the effect that not every customer is billed in every month (i.e., billing data from a single month may understate total installed capacity). Remaining references to installed capacity in this report refer to this cleaned version, after degradation²⁷.

²⁷ This analysis uses the DG billing data provided for Improvement 5 (and Improvement 7). As noted above, these values are aggregated from individual customer data provided by LUMA as part of its SUB006 report, and may not match aggregated values derived from other LUMA reports or sources..

Figure 4: Installed Capacity by Month

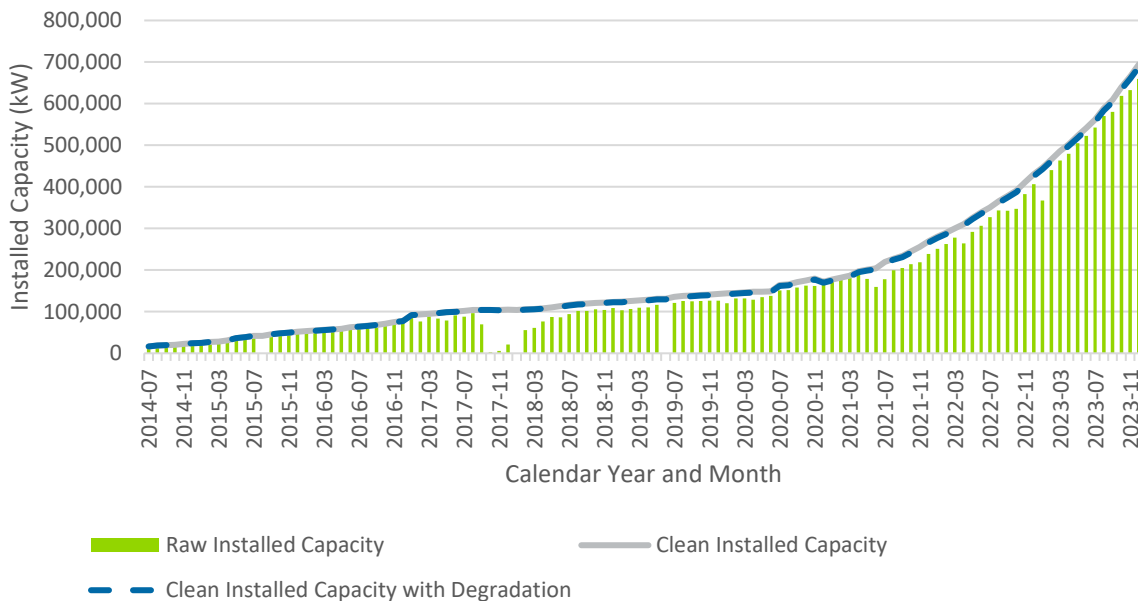
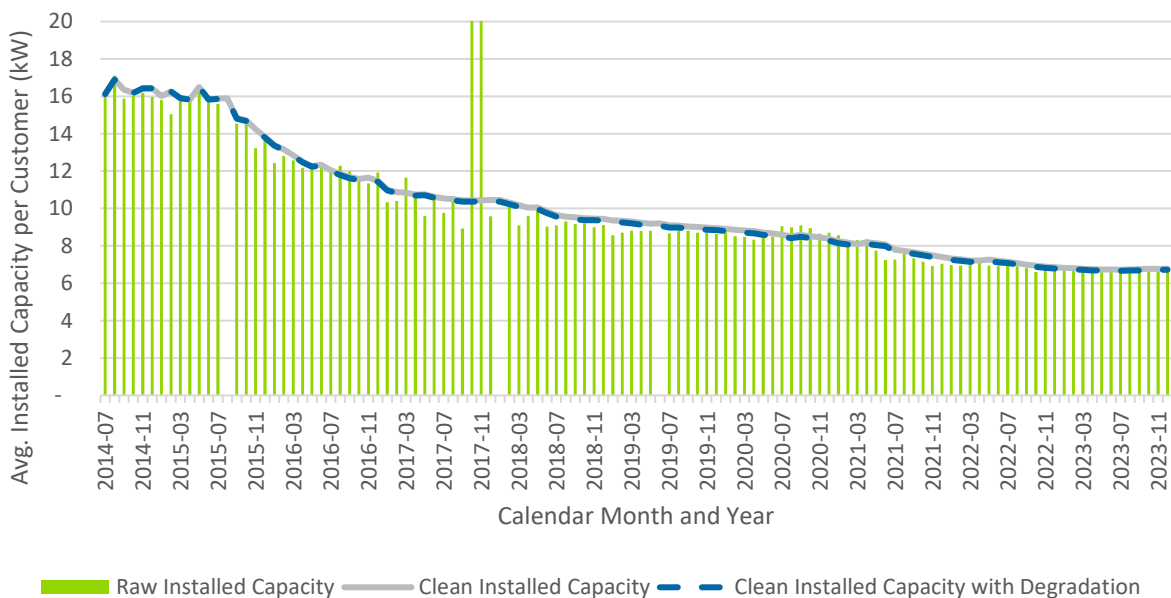


Figure 5: Average Installed Capacity per Customer (all rate class) by Month



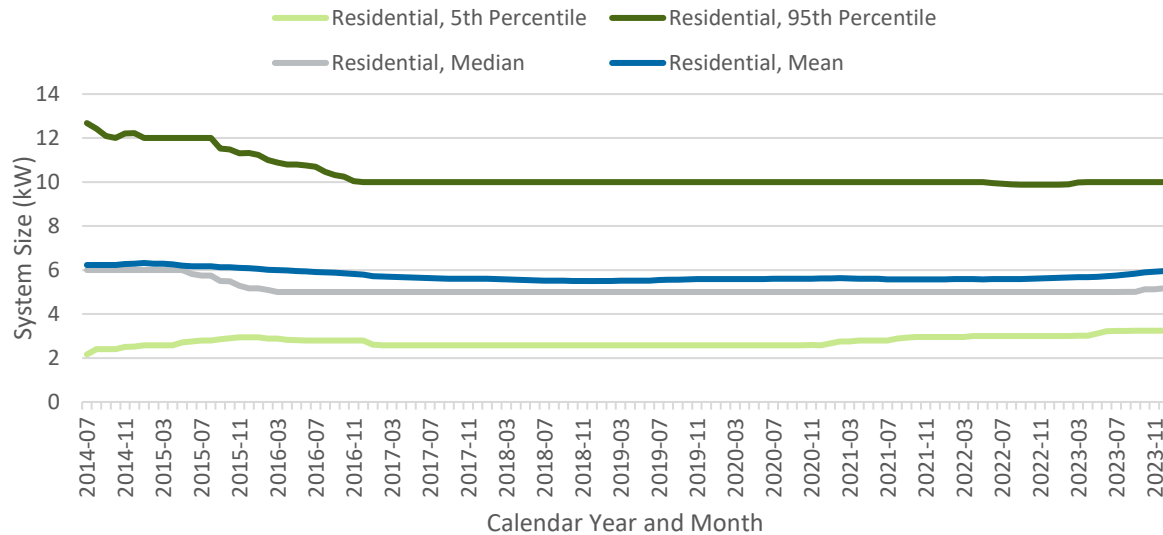
3.1.2 Installed PV Capacity Over Time

To better understand the solar PV population in Puerto Rico, a system size analysis was conducted. Figure 6 to Figure 8 present, for each sector, the mean, median, the 5th, and the 95th

percentile system size. Note that where capacity values for individual customers were unknown, LUMA applied default values derived based on internal analyses²⁸. They are:

- 5 kW for residential systems
- 25 kW for commercial systems
- 145 kW for industrial systems

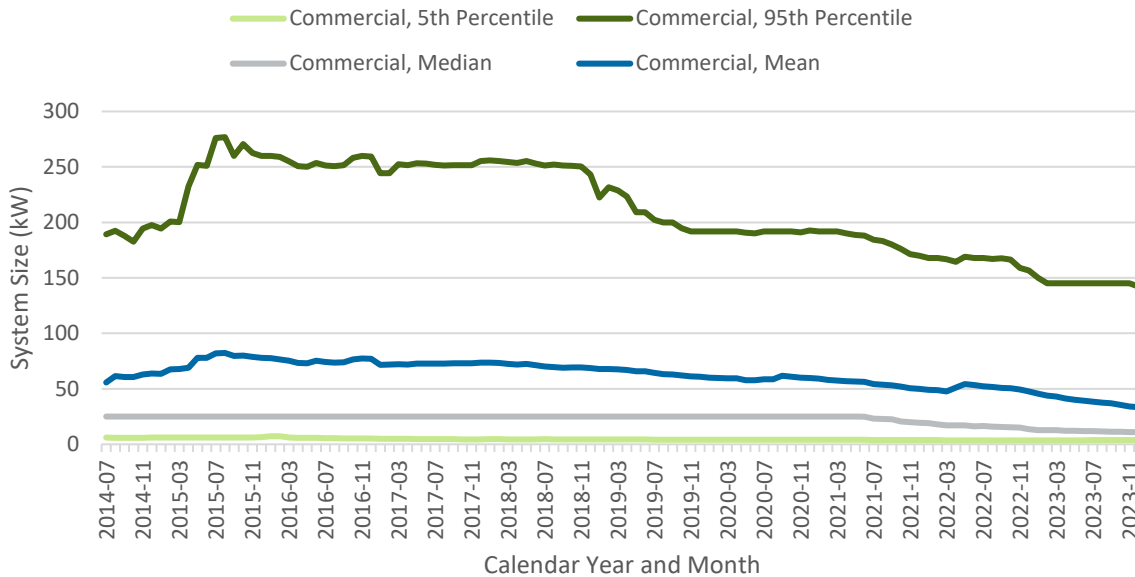
Figure 6: Residential System Size by Month



The residential system size has been consistent over time, as has the largest sizes of systems (since 2016). However, the smaller system has been increasing in size, while the mean and the median are relatively constant.

