TESIS DE LA UNIVERSIDAD
DE ZARAGOZA

2024

291

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Poverty, inequality and violence in the United States

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ISSN 2254-7606

Prensas de la Universidad
Universidad Zaragoza

Universidad de Zaragoza
Servicio de Publicaciones

ISSN 2254-7606

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UNIVERSIDAD DE ZARAGOZA
Escuela de Doctorado

Programa de Doctorado en Economía

2024

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Facultad de Economía y Empresa
2024

Agradecimientos

El primer agradecimiento es para mis directores de tesis, Fernando y Marcos, y es por partida doble: en primer lugar, quiero darles las gracias por sus consejos, recomendaciones y orientación en todas las etapas de la investigación. Han sido unos excelentes guías académicos. Y en segundo lugar, quiero agradecerles su paciencia y comprensión, sobre todo en los momentos de más incertidumbre.

El siguiente agradecimiento es para mi familia y amigos, quienes me han apoyado desde el inicio de este largo camino. Y también va para aquellas personas que han llegado una vez comenzado. Pero, sobre todo, quiero dedicar esta tesis a quienes no están en el momento de su finalización, en especial, a mi padre.

El último agradecimiento se lo reservo a mi madre. Sin contar con ella, no habría sido capaz de llevar esta tesis hasta su conclusión.

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Resumen

Esta tesis cuenta con tres capítulos que han sido elaborados siguiendo un único hilo conductor: el uso del análisis económico como una herramienta que permite recopilar información sobre problemas directamente vinculados al bienestar social. De esta manera, la tesis, en cada uno de sus capítulos, analiza la pobreza, la desigualdad y el impacto económico de los tiroteos masivos, tomando a los Estados Unidos (EE. UU.) como caso de estudio.

El primer capítulo, titulado *"An assessment of poverty determinants in census tracts, 1970-2010"*, examina los factores que influyen en la pobreza dentro de EE. UU. a nivel de *census tract*. Este enfoque ayuda a evitar potenciales errores de agregación que pueden surgir cuando se utilizan unidades geográficas más grandes. Con este objetivo, aprovechamos un conjunto de datos geográficamente consistente que abarca desde 1970 hasta 2010 y todas las áreas estadísticas metropolitanas. Nuestra metodología incluye el uso del método de momentos generalizados adaptado para datos de panel dinámicos. Los hallazgos resaltan la naturaleza persistente de la pobreza, particularmente en *tracts* con tasas elevadas. El análisis también revela que el mercado laboral juega un papel significativo en la configuración de los niveles de pobreza. Además, nuestra investigación indica que las mujeres se ven especialmente afectadas por la pobreza. Estos resultados contribuyen a la discusión en curso sobre el diseño óptimo de estrategias de desarrollo local, sugiriendo que las políticas enfocadas en el lugar y aquellas centradas en los individuos pueden considerarse complementarias en lugar de sustitutas.

El segundo capítulo, titulado *"Long-run inequality persistence, 1870-2019"*, profundiza en la persistencia de la desigualdad en EE. UU., analizando series de desigualdad tanto de ingresos como de riqueza desde 1870 hasta 2019. Este estudio evalúa la persistencia de la desigualdad mediante la aplicación de contrastes de raíz unitaria y de ruptura estructural

para series temporales. Además, exploramos qué impulsa la naturaleza duradera de la desigualdad mediante el uso de métodos de *Bayesian model averaging* dentro del marco de un modelo lineal generalizado. Los hallazgos indican que el ratio riqueza-ingreso exhibe un comportamiento no estacionario a lo largo de todo el periodo analizado. Por el contrario, el coeficiente de Gini para el ingreso disponible y la participación del ingreso del 10 % superior alternan entre regímenes I(0) e I(1). El análisis revela que un mayor grado de globalización tiende a reforzar la persistencia de la desigualdad de ingresos, mientras que niveles más altos de escolarización y de afiliación sindical tienen el efecto opuesto.

El tercer y último capítulo, *"Mass shooting, employment and housing prices: Evidence from different geographic entities"*, examina las repercusiones económicas de los tiroteos masivos. Para ello, hemos creado una base de datos única que incluye información detallada sobre la ubicación de estos trágicos incidentes. Aprovechando los últimos avances en los métodos de diferencias en diferencias, evaluamos el impacto de los tiroteos masivos en el empleo y los precios de la vivienda en tres niveles de desagregación geográfica. Las consecuencias económicas de los tiroteos masivos son particularmente pronunciadas en los *census tracts* y cuando estos incidentes ocurren en sitios públicos. Además, nuestros resultados indican que los tiroteos masivos afectan principalmente el empleo en sectores fuertemente dependientes de las interacciones cara a cara con el público.

Abstract

This thesis consists of three chapters, each developed following a single thread: the use of economic analysis as a tool to gather information about issues directly linked to social welfare. In this way, the thesis analyzes poverty, inequality, and the economic impact of mass shootings in each of its chapters, taking the United States (U.S.) as a case study.

The first chapter titled *"An assessment of poverty determinants in census tracts, 1970-2010"*, examines the factors influencing poverty within the U.S. at the granularity of census tracts. This approach helps circumvent the potential for aggregation errors that can arise when larger geographic units are used. With this aim, we leverage a geographically consistent dataset spanning from 1970 to 2010 and encompassing all metropolitan statistical areas. Our methodology includes the use of the generalized method of moments framework for dynamic panels. The findings highlight the enduring nature of poverty, particularly in tracts with elevated poverty rates. The analysis also reveals that the labor market plays a significant role in shaping poverty levels. Additionally, our research indicates that women are especially affected by poverty. These insights contribute to the ongoing discussion regarding the optimal design of local development strategies, suggesting that place-based and person-centered policies can be considered as complementary rather than as substitutes.

The second chapter, titled *"Long-run inequality persistence, 1870-2019"*, delves into the persistence of inequality within the U.S., analyzing both income and wealth inequality series from 1870 to 2019. This study assesses the persistence of inequality through the application of unit root and structural break tests for time series. In addition, we explore what drives the lasting nature of inequality by employing Bayesian model averaging methods within a generalized linear model framework. The findings indicate that the wealth-to-income ratio exhibits non-stationary behavior across the entire period an-

alyzed. Conversely, the Gini coefficient for disposable income and the top 10% income share alternate between I(0) and I(1) regimes. The analysis reveals that higher degrees of globalization tend to reinforce the persistence of income inequality, while higher levels of educational attainment and trade union membership have the opposite effect.

The third and last chapter, *"Mass shooting, employment and housing prices: Evidence from different geographic entities"*, examines the economic repercussions of mass shootings. To facilitate this analysis, we have created a unique dataset encompassing detailed information about the location of these tragic incidents. Leveraging recent advances in difference-in-differences methods, we evaluate the impact of mass shootings on employment and housing prices across three levels of geographic disaggregation. The economic consequences of mass shootings become particularly pronounced at the census tract level and when these incidents occur in public areas. Furthermore, our findings indicate that mass shootings mainly affect employment in sectors heavily dependent on face-to-face interactions.

Introducción

El establecimiento de los Objetivos de Desarrollo Sostenible (ODS) en la Agenda 2030, elaborada por la Organización de las Naciones Unidas (ONU) y su posterior adopción generalizada representa un cambio de paradigma en el panorama político y social internacional. Estos objetivos, ambiciosos por la diversidad de metas y su visión a largo plazo, trazan un camino para que gobiernos, sector privado y sociedad civil afronten juntos los desafíos sociales y medioambientales actuales. Este ímpetu transformador de los ODS ha ido permeando en la sociedad durante los últimos años, llegando a incidir en el desarrollo de esta tesis, la cual utiliza el amplio abanico de metodologías y herramientas que ofrece el análisis económico para profundizar en el conocimiento de distintos problemas directamente relacionados con el bienestar social.

Así, la tesis se articula en tres capítulos diferenciados e independientes que abordan, con rigor metodológico y originalidad, cuestiones vinculadas a la calidad de vida de todos los ciudadanos. Estos temas son: la pobreza en los barrios urbanos, la persistencia de la desigualdad en el largo plazo y los impactos adversos de los tiroteos en masa en las economías locales; todos ellos tomando a Estados Unidos (EE.UU.) como referencia. Es notable destacar cómo la elección de estos temas no solo coincide con el espíritu de compromiso de los ODS, sino que, de hecho, se alinea con algunos de sus objetivos, en particular aquellos de índole más social. Para ser más específicos, en los ODS se tocan puntos como la erradicación de la pobreza (Objetivo 1), la reducción de disparidades económicas (Objetivo 10), el refuerzo de la seguridad y la resiliencia urbana (Objetivo 11) o la reducción de la violencia (Objetivo 16), que coinciden con los temas analizados en los capítulos de esta tesis. Sin embargo, es vital subrayar que la elección de estos responde a razones que trascienden dicha concordancia.

En primer lugar, la pobreza, lejos de ser sólo un indicador económico, representa un desafío multifacético que afecta de manera fundamental la calidad de vida de quienes la padecen. Aquellos que viven en condiciones de pobreza, además de enfrentar adversidades diarias, también están expuestos a riesgos significativos para su salud física y mental (Raphael, 2011; Ridley, Rao, Schilbach y Patel, 2020). No obstante, las repercusiones de la pobreza no se limitan a quienes la experimentan directamente. Cuando la pobreza se concentra en áreas específicas, sus efectos se magnifican y afectan a la comunidad en su totalidad. Una amplia literatura ha documentado la relación directa entre la concentración de pobreza en determinados barrios y unos mayores índices de criminalidad en estos (Patterson, 1991; Stretesky, Schuck y Hogan, 2004; Friedson y Sharkey, 2015; Sharkey, Besbris y Friedson, 2016). Además, las personas que residen en barrios con tasas de pobreza elevadas, y en particular en los urbanos, suelen presentar peores condiciones de salud tanto física (Diez-Roux y Mair, 2010) como mental (Anakwenze y Zuberi, 2013).

Un estudio que da buena cuenta sobre esta relación entre la concentración de pobreza y la salud es el realizado por Ludwig, Duncan, Gennetian, Katz, Kessler, Kling y Sanbonmatsu (2012). En él se utilizan datos vinculados al programa *"Moving to Opportunity"* (MTO), a través del cual se subvencionó a un gran número de familias para reubicarse desde *census tracts* con altos índices de pobreza a otros con niveles de pobreza más bajos mediante una lotería aleatoria entre los solicitantes. Sus resultados muestran que las familias que se reubicaron experimentaron mejoras significativas en su salud física, tales como una menor incidencia de diabetes u obesidad, así como en su salud mental. Por otro lado, Wodtke, Harding y Elwert (2011) encontraron que una exposición prolongada a la pobreza durante la niñez se relaciona con menores probabilidades de culminar la educación secundaria. En esta misma línea, Chetty, Hendren y Katz (2016), al analizar los resultados del programa MTO, identificaron que los niños que fueron reubicados a áreas con menor pobreza en edades tempranas tienen mayores probabilidades de haber asistido a la universidad y de tener ingresos superiores en su vida adulta en comparación con aquellos que no se beneficiaron del programa.

En resumen, la literatura económica subraya las profundas repercusiones de la pobreza en cuanto a crimen, salud o desarrollo educativo y personal, tanto para aquellos que la sufren directamente, como para las comunidades que conviven con ella. Estas consecuencias motivan la elección de la pobreza como objeto de estudio en el primer capítulo de esta tesis, titulado *"An assessment of poverty determinants in census tracts, 1970-2010"*. Hasta ahora, la pobreza en la literatura económica había sido analizada centrándose principalmente en unidades geográficas más extensas como los condados, lo que podría no tener en cuenta que muchos de los efectos negativos de esta se dan en áreas más pequeñas y, además, podría estar enmascarando la heterogeneidad de este fenómeno. Por ello, en este capítulo se pretende abordar este vacío, examinando la tasa de pobreza de los *census tracts* de todas las Áreas Estadísticas Metropolitanas (MSAs, por sus siglas en inglés) en EE.UU. Con este objetivo, se analiza la persistencia de la pobreza mediante contrastes de raíz unitaria para datos de panel, concluyendo que la tasa de pobreza en los *tracts* es estacionaria. Posteriormente, a través de una estimación que utiliza el método de los momentos generalizado para paneles dinámicos, se examina la influencia de diversos factores socioeconómicos, así como relacionados con el mercado laboral y con el parque de vivienda, en la pobreza. Los principales resultados muestran que el empleo tiene una relación negativa y consistente con la pobreza mientras que el porcentaje de familias monoparentales encabezadas por mujeres se asocia positivamente con ésta. El análisis se realiza segmentando según la ubicación de los *census tracts* dentro de las MSAs (centro o periferia), el tamaño de la MSA donde se encuentran y su estatus en cuanto a la distribución de la propia tasa de pobreza. Finalmente, los resultados obtenidos se interpretan dentro del debate entre las políticas del tipo *place-based*, que buscan mitigar la pobreza interviniendo en áreas con alta concentración de la misma, y las políticas *person-centered*, que apuntan a ayudar directamente a quienes sufren dicha pobreza, concluyéndose que la mejor estrategia es la combinación de ambas.

El segundo tema objeto de estudio en esta tesis es la desigualdad. Al contrario que con la pobreza, cuyas consecuencias son ampliamente reconocidas, enumerar las implicaciones negativas de la desigualdad resulta más controvertido. Tradicionalmente, se ha sostenido que los problemas comúnmente asociados con la desigualdad en realidad provienen de una escasez de recursos o de la pobreza misma, más que de la desigualdad económica per se. Concretamente, se ha venido argumentando que la acumulación de riqueza fomenta el ahorro y, consecuentemente, la inversión y el crecimiento económico. No obstante, estudios recientes como el de Berg y Ostry (2017), cuestionan la dirección de esta relación, sugiriendo que la desigualdad podría en realidad socavar dicho crecimiento. En este sentido, las revisiones de la literatura de Neves y Silva (2014) y Ferreira, Gisselquist y Tarp (2022) documentan vías mediante las cuales la desigualdad puede afectar negativamente el desarrollo económico. Una de ellas es la reducción de inversiones a causa de conflictos sociopolíticos originados por el desigual reparto de los recursos (Rodrik, 1999; Keefer y Knack, 2002). De hecho, este conflicto social podría considerarse, en sí mismo, una repercusión negativa de la desigualdad. Además de ello, la desigualdad también trae consigo la aparición y promoción de partidos políticos de carácter populista (Nolan y Valenzuela, 2019; Stoetzer, Giesecke y Klüver, 2021).

La desigualdad también ejerce una influencia negativa en la educación, como se muestra en la recopilación de la literatura elaborada por Ferreira, Gisselquist y Tarp (2022). Entre los estudios examinados por estos autores es particularmente interesante para nuestro caso el trabajo de Mayer (2001), centrado en EE.UU., que muestra cómo el crecimiento de la desigualdad entre 1970 y 1990 afectó de manera desigual a las tasas de graduación entre distintos estratos socioeconómicos. Asimismo, las investigaciones de Wilkinson y Pickett (2006) y Ribeiro, Bauer, Andrade, York-Smith, Pan, Pingani, Knapp, Coutinho y Evans-Lacko (2017) evidencian una correlación entre la desigualdad y peores resultados en salud física y mental, respectivamente. Por último, cabe destacar el trabajo de Castells-Quintana, Royuela y Thiel (2019), donde se muestran las repercusiones de la desigualdad en el Índice de Desarrollo Humano, subrayando su impacto a largo plazo, algo que aglutina muchas de las consecuencias negativas previamente mencionadas.

De nuevo, las numerosas consecuencias negativas asociadas con la desigualdad hacen que profundizar en el conocimiento de la evolución histórica de la desigualdad en los EE.UU. sea algo de relevancia social. De este modo, en el segundo capítulo de esta tesis, titulado *"Long-run inequality persistence, 1870–2019"*, se investigan series temporales de desigualdad tanto en renta como en riqueza, retrocediendo hasta 1870, la fecha más temprana que nos permite la disponibilidad de datos. Específicamente, se examina la persistencia del índice de Gini, el porcentaje de renta del *top 10 %* y el ratio riqueza-renta. Para ello se aplican contrastes de raíz unitaria que permiten la posibilidad de que las series contengan rupturas estructurales tanto en la hipótesis nula como en la alternativa, solventando así el problema circular que se presenta cuando ambas cuestiones están presentes en los datos analizados (Perron, 2006). Además, en este capítulo, se adopta un enfoque menos común en la literatura, examinando si las series de desigualdad oscilan entre regímenes estacionarios y no estacionarios. Se concluye que la desigualdad en riqueza permanece como un régimen I(1) durante todo el período analizado, mientras que las dos series de desigualdad en renta muestran una alternancia entre regímenes I(1) e I(0). Por último, se investigan los factores que podrían estar influyendo en estos cambios, para lo que se aplican técnicas de *Bayesian model averaging* en el marco de un modelo lineal generalizado sobre un amplio conjunto de potenciales determinantes. Los resultados sugieren que un mayor grado de globalización intensifica la persistencia de la desigualdad de renta, mientras que dicha persistencia se relaciona inversamente con niveles elevados de educación y afiliación sindical.

El tercer y último tema que se analizará en esta tesis son los tiroteos en masa. Estos son actos de violencia extrema, muchas veces indiscriminada, cuyo estudio se justifica en sí mismo debido al profundo impacto que generan en la sociedad al ocasionar la pérdida de vidas humanas. Si habíamos enfatizado la importancia de analizar fenómenos económicos como la pobreza y la desigualdad debido a sus efectos adversos en áreas fundamentales del bienestar ciudadano, como la salud, la educación y la seguridad, en el último capítulo de la tesis nuestro enfoque cambia: buscamos entender cómo un fenómeno primordialmente no económico repercute en la economía. La literatura académica al respecto nos ha mostrado que estos eventos tienen implicaciones profundamente negativas en la salud mental (Rossin–Slater, Schnell, Schwandt, Trejo y Uniat, 2020), llegando incluso a generar un estrés en aquellas mujeres embarazadas expuestas a dichos eventos que afecta a los neonatos (Dursun, 2019). Además, también influyen en resultados electorales (Yousaf, 2021) y su influencia en la regulación sobre las armas de fuego supera a la de otros tipos de violencia armada (Luca, Malhotra y Poliquin, 2020). Sin embargo, en relación con su impacto económico, área central de esta tesis, la literatura es aún escasa. Se ha observado que perturban el mercado de valores (Sakariyahu, Lawal, Yusuf y Olatunji, 2023) y algunos, particularmente los ocurridos en colegios, han mermado el valor de las propiedades situadas en las zonas afectadas (Muñoz–Morales y Singh, 2023). A este respecto, sólo el estudio de Brodeur y Yousaf (2022) ofrece evidencia sobre su impacto en las economías locales.

Con el objetivo de profundizar en este tema, el tercer capítulo titulado *"Mass shootings, employment, and housing prices: Evidence from different geographic entities"* aborda el impacto de los tiroteos en masa en la economía, poniendo un énfasis particular en la dimensión geográfica de sus efectos. Para ello, se ha desarrollado una base de datos única que recopila información detallada sobre la ubicación de estos incidentes. Utilizando los últimos avances en las técnicas de diferencias en diferencias, que permiten solventar ciertas limitaciones metodológicas y considerar la posibilidad de heterogeneidad en los efectos del tratamiento, se examina la influencia de estos eventos en el empleo y los precios de la vivienda en los condados, códigos postales y *census tracts* afectados entre 2003 y 2019. Los hallazgos revelan que los impactos son más significativos en los *census tracts*, demostrando un patrón persistente y acumulativo a lo largo del tiempo. Estos eventos afectan en mayor medida a los sectores que dependen de interacciones directas con el público. Además, se ha comprobado que los tiroteos sucedidos en lugares públicos tienen un mayor impacto en el empleo. Por último, se investigó si los tiroteos en masa provocan la expulsión de los trabajadores más cualificados de las zonas afectadas, analizando su impacto en la composición del empleo por salarios y nivel educativo. Los resultados muestran que estos efectos, aunque limitados, se extienden más allá de los *census tracts*.

Finalmente, la elección de EE.UU. como unidad de análisis para el estudio de estas tres problemáticas no es casual, sino premeditada. En primer lugar, la posibilidad de acceder a datos con un nivel de granularidad que llega hasta los *census tracts* permite adoptar en el primer y último capítulos un enfoque geográfico adecuado para el estudio de la pobreza y de los impactos que tienen los tiroteos en masa. Además, la disponibilidad de series temporales que se remontan hasta 1870, cinco años después de la conclusión de la Guerra Civil Americana, posibilita, en el segundo capítulo, un exhaustivo estudio de la desigualdad que abarca prácticamente toda la historia contemporánea del país. Esta disponibilidad de datos nos permite además utilizar la amplia variedad de metodologías necesarias para cada caso particular.

Sin embargo, más allá de la abundancia de datos disponibles, EE.UU. se destaca no sólo como una elección práctica sino también como un caso de estudio particularmente relevante para los temas tratados en esta tesis. A pesar de ser uno de los países más ricos del mundo, presenta graves problemas de pobreza y desigualdad y es un caso especial en cuanto al grado de violencia llevada a cabo con armas de fuego, siendo el fenómeno de los tiroteos en masa algo casi exclusivo de este país. Para contextualizar estas afirmaciones, las Figuras 1 y 2 nos ofrecen una imagen de la situación de EE.UU. en el panorama internacional en el

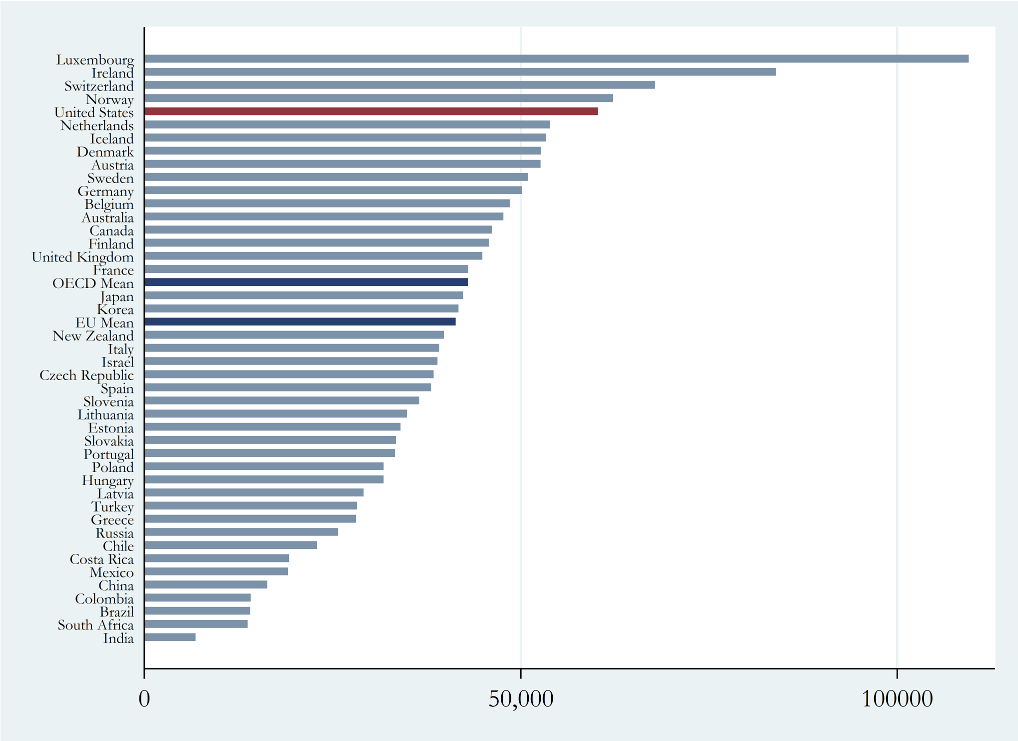


Figura 1: PIB per cápita, US$, precios constantes y PPPs. OCDE y BRICS. Fuente: *OECD Statistics* (2019)

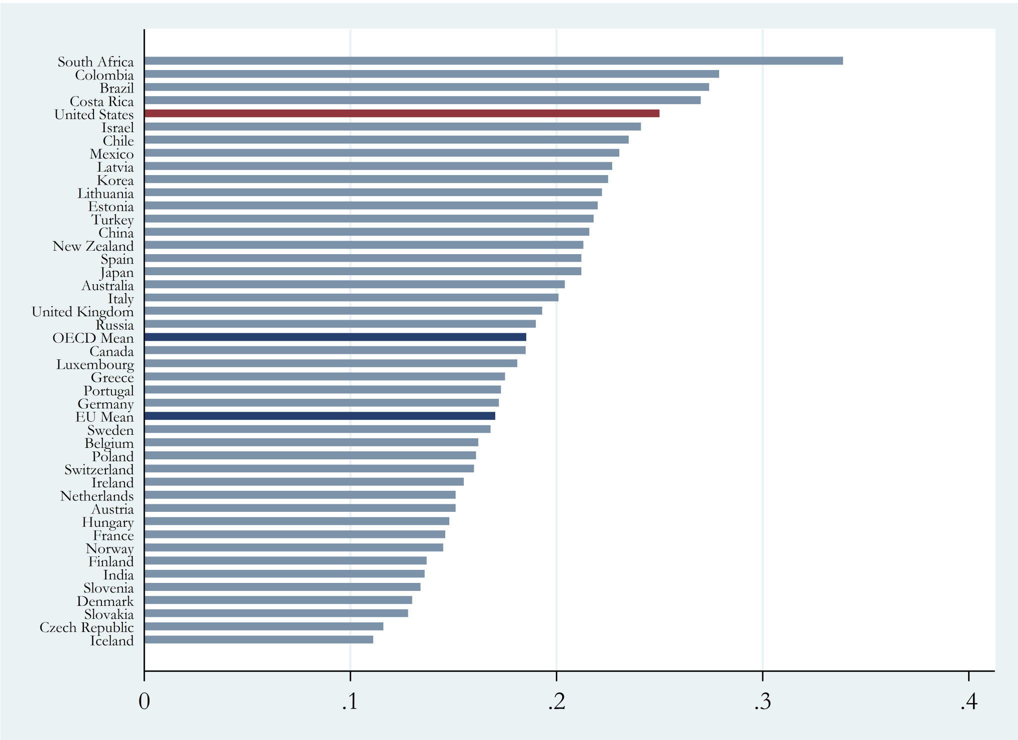


Figura 2: Pobreza relativa (60 % de la renta mediana). OCDE y BRICS. Fuente: *OECD Statistics* (2019)

año 2019, en lo relativo a la renta per cápita y a la tasa de pobreza relativa. Comparando su situación entre los países pertenecientes a la Organización para la Cooperación y el Desarrollo (OCDE) y los llamados BRICS (Brasil, Rusia, India, China y Sudáfrica), EE.UU. se sitúa como el quinto país con mayor PIB per cápita y, simultáneamente, es el quinto país en cuanto a pobreza.

La tasa de pobreza relativa corresponde al porcentaje de personas cuya renta es inferior al 60 % de la renta mediana, algo que resulta útil al permitir una comparativa entre países con contextos económicos bastante diferentes. La alternativa, que de hecho es el tipo de medida analizada en el primer capítulo, es la tasa de pobreza objetiva. Esta se obtiene calculando el porcentaje de población que está por debajo de un determinado umbral mínimo de renta que sería el necesario para obtener los bienes y servicios considerados básicos. Pues bien, para terminar de ilustrar la dicotomía entre el nivel de renta y los problemas de pobreza que presenta EE.UU., nos valdremos del dato referente a este umbral, que en 2019, para una familia de cuatro miembros, se situaba en 25,926$. Cifra que contrasta significativamente con la renta per cápita del país en el mismo año, que alcanzaba los 51,406$ dólares, casi el doble. A pesar de este alto nivel de ingreso medio, el 10.5 % de la población estadounidense vivía por debajo de este umbral de pobreza (U.S. Census Bureau, 2020), lo que equivale a aproximadamente 34 millones de personas con una renta insuficientes para cubrir sus necesidades básicas.

Las Figuras 3 y 4 amplían nuestra perspectiva al presentar la situación de EE.UU. en el contexto internacional en términos de desigualdad. A pesar de ser una economía líder a nivel mundial, con un PIB que sólo es comparable al de China o al de la suma total de las economías europeas, EE.UU. se clasifica en el décimo lugar entre los países de la OCDE y los BRICS en cuanto al índice de Gini después de impuestos y transferencias, revelando su desigual distribución de ingresos. Esta cifra se sitúa sustancialmente por encima del promedio de la OCDE y muestra una brecha aún mayor en comparación con la desigualdad promedio de la Unión Europea. Además, al observar el porcentaje de ingresos que acumula el 10 % más rico de la población, EE.UU. ocupa una posición similar, situándose en el undécimo lugar. Este dato es especialmente significativo, ya que indica que casi la mitad de las rentas totales del país, un 45.7 %, está concentrada en manos del 10 % de la población.

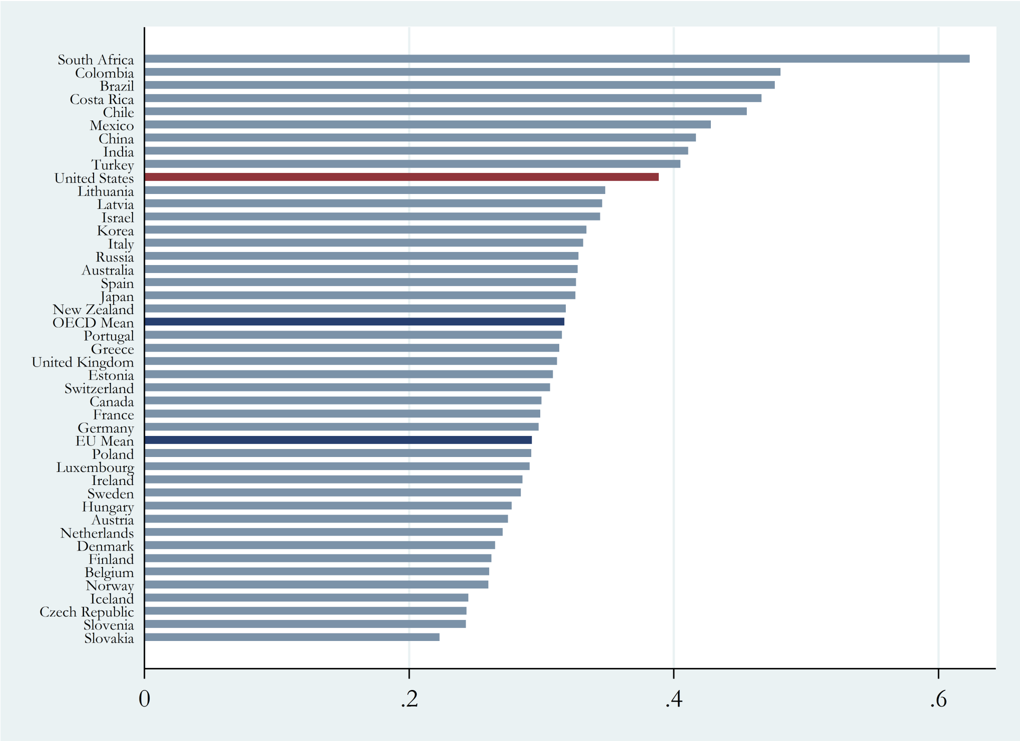


Figura 3: Gini para la renta disponible. OCDE y BRICS. Fuente: *World Inequality Database* (2019)

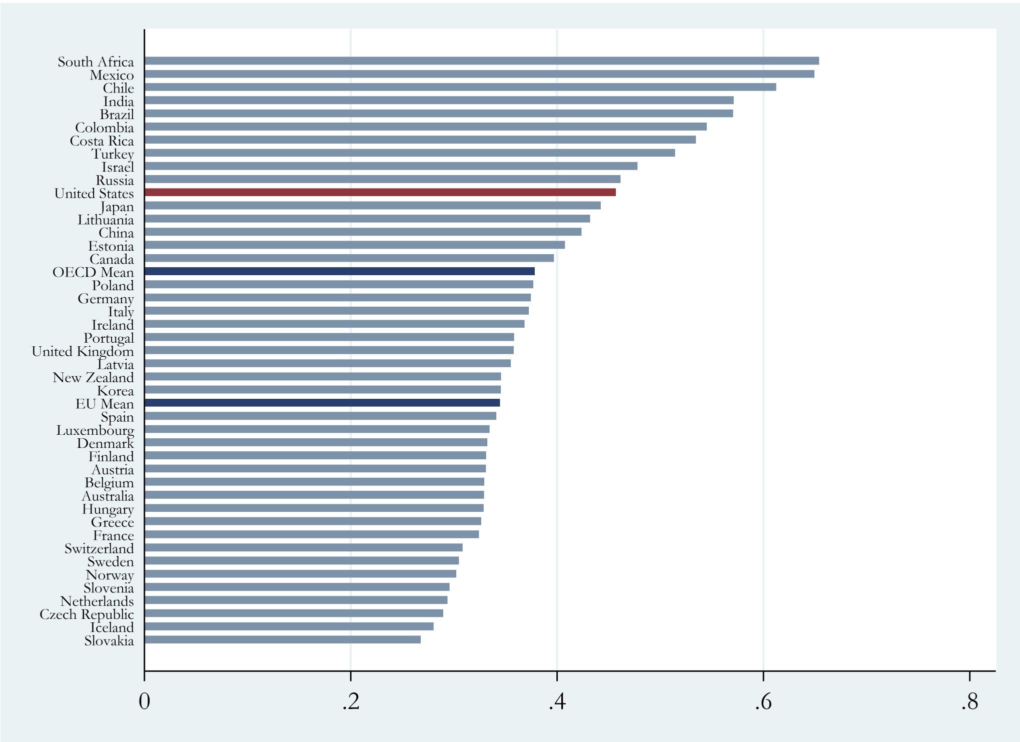


Figura 4: Porcentaje de renta del *top* 10 % OCDE y BRICS. Fuente: *World Inequality Database* (2019)

Las Figura 5 y 6 ilustran el particular contexto en el que EE.UU. sobresale como uno de los pocos países el mundo donde los tiroteos en masa son un fenómeno recurrente. La singularidad de la situación legal y cultural de EE.UU. respecto a la posesión de armas de fuego queda evidenciada en la Figura 5, donde se muestra cómo este país cuenta con una tasa de tenencia de este tipo de armas extremadamente elevada, con aproximadamente 120 armas por cada 100 habitantes, es decir, más de una por persona. Esta estadística es especialmente alarmante dados los más de 15,000 homicidios con armas de fuego registrados en 2017, cifra que ha aumentado a más de 21,000 muertes en 2021 (*Gun Violence Archive* 2023). A este respecto, la Figura 6 presenta la excepcionalidad de estos números en el panorama internacional. En términos de homicidios con armas de fuego, EE.UU. cuenta con más de cinco muertes por cada 1,000 habitantes, lo que sitúa al país en el sexto lugar del ranking, solo por detrás de Colombia, México, Brasil, Costa Rica y Sudáfrica.

