UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

PLACE, PEOPLE, AND POLICY: ESSAYS ON REGIONAL DEVELOPMENT, MIGRATION, AND ENTREPRENEURSHIP

A DISSERTATION

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

DOCTOR OF PHILOSOPHY

By

BOWEI DONG

Norman, Oklahoma

2026

PLACE, PEOPLE, AND POLICY: ESSAYS ON REGIONAL DEVELOPMENT, MIGRATION, AND ENTREPRENEURSHIP

A DISSERTATION APPROVED FOR THE
DEPARTMENT OF ECONOMICS

BY THE COMMITTEE CONSISTING OF

Dr. Tyler Ransom (Chair)

Dr. Cynthia Rogers (Co-Chair)

Dr. Gregory Burge

Dr. Deven Carlson

DEDICATED

To my wife,

CASSIDY B MURRAY,

the greatest discovery of my life's journey.

Acknowledgments

Achievements mean more when they are shared with those who walk beside you. This dissertation is not mine alone — it belongs to everyone who believed in me before I fully believed in myself.

To my parents, who carried dreams for me long before I knew how to carry them myself. Your sacrifices are written into every page of this work, even where your names are not. And to my grandmother, whose prayers and endless love have been a constant source of warmth throughout my life — thank you for always believing in me.

To my wife Cassidy: you are my driving force and my peace. You stood with me through every late night, every revision, every moment of doubt, and every small victory. This degree belongs to you as much as it belongs to me. Thank you for choosing this journey with me.

I am deeply grateful to my committee, whose guidance shaped me into the researcher I am today. To Dr. Tyler Ransom and Dr. Cynthia Rogers, my advisors — thank you for your patience, your wisdom, and your unwavering investment in my growth. To Dr. Greg Burge and Dr. Deven Carlson — your challenges pushed me further than I thought I could go, and I am a better scholar for it.

All stories of success are stories of struggle. Throughout this PhD, I did not only complete a dissertation — I completed a transformation. I came into this journey uncertain and unformed, like a caterpillar, and I leave it with wings I did not know I had.

Contents

List of Tables

List of Figures

Abstract

This dissertation examines how localized shocks and place-based policy interventions shape entrepreneurial activity, migration dynamics, and regional development in the United States. The first chapter studies the impact of violent tornadoes on ZIP code-level entrepreneurship. Combining tornado path data from the National Weather Service with startup data from the Startup Cartography Project and employing an event-study framework, I find that startup formation increases by approximately 20% immediately following a tornado before reverting within four years. Entrepreneurial quality does not change in the short run but improves over time. Additional analysis reveals a strong association between SBA disaster loan programs and post-disaster startup formation, underscoring the importance of institutional responses in local recovery. The second chapter evaluates the Tulsa Remote program, a large-scale remote-worker attraction initiative offering $10,000 relocation grants. Using county-level migration data and individual microdata, I document increased interstate in-migration alongside reduced intrastate inflows and higher intrastate outflows. Migration responses are strongest among married, middle-aged individuals with moderate incomes from high-cost metropolitan areas, highlighting both the potential and trade-offs of place-based incentives. The third chapter (joint with Cynthia Rogers) provides a comprehensive overview of Remote Worker Attraction programs nationwide, documenting substantial heterogeneity in program design. Drawing on the Tiebout Hypothesis and yardstick competition theory, we argue that remote work decouples employment from residential location, intensifying interjurisdictional competition. Together, the findings demonstrate that both natural shocks and policy interventions meaningfully shape entrepreneurship and migration patterns, contributing to a broader understanding of regional development in an era of increasing geographic flexibility.

Chapter 1

Entrepreneurship and Economic Resilience After Violent Tornadoes

1.1 Introduction

Natural disasters impose severe human and economic costs, from loss of life to destruction of infrastructure. Hurricane Katrina in 2005 caused about 1,570 deaths in Louisiana and $40–50 billion in damages (Kates et al., 2006). The 2013 Moore, Oklahoma tornado destroyed over 1,100 homes, affected 13,500 people, and caused $2 billion in losses, making it the costliest tornado since the 2011 Joplin disaster (National Weather Service, 2013). The 2018 California wildfires caused $148.5 billion in damages—about 1.5% of state GDP—with 52% of losses occurring outside the state through indirect ripple effects (Wang et al., 2021).