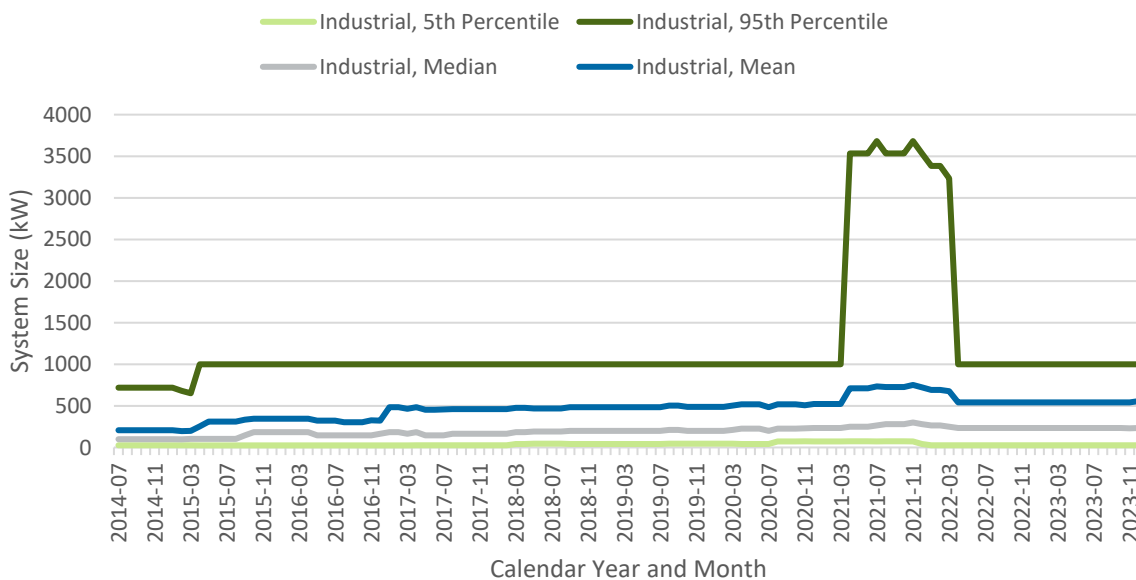
²⁸ Approximately 7% of residential system capacities are exactly 5 kW and approximately 0.4% of commercial system capacities are exactly 25 kW. These values represent the upper bound of default values applied by LUMA in preparing the data.

Figure 7: Commercial System Size by Month



Average system size installed by commercial customers appears to be decreasing over time. The decline over time of the 95th percentile sized systems suggests that as adoption has grown the distribution of system sizes has tightened around the mean. This, and the observation that average commercial DG customer gross billed consumption (withdrawals from the grid) has declined over time suggests that over time customers with smaller buildings are increasingly participating in the NEM program.

Figure 8: Industrial System Size by Month



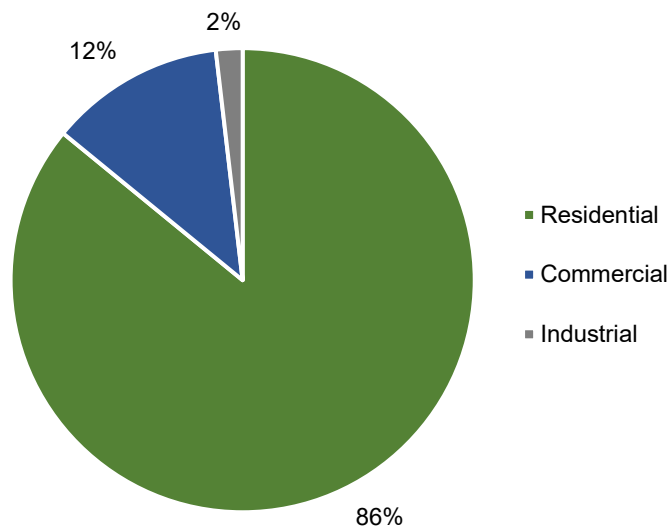
Mean industrial system size is consistent across the study period. In 2021, the largest system sizes (95th percentile) increased drastically to 3500 kW before reducing again to 1000 kW. A 3,980 kW system is recorded in the billing data from January 2017 through October 2021 and is therefore removed from the cleaned capacity data in April 2022²⁹, leading to a large reduction in the 95th percentile of industrial system sizes. In April 2021, a new 5000 kW system is present in the billing data, causing a large jump in the 95th percentile values. These two systems are the only two systems in the dataset with a capacity exceeding 1000 kW.

As of December of 2023, average installed capacity per customer, by class was:

- Residential, 6 kW (mean), or 5.2 kW (median)
- Commercial, 33.4 kW (mean), or 11 kW (median)
- Industrial, 558 kW (mean), or 233 kW (median)

The distribution of installed capacity in December of calendar year 2023, by the three customer classes of interest, is shown in Figure 9, below.

Figure 9. Distribution of Installed Capacity by Class



3.2 Hourly Historical Weather Data

The engineering approach uses historical Puerto Rico weather data to estimate the irradiance that drives solar energy production. Weather data was extracted from NREL's solar radiation database for the calendar year 2014-2022. The data for 2023 was not available at the time this report was written. A single weather point is used in this study (latitude: 18.25, longitude: -

²⁹ Guidehouse removes the capacity value for an individual customer from the set when no monthly values are recorded for that customer for six months in a row.

66.41)³⁰ to evaluate all of Puerto Rico to limit the scope of the analysis while maximizing learnings for the LUMA's LFR team.

Weather data was used to calculate the plane of array (POA) irradiance Figure 10 presents the global horizontal irradiance (GHI) used in this study. The seasonality is evident, with summer irradiance peaking at about 45% greater than winter irradiance.

Figure 10: Monthly Global Horizontal Irradiance

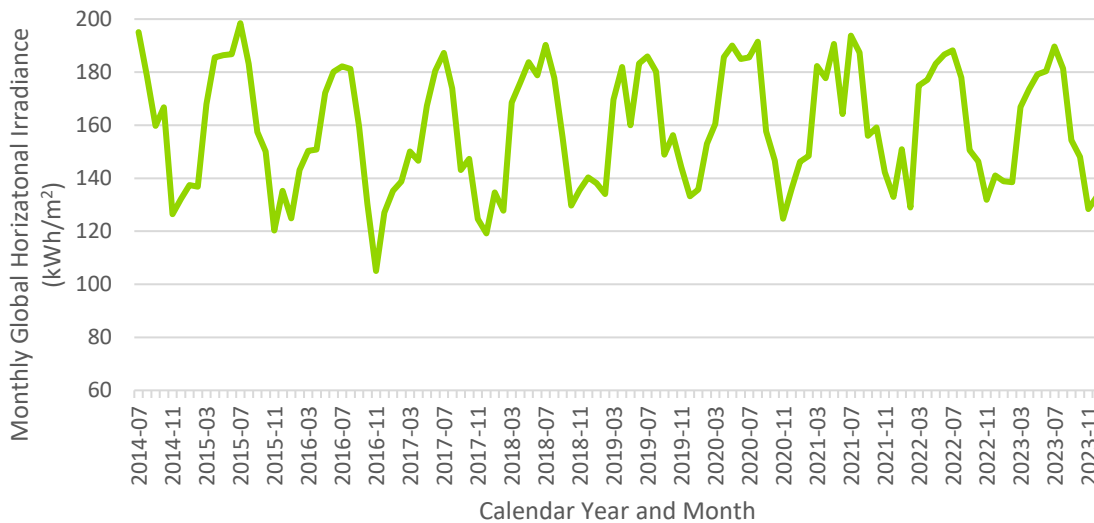


Figure 11 presents the POA by month over the study period. Despite a strong seasonality in the GHI, smaller seasonal variations are observed in the POA. This is due to the assumption of the panels being south facing. Because Puerto Rico's latitude (about 18°) is smaller than the earth's declination (23.45°), the sun is north facing for a few months in summer, reducing the irradiance on the south facing surface. Despite this loss, a south facing system produces annually more than a north facing system that would maximize summer production.

³⁰ 18°15'00.0"N 66°24'36.0"W

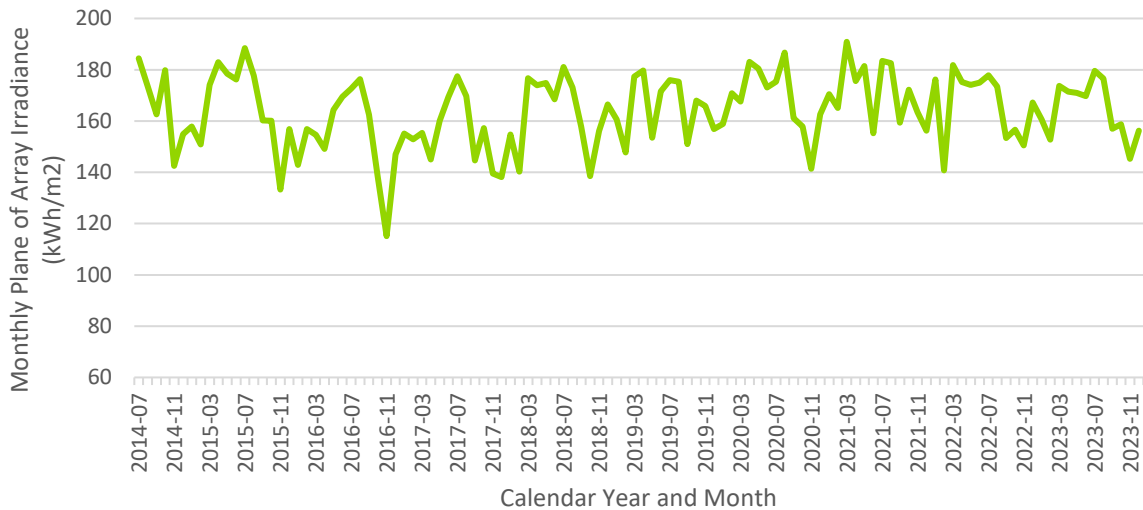
Figure 11: Monthly Plane of Array Irradiance

Figure 12 shows seasonal average solar irradiance on the plane of array by hour of the day. Summer months (May to September) peak on average at 765 W/m^2 , while winter months (November to March) average peak irradiance reaches 740 W/m^2 . The area under the curve of the mean curves, representing the total energy reaching the panels on average, is 5224 Wh/m^2 per day in winter and 5580 Wh/m^2 per day in summer, which is a 7% increase.