En resumen, dentro de un contexto global donde la preocupación por las problemáticas sociales se ha intensificado, con iniciativas como los ODS liderando la vanguardia de estas inquietudes, las cuestiones estudiadas en esta tesis, a saber, pobreza, desigualdad y tiroteos en masa, tienen justificado su interés desde el punto de vista público. Esto se debe a que no sólo afectan al bienestar individual y colectivo, sino también a que ponen prueba la cohesión social y la estabilidad de las naciones, al traer aparejadas consecuencias negativas en ámbitos esenciales del desarrollo de los individuos, como su salud, su seguridad o su educación. EE.UU., como potencia global, presenta una paradójica y particular situación: a pesar de su inmensa riqueza y prominencia en el escenario mundial, enfrenta retos significativos en estas tres áreas. Esta nación no es inmune a los graves problemas que presentan la pobreza y la desigualdad, y su singular relación con las armas de fuego la sitúa en una posición distintiva en cuanto a la ocurrencia de los tiroteos en masa. Por ello, en esta tesis, se pone el foco en el singular contexto estadounidense, buscando, además de desentrañar los matices de la situación en este país, extraer información que pueda ser valiosa para otras naciones.

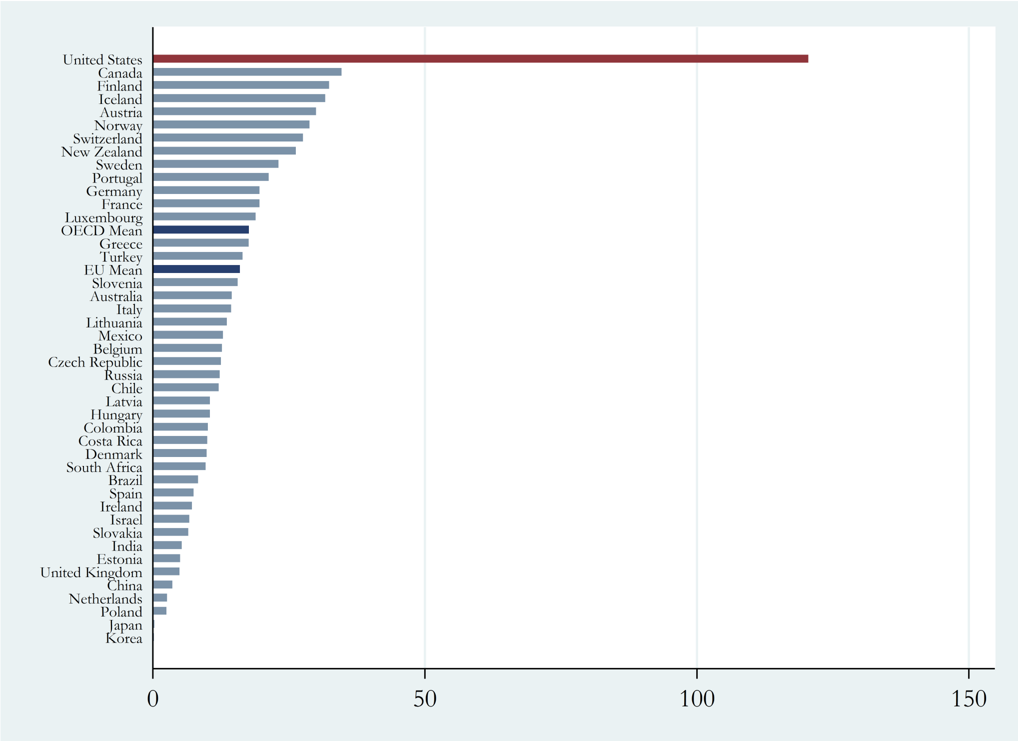


Figura 5: Tasa de posesión de armas de fuego por cada 100 habitantes. OCDE y BRICS. Fuente: Karp (2018)

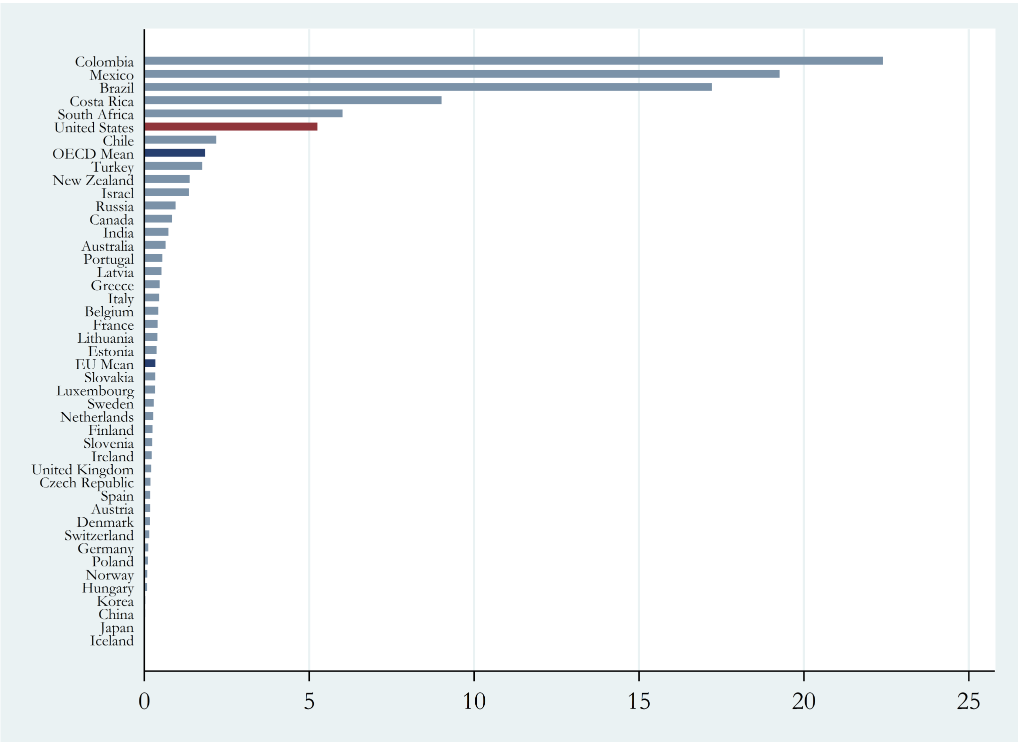


Figura 6: Muertes violentas por armas de fuego por cada 1,000 habitantes. OCDE y BRICS. Fuente: *Global Violent Deaths (GVD) Database* (2019)

Introduction

The establishment of the Sustainable Development Goals (SDGs) within the 2030 Agenda, crafted by the United Nations (UN) and their subsequent widespread adoption represent a paradigm shift in the international political and social landscape. These goals, ambitious due to the diversity of their targets and their long-term vision, pave a path for governments, the private sector, and civil society to jointly address the current social and environmental challenges. This transformative momentum of the SDGs has been permeating society over the last few years, and it is reflected in the development of this thesis, which employs the wide array of methodologies and tools provided by economic analysis to delve into the understanding of various issues directly linked to social welfare.

Accordingly, the thesis is structured into three distinct and independent chapters that rigorously and innovatively address issues related to the quality of life of all citizens. These themes include: urban poverty at the neighborhood level, the persistence of inequality over the long term, and the adverse impacts of mass shootings on local economies, all using the United States (U.S.) as a reference point. It is significant to note how the selection of these topics not only aligns with the spirit of commitment of the SDGs but also coincides with some of their goals, especially those more socially oriented. To be more specific, the SDGs cover areas such as the eradication of poverty (Goal 1), the reduction of economic disparities (Goal 10), the strengthening of urban safety and resilience (Goal 11), and the reduction of violence (Goal 16), which align with the subjects analyzed in the chapters of this thesis. However, it is crucial to underline that the choice of these topics is based on reasons that extend beyond this concordance.

Firstly, poverty is more than just an economic indicator, it represents a multifaceted challenge that significantly affects the quality of life for those suffering from it. Individuals living in poverty are not only confronted with daily hardships but also face significant risks to both their physical and mental health (Raphael, 2011; Ridley, Rao, Schilbach, and Patel, 2020). However, the ramifications of poverty reach beyond those who directly endure it. When poverty is concentrated in particular areas, its repercussions are amplified, influencing the entire community. Extensive literature has documented a clear link between the concentration of poverty in certain neighborhoods and elevated crime rates in these areas (Patterson, 1991; Stretesky, Schuck, and Hogan, 2004; Friedson and Sharkey, 2015; Sharkey, Besbris, and Friedson, 2016). Moreover, residents of neighborhoods with high poverty rates, especially in urban areas, often exhibit poorer physical (Diez-Roux and Mair, 2010) and mental health outcomes (Anakwenze and Zuberi, 2013).

A notable study illustrating this link between poverty concentration and health was conducted by Ludwig, Duncan, Gennetian, Katz, Kessler, Kling, and Sanbonmatsu (2012). This study leveraged data from the "Moving to Opportunity" (MTO) program, by which numerous families were financially assisted to move from high-poverty census tracts to areas with lower poverty levels through a random lottery among applicants. The findings revealed that families who relocated experienced significant improvements in their physical health, including reduced rates of diabetes and obesity, as well as better mental health. Additionally, Wodtke, Harding, and Elwert (2011) discovered that prolonged exposure to poverty during childhood correlates with decreased likelihood of completing secondary education. In a similar vein, Chetty, Hendren, and Katz (2016) analyzing the MTO program outcomes, determined that children relocated to areas with lower poverty at early ages are more likely to attend college and achieve higher incomes in adulthood compared to those who did not benefit from the program.

In summary, economic literature underscores the deep impact of poverty on areas such as crime, health, and educational and personal development, impacting not only those who directly endure it but also the broader communities. These profound effects motivate the focus on poverty in the first chapter of this thesis, titled *"An assessment of poverty determinants in census tracts, 1970-2010"*. Previously, economic studies often analyzed poverty at larger geographical scales, like counties, potentially overlooking its nuanced effects in smaller areas and the heterogeneity of the phenomenon. This chapter aims to fill this gap by investigating the poverty rates in census tracts across all U.S. Metropolitan Statistical

Areas (MSAs). The research begins with an analysis of poverty's persistence using panel data unit root tests, finding that poverty rates in these tracts are stationary. It then delves into how various socioeconomic, labor market, and housing factors influence poverty, using the generalized method of moments for dynamic panels. Key findings reveal a consistent negative correlation between employment and poverty, and a positive association between poverty and the percentage of single-parent families led by women. The study further segments the analysis based on the census tracts' locations within the MSAs (urban center or suburb), the size of the MSAs, and their status in the poverty rate distribution. Finally, the findings are discussed in the context of the debate between place-based policies, aimed at alleviating poverty in highly concentrated areas, and person-centered policies, focused on directly assisting those affected by poverty, suggesting that a blend of both approaches may be the most effective strategy.

The second subject of study in this thesis is inequality. Unlike poverty, whose consequences are widely recognized, listing the negative implications of inequality is more controversial. Traditionally, it has been argued that the problems commonly associated with inequality actually stem from a scarcity of resources or from poverty itself, rather than from economic inequality per se. Specifically, it has been contended that wealth accumulation promotes savings and, consequently, investment and economic growth. However, recent studies, such as that of Berg and Ostry (2017), question the direction of this relationship, suggesting that inequality might actually undermine growth. In this regard, literature reviews by Neves and Silva (2014) and Ferreira, Gisselquist, and Tarp (2022) document pathways through which inequality can negatively affect economic development. One such pathway is the reduction in investments due to sociopolitical conflicts arising from unequal resource distribution (Rodrik, 1999; Keefer and Knack, 2002). In fact, this social conflict could be seen as a negative repercussion of inequality in itself. Additionally, inequality also leads to the emergence and promotion of populist political parties (Nolan and Valenzuela, 2019; Stoetzer, Giesecke, and Klüver, 2021).

Inequality also exerts a negative influence on education, as shown in the literature review compiled by Ferreira, Gisselquist, and Tarp (2022). Among the studies analyzed by these authors, the work of Mayer (2001), focused on the U.S., is particularly interesting for our case. It demonstrates how the increase in inequality between 1970 and 1990 unevenly affected graduation rates across different socioeconomic strata. In addition, research by Wilkinson and Pickett (2006) and Ribeiro, Bauer, Andrade, York-Smith, Pan, Pingani, Knapp, Coutinho, and Evans-Lacko (2017) shows a correlation between inequality and poorer outcomes in physical and mental health, respectively. Lastly, it's worth noting the work of Castells-Quintana, Royuela, and Thiel (2019), which reveals the repercussions of inequality on the Human Development Index, underscoring its long-term impact that encompasses many of the negative consequences previously mentioned.

Once again, the numerous negative consequences associated with inequality highlight the social relevance of exploring in-depth the historical evolution of inequality in the U.S. Thus, the second chapter of this thesis, titled *"Long-run Inequality Persistence, 1870-2019"*, investigates time series of both income and wealth inequality dating back to 1870, the earliest date for which data is available. Specifically, the persistence of the Gini index, the income share of the top 10%, and the wealth-to-income ratio are examined. Unit root tests that allow for the possibility of structural breaks in both the null and alternative hypotheses are applied, addressing the circular problem that arises when both issues are present in the analyzed data (Perron, 2006). Additionally, this chapter takes a less common approach in the literature by examining whether inequality series fluctuate between stationary and non-stationary regimes. It concludes that wealth inequality remains an I(1) regime throughout the analyzed period, while the two series of income inequality show alternation between I(1) and I(0) regimes. Finally, factors that may be influencing these changes are investigated, employing Bayesian model averaging techniques within the framework of a generalized linear model on a broad set of potential determinants. The results suggest that greater globalization intensifies the persistence of income inequality, while such persistence is inversely related to higher levels of education and union membership.

The third and final topic analyzed in this thesis is mass shootings. These are acts of extreme violence, often indiscriminate, whose study is justified due to the profound societal impact they cause, particularly in terms of human lives lost. While we emphasized the importance of analyzing economic phenomena such as poverty and inequality due to their adverse effects on critical aspects of citizen welfare like health, education, and safety, the focus in the last chapter of the thesis shifts: we aim to understand how a primarily non-economic phenomenon impacts the economy. Academic literature has shown that these events have deeply negative implications on mental health (Rossin–Slater, Schnell, Schwandt, Trejo, and Uniat, 2020), and can even induce stress in pregnant women exposed to these events, impacting neonates (Dursun, 2019). Moreover, they influence electoral outcomes (Yousaf, 2021) and their impact on firearm regulation is more significant than that of other types of armed violence (Luca, Malhotra, and Poliquin, 2020). However, regarding their economic impact, the central focus of this thesis, the literature is still limited. It has been observed that mass shootings disrupt the stock market (Sakariyahu, Lawal, Yusuf, and Olatunji, 2023) and some, particularly those occurring in schools, have reduced the value of nearby properties (Muñoz–Morales and Singh, 2023). To date, only the study by Brodeur and Yousaf (2022) provides evidence of their impact on local economies.

To delve deeper into this issue, the third chapter, titled *"Mass Shootings, Employment, and Housing Prices: Evidence from Different Geographic Entities"*, addresses the impact of mass shootings on the economy, with a particular focus on the geographic dimension of their effects. For this purpose, a unique database has been developed, gathering detailed information on the location of these incidents. Utilizing recent advancements in difference-in-differences techniques, which overcome certain methodological limitations and allow for the consideration of heterogeneity in treatment effects, we examine the influence of these events on employment and housing prices in the affected counties, zip codes, and census tracts between 2003 and 2019. The findings reveal that the impacts are most significant in the census tracts, exhibiting a persistent and cumulative pattern over time. These events more severely affect sectors reliant on direct public interactions. Moreover, it has been confirmed that shootings in public places have a greater impact on employment. Lastly, the chapter investigates whether mass shootings displace more skilled workers from affected areas, analyzing their impact on the composition of employment by wages and educational level. The results show that these effects, although limited, extend beyond the census tracts.

Finally, the choice of the U.S. as the unit of analysis for studying these three issues is not arbitrary but deliberate. Firstly, the ability to access data with a level of granularity extending to the census tracts allows for an appropriate geographic approach in the first and last chapters for studying poverty and the impacts of mass shootings. Additionally, the availability of time series data dating back to 1870, just five years after the end of the

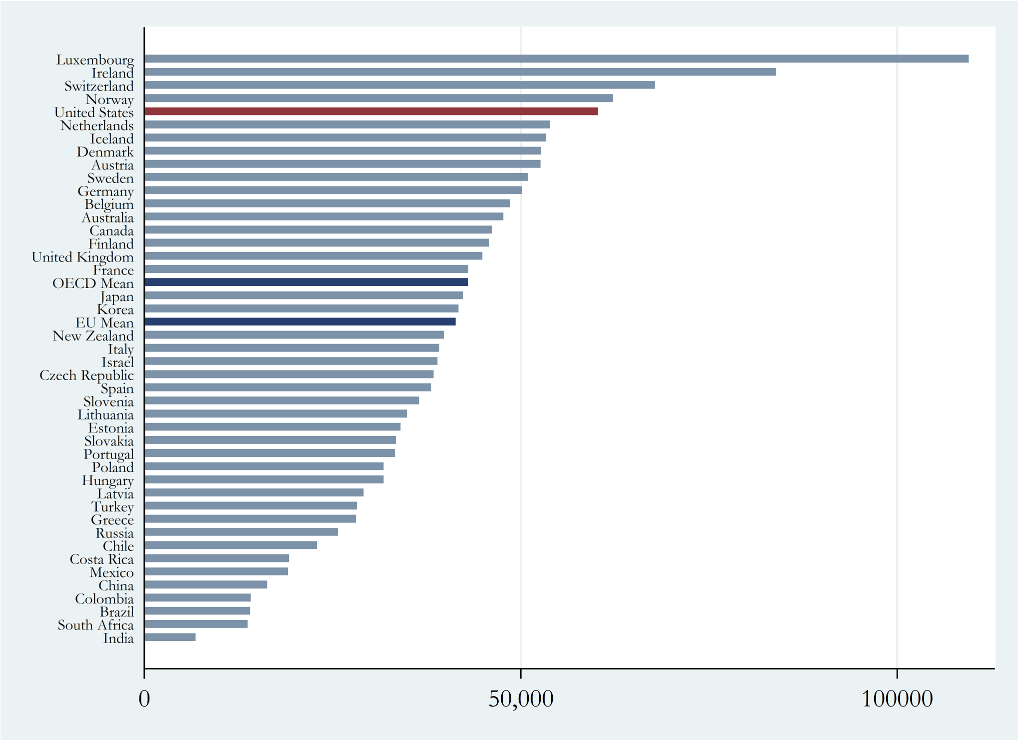


Figure 1: GDP per capita, US$, constant prices and PPPs. OECD and BRICS. Source: *OECD Statistics* (2019)

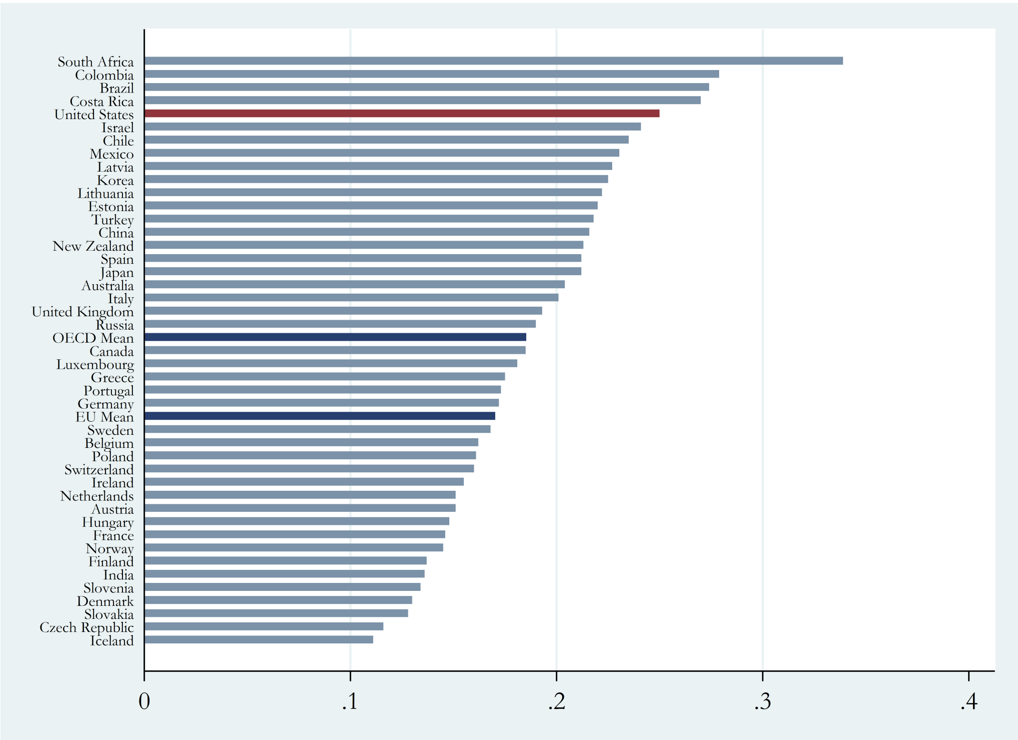


Figure 2: Relative poverty (60% of the median income). OECD and BRICS. Source: *OECD Statistics* (2019)

American Civil War, enables a comprehensive study of inequality in the second chapter, covering almost the entire contemporary history of the country. This data availability also allows us to utilize the wide range of methodologies necessary for each specific case.

However, beyond the abundance of available data, the U.S. stands out not only as a practical choice but also as a particularly relevant case study for the topics addressed in this thesis. Despite being one of the wealthiest countries in the world, it faces serious problems of poverty and inequality, and is a unique case in terms of the degree of firearm-related violence, with mass shootings being almost exclusively an phenomenon of this country. To contextualize these assertions, Figures 1 and 2 provide a picture of the U.S. situation in the international landscape in 2019, in terms of per capita income and relative poverty rate. When compared among countries belonging to the Organisation for Economic Co-operation and Development (OECD) and the BRICS nations (Brazil, Russia, India, China, and South Africa), the U.S. ranks as the fifth country with the highest GDP per capita and, simultaneously, as the fifth in terms of poverty.

The relative poverty rate corresponds to the percentage of people whose income is below 60% of the median income, a measure that is useful for comparing countries with significantly different economic contexts. The alternative, which is indeed the type of measure analyzed in the first chapter, is the objective poverty rate. This rate is calculated by determining the percentage of the population that falls below a certain minimum income threshold, which would be necessary to acquire basic goods and services. To further illustrate the dichotomy between the income level and the poverty issues in the U.S., we will use the data related to this threshold, which in 2019, for a family of four, was set at $25,926. This figure stands in stark contrast to the country's per capita income in the same year, which reached $51,406, nearly double. Despite this high average income level, 10.5% of the U.S. population lived below this poverty threshold (U.S. Census Bureau, 2020), equating to approximately 34 million people with incomes insufficient to cover their basic needs.

Figures 3 and 4 broaden our perspective by presenting the U.S. situation in the international context regarding inequality. Despite being a global economic leader with a GDP comparable only to China's or the total combined economies of Europe, the U.S. ranks tenth among OECD and BRICS countries in terms of the Gini index after taxes and transfers, highlighting its unequal income distribution. This figure stands well above

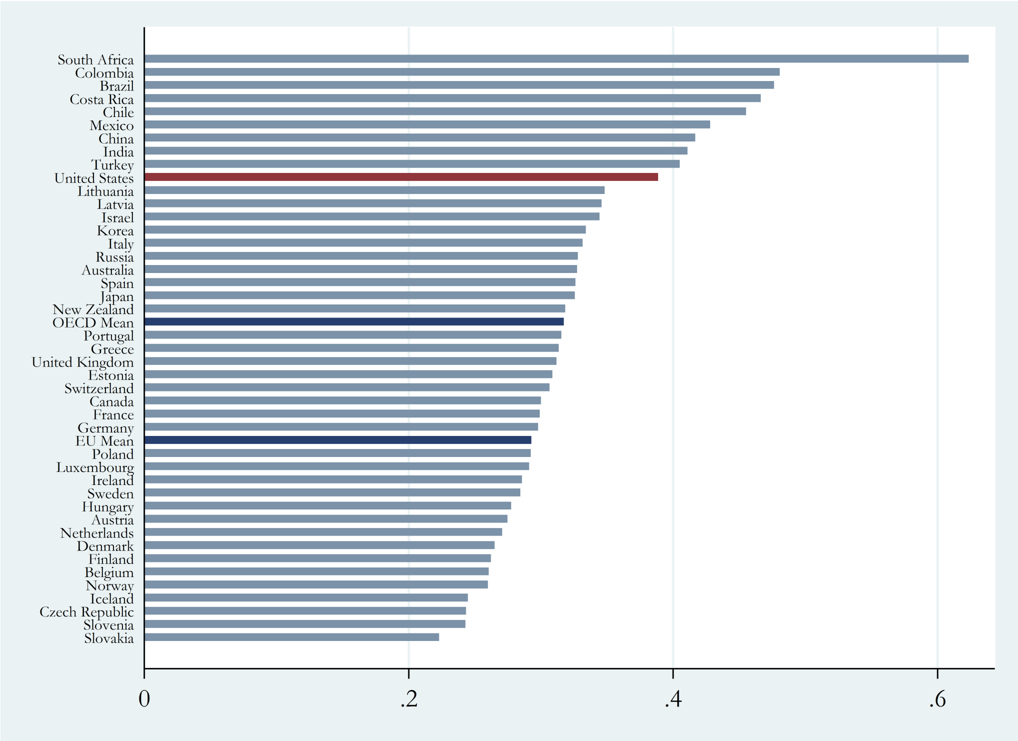


Figure 3: Gini for disposable income. OECD and BRICS. Source: *World Inequality Database* (2019)

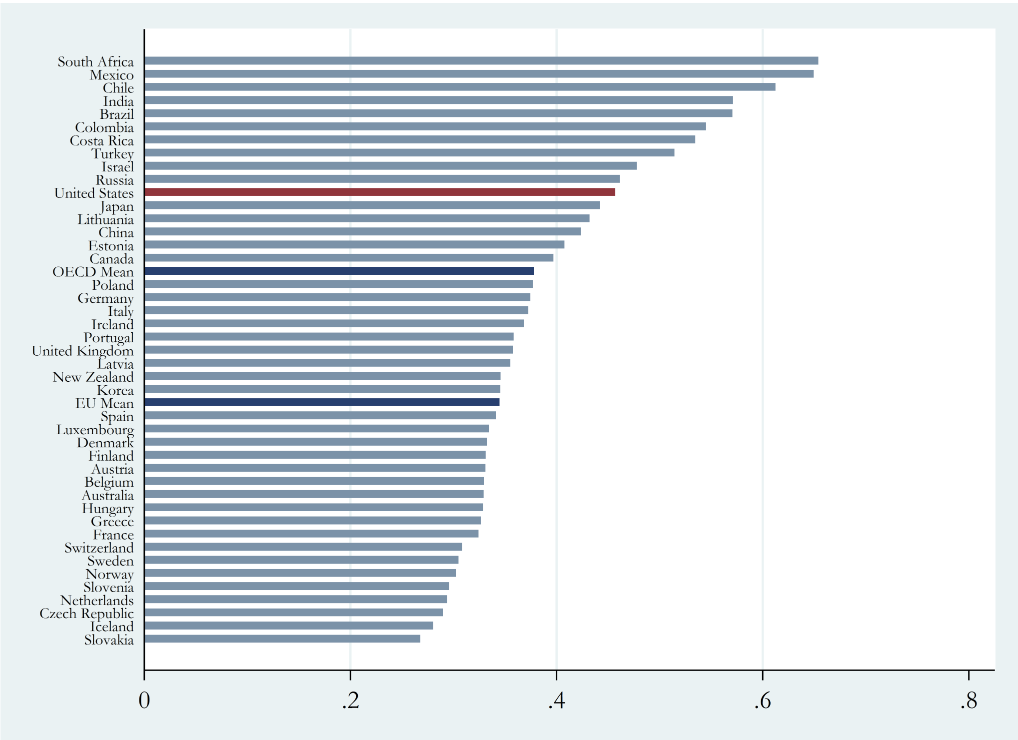


Figure 4: Top 10% income share. OECD and BRICS. Source: *World Inequality Database* (2019)

the OECD average and indicates an even wider gap compared to the average inequality within the European Union. Additionally, looking at the income share of the top 10% of the population, the U.S. holds a similar position, ranking eleventh. This is particularly noteworthy, as it shows that nearly half of the nation's total income, 45.7%, is concentrated in the hands of only a 10% of the population.

Figures 5 and 6 illustrate the unique context in which the U.S. emerges as one of the few countries in the world where mass shootings are a recurring phenomenon. The distinctiveness of the U.S.'s legal and cultural situation regarding firearm ownership is evidenced in Figure 5, which shows an extremely high rate of firearm possession in the country, with approximately 120 guns for every 100 inhabitants, equating to more than one per person. This statistic is particularly alarming considering the more than 15,000 firearm-related homicides recorded in 2017, a figure that has risen to over 21,000 deaths in 2021 (*Gun Violence Archive* 2023). In this regard, Figure 6 presents these exceptional numbers in the international landscape. In terms of firearm-related homicides, the U.S. experiences more than five deaths per 1,000 inhabitants, placing the country sixth in the ranking, only behind Colombia, Mexico, Brazil, Costa Rica, and South Africa.

In summary, within a global context where concern for social issues has intensified, with initiatives such as the SDGs leading the forefront of these worries, the topics studied in this thesis, namely poverty, inequality, and mass shootings, are justified in garnering public interest. This is because they not only affect individual and collective well-being but also test social cohesion and the stability of nations by bringing negative consequences in essential areas of individual development, such as health, safety, and education. The U.S., as a global power, presents a paradoxical and unique situation: despite its immense wealth and prominence on the world stage, it faces significant challenges in these three areas. This nation is not immune to the severe problems posed by poverty and inequality, and its unique relationship with firearms places it in a distinctive position regarding the occurrence of mass shootings. Therefore, this thesis focuses on the singular U.S. context, seeking not only to unravel the nuances of the situation in this country but also to extract information that may be valuable for other nations.

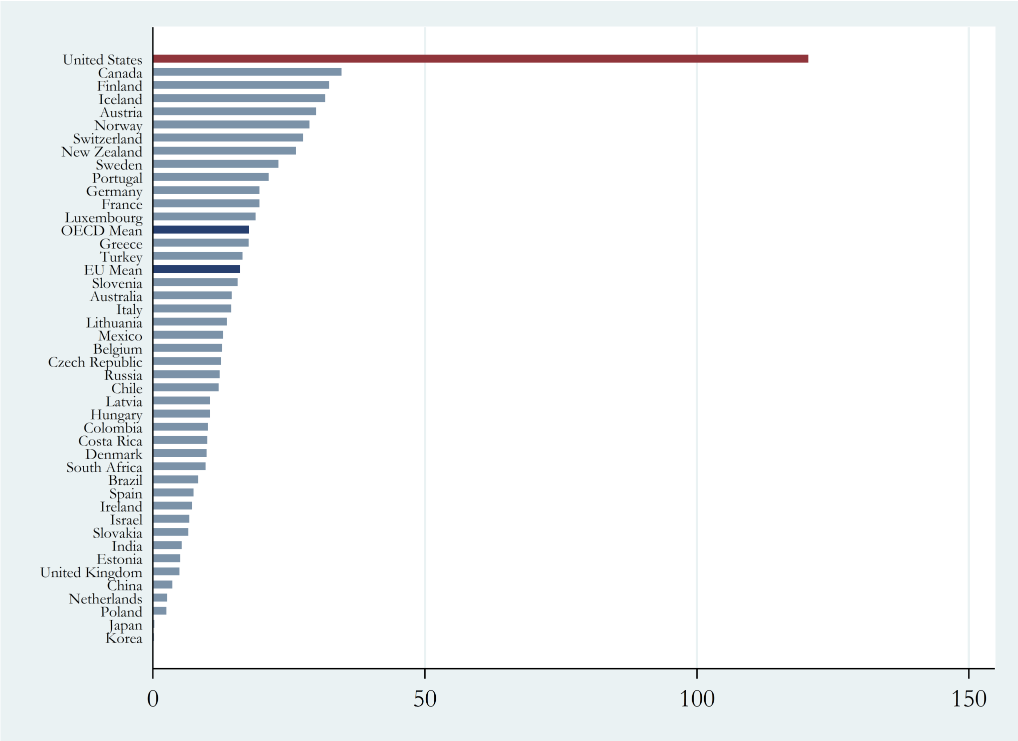


Figure 5: Firearm ownership rate per 100 inhabitants. OECD and BRICS. Source: Karp (2018)

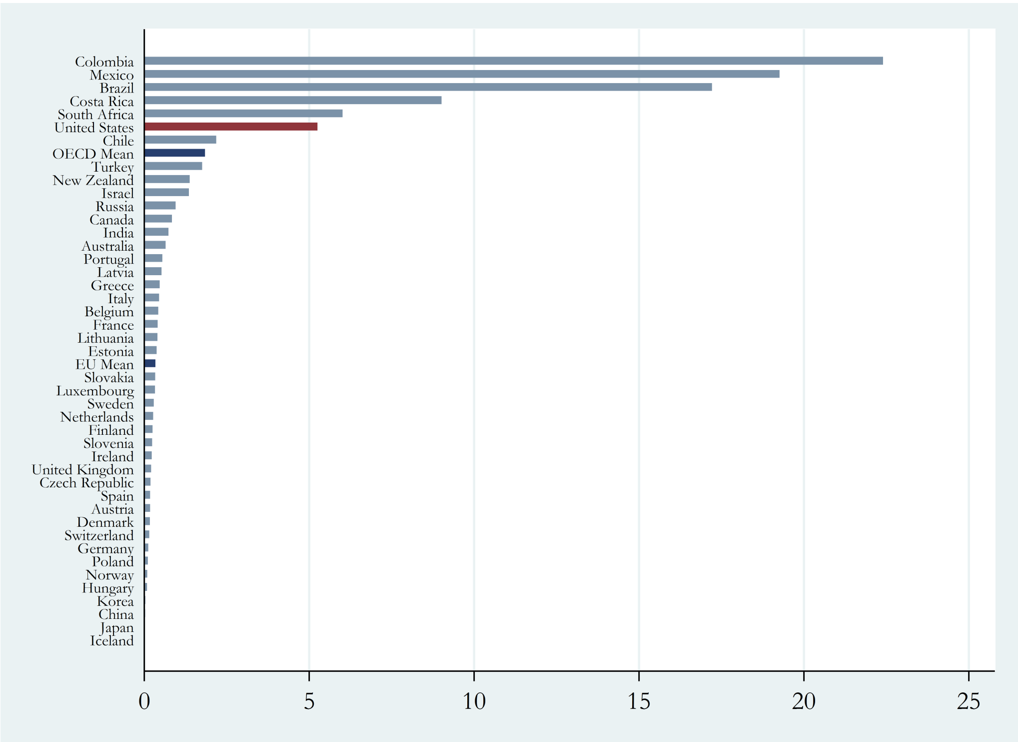


Figure 6: Firearm violent deaths per 1,000 inhabitants. OECD and BRICS. Source: *Global Violent Deaths (GVD) Database* (2019)

Chapter 1

An assesment of poverty determinants in census tracts, 1970–2010

1.1 Introduction

Poverty is one of the main concerns of citizens, in general, and altruistic organizations, in particular. The impact of poverty goes beyond those who are directly afflicted, concerning neighboring communities and eliciting worries even among the more affluent segments of the population (Firebaugh and Schroeder, 2009). Moreover, the designation of poverty eradication as the primary objective by the United Nations in the 2030 Agenda for Sustainable Development Goals further highlights the political significance of this issue. While poverty is specially relevant in less developed countries, wealthy nations are not exempt from its challenges. This is the case of the United States (U.S.), one of the richest countries globally, which in 2010 faced a considerable poverty rate of around 15%, as reported by the U.S. Census Bureau. Therefore, a first step in formulating effective strategies to mitigate poverty is to disentagle its main driving factors.