While the immediate consequences of natural disasters typically manifest as severe economic and social hardships (Ellson, Milliman, & Roberts, 1984), these catastrophic events can paradoxically function as catalysts for economic renewal. This phenomenon aligns with Schumpeter's concept of *creative destruction*, which describes a process in which new innovations replace and make obsolete older innovations (Schumpeter, 1942). Through this lens, natural disasters may generate positive long-term economic effects by accelerating capital replacement, modernizing infrastructure, and triggering knowledge spillovers (Crespo Cuaresma, Hlouskova, & Obersteiner, 2008; Hallegatte & Dumas, 2009; Loayza et al., 2012; Skidmore & Toya, 2002).

I examine the effects of violent tornadoes on entrepreneurship quantity and quality, evaluating whether they result in creative destruction or economic disruption. Violent tornadoes can destroy not only physical infrastructure but also economic foundations. Despite their destructive power and repeated occurrence, tornadoes remain relatively underexplored in the disaster economics literature compared to hurricanes, floods, or wildfires.

Entrepreneurship and business start-ups contribute to economic development through job creation, innovation, and broader welfare gains (Acs & Audretsch, 1988; Baumol, 2014; Haltiwanger, Jarmin, & Miranda, 2013; Schumpeter, 1934; Wennekers & Thurik, 1999). Examining how tornadoes affect entrepreneurial activity is therefore crucial for designing recovery strategies that not only address immediate needs but also strengthen long-term resilience and growth.

This research contributes to the disaster economics and entrepreneurship literature in several key ways. First, it provides the first rigorous evidence on how violent tornadoes affect both the quantity and quality of entrepreneurship on the ZIP code level. Second, it introduces Small Business Administration (SBA) disaster loans—especially home and business loans—as key recovery mechanisms, revealing that housing stability plays a crucial role in promoting startup activity. Third, it demonstrates important temporal and qualitative differences in entrepreneurial responses, showing that while startup formation increases sharply, quality improvements are limited and delayed.

I use ZIP code-level data from multiple sources: tornado tracks and intensity from the National Oceanic and Atmospheric Administration (NOAA)'s National Weather Service Storm Prediction Center (SPC); entrepreneurship measures from the Startup Cartography Project (SCP); socioeconomic characteristics, such as population and median household income, from the American Community Survey (ACS); industry-level data from the U.S. Census ZIP Code Business Patterns (ZBP); disaster declarations from the Federal Emergency Management Agency (FEMA); and disaster loan program statistics from the U.S. Small Business Administration (SBA).

While existing literature on tornadoes' socioeconomic impacts has predominantly employed county-level analysis (e.g., Paudel (2022); Huesler (2024); Kukeli (2025)), I advance the literature by using ZIP code-level data, which provides finer geographic granularity and more precise estimates of tornado impacts on entrepreneurship. This approach offers three main advantages: First, tornadoes are highly localized, so ZIP-level analysis better captures true treatment effects; second, it reduces spillover bias, as county-level studies may mix treated and untreated areas; and finally, it allows for improved control of local heterogeneity.

I analyze 227 tornado tracks that occurred in 18 states across the United States during a 29-year period from 1988 through 2016. The primary econometric approach in this study is a staggered event-study design estimated using two-way fixed effects (TWFE). To address potential biases associated with staggered treatment timing, I also implement the Sun and Abraham (2021) estimator, as well as the Callaway and Sant'Anna (2021) difference-in-differences framework, as robustness checks. These complementary methods ensure that the estimated dynamic treatment effects are not driven by model specification or heterogeneity in treatment timing.