This seasonality underlines an important point: for the purposes of projecting energy output on an annual basis it is appropriate to use a constant capacity factor (because the mean annual irradiance is stable), but care should be used in selecting that factor to ensure it reflects the capacity factor across the entire year, and not just that of the summer months.

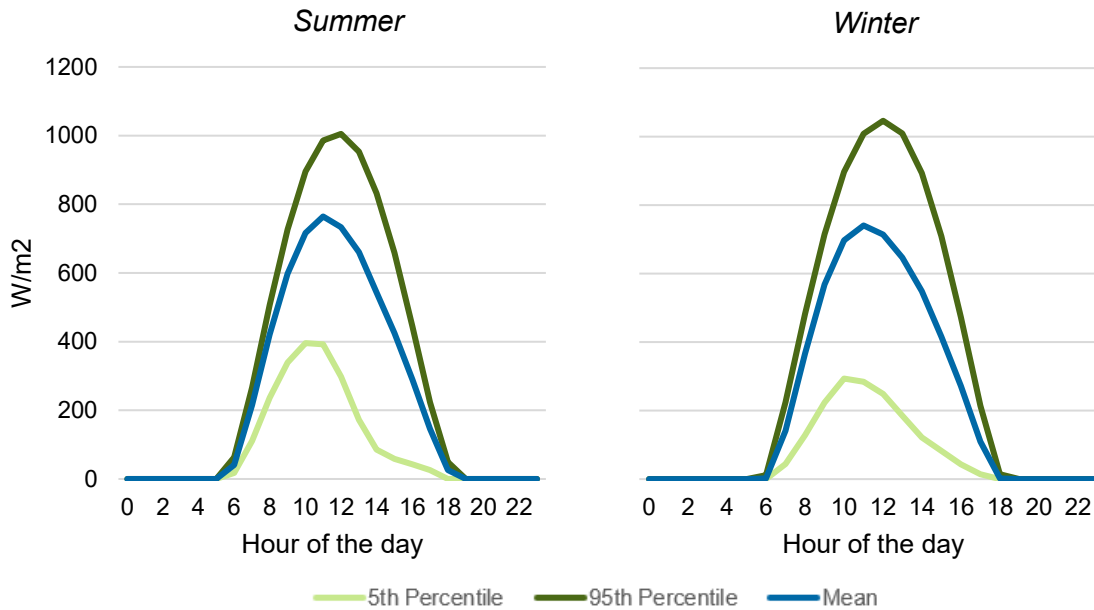
Figure 12: Plane of Array Irradiance Per Hour³¹ (Summer and Winter)

Table 4 and Table 5 presents the value range of the variables used in the engineering estimation for the data identified in Section **Error! Reference source not found.**, above.

Table 4: Known Parameters Values

Symbol	Parameter	Source	Range
$kW_{installed}$	Installed capacity	LUMA's Distributed Generation Billing Data	(0, 5000) kW
GHI	GHI	NREL Solar Radiation Database	(0, 1073) W/m²
DHI	DHI	NREL Solar Radiation Database	(0, 585) W/m²
DNI	DNI	NREL Solar Radiation Database	(0, 1015) W/m²
ϕ_z	Solar Zenith	NREL Solar Radiation Database	(0.49°, 178.02°)
Φ	Latitude	Google Maps	18.25°
$albedo$	Albedo	NREL Solar Radiation Database	(0.13, 0.19)

Table 5: Calculated Parameters Values

Symbol	Parameter	Source	Range
δ	Earth's declination	Derived from the day of the year	(-23.45°, 23.45°)
h_a	Hour angle	Derived from the day of the year, the local time, and the longitude	(-175°, 177°)

³¹ Hour of the day starting (e.g., 0 is from 0:00 to 0:59)

Symbol	Parameter	Source	Range
ϕ_A	Solar Azimuth	Derived from solar zenith and Earth's declination	(0°, 180°)
AOI	Angle of incidence	Derived from solar and panel angles	(2°, 175°)
POA	Plane of array Irradiance	Derived from AOI, irradiance, albedo, and panel tilt	Hourly: (0, 1087) W/m ² Monthly: (115-191) kWh/m ²

4. Results

This section of the Improvement 5 report presents the results of the solar analysis.

This section is divided into two sub-sections:

1. Estimated Solar Production
2. Estimated Displaced Load.

Important Note

Guidehouse's results presented below are based on a number of different data sets provided by LUMA over a period from early 2023 to early 2024.

Guidehouse understands that over this time LUMA's internal processes and database queries have been evolving and improving, thus some of the aggregate counts, capacity measurements, or consumption volumes of customer groups discussed in this report may not reflect the latest data available to LUMA.

The core analysis covered by this report, however, is based principally on individual customer installed capacity and monthly exports data. In the case of solar PV net energy metering customers while this is not a complete census of all such customers, the data provided by LUMA cover a super-majority of these customers.

Guidehouse is confident therefore in the robustness of its analysis, in the representativeness of its results, and in the accuracy of its conclusions.

Guidehouse notes, however, that the underlying population of DG customers continues to evolve quickly and that LUMA may find it prudent to, based on the foundation of the work developed for this Improvement, consider assembling the data necessary to extend the analysis over a longer time horizon, and to periodically (e.g., annually or semi-annually) update the inputs to ensure the ongoing accuracy of its assumptions about DG customers and their patterns of electricity use.

4.1 Estimated Solar Production

This section provides Guidehouse's estimate of energy production per month. This series of values (by class) can then be applied to observed average exports per customer to derive an estimate of average self-use of self-generated electricity – termed "onsite consumption" in this report.

The values below reflect the installed capacity values included in the individual customer billing data provided to Guidehouse for this Improvement.

Figure 13, Figure 14, and Figure 15 each show, respectively the estimated solar PV production per Residential, Commercial, and Industrial customer in each month. At the time of writing, no NREL data were available for calendar year 2023. Guidehouse used the 2022 irradiance data was used to estimate generation in that year.

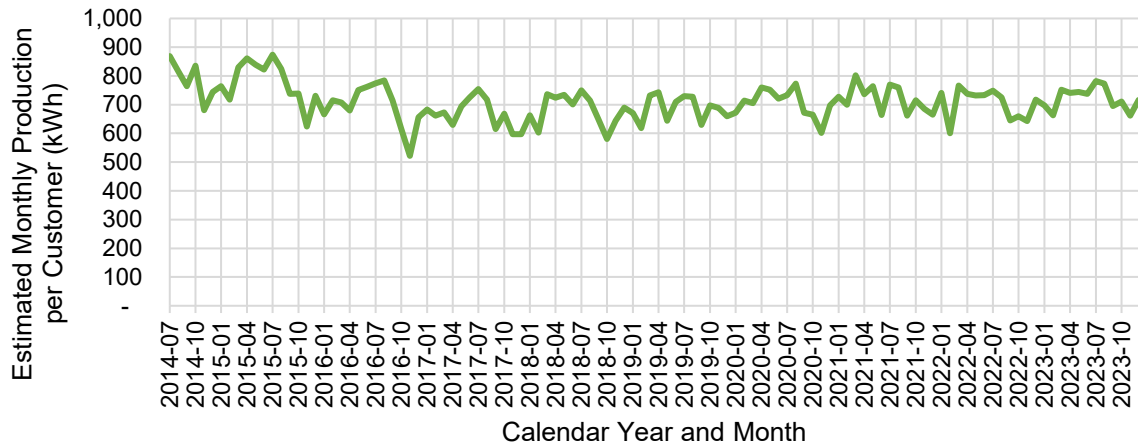
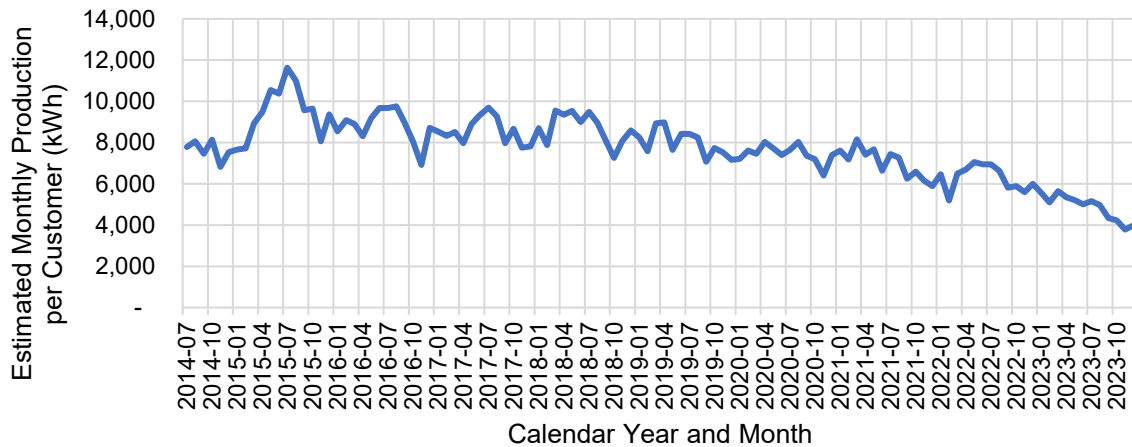
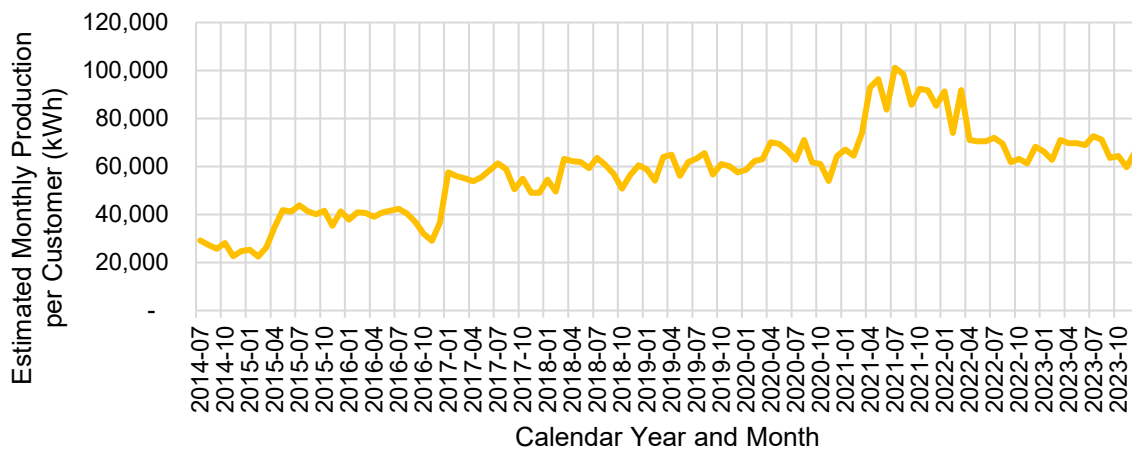
Figure 13: Estimated Solar PV Production by Month per Customer - Residential