The distribution of individuals based on their income in U.S. cities has been studied by Glaeser, Kahn, and Rappaport (2008) and Brueckner and Rosenthal (2009). The former authors emphasize that lower-income individuals tend to reside in city centers due to their higher reliance on public transportation, which is more prevalent in these areas compared to the suburbs. On the other hand, the latter authors attribute the residential choices to cycles triggered by the deterioration of the housing stock. This decline leads to more affordable housing options, thereby attracting lower-income individuals through a process known as 'filtering'. Conversely, the renovation of these housing units tends to draw higher-income residents, in a phenomenon termed 'gentrification'.

The analysis of poverty has mostly been confined to geographical units larger than census tracts, such as metropolitan statistical areas (MSAs) (Madden, 1996), counties (Levernier, Partridge, and Rickman, 2000; Partridge and Rickman, 2007; Partridge and Rickman, 2008), or zip codes (Murphy and Wallace, 2010). Yet, as pointed out by Allard (2004) and Holliday and Dwyer (2009), this approach may obscure suburban poverty, diminish its heterogeneity, and conceal complexities of the labor market. This, coupled with the fact that most of poverty negative externalities – such as those associated with crime (Sharkey, Besbris, and Friedson, 2016), health (Ludwig, Duncan, Gennetian, Katz, Kessler, Kling, and Sanbonmatsu, 2012), or educational outcomes (Chetty, Hendren, and Katz, 2016) – are concentrated at the neighborhood level, suggests that the optimal approach is to use census tracts as the unit of reference to address this issue. Researchers like Jargowsky (2014), Kneebone (2014), and Allard (2017) have conducted comprehensive analyses of poverty at this geographic level, though primarily utilizing descriptive methods. To the best of our knowledge, the only study addressing this topic using econometric methods is that conducted by Rosenthal (2008), who employed census tracts relative income as a proxy to examine the evolution of its socioeconomic status. Nonetheless, analyzing poverty rates seems to be more suitable for the optimal design of local development strategies, and to inform the debate on the implementation of place-based or person-centered policies.

The present study delves into this strand of literature by undertaking an empirical analysis of the determinants of poverty rates in U.S. census tracts. To achieve this, we leverage a geographically consistent dataset spanning 368 MSAs from 1970–2010. Initially, our approach incorporates panel data tests to assess the unit root characteristics of poverty rates. Subsequently, we employ a dynamic panel data framework using the system generalized method of moments (GMM) estimator to evaluate its determinants. This approach allows us to account for unobserved heterogeneity and to address potential reverse causality. Our findings indicate that while poverty rates can be perceived as stationary processes, they exhibit some degree of persistence. Key variables displaying a direct and significant relationship with poverty include the percentages of the Hispanic origin population, female-headed families, and renter-occupied housing. Conversely, educational attainment, population percentages under 18, employment and female labor force participation relate inversely with poverty. Our data also suggest that the impact of employment on poverty manifests in a sector-specific manner, and no significant association was observed between poverty and the age of the housing stock. We have framed these insights into the debate comparing place-based and person-centered policies mentioned above. Our findings bolster arguments in favor of both strategies, suggesting that an integrated approach is the most effective way to tackle poverty at this geographic level.

The rest of the chapter is organized as follows. Section 1.2 contextualizes this study by providing the theoretical background regarding the origins of poverty, and reviewing the related literature. Section 1.3 describes the data sources and the variables included in the empirical study, and justifies the geographical level of disaggregation adopted. Section 1.4 presents a preliminary analysis of the stationary character of poverty rates at the census tract level, and establishes the estimation strategy. Section 1.5 shows the main results, which are later discussed within the debate about the design of optimal local development strategies in Section 1.6. Finally, Section 1.7 concludes.

1.2 Background

1.2.1 Theoretical underpinnings

There are two main theories that seek to explain the emergence of poverty. The first one is rooted in psychological underpinnings and revolves around the concept of 'aspiration failure', as described by Dalton, Ghosal, and Mani (2016). According to this viewpoint, the shackles of poverty reduce the aspirations of the impoverished concerning their potential achievements. As a result, their ambitions fall below an optimal level, driving them further into the clutches of poverty. This, combined with external constraints such as credit market imperfections, institutional shortfalls, or familial contexts could lead to the emergence of the so-called poverty traps.

The second main theory emerges from the 'membership theory', as delineated by Durlauf (2006). This perspective attributes the existence of poverty traps to the influence of social or communal groups an individual associates with. Essentially, the groups – be it neighborhoods, racial communities, educational institutions, or workplace environments – and their inherent characteristics significantly influence the preferences, constraints, and beliefs of their members. Two predominant effects are noted within this framework. The first one is the role model effect, where the historical or past behaviors of a group impact individual actions. The second effect is the peer group influence, suggesting that the decisions and actions individuals are swayed by the current behaviors exhibited by their group.

The 'aspiration failure' theory implies that antipoverty interventions should focus on boosting the aspirations of the disadvantaged. Such initiatives include examples as the SPOKE (Supporting Parents on Kids Education) program in the UK or an antipoverty program for women in Bangladesh, which integrates livestock transfers with training, as emphasized by Bandiera, Burgess, Das, Gulesci, Rasul, and Sulaiman (2017). In contrast, the 'membership theory' promotes strategies that involve both income redistribution and fostering changes in social or communal group associations as potential pathways to combat poverty.

1.2.2 Literature review

The geographic dimension of poverty has received considerable attention in the academic literature. A first study to highlight in this regard is that of Lemanski (2016), who posits that the global rise of poverty in urban areas is not solely due to an increase in urban population, but also as a direct consequence of the urbanization process itself. This author further emphasizes that poverty, being multifaceted in nature, has distinct characteristics when manifesting in urban settings. Focusing on the U.S., Fisher (2007) delves into the disparities between metropolitan and nonmetropolitan areas. This study, anchored on a sample of low-income families, elucidates that the drivers for pronounced poverty in nonmetropolitan areas are both a significant sorting of individuals with limited human capital, and fewer economic opportunities relative to their metropolitan counterparts.

Kneebone and Berube (2013) underscore that, for the first time in history, a greater proportion of the impoverished population found themselves in suburban areas rather than city centers. This shift prompted them to advise against merely extending existing urban-centric policies to suburban regions. Instead, these authors propose the "Metropolitan Opportunity Agenda" as a more fitting strategy to address suburban poverty. Adding nuance to this topic, Murphy and Allard (2015) point out that while suburban poverty has been rising, it has not led to a parallel decline in at the urban level. This implies that policy solutions tailored for urban areas might not necessarily translate effectively to suburban contexts. They further observe that contemporary safety nets for suburban poverty are more robust than those that existed during urban poverty surges in the mid-20th century. These viewpoints are corroborated by Murphy and Wallace (2010) at the zip code level.

A notable contribution directed at the county level exploration of poverty rates is that by Levernier, Partridge, and Rickman (2000), who undertook their analysis considering both the area economic performance and its demography. Their findings stress the pivotal role of factors such as employment growth and structural change, while also lending support to the spatial mismatch hypothesis (Ihlanfeldt and Sjoquist, 1998). Building upon the same geographic lens, Partridge and Rickman (2007) centered their analysis on U.S. counties across three distinct time periods: 1979, 1989, and 1999. They categorized counties with a consistent poverty rate exceeding 20% across these years as 'poverty persistent' (PP), hinting at the potential existence of 'ethno-geographic poverty traps'. Framing their investigation, these authors review the merits and limitations of place-based and person-centered policies. Central to their research was an effort to determine whether employment increments, holding other factors constant, have a more pronounced impact on the poverty rates of PP counties. After considering a range of socioeconomic and demographic variables, their conclusions leaned toward PP counties being, effectively, more susceptible to employment rate fluctuations. Emphasizing policy implications, Partridge and Rickman (2007) advocate for a blend of place-based and person-centered strategies, particularly in regions facing significant challenges. Subsequently, Partridge and Rickman (2008) examine 824 metropolitan counties to address the impact of employment growth on poverty rates from 1989 to 1999. They propose the disequilibrium adjustment process to modelize poverty. This approach, in line with the present study, suggests that poverty is shaped not only by current determinats, but is also rooted in its historical context.

1.3 Data and prelimanary insights

1.3.1 Data

The investigation of poverty dynamics within U.S. census tracts necessitates the compilation of a geographically consistent dataset unaffected by changes in tract boundaries. The principal source of such data is the Longitudinal Tract Database (LTDB; Logan, Xu, and Stults, 2014), which offers standardized information aligned with the 2010 census tract delineations. We have further enriched our dataset with supplementary information from the National Historical Geographic Information System (NHGIS; Manson, Schroeder, Van Riper, and Ruggles, 2017), and we have standardized it using the LTDB cross-walk files. Consequently, our study comprises a panel that includes the tracts in all the 368 MSAs recognized in 2010, covering the period from 1970 to 2010 on a decennial basis[1]. A comprehensive list of the variables used in our empirical analysis, along with their corresponding definition and sources, is provided in Table 1.1.

The main variable of interest in the present study is the poverty rate, defined as the percentage of individuals in a census tract whose income falls below the poverty threshold, which is established by the U.S. Census Bureau[2]. In addition, average poverty rates in adjacent tracts have been included as a regressor to account for the possible presence of spatial dependence. These rates are calculated using a row-standardized contiguity spatial weights matrix (Jargowsky, 2014). The remaining variables, intended to capture potential determinants of poverty, are consistent with those employed by Levernier, Partridge, and Rickman (2000), and Partridge and Rickman (2007) and Partridge and Rickman (2008). The first category of regressors reflects labor market conditions and includes employment rates, female labor force participation, and the percentage of individuals employed across

[1] Prior to 1970, the U.S. was not divided into census tracts. Subsequent years witnessed the progressive inclusion of the entire territory into these delimitations, and the creation of new tracts due to population growth. Therefore, our dataset forms an unbalanced panel.

[2] The U.S. Census Bureau defines poverty in absolute terms, as opposed to the relative terms criterion, which sets the poverty threshold as a proportion of the mean or median income level (Bourguignon, 2019). Although this method has faced criticism for considering only monetary income, and not adjusting for geographic differences in prices or wages (Madden, 1996), it has been the official measure in the U.S. since 1965. It was originally set at three times the cost of a minimum food diet in 1963, and is updated annually based on the Consumer Price Index, further accounting for family size, composition, and the age of the householder. As an example, the threshold for a four members family in 2010 was $22,050. For a broader perspective on the different ways to define poverty, interested readers may consult Sen (1992), Sen (2009), and Atkinson (2019). Additionally, Bourguignon and Chakravarty (2003) and Alkire and Jahan (2018) provide insights about the multi-dimensional perspectives to measure poverty.

Table 1.1: Poverty and its potential determinants: Definition and source

Variables	Definition	Source
povrate	Persons below the poverty level, as percentage of total population	LTDB
wpovrate	Average poverty rate in adjacent tracts	LTDB, NHGIS
empl	Employed persons, as percentage of population 16 years and over	LTDB
femlab	Women in labour force (except in armed forces), as percentage of population 16 years and over	LTDB
farming	Persons employed in farming, fishing and forestry occupations, per cent	NHGIS
transport	Persons employed in production, transport and material moving occupations, per cent	NHGIS
sales	Persons employed in sales and office occupations, per cent	NHGIS
services	Persons employed in service occupations, per cent	NHGIS
highsch	Persons with high school degree, as percentage of population 25 years and over	NHGIS
college	Persons with at least a four-year college degree, as percentage of population 25 years and over	LTDB
popul	Total population	LTDB
under18	Persons aged 17 years and under, per cent	LTDB
over60	Persons aged 60 years and over, per cent	LTDB
black	Persons of black race (not Hispanic origin), per cent	LTDB
hispanic	Persons of Hispanic origin, per cent	LTDB
asian	Persons of Asian race (and Pacific Islander), per cent	LTDB
femhead	Female-headed families with children, as percentage of total number of families	LTDB
rent	Renter-occupied housing units, per cent	LTDB
housing5	Housing units built less than 5 years ago, per cent	NHGIS
housing10	Housing units built from 6 to 10 years ago, per cent	NHGIS
housing20	Housing units built from 11 to 20 years ago, per cent	NHGIS
housing30	Housing units built from 21 to 30 years ago, per cent	NHGIS

Note: The poverty level is established by the U.S. Census Bureau at three times the cost of a minimum food diet. As an example, the threshold for a four members family in 2010 was $22,050. Sources are the Longitudinal Tract Database (LTDB; Logan, Xu, and Stults, 2014) and the National Historical Geographic Information System (NHGIS; Manson, Schroeder, Van Riper, and Ruggles, 2017).

various occupational sectors. This encompasses all major sectors defined by the U.S. Census Bureau, including farming, fishing, and forestry; production, transport, and material moving; sales and office; as well as services.

The educational attainment within census tracts is approximated by the percentages of residents aged 25 and older who have completed high school, and those who hold a four-year college degree. In assessing other socioeconomic indicators, we have considered the total population, the age distribution – specifically the percentages of individuals younger than 18, and those older than 60 –, the proportion of various racial groups, the percentages of families headed by single mothers, and the share of renter-occupied housing units. Additionally, to explore the potential link between housing age and poverty, four variables reflecting how old is the housing stock have been incorporated into the estimations: the percentage of housing units constructed within the last 5 years, those built between 5 and 10 years ago, between 10 and 20 years ago, and between 20 and 30 years ago. Descriptive statistics, including means and standard deviations for the year 2010 of the variables listed in Table 1.1, can be found in Table A1, for the full sample and distinguishing tracts by their location, the size of the MSA to which they belong, and their level of poverty. The U.S. Census Bureau defines a suburb as a municipality with more than 2,500 inhabitants and not being in a central city. To classify MSAs according to their size, the whole distribution in each period has been used[3]. Small MSAs are those in the lower quartile, medium MSAs are those in both intermedium quartiles, and large MSAs are those in the upper quartile. A similar distinction has been applied to classify tracts by their poverty level.

1.3.2 Preliminary insights

To provide a preliminary overview of urban poverty in the U.S., Tables 1.2 and 1.3 list the 30 MSAs that exhibited the lowest and highest poverty rates in 1970 and 2010, respectively. Regarding richer MSAs there has been an increase in poverty. In 1970, the poverty rates among the 30 MSAs with the lowest levels ranged from 5.97% (Janesville, WI) to 7.51% (Lansing-East Lansing, MI). By 2010, this spectrum had shifted upwards, with the lowest observed rate being 8.31% (Norwich-New London, CT), surpassing the 1970 figures. In contrast, the MSA with the highest recorded poverty rate saw a notable decline

[3]This explains that a significant number of tracts appear in more than one category throughout the sample period.

Table 1.2: Metropolitan statistical areas: Lowest poverty rates (%)

1970		2010	
Janesville, WI	5.97	Norwich-New London, CT	8.31
Holland-Grand Haven, MI	6.08	Bismarck, ND	8.42
Appleton, WI	6.13	Appleton, WI	8.43
Fort Wayne, IN	6.20	Washington-Arlington-Alexandria, DC-VA-MD-WV	8.48
Hartford-West Hartford-East Hartford, CT	6.24	Fairbanks, AK	8.59
Bridgeport-Stamford-Norwalk, CT	6.24	Rochester, MN	8.80
Elkhart-Goshen, IN	6.26	Anchorage, AK	9.09
Sandusky, OH	6.33	Sheboygan, WI	9.10
Anchorage, AK	6.34	Sioux Falls, SD	9.29
Minneapolis-St. Paul-Bloomington, MN-WI	6.37	Barnstable Town, MA	9.31
Racine, WI	6.47	Manchester-Nashua, NH	9.39
Poughkeepsie-Newburgh-Middletown, NY	6.58	Bridgeport-Stamford-Norwalk, CT	9.58
Monroe, MI	6.74	Ocean City, NJ	9.89
Dayton, OH	6.76	San Jose-Sunnyvale-Santa Clara, CA	9.96
Lebanon, PA	6.76	Cheyenne, WY	10.05
Oshkosh-Neenah, WI	6.99	Honolulu, HI	10.05
Las Vegas-Paradise, NV	7.02	Oxnard-Thousand Oaks-Ventura, CA	10.21
Detroit-Warren-Livonia, MI	7.03	Casper, WY	10.27
Pittsfield, MA	7.04	Fond du Lac, WI	10.29
Canton-Massillon, OH	7.12	Lebanon, PA	10.31
Indianapolis-Carmel, IN	7.14	Poughkeepsie-Newburgh-Middletown, NY	10.54
Allentown-Bethlehem-Easton, PA-NJ	7.18	Holland-Grand Haven, MI	10.61
Rochester, NY	7.28	Dubuque, IA	10.72
Flint, MI	7.22	Midland, TX	10.88
Cedar Rapids, IA	7.35	Cedar Rapids, IA	10.88
Youngstown-Warren-Boardman, OH-PA	7.37	Ogden-Clearfield, UT	11.07
Peoria, IL	7.44	Bremerton-Silverdale, WA	11.08
Worcester, MA	7.44	Portland-South Portland-Biddeford, ME	11.18
Reading, PA	7.49	Lancaster, PA	11.22
Lansing-East Lansing, MI	7.51	Seattle-Tacoma-Bellevue, WA	11.23

from 49.04% in 1970 (McAllen-Edinburg-Mission, TX) to 36.42% in 2010 (Brownsville-Harlingen, TX). Moreover, it can be observed some persistence of those MSAs with the highest rates, as half of them in 1970 remained classified as such in 2010. Complementing tabular data, Figure 1.1 illustrates the geographical distribution of the MSAs listed in the aforementioned tables. This visual representation highlights a consistent regional pattern: MSAs with the lowest poverty rates are predominantly situated in the Northeast, while those with the highest rates are concentrated in the South.

To motivate the disaggregated approach of our analysis, we spotlight the median MSA based on the distribution of poverty rates throughout the full period considered. This MSA is Altoona (PA), that saw its poverty rate rise from 11.84% in 1970 to 14.57% in 2010.

Table 1.3: Metropolitan statistical areas: Highest poverty rates (%)

1970		2010	
McAllen-Edinburg-Mission, TX	49.04	Brownsville-Harlingen, TX	36.42
Brownsville-Harlingen, TX	41.42	McAllen-Edinburg-Mission, TX	35.14
Laredo, TX	36.69	Laredo, TX	33.59
Merced, CA	34.79	Athens-Clarke County, GA	29.39
Maysville, KY	32.04	Albany, GA	27.46
Greenville, NC	30.50	Muncie, IN	27.43
Sumter, SC	29.92	Las Cruces, NM	27.33
Pine Bluff, AR	27.58	College Station-Bryan, TX	27.13
Goldsboro, NC	26.35	Monroe, LA	26.51
Auburn-Opelika, AL	26.27	Pine Bluff, AR	26.49
Farmington, NM	26.25	El Paso, TX	26.28
Montgomery, AL	26.00	Visalia-Porterville, CA	25.94
Las Cruces, NM	24.90	Hattiesburg, MS	25.41
El Paso, TX	24.69	Macon, GA	25.39
Charleston-North Charleston--Summerville, SC	24.26	Tallahassee, FL	25.27
Monroe, LA	23.60	Merced, CA	25.26
Fort Smith, AR-OK	23.55	Gainesville, FL	25.18
Ocala, FL	23.53	Fresno, CA	24.99
Jackson, TN	23.41	Corvallis, OR	24.78
College Station-Bryan, TX	23.08	Auburn-Opelika, AL	24.76
Tuscaloosa, AL	22.83	Valdosta, GA	24.73
Lafayette, LA	22.62	Greenville, NC	24.54
Shreveport-Bossier City, LA	22.43	Tuscaloosa, AL	23.95
Memphis, TN-MS-AR	22.06	Bloomington, IN	23.56
Danville, VA	21.95	Florence, SC	23.41
Florence-Muscle Shoals, AL	21.60	Goldsboro, NC	23.33
Jackson, MS	21.40	Columbia, MO	23.31
Gainesville, FL	21.38	El Centro, CA	23.31
Port St. Lucie, FL	21.10	Mobile, AL	23.15
Gadsden, AL	20.94	Gadsden, AL	23.14

However, Figure 1.2 visually represents the uneven distribution of poverty rates among the census tracts within this MSA, showcasing significant variability. In 1970, certain tracts had poverty rates that more than doubled the overall mean, climbing above 25%; whereas others had rates as low as 5%. By 2010, the increase was far from uniform, with some tracts showing little to no change, while others in the urban center saw substantial rises, reaching poverty rates exceeding 40%. Furthermore, the average poverty rate for tracts in the city center was 19.24%, depicting a stark disparity from the suburban tracts mean of

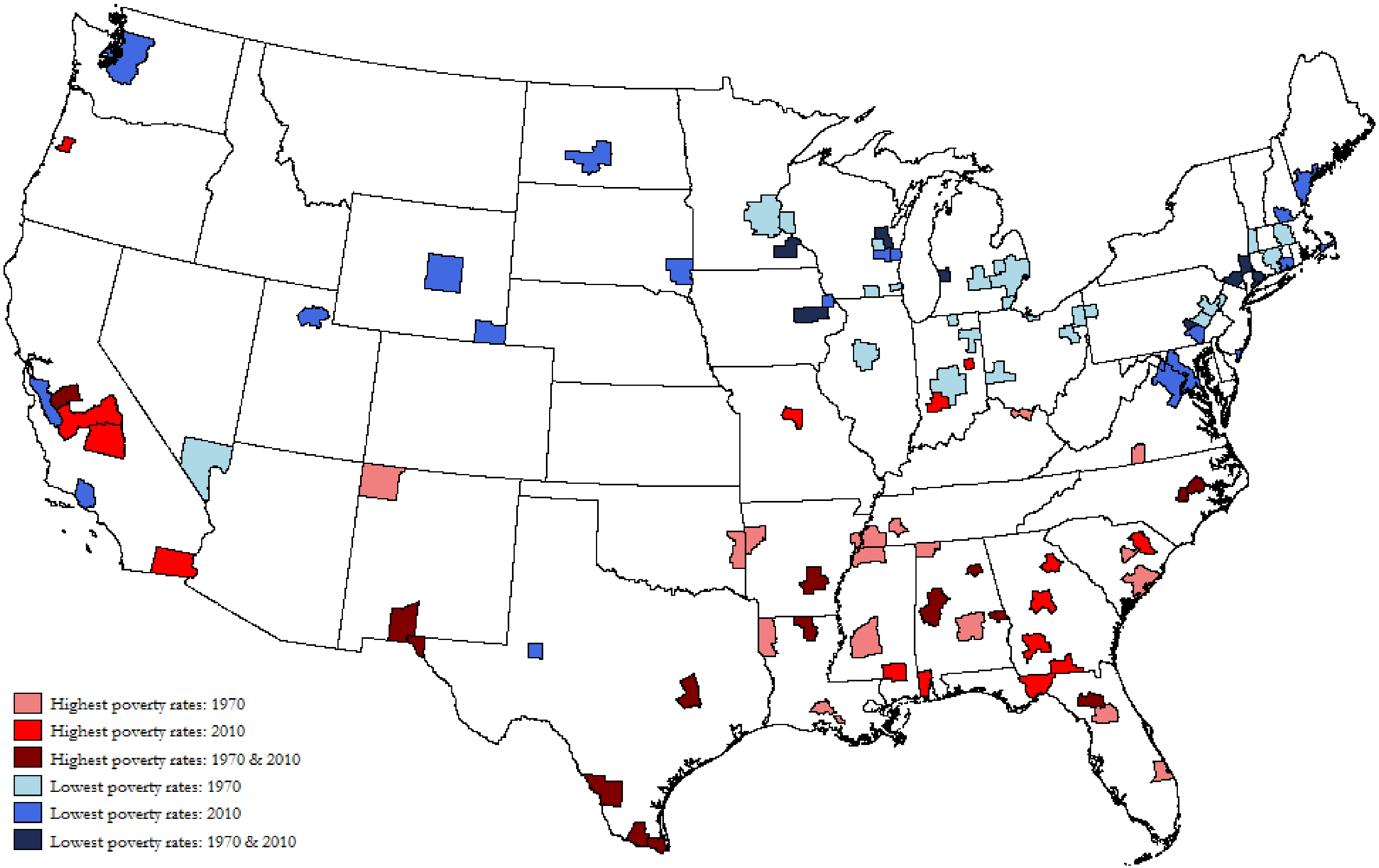


Figure 1.1: Metropolitan statistical areas with the highest and lowest poverty rates. Anchorage (AK), Fairbanks (AK), and Homolulu (HI) have been omitted

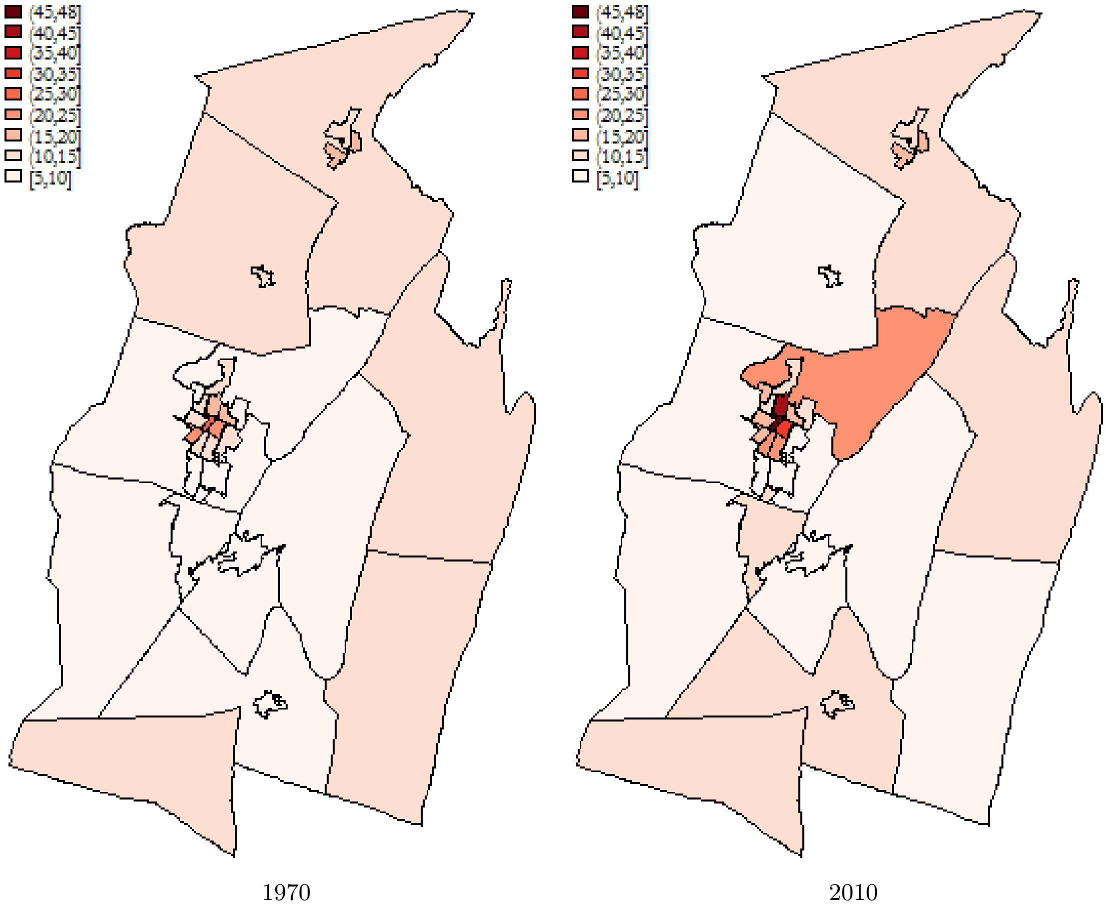


Figure 1.2: Poverty rates by census tract in the median MSA of the distribution: Altoona (PA), 1970 and 2010

10.42%. Such diversity in poverty rates at this scale effectively serves as an example to highlight the rationale behind the geographical level chosen.

Nonetheless, for a more comprehensive overview, Table 1.4 provides descriptive statistics of poverty rates at the MSA and tract levels. Despite the overall increase in poverty across both domains, the amplification was more pronounced at the tract level, indicating a higher concentration of poverty. This, together with tracts demonstrating greater variance, emphasizes the importance of addressing poverty with a focus on these smaller areas. A premise which is further supported by Figure 1.3, which depicts kernel density estimates of tract poverty rates, highlighting an increased probability mass in the upper tail of the distribution between 1970 and 2010.

The mean poverty rates and their standard deviations in census tracts are broken down in Table 1.5, categorizing the sample by their location, the size of the MSA to which they belong, and by poverty levels. The general upward trend observed in Table 1.4 persists

Table 1.4: Descriptive statistics of poverty rates: Census tracts and MSAs (%)

	Census tracts			MSAs		
Year	Mean	S.D.	(Min, Max)	Mean	S.D.	(Min, Max)
1970	10.80	9.40	(0, 86.48)	13.08	6.21	(5.97, 49.04)
1980	11.22	10.24	(0, 100)	12.07	8.39	(1.53, 34.79)
1990	12.36	12.02	(0, 100)	13.98	10.21	(5.75, 42.17)
2000	12.43	11.45	(0, 100)	13.32	9.77	(4.43, 35.45)
2010	15.60	13.18	(0, 100)	16.99	4.43	(8.31, 36.42)

Table 1.5: Poverty rates evolution: Different subsamples (%)

			Location				MSA size						Poverty level					
	Full sample		Center		Suburbs		Small		Medium		Large		Lower		Middle		Upper	
Year	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
1970	10.80	9.40	12.60	10.65	9.23	7.83	13.55	11.14	10.30	8.66	9.06	8.26	3.07	1.03	8.26	2.49	23.63	10.14
1980	11.22	10.24	14.66	12.59	8.43	6.63	12.53	9.76	10.37	9.57	11.62	11.67	2.99	1.05	8.27	2.54	25.33	11.02
1990	12.36	12.02	16.91	14.65	8.91	8.00	14.36	12.14	11.70	11.70	11.64	12.31	2.64	1.03	8.78	3.20	29.22	12.33
2000	12.43	11.45	17.28	13.56	8.76	7.73	13.43	11.25	11.56	11.06	13.04	12.17	2.75	1.07	9.23	3.44	28.96	10.99
2010	15.60	13.18	20.97	15.20	11.55	9.59	17.37	13.53	15.27	13.12	14.55	12.79	3.43	1.55	12.29	4.34	34.41	11.45

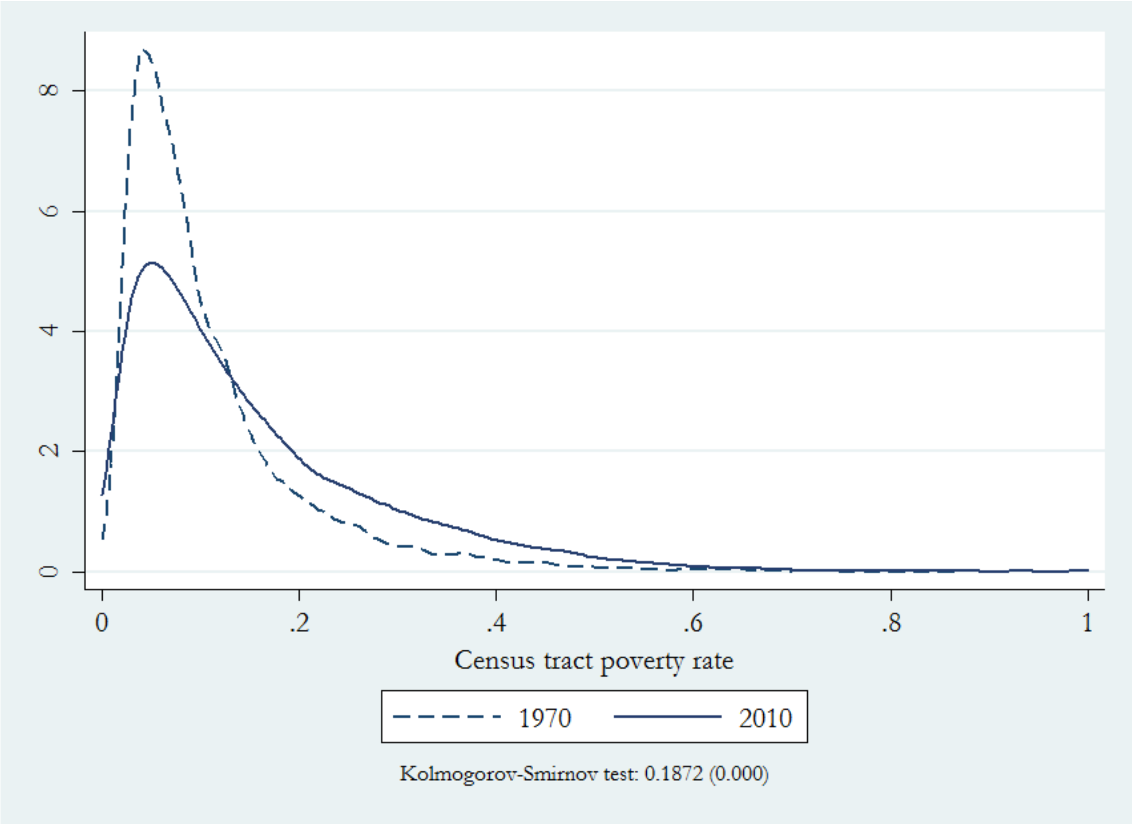


Figure 1.3: Kernel density estimation of poverty rates in U.S. census tracts, 1970 and 2010

across all subdivisions. Nonetheless, tracts within city centers exhibit substantially higher poverty rates, particularly in the decade of 2010, reinforcing the necessity to analyze these areas distinctly. Furthermore, we find notable differences in the poverty rates of the tracts depending on the size of the MSA they belong, being the poverty rate smaller the larger is the MSA. Finally, distributional differences show that much of the urban poverty is clustered at the tract level. Hence, recognizing this segmentation could provide deeper insights into the self-perpetuating effects of poverty.