I find that violent tornadoes lead to an approximately 20% increase in startup formation immediately, which normalizes within four years. In contrast, entrepreneurial quality remains largely unchanged in the short term—likely due to the low survival rates of new ventures (Bayar, Boudreaux, & Yarbrough, 2025; Gallagher, Hartley, & Rohlin, 2023)—but rises gradually over the long run. These patterns are robust across multiple specifications and alternative estimators, offering actionable insights for urban planners and local economic stakeholders.

Additionally, I examine the effects of violent tornadoes on establishment size and industry composition. The results show that while startup formation rises significantly after such events, the overall number of establishments remains largely unchanged. This pattern is consistent with the concept of creative destruction, where new businesses replace older ones rather than expanding the total market size.

I also observe heterogeneity effects across tornado intensities, with EF5 tornadoes exhibiting roughly twice the impact on entrepreneurship quantity as EF4 tornadoes.[1] EF4 tornadoes are associated with an immediate startup formation increase of about 20%, which normalizes after three years, whereas EF5 tornadoes generate approximately 40% increases that may persist up to five years. This divergence aligns with the catastrophic nature of EF5 events, supporting both the causal model and the view that intensity matters in the creative destruction process. While both

[1]The Enhanced Fujita Scale (EF Scale), implemented on February 1, 2007, is utilized to assign a tornado a rating based on estimated wind speeds and associated damage levels (ranging from EF0 to EF5).

categories spur new firm creation, the larger and more persistent surge following EF5 tornadoes suggests a need for specialized entrepreneurship centers, tailored loan programs, and extended development services to channel heightened entrepreneurial activity toward sustainable recovery and to mitigate potential market instability.

These contributions enhance our understanding of how natural disasters can function as catalysts for economic renewal through entrepreneurship, while also identifying the specific conditions, mechanisms, and temporal patterns that govern this process. The findings have important implications for disaster recovery policies, suggesting that targeted support for new business startups during a specific post-disaster window may optimize long-term entrepreneurial quality and resilience.

This paper is organized as follows: Section 1.2 describes the datasets used in this study. Section 1.3 outlines the empirical models, methodology, and key identification challenges. Section 1.4 presents the preliminary results. Section 1.5 investigates heterogeneity of tornado intensity. Section 1.6 explores underlying mechanisms. Section 1.7 provides robustness checks. Section 1.8 concludes.

1.2 Data

1.2.1 Tornado Data

I use ZIP code-level tornado data from the National Weather Service (NWS), specifically from the Storm Prediction Center (SPC), which covers the period from 1950 to 2023. I specifically examine tornado events occurring between 1988 and 2016. I focus on 227 violent tornado tracks in 18 states: Alabama, Arkansas, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Minnesota, Mississippi, Missouri, Nebraska, North Dakota, Ohio, Oklahoma, South Dakota, Tennessee, and Texas.[2] These states accounted for 90.1% of all (252) violent tornadoes in the U.S. during this time frame. The National Weather Service (2025a) categorizes tornadoes on

[2]According to Gallagher et al. (2023), they use several standards to decide if a tornado should be included: (1) the tornado occurred from 2002–2013 to match the period covered by individual and business financial data; (2) it had a Fujita (F) or Enhanced Fujita (EF) rating of 4 or 5; and (3) a high-quality damage path map, generally created by the NWS, was available. My selection of tornado tracks follows their work.

a spectrum of intensity: EF0-1 tornadoes are classified as weak, EF2-3 as strong, and EF4-5 as violent. This official classification framework distinguishes the most destructive tornadoes (EF4-5) from those with moderate or minimal impact. The distribution of all tornadoes (EF0-EF5) can be found in Figure 1. As seen, weak tornadoes make up the vast majority. As the EF level increases, the number of occurrences decreases. According to the National Weather Service (2025b), violent tornadoes are extremely rare, accounting for only about 2% of all tornadoes. However, when they do strike, they cause devastating destruction, demolishing homes and businesses and often resulting in loss of life. Among the 227 violent tornadoes, 206 are classified as EF4, while 21 are categorized as EF5. Based on this dataset, I illustrate the spatial and temporal distributions of violent tornadoes, as shown in Figure 2 and Figure 3.