Figure 14: Estimated Solar PV Production by Month per Customer - Commercial

Figure 15: Estimated Solar PV Production by Month per Customer - Industrial


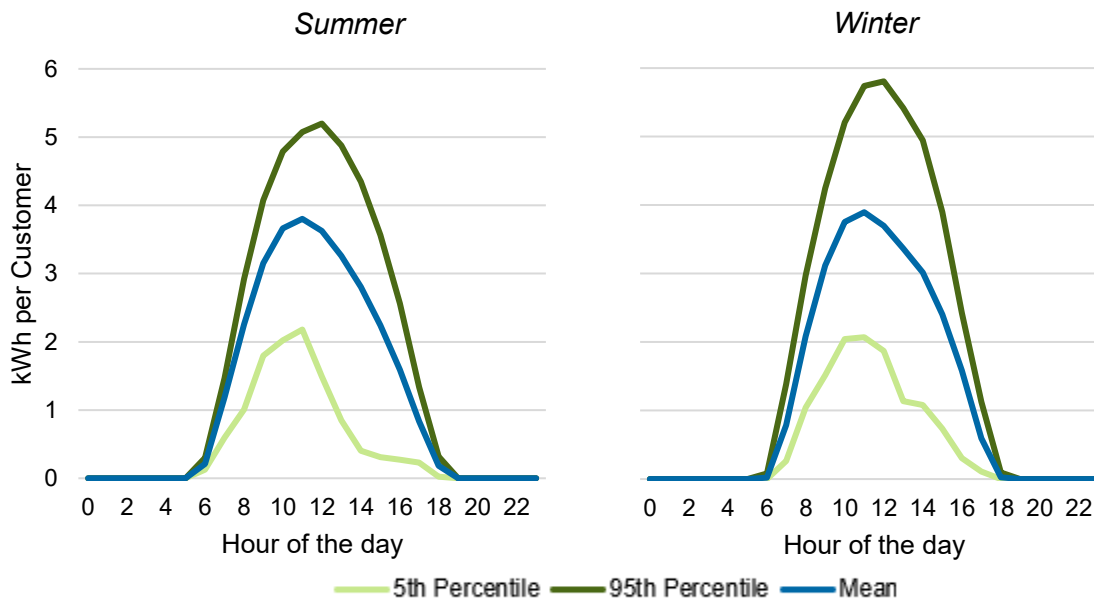
Table 6, below shows the number of DG customers for whom Guidehouse had the capacity data to estimate production for each of the three classes shown above. This should be understood *not* to be a complete census of all DG customers registered in each month, but the count of such customers for whom Guidehouse had data.

Table 6. Count of Customers in Data as of December of Each Calendar Year

Calendar Year	Residential	Commercial	Industrial
2015	3,384	308	15
2016	6,287	424	22
2017	9,435	520	26
2018	12,435	608	25
2019	15,195	713	27
2020	19,637	799	23
2021	35,208	1,061	24
2022	61,146	1,457	25
2023	99,807	2,530	23

Figure 16 presents the average estimated production by hour of the day for both summer and winter in calendar year 2022.³² Average estimated production peaks near 3.85 kWh in both summer and in winter. In the area under the curve, the average energy production per day of the month in calendar year 2022 was 29 kWh in summer and 28 kWh in winter. Production for 2023 was estimated by applying the NREL 2022 observed values to the 2023 installed capacity values.

Figure 16: Average Solar PV Production Per Hour³³ (Summer and Winter) in 2022 (Calendar Year)



³² Calendar year 2022 was used based on the available NREL data at time of writing.

³³ Hour of the day starting (e.g., 0 is from 0:00 to 0:59)

Table 7 shows the average annual estimated production by class in each year.

Table 7: Average Solar Production, kWh Per Customer, per Year

Year	Residential	Commercial	Industrial
2014	4,710	45,821	157,689
2015	9,363	114,013	435,072
2016	8,348	105,803	458,170
2017	8,018	102,752	660,128
2018	8,189	104,534	699,662
2019	8,252	96,054	724,159
2020	8,455	87,534	776,126
2021	8,606	79,075	1,034,529
2022	8,416	66,156	865,427
2023	8,674	58,355	806,057

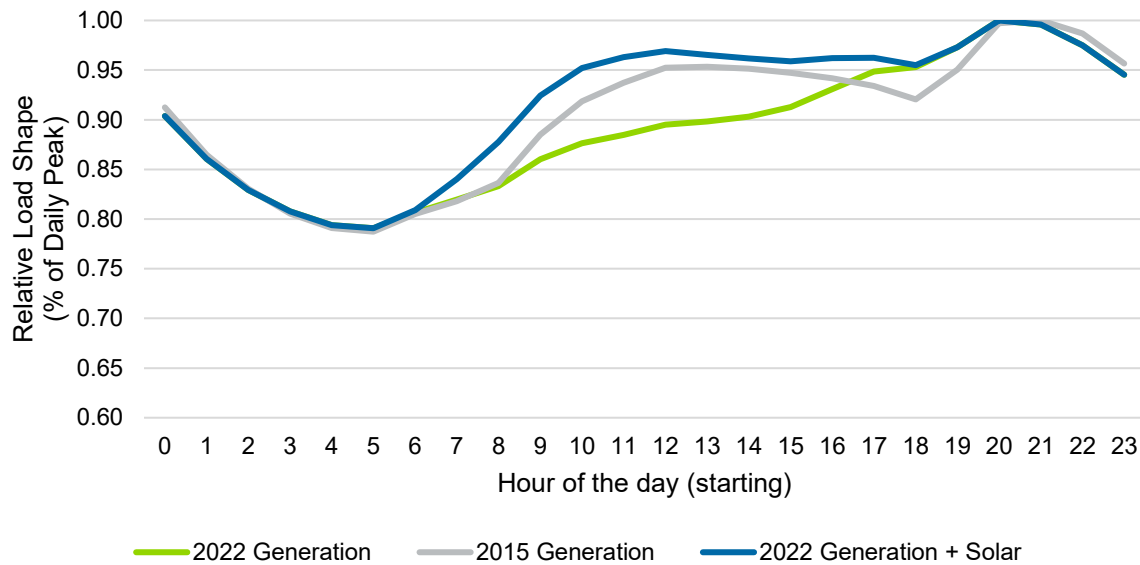
The hourly generation profile of the distributed photovoltaic system also impacts LUMA's total system load profile (represented by hourly generation output). Figure 17, below, presents three series.

- The green line represents average hourly generation profile by hour of day in calendar year 2022. These are observed actual values.
- The blue line shows average hourly generation output by hour of day *plus* average hourly solar output in calendar year 2022.
- The grey line shows average hourly generation output by hour of day in calendar year 2015.

All three profiles are normalized as a percent of daily total to assist with comparisons. The blue line represents what LUMA's generation output *would have been* had there been no solar production.³⁴ If it can be assumed that the 2015 generation profile is a suitable baseline for 2022, then the distance between the grey line and the green line can be thought of as a very rough approximation of the displaced load. The distance between the blue line and the grey line can be thought of as a very rough approximation of total exports. These approximations are, of course, very imprecise given all the other structural changes in load drivers since 2015 but are helpful in providing some intuition for the potential magnitude of displaced load.

³⁴ Aggregate values for production are somewhat uncertain due to some uncertainties regarding customer counts. Aggregate production values to estimate this plot should be understood to be the product of the average per-customer values in Figure 13 through Figure 15 and the customer counts summarized in Table 6

Figure 17: Hourly Impact of Distributed Solar PV in 2022 (Calendar Year)



Source: Guidehouse analysis

Although this figure compares only 2022 to 2015 year, this small “duck curve” phenomenon will keep increasing as more and more solar PV is installed by LUMA’s customers. In the same way, the impact before 2022, for example in 2015, is smaller as less solar PV was in place.

Figure 18 compares solar production estimated using the monthly variable irradiance (i.e., the approach used by the engineering analysis) with an estimate of production using a constant 20% capacity factor.

Figure 18: Guidehouse’s Approach vs. Fixed Capacity Factor

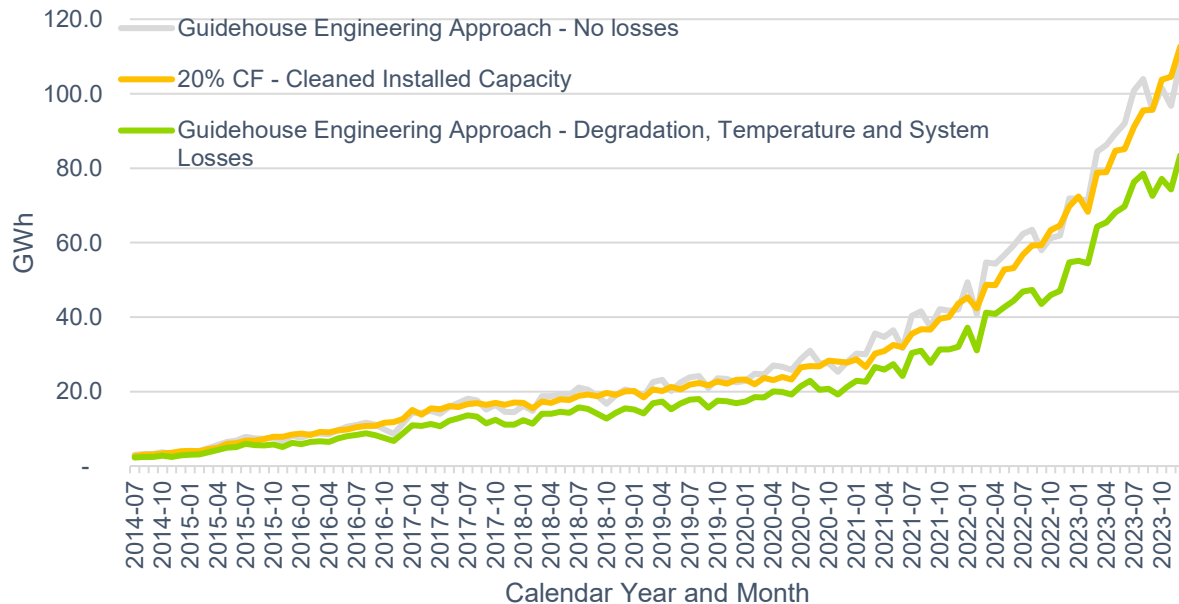


Table 8 presents monthly capacity factors. It should be noted that the addition of losses and temperature impact does impact summer production a little more than winter production, bringing the capacity factors of summer closer to the winter ones. The average annual capacity factor found in this study is 17.0%, which is lower than the 20% assumption previously used by LUMA.