1.4 Dynamic analysis and empirical framework

1.4.1 Dynamic analysis

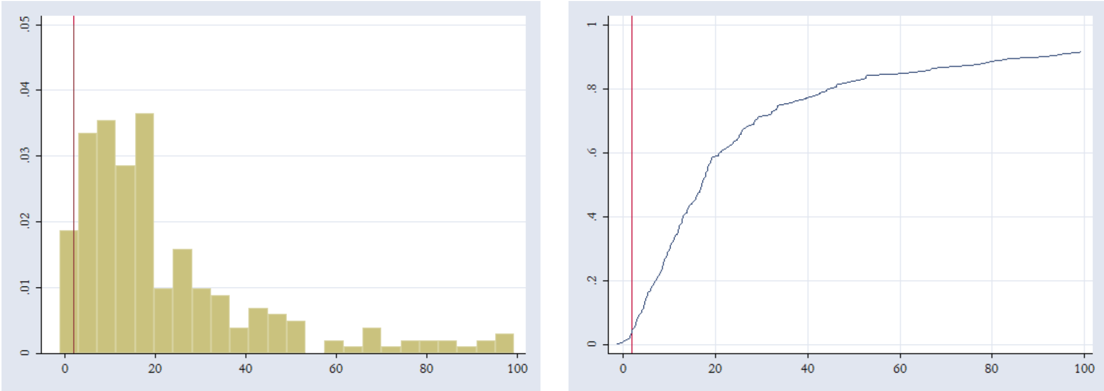
Poverty rates can be conceptualized either as an equilibrium process, in which they quickly react to exogenous shocks, or as a disequilibrium adjustment process, according to which poverty rates are related to both socioeconomic variables and their own evolution (Partridge and Rickman, 2008, page 288). This suggests that poverty is affected not only by contemporary factors but also by self-perpetuating effects within the tails of its distribution, which may slow the transition towards equilibrium. Furthermore, poverty can engender its own adverse impacts through persistence and the creation of poverty traps. This temporal dimension warrants to test for the possible presence of a unit root which would illuminate whether the impacts of economic shocks on poverty rates are permanent or transitory[4].

The decennial nature of our data results in a relatively short time series, from which it is challenging to derive reliable inferences about the order of integration of tract poverty rates. We can mitigate this issue by implementing panel unit root tests that leverage both the cross-sectional and temporal dimensions of the data. In doing so, we will assume that all tracts within a MSA comprise a panel. However, we must proceed with caution, as these methods may be subject to bias – in this case, size distortion – due to the presence of cross-sectional dependence (Banerjee, Marcellino, and Osbat, 2004). As a preliminary step, we have applied the weak cross-sectional dependence test (CD) developed by Pesaran (2015) to determine if this is the case for poverty rates at the tract level within each MSA.

The graphs included in Figure 1.4 show the histogram and cumulative density function (CDF) of the CD test statistics for all MSAs in our sample. The red vertical line in each graph indicates the 95 percent critical value. The CD test results suggest that we can reject the null hypothesis of no cross-sectional dependence among tract-level poverty rates in most MSAs. This finding prompts us to measure the extent of this dependence using the method proposed by Bailey, Kapetanios, and Pesaran (2016). The distribution of the α exponent estimates, as displayed in Figure 1.5, shows a concentration of estimated exponents between 0.9 and 1. This indicates a strong dependence among poverty rates in census tracts within MSAs, pointing to the need for incorporating a factor structure in our analysis to account for this dependence.

Pesaran (2007) introduced a panel unit root test that is robust to the presence of cross-sectional dependence. Following previous results, this feature is controlled for by assuming the presence of a single common factor, that, in line with the common correlated effects estimator (CCE) framework (Pesaran, 2006), is proxied by the cross-sectional mean of the

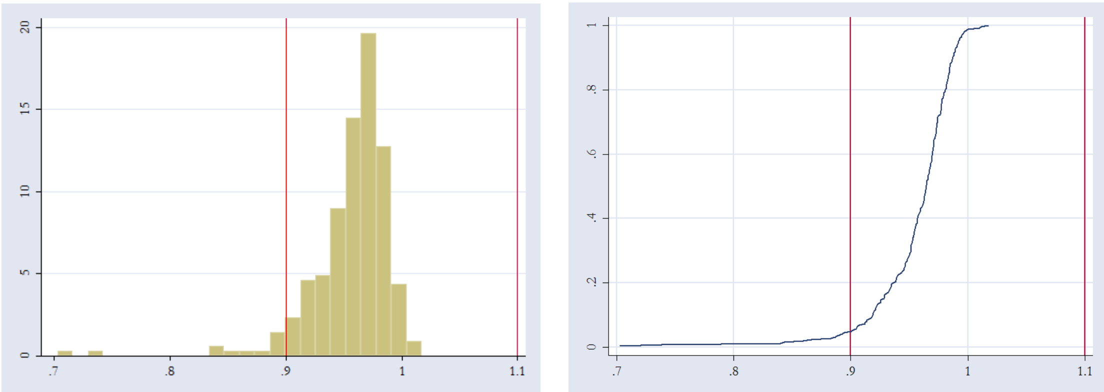
[4]Theoretically, the poverty rate should not contain a unit root since it is a bounded variable. Apparent nonstationarity in this rate within finite samples could be attributable to protracted adjustments towards its long-term mean.



Histogram

Cumulative density function

Figure 1.4: Cross-sectional dependence test statistics (Pesaran, 2015). 95% critical value on red vertical lines.



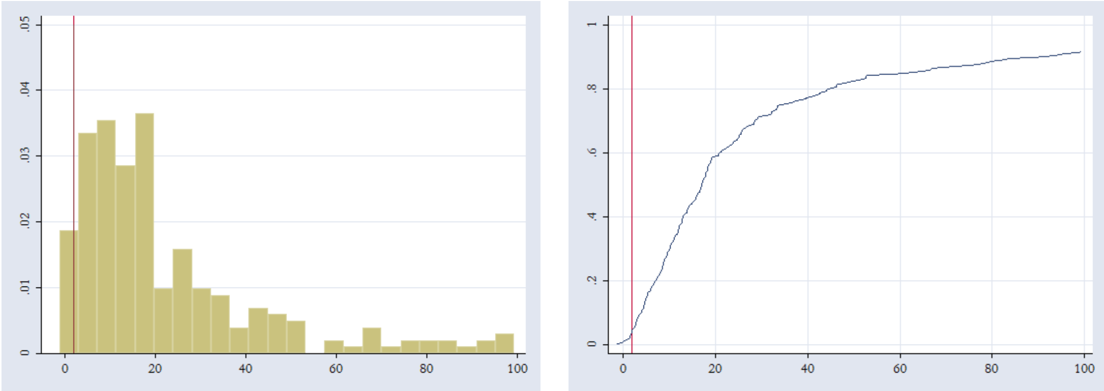
Histogram

Cumulative density function

Figure 1.5: Estimation of the α exponent (Bailey, Kapetanios, and Pesaran, 2016). Interval for strong cross-sectional dependence on red vertical lines.

individual time series. The efficacy of the CCE estimator, as demonstrated by Pesaran and Tosetti (2011), lies in its ability to neutralize all types of correlation effects, regardless of their origin in spatial or unobserved common factors. Similarly, Breinlich, Ottaviano, and Temple (2014) suggest that using a common factor structure is a plausible alternative to spatial econometric models that rely on geographical proximity and inter-unit distance to define cross-sectional correlations.

To apply the unit root test developed by Pesaran (2007) for heterogeneous panels (CIPS) to our data, we first calculate individual unit root test statistics for each tract from augmented Dickey-Fuller regressions that have been adjusted to include the cross-sectional averages of both lagged levels and first differences of the time series. The compilation of these CIPS test statistics for poverty rates is depicted in Figure 1.6. Our findings show



Histogram

Cumulative density function

Figure 1.6: CIPS unit root test statistics (Pesaran, 2007). 95% critical value on red vertical lines.

that the null hypothesis of a unit root can be rejected for, approximately, 90 percent of the MSAs in the sample, indicating that shocks to poverty rates are predominantly transitory. Thus, poverty rates can be interpreted as stationary processes fluctuating around a long-term mean.

1.4.2 Empirical framework

As pointed out before, conceptualizing poverty as a disequilibrium adjustment process entails assuming that it is influenced by its own past. Additionally, our previous results, which suggest that poverty rates at census tracts predominantly behave as stationary processes, support the inclusion of temporal lags of poverty in the empirical analysis of its drivers. Therefore, the long-run equilibrium relationship between poverty and its determinants will be given by:

$$y_{it} = \alpha_i + \mu_t + \delta_{m(i)} + \rho_1 y_{it-1} + \rho_2 y_{a(i)t} + \beta X_{it} + \epsilon_{it} \tag{1.1}$$

where y_{it} denotes the poverty rate of census tract i in year t, and X_{it} is a matrix that contains its potential determinants. $y_{a(i)t}$ refers to the average poverty rate in adjacent tracts to i, while $\delta_{m(i)}$ denotes state fixed effects that control for policy implications. As suggested by Roodman (2009b), to prevent contemporaneous correlation, our empirical model also considers time dummies μ_t. Finally, ϵ_{it} is an error term.

The relationship between poverty rates and housing stock variables – rented units and age – may be subject to reverse causation. Additionally, concerns about endogeneity arise regarding total population, which is included in the calculation of the dependent variable, and the average poverty in adjacent tracts, as is commonly noted in the spatial econometrics literature (Elhorst, 2014). Moreover, while the lagged dependent variable is predetermined, it is not strictly exogenous. Given these factors, and the presence of the temporal lag of the poverty rate in (1.1), we have proceeded by adopting a dynamic panel data framework.

Dynamic panel data estimators are mainly designed for datasets encompassing a large number of cross-sectional units and a relatively small number of time periods. An ordinary least squares (OLS) estimation of (1.1) would yield biased results due to the correlation between individual fixed effects and the lagged dependent variable. To address these issues, the difference GMM estimator (Arellano and Bond, 1991; Holtz-Eakin, Newey, and Rosen, 1988), which transforms the data to remove the fixed effects and employs temporal lags of the relevant regressors as instruments is a feasible alternative to handle endogeneity. However, given that past levels may not adequately predict future changes, we have applied a system GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) that further instruments the endogenous variables in levels with their first differences. We employ all available lags for predetermined and endogenous regressors as instruments. Consequently, while our dataset spans from 1970 to 2010, the initial observation used for the poverty rate is from the year 1980.

1.5 Results

Estimation results of equation (1.1) are shown in Table 1.6. The positive coefficients for the temporal lags of poverty in most subsamples highlight its persistence over time, especially in the case of suburbs and those tracts with the highest rates. The negative externalities indicated by the spatial lag are confirmed predominantly in smaller and medium size MSAs as well as in tracts with intermediate poverty rates. Regarding labor market issues, the results demonstrate notable homogeneity across subsamples. A strong, consistent inverse relationship is observed between employment rates and poverty despite of tract location or MSA size. The results also suggest that higher participation rates in the labor force among women are associated with lower poverty rates.

Table 1.6: Poverty determinants in U.S. census tracts, 1980-2010: System GMM estimations

		Location		MSA size			Poverty level		
	Full sample	Center	Suburbs	Small	Medium	Large	Lower	Middle	Upper
lagpovrate	0.3041***	0.1974***	0.4375***	0.3698***	0.3031***	0.1754***	0.3418	0.1074	0.4065***
	(0.037)	(0.051)	(0.0652)	(0.0425)	(0.0471)	(0.0486)	(0.2105)	(0.1145)	(0.0663)
wpovrate	0.0183	-0.0017	-0.0200	0.1196***	0.0658**	0.0407	0.007	0.0780***	0.0410
	(0.0343)	(0.0354)	(0.0337)	(0.0342)	(0.0319)	(0.0389)	(0.0148)	(0.0167)	(0.0402)
empl	-0.3741***	-0.4061***	-0.3235***	-0.3759***	-0.3440***	-0.3579***	-0.0350***	-0.1504***	-0.3626***
	(0.0159)	(0.0196)	(0.0236)	(0.0255)	(0.0189)	(0.0474)	(0.0058)	(0.0102)	(0.0418)
femlab	-0.2371***	-0.3187***	-0.1604***	-0.2016***	-0.2173***	-0.2451***	-0.0103***	-0.0875***	-0.3468***
	(0.0087)	(0.0222)	(0.0137)	(0.0123)	(0.011)	(0.0092)	(0.0027)	(0.0059)	(0.0196)
farming	0.1330***	0.1979***	0.1213***	0.1476***	0.1710***	-0.0729	0.0241	0.0575	0.1700***
	(0.0369)	(0.0678)	(0.0351)	(0.0333)	(0.0277)	(0.0889)	(0.0207)	(0.0381)	(0.0612)
transport	0.0030	0.0246	0.0206	-0.0097	-0.0041	0.0137	0.0089	0.0332*	-0.0371
	(0.0191)	(0.0273)	(0.0194)	(0.0202)	(0.0153)	(0.038)	(0.0113)	(0.0181)	(0.0288)
sales	-0.0644***	-0.0882***	-0.0339*	-0.0514***	-0.0768***	-0.0453***	-0.0038	-0.0343***	0.0538***
	(0.0172)	(0.0221)	(0.0184)	(0.0146)	(0.0195)	(0.0132)	(0.0040)	(0.0106)	(0.0176)
services	0.1878***	0.2335***	0.1151***	0.192***	0.1769***	0.1640***	0.0101	0.0624***	0.1563***
	(0.0204)	(0.0228)	(0.0219)	(0.0206)	(0.0156)	(0.0567)	(0.0055)	(0.0104)	(0.0246)
highsch	-0.0820***	-0.1379***	-0.0279***	-0.0938***	-0.0571***	-0.1179***	0.0057**	0.0014	-0.1029
	(0.0122)	(0.0238)	(0.0088)	(0.0142)	(0.0172)	(0.0134)	(0.0027)	(0.0125)	(0.0246)
college	-0.0659***	-0.1012***	-0.0322*	-0.0680***	-0.0527***	-0.0924***	-0.0038*	-0.0192	0.0714***
	(0.0128)	(0.0263)	(0.0166)	(0.0219)	(0.016)	(0.0159)	(0.0022)	(0.0191)	(0.0237)

(Continues)

Table 1.6: Poverty determinants in U.S. census tracts, 1980-2010: System GMM estimations (Continued)

		Location		MSA size			Poverty level		
	Full sample	Center	Suburbs	Small	Medium	Large	Lower	Middle	Upper
popul	0.0085***	0.0085***	0.0071***	0.0037***	0.0079***	0.0043*	0.0009**	0.0019**	-0.0033
	(0.0026)	(0.0032)	(0.0024)	(0.0012)	(0.0023)	(0.0023)	(0.0004)	(0.0009)	(0.0017)
under18	-0.2139***	-0.2632***	-0.1083**	-0.1927***	-0.1403***	-0.1783*	-0.013	-0.0493**	0.0784
	(0.0306)	(0.0497)	(0.0437)	(0.0311)	(0.0389)	(0.0957)	(0.0086)	(0.0244)	(0.041)
over60	-0.0646	-0.0229	-0.0677**	-0.0788***	-0.0431	-0.0066	0.0067	-0.0306	-0.2741***
	(0.0436)	(0.061)	(0.0303)	(0.0276)	(0.036)	(0.0468)	(0.0093)	(0.0203)	(0.0286)
black	0.0117	0.0201	0.0028	0.0078	0.0046	0.0086	-0.0034	0.0027	-0.0592**
	(0.0105)	(0.0181)	(0.0118)	(0.0138)	(0.0099)	(0.0112)	(0.0026)	(0.0060)	(0.0235)
hispanic	0.0512***	0.0553***	0.0471***	0.0347***	0.0514***	0.0520***	-0.0013	0.0212***	-0.0406***
	(0.0096)	(0.0119)	(0.015)	(0.0117)	(0.0132)	(0.0189)	(0.0063)	(0.0059)	(0.0156)
asian	0.0147	0.0330	-0.0181	0.0269	0.0299	0.0352***	-0.0001	0.0009	0.0248**
	(0.0115)	(0.0207)	(0.0127)	(0.0289)	(0.0188)	(0.0125)	(0.0023)	(0.0059)	(0.0119)
femhead	0.3534***	0.3708***	0.2935***	0.3054***	0.3398***	0.3606***	0.0657***	0.1468***	0.2054***
	(0.0196)	(0.0282)	(0.0341)	(0.0269)	(0.0317)	(0.0488)	(0.0127)	(0.0276)	(0.0158)
rent	0.0734***	0.1154***	0.0402***	0.1026***	0.0941***	0.0690***	0.012**	0.0565***	0.0586
	(0.0229)	(0.0275)	(0.0119)	(0.023)	(0.0212)	(0.0191)	(0.0056)	(0.0117)	(0.0454)
housing5	0.0794	0.2211**	-0.0323	0.193***	0.1769***	0.1384	-0.0009	-0.0474	0.0404
	(0.0988)	(0.1109)	(0.0701)	(0.0431)	(0.0601)	(0.1591)	(0.0131)	(0.0571)	(0.1615)
housing10	0.1308*	0.4095*	-0.0475	0.0957	0.0162	0.7501***	0.0028	0.0376	-0.3511***
	(0.0731)	(0.2198)	(0.082)	(0.1574)	(0.0833)	(0.1181)	(0.0259)	(0.0952)	(0.1657)

(Continues)

Table 1.6: Poverty determinants in U.S. census tracts, 1980-2010: System GMM estimations (Continued)

		Location		MSA size			Poverty level		
	Full sample	Center	Suburbs	Small	Medium	Large	Lower	Middle	Upper
housing20	0.1809	0.0027	0.2566***	0.0627	0.0682	-0.2125	-0.0033	0.1196	-0.0429
	(0.1184)	(0.1361)	(0.094)	(0.1134)	(0.0812)	(0.1555)	(0.0193)	(0.1063)	(0.3426)
housing30	-0.1803**	-0.124	-0.1779***	-0.0752	-0.0857	0.0003	-0.0032	-0.0946	0.2334
	(0.0748)	(0.1057)	(0.0551)	(0.0612)	(0.0605)	(0.1173)	(0.0094)	(0.051)	(0.1942)
Observations	215,044	95,173	119,871	50,499	100,296	53,926	35,339	76,715	40,518
Census tracts	59,214	25,473	33,741	15,922	31,497	17,998	16,314	34,220	15,405
AR (1) test	-19.94	-2.05	-5.27	-7.26	-7.04	-1.93	-3.42	-4.27	-12.48
p-value	0.00	0.04	0.00	0.00	0.00	0.05	0.00	0.00	0.00
AR (2) test	-0.50	-0.30	3.76	0.68	0.88	0.39	1.59	0.20	2.68
p-value	0.61	0.76	0.00	0.50	0.38	0.70	0.11	0.84	0.01
Hansen test	5.91	3.62	4.40	20.77	0.00	0.00	2.87	2.99	5.66
p-value	0.32	0.61	0.49	0.00	1.00	1.00	0.72	0.70	0.34

Note: Dependent variable is the poverty rate. State fixed effects are included. Predetermined and endogenous regressors (lagpovrate, wpovrate, popul, rent, and housing ages) have been instrumented using all available lags. They have also been collapsed to reduce their count (Roodman, 2009a). Robust standard erros, clustered at MSA level, are reported in parentheses. *** p<0.01; ** p<0.05; * p<0.1.

While there is not a predetermined sign for the percentages of employment in the different activities, our findings reveal that the higher the share of employment in sales and office occupations the lower the poverty rates. With the exception of large MSAs, the opposite is found for the share of farming, fishing and forestry. A plausible explanation for this result is the typically seasonal nature and lower wages associated with these jobs. Our findings also reveal a positive correlation between the employment share of the service sector and poverty rates. This aligns with the characterization by Lauer, Coleman, and Haywood (2016), who describe the 'average poor' as predominantly women, frequently with children, black or Hispanic, with lower levels of education, and often employed part-time in the service sector. Tracts whose residents have higher levels of education are supposed to have lower poverty rates, as high-skilled workers generally earn higher wages. This expectation is confirmed by the negative coefficients for educational attainment variables, observed consistently across the overall sample and within tract location and MSA size subsamples.

In examining socioeconomic variables as potential determinants of poverty, it is observed that population size is positive and significantly correlated with poverty rates. Tracts with a greater proportion of the population under 18 years of age generally exhibit lower poverty rates across all subsamples. However, tracts with a larger percentage of the population over 60 only show lower poverty rates in suburban areas and small MSAs. Among those variables representing the relative size of racial groups, only the proportion of the population of Hispanic origin is consistently and positively related to poverty. The percentage of families with children headed by women presents a robust and positive association with poverty, aligning with previous findings in poverty research; see, among others, Levernier, Partridge, and Rickman (2000), and Jargowsky (2014). In accordance with the conclusions drawn by Tunstall, Bevan, Bradshaw, Croucher, Duffy, Hunter, Jones, Rugg, Wallace, and Wilcox (2013), who found that homeowners tend to be less impoverished compared to renters, our results also indicate a strong direct relationship between the prevalence of poverty and the proportion of renter-occupied housing units.

As highlighted earlier, examining the results for subsamples segmented by poverty levels, presented in the last three columns of Table 1.6, may provide further insights into the self-reinforcing nature of poverty. The disparities observed here are more pronounced than those obtained when dividing tracts by location or city size, and they reveal contrasting implications regarding poverty determinants along its distribution. A key observation is that while the temporal lag of the poverty rate does not exhibit statistical significance in the least and moderately poor tracts, it becomes positively significant in the most impoverished quartile. This result suggests that the persistence of poverty intensifies as its severity increases. Regarding employment and female labor force participation, a consistent negative correlation with poverty is evident across all quartiles. Interestingly, this relationship strengthens in tracts with higher poverty rates. No significant sectoral effects are observed in tracts with lower poverty rates. While the share of people employed in sales and office occupations is positive in the poorer tracts, it is negative in intermediate tracts.

Educational attainment displays varied associations with poverty across quartiles. The presence of high school graduates is positively associated with poverty at the lower end of its spectrum, implying that this level of education may not suffice to alleviate poverty and might even be detrimental in areas with better economic opportunities. Conversely, a higher proportion of college graduates is linked to lower poverty rates in the least impoverished quartiles, but higher in the poorest quartile. This striking result could hypothetically be explained by migration of college educated individuals away from highly disadvantaged tracts, potentially exacerbating the existing conditions. Another possible reason is that weak local economies cannot absorb these graduates into the workforce.

The impact of population size on poverty varies by quartile; it negatively influences poverty in the lower and middle quartiles. Higher proportions of minors only reduce poverty in the middle quartiles, while an increased share of the population over 60 correlates with lower poverty rates exclusively in the upper quartile. Regarding racial composition, its relationship with poverty differs across quartiles. No significant relations are found in the lower quartile, while in the middle quartiles, only the population of Hispanic origin is associated with increased poverty. Contrarily, in the upper quartile, a higher share of Asian population relates to more poverty, but larger proportions of black race and Hispanic origin populations are linked with lower poverty rates. As expected, a higher percentage of female-headed families with children positively associates with poverty, particularly in the upper quartile. The proportion of rented housing units is positively related with poverty in the lower and middle quartiles. Finally, the impact of the age of the housing stock on poverty is mostly insignificant when tracts are categorized by poverty rates.

The suitability of the adopted dynamic panel data estimation framework is corroborated by the application of the serial correlation test for differenced residuals, as proposed by **ArellanoBond1991**, which validates the use of lags of predetermined and endogenous regressors as instruments. However, there are exceptions in the regressions for tracts situated in suburban areas and those exhibiting high poverty levels. Despite this, it is important to highlight that the over-identifying restrictions test statistic, developed by Hansen (1982), does not reject the null hypothesis in these cases. This indicates that the instruments employed are not correlated with the error term and, therefore, they are correctly excluded from the estimation.

1.6 Discussion

The previous findings bear significant implications for policy formulation, particularly in the context of the ongoing debate on the optimal design of local development strategies. This discussion, as depicted earlier, is primarily centered around two approaches: place-based and person-centered policies. The former typically involve subsidies or tax incentives aimed at economically disadvantaged areas to improve the living conditions of their residents. In contrast, person-centered policies are tailored to directly address the needs of impoverished individuals, with the objective of enhancing their quality of life and access to opportunities. Our study have tried to shed light on the persistence and key determinants of poverty in U.S. census tracts, therefore, we endeavor to elucidate the strengths and limitations of both policy types[5].

A persistent nature of poverty in census tracts would strongly support the implementation of place-based policies since they would help to mitigate its self-perpetuating effects. Our results indicate that poverty rates in tracts are stationary, which would counter this argument. Even so, given the statistical significance and positive sign of the coefficients for lags of poverty rates, place-based policies should not be discarded, especially in tracts most in need. Furthermore, free movement of people could make geographic income differences

[5] For a comprehensive review of these policy approaches, readers are referred to Partridge and Rickman (2007).

disappear through arbitrage, hence discouraging place-blased policies. In this context, the relationship between employment and poverty rates becomes crucial. Our findings indicate that employment relates negatively with poverty across all examined subsamples. This suggests that place-based policies focused on fostering job opportunities could be benefitial, particularly in poorer tracts, as evidenced by the more substantial coefficients observed in the corresponding subsample. Conversely, the inverse relationship between female headed families and poverty – which holds true across different tract locations and MSA sizes – lends support to person-centered policies targeting vulnerable demographics. Furthermore, the effectiveness of this type of policy is reinforced by the results about the share of population of Hispanic origin.

Estimation results for the sectoral employment composition could serve as an usefull guideline on the kinds of employment that could most effectively mitigate poverty. In this regard, Table 1.6 shows that the share of employment in the primary and service sectors is positvely associated with poverty. Consequently, while designing place-based policies that encourage job creation, it is crucial to consider the unique characteristics of each area to ensure these initiatives are effective. Given that the relationship between human capital and poverty is not homogeneous when dividing tracts by poverty levels, person-centered policies aimed to improve educational attainment should be designed carefully. A good strategy could be to complement them with other policies of the place-based type enhancing the creation of skilled jobs.

Fiscal policies designed to boost home-ownership could play a role in poverty alleviation. Such policies can be executed through person-centered approaches, such as offering tax benefits for home purchases. Alternatively, they could take a place-based form, involving the subsidization of housing in economically disadvantaged areas. Our research do not establish a clear connection between the age of housing stock and poverty rates. This lack of a consistent relationship constrains our capacity to make conclusive statements about the effectiveness of policies focused on the refurbishment or upkeep of older housing units in reducing poverty.

1.7 Concluding remarks

Disentangling the main drivers of poverty is an essential condition for its alleviation. The related literature on this topic has generally considered counties as the unit of reference, potentially overlooking crucial aspects. This oversight arises because poverty affects particular persons living in definite areas who both influence and are influenced by the economic conditions of their neighbors. Therefore, a deeper knowledge of the factors behind poverty requires the adoption of a higher level of geographical disaggregation. To address this need, our study delves into the determinants of poverty rates within U.S. census tracts by analyzing a geographically consistent data set covering 368 MSAs during 1970-2010 on a decennial basis.

Our analysis reveals that poverty rates, while stationary, exhibit persistence and a certain level of spatial dependence. There is a negative and significant relationship between employment and female labour force participation with poverty. Furthermore, a higher level of educational attainment is generally related to lower poverty rates. We have also provided evidence of the sectoral, demographic, and ethnic origins of poverty. Higher percentages of home renters and female-headed families exert a robust and positive influence on poverty rates at the tract level. However, the relationship between the age of the housing stock and poverty is not robust. The insights derived from our findings hold significant implications for policy formulation, particularly in the context of the ongoing debate concerning the optimal design of local development strategies. While there are compelling arguments supporting both place-based and people-centered policies, our results suggest that the most effective approach to alleviating poverty might lie in treating these strategies as complementary rather than substitutes.

Several avenues for future research emerge from our study. The first of them, which depends on data quality and availability, is to replicate this analysis in other countries, especially in those less developed. This would provide valuable comparative insights into poverty dynamics in varied economic contexts. Another potential extension is to delve deeper into the geographic aspects of the relationship between poverty and its determinants. Key areas in this regard are the multi-dimensional link between employment, poverty, and space (Partridge and Rickman, 2008), intrinsically related to the 'spatial mismatch' hypothesis (Ihlanfeldt and Sjoquist, 1998), and the efficiency of safety net programs (Murphy and Wallace, 2010; Kneebone and Berube, 2013; Murphy and Allard, 2015). The latter topic is particularly pertinent given that, as mentioned in Section 1.2, there has been a significant shift in the U.S. poverty landscape, with a higher number of impoverished population residing in the suburbs than in the city centers. However, this demographic shift has not corresponded with a decrease in urban poverty rates. Following Allard (2017, page 38), who identified the beginning of the 21st century as a pivotal moment, a more extended time frame than that analyzed in the present study would be essential to thoroughly investigate the causes, consequences, and policy responses to this significant shift in the geographical distribution of poverty in the U.S.

Appendix A

Table A1: Descriptive statisctics for poverty and its potential determinants

		Tract location		MSA size			Poverty level		
	Full sample	Center	Suburbs	Small	Medium	Large	Low	Medium	High
povrate	0.16	0.21	0.12	0.17	0.15	0.15	0.03	0.12	0.34
	(0.13)	(0.15)	(0.10)	(0.14)	(0.13)	(0.13)	(0.02)	(0.04)	(0.11)
wpovrate	0.15	0.20	0.12	0.17	0.15	0.14	0.08	0.14	0.26
	(0.10)	(0.11)	(0.07)	(0.10)	(0.10)	(0.10)	(0.05)	(0.07)	(0.10)
empl	0.91	0.90	0.92	0.91	0.91	0.91	0.95	0.92	0.85
	(0.07)	(0.08)	(0.05)	(0.07)	(0.07)	(0.06)	(0.04)	(0.05)	(0.08)
femlab	0.60	0.60	0.60	0.58	0.61	0.60	0.62	0.61	0.55
	(0.11)	(0.11)	(0.10)	(0.10)	(0.11)	(0.11)	(0.10)	(0.10)	(0.11)
farming	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01
	(0.10)	(0.15)	(0.02)	(0.20)	(0.02)	(0.01)	(0.01)	(0.02)	(0.20)
transport	0.11	0.11	0.11	0.13	0.10	0.10	0.07	0.11	0.14
	(0.08)	(0.09)	(0.08)	(0.10)	(0.08)	(0.07)	(0.05)	(0.06)	(0.12)
sales	0.24	0.23	0.24	0.23	0.24	0.24	0.24	0.24	0.22
	(0.10)	(0.13)	(0.06)	(0.14)	(0.07)	(0.09)	(0.07)	(0.06)	(0.15)
services	0.16	0.18	0.15	0.17	0.16	0.16	0.11	0.16	0.22
	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.11)	(0.06)	(0.06)	(0.20)
highsch	0.27	0.26	0.28	0.31	0.27	0.25	0.21	0.28	0.31
	(0.24)	(0.34)	(0.11)	(0.15)	(0.11)	(0.40)	(0.11)	(0.11)	(0.43)
college	0.30	0.30	0.30	0.25	0.30	0.33	0.45	0.29	0.17
	(0.19)	(0.21)	(0.18)	(0.16)	(0.19)	(0.21)	(0.18)	(0.17)	(0.15)
popul	4.33	3.96	4.61	4.30	4.30	4.40	4.58	4.49	3.77
	(2.04)	(1.92)	(2.08)	(2.00)	(2.05)	(2.07)	(2.12)	(2.02)	(1.91)
under18	0.23	0.23	0.24	0.23	0.23	0.23	0.23	0.22	0.25
	(0.07)	(0.08)	(0.06)	(0.07)	(0.07)	(0.08)	(0.06)	(0.06)	(0.09)
over60	0.19	0.17	0.20	0.20	0.18	0.18	0.21	0.20	0.15
	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)	(0.09)	(0.10)	(0.09)	(0.07)
black	0.15	0.21	0.09	0.11	0.15	0.17	0.05	0.11	0.30
	(0.23)	(0.28)	(0.17)	(0.19)	(0.23)	(0.26)	(0.11)	(0.18)	(0.31)
hispanic	0.17	0.21	0.14	0.11	0.15	0.26	0.08	0.16	0.28
	(0.22)	(0.24)	(0.20)	(0.18)	(0.20)	(0.26)	(0.10)	(0.19)	(0.30)
asian	0.05	0.07	0.04	0.02	0.05	0.08	0.07	0.05	0.04
	(0.09)	(0.11)	(0.08)	(0.04)	(0.10)	(0.12)	(0.10)	(0.09)	(0.08)
femhead	0.15	0.19	0.11	0.14	0.15	0.15	0.07	0.13	0.26
	(0.12)	(0.14)	(0.09)	(0.11)	(0.12)	(0.12)	(0.05)	(0.08)	(0.14)
rent	0.33	0.43	0.25	0.30	0.31	0.37	0.17	0.31	0.50
	(0.21)	(0.21)	(0.17)	(0.18)	(0.20)	(0.24)	(0.14)	(0.18)	(0.19)
housing5	0.04	0.03	0.04	0.04	0.04	0.03	0.05	0.04	0.03
	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.08)	(0.06)	(0.07)
housing10	0.08	0.06	0.09	0.08	0.09	0.06	0.11	0.08	0.05
	(0.10)	(0.10)	(0.11)	(0.09)	(0.12)	(0.10)	(0.13)	(0.10)	(0.07)
housing20	0.13	0.09	0.15	0.14	0.13	0.09	0.17	0.13	0.08
	(0.13)	(0.12)	(0.13)	(0.11)	(0.14)	(0.13)	(0.17)	(0.12)	(0.09)
housing30	0.13	0.11	0.15	0.13	0.14	0.12	0.15	0.14	0.10
	(0.13)	(0.14)	(0.12)	(0.10)	(0.14)	(0.14)	(0.17)	(0.12)	(0.11)

Note: Standard deviations are reported in parentheses.

Chapter 2

Long-run inequality persistence, 1870–2019

2.1 Introduction

There is a great social and political concern about inequality, reflected in the fact that the United Nations has established its reduction as one of the Sustainable Development Goals to achieve their 2030 Agenda. The reason is that inequality has been related to economic, social, and political instability (Rodrik, 1999; Alvaredo, Chancel, Piketty, Saez, and Zucman, 2018), as it hampers growth (Berg and Ostry, 2017; Berg, Ostry, Tsangarides, and Yakhshilikov, 2018), encourage the support for populist parties (Nolan and Valenzuela, 2019; Stoetzer, Giesecke, and Klüver, 2021), and has an adverse influence on the health status of the population (Wilkinson and Pickett, 2006).

Interest in the evolution of inequality dates back to the seminal contribution of Kuznets (1955), who established an inverted U-shaped relationship with economic growth. More recently, Milanovic (2016) has argued that inequality is cyclical – influenced by economic, demographic, and political factors – and, as such, it may not experience unlimited growth. Piketty (2014) contends that inequality has been increasing in developed countries since the 1980s. This author also expects that this trend will continue during the next century, driven by a greater rate of return to assets as compared to GDP growth. Corroborating this prediction, theories aligned with the "Great Gatsby Curve" (Durlauf, Kourtellos, and Tan, 2022) suggest that initial levels of inequality are associated with persistent intergenerational income.

Together with a wider availability of long-run inequality data, a growing body of literature investigating the persistence of its time series has appeared. This is the case of Islam and Madsen (2015), who study the stationary character of the Gini index and the top 10% income share for a panel of 21 OECD countries during the period 1870–2011. Their main conclusion is that income inequality can be considered to be a stationary – or I(0) – process. Quite the opposite is found by Christopoulos and McAdam (2017), who were not able to reject the null hypothesis that the Gini coefficient is a unit root – or I(1) – process in a panel of 47 countries during 1975–2013. Similarly, and for a panel covering 60 countries from 1989 to 2015, Ghoshray, Monfort, and Ordóñez (2020) show that the Gini indexes for net and market income exhibit a unit root. In a sample of 34 countries covering the period 1960–2020, Makhlouf (2023) concludes that inequality trends have been relatively stable in developed countries, while both increasing or decreasing trends can be found in developing countries. These results lead this author to claim that national factors have exerted a stronger influence on inequality than global ones.