Since a tornado can traverse multiple ZIP codes, this research utilizes datasets that include both initial points and paths. The data is primarily provided at the county level; however, the county level may not accurately capture a highly localized event like tornadoes. To address this issue, I first connect the starting point (longitude and latitude) with the ending point (longitude and latitude), then extract the ZIP codes covered by this path. I roughly assume that the paths follow a straight line and use the variable "width" as a buffer around each tornado to plot the affected ZIP codes.

An example is the 2013 Moore tornado, which occurred on May 20th, 2013, in Moore (Cleveland County), Oklahoma. This can be seen in Figure A.1, where I compare the actual preliminary track of this tornado (Figure A.1, panel (a)) with the tornado path I generated using the data available from NOAA (Figure A.1, panel (b)). These two paths roughly capture the same tracks and cover the same ZIP code districts.

1.2.2 The Measurement of Entrepreneurship

Entrepreneurship serves as the main outcome variable and is obtained from the Startup Cartography Project (SCP) (Andrews et al., 2019). SCP provides a new set of entrepreneurial ecosystem statistics for the United States, covering the years 1988 to 2016. It offers users four key entrepreneurship statistics: the rate of formation of registered firms, the level of entrepreneurial quality for a given population of startups, the potential for entrepreneurship growth within a given region and startup cohort, and the performance over time of a regional entrepreneurial ecosystem in realizing the potential performance of firms founded within a given location and time period ((Fazio et al., 2019)).

Startup Formation Rate (SFR): Represents the number of for-profit, new business registrations over a specific time period and geographic region. Denoted as N_{rt}, it is simply measured as the total count of new business registrations in ZIP code Tabulation Areas (ZCTA) region r during year t (Tartari & Stern, 2021). SFR closely aligns with other quantity-based entrepreneurship metrics, such as the Business Dynamics Statistics (BDS) and the Global Entrepreneurship Monitor (GEM). This variable serves as a measure of entrepreneurial *quantity*.

Entrepreneurial Quality Index (EQI): The predictive analytics approach outlined above is then integrated with the population of business registrants to develop an index of entrepreneurial quality for any specified group of firms (e.g., all firms within a particular cohort or those meeting specific criteria). Specifically, EQI is constructed at the ZCTA-year level by aggregating entrepreneurial quality estimates, denoted as $\theta_{i,r,t}$, and calculating their average within a given ZCTA region and year.

$$\theta_{i,r,t} = P(g_{i,r,t+s} \mid H_{i,r,t}) = f(\alpha + \beta H_{i,r,t}) \tag{1.1}$$

Entrepreneurial quality is measured by analyzing the relationship between observed growth outcomes and the initial characteristics of start-ups within the population of at-risk firms. Specifically, for a firm i established in region r at time t, with start-up characteristics $H_{i,r,t}$ at birth, its growth outcome $g_{i,r,t+s}$ is observed s years after founding. This relationship is then estimated to assess entrepreneurial *quality*:

$$EQI_{r,t} = \frac{1}{N_{r,t}} \sum_{i \in \{I_{r,t}\}} \theta_{i,r,t} \tag{1.2}$$

In the context of estimating entrepreneurial quality in a specific region and year, denote: $\{I_{r,t}\}$ is the set of all firms in region r during year t.

Regional Entrepreneurship Cohort Potential Index (RECPI): represents the overall inherent potential of a cohort of start-ups within a specific region, so it is considered *quality-adjusted* *quantity*. This potential is determined by both the quality of entrepreneurship in that area and the number of firms operating there, serving as a measure of quantity. Therefore, Fazio et al. (2019) define the RECPI as the product of the entrepreneurial quality in region r during year t ($EQI_{r,t}$) and the number of firms in that region-year.