Table 8: Average Capacity Factor per Month

Month	Average Capacity Factor
January	16.5%
February	17.3%
March	17.6%
April	18.0%
May	17.5%
June	17.9%
July	18.3%
August	17.9%
September	16.5%
October	16.2%
November	15.4%
December	16.1%

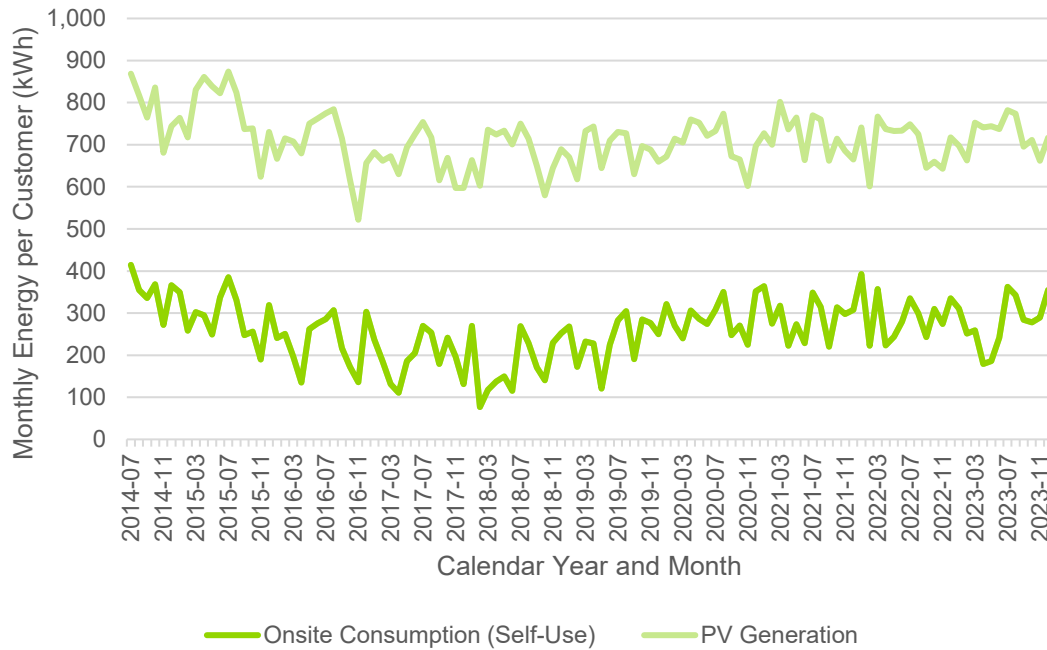
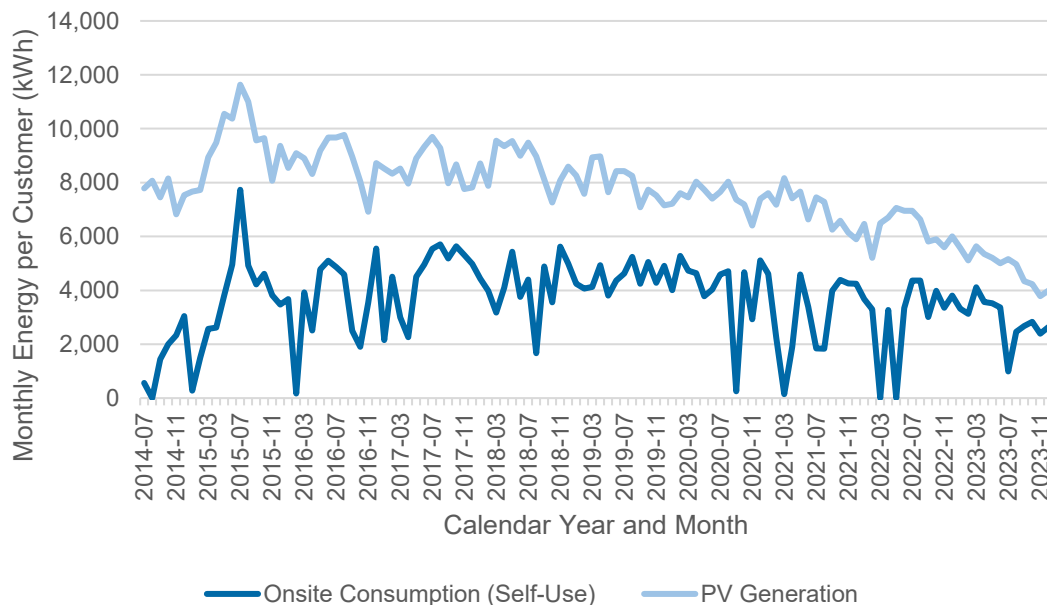
The value of the engineering approach is to allow a highly granular analysis, both temporally and (potentially) spatially, being limited only by the temporal and spatial resolution of the weather data and the information gathered on each photovoltaic systems (tilt, azimuth, installed capacity).

For this study, Guidehouse did not have any information on the angle of the solar panels, limiting the precision when estimating the production at the SA level. In the same way, a single data point was used for the weather data, blending all weather differences on the island. This approach could be improved in the long run by gathering more data on solar systems installed within LUMA's jurisdiction, such as the panel angles, panel types, efficiency, etc. to allow for accurate modeling of all SA (and all solar systems) independently. It could also be improved by using multiple weather data points to get a regional or even local read on weather patterns.

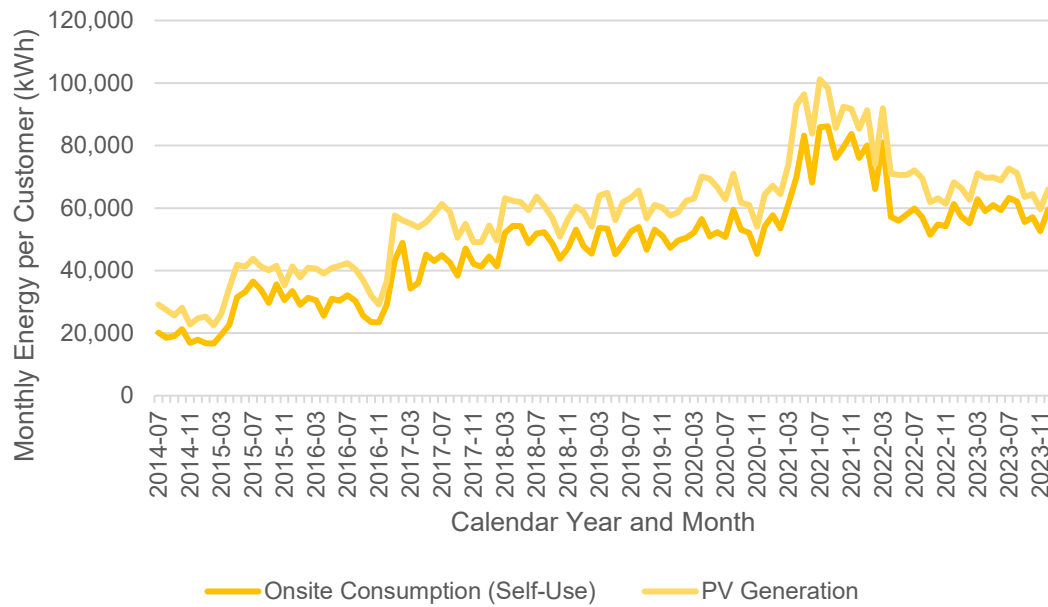
4.2 Estimated Displaced Load

Using the engineering approach and observed customer's grid import and export, Guidehouse can estimate the average monthly onsite consumption per customer. Assuming no rebound effect (see Section 1) this is equivalent the displaced consumption – the reduced amount of withdrawals from LUMA's grid.

. Figure 19 to Figure 21 present the estimated onsite consumption, displaced consumption, and the PV generation, per customer, for every month of the study. The monthly values associated with these graphical outputs may be found in the "OUT-07b-Estimated Displaced" tab of the workbook that accompanies this report.

Figure 19: Monthly Residential Displaced Consumption and PV Generation Per Customer**Figure 20: Monthly Commercial Onsite Consumption and PV Generation Per Customer ³⁵**

³⁵ Onsite consumption for the commercial sector falls to low values (sometimes 0) in some months as exports from the billing data exceed solar production. This is due to a billing artefact (e.g., customers billed more or less than once in a month). Guidehouse recommends using the general trend rather than any specific month for the commercial customers (e.g., moving averages).

Figure 21: Monthly Industrial Onsite Consumption and PV Generation Per Customer

5. Conclusions & Recommendations

The goal of the solar analysis was to develop a historical monthly estimate of displaced load (i.e., the reduction in billed consumption attributable to the adoption of DG) to assist with the regression modeling used the LFR team to forecast billed consumption. A secondary goal of the Guidehouse team was to develop methods (and, particularly) outputs that could be used by the LFR team to assist in their ongoing development of forecast load modifiers.

The average monthly displaced consumption by class and fiscal year³⁶ is presented in Table 9, below.