In a comprehensive study covering the period from 1870 to 2020 and a sample of 21 OECD countries, Solarin, Lafuente, Gil-Alana, and Blanch (2022) implement both linear and non-linear fractional integration techniques to show that shocks to inequality generally exhibit a persistent nature. With a similar aim, but adopting a different empirical approach, Roine and Waldenström (2011) test for the presence of structural breaks in the top income shares of a group of developed countries applying both time series and panel data methods. These authors find common breaks after the Second World War (WWII) and during the 1970s, as well as differential patterns across country groups. Using a Gaussian mixture autoregressive models, Kalliovirta and Malinen (2020) show that the breaks detected by Roine and Waldenström (2011) are, in fact, regime changes.

Ghoshray, Malki, and Ordóñez (2021) apply time series methods that control for the presence of structural breaks both under the null and the alternative hypotheses when testing for a unit root. For time spans close to a century, they conclude that both top income and wealth shares present high levels of persistence in groups of Anglo-Saxon, continental European, and Asian countries. This framework is similar to that implemented by Sanso-Navarro and Vera-Cabello (2020), who, for a sample of both developed and emerging economies during the years from 1960 to 2017, show that the Gini coefficient for disposable income displayed a persistent behavior. These authors also assess the existence of changes in persistence finding that, in most of the countries included in their sample, inequality alternates between stationary and non-stationary regimes. The main exceptions are South Africa and the United States (U.S.).

The U.S. not only presents one of the highest levels of inequality among developed countries (Alvaredo, Chancel, Piketty, Saez, and Zucman, 2018), but it has also been shown to exert a non-negligible influence on the inequality of other advanced economies (Kalliovirta and Malinen, 2020). In the present paper, we are extending the sample back to 1870 in order to check whether the results obtained by Sanso-Navarro and Vera-Cabello (2020) are influenced by the time span covered, as it excludes significant periods – such as the pre-industrial era and the two World Wars – during which inequality is known to have behaved differently. As another contribution, we consider both income and wealth inequality measures. In particular, we will evaluate the persistence of the Gini index for disposable income, which provides an overall indication of income inequality; the top 10% income share, which reflects income concentration among the highest earners; and the wealth-to-income ratio, which represents wealth concentration.

Figure 2.1 shows the evolution of the three above-mentioned inequality measures in the U.S. from 1870 to 2019. It can be observed that income inequality followed a steady decreasing trend from the end of the 19th century until the First World War (WWI), experiencing a sudden increase after this historical event. In contrast, the wealth-to-income ratio followed an overall increase, with some episodes of high volatility. During the interwar period, and while the top 10% income share displayed an increasing trend, the Gini coefficient fluctuated around constant values with a slight drop before WWII. After that moment, the three time series present a significant drop, being more moderate in the case of the Gini index due to its lower starting values. The wealth-to-income ratio displayed a staggered upward trend afterwards, alternating sharp increases with stable periods. This measure of wealth inequality also experienced a short drop in the 2000s, that reversed after the Great Recession. Income inequality almost remained stable until the 1980s, when

Figure 2.1: Gini coefficient for disposable income, top 10% income share, and wealth-to-income ratio in the U.S., 1870–2019.

pronounced upward trends emerged. They moderated in the 1990s, especially for the Gini index.

Our empirical analysis follows the approach adopted by Sanso-Navarro and Vera-Cabello (2020), based on the implementation of unit root tests that allow for the presence of structural breaks both under the null and the alternative hypotheses. Proceeding this way, we deal with the circular problem that arises when both features are present in the data (Perron, 2006). Subsequently, we examine the presence of changes between I(0) and I(1) regimes in those inequality measures that have an overall non-stationary behavior. Obtained results suggest that, while the wealth-to-income ratio presents a high level of persistence throughout the sample period analyzed, income inequality measures experience multiple regime changes.

Although Sanso-Navarro and Vera-Cabello (2020) state that the persistence of income inequality appears to be influenced by tax progressivity, income for top earners, and working conditions, they do not establish any statistical relationships regarding the drivers of inequality persistence. To delve deeper into this aspect, we draw on the existing literature about the determinants of inequality in order to examine which socio-economic variables are associated with the probability of inequality being in a stationary or a non-stationary regime. This strand of the literature – as reviewed by Förster and Tóth (2015) and Nolan, Richiardi, and Valenzuela (2019) – provides a wide range of theories and mechanisms through which factors such as globalization, technological change, macroeconomic and financial conditions, as well as labor institutions and demographics, affect income inequality.

Therefore, and as another contribution to the related literature, we examine the variables that are related to the persistence (rather than the level) of inequality. This has been done by implementing Bayesian model averaging (BMA) techniques in a generalized linear model (logistic regression) framework. On the one hand, obtained results suggest that globalization is associated with a higher persistence of income inequality. On the other hand, we also provide evidence that higher levels of educational attainment and trade union membership are linked to a higher probability of income inequality being in a stationary regime.

The rest of the chapter is organized as follows. Section 2.2 motivates the inequality measures that have been studied, describes the main data sources, and carries out the time series analysis. Section 2.3 deals with the study of those socio-economic factors that display a robust relationship with the persistence of income inequality. Section 2.4 interprets and discusses the main results obtained in the empirical analysis and, finally, Section 2.5 concludes.

2.2 A time series analysis of income and wealth inequality in the U.S.

2.2.1 Inequality measures

The standard measure for the study of income inequality is the Gini coefficient which takes a value of one when all income is concentrated in one unit of reference, zero when income is equally distributed across units. This information for the U.S. has been extracted from the Standardized Income Inequality Database (SWIID; Solt, 2020) for the period that covers the years from 1913 to 2019. The Gini index provided by this dataset refers to disposable income, and takes households weighted by their respective number of members as the unit of reference. This information has been extended back to 1870 with the data compiled by Madsen, Minniti, and Venturini (2018) implementing the procedure proposed by Prados De La Escosura (2008). Despite the widespread use of the Gini index as a measure of income inequality, it is not exempt of problems. On the one hand, and given the aggregate character of the coefficient, it is difficult to determine whether a given value reflects a high or a low level of inequality. On the other hand, and due to the mathematical properties of this index, it tends to disguise the changes experienced in both the lower and the upper tails of the distribution of income (Alvaredo, Chancel, Piketty, Saez, and Zucman, 2018). In order to overcome these limitations – especially the second one – we have also considered the share of income of the top 10% of the distribution as an alternative a measure of income concentration. This information has been collected from the World Inequality Database (WID) for the period 1913–2019 and, similarly to the Gini coefficient, completed until 1870 using the data set created by Madsen, Minniti, and Venturini (2018).

Wealth inequality has been proxied using the wealth-to-income ratio. This measure of wealth inequality is based on the 'second law of capitalism' formulated by Piketty (2014), which considers that a higher value of this ratio reflects an increase in the gains of capital obtained by its owners, hence increasing wealth inequality. In other words, the wealth-to-income ratio can be understood as a measure of wealth accumulation. The time series of this variable for the period 1870–2019 has been constructed by combining the information provided by the WID and by Piketty and Zucman (2014).

2.2.2 Unit roots and trend shifts

As a first attempt to assess the persistence of inequality, we have performed a battery of unit root tests choosing the augmentation lag with the procedure proposed by Ng and Perron (2001), and considering that the deterministic component is made up by both a constant and a trend. Resulting test statistics are presented in Table 2.1, which show that the unit root null for the three inequality measures described in the previous subsection cannot be rejected. Although these results have been obtained after applying a modified information criterion for the selection of the truncation lag and a generalized least squares (GLS) detrending procedure to improve the empirical size and power of the unit root tests, the conclusions drawn should be considered as preliminar. The reason is that the unit root tests that have been implemented do not consider the possible presence of changes in the deterministic component of the time series under scrutiny. As demonstrated by (Perron, 1989), level and/or trend shifts reduce the power of unit root tests and, given the length of the time series that have been analyzed, this is an issue that should not be discarded in our context.

The potential limitations of the tests implemented in Table 2.1 are determined by the interrelation between testing for unit roots and for the presence of structural breaks exposed in Perron (2006). If we are analyzing the order of integration of a time series and it displays shifts in its determistic component that are not taken into account, the unit root test will tend to fail in rejecting the null hypothesis. Alternatively, if we are looking for shifts in the deterministic component and the time series is non-stationary, the structural change test will tend to over-reject the null hypothesis of an absence of breaks. To address these issues we first take advantage of the trend shift test proposed by Perron and Yabu (2009). This test is based on a quasi-feasible GLS detrending approach, and is valid for both I(0) and I(1) processes. We have performed the test considering a shift in the intercept and in the slope parameters, and allowing for several structural breaks by implementing

Table 2.1: Unit root testing

	P_t	MP_t	ADF	Z_α	MZ_α	MSB	MZ_t
Gini coefficient	42.5610	38.7540	-0.5390	-1.5320	-1.4190	0.4150	-0.5390
Top 10% income share	25.1630	23.7990	-1.1360	-3.4380	-3.3390	0.3300	-1.1030
Wealth-to-income ratio	13.6223	13.7191	-1.5111	-6.8241	-6.6782	0.2600	-1.7361

Note: P_t is the Point Optimal test proposed by Elliott, Rothenberg, and Stock (1996). ADF is the augmented Dickey-Fuller test. Z and M-class tests are discussed in Ng and Perron (2001).The deterministic component contains a constant and a linear trend, and the number of augmentation lags has been selected by the modified AIC.

the sequential procedure proposed by Kejriwal and Perron (2010), that consists of testing for the null hypothesis of l breaks against the alternative of $l+1$ breaks. Under the null hypothesis, break dates are the global minimizers of the sum of squared residuals from an ordinary least squares estimation, and are obtained using the algorithm developed by Bai and Perron (2003).

Resulting trend shift test statistics and estimated break dates are reported in Table 2.2. These figures show that the two measures of income inequality and the wealth-to-income ratio experience a trend shift around WWII. The test statistic detects further breaks for the Gini coefficient and the top 10% income share, being some of them coincident. In particular, both time series present a trend shift at the beginning of the 20th century, and in the early 1980s. Moreover, the Gini coefficient displays two breaks in 1965 and in 1993, and the top 10% income share another one in 2001. At this point, it is worth noting that we are not yet interested in the particular interpretation of the shifts detected. The reason is that, as explained by Kurozumi (2005) and as it will be studied in the next subsection, they may be related to changes in the order of integration of the series. Nonetheless, it is necessary to detect these breaks in order to control for their presence when testing for unit roots.

The study of the non-stationary character of the income and wealth inequality measures accounting for the detected trend shifts has been carried out using the procedure developed by Carrion-i-Silvestre, Kim, and Perron (2009). These authors propose to extend the quasi-GLS detrending method of Elliott, Rothenberg, and Stock (1996) to allow the unit root tests implemented before to consider structural breaks both under the null and the alternative hypotheses. Resulting test statistics are presented in Table 2.3, only providing

Table 2.2: Trend shift test statistic (Perron and Yabu, 2009) and estimated break dates.

	Exp - W_{FS}	F_T (2 | 1)	F_T (3 | 2)	F_T (4 | 3)	F_T(5 | 4)	TB_1	TB_2	TB_3	TB_4	TB_5
Gini coefficient	5.9028***	4.5744**	10.3449***	30.7594***	9.0741***	1980	1905	1993	1946	1965
Top 10% income share	4.3999**	17.0284***	99.3356***	6.0225***		1942	1900	1983	2001	
Wealth-to-income ratio	2.9010*					1940				

Note: The trimming parameter has been set to 0.15. Break dates are reported in the order of appearance in the sequential implementation (Kejriwal and Perron, 2010). * p<0.10, **p<0.05, *** p<0.01.

Table 2.3: Unit root testing in the presence of trend shifts.

	P_t	MP_t	ADF	Z_α	MZ_α	MSB	MZ_t
Gini coefficient	13.3416	11.3442	-4.9168**	-41.3771*	-35.4032	0.1188	-4.2070
Top 10% income share	15.6839	13.2450	-4.0565	-29.6265	-26.6507	0.1369	-3.6490
Wealth-to-income ratio	12.7447	11.3418	-2.8039	-15.2779	-14.4416	0.1835	-2.6504

Note: P_t is the Point Optimal test proposed by Elliott, Rothenberg, and Stock (1996). ADF is the augmented Dickey-Fuller test. Z and M-class tests are discussed in Ng and Perron (2001). The deterministic component contains a constant and a linear trend, and the number of augmentation lags has been selected by the modified AIC. Estimated break dates reported in Table 2.2 have been controlled for (Carrion-i-Silvestre, Kim, and Perron, 2009). * $p<0.10$,**$p<0.05$,***$p<0.01$.

some weak evidence against the unit root null in the case of the Gini coefficient for disposable income. Therefore, it can be claimed that the inequality measures that have been analyzed are non-stationary and, as a consequence, have a persistent character. However, the Gini index and the top 10% income share are bounded variables. Although this is not the case of the wealth-to-income ratio in theory, it is implausible that this variable may display an explosive behavior in practice. For these reasons, it is difficult to consider that these inequality measures are I(1). In fact, and following the arguments put forward by Christopoulos and McAdam (2017), the unit root behavior of inequality measures might be reflecting that they are not adjusting to a long-run mean or, at most, doing it very slowly, hence showing high persistence.

2.2.3 Persistence changes

Similarly to Sanso-Navarro and Vera-Cabello (2020), and given the long sample period covered by the time series being studied, we can go a step further in the analysis of the measures of inequality. It is reasonable to check whether these variables behave as a unit root process from 1870 to 2019 or if they alternate between I(0) and I(1) regimes. This has been made using the persistence change test statistic developed by Leybourne, Kim, and Taylor (2007), which contrasts the null hypothesis that the time series is I(1) against the alternative hypothesis that it experiences, at least, one change to an I(0) regime. This testing procedure is based on doubly-recursive sequences of augmented Dickey-Fuller unit root statistics, and has the advantage of being valid when the time series have multiple changes in persistence. That is to say, the persistence change test can be implemented in a sequential manner in order to detect multiple breaks. In this way, when an I(0) regime is detected, the test is applied again to the remaining I(1) subperiods of the time series.

Table 2.4: Persistence change test (Leybourne, Kim, and Taylor, 2007).

	Period	M test	I(0) start	I(0) end
Gini coefficient	1870 - 2019	-5.5960***	1907	1944
	1870 - 1906	-1.9290	1879	1901
	1945 - 2019	-4.7730*	1990	2006
	1945 - 1989	-4.6380**	1949	1978
Top 10% income share	1870 - 2019	-4.9640**	1909	1940
	1870 - 1908	-1.9290	1879	1901
	1941 - 2019	-5.3810**	1997	2018
Wealth-to-income ratio	1870 - 2019	-4.1420	1944	2018

Note: The deterministic component contains a constant and a linear trend, and the lag length has been selected using the procedure proposed by Ng and Perron (1995). * $p<0.10$, **$p<0.05$, ***$p<0.01$.

The minimum time span allowed for these I(1) regimes is 20 years, as determined by the critical values calculated in Leybourne, Kim, and Taylor (2007).

Table 2.4 reports the resuls obtained when the persistence change test is applied sequentially. These figures show that the Gini coefficient for disposable income is the indicator that has experienced a higher number of regime changes. This may be because this index is a measure of overall inequality, rather than an indicator of income concentration. The Gini index displays a persistent character from 1870 to 1907, when it turned into a stationary process. This first I(0) regime covers WWI, the Great Depression, and the beginning of WWII. A second short non-stationary regime began in 1944 and lasted five years. The upward change of income inequality experienced at the end of the 1970s as a consequence of policy shifts towards free market and tax cuts triggered a new I(1) regime that lasted until the 1990s. After that moment, the Gini coefficient for disposable income behaved again as a stationary process until the aftermath of the financial crisis that began in 2007.

The persistence change test detects a more limited number of regime shifts in the time series of the top 10% income share. Similarly to the Gini coefficient, a first stationary regime started in 1909, lasting until the beginning of WWII. However, the top 10% income share behaves as a non-stationary process until the late 1990s. Also in line with the other measure of income inequality, the top 10% is in an I(1) regime at the end of our sample period. Finally, the results reported in Table 2.4 shows that the wealth-to-income ratio does not suffer any regime change, what can be interpreted as an indication that wealth inequality is more persistent and difficult to mitigate than income inequality. We will discuss further these results in Section 2.4.

2.3 Searching for robust determinants of income inequality persistence

2.3.1 Data and variables

Apart from the larger time span analyzed in the present paper, as well as to the consideration of wealth inequality, we further extend the study carried out by Sanso-Navarro and Vera-Cabello (2020) by trying to disentangle the variables that determine the probability of being in a stationary or a non-stationary regime of income inequality. Despite we are interested in finding the factors that affect the persistence of inequality (instead of its level), a reasonable starting point would involve examining whether the factors that contribute to a higher level of income inequality are also associated with a greater persistence, and vice versa.

In this line of research we come across studies that consider a wide set of determinants such as Hailemariam, Sakutukwa, and Dzhumashev (2021), who apply panel vector autoregressions to a dataset comprising OECD countries. These authors conclude that real interest rates, government spending shares, and financial development indicators are inversely related to inequality. Another remarkable work is that of Furceri and Ostry (2019), who implement model averaging techniques and find that unemployment, technological change, and globalization are robust determinants of income inequality.

To provide a comprehensive overview of both the theoretical backgorund and empirical evidence, we draw upon the reviews of Förster and Tóth (2015) and, more specifically, Nolan, Richiardi, and Valenzuela (2019), as they focus on the determinants of income high-income countries. These authors divide the main driving forces behind income inequality, as well as their transmission channels, into several groups. Taking these references into account, we have encompassed them taking into account data availability without favoring any particular one. As a result, we have considered six groups of covariates, which are listed in Table 2.5, along their definitions, and data sources.

Table 2.5: Potential determinants of income inequality persistence: Definition and data sources.

Groups and variables	Definition	Sources
Globalization		
Foreign inverstment	Non-residential investment ratio (% of GDP)	Madsen, Islam, and Doucouliagos (2018) / FRED[1]
Trade volume	Ratio of imports plus exports to GDP	J-S-T Macrohistory Database[2] / WDI[3]
Foreign patents	Patent applications by foreign residents	USPTO[4]
Technological change		
Patent stock	Patent stock (15% of yearly depreciation)	Madsen, Islam, and Doucouliagos (2018) / USPTO[4]
R&D expenditure	Expenditure on research and development (% of GDP)	Madsen, Islam, and Doucouliagos (2018) / WDI[3]
Financial development		
Savings	Gross private savings ratio (% of GDP)	Madsen, Islam, and Doucouliagos (2018) / FRED[1]
Credit	Bank credit to the non-bank private sector (% of GDP)	Madsen, Islam, and Doucouliagos (2018) / FRED[1]
Interest rate	Real interest rate, long-term goverment bonds	Madsen, Islam, and Doucouliagos (2018) / FRED[1]
Fiscal and monetary policy		
Inflation	Inflation rate, consumer price index	J-S-T Macrohistory Database[2] / WDI[3]
Tax revenue	Ratio of overall tax revenues to GDP	Mitchell (2007)/WDI[3]
Gov. expenditure	Ratio of goverment expenditure to GDP	J-S-T Macrohistory Database[2] / WDI[3]
Demographics and societal structure		
Enrollment rate	Gross school enrollment rate	Madsen, Islam, and Doucouliagos (2018) / WDI[3]
Life expectancy	Life expectancy at age 10	Madsen, Islam, and Doucouliagos (2018) / SSA[5]
Labor institutions and regulations		
Unemployment	Unemployment share of the civilian labor force	Vernon (1994) / Lebergott (1957) / BLS[6]
Union membership	Union membership share of the civilian labor force	Friedman (1999)/Troy (1965) / Mayer (2004) / BLS[6]

[1]Federal Reserve Economic Data, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/ [2]Jordà-Schularick-Taylor Macro-history Database; Jordà, Schularick, and Taylor (2017) [3]World Development Indicators, The World Bank Group; https://databank.worldbank.org/ [4]United States Patents and Trademark Office, Open Data Portal; https://www.uspto.gov/ [5]Social Security Agency, Data Page; https://www.ssa.gov/data/ [6]U.S. Bureau of Labour Statistics, data tools; https://www.bls.gov/data/

The first group includes variables related to globalization, which is one of the most commonly studied driver of inequality. The way that this phenomenon may have affected inequality depends on the theoretical framework adopted. For example, in models *à la* Heckscher-Ohlin (Wood, 1995), trade is supposed to increase inequality in developed countries because they are more abundant in skilled labor and capital, hence increasing the wage gap. Predictions about capital flows go in the same line, as they should move towards the more productive sectors. This would increase the demand for skilled labour and capital gains both in developed and developing countries (Feenstra and Hanson, 1996). Trade volume has been proxied using the openness ratio (imports plus exports as a percentage of GDP), and capital flows have been measured by non-residential investment, which is also an indicator of financial globalization. As another dimension of globalization, the number of foreign patent applications tries to capture technological transfers.

The wage gap – a factor driving income inequality – is supposed to depend on technological change, our second set of determinants. It includes the stock of patents and the expenditure on research and development (R&D) as a percentage of GDP. Claessens and Perotti (2007) claim that the link between financial development and inequality is not clear. The development of the financial sector may facilitate the access to credit of the poorer share of population, enabling their ability to get their productive projects off the ground and, as a consequence, reducing inequality. However, if credit facilities increase in a context of asymmetric information, only the richer population will take advantage. Whatever the case may be, financial development has been proxied by the percentages over GDP of gross private savings and of the bank credit to the private sector. The role of financial institutions through this channel has been captured using the interest rate of long-term government bonds.

Without question, economic policy can also influence income inequality. On the one hand, monetary policy effectiveness has been captured using the inflation rate. On the other, we have included tax revenues and government expenditures as variables related to fiscal policy. Demographics and social structure have been proxied with life expectancy – reflecting the income gap between age groups and the economic weigth of pensions – and the schooling enrollment rate, which is expected to reduce the skill wage gap. Finally, we have included the unemployment rate and the share of trade union membership as indicators of the bargaining power of the labour force; i.e., the labor institutions and regulations.

2.3.2 Methodology and results

Given that we are giving the same plausibility to all the potential drivers of income inequality described above as well as their related theories, and due to the large number of covariates involved, we are applying Bayesian model averaging (BMA) to assess which of them display a more robust relationship with the probability of being in an I(0) or an I(1) regime of the income inequality measures. BMA techniques deal with variable selection, estimation, and inference simultaneously by enumerating the full model space and assigning a posterior inclusion probability (PIP) to each regressor. In fact, these inclusion probabilities are considered as one of the main advantages of these methods, see Steel (2020). BMA also permits to obtain the mean coefficients and their standard deviations for each covariate and, more importantly for our context, has been extended to be applied in a generalized linear model framework. The latter includes a logit estimation when the link function between the dependent variable and the regressors is binomial. Therefore, and according to the results in Table 2.5, we have created indicator variables that take a value of one if the Gini index for disposable income or the top 10% income share are in an I(1) regime, zero otherwise. Proceeding this way, we will be able to disentangle those factors that display a more robust relationship with income inequality persistence.

In order to be implemented, BMA methods require to control for the level of uncertainity about the importance of the variables and the value of their corresponding coefficients by selecting prior probability distributions for the model space and their related parameters, see Olmo and Sanso-Navarro (2021). In our case, we have established an uniform prior for the model space which assigns equal probability to all combinations of covariates and, following the recommendations in Ley and Steel (2012) and Li and Clyde (2018), we have elicited the hyper-g\n and benchmark priors for model-specific parameters. BMA has been specified in a logit regression framework using the Bayesian Adaptative Sampling (BAS) R package (Clyde, Ghosh, and Littman, 2011) which, as is our case, enumerates all models when there are less than nineteen regressors included.

Results for the Gini index and for the top 10% income share are shown, respectively, in Tables 2.6 and 2.7. It can be observed that the PIPs received by the covariates are high, especially when the Gini coefficient for disposable income is considered as the measure of inequality. In fact, these inclusion probabilities are higher than 0.47 in all cases. This can be interpreted as evidence of the suitability of the regressors considered as potential determinats of income inequality. Nonetheless, and as it has been pointed out by Li and Clyde (2018), it is worth noting that elicited priors tend to favor large models. For this reason, we include in the Appendix the PIPs obtained using alternative priors for model-specific parameters. Although the inclusion probabilities displayed in Tables B1 and B2 tend to be lower, the main conclusions drawn about the relative importance of the regressors do ont change significantly.

Our results suggest that globalization – in terms of investment and trade – favors both overall and cumulative income inequality to be more persistent. Technology transfers, captured by foreing patent applications, make the Gini coefficient (top 10% income share) to be less (more) persistent. We also find that the higher the stock of patents and R&D expenditures, the higher the probability of being in a non-stationary regime. This is also the case of gross private savings as a percentage of GDP, what might be an indication that people with higher incomes have a higher propensity to save, hence perpetuating income inequality. While there is an inverse relationship between bank credit to the private sector and the persistence of the concentration of income, the converse is true when inequality is measured using the Gini coefficient. This reflects that credit rationing mainly affects people with lower levels of income. In addition, a higher long-term interest rate of government bonds increases the probability of income inequality being in an I(0) regime.

The variables related to fiscal and monetary policy receive the lower PIPs. Inflation is expected to be harmful to lower incomes and/or higher labor income shares. For this reason, the inflation rate has a direct relationship with the persistence of the Gini coefficient of disposable income. Contrarily, higher inflation lessens the probability of being in an I(1) regime of the top 10% income share, reflecting the erosion of incomes in the upper tail of the distribution. Overall tax revenues as a percentage of GDP increases (decreases) the persistence of overall income inequality (income concentration). In this regard, it is worth noting that an alternative measure of tax progressivity may have lead to different

Table 2.6: Bayesian model averaging: Persistence of the Gini coefficient.

	Hyper-g/n prior			Benchmark prior		
	PIP	Mean Coef.	Std. Dev.	PIP	Mean Coef.	Std. Dev.
Foreign investment	0.9466	7.8807	6.9365	0.9447	8.6896	7.3623
Trade volume	0.9187	0.3544	0.2983	0.9240	0.3910	0.3111
Foreign patents	0.9998	-5.0943	2.8316	0.9996	-5.5847	2.8957
Patent stock	0.9036	-4.8449	4.7259	0.8990	-5.3654	5.0518
R&D expenditure	0.9988	10.3137	6.3778	0.9988	11.3199	6.6373
Savings	0.9955	0.4540	0.2735	0.9956	0.4989	0.2881
Credit	0.6390	0.0164	0.0327	0.6287	0.0180	0.0349
Interest rate	0.8846	-0.3884	0.3803	0.8824	-0.4298	0.4054
Inflation	0.5276	0.0681	0.2090	0.5174	0.0743	0.2226
Tax revenue	0.4912	0.0651	0.2910	0.4762	0.0699	0.3073
Gov. expenditure	0.5875	0.0684	0.1835	0.5824	0.0761	0.1951
Enrollment rate	1	-0.5234	0.2754	1	-0.5759	0.2880
Life expectancy	0.9940	1.1566	0.7698	0.9941	1.2741	0.8096
Unemployment	0.9996	-0.6319	0.3673	0.9993	-0.6947	0.3818
Union membership	1	-0.9774	0.5062	1	-1.0720	0.5273

Note: A uniform prior has been established for all models.

Table 2.7: Bayesian model averaging: Persistence of the top 10% income share.

	Hyper-g/n prior			Benchmark prior		
	PIP	Mean Coef.	Std. Dev.	PIP	Mean Coef.	Std. Dev.
Foreign inverstment	0.9197	16.0662	23.0919	0.9148	21.6182	27.0119
Trade volume	0.4775	0.0095	0.3223	0.4676	0.0120	0.3784
Foreign patents	0.5352	0.7064	3.5332	0.5164	0.9334	4.1038
Patent stock	0.9770	-10.6351	15.6420	0.9739	-14.2584	18.1841
R&D expenditure	0.5934	2.0500	7.4528	0.5793	2.7433	8.6937
Savings	0.9997	0.8693	1.2000	0.9993	1.1660	1.3985
Credit	0.9867	-0.1554	0.1942	0.9857	-0.2087	0.2262
Interest rate	0.9189	-1.2215	2.0067	0.9078	-1.6354	2.3480
Inflation	0.5202	-0.0389	0.3365	0.5082	-0.0542	0.3896
Tax revenue	0.4919	-0.0764	0.6696	0.4871	-0.1031	0.7879
Gov. expenditure	0.7890	-0.3561	0.7970	0.7709	-0.4761	0.9374
Enrollment rate	0.6463	-0.1307	0.4221	0.6309	-0.1760	0.4971
Life expectancy	0.9995	2.2578	2.9767	0.9994	3.0340	3.4614
Unemployment	1	-1.2278	1.5216	1	-1.6491	1.7703
Union membership	0.5165	-0.0549	0.6771	0.5077	-0.0747	0.7955

Note: A uniform prior has been established for all models.

results. However, data availability has forced us to use this general indicator. Similar results are found for government expenditure, which seems to increase the persistence of overall inequality of income and reduce that of its concentration. Again, it would have been more appropriate to use a covariate reflecting social spending rather than the total amount of government expenditures. As expected, a higher school enrollment rate reduces income inequality, reflecting the favorable effects of education on labor market prospects and wages. Nonetheless, differences across age groups, captured by life expectancy, are associated to more persistent income inequality. Furthermore, union membership reduces the probability of being in a persistent regime of income inequality. This influence is more pronounced in overall inequality than in the share of the top 10%. Finally, we find that the unemployment rate is inversely related to the persistence of income inequality. This striking result may be determined by the fact that unemployment reduces the wages of less skilled workers and, as a consequence, increases the wage gap.

2.4 Discussion

This section tries to make a depiction of long-run inequality in the U.S. according to the results obtained so far. The wealth-to-income ratio has behaved as an I(1) process during the whole sample period analyzed. This implies that the time series of our measure of wealth inequality is a stochastic process whose shocks have permanent effects. Similarly to related studies about wealth inequality, such as Piketty and Zucman (2014), the most prominent shifts of this variable are the sharp drop in the aftermath of WWII, and its subsequent change of tendency. These shocks can be considered to have affected the evolution of the wealth-to-income ratio in a permanent way, suggesting that redistribution policies are expected to have had long lasting effects.

Grounded on the results displayed in Table 2.4, and in contrast to the wealth-to-income ratio, Figures 2.2 and 2.3 show, respectively, that both the Gini coefficient for disposable income and the top 10% income share have experienced persistence changes. Overall income inequality, as measured by the Gini index, behaved as an I(1) process between 1870 and 1907. This is also the case of income concentration, captured by the top 10% share, whose non-stationary regime lasted until 1909. This is in line with BMA results showing that globalization has been found to make income inequality more persistent,

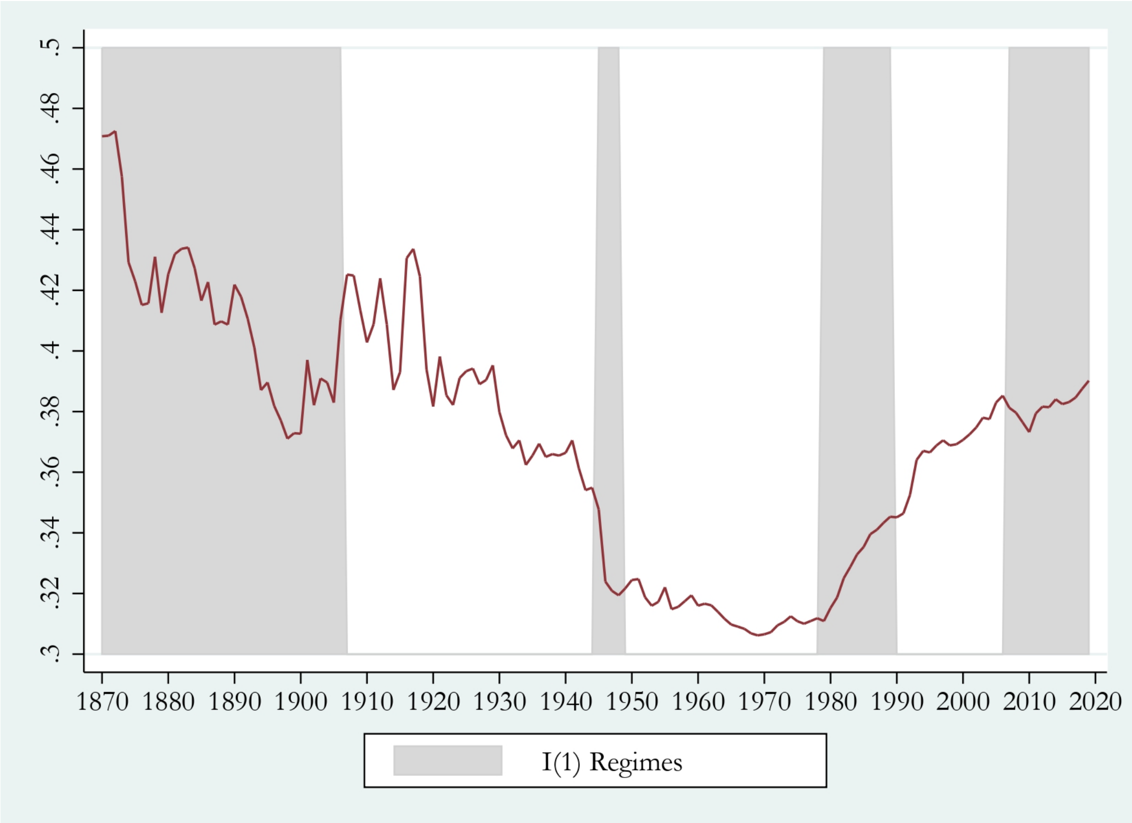


Figure 2.2: U.S. Gini coefficient for disposable income, 1870–2019.

as this non-stationary period matches the so-called 'First Globalization' (Daudin, Morys, and O'Rourke, 2010). Moreover, the following structural breaks take place in a decade when union membership – a factor inversely related to persistence – experienced a rapid growth (Taft, 1976). After that moment, both time series follow deterministic trends; slightly decreasing in the case of the Gini coefficient, and increasing in that of the top 10% share. During this stationary period, policies intended to reduce inequality only had transitory effects. According to this, drops of income inequality due to the WWI or the Great Recession and the 'New Deal' were just temporary changes that did not alter its trend. Nonetheless, we can consider that these shocks could have induced reductions on overall inequality time serie by altering the mean of the time series that have been analyzed.

The Gini coefficient and, especially, the top 10% share exhibit their largest drop during WWII. This evolution is in parallel to that of the wealth-to-income ratio. This is in line with Kopczuk and Saez (2004) who show that, to a great extent, top incomes are derived from capital. Furthermore, this reduction in the top 10% income share takes place during an I(1) regime that lasted until 1997. The second non-stationary period of the Gini coefficient

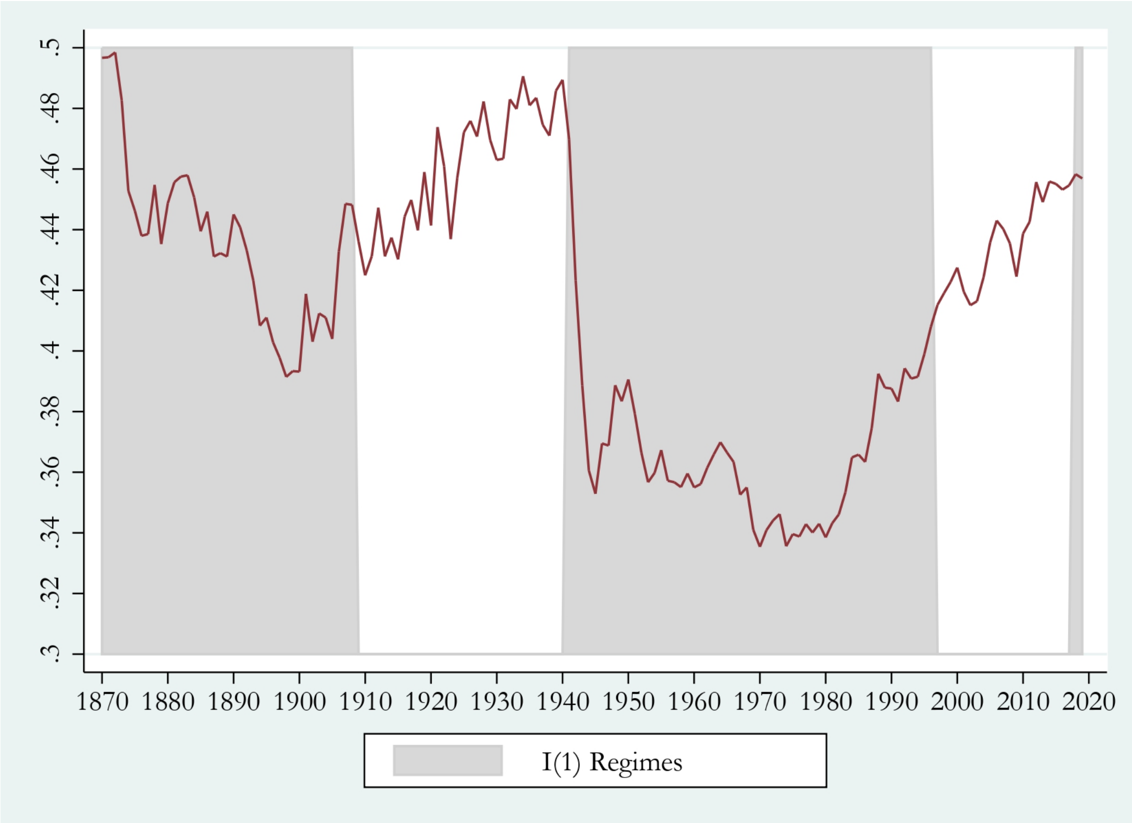


Figure 2.3: U.S. top 10% income share, 1870–2019.

only lasted five years, starting in 1944 and ending in 1949. These I(1) regimes corroborate the results obtained in the BMA exercise because their beginning coincide with the 'Second Globalization' marked by the Bretton Woods Agreements and the increase in variables with a direct relationship with income inequality persistence, such as R&D expenditures or the amount of credit to the private sector as a percentage of GDP. The short duration of the second non-stationary regime of the Gini coefficient may be linked to the endorsement of the 'Fair Deal' in 1949. Among others, this package of structural reforms improved the ways of action of trade unions, and increased the minimun wage. Therefore, it can be claimed that this latter influence compensates that of technological change on the persistence of income inequality.

The decades after WWII were characterized by a stable and low income inequality until the early 1980s. While the top 10% share was in an I(1) regime during this period, the Gini coefficient changed to a persistent regime in 1978. This regime shift may have been driven by a period of globalization in terms of trade, a recovery of R&D expenditures, and a decline in unionization as a consequence of the 1973 energy crisis. In addition, tax cuts during the Reagan mandate (1981-1989) provoked a change in redistribution than induced a permanent shock in income inequality. During the 1990s, the increasing trend of our measures of income inequality became again a deterministic trend. The corresponding stationary period has a shorter duration in the Gini coefficient (until 2006) that in the top 10% income share (until 2018). This result may be related to the different influence of credit on the two measures of income inequality. Although the last change in the top 10% income share may need to be checked in a wider temporal perspective, it is worth noting that all measures of inequality behave as non-stationary time series at the end of our sample period. Therefore, redistributive policies intended to reduce both income and wealth inequality are nowadays expected to exert permanent effects.

2.5 Concluding remarks

The increasing social concern about inequality has created a necessity for a proper knowledge of its behavior and determinants. This study deals with the long-run evolution of income and wealth inequality in the U.S. To do so, we have carried out a time series analysis of the Gini coefficient for disposable income, the top 10% income share, and the wealth-to-income ratio covering the period 1870–2019. The study has been structured in three stages. First, we have assessed the unit root character of the variables under scrutiny allowing for the presence of multiple trend shifts both under the null and the alternative hypotheses. Proceeding this way, we have circumvented the circular problem between these two data features posed by Perron (2006). Second, we have analyzed whether the time series have experienced structural breaks alternating between stationary and non-stationary regimes throughout the sample period. Finally, we have implemented Bayesian model averaging techniques in a logistic regression framework to study those socio-economic variables that display a more robust relationship with the persistence of inequality.

We find that overall income inequality and income accumulation have experienced several shifts between I(0) and I(1) regimes during the sample period covered in our study. Contrarily, our proxy for wealth inequality behaves as a unit root process, even after accounting for shifts in its deterministic component. In any case, the three time series are in a non-stationary regime at the end of the sample period. Therefore, contemporary redistributive efforts are expected to have persistent effects. The great majority of the potential determinants of income inequality persistence affect the two measures analyzed in the same direction. On the one hand, globalization, technological change, and life expectancy are directly related to the probability of being in a persistent regime of income inequality. On the other hand, a higher school enrollment, unemployment and union membership rates display an inverse relationship. The regressors that try to capture the effects of fiscal and monetary policies are those that have a less robust link with inequality persistence.

Appendix B

Table B1: BMA results for the Gini coefficient: PIPs using alternative priors for model-specific parameters.

	Beta prime	ZS adapted	Robust	Intrinsic
Foreign investment	0.8706	0.8691	0.9111	0.9129
Trade volume	0.9243	0.9252	0.9351	0.9307
Foreign patents	0.9998	0.9997	0.9995	0.9996
Patent stock	0.5098	0.4853	0.6649	0.6525
R&D expenditure	0.9975	0.9978	0.9982	0.9978
Savings	0.9786	0.9727	0.9837	0.9821
Credit	0.3053	0.2837	0.3987	0.3988
Interest rate	0.5285	0.5051	0.6679	0.6595
Inflation	0.2473	0.2333	0.3374	0.3279
Tax revenue	0.2450	0.2238	0.3243	0.3207
Gov. expenditure	0.3393	0.3374	0.4319	0.4260
Enrollment rate	1	0.9998	0.9999	1
Life expectancy	0.9500	0.9419	0.9733	0.9743
Unemployment	0.9949	0.9922	0.9961	0.9958
Union membership	1	1	0.9998	1

Note: A uniform prior has been established for all models.

Table B2: BMA results for the top 10% income share: PIPs using alternative priors for model-specific parameters.

	Beta prime	ZS Adapted	Robust	Intrinsic
Foreign inverstment	0.9013	0.8965	0.8926	0.8910
Trade volume	0.2349	0.2342	0.3031	0.3078
Foreign patents	0.2387	0.2398	0.3226	0.3276
Patent stock	0.8960	0.8932	0.9160	0.9113
R&D expenditure	0.3680	0.3672	0.4444	0.4470
Savings	0.9945	0.9931	0.9957	0.9958
Credit	0.9722	0.9703	0.9738	0.9736
Interest rate	0.7610	0.7487	0.7886	0.7849
Inflation	0.4187	0.4190	0.4628	0.4618
Tax revenue	0.2599	0.2590	0.3352	0.3378
Gov. expenditure	0.4296	0.4251	0.5286	0.5234
Enrollment rate	0.4246	0.4285	0.4819	0.4934
Life expectancy	0.9975	0.9965	0.9971	0.9971
Unemployment	0.9999	0.9998	0.9999	0.9999
Union membership	0.3263	0.3263	0.3962	0.4055

Note: A uniform prior has been established for all models.

Chapter 3

Mass shootings, employment, and housing prices: Evidence from different geographic entities

3.1 Introduction

Gun violence is a relentless issue in the United States (U.S.), with a staggering death-toll of 21,009 in 2021 alone[1]. Among the different types of gun violence, mass shootings stand out as one of its most prominent and attention-grabbing forms. Although it is difficult to assert that these incidents are experiencing an increasing trend[2], and even though they account for a relatively small percentage of overall gun-related deaths (Duwe, 2020), mass shootings are receiving a significant media coverage as compared to other kinds of gun violence (Schildkraut, Elsass, and Meredith, 2018). Furthermore, 47.4% of U.S. citizens reported being "afraid or very afraid" of "random/mass shootings" in 2019 (Sheth, 2019). Remarkably, and despite the occurence of the COVID-19 pandemic, this level of dread has persisted at 36.7% in subsequent years (Amirazizi, 2022).

[1] Together with 26,328 firearm-related suicides, and 40,603 injuries (*Gun Violence Archive* 2023).

[2] Smart and Schell (2021) review how the consideration of alternative definitions, data sources, and sample periods leads to different claims about the dynamics of mass shootings.

In parallel to this societal concern regarding mass shootings, it has appeared a growing body of academic literature that explores the impact of these violent incidents beyond the loss of human lives. Lowe and Galea (2017) review the studies about the mental health consequences of mass shootings, concluding that they are related to adverse psychological outcomes in survivors, and to a decline in the perceived safety of indirectly exposed individuals. Rossin–Slater, Schnell, Schwandt, Trejo, and Uniat (2020) find that these attacks increase the use of antidepressants among the youth, especially when they occur in schools. Dursun (2019) show that in-utero exposure to mass shootings is associated with higher rates of premature birth and low birthweight. Luca, Malhotra, and Poliquin (2020) conclude that these events increase firearm bills in a 15%, indicating a disproportionate effect with respect to other forms of gun deaths. At the county level, Yousaf (2021) shows that the attacks influence electoral outcomes.

The literature that provides evidence on the economic impact of mass shootings is rather scarce. Sakariyahu, Lawal, Yusuf, and Olatunji (2023) analyze their influence on investor sentiment in the stock market. These authors show that the attacks adversely affect market indices during the following days, but in a heterogeneous manner across sectors. Using a sample of eleven mass shootings perpetrated at schools, Muñoz–Morales and Singh (2023) find that they have a negative causal relationship with property values and school enrollment rates in neighboring areas. To the best of our knowledge, only Brodeur and Yousaf (2022) conduct a broad study about the impact of mass shootings on local economies (counties). Applying differences-in-differences (DiD) estimation techniques, they show that the attacks lead to lower levels of both earnings and employment, mainly in the goods production, manufacturing, and services sectors. These authors also suggest that these violent events are related to negative mental health outcomes and reductions in the wealth of households, through lower housing prices.

The present research tries to shed further light on the economic effects of mass shootings. With this aim, we have constructed a comprehensive dataset about this type of attack by resorting to information sources that contain details about their location. This endeavor allows us to delve into the geographical extent of the impacts by encompassing the analysis for counties, zip codes, and census tracts. Proceeding this way, we will be able to ascertain whether the effects of these tragic incidents are concentrated primarily within the immediate vicinity of occurrence. Leveraging the latest advancements in DiD estimation techniques – that circumvent some methodological limitations, and consider the presence of heterogeneous treatment effects and variation in treatment dates – we provide evidence of a spatial dimension in the economic impact of mass shootings, being census tracts the administrative division for which the more significant results are obtained.

According to our results, the economic impact of mass shootings is principally reflected in persistent and self-reinforcing employment reductions. These adverse effects are more apparent in those economic activities that entail to work directly with the public. Moreover, we find that the attacks that occur in public spaces – with an inherent heightened level of indiscriminate violence – tend to cause greater impacts. Using information about the compositon of employment by wage and educational attainment, we further investigate if mass shootings lead to the crowding-out of skilled workers. Our results provide little evidence in this respect, mainly restricted to broader geographical areas. As a second economic outcome of interest, we also examine the potential influence of mass shootings on housing prices. After controlling by commuting times in order to capture employment location effects on prices, we find that the attacks contribute to a decline in housing prices within affected census tracts. To sum it all up, the empirical analysis carried out in the present paper suggests that the spatial range of the economic impact of mass shootings is somewhat limited, but that they induce subtantial decline in the vicinity where they take place.

The remainder of the chapter is structured as follows. Section 3.2 contains a review of the literature on the impact of crime and violent shocks on local economies, thereby establishing a foundation for examining the effects of mass shootings at different levels of geographical disaggregation. Section 3.3 explains the construction of our dataset, and details the sources of information from which the data of employment, housing prices, and other control variables have been extracted. Section 3.4 presents the estimation methods that have been implemented. While Section 3.5 delves into the impact of mass shootings in terms of employment, Section 3.6 shows the analysis for housing prices. In Section 3.7, we engage a discussion of the magnitude of the estimated effects, and present the results obtained using an alternative sample at the county level. Finally, Section 3.8 concludes.

3.2 Background

The study of the economic impact of mass shootings can be framed within two strands of literature. Firstly, this topic is related to the analyses of the behavior of economic agents in the face of crime in their areas of influence. In this regard, Greenbaum and Tita (2004) claim that businesses, on the one hand, may choose not to locate in or to leave neighborhoods with high crime rates due to the associated security costs. On the other hand, both customers and employees may fear becoming victims, thus reducing business activity in these areas. Building upon these premises, these authors examine zip codes in five U.S. cities and, after controlling for previous crime trends, find that surges in violent crime, such as homicides, lead to reductions in the growth of the number of both businesses and jobs, especially in those sectors working closely with the public.

The distinct impact of illegal acts across economic sectors is further investigated by Rosenthal and Ross (2010), who develop a theoretical model where the retail and wholesale sectors make their location decisions taking into account the presence of crime. In addition, these authors provide empirical evidence that the share of total activity and employment of the retail sector is lower in those areas that suffer violent crimes. At the census tract level in Southern California, Hipp, Williams, Kim, and Kim (2019) find that criminality increases lead to business closures and/or relocations. They also show that property crimes have a greater impact on the retail sector, whereas violent crimes affect white-collar businesses to a greater extent, hence suggesting a higher sensitivity of employees in these firms to this type of crime. Fe and Sanfelice (2022) explore the influence of crime on local economies from the point of view of consumers. These authors combine mobile device data on customer visits to venues and geolocated crime data from the Chicago Police Department, showing an inverse relationship between these to measures. There are also studies about the influence of crime on the decision of households about their place of residence. In particular, Dugan (1999) reveals that personal crime victimization is directly associated with a higher probability of household relocation. Tita, Petras, and Greenbaum (2006) show that crime has an adverse effect on house values in U.S. census tracts, that varies across income levels, and that the negative effect of homicides is greater but more homogeneous.

It might be useful to draw a parallelism between the mechanisms through which common crime and mass shootings affect local economies and the desirability for living in the areas where they occur. In doing so, the analysis of mass shootings would help to overcome some of the existing challenges such as the fact that economic factors influence criminal activity (Stacy, Ho, and Pendall, 2017; Kim and Hipp, 2022), or that businesses operating in areas with high crime rates are those more resilient to it (Greenbaum and Tita, 2004). The reason is that, according to the definition of mass shootings that will be adopted in the present study, these occasional acts of violence are non-felony related and, therefore, not driven by economic reasons. However, due to the sporadic nature of mass shootings, one might question whether their impact is equivalent to that of common crime or even violent crime, that is much more frequent and concentrated in certain areas. If this is the case, these attacks should be considered as external violent shocks, what can be linked to the second strand of literature.

The analysis of the effects of external violent shocks on urban structures dates back to the seminal work of Davis and Weinstein (2002), who analyzed the impact of Allied bombings on Japanese cities during World War II. The relevance of this branch of the literature lies in its contribution to the debate between alternative theories of urban growth. If the effects from these shocks are of a temporary nature, it is considered as evidence supporting the theory of locational fundamentals, in contrast to the theories of random growth. Related studies not only deal with the consequences of wars, but also that of other exogenous shocks such as pandemics or natural disasters; see Glaeser (2022) for a review. While it could be claimed that these shocks are of a larger magnitude than mass shootings, this line of research also considers the analysis of other events that occur more frequently but have a lower intensity: terrorist attacks. In contrast to mass shootings, terrorism generally pursues political, social, or religious aims. Therefore, the occurence of terrorist attacks is not entirely random[3]. Moreover, terrorism often targets critical infrastructures, public facilities, or symbolic landmarks, resulting in significant physical damage which should be leading to differences in the scale of the attacks as compared

[3] This is taken into account by Brodeur (2018), who proposes a theoretical framework that distinguish between failed and successful attacks.

with mass shootings. Nonetheless, the mechanisms through which terrorims affects local economies could be similar to those of mass shootings[4].

Hazam and Felsenstein (2007) show that terrorims exerts a negative effect on housing prices, mainly when the attacks are sporadic and notably violent. These results agree with the 'fear hypothesis' (Becker and Rubinstein, 2011) which states that there are two main forces affecting the (heterogeneous) behavior of individuals in the face of terror: the objective risk of being a victim, and the related subjective fear. Abadie and Dermisi (2008) find that the 9/11 attacks resulted in higher vacancy rates in landmark buildings and nearby areas in Chicago due to an increased perceived risk. Sanso-Navarro, Sanz-Gracia, and Vera-Cabello (2019) analyze the demographic impact of terrorist attacks in the municipalities of the Basque Country and Navarre (Spain), concluding that their associated shocks had a transient nature. Brodeur (2018) investigated the influence of terror in U.S. counties, considering that related incidents lead to higher consumer uncertainty and business security costs in affected areas (Joint Economic Committee, 2002). This author finds that the counties experiencing successful terrorist attacks display subsequent lower levels of employment and earnings. Fich, Nguyen, and Petmezas (2023) show that terror reduces the productivity of inventors residing near the attacks what, besides their mobility, is attributed to the financial conditions of firms after the attacks. It is worth noting that the study of the economic impact of violence is not limited to terrorism. For instance, Collins and Margo (2007) find that violent race-related riots during the 1960s in the U.S. depressed median values of black-owned properties, with long-lasting effects extending into the 1970s. Rozo (2018) develops a theoretical framework linking violence with the costs faced and prices set by firms. Moreover, this author empirically tests the predictions of the model by examining abrupt security improvements in Colombia, concluding that firms located in more violent municipalities experience larger reductions in output prices compared to input costs, leading to market exits.

Taken together, the two strands of literature described above provide conceptual frameworks and empirical evidence to link the occurrence of mass shootings with the desirability

[4] While focused on aggregated impacts instead of local, it worth citing here the work of Abadie and Gardeazabal (2003) where they examine the impact of terrorism on per capita GDP in the Basque Country. Additionally, Abadie and Gardeazabal (2008) develop a theoretical model that illustrates how terrorism can affect the allocation of capital between countries.

of the places where they occur for both living and establishing businesses. Consequently, several questions arise. First, while the effects of common crime have been studied in small areas, mainly census tracts or zip codes, the impact of terrorism has been analyzed at broader geographical levels, such as municipalities or counties. Although mass shootings are also expected to affect economic activity and housing prices, it is not clear the spatial extent of these effects. Second, it would be interesting to know whether mass shootings have a differential effect on those economic sectors with a higher contact with the public, as it is the case of crime and terrorism. Third, and according to the 'fear hypothesis', the more sporadic is an attack the greater its influence on the behavior of individuals. Extending this argument to mass shootings, their impact should be higher when perpetrated in public spaces. Fourth, given that both crime (Hipp, Williams, Kim, and Kim, 2019) and terrorism (Fich, Nguyen, and Petmezas, 2023) are known to have a more important impact on workers with higher skills, and as suggested by Yousaf (2022), it is also worth investigating how mass shootings affect the composition of employment in the affected areas. Lastly, the analysis of the persistence of the effects induced by these events on local economies would contribute to the understanding of their resilience to adverse shocks.

3.3 Data

3.3.1 Mass shootings

There is no standard definition of what constitutes a mass shooting, to some degree because it has never been enacted legislation considering this type of attack as a separate crime in the U.S. Consequently, there exist various definitions of mass shootings that, in practical terms, differ on the criteria established such as the threshold for the number of victims, the motivation behind the attack, or the type of place where it is perpetrated. As a result, there are different figures regarding the number of mass shootings and their related victims. Smart and Schell (2021) provide a review of several databases that track mass shootings, and show that the differences can be very significant, ranging from 6 to 502 mass shootings, and from 60 to 628 victims, in the year 2019. In the present paper, we are adopting the definition of mass shootings established by the Federal Bureau of Investigation (FBI), which sets the casualty threshold at four victims, apart from the perpetrator(s) (Krouse and Richardson, 2015). In addition, we have excluded felony-related mass shootings, such as armed robberies or those associated with gangs and organized crime.

There are two main sources of information that can be exploited to analyze issues related to mass shootings. One alternative is to filter the Supplementary Homicide Report (SHR), elaborated by the FBI, to identify those cases that match the above-mentioned criteria. Although this report is a voluntary program for law enforcement agencies that suffers some coverage limitations (Duwe, 2020), it is an official source and one of the most comprehensive databases for homicides in the U.S. Nevertheless, the SHR lacks information regarding the particulars of the incidents, especially those concerning their location. For this reason, we have relied on the second alternative, which involves the use of databases from media and academic institutions containing more detailed information. It is important to acknowledge that media-based data sets may also have restrictions, missing less notorious incidents or those occurring at the same time that other prominent events, particularly when accounting for older attacks only reported in print media or on television. To minimize this potential missing information, we have exploited four data sets.

The first of them is the Violence Project Mass Shooter Database (Peterson and Densley, 2022), which focuses on mass public shootings – defined as indiscriminate attacks taking place at public spaces – and establishes a threshold of four victims. Given that both criteria match our adopted definition, all incidents included in this database have been taken into account. The Mother Jones Database (Follman, Aronsen, and Pan, 2020) also focuses on mass public shootings, but it changed it criterion in 2013, establishing a threshold of three victims. Therefore, these cases have been excluded from our sample. Besides, the Associated Press and USA Today Mass Killing Database (Fox, 2022) establishes a threshold of four victims, but focuses on mass killings. Thus, those events not involving a firearm or felony-related have been ruled out. Finally, the Stanford Mass Shootings in America Database (Peterson and Densley, 2022), that ends in 2016, leaves incidents related with gangs or organized crime out[5], but the threshold of victims is set to three

[5] Although the criterion regarding the motivation of the assailant is similar to ours, there were three cases associated with robberies that have not been included in our sample.

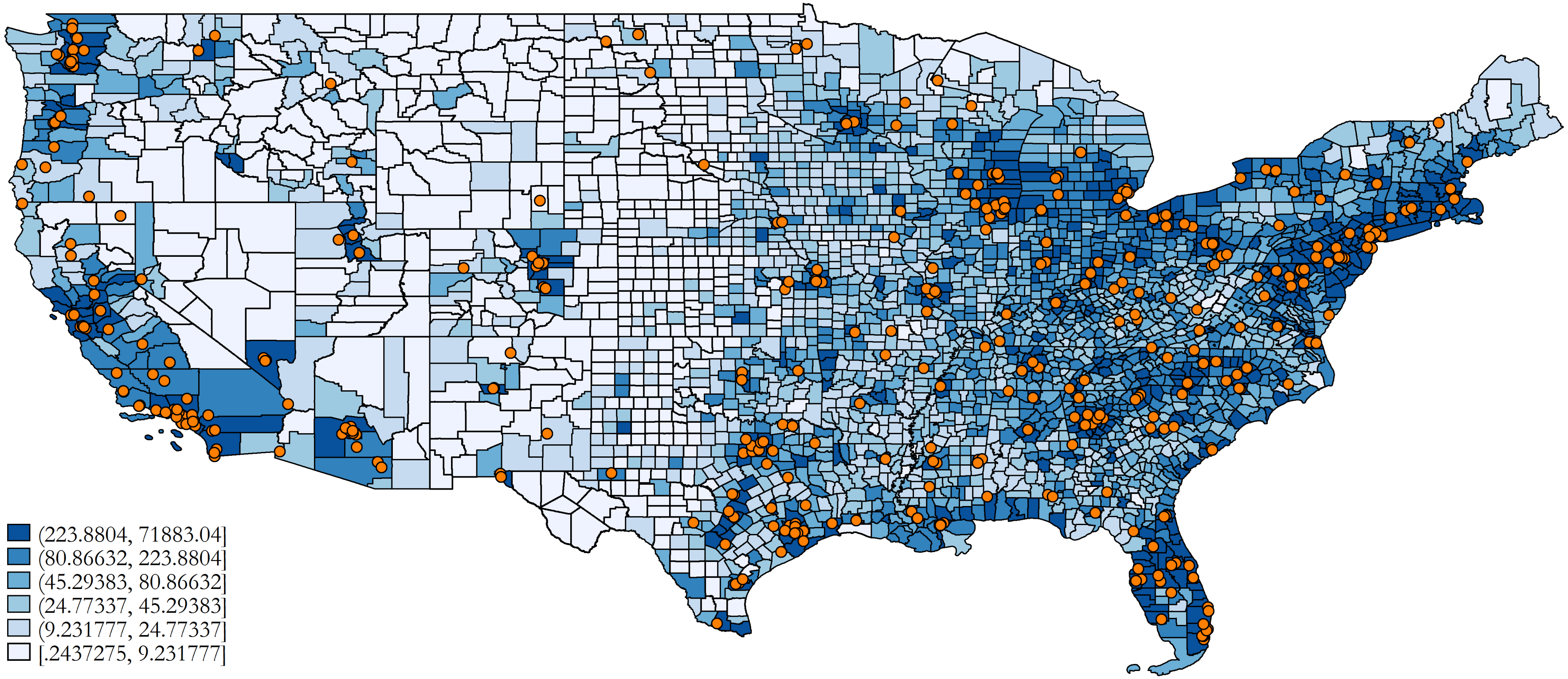


Figure 3.1: Mass shootings location (dots) and population density. U.S. counties, 1966–2021.

people injured, including the attacker. Hence, we have disregarded those attacks with less than four victims fatally injured.

It should be pointed out that the four databases cover events considered as ‘spree’ – i.e., committed in various locations but within a short period of time – that have been included in our sample. After merging the information from these data sets that fulfill our criteria, it results a sample of 399 mass shootings from 1966 to 2021, that entailed 2,277 fatalities and 2,113 persons injured. Figure 3.1 represents a chloropleth map with the geographical distribution of these incidents and population density at the county level. It can be observed that the spatial distribution of mass shootings aligns with that of population, with denser areas experiencing a higher number of attacks. The data on employment, one of our indicators of economic conditions as described in the next subsection, constrains our analysis to the period 2003–2019. This time span includes 274 mass shootings, that resulted in 1,567 fatalities and 1,610 persons injured.

3.3.2 Employment and housing prices

As pointed out in Section 3.1, beyond counties, we are interested in analyzing more granular data at the zip code[6] and census tract levels. To do so, we have exploited data from the Longitudinal Employer-Household Dynamics (LEHD) program of the U.S. Census Bureau. In particular, we have drawn upon the Origin-Destination Employment Statistics (LODES) dataset (U.S. Census Bureau, 2022), that provides information on both residence (RAC) and workplace (WAC) area characteristics. Our focus is on the WAC data, which includes the number of jobs – excluding federal employment – by blocks. WAC files have been extracted from the Urban Institute, that aggregates the information at both the ZCTA (Urban Institute, 2022a) and census tract (Urban Institute, 2022b) levels. Given that census tracts have been designed to align within county boundaries, we are able to further aggregate the data of census tracts to obtain that for counties. These data cover the period from 2002 to 2019, and provide comprehensive information including 2-digit

[6] Zip codes are primarily designed as routing tools for the U.S. Postal Service, hence not being considered as proper spatial units. In order to facilitate the analysis at this geographic level, the U.S. Census Bureau created ZIP Code Tabulation Areas (ZCTAs) in the year 2000, which are areal representations of zip codes and serve as a practical way to examine data. Nevertheless, it is worth acknowledging that the use of ZCTAs as the unit of analysis entails some limitations. On the one hand, ZCTAs may span across multiple county and, in some cases, state borders. On the other, ZCTAs are not designed to be homogeneous in terms of demographic or socio-economic characteristics.

Table 3.1: Descriptive statistics for employment and housing prices, 2003–2019.

	Counties		ZCTAs		Census tracts	
	All	Affected	All	Affected	All	Affected
Total employment	41,471.86	161,434.70	4,133.61	15,450.15	1,805.17	6,486.34
	(149,565.80)	(195,857.40)	(8,587.62)	(19,989.05)	(3,718.51)	(15,138.97)
NAICS:						
44-45: Retail trade	4,733.03	18,302.56	471.75	1,442.55	206.02	366.7
	(15,406.89)	(21,075.49)	(979.10)	(1,755.01)	(403.10)	(626.82)
71: Arts, entertainment, and recreation	717.11	3,032.79	71.48	338.12	31.21	215.26
	(3,281.71)	(6,229.46)	(370.01)	(1,342.66)	(224.42)	(1,293.35)
72: Accomodation and food services	3,699.26	14,116.56	368.71	1,716.58	161.02	547.84
	(13,706.53)	(17,794.33)	(1,048.85)	(6,479.38)	(489.64)	(1,699.83)
Wage level (%):						
Low (<1250$/month)	30.64	28.34	32.5	27.91	31.66	29.14
	(6.92)	(5.55)	(15.64)	(9.51)	(12.32)	(12.10)
Medium (1250–3333$/month)	41.12	39.08	39.17	38.87	38.79	39.07
	(6.65)	(5.81)	(13.15)	(7.90)	(9.40)	(9.62)
High (>3333$/month)	28.24	32.59	28.33	33.22	29.55	31.8
	(10.28)	(9.71)	(16.47)	(13.74)	(14.57)	(16.05)
Educational attainment[1] (%):						
Less than high school	12.26	12.83	12.83	14.05	14.27	14.38
	(4.20)	(4.52)	(7.93)	(5.82)	(6.62)	(6.80)
High school or associate's degree	66.02	62.28	64.76	60.61	60.52	60.9
	(4.97)	(5.24)	(10.93)	(6.59)	(8.12)	(7.63)
Bachelor degree or higher	21.73	24.88	22.41	25.34	25.21	24.72
	(4.92)	-5.55	(10.21)	(7.63)	(8.55)	(8.49)
House price index	261.72	375.08	274.16	347.71	224.24	211.88
	(169.44)	(209.36)	(221.90)	(262.21)	(133.08)	(122.66)

Notes: This table reports average values and their corresponding standard deviations in parentheses. [1]This data is only available for the period 2009–2019.

NAICS codes, and the educational attainment as well as earnings of workers in each job. The upper panel of Table 3.1 reports descriptive statistics for the level of employment in counties, ZCTAs, and census tracts, distinguishing the data for those units that have experienced a mass shooting. It can be observed that, on average, total employment in the affected areas is higher at all geographical levels of disaggregation. As reflected by the standard deviations, this may be related to the pronounced levels in some of the units that suffered this type of incidents. Something similar happens when we focus on the employment levels of those economic sectors that work closely with the public; see Subsection 3.5.2. However, the spatial units where mass shootings have occured do not display relevant differences in terms of educational attainment and wage composition.

The information about housing prices has been extracted from the Federal Housing Finance Agency (FHFA), that elaborates an index (HPI) using a weighted, repeated-sales methodology from mortgage data about transactions all over the U.S. (Bogin, Doerner, and Larson, 2019). Among other geographical levels, the HPI is calculated for counties, 5-digit zip codes[7], and census tracts. Descriptive statistics for the HPI are displayed in the lower panel of Table 3.1. These figures show that counties and ZCTAs that suffered a mass shooting during the sample period analyzed display higher average values of the HPI. On the contrary, affected census tracts tend to have lower housing prices.

3.3.3 Control variables

We have used the National Historical Geographic Information System (NHGIS, Manson, Schroeder, Van Riper, Kugler, and Ruggles, 2022) as the source of information for control variables. For each unit of analysis and regressor, we have extracted the latest available data prior to a mass shooting. Given that the census is elaborated on a decennial basis, this implies that for those attacks between 2003 and 2010 we have used information referred to the year 2000, and data for the year 2010 for those incidents in the 2010s have been considered. The control variables used depend on the economic outcome that is being analyzed.

In the case of employment, we are controlling for factors related to population, the urban/rural status, and other socio-economic characteristics shown in Table 3.2. These variables reflect the size – measured as the number of residents – and density of each geographical unit, an indicator variable reflecting if the majority of the population lives in urban areas, its ethnographic, age and educational attainment composition, per capita income, and the poverty rate. To deal with the influence of mass shootings on the HPI, we are considering variables that try to capture the urban/rural status, the housing stock, and commuting times; see also Table 3.2. These variables reflect the size – using the total housing stock – and density of the unit, as well as the share of vacant housing. We also include the indicator variable capturing the urban character of the area, and the share of people divided by commuting times. At this point, it is important to note that census tracts are defined using 2010 boundaries when employment is the outcome variable under scrutiny, while the data for the HPI is based on 2020 limits. Therefore, to ensure compatibility, the data for the control variables in each analysis have been standardized to the correct boundaries using the crosswalk files provided by the NHGIS.

[7] These data have been aggregated to ZCTAs by using the crosswalk file provided by the Uniform Data System Mapper site, see https://udsmapper.org/zip-code-to-zcta-crosswalk/.

Table 3.2: Descriptive statistics for control variables, 2003–2019.