Table 9. Average Solar PV Onsite and Displaced Consumption per Customer, kWh Per Month

Calendar Year	Residential	Commercial	Industrial
2015	293	3,710	28,334
2016	232	3,591	28,478
2017	194	4,479	42,259
2018	180	4,166	49,341
2019	236	4,489	49,840
2020	288	4,059	52,212
2021	290	3,120	73,415
2022	293	3,646	61,396
2023	278	2,915	58,715

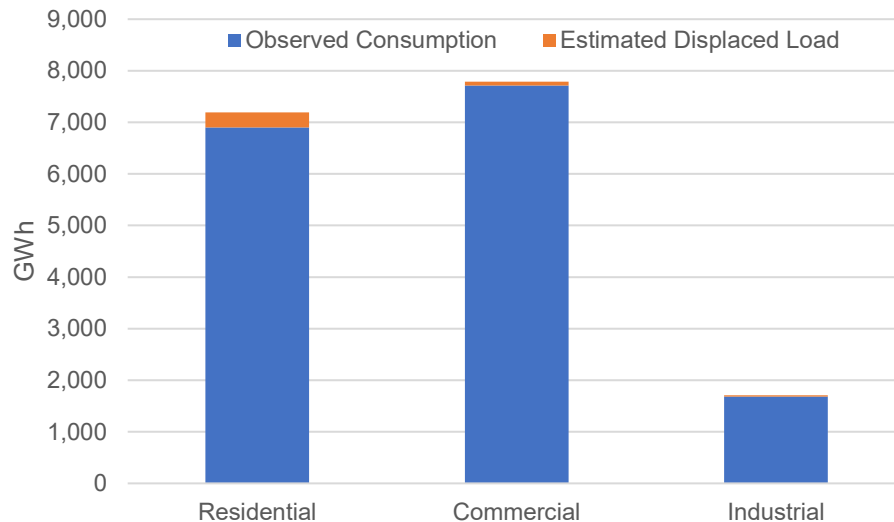
As previously noted, these estimates of displaced consumption do not account any rebound effects, effects Guidehouse is currently investigating in the summer of 2023 (the heat wave summer). These values can be applied to the total count of registered DG customers to obtain an estimate of the aggregate volume of displaced consumption in each month of 2023, and for the year as a whole.

Total class-level observed consumption (blue) and estimated displaced load (orange) are presented in Figure 2.³⁷

³⁶ Data provided to Guidehouse as part of Improvement 5 extends only through May of fiscal year 2023, and as such, the value presented here may not precisely match the full 12-month average.

³⁷ The values and calculations for this graph may be found in the tab "OUT-10-DG Compared to Load" of the workbook that accompanies this report.

**Figure 22. Observed Consumption and Estimated Displaced Load,
Calendar Year 2023, by Class**



Although the total volume of displaced consumption is relatively small at present (residential displaced consumption is approximately 4% of total residential consumption), the rapid growth of the number of DG customers suggests that the share of residential consumption that is self-supplied is likely to continue to grow rapidly for the near future.

Based on the outcomes of this analysis, Guidehouse has proposed two sets of recommendations, the first set related directly to the consideration of DG customer displaced consumption in the load forecast, and the second set related to data collection considerations for DG customers.

5.1 Load Forecasting Recommendations

Guidehouse's findings suggest three important recommendations related directly to the Fiscal Plan load forecast for consideration by the LFR team:

- first, that the LFR team should consider either using displaced consumption to adjust historical loads prior to regression estimation or
- second consider adopting a use-per-customer times customer count forecast approach distinguishing between DG and non-DG customers; and,
- third, that the LFR team should continue to use the available data to understand DG customer characteristics to help to improve the accuracy of the LFR team's load modifier forecast.

Recommendation 1: Historical Consumption Adjustments

If the LUMA LFR team plans to continue to use an aggregate consumption forecasting approach for the near future (as opposed to a use-per customer times customer count approach)

Guidehouse recommends that LUMA consider experimenting with the use of “DG-corrected” historical loads.

That is, the LUMA LFR team should consider using historically estimated displaced load due to DG to adjust observed historical load prior to using that data in the regression analysis. The historical load used to estimate the regression would be an estimate of what historical load would have been if there had been no DG at all.

This is a procedure used by many North American utilities to control for the effects for structural changes to load drivers (such as electric vehicles, demand side management, and distributed generation) in historical loads, when doing so through the inclusion of an additional independent variable in the regression equation would be unsuitable (e.g., due to issues of multi-collinearity or the magnitude of the effect).³⁸ Guidehouse understands that before to the restructuring of PREPA into LUMA, this approach was used to control for the effects of self-generation by large electricity users.

This would then allow for a conceptually simpler forward-looking adjustment than the current approach.

The current approach (also common in many utility load forecasts) is to assume that the average effects of the historical load modifiers are embedded in the other model parameters and to adjust forecast future loads using only incremental (new) DG adoption not captured in history. The number of customers with DG has grown so quickly and the total energy displaced by these customers is sufficiently large that there is a risk that not explicitly controlling for the historical displaced loads may materially bias the regression parameter estimates.

The LUMA LFR team should consider whether adjusting historical loads is a prudent way to address this risk.

Recommendation 2: Use-Per-Customer Forecasting

Guidehouse has previously recommended that the LUMA LFR team consider adopting a use-per-customer times customer count forecasting approach. The Guidehouse team did, in fact, make substantial progress in developing this approach through Improvement 7.

This work was paused when it was determined that it would be too large a change to the forecasting approach to apply to Fiscal Plan 2024 without more testing. When the LFR team determines it is appropriate, it should consider running the current approach (modified as needed) in parallel with a use-per-customer times customer count forecast approach.

The UPC times customer count forecast would allow the forecast team to control for the effects of DG explicitly in the forecast without having to adjust historical loads or include another independent variable in the regression equation to control for DG. Another advantage of this approach is that it provides a framework that is relatively easy to modify for integrating other structural load modifiers in the future (e.g., EV adoption).

³⁸ Because DG adoption has been growing over time, any variable to control for DG adoption that is included in the regression equation will be correlated with other trend-capturing variables (e.g., GNP in commercial, population and COVID variables in residential, etc.) Too much correlation between the independent variables can result in multi-collinearity, parameter estimates that are very sensitive to model specification (not robust) and to potentially spurious out-of-sample prediction (i.e., forecast inaccuracy).

Guidehouse recommends that the LUMA LFR team consider additional testing of use-per-customer models, starting with a single class (e.g., residential), informed by additional analysis of DG customer characteristics (see below) and by the estimated volume of load displaced by DG (per the reporting above).

Recommendation 3: Understand DG Customer Characteristics

The number of residential and commercial DG customers is growing at a spectacular rate; in December 2023 there were twice as many registered DG customers as there were in July of 2022, in these classes. Although the installed system characteristics selected by these customers has appeared to be relatively consistent over time (e.g., see Figure 6), the average consumption of these customers has steadily declined. This suggests that most recent growth in the adoption of DG is being driven by smaller customers than in the past.

Developing a better understanding of the characteristics of those customers adopting DG, both through analysis of billing data and the hourly load research sample data, as well as through surveys (see below), may better help the LFR team to better understand future patterns of DG adoption, and improve the accuracy of its load modifier forecast. For example, developing a better understanding of how DG customer characteristics are changing may help the LFR team better identify when growth in DG adoption could be expected slow.

Guidehouse recommends that the LUMA LFR team continue to analyze DG customer data to better understand how these customers are changing over time, and so better forecast their changes in number and consumption.

5.2 Data Collection Recommendations

Access to complete and accurate data remains the LUMA LFR team's greatest challenge. Guidehouse recommends that the LFR team continue to work with the IT team to establish an internally consistent robust database of DG customers' consumption (both before and after NEM program enrollment) and cross-sectional characteristics. Guidehouse further recommends that the LFR team works with other teams within LUMA to expand the types of data collected from these customers, and so to better support the load modifier forecast.

Recommendation 1: DG Customer Monthly Bill Consumption and Cross-Sectional Database

Guidehouse recommends that the LFR team build out a monthly data set that includes:

- Monthly net and gross billed consumption
- Monthly estimated production
- Monthly exports

For all DG customers. This data set should include consumption data for each customer both after enrollment in the NEM program, but also prior to enrollment. This will mean combining multiple data sets, and working with IT to develop additional queries that should be run monthly.

Guidehouse has, to support its Improvement 5 and Improvement 7 work developed an initial data set that includes this information which may be used as a starting point, but the LUMA LFR team should develop a workflow to enable it to have an internally consistent, and continuously updated tracker of individual DG customer consumption and estimated production. This workflow may initially be developed principally through R, but data growth will likely require a relational database solution (e.g., SQL) within 2 – 3 years.

In addition to this time series, the LUMA LFR team should maintain an up-to-date cross-sectional data table of all DG customers identifying: installed capacity, date of enrollment, and whether or not they have on-site energy storage.

Recommendation 2: Expand DG Customer Data Collection

In order to more accurately project DG customer growth and the ongoing evolution of displaced customer loads (e.g., through changing customer characteristics and equipment like batteries), Guidehouse recommends that the LFR team work to collect more data from DG customers.

The three main sources of additional data Guidehouse recommends that the LUMA LFR team consider are:

- *Hourly consumption data from the Improvement 4 Load Research Sample.* These data are important to help the LUMA LFR team better assess the peak demand implications of increasing DG adoption
- *Hourly production data.* This is a longer-term recommendation, as it would require the deployment of production metering to a sample of DG participants. These data are important for validating (and if necessary) correcting PV production estimates and so ensuring the accuracy of the load forecast.
- *Behavioral survey data.* There are some important questions that can only be answered by asking customers directly. A well developed and robustly implemented survey can assist the LUMA LFR team to better characterize the available market for DG and better understand what the upper limit of likely adopters is. Such a survey could also better inform LUMA about battery use behavior and how that is evolving, crucial information for understanding the impact of DG growth on both energy consumption and peak demand.

Guidehouse recommends that once the LFR team has established (or procured) a workflow that ensures the ongoing availability of an internally consistent database of DG customer consumption (recommendation 1) it work to plan out the collection of some of the other important additional pieces of data noted above.

LUMA Ex. 72.05 (Attachment 1 to LUMA's Response to SESA-of-LUMA-DIST-26).