	Counties		ZCTAs		Census tracts	
	All	Affected	All	Affected	All	Affected
Population:						
Total population	94,439.06 (304,949.80)	345,604.90 (398,692.30)	9,350.10 (13354.65)	24,395.19 (17476.76)	4,085.61 (1819.41)	4,442.25 (2,257.84)
Population density[1]	248.61 (1714.38)	703.50 (1,599.10)	1,231.72 (4,829.31)	2,425.64 (3,723.31)	5,181.56 (11,657.09)	3,295.83 (5,178.85)
Urban/rural status:						
Urbanized area[2] (%)	21.75 (41.26)	64.16 (47.96)	30.56 (46.06)	69.89 (45.88)	69.67 (45.97)	67.62 (46.80)
Urban cluster[3] (%)	17.69 (38.16)	12.02 (32.53)	10.11 (30.14)	11.38 (31.76)	10.06 (30.08)	9.49 (29.31)
Rural area (%)	60.56 (48.87)	23.82 (42.60)	59.06 (49.17)	18.74 (39.02)	20.12 (40.09)	22.89 (42.01)
Socio-economic characteristics:						
Whites (%)	83.93 (16.29)	77.79 (13.80)	84.09 (20.24)	70.95 (23.98)	66.27 (30.03)	62.65 (29.53)
Blacks (%)	8.73 (14.35)	11.53 (12.12)	7.58 (15.77)	15.50 (21.83)	13.77 (22.37)	15.36 (23.35)
Hispanics (%)	7.38 (12.77)	11.44 (14.82)	7.68 (14.54)	15.48 (20.79)	13.81 (20.18)	16.23 (23.04)
<21 years old (%)	29.70 (4.02)	30.71 (3.67)	27.28 (6.80)	28.77 (7.65)	29.99 (7.93)	29.81 (9.32)
22-64 years old (%)	51.70 (3.39)	52.87 (3.20)	57.47 (5.88)	58.52 (7.21)	56.76 (6.89)	57.68 (8.81)
>65 years old (%)	18.61 (4.78)	16.42 (4.68)	15.25 (6.46)	12.71 (5.48)	13.25 (7.36)	12.51 (6.21)
Less than high school (%)	19.31 (8.46)	17.39 (7.40)	17.16 (11.30)	18.81 (11.58)	17.31 (12.87)	20.20 (13.27)
High scool or associate degree (%)	62.79 (7.20)	59.37 (6.71)	62.33 (12.46)	57.21 (11.18)	57.08 (13.08)	57.25 (12.35)
Bachelor degree or higher (%)	17.90 (8.37)	23.24 (9.61)	20.51 (14.84)	23.98 (15.61)	25.61 (17.82)	22.56 (16.38)
Per capita income	20,762.14 (5,635.86)	23,148.82 (6,104.04)	23,123.63 (11,337.50)	23,162.71 (9,820.92)	24,738.56 (13,083.82)	22,498.96 (11,181.62)
Poverty rate (%)	15.32 (6.50)	14.50 (5.76)	13.50 (9.55)	16.91 (11.26)	14.59 (12.07)	19.07 (14.13)
Housing stock:						
Total housing units	45,003.69 (124,847.40)	145,566.10 (164,225.30)	6,176.74 (5,839.43)	11,119.18 (6,411.21)	1,571.99 (583.39)	1,658.09 (592.97)
Housing density[4]	123.60 (862.20)	316.29 (738.37)	659.17 (1612.40)	1,065.11 (1,539.14)	1,363.03 (1963.22)	1,147.95 (1,760.82)
Vacant housing units (%)	14.33 (9.45)	11.50 (7.75)	11.26 (11.12)	9.88 (6.54)	8.65 (8.88)	8.91 (6.20)
Commuting times:						
Less than 30 min. to work (%)	69.66 (11.76)	68.80 (11.09)	64.56 (14.83)	67.40 (13.68)	65.72 (15.56)	66.79 (14.65)
30 - 60 min. to work (%)	22.91 (9.10)	23.99 (8.47)	27.29 (11.78)	25.00 (10.72)	26.51 (12.22)	25.30 (11.81)
More than 60 min. (%)	7.43 (4.46)	7.20 (4.42)	8.15 (6.03)	7.60 (5.09)	7.77 (6.55)	7.91 (6.04)

Notes: This table reports average values and their corresponding standard deviations in parentheses. [1]Population per square mile. [2]Most people living in an area with a population greater than 50,000. [3]Most people living in an area with a population between 2,500 and 50,000. [4]Housing units per square mile.

Table 3.2 also provides descriptive statistics for the control variables, showing that those counties and ZCTAs that suffered mass shootings tend to display larger populations and higher densities, as compared to the whole country. Regarding census tracts, while the total population remains higher in the affected units, population density is lower than the U.S. average. A similar pattern is observed for the variables reflecting the urban/rural status, with counties and ZCTAs suffering the attacks presenting a higher degree of urbanization, while affected census tracts exhibit similar mean rates to those of the total sample. Regarding ethnic composition, the three spatial units with mass shootings show a slightly lower (higher) share of white (Hispanic and black) population. At all geographical levels of disaggregation, the differences between affected and non-affected areas in terms of wage composition and educational attainment are subtle. Income per capita tends to be higher in those counties experiencing mass shootings, remains similar in all ZCTAs, and is lower in affected census tracts. Poverty rates are generally higher in those areas where mass shootings occur, with more pronounced differences at the census tract level. The housing stock, both in absolute and relative terms, shows a pattern similar to that of demographic variables. Finally, the values displayed by commuting times in attacked and non-attacked areas appear to be relatively similar across all units.

3.4 Methodology

The geographic entities affected by a mass shooting can be considered as having received and adverse binary 'treatment'; i.e., being attacked vs. non-attacked. Therefore, and given the potential randomness and exogenous character of these events, a DiD estimation setup can be adopted to conduct an empirical analysis of their economic effects. A standard approach would consist of using a staggered treatment framework in the context of both static and dynamic two-way fixed effects (TWFE) regressions. Under the assumptions of no anticipation and parallel trends, these estimations were supposed to result in parameters with a causal interpretation. Nonetheless, recent studies show that the static TWFE parameters are convex weighted averages of DiD comparisons between different units and time periods, including those between treated units in different periods, which are referred to as 'forbidden comparisons'; see Chaisemartin and D'Haultfœuille (2020), Goodman–Bacon (2021), and Borusyak, Jaravel, and Spiess (2023). For this reason, resulting coefficients

coefficients are not suitable estimates of causal treatment effects. Additionally, Sun and Abraham (2021) demostrate that this problem also arises in dynamic TWFE specifications.

To circumvent this issue, we rely on Callaway and Sant'Anna (2021a) who develop a DiD estimator with a conditional parallel trends assumption are based on never-treated and not-yet-treated 'control' groups. Under a staggered treatment framework, and in a panel data context, let us consider: $\{Y_{i,1}, Y_{i,2}, ..., Y_{i,\tau}, X_i, D_{i,1}, D_{i,2}, ..., D_{i,\tau}\}_{i=1,...,n}$; where $Y_{i,t}$ is the outcome of interest, X_i is a vector of pre-treatment covariates associated with the outcome. $D_{i,t} = 1$ implies that $D_{i,t+1} = 1$ for $t = 1, 2, ..., \tau$. The starting time of the treatment is modelled using dummies, G_{ig}, which are equal to one if the unit i experienced the treatment (shock, in our context) at period g, zero otherwise. In the case where the never-treated units, $C = 1$, are used as the comparison group, the conditional parallel trends assumption, in a simplified way, takes the form:

$$E\left[Y_t(0) - Y_{t-1}(0)|X, G_g = 1\right] = E\left[Y_t(0) - Y_{t-1}(0)|X, C = 1\right] \tag{3.1}$$

for each $g \in G$ and $t \in \{2, ..., \tau\}$, such that $t \geq g$.

If the control group is made up by the not-yet-treated units, the assumption can be specified as:

$$E\left[Y_t(0) - Y_{t-1}(0)|X, G_g = 1\right] = E\left[Y_t(0) - Y_{t-1}(0)|X, D_s = 0, G_g = 0\right] \tag{3.2}$$

for each $g \in G$ and $(s, t) \in \{2, ..., \tau\}\text{x}\{2, ..., \tau\}$, such that $g \leq t \leq s$.

Callaway and Sant'Anna (2021a) set a further overlap assumption stating that, for each $t \in \{2, ..., \tau\}$, there exist some $\varepsilon > 0$ such that $P(G_g = 1) > \varepsilon$, and that $p_{g,t}(X) < 1 - \varepsilon$. This means that, at least, a positive fraction of the units starts treatment at period g. Moreover, for all g and t, the propensity score is uniformly bounded away from one, thus ruling out 'irregular indentification' (Khan and Tamer, 2010). The authors propose three alternative methods to recover the average treatment effect on the treated (ATT), our main parameter of interest: outcome regression (OR), inverse probability weighting (IPW), and doubly robust (DR) estimates. Among them, we have opted for the DR estimation developed by Sant'Anna and Zhao (2020) because it is consistent if either the OR or the IPW are correctly specified, but not necessarily both.

When the control group includes the units that have never been treated, the DR estimator is:

$$ATT(g,t) = E\left[\left(\frac{G_g}{E\left[G_g\right]} - \frac{\dfrac{p_g(X)C}{1-p_g(X)}}{E\left[\dfrac{p_g(X)C}{1-p_g(X)}\right]}\right)\left(Y_t - Y_{t-1} - m^{nev}_{g,t}(X)\right)\right] \tag{3.3}$$

with $m^{nev}_{g,t}(X) = E\left[Y_t - Y_{g-1}|X, C = 1\right]$ being the outcome of a regression for the never-treated group.

Analagously, when the comparison group is made up by those units that have not been treated yet, the DR estimator takes the form:

$$ATT(g,t) = E\left[\left(\frac{G_g}{E\left[G_g\right]} - \frac{\dfrac{p_{g,t}(X)(1-D_t)(1-G_g)}{1-p_{g,t}(X)}}{E\left[\dfrac{p_{g,t}(X)(1-D_t)(1-G_g)}{1-p_{g,t}(X)}\right]}\right)\left(Y_t - Y_{t-1} - m^{ny}_{g,t}(X)\right)\right] \tag{3.4}$$

where $m^{ny}_{g,t}(X) = E\left[Y_t - Y_{g-1}|X, D_T = 0, G_g = 0\right]$ is obtained from a regression for the not-yet-treated group.

Our sample includes 274 mass shootings that were perpetrated in a time span of 17 years. Although this might result in difficult to interpret ATTs, Callaway and Sant'Anna (2021a) have foreseen this type of situations, providing the researchers different grouping schemes:

$$\theta = \sum_{g \in G} \sum_{\tau}^{t=2} \omega(g,t) ATT(g,t) \tag{3.5}$$

with $\omega(g,t)$ denoting a weighting function set by the researcher, that can belong to four alternatives.

The first grouping scheme corresponds to a simple average, that calculates the mean effect of all events across all periods. This provides an overall estimate of the ATT. Second, the group average effect is obtained as the average effect of each group of events occuring in a given period. This allows us to examine the mean effects of the events as if there were different 'cohorts' each year. Third, the calendar average effect, that can be considered as the reciprocal of the group average effect. This scheme calculates the mean effect in each period based on all previous events. Fourth, the dynamic scheme estimates the effects for each period relative to that when the treatment took place. This allows researchers to define a time window and calculate pre- and post-treatment effects during the corresponding interval. Consequently, dynamic average effects can provide insights of long-run impacts, as well as pre-treatment mean effects, which may serve as a test for the presence of pre-existing trends. In the present research, we are setting the time window to span 10 years before and after a mass shooting, and calculating pre-treatment effects by using the preceding period to the mass shooting, $g-1$, as the reference point. This approach aligns with the calculation method in the dynamic TWFE specification, where the omitted dummy precisely corresponds to $g-1$.

Lastly, in order to maintain consistency with the staggered treatment approach, we find it more rigorous from a methodological point of view to exclude those units that have been affected a mass shootings before the start of our sample period. Although the number of these units is relatively small, their inclusion could potentially distort the analysis by treating repeatedly affected units as if they were treated for the first time. As mentioned in Section 3.2, our sample period covers the years 2003 to 2019, comprising 274 incidents. Therefore, we are excluding those units that suffered an attack between 1966 and 2003, resulting in 171 counties, 265 ZCTAs, and 271 census tracts suffering their first mass shooting during our sample period[8].

3.5 The impact of mass shootings on employment

Our primary objective is to analyze how mass shootings affect employment at different levels of geographical disaggregation. With this aim, we employ the natural logarithm of total employment as the dependent variable. In what follows, we present two specifications for the estimation of the effects: (i) an unconditional approach, that involves conducting raw comparisons between affected and non-affected areas; and (ii) a conditional specification, grounded on the comprehensive set of variables detailed in Section 3.3.3. By

[8]The estimation has been carried out using the 'csdid' Stata package developed by Rios–Avila, Sant'Anna, and Callaway (2021) that, compared to the 'did' R package (Callaway and Sant'Anna, 2021b), has the advantage of not requiring a balanced sample. To do so, 'csdid' considers all possible 2x2 specific combinations for each estimation procedure, thereby minimizing the loss of information when panels are not strongly balanced.

Table 3.3: Mass shootings average effects on employment.

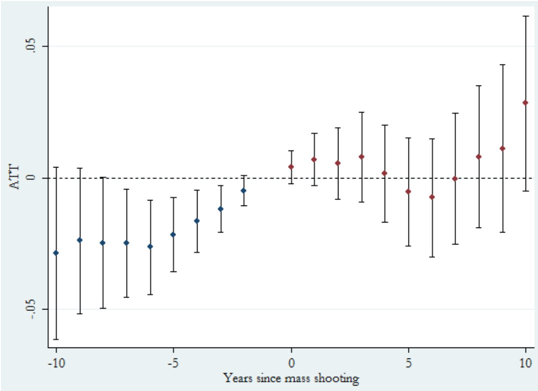
	Counties		ZCTAs		Census tracts	
	(1)	(2)	(1)	(2)	(1)	(2)
Group	0.0133 **	0.0016	-0.0050	-0.0104	-0.0968 ***	-0.0993 ***
	(0.0057)	(0.0055)	(0.0131)	(0.0125)	(0.0254)	(0.0262)
Calendar	0.0052	-0.0009	-0.0184	-0.0170	-0.1153 ***	-0.1114 ***
	(0.0066)	(0.0064)	(0.0168)	(0.0158)	(0.0300)	(0.0319)
Simple	0.0080	-0.0024	-0.0178	-0.0224	-0.1404 ***	-0.1434 ***
	(0.0077)	(0.0072)	(0.0190)	(0.0183)	(0.0348)	(0.0364)
Dynamic:						
Pre-treatment	-0.0204 **	-0.0074	0.0164	0.0125	0.0050	0.0115
	(0.0082)	(0.0076)	(0.0160)	(0.0156)	(0.0260)	(0.0257)
Post-treatment	0.0055	-0.0050	-0.0188	-0.0247	-0.1555 ***	-0.1601 ***
	(0.0088)	(0.0082)	(0.0216)	(0.0215)	(0.0397)	(0.0417)

Notes: (1) Unconditonal especification; (2) Conditional especification. The sample covers 3,145 counties, 32,817 ZCTAs, and 72,698 census tracts during the period 2002–2019. *p<0.1, **p<0.05, ***p<0.01.

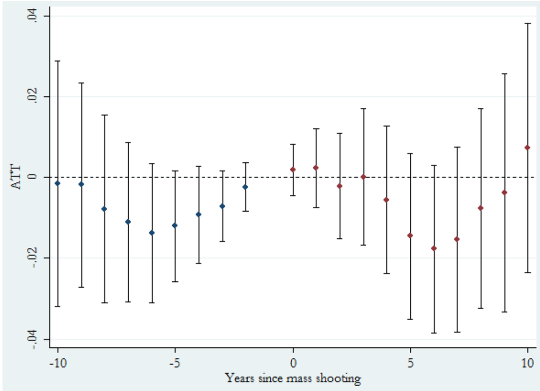
incorporating these regressors the comparisons are established between more similar units, hence ensuring a more restricted and targeted assessment.

Table 3.3 presents the average estimation results from each grouping scheme outlined in the previous section, for the three spatial units analyzed, and considering both an unconditional and a conditional specification. One notable finding is that, in the case of counties, the use of the unconditional specification appears to be inappropriate due to the presence of pre-existing trends, as reflected by the significant value of the pre-treatment average. Moreover, results for ZCTAs and census tracts show a more pronounced effect in the context of the conditional specification as compared to the unconditional one. This implies that the impact of mass shootings becomes more evident when areas with similar characteristics are compared. However, despite the influence of mass shootings on employment is negative in all geographic entities, estimated ATTs are only statistically significant in census tracts. This finding suggests that the economic effects of mass shootings have limited spatial reach, much like those of violent common crime.

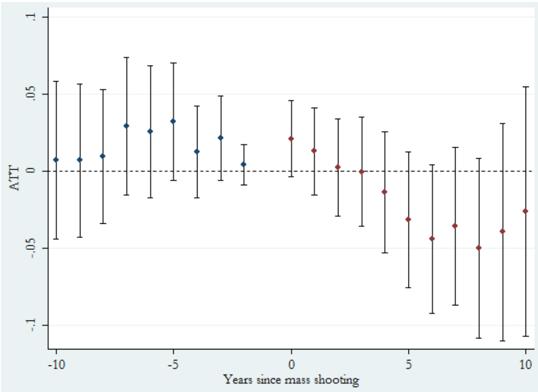
The group average effect – which represents the mean impact obtained by grouping the attacks according to the year when they occur – indicates that mass shootings resulted in, approximately, a mean employment reduction of 9.5% at the census tract level. Similarly, calendar effects show that, in each year of the sample, the effect of previous mass shootings



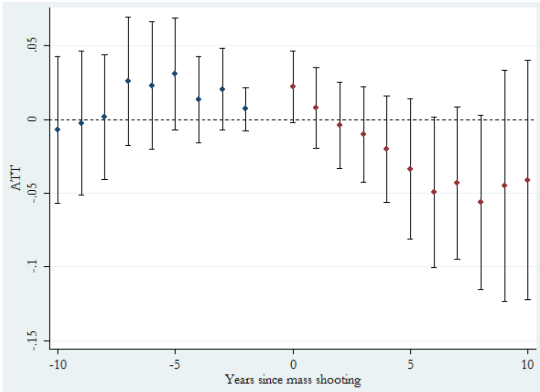
(a) Counties - Unconditional



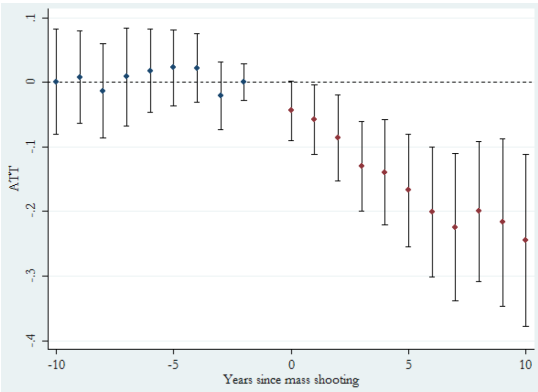
(b) Counties - Conditional



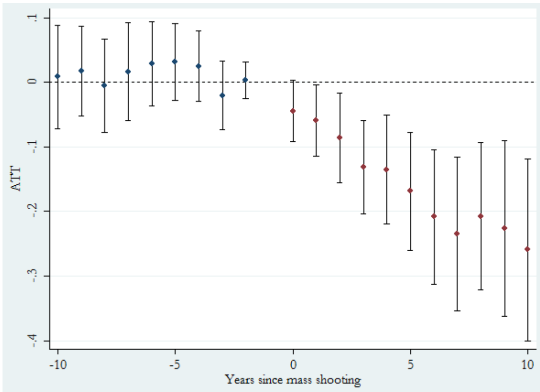
(c) ZCTAs - Unconditional



(d) ZCTAs - Conditional



(e) Census tracts - Unconditional



(f) Census tracts - Conditional

Figure 3.2: Dynamic average effects of mass shootings on employment.

entailed a mean employment reduction of 10.6%. The simple average effect, that can be interpreted as a gross mean impact of all attacks across all years, estimates an employment reduction of 13.4% in affected census tracts. The dynamic effects depict the evolution of the impact, setting a threshold of ten years before and after a mass shooting. In this case, there is an average yearly reduction in employment of 14.8%. These results are portrayed in

Figure 3.2. At the county level, the large difference in the evolution of employment before the attacks is evident when comparing the unconditional and conditional specifications. Furthermore, the dynamic effects for census tracts show that employment reductions are somewhat persistent and cumulative, suggesting that mass shootings cause substantial employment declines in the areas where they are perpetrated.

3.5.1 Mass public shootings

The 'fear hypothesis' (Becker and Rubinstein, 2011) establishes that the more occasional and violent is an attack, the greater should be its influence on the behavior of individuals. In order to test this prediction in the present context, we have focused on a subsample of 118 mass shootings[9] that occurred in public spaces; i.e., 'mass public shootings' as defined by Duwe (2020). While our definition encompasses a range of incidents, including 'familicides', mass public shootings are characterized by their indiscriminate nature, that typically results in a higher number of fatalities. On average, the mass public shootings included in our sample involve more than seven victims, compared to an overall mean of less than five. Therefore, if the 'fear hypothesis' applies in this type of attacks, we should find greater effects than those estimated using the full sample.

Table 3.4: Mass public shootings average effects on employment.

	Counties		ZCTAs		Census tracts	
	(1)	(2)	(1)	(2)	(1)	(2)
Group	0.0258 ***	0.0036	-0.0008	-0.0221	-0.1078 ***	-0.1192 ***
	(0.0089)	(0.0085)	(0.0253)	(0.0247)	(0.0359)	(0.0400)
Calendar	0.0178 *	0.0036	-0.0047	-0.0214	-0.1238 ***	-0.1290 **
	(0.0100)	(0.0085)	(0.0314)	(0.0302)	(0.0446)	(0.0511)
Simple	0.0239 *	0.0027	-0.0051	-0.0322	-0.1643 ***	-0.1818 ***
	(0.0124)	(0.0113)	(0.0376)	(0.0368)	(0.0553)	(0.0626)
Dynamic:						
Pre-treatment	-0.0296 **	-0.0084	-0.0006	0.0038	-0.0205	-0.0030
	(0.0130)	(0.0149)	(0.0209)	(0.0208)	(0.0395)	(0.0404)
Post-treatment	0.0205	-0.0002	-0.0051	-0.0338	-0.1938 ***	-0.2154 ***
	(0.0144)	(0.0130)	(0.0434)	(0.0440)	(0.0638)	(0.0732)

Notes: (1) Unconditonal especification; (2) Conditional especification. The sample covers 3,145 counties, 32,817 ZCTAs, and 72,698 census tracts during the period 2002–2019. *p<0.1, **p<0.05, ***p<0.01.

[9] This figure increases to 216 if the period from 1996 to 2021 is considered.

The figures reported in Table 3.4 corroborate the lack of significance of the effects of mass shootings on employment at the county and ZCTA levels. However, and regardless of the grouping scheme applied, the estimated impact in census tracts is larger than those obtained from the analysis with the entire sample. Focusing on the conditional specification, the average group effect is 11.2% (compared to 9.4%), the average calendar effect is 12.1% (10.6%), and the simple average effect is 16.6% (13.4%). Furthermore, the average dynamic effect ten years after the attacks is 19.3% (14.8%), indicating a higher persistence of the impact. These findings corroborate our initial idea that the more indiscriminate and violent a mass shooting is, the more adverse its effect on employment.

3.5.2 Economic activities

Section 3.2 provides both theoretical and empirical arguments supporting the idea that crime exerts a greater effect on economic sectors that are more reliant on working in contact with the general public. Taking advantage of the disaggregation of employment data at the 2-digits NAICS code, we checking whether this is also the case of mass shootings by conducting a separate analysis for the employment of business establishments working as retail trade (NAICS 44-45); arts, entertainment, and recreation (NAICS 71); and accomodation and food services (NAICS 72). While the public character of the retail trade sector is evident, it also encompasses subsectors like grocery stores or supermarkets, which provide essential goods that remain necessary even after violent events. NAICS codes 71 and 72 include businesses related to museums or artistic events, sport events, or restaurants and hotels, that are expected to be more vulnerable to the adverse effects of mass shootings.

Estimation results are reported in Table 3.5, both for the unconditional and conditional specifications. It is important to acknowledge that the latter incorporates the share of employment in each sector to capture specialization and control for the potential existence of employment clusters. The first noteworthy finding is that the negative effect of mass shootings turns statistically significant for the retail trade and the arts, entertainment and recreation sectors in ZCTAs, suggesting that these economic activities are more vulnerable to the adverse effects of mass shootings. Specifically, we obtain a simple average effect of a 3.8% employment reduction in the retail trade sector, with a slightly higher calendar effect

Table 3.5: Mass shootings average effects on employment by NAICS code.

	44-45		71		72	
	(1)	(2)	(1)	(2)	(1)	(2)
Counties						
Group	0.0046	0.0031	0.0177	-0.0096	0.0357 ***	0.0084
	(0.0072)	(0.0093)	(0.0225)	(0.0218)	(0.0080)	(0.0083)
Calendar	-0.0012	-0.0038	-0.0031	-0.0245	0.0369 ***	0.0129
	(0.0108)	(0.0105)	(0.0251)	(0.0218)	(0.0124)	(0.0119)
Simple	0.0005	-0.0042	0.0201	-0.0152	0.0393 ***	0.0038
	(0.0100)	(0.0102)	(0.0270)	(0.0257)	(0.0108)	(0.0107)
Dynamic:						
Pre-treatment	-0.0123	-0.0057	-0.0285	0.0043	-0.0509 ***	-0.0124
	(0.0106)	(0.0102)	(0.0216)	(0.0212)	(0.0133)	(0.0128)
Post-treatment	0.0006	-0.0038	0.0203	-0.0179	0.0404 ***	0.0028
	(0.0103)	(0.0108)	(0.0271)	(0.0264)	(0.0110)	(0.0112)
ZCTAs						
Group	0.0042	-0.0110	-0.0363	-0.0613 **	-0.0115	-0.0177
	(0.0161)	(0.0141)	(0.0277)	(0.0284)	(0.0180)	(0.0168)
Calendar	-0.0322	-0.0540 **	-0.0835 *	-0.1005 **	-0.0002	-0.0165
	(0.0296)	(0.0264)	(0.0428)	(0.0425)	(0.0504)	(0.0397)
Simple	-0.0164	-0.0394 *	-0.0618	-0.0915 **	-0.0254	-0.0316
	(0.0242)	(0.0201)	(0.0418)	(0.0427)	(0.0299)	(0.0265)
Dynamic:						
Pre-treatment	0.0070	0.0123	0.0215	0.0244	-0.0511 **	-0.0304
	(0.0166)	(0.0172)	(0.0469)	(0.0462)	(0.0218)	(0.0212)
Post-treatment	-0.0111	-0.0362 *	-0.0695	-0.0977 **	-0.0260	-0.0323
	(0.0247)	(0.0215)	(0.0458)	(0.0464)	(0.0292)	(0.0274)
Census tracts						
Group	0.0007	-0.0214	-0.0703	-0.1245 ***	-0.0871 ***	-0.1115 ***
	(0.0272)	(0.0277)	(0.0454)	(0.0450)	(0.0310)	(0.0295)
Calendar	0.0202	-0.0061	-0.1443 ***	-0.2125 ***	-0.1063 ***	-0.1372 ***
	(0.0530)	(0.0563)	(0.0553)	(0.0551)	(0.0385)	(0.0364)
Simple	-0.0128	-0.0413	-0.1148 *	-0.1935 ***	-0.1250 ***	-0.1584 ***
	(0.0403)	(0.0413)	(0.0594)	(0.0597)	(0.0415)	(0.0382)
Dynamic:						
Pre-treatment	0.0425	0.0728 **	0.0269	0.0739	-0.0102	0.0134
	(0.0330)	(0.0337)	(0.0648)	(0.0643)	(0.0351)	(0.0348)
Post-treatment	-0.0128	-0.0423	-0.1308 **	-0.2166 ***	-0.1377 ***	-0.1716 ***
	(0.0445)	(0.0454)	(0.0643)	(0.0626)	(0.0443)	(0.0416)

Notes: 44-45: Retail trade; 71: Arts, entertainment and recreation; 72: Accomodation and food services. (1) Unconditonal especification; (2) Conditional especification. The sample covers 3,145 counties, 32,817 ZCTAs, and 72,698 census tracts during the period 2002–2019. *p<0.1, **p<0.05, ***p<0.01.

of 5.3%. The impact also displays persistence, as reflected by the statistical significance of the average post-treatment effects. The effect on the arts, entertainment, and recreation sector is more pronounced, being negative and significant independently of the grouping scheme, estimating a 8.7% reduction on a simple average basis. At the census tract level, we do not find a significant effect in the retail sector and, strikingly, those units that experienced an attack exhibit a positive pre-trend in its employment when compared to those with similar characteristics. However, and regardless the grouping scheme adopted, the adverse influence on the employment in the accomodation and food services sector is greater than the overall estimated effect. The impact on the arts, entertainment and recreation sector is also quite pronounced, as it reaches a simple average employment reduction of 17.5%, and exceed a 19% on calendar and post-treatment averages. To sum it all up, economic activities that imply working closely with the public seem to be more sensitive to mass shootings. This is evident in their broader negative impact on employment, that becomes statistically significant at the ZCTA level, and that has a higher magnitude than that for all economic activities in census tracts.

3.5.3 Employment composition

Another question that arises when examining the economic impact of mass shootings is if they alter the composition of employment in the affected areas through the ousting of skilled workers. We have ivestigated this possibility by analyzing the changes in the shares of employment by wage and educational attainment levels after an attack. To do so, we have considered the share of workers that belong to three wage ranks – less than 1,250$/month, between 1,250 and 3,333$/month, and more than 3333$/month – and to three categories of education: less than high school, with high school or associate's degree, and with bachelor's degree or higher.

Table 3.6 reports the results for changes in the composition of employment by wage level. These figures show that, besides a modest increase in the proportion of lower-paid jobs at the county level, there appears to be no significant effect of mass shootings on the wage employment composition. Table 3.7 provides the insights about the changes induced by the attacks on employment by educational attainment. The presence of pre-existing trends in the shares of workers with different levels of education cannot be entirely ruled

Table 3.6: Mass shootings average effects on employment composition by wage level.

	Low		Medium		High	
	(1)	(2)	(1)	(2)	(1)	(2)
Counties						
Group	0.0053 ***	0.0017	0.0003	-0.0008	-0.0056 ***	-0.0008
	(0.0011)	(0.0011)	(0.0014)	(0.0015)	(0.0017)	(0.0017)
Calendar	0.0068 ***	0.0018	-0.0021	-0.0018	-0.0046 **	-0.0001
	(0.0017)	(0.0014)	(0.0022)	(0.0022)	(0.0019)	(0.0020)
Simple	0.0091 ***	0.0033 **	-0.0017	-0.0026	-0.0074 ***	-0.0007
	(0.0016)	(0.0015)	(0.0021)	(0.0022)	(0.0023)	(0.0023)
Dynamic:						
Pre-treatment	-0.0067 ***	-0.0006	0.0047 **	0.0025	0.0020	-0.0018
	(0.0017)	(0.0014)	(0.0020)	(0.0020)	(0.0026)	(0.0026)
Post-treatment	0.0101 ***	0.0037 **	-0.0014	-0.0024	-0.0087 ***	-0.0012
	(0.0016)	(0.0017)	(0.0022)	(0.0023)	(0.0025)	(0.0026)
ZCTAs						
Group	0.0046 *	0.0016	-0.0034	-0.0035	-0.0012	0.0019
	(0.0025)	(0.0024)	(0.0028)	(0.0027)	(0.0027)	(0.0026)
Calendar	0.0024	-0.0012	-0.0030	-0.0012	0.0006	0.0024
	(0.0059)	(0.0058)	(0.0059)	(0.0058)	(0.0029)	(0.0027)
Simple	0.0064 *	0.0014	-0.0046	-0.0032	-0.0018	0.0018
	(0.0037)	(0.0036)	(0.0043)	(0.0042)	(0.0035)	(0.0033)
Dynamic:						
Pre-treatment	-0.0051 *	0.0001	0.0044	0.0034	0.0007	-0.0035
	(0.0026)	(0.0027)	(0.0028)	(0.0028)	(0.0027)	(0.0026)
Post-treatment	0.0070 *	0.0016	-0.0041	-0.0028	-0.0029	0.0012
	(0.0038)	(0.0038)	(0.0043)	(0.0042)	(0.0037)	(0.0035)
Census tracts						
Group	0.0034	0.0040	-0.0014	0.0013	-0.0020	-0.0053
	(0.0035)	(0.0036)	(0.0033)	(0.0033)	(0.0044)	(0.0044)
Calendar	-0.0017	-0.0008	-0.0017	0.0024	0.0033	-0.0016
	(0.0056)	(0.0060)	(0.0057)	(0.0059)	(0.0047)	(0.0048)
Simple	0.0035	0.0052	-0.0036	-0.0002	0.00005	-0.0051
	(0.0049)	(0.0051)	(0.0048)	(0.0049)	(0.0058)	(0.0058)
Dynamic:						
Pre-treatment	-0.0018	-0.0034	0.0048	0.0037	-0.0030	-0.0003
	(0.0042)	(0.0042)	(0.0039)	(0.0039)	(0.0042)	(0.0043)
Post-treatment	0.0044	0.0065	-0.0030	0.0004	-0.0014	-0.0068
	(0.0054)	(0.0057)	(0.0050)	(0.0052)	(0.0066)	(0.0067)

Notes: Low: <1250$/month; Medium: 1250-3333$/month; High: >3333$/month. (1) Uncon-ditonal especification; (2) Conditional especification. The sample covers 3,145 counties, 32,817 ZCTAs, and 72,698 census tracts during the period 2002–2019. *p<0.1, **p<0.05, ***p<0.01

Table 3.7: Mass shootings average effects on employment composition by educational attainment.

	(A)		(B)		(C)	
	(1)	(2)	(1)	(2)	(1)	(2)
Counties						
Group	0.0028 ***	0.0013 **	0.0002	0.0001	-0.0030 ***	-0.0014 *
	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Calendar	0.0025 ***	0.0012 **	0.0002	0.0001	-0.0028 ***	-0.0012
	(0.0006)	(0.0006)	(0.0009)	(0.0010)	(0.0010)	(0.0010)
Simple	0.0033 ***	0.0015 **	0.0006	0.0004	-0.0039 ***	-0.0020 *
	(0.0007)	(0.0006)	(0.0010)	(0.0010)	(0.0011)	(0.0012)
Dynamic:						
Pre-treatment	-0.0052 ***	-0.0017 **	-0.0020 *	-0.0012	0.0072 ***	0.0029 ***
	(0.0009)	(0.0007)	(0.0012)	(0.0011)	(0.0009)	(0.0009)
Post-treatment	0.0043 ***	0.0020 ***	0.0007	0.0004	-0.0050 ***	-0.0024
	(0.0009)	(0.0007)	(0.0012)	(0.0013)	(0.0015)	(0.0015)
ZCTAs						
Group	0.0040 ***	0.0016 *	-0.00001	0.0006	-0.0040 ***	-0.0021
	(0.0008)	(0.0008)	(0.0014)	(0.0015)	(0.0014)	(0.0014)
Calendar	0.0040 ***	0.0020	0.0007	0.0007	-0.0047 **	-0.0027
	(0.0012)	(0.0013)	(0.0024)	(0.0025)	(0.0024)	(0.0023)
Simple	0.0049 ***	0.0020 *	0.0010	0.0014	-0.0059 ***	-0.0034 *
	(0.0010)	(0.0010)	(0.0022)	(0.0022)	(0.0021)	(0.0021)
Dynamic:						
Pre-treatment	-0.0039 **	-0.0001	0.0012	0.0017	0.0028	-0.0016
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0017)	(0.0017)
Post-treatment	0.0061 ***	0.0025 *	0.0016	0.0023	-0.0077 ***	-0.0048 *
	(0.0013)	(0.0013)	(0.0028)	(0.0028)	(0.0026)	(0.0025)
Census tracts						
Group	0.0031	0.0031	0.0033	0.0032	-0.0064 **	-0.0062 **
	(0.0022)	(0.0022)	(0.0034)	(0.0034)	(0.0028)	(0.0028)
Calendar	0.0021	0.0023	0.0028	0.0030	-0.0049	-0.0052
	(0.0021)	(0.0021)	(0.0039)	(0.0039)	(0.0040)	(0.0040)
Simple	0.0033	0.0033	0.0026	0.0026	-0.0059	-0.0060
	(0.0024)	(0.0024)	(0.0044)	(0.0043)	(0.0039)	(0.0039)
Dynamic:						
Pre-treatment	0.0015	0.0017	0.0021	0.0024	-0.0036	-0.0041
	(0.0024)	(0.0025)	(0.0042)	(0.0042)	(0.0038)	(0.0039)
Post-treatment	0.0052	0.0053	-0.0005	-0.0003	-0.0047	-0.0050
	(0.0037)	(0.0038)	(0.0077)	(0.0077)	(0.0056)	(0.0056)

Notes: : (A) Less than high school; (B) High school or associate's degree; and (C) Bachelor degree or higher. (1) Uncondítonal especification. (2) Conditional especification. The sample covers 3,145 counties, 32,817 ZCTAs, and 72,686 census tracts during the period 2009–2019. *p<0.1, **p<0.05, ***p<0.01.

out in counties, even when those with similar characteristics are compared. There is a slight increase (decrease) in the share of workers with no high school completion (bachelor's or higher degree) in ZCTAs. If we consider the group average effect in census tracts, we observe a small reduction in the proportion of highly educated workers. In summary, both sets of results indicate that changes in the composition of employment prompted by mass shootings, although taking place at broader levels than employment reductions, are minor. This suggests that these incidents do not exert a distinct impact on any particular share of workers in terms of wage or educational attainment.