Annex 6

LUMA Exhibit 73 - Mr. Alejandro Figueroa's Surrebuttal Testimony (Notarized)

**GOVERNMENT OF PUERTO RICO
PUERTO RICO PUBLIC SERVICE REGULATORY BOARD
PUERTO RICO ENERGY BUREAU**

IN RE:

**PUERTO RICO ELECTRIC POWER
AUTHORITY RATE REVIEW**

CASE NO.: NEPR-AP-2023-0003

**SUBJECT: REVENUE DECOUPLING
MECHANISM**

Surrebuttal Testimony of

Alejandro Figueroa-Ramírez

Chief Regulatory Officer, LUMA Energy ServCo, LLC

October 30, 2025

**Summary of Surrebuttal Testimony of
ALEJANDRO FIGUEROA
ON BEHALF OF
LUMA ENERGY LLC AND LUMA ENERGY SERVCO, LLC**

Mr. Alejandro Figueroa-Ramírez presents this Surrebuttal Testimony on behalf of LUMA Energy LLC and LUMA Energy ServCo, LLC (collectively, “LUMA”). The purpose of Mr. Figueroa’s Surrebuttal Testimony is to address some issues and differences in opinion from portions of the answering testimonies of Mr. E. Kyle Datta on behalf of the Solar and Energy Storage Association of Puerto Rico (“SESA”) and the expert report of Ms. Melissa Whited of Synapse Energy Economics, Inc., a consultant to the Energy Bureau, filed on September 8, 2025, and October 6, 2025, respectively, in Case No. NEPR-AP-2023-0003, *In Re: Puerto Rico Electric Power Authority Rate Review*.

First, Mr. Figueroa refutes the conclusion made by Mr. Datta in his answering testimony that LUMA should not need to increase the fixed customer charge if a revenue decoupling mechanism is implemented. Mr. Figueroa clarifies that increasing the customer charge accomplishes a different objective than revenue decoupling and confirms that both are needed.

From there, Mr. Figueroa addresses the recommendations made by Ms. Whited in her reports. Mr. Figueroa responds to Ms. Whited’s recommendation that LUMA base the decoupling target revenue on the total utility revenue requirement across all customer classes. LUMA builds the target revenue based on revenues per class but agrees that the decoupling rate be calculated based upon a comparison of over or under collection of the total allowed revenues across all classes. As explained by Mr. Figueroa, Mr. Figueroa agrees with Ms. Whited’s recommendation that LUMA exclude variable costs, such as fuel and purchased power, from the decoupling formula because separate riders already reconcile those costs. Mr. Figueroa does not agree with Ms. Whited’s recommendation to implement *full decoupling* without weather normalization to improve transparency and reduce complexity because LUMA’s sales forecast incorporates weather-normalized sales units, so it is appropriate to compare weather normalized billed sales to ensure a true comparison. Mr. Figueroa also agrees with Ms. Whited’s recommendation that LUMA include sales lost due to outages in the decoupling calculation. PREB should address reliability and performance accountability through separate incentive mechanisms.

Mr. Figueroa agrees with Ms. Whited’s recommendation that the mechanism operate in both directions, with surcharges when revenues fall short of the authorized amount and refunds when revenues exceed it. Mr. Figueroa notes that LUMA’s proposal is the same as Ms. Whited’s recommendation to require annual decoupling adjustments to limit administrative burden and minimize rate volatility, while still providing timely revenue recovery. Mr. Figueroa indicates that LUMA also agrees with her recommendation to establish a soft cap on upward adjustments equal to 3 percent of annual revenues subject to the decoupling mechanism but takes the position that a similar cap should be placed on downward adjustments (refunds in the form of bill credits). To the extent that LUMA recovers beyond the 3 percent cap, Mr. Figueroa asserts that the utility should be able to reinvest the additional revenues. LUMA is not an investor-owned

utility, so the funds belong ultimately to the citizens of Puerto Rico. Any incremental funding available to support incremental projects, beyond those requested in the rate case, would inure to the benefit of electric customers. Mr. Figueroa also agrees with Ms. Whited's recommendation that LUMA implement the decoupling mechanism through a rider rather than through deferral accounting to promote timely, transparent reconciliation of decoupling revenues, support stable utility cash flow, and avoid large, accumulated balances of decoupling under or overcollections.

Finally, Mr. Figueroa agrees with Ms. Whited's recommendation that LUMA file a complete description of the decoupling mechanism before implementation, including formulas, inputs, data sources, and workpapers. Regarding annual updates, Mr. Figueroa recommends that the PREB treat the update to this rider similar to other periodic updates to riders. He also indicates that LUMA agrees with the PREB reviewing the decoupling mechanism during a future base rate case but suggests that the next rate case will occur prior to any actual experience with the rider and recommends that the review be conducted in a subsequent rate case when there have been some years of information as to how the rider operated.

I. BACKGROUND/INTRODUCTION

Q. 1 Please state your name, business address, title, and employer.

A. My name is Alejandro Figueroa Ramirez. My business address is LUMA Energy, PO Box 363508, San Juan, Puerto Rico 00936-3508. I am the Chief Regulatory Officer for LUMA Energy ServCo, LLC (“LUMA ServCo”).

Q. 2 On whose behalf are you submitting this Surrebuttal Testimony?

A. My surrebuttal testimony is provided on behalf of LUMA Energy, LLC and LUMA Energy ServCo, LLC (jointly referred to as “LUMA”).

Q. 3 What is the purpose of your surrebuttal testimony?

A. My testimony responds to several portions of the report of Melissa Whited of Synapse Energy Economics, Inc., a consultant to the Puerto Rico Energy Bureau (“PREB” or “Energy Bureau”), dated October 6, 2025.¹ The main purpose of my surrebuttal testimony is to respond to recommendations made by Ms. Whited regarding the proposed decoupling mechanism in her report. I also respond to the testimony of Mr. E. Kyle Datta (“Datta Testimony”) filed in this proceeding on September 8, 2025, on behalf of Solar & Energy Storage Association (“SESA”) to the extent it addresses LUMA’s decoupling mechanism.

Q. 4 Are there any exhibits attached to your testimony?

A. No.

Q. 5 What initiated the proposal for a revenue decoupling mechanism?

A. In my testimony, filed earlier in this rate review as LUMA Exhibit 1.0, I acknowledged the Energy Bureau’s February 27, 2025, resolution and order adding

¹ See PC Ex. 59.0 Expert Report of Melissa Whited.

two filing requirements that required “Schedule I,” a revenue decoupling mechanism with a proposed reconciliation.

Q. 6 Did LUMA provide this proposal?

A. Yes. LUMA witness Sam Shannon, in his testimony filed as LUMA Ex. 20.0, described a revenue decoupling mechanism, and how it could help protect the utility’s financial position in Puerto Rico in the face of energy efficiency programs and the high penetration of distributed generation. Witness Shannon stated that “pending approval from the Energy Bureau, a decoupling mechanism would commence in FY2028, reconciling FY2027.”² LUMA witness Andrew Smith also supported the development of a mechanism to “decouple” revenue from billing determinants. On August 19, 2025, the Energy Bureau issued a determination of completeness meaning that LUMA’s application, as filed and supplemented by responses to requests for information, is complete.

II. REVENUE DECOUPLING

Q. 7 What is LUMA’s objective of decoupling?

A. The objective of a revenue decoupling mechanism is to stabilize the Utility’s revenues and provide a hedge against revenue erosion. It does this by providing an annual true-up in the event that actual billed revenues are less than target revenues. If actual billed revenues exceed target revenues, the Energy Bureau could opt for these amounts to be returned to customers or to accrue to PREPA’s bank accounts that ultimately fund investment in the System as discussed in further detail below. I note that more investments into the System are required than what current funding levels

² LUMA Ex. 20.0, Sam Shannon’s Expert Testimony

45 provide. Therefore, any incremental revenue that is redirected to fund incremental
46 investments beyond those initially projected will result in a benefit to customers.

47 **Q.8 Does a revenue decoupling mechanism reduce the need for LUMA to increase**
48 **its fixed charges?**

49 A. No. Revenue decoupling and the revenue allocation based on the results of Mr.
50 Shannon's Cost-of-Service Study (COSS") are two separate and distinct things. The
51 purpose of a revenue decoupling mechanism is to permit a surcharge to recover the
52 full revenue authorized by the Energy Bureau without the need for a full rate case to
53 reset rates. The purpose of a COSS is to allocate a utility's embedded costs to its
54 various customer classes based on cost causation and cost allocation principles.
55 Therefore, in its intervener answering testimony, SESA's witness Mr. Datta
56 mischaracterized the impact of the revenue decoupling mechanism in that he asserted
57 that such mechanism would provide the utility with sufficient revenue stability such
58 that an increase to the fixed charges is not warranted.

59 **Q.9 Does a revenue decoupling mechanism solve revenue erosion due to distributed**
60 **generation?**

61 A. No. As I stated in the September 4th Technical Conference, revenue decoupling can
62 provide a useful bridge while broader policy decisions around solar energy are being
63 studied.³ LUMA acknowledges and agrees that this rate review is not intended to set
64 solar policy.

65 **Q.10 The PREB consultant's report recommends that LUMA base the decoupling**
66 **revenue target on the utility's revenue requirement across all customer classes**

³ <https://www.youtube.com/watch?v=Tujq4QtJS6c>, 1:32:28

67 **with annual adjustments. How does LUMA propose the target revenues be**
68 **established?**

69 A. LUMA agrees with the recommendation for an annual decoupling mechanism with a
70 decoupling rate based on the utility's total revenue requirement. LUMA proposes
71 that in present and future rates cases, the Energy Bureau establish authorized
72 revenue requirements for the test years, and that the target revenue would be a
73 function of the authorized revenue requirement. LUMA proposes that target revenue
74 for the purposes of a revenue decoupling mechanism be identified as a revenue per
75 customer number for each customer class. In other words, the authorized revenue
76 allocation for each participating customer class would be translated into a revenue
77 per customer number. The target revenue number(s) would set the basis for
78 comparing actual billed revenue to authorized revenue to determine the annual
79 surcharge (if any). However, the decoupling rate calculation would be based on the
80 total variance in revenue for all classes.