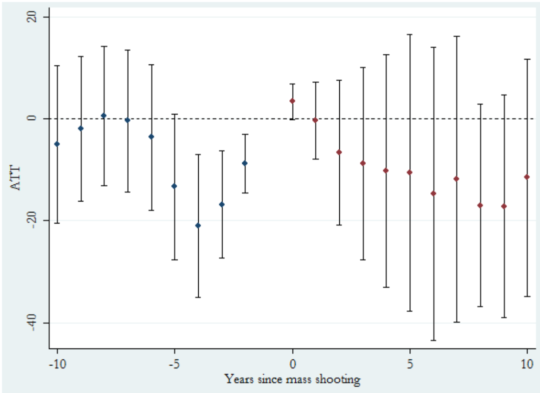
3.6 Mass shootings and housing prices

The limited avalability of population data with a yearly frequency restricts our understanding of the demographic response to mass shootings. Nevertheless, we are able to analyze the potential effects of these incidents on the residential attractiveness of the areas where they are perpetrated. A decline in housing prices does not necessarily entail a reduction in total population. In fact, falling prices might attract individuals with lower levels of income through a process known as 'filtering' (Rosenthal and Strange, 2004; Liu, McManus, and Yannopoulos, 2022). Despite this, a reduction in housing prices unmistakably reflects a lower willingness to pay for residing in a given area.

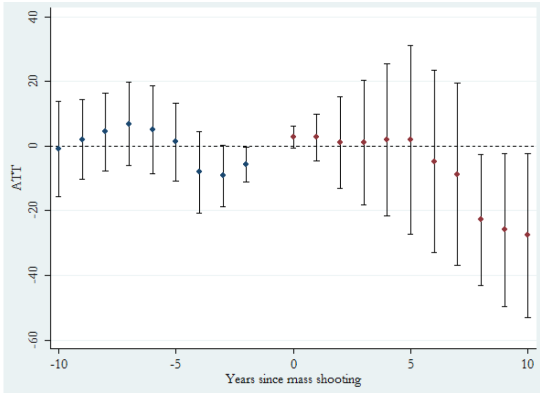
Table 3.8: Mass shootings average effects on housing prices.

	Counties		ZCTAs		Census tracts	
	(1)	(2)	(1)	(2)	(1)	(2)
Group	3.5065	-0.5464	9.3597 **	1.1565	-5.5529 **	-2.8585
	(5.1668)	(5.9658)	(4.4792)	(4.0258)	(2.3587)	(2.1976)
Calendar	-12.0485 *	-7.4777	-4.3903	-9.3781 *	-9.0213 ***	-6.5239 **
	(6.9372)	(6.9854)	(5.2186)	(4.8848)	(3.0244)	(2.8925)
Simple	-7.4039	-5.7386	4.7788	-1.8398	-9.1340 ***	-6.6226 **
	(8.0106)	(8.2151)	(6.1173)	(5.6819)	(3.3530)	(3.1855)
Dynamic:						
Pre-treatment	-7.8290 *	-0.4801	-8.7035	-0.7818	1.0356	0.6265
	(4.5960)	(4.3884)	(5.4185)	(5.2142)	(2.7158)	(2.5883)
Post-treatment	-9.6050	-7.1062	7.9992	0.8244	-10.2959 ***	-7.9462 **
	(8.6114)	(8.7128)	(7.2541)	(6.8742)	(3.5739)	(3.4266)

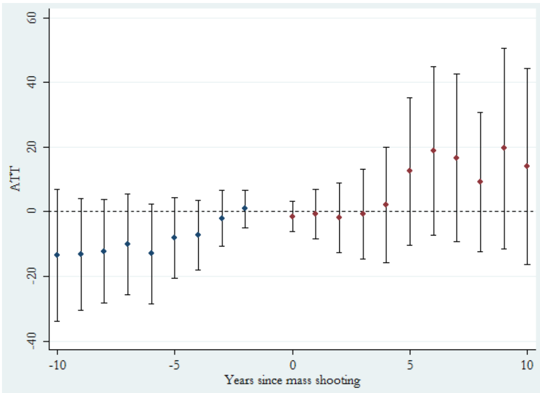
Notes: (1) Unconditonal especification; (2) Conditional especification. The sample covers 2,773 counties, 18,891, ZCTAs and 63,747 census tracts during the period 2002–2019. *p<0.1, **p<0.05, ***p<0.01.



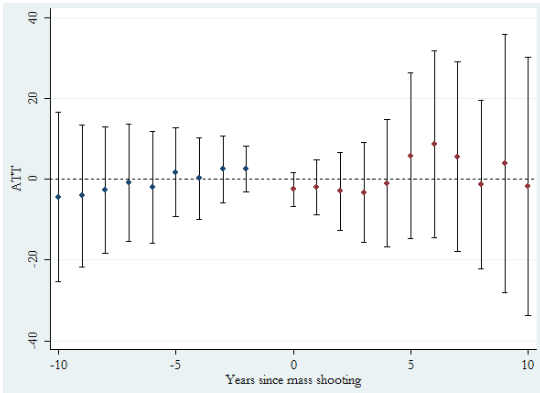
(a) Counties - Unconditional



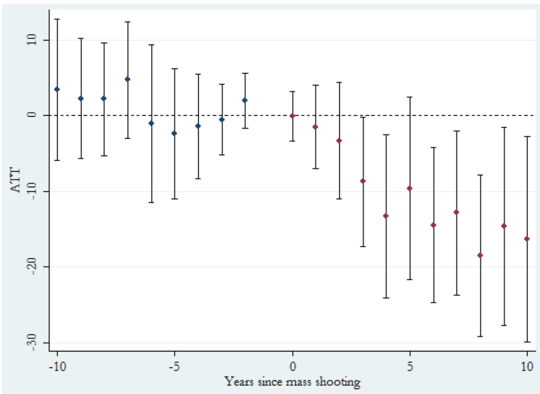
(b) Counties - Conditional



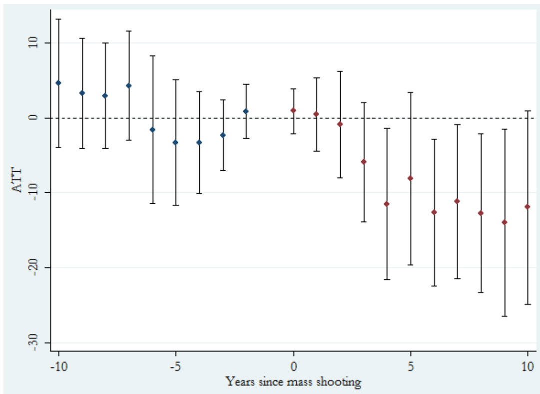
(c) ZCTAs - Unconditional



(d) ZCTAs - Conditional



(e) Census tracts - Unconditional



(f) Census tracts - Conditional

Figure 3.3: Dynamic average effects of mass shootings on housing prices.

As described in Section 3.3.2, the HPI that is being analyzed has been calculated through repeated sales, including transactions that involve the same property within the same time period. This methodology boasts the advantage of incorporating both housing stock quality and neighborhood externalities that influence prices. However, this data source presents a limitation with regards to the number of complete panels that it provides because the HPI computation is not possible when there is an insufficient number of repeated sales. As a consequence, the analysis carried out in this section is based on 187 mass shootings. The conditional specification controls for the urban/rural character of the unit, the housing stock, as well as its density and vacant share, and the commuting time of the residents. This last variable seems pertinent given that mass shootings influence the location of employment, which is a factor correlated with housing prices.

Table 3.8 shows the results for the estimated response of the HPI to the occurence of mass shootings. The conditional specification appears to better capture their effects, especially in the case of counties as it mitigates the pre-existing trends observed in the unconditional analysis. It can be observed that the attacks exert a modest negative average effect at the county level when grouped by calendar time, whereas no discernible effect impact is found when alternative grouping schemes are employed. This outcome is consistent with the dynamics plotted in graphic (d) of Figure 3.3, where cumulative effects become significant at the end of the 10-year window. No significant impact is obtained at the ZCTA level and, in line with the results presented in Section 3.5, the most pronounced influence is found in census tracts. Taking into account the conditional specification that tries to control for employment reductions, the simple average effect induced by mass shootings on the HPI reflects a reduction of 6.6. This effect is also persistent, as the average annual HPI reduction after the attack is 7.9. Unlike the estimation result for employment, the impact of mass shootings on census tracts – depicted in graphics (e) and (f) of Figure 3.3 – is persistent but not cumulative.

3.7 Discussion

According to Table 3.1, the mean number of persons employed in census tracts is $1,805$. In addition, Table 3.3 shows that, on average, mass shootings cause an employment reduction of 13.4%. Taking these figures into consideration, an attack in these geographic entities would imply an average loss – or relocation – of 242 jobs. As depicted in Figure 2, this effect displays persistence and accumulates over time. Using a conditional specification, the estimated coefficient for the average dynamic effect ten years after the incidents is -0.26. This reflects that roughly one out of five jobs in affectd census tracts would have been destroyed or displaced in a decade after the attack. While the results show that mass shootings bring on substantial economic decline in the immediate areas where they take place, our estimations for broader spatial units, such as counties, are of a much lower magnitude than those obtained by Brodeur and Yousaf (2022). At this geographical level, these authors find a statistically significant employment reduction of 1.3%, implying an average loss of 466 jobs in their sample.

The different magnitude of the estimated effects in the present paper with respect to that in Brodeur and Yousaf (2022) may be driven by the distinct time period analyzed, data sources exploited, and metholodogy employed. More specifically, our information about mass shootings has been extracted from press and academic sources that provide detailed information about the location. This has allowed us to determine the spatial scope of the economic impact of the attacks, but including a different set of incidents in our database. To further explore whether the disparities in county-level results stem from the attacks covered in our sample, we have constructed an alternative sample using information from the SHR (Kaplan, 2021), along with the Associated Press and USA Today Mass Killing Database (Fox, 2022). Proceeding this way, as long as the primary sources of information are the same, we should be able to compare the obtained results with those in Brodeur and Yousaf (2022). The alternative data set comprises 707 mass shootings perpetrated in 593 different counties between 1976 and 2021. Within our sample period, that spans from 2003 to 2019, there are 196 counties experiencing an attack for the first time.

The results for this alternative sample are reported in Table 3.9. At the 10% significance level, the conditional specification estimates that the employment reduction after an attack is 1.2%. Given that the mean total employment at the county level is $41,472$ (see Table 3.1), it implies an average of 507 job losses after a mass shooting, a value that is similar to that estimated by Brodeur and Yousaf (2022). We have also checked if this alternative data set leads to different conclusions regarding housing prices, obtaining no significant changes. These findings show that when mass shootings are analyzed at a broader geographical scale, the estimated impact on employment is sensitive to the events included, hence suggesting that the results are influenced by the unique characteristics and reactions of each unit. If we assume that this imply that our sample of incidents might have a relatively smaller impact than the alternative, and take into account the estimations for census tracts, these

Table 3.9: Mass shootings average effects on employment and housing prices at the county level using alternative data sources.

	Employment		HPI	
	(1)	(2)	(1)	(2)
Group	0.0062	-0.0046	10.7569 **	-0.8155
	(0.0056)	(0.0053)	(4.2373)	(4.5301)
Calendar	-0.0098	-0.0139 **	3.6233	-6.1557
	(0.0073)	(0.0065)	(5.7654)	(5.4506)
Simple	-0.0029	-0.0123 *	6.8162	-3.9696
	(0.0081)	(0.0071)	(6.0303)	(5.7190)
Dynamic:				
Pre-treatment	-0.0103	0.0023	-4.6486	1.3229
	(0.0075)	(0.0069)	(4.3504)	(3.9348)
Post-treatment	-0.0049	-0.0137 *	4.4647	-3.3712
	(0.0087)	(0.0077)	(6.6181)	(6.1204)

Note: (1) Unconditonal especification. (2) Conditional especification. The sample covers 3,145 (2,773) counties for the period 2002–2019 when employment (HPI) is the outcome. *p<0.1, **p<0.05, ***p<0.01.

results further highlight the concentrated nature of the adverse economic effects of mass shootings.

Table 3.6 hints at a subtle increase in the share of workers with lower wages at the county level. This finding, together with the changes in the shares of workers with different educational attainment levels in ZCTAs, suggests that the estimated effects in broader areas might stem from wage or employment composition rather than from job losses. Despite the geographic detail of our data, it is not possible to further inquire into these mechanisms due to the lack of information about the number of businesses or wages. Nonetheless, our main hypothesis regarding the granularity of the effects becomes more apparent upon closer examination of the right panel of Figure 2, that portrays the estimated dynamic effects of mass shootings on employment using a conditional specification. The adverse influence in counties and ZCTAs is slow and reaches the highest value between six and eight periods after the attack, displaying some signs of recovery after that moment. This result contrasts with the cumulative and, consequently, persistent effect found at the census tract level. These findings may be interpreted as evidence that the adverse effects induced by mass shootings induce negative externalities that reinforce their impact in smaller areas.

The results for housing prices align with this claim, as the related index only shows a decline after an attack in census tracts. Assuming that the variable that measures commuting times controls for the effect of job disappearance or relocation in the HPI, the most plausible explanation, given that we are analyzing a repeated sales index (calculated on houses that have been effectively bought) is that a filtering process has taken place in the affected units. Therefore, the population in these areas would have lower incomes, hence reinforcing the impact on the level of employment. There also exists the possibility that a concentration of lower incomes, in turn, brings about some of its inherent negative externalities in the affected census tracts, such as a higher common crime rate, further amplifying the previous effect.

3.8 Concluding remarks

Drawing upon the literature about the consequences of crime and violent shocks on local economies, this chapter deals with the impact of mass shootings in the U.S. in three geographic entities: counties, ZCTAs, and census tracts. Using recent advances in DiD estimation methods, we have obtained evidence that these incidents lead to significant employment reductions in adjacent areas – especially in the case of census tracts – that persist and accumulate over time. Furthermore, those attacks that are conducted in public spaces, characterized by their indiscriminate and violent nature, seem to exert a more pronounced impact. We also find that those economic activities that rely more heavily on face-to-face interactions experience a greater number of job losses after a mass shooting, and that these incidents slightly affect the composition of employment by wage and educational attainment levels. In addition, we have explored whether mass shootings affect the desirability for living in the affected areas, finding an adverse effect on housing prices at the census tract level. The robustness of our results has been tested using an alternative sample, similar to that in Brodeur and Yousaf (2022), referred to U.S. counties. Although we still obtain a statistically significant impact on employment, this is not the case of housing prices. This higher sensitivity of the estimated effects at broader geographical levels underscores the substantial impact identified in census tracts. Our study, in essence, shows that while the adverse economic effects of mass shootings may extend to larger areas, it is the use of more granular data what permits to uncover the economic decline induced by these dramatic incidents.

Conclusions

In the first chapter of this thesis, with the aim of preventing the potential dilution of poverty's heterogeneity when considering broader geographical units, and understanding that its direct study is necessary for designing effective interventions, we have focused on analyzing the poverty rate in the census tracts of 368 Metropolitan Statistical Areas (MSAs) during the 1970–2010 period, constructing a geographically consistent data panel for this purpose. As a first step, recognizing that poverty can generate effects that make it persist over time, creating so-called poverty traps, we have conducted unit root tests for panel data, concluding that these rates are stationary. Following this, we have modeled the poverty rate through a disequilibrium adjustment process, implying that it can depend on both its past values and a set of socioeconomic variables identified in related literature. Given the potential endogeneity of some of these variables, the GMM method by Arellano and Bond (1991) was used to estimate this model. The results indicate that, although poverty is stationary, it exhibits a degree of persistence, especially in the more disadvantaged tracts, and also a degree of spatial dependency. Furthermore, our findings show that employment and educational level have a negative association with poverty, while the percentage of rented housing and single-parent families headed by women are positively associated with it. Lastly, these results have been aligned to support either place-based or people-centered policies, concluding that the best approach to tackling poverty is a combination of both.

In the second chapter, we have carried out a comprehensive study on the temporal dynamics and persistence of inequality. After reviewing the broad body of economic literature on this topic, which has expanded alongside the increased availability of long-term data, we observed that few studies consider the possibility that the persistence of inequality may vary over time. For this reason, this chapter delves into this issue in the context of the United States, analyzing inequality from 1870 to 2019, thus covering crucial periods such as the two World Wars, and focusing not only on income inequality but also on wealth disparity. For this purpose, in addition to using the Gini index as a general measure of inequality, we have investigated income concentration, specifically the share of the top 10% of earners, and a metric of wealth inequality, the wealth-to-income ratio. As a first step, we have adopted an empirical strategy that addresses the circular problem between estimating structural breaks and unit root analysis. Then, we checked whether the analyzed time series exhibited regime changes during the period under study. We found that while wealth inequality is an I(1) process throughout the entire period, the two measures of income inequality alternated between I(1) and I(0) regimes. We also investigated the determinants that might be influencing these changes. For this, we employed Bayesian model averaging techniques in a logistic regression framework, allowing us to test the explanatory robustness of a wide array of variables selected based on literature and data availability. Our findings indicate that globalization is associated with greater persistence of income inequality, while an inverse relationship exists between this persistence and the levels of education and union membership. Interpreting these results collectively provides insights such as periods of non-stationary income inequality coinciding with times of globalization, or the decline in union membership during the 1980s contributing to the persistence of inequality increases following the reforms during President Reagan's term (1981–1989). Moreover, these results offer important information about the potential influence of economic policy on inequality: a redistributive shock in inequality when it behaves as an I(1) regime should have a lasting impact over time.

In the third and final chapter, we have explored the economic impact of a specific type of firearm violence: mass shootings. Based on the FBI's definition, which describes these events as situations where one or more shooters kill four or more people in incidents not related to other major crimes (such as drug trafficking or robberies), we have created a database of such incidents with detailed geographical information. Using the latest advancements in difference-in-differences techniques, we analyzed the geographical scope of the impacts of these events from 2003 to 2019, investigating their effects on employment and housing prices in the affected counties, zip codes, and census tracts. The greatest reduction in employment was found in the census tracts, with persistent and cumulative effects over time. It was also observed that shootings in public places have a more pronounced impact on job losses, supporting the 'fear hypothesis' (Becker and Rubinstein, 2011), which suggests that the more random and violent an attack, the greater its effect. Sectors dependent on direct public contact are most affected, with significant repercussions even at the zip code level. Lastly, the chapter investigated whether mass shootings affect productivity by displacing highly skilled workers, examining their impact on the labor market composition in terms of wages and education level. It was found that this effect, while extending beyond census tracts, was limited. Regarding housing prices, a concentrated negative effect was also found in the census tracts. In conclusion, the impacts of mass shootings, beyond the loss of lives, extend to local economies, causing a sustained and cumulative decline over time in the areas closest to their occurrence.

Throughout this thesis, we have analyzed each subject individually, detailing their specificities, the appropriate empirical strategy for each, as well as the necessary methodology and corresponding findings. However, while each thematic area has its own complexity, we cannot overlook the fact that, in reality, they do not exist in isolation. Although it is beyond the scope and main objectives of this thesis, we believe it is important to point out the possibility of significant interconnections between them. Therefore, before concluding, we wish to outline a general overview of how poverty, inequality, and mass shootings might be interconnected, so that these final, albeit preliminary, reflections can lay the groundwork for future research.

Regarding the relationship between poverty and inequality, a circular dynamic can be identified. As previously emphasized, the poverty rate in census tracts shows a degree of persistence, particularly in those tracts with higher rates. This suggests that in the lower segment of the income distribution, there are effects that make it difficult for individuals within it to move upwards. Such persistence may contribute to income inequality. Conversely, there are theories related to the so-called "Great Gatsby Curve" (Durlauf, Kourtellos, and Tan, 2022), an empirically observed correlation where greater income inequality is associated with lower intergenerational income mobility. These theories suggest mechanisms based on family investment decisions in education, skill transmission, and social capital, among others. If this relationship is valid, we could infer from the results of the second chapter that periods of persistent inequality have also encouraged the persistence of poverty rates in the census tracts. Additionally, bringing a geographical focus to this relationship, economic literature associates greater income inequality with increased socioeconomic segregation, particularly in urban areas (Watson, 2009; Reardon and Bischoff, 2011; Ham, Tammaru, Ubarevičienė, and Janssen, 2021). Simply put, the theoretical explanation is that as the differences in purchasing power among various income groups widen, those at the lower end are forced to reside in areas not chosen by those at the higher end. Therefore, in our context, this implies that inequality could be a determinant of the differences in poverty rates among tracts, as it leads to the concentration of lower-income individuals in the same areas. Moreover, if inequality is reflected in income differences between different social groups, it also influences which socioeconomic variables are linked to poverty in these tracts.

Concerning the interplay between mass shootings and poverty and inequality, a clear initial link emerges from the findings of the third chapter. If the decreases in housing prices caused by these events in the census tracts are followed by a 'filtering' process – which implies that housing is successively occupied by individuals of lower income – the reduction in residents' income in that tract could lead to increases in its poverty rate. Additionally, the destruction or displacement of jobs located in these areas acts as a reverse place-based policy. Hence, a potential extension, subject to the availability of annual data, would be to examine how mass shootings affect income levels or poverty rates in the affected areas. The inverse relationship, deciphering how inequality and poverty interconnect with mass shootings, is more nuanced. By definition, our study excludes events with a direct economic motivation as it omits cases linked to other types of crimes. However, Brodeur and Yousaf (2020) have documented the socioeconomic characteristics of a sample of shooters, finding that about 40% faced financial difficulties, and at least 43% showed signs of mental illness or had related clinical histories. This connection is also supported by other studies, such as Yelderman, Joseph, West, and Butler (2019) or Lankford and Cowan (2020). Considering that poverty and inequality are linked to worse mental health conditions, as discussed in the introduction and motivations of the respective chapters, a hypothesis worth testing, requiring a multidisciplinary approach, is whether these economic phenomena foster a conducive context for the occurrence of mass shootings.

These final reflections on the interconnections among the topics discussed in this thesis underscore the extensive research still needed for a deeper understanding of poverty, inequality, and gun violence. In the context where the Sustainable Development Goals (SDGs) have set objectives for future well-being improvement collectively, and these have been adopted by numerous social actors who have consequently modified their decisions and actions, it can be said that this thesis, in its unique way, has been developed parallel to these developments, either directly or indirectly. It positions economic analysis as a framework for knowledge acquisition, serving not only for academic enrichment but also addressing social interest.

Conclusiones

En el primer capítulo de esta tesis, con el objeto de evitar que la consideración de unidades geográficas más amplias pudiera diluir la heterogeneidad de un fenómeno como la pobreza, y entendiendo que su estudio directo es necesario para diseñar actuaciones sobre ella, nos hemos centrado en analizar la tasa de pobreza en los *census tracts* de 368 MSAs durante el periodo 1970–2010, construyendo para ello un panel de datos geográficamente consistente. Como primer paso, reconociendo que la pobreza puede generar efectos que la hagan persistente en el tiempo, generando las llamadas trampas de pobreza, hemos realizado contrastes de raíz unitaria para datos de panel, concluyendo que dichas tasas tienen un carácter estacionario. Tras ello, se ha planteado la modelización de la tasa de pobreza a través de un proceso de ajuste de los desequilibrios, lo que implica que ésta puede depender tanto de sus valores anteriores como de un conjunto de variables socioeconómicas identificadas en la literatura relacionada. Dada la posible endogeneidad de algunas de estas variables, se ha empleado el método GMM de Arellano and Bond (1991) para estimar dicho modelo. Los resultados nos indican que, aunque la pobreza sea estacionaria, presenta cierto grado de persistencia, especialmente en los *tracts* más desfavorecidos, y también cierto grado de dependencia espacial. Además, nuestros hallazgos indican que el empleo y el nivel educativo tienen una asociación negativa con la pobreza, mientras que el porcentaje de alquilados y el de familias monoparentales encabezadas por mujeres tienen una relación positiva con ésta. Por último, se han alineado estos resultados según sirvan para respaldar políticas del tipo *place-based* o *people-centered*, concluyendo que la mejor receta para atacar la pobreza es la combinación de ambas.

En el segundo capítulo, hemos llevado a cabo un estudio exhaustivo sobre las dinámicas temporales y la persistencia de la desigualdad. Tras revisar la amplia literatura económica al respecto, la cual ha crecido en paralelo a la mayor disponibilidad de datos a largo plazo, hemos observado que son pocos los estudios que consideran que la persistencia de la desigualdad puede variar a lo largo del tiempo. Por esta razón, este capítulo ahonda en esta cuestión en el contexto de los Estados Unidos, analizando la desigualdad desde 1870 hasta 2019, abarcando así periodos cruciales como las dos Guerras Mundiales, y centrándose no sólo en la desigualdad de ingresos sino también en la de riqueza. Con este propósito, además de utilizar el índice de Gini como medida general de desigualdad, hemos investigado la concentración de ingresos, específicamente la participación del 10% superior, y una métrica de desigualdad de riqueza, el ratio riqueza-renta.

Como primer paso, hemos seguido una estrategia empírica que permite solventar el problema circular entre la estimación de rupturas estructurales y el análisis de raíz unitaria. Posteriormente, hemos comprobado si las series temporales analizadas presentan cambios de régimen durante el periodo analizado, hallando que mientras la desigualdad en riqueza es un proceso I(1) durante todo el periodo, las dos medidas de desigualdad en renta alternan entre regímenes I(1) e I(0). Además, hemos comprobado qué determinantes pueden estar influyendo en estos cambios. Para ello, hemos utilizado técnicas de *Bayesian model averaging* en un contexto de regresión logística, que nos han servido para comprobar la robustez explicativa de un amplio número de variables seleccionadas siguiendo la literatura y la disponibilidad de datos. Hemos encontrado que la globalización está asociada a una mayor persistencia de la desigualdad en renta, mientras que se da la relación inversa entre ésta y el nivel de escolarización, así como de afiliación sindical. Interpretar estos resultados conjuntamente nos da claves como que los periodos donde la desigualdad en renta es no estacionaria coinciden efectivamente con periodos de globalización, o que la caída de la tasa de afiliación sindical durante los años 80 favoreció que los aumentos de desigualdad tras las reformas realizadas durante el mandato del presidente Reagan (1981-1989) fueran persistentes. Además, estos resultados también proporcionan información relevante para conocer el grado de influencia que puede tener la política económica en la desigualdad: un shock redistributivo en la desigualdad cuando esta se comporta como un régimen I(1) debería tener una influencia persistente en el tiempo.

En el tercer y último capítulo, se ha explorado el impacto económico de un tipo específico de violencia con armas de fuego: los tiroteos en masa. Basándonos en la definición del FBI, que describe estos eventos como situaciones en las que uno o varios tiradores asesinan a cuatro o más personas sin relación con otros delitos graves (como tráfico de drogas o atracos), hemos creado una base de datos de aquellos incidentes con información geográfica detallada. Utilizando los últimos avances en las técnicas de diferencias en diferencias, hemos analizado el alcance geográfico de los impactos de estos eventos entre 2003 y 2019, investigando su efecto en el empleo y en el valor de las viviendas en los condados, códigos postales y *census tracts* afectados. La mayor reducción en el empleo se ha encontrado en los *tracts*, presentando, además, un carácter persistente y acumulado en el tiempo. También se observó que los tiroteos en lugares públicos tienen un impacto más pronunciado en la pérdida de empleos, respaldando la llamada *'fear hypothesis'* (Becker and Rubinstein, 2011), según la cual cuanto más aleatorio y violento es un ataque mayor será su efecto. Los sectores que dependen del contacto directo con el público son los más afectados, con repercusiones notables incluso a nivel de código postal. Finalmente, se investigó si los tiroteos influían en la productividad al desplazar a trabajadores altamente cualificados, comprobando su impacto en la composición del mercado laboral según salario y nivel educativo. Se encontró que este efecto, aunque presente en áreas más extensas que los *census tracts*, fue limitado. Por último, para los precios de la vivienda, también se ha encontrado que el efecto negativo se concentra en los *census tracts*. En definitiva, se puede concluir que los impactos de los tiroteos en masa, más allá de la pérdida de vidas, también se extienden a las economías locales, generando un declive sostenido y acumulado en el tiempo en las áreas más cercanas a su ocurrencia.

En el transcurso de esta tesis, hemos analizado cada tema individualmente, exponiendo sus especificidades, la estrategia empírica adecuada para cada uno de ellos, junto con la metodología requerida y los hallazgos correspondientes. Sin embargo, mientras cada área temática posee su propia complejidad, no podemos pasar por alto que, en la realidad, no existen de forma aislada. Aunque queda fuera del alcance y de los objetivos principales de esta tesis, consideramos importante señalar la posibilidad de interconexiones significativas entre ellos. Es por ello que, antes de concluir, deseamos esbozar una panorámica general de cómo la pobreza, la desigualdad y los tiroteos en masa pueden estar vinculados, de modo que estas reflexiones finales, aunque preliminares, sirvan para sentar algunas bases para futuras investigaciones.

Respecto a la pobreza y a la desigualdad se puede apuntar a una relación circular. Tal y como habíamos resaltado antes, la tasa de pobreza en los *census tracts* presenta cierta persistencia, especialmente en aquellos tracts donde mayores son estas tasas. Esto quiere decir que en el segmento más bajo de la distribución de la renta se dan efectos que dificultan a las personas ubicadas en él moverse hacia arriba en dicha distribución. Esta persistencia puede ser un factor que favorezca la desigualdad de la renta. Recíprocamente, existe una serie de teorías vinculadas a la llamada *"Great Gatsby Curve"* (Durlauf, Kourtellos, and Tan, 2022), una relación observada empíricamente por la que una mayor desigualdad en renta correlaciona con una menor movilidad intergeneracional en ingresos. Estas teorías proponen mecanismos basados en decisiones de inversión familiar en educación, transmisión de habilidades y capital social, entre otros. De cumplirse esta relación, podríamos inferir, según los resultados del segundo capítulo, que los periodos en los que la desigualdad ha sido persistente, han favorecido que las tasas de pobreza en los *census tracts* también lo fueran. Adicionalmente, dando un enfoque más geográfico a esta relación, la literatura económica vincula una mayor desigualdad en la renta con una mayor segregación socioeconómica, sobre todo en áreas urbanas (Watson, 2009; Reardon and Bischoff, 2011; Ham, Tammaru, Ubarevičienė, and Janssen, 2021). La explicación teórica a esto, de forma simple y resumida, es que al ensancharse las diferencias en la capacidad adquisitiva de los diferentes grupos de renta, aquellos en el extremo inferior se ven forzados a residir en aquellas zonas que no han sido previamente elegidas por los individuos del extremo superior. Por tanto, en nuestro contexto, esto sugiere que la desigualdad podría ser un determinante de las diferencias entre tasas de pobreza de los *tracts*, al hacer que las personas de menores rentas se concentren en los mismos lugares. Y si, además, la desigualdad se ve reflejada en diferencias de renta entre distintos grupos sociales, esta también influirá en qué variables socioeconómicas están ligadas a la pobreza en dichos *tracts*.

En lo que concierne a la relación de los tiroteos en masa con la pobreza y la desigualdad, un primer vínculo que parece claro a la luz de los resultados del tercer capítulo es que, si los descensos en el precio de la vivienda provocados por estos eventos en los *census tracts* van seguidos de un proceso de *'filtering'* – según el cual las viviendas son ocupadas sucesivamente por individuos de menor renta –, la disminución de la renta de los habitantes en dicho *tract* puede favorecer incrementos en la tasa de pobreza del mismo. Además, la destrucción o desplazamiento de puestos de trabajo localizados en él actuaría como una política *place-based* inversa. De aquí que una posible primera extensión, condicionada a la disponibilidad de datos anuales, sería comprobar cómo afectan los tiroteos en masa al nivel de renta o a la tasa de pobreza de las áreas afectadas. En cuanto a la relación inversa, desentrañar cómo enlazan la desigualdad y la pobreza con los tiroteos en masa, es algo más sutil. Por definición, al descartar los casos vinculados a otro tipo de delitos, quedan fuera de nuestro estudio aquellos eventos que tienen una motivación directamente económica. Sin embargo, Brodeur and Yousaf (2020) han documentado las características socioeconómicas de una muestra de tiradores, hallando que cerca del 40% enfrentaba dificultades financieras, y que, al menos, un 43% mostraba signos de enfermedad mental o contaba con antecedentes clínicos relacionados. Este último vínculo también es respaldado por otros estudios, como Yelderman, Joseph, West, and Butler (2019) o Lankford and Cowan (2020). Teniendo en cuenta que, tanto en la introducción de la tesis como en las motivaciones de los correspondientes capítulos, hemos visto que la pobreza y la desigualdad están vinculadas a peores condiciones de salud mental, una hipótesis a contrastar, que requeriría de un enfoque multidisciplinar, sería si estos fenómenos económicos favorecen o, mejor dicho, crean el contexto propicio para la ocurrencia de los tiroteos en masa.

Estas últimas reflexiones sobre las interrelaciones de los temas tratados en la presente tesis resaltan la extensa labor investigadora que aún está pendiente para una comprensión más profunda de la pobreza, la desigualdad y la violencia con armas de fuego. En el contexto en el que los ODS han fijado unas metas para la mejora del bienestar futuro pensando en conjunto y que éstas han sido adoptadas por un gran número de agentes sociales modificando sus decisiones y acciones en consecuencia, se puede decir que esta tesis, a su particular manera, ha sido elaborada en paralelo a esto, ya sea directa o indirectamente, al poner el análisis económico como marco de obtención de conocimiento al servicio no solo del enriquecimiento académico, sino también del interés social.

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