81 **Q.11 The PREB consultant report recommends that the target revenue exclude**
82 **variable costs, such as fuel and purchased power, from the decoupling formula**
83 **because separate riders already reconcile those costs. Does LUMA propose that**
84 **the target revenue per customer include fuel and purchased power revenue?**

85 A. No, it would only be calculated to include the base rates. Riders such as FCA,
86 PPCA, CILT, and SUBA are pass-through riders that collect funds to match specific
87 expenses. Their formulas for these riders already include a prior period
88 reconciliation, which accomplishes the same objective as a revenue decoupling
89 mechanism.

90 **Q.12 Which customer classes will participate in the decoupling mechanism?**

91 A. As a starting point, all non-lighting customer classes except the subsidized rates
92 would participate in the decoupling mechanism i.e., GRS, GSS, GSP, TOU-P, GST,
93 and TOU-T. Target revenues would be developed for each of the participating
94 customer classes and the decoupling charges would only apply to these classes. This
95 approach would be consistent with prior determinations by the Energy Bureau,
96 including the July 31, 2025 Provisional Rate Order.

97 **Q.13 Under the proposal, would each participating customer class be reviewed in**
98 **isolation, or as a total population?**

99 A. Both the participating customer class and the total population for all the classes
100 would be considered. Each customer class would be evaluated based on its variance
101 from the target revenue number. However, the decoupling rate calculation would be
102 based on the total variance. If, for example, the GRS customer class falls short of its
103 target revenue, but the utility's total revenue reaches or exceeds the authorized
104 revenue requirement, then there would be no surcharge to any customer class.
105 However, if there is a total revenue shortfall, then the surcharge would apply to all
106 classes subject to decoupling.

107 **Q.14 If the decoupling mechanism fundamentally operates based on the total**
108 **variance, why use class-specific revenues as the basis for targets?**

109 A, Using class-specific revenue targets protects both customers and the utility. First, it
110 accounts for customer growth within a customer class, or conversely, the loss of
111 customers. Second, class-specific revenue targets reflect the fact that some customer
112 classes have vastly greater revenues per customer than others. For these classes, a
113 handful of individual customers can swing the actual billed revenue numbers.
114 Keeping these classes separate from mass classes, like GRS or GSS, provides more

115 transparency in the reporting of the decoupling mechanism and gives a clearer
116 picture of the utility's sales.

117 **Q.15 The PREB Expert Reports proposed to recover or refund any under or over**
118 **collected revenues to customers using a rider mechanism instead of deferral**
119 **accounting. What is LUMA's opinion?**

120 A. LUMA agrees with the recommendation to recover decoupling adjustments through
121 a separate rider. Any variance from forecast revenue would be recovered via the
122 decoupling rider annually. Separately from the revenue decoupling mechanism, in
123 the surrebuttal testimony on costs due November 3, LUMA will discuss the use of
124 deferral accounting to facilitate the rolling over of any accumulated variance in the
125 bad debt provision (i.e., between the amount that is forecast and what the actual bad
126 debt amount is) into the revenue requirement for the next rate case.

127 **Q.16 How frequently would the decoupling mechanism operate?**

128 A. LUMA agrees with the PREB consultants that the mechanism should operate on an
129 annual basis. Similar to how the other riders operate, LUMA will submit, in this
130 case, an annual filing with the Energy Bureau in May, two months before the end of
131 the fiscal year with ten months of actuals and two months of forecast. The
132 decoupling mechanism surcharge (if any) would be in effect for the entire following
133 fiscal year.

134 **Q.17 Why would the decoupling mechanism not operate more frequently than**
135 **annually?**

136 A. LUMA agrees with the PREB consultants that an annual reconciliation strikes the
137 right balance between reducing administrative burden and reducing bill volatility
138 while still providing timely revenue recovery. Because authorized revenue

requirements are set for test years, the target revenue and decoupling mechanism should match that time period. Also, attempting to define actual revenue versus target revenue for part of the test year may be complicated by the seasonality of electricity sales. Having an annual reconciliation for decoupling avoids this issue. It also allows the utility to smooth the surcharge (if any) and thereby reduce the rate impact, again noting the Hearing Examiner's comments on the presence of a decoupling mechanism versus customers' ability to pay.

Q.18 The PREB Expert Report recommends full decoupling without weather normalization. What is LUMA's opinion? Should the actual revenue be weather normalized prior to comparison with target revenues?

A. Yes. The decoupling mechanism should account for weather normalization. This is necessary because the sales forecast incorporates weather-normalized sales units adjusted for cooling degree days, and so the actual revenues for a fiscal year would be adjusted to remove the effect of deviations due to weather. Because the sales forecast already uses weather-normalized sales, the authorized target revenues will be a weather-normalized number. Evaluating the target against the weather-normalized actual billed sales ensures a true apples-to-apples comparison.

Q.19 The PREB Expert Report recommends that LUMA include outages in the decoupling calculation. Should the decoupling mechanism incorporate revenue reduction due to storm outages?

A. Yes. LUMA's sales forecast does not account for storm outages therefore, to the extent that storm outages reduce PREPA's revenues, these losses would be captured by the decoupling mechanism. As Ms. Whited explains, "excluding outage-related sales would deprive the utility of necessary revenues for maintenance and

investment, which would ultimately harm customers by undermining system reliability.”⁴ LUMA agrees with this statement. The purpose of a decoupling mechanism is to provide a tool for the utility to gain stability and predictability in revenues such that it can continue to invest in the system at the levels necessary to maintain and improve service quality levels. Not accounting for storm-related outages defeats the purpose as the overall needs of the utility will remain the same, while the revenues would fall short of those required to meet those needs.

Q.20 Would the decoupling mechanism incorporate revenue reduction due to transmission, distribution or generation outages?

A. Yes. As I describe above, depriving the utility of revenues undermines reliability by creating a situation in which the utility does not have the funds to invest in the system. LUMA agrees with Ms. Whited’s conclusion that this is why performance incentives should be addressed separately.

Q.21 How would the decoupling mechanism apply to customers?

A. The decoupling rate would be a monthly volumetric charge applied to all the participating customer classes. The allocation of the decoupling recovery amount would be based on the forecast energy sales for the following fiscal year. The Utility requests the Energy Bureau establish a Decoupling Rider with an initial rate of zero in the event that the Energy Bureau approves a decoupling mechanism.

Q.22 When would the decoupling mechanism begin?

A. If approved by the Energy Bureau in its final Order in February, March or April of 2026, then the decoupling mechanism would begin in FY2027, with the first

⁴ See PC Ex. 59.0 Expert Report of Melissa Whited.

185 potential decoupling surcharge (if any) going into effect for beginning of fiscal year
186 2028, to reconcile revenues from FY2027.

187 **Q.23 Will the decoupling mechanism take into account effects of energy efficiency**
188 **activities?**

189 A. No. The sales forecast prepared by Ms. Joseline Estrada for LUMA already contains
190 modifiers for energy efficiency impacts. Therefore, the potential impact has already
191 been incorporated into rates.

192 **Q.24 The PREB Expert Report proposes a one-way cap of 3% on the decoupling**
193 **mechanism. Do you have any comments on that cap?**

194 A. Yes. Any cap should be bidirectional such that the utility has a reasonable
195 opportunity to both collect and credit customers as needed. To the extent that there is
196 an overcollection, then a cap would provide an opportunity for a portion of the
197 overcollection to be reinvested into the system to support incremental investments
198 that may be urgently required or otherwise provide incremental benefits to
199 customers. In the event that PREPA gains access to capital markets in the future,
200 then the proposed cap on credits for overcollection can be reassessed.

201 **Q. 25 Do you have comments on the PREB Expert Report's recommendations filing**
202 **description, workpapers, etc. and regarding stakeholder review?**

203 A. Yes. The Energy Bureau should conduct this review in the same manner in which it
204 reviews all other periodic rate adjustments such as FCA, PPCA, and the other riders.

205 **Q. 26 Do you have a response to the recommendation that the pilot program be**
206 **evaluated in next rate case?**

207 A. Yes. LUMA suggests that the next rate case may be premature to evaluate this
208 mechanism. The first year that the revenue decoupling mechanism will be in place is

209 FY2028, to true up revenues for FY2027. Therefore, assuming the following rate
210 case occurs sometime around FY2028, it is unlikely that there will be enough
211 information available regarding the application and implementation of the
212 decoupling mechanism to support any modifications. Accordingly, LUMA proposes
213 that any assessment of the decoupling mechanism be performed after such
214 mechanism has been in place for at least more than one fiscal year.

215 **Q. 27 The PREB Expert Reports noted that LUMA stated in response to a request for**
216 **information that the cost of implementing the decoupling mechanism is not in**
217 **the rate case, do you plan to address that cost?**

218 A. Yes. LUMA will address this in its surrebuttal on costs to be filed November 3rd.

219 **Q.28 Does this conclude your testimony?**

220 A. Yes.

ATTESTATION

Affiant, Alejandro Figueroa-Ramírez, being first duly sworn, states the following:

The prepared Surrebuttal Testimony and exhibits constitutes my Surrebuttal Testimony in the above-styled case before the Puerto Rico Energy Bureau. I would give the answers set forth in the Surrebuttal Testimony if asked the questions that are included in the Surrebuttal Testimony. I further state that the facts and statements provided herein are my Surrebuttal Testimony and to the best of my knowledge are true and correct.

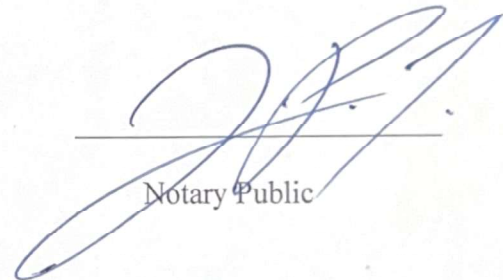

Alejandro Figueroa-Ramírez

Affidavit No. 146

Acknowledged and subscribed before me by Alejandro Figueroa-Ramírez, in his capacity as Chief Regulatory Officer of LUMA of legal age, married, and resident of San Juan, Puerto Rico, who is personally known to me.

In San Juan, Puerto Rico, this 4th day of November 2025.




Notary Public