$$RECPI_{r,t} = EQI_{r,t} \times N_{r,t} \tag{1.3}$$

Regional Ecosystem Acceleration Index (REAI): While RECPI estimates the expected number of growth events for a given group of firms, over time we can observe the realized number of growth events from that cohort. This difference can be interpreted as the relative ability of firms within a given region to grow, conditional on their initial entrepreneurial quality, or *trends in the effect of the US entrepreneurial ecosystem*. Variation in ecosystem performance could result from differences across regional ecosystems in their ability to nurture the growth of start-up firms, or changes over time due to financing cycles or economic conditions. REAI is defined as the ratio of realized growth events to expected growth events:

$$REAI_{r,t} = \frac{\sum g_{i,r,t}}{RECPI_{r,t}} \tag{1.4}$$

These public records are generated when individuals register a new business, such as a corporation, LLC, or partnership (Fazio et al., 2019).

1.2.3 Socioeconomic Demographics

To ensure comparability between treated and control ZIP codes, I incorporate a range of socioeconomic variables, including population size, household income, and industry composition. Population data is sourced from the American Community Survey (ACS) 5-year estimates provided by the U.S. Census Bureau, using total population figures from 2011 at the ZIP code level (U.S. Census Bureau, 2023a). These values serve as a threshold criterion to filter ZIP codes and maintain demographic consistency across treatment groups. A key limitation of this dataset, however, is that it does not extend back to the primary study period (1988–2016), preventing the establishment of a true pre-treatment population baseline.

Household income is similarly drawn from the ACS 5-year estimates, with 2011 data used to classify ZIP codes into low-income and high-income groups (U.S. Census Bureau, 2023b). This classification is applied uniformly across all years of the study to ensure internal consistency. As with population data, the absence of earlier-year figures limits the ability to capture pre-existing income differences that may influence post-disaster entrepreneurial behavior.

Industry-level data is obtained from the U.S. Census County Business Patterns (CBP) and ZIP Code Business Patterns (ZBP), which span from 1993 to 2022. For the purposes of this analysis, data from 1998 to 2016 is used, reflecting the period after the introduction of ZIP code-level detail in 1994 and the full implementation of the North American Industry Classification System (NAICS) in 1997 (Bureau of Labor Statistics, 2023). This dataset offers granular information on the number of establishments across industries, classified by NAICS codes and employment size. It provides a valuable basis for investigating whether observed increases in startup formation after tornadoes contribute to growth in the number of active business establishments.

1.2.4 Disaster Declarations and Loan Data

The Disaster Declarations Summaries dataset, provided by the Federal Emergency Management Agency (FEMA), is a comprehensive record of all federally declared disasters. The FEMA Disaster Declarations Summary includes all official disaster declarations dating back to 1953, covering three types of declarations: major disasters, emergencies, and fire management assistance. This dataset contains information on declared recovery programs and affected geographic areas, though county-level data is only available from 1964 onward, and fire management records are incomplete due to historical limitations (FEMA, 2020). For this research, I use this dataset to identify tornado-specific declarations, extracting relevant details such as disaster type and disaster number to focus on tornado-related impacts.

Following a declared disaster, the SBA provides low-interest, long-term disaster loans to assist with damages not covered by insurance or other sources of recovery. These loans are available to businesses of all sizes, private nonprofit organizations, homeowners, and renters. The disaster loan dataset contains non-personally identifiable (non-PII) data from the U.S. Small Business Administration (SBA) Disaster Loan Program provides data from 2000 to 2022 (U.S.

Small Business Administration, 2025a), which I use for the period 2000 to 2016.

To ensure a targeted analysis of tornado-affected areas, I link this dataset with the FEMA Disasters and Other Declarations database. This integration allows me to focus exclusively on SBA disaster loans provided to regions impacted by tornadoes, ensuring that the analysis accurately reflects the economic recovery process and financial assistance dynamics specific to tornado disasters.

1.3 Empirical Framework

Consider a ZIP code-level staggered event study expressed by Equation 1.5 (Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021; Sun & Abraham, 2021):

$$Y_{zt} = \alpha + \sum_{\substack{k=m, \\ k \neq -1}}^{n} \beta_k T_{zk} + \phi_z + \gamma_t + \epsilon_{zt} \tag{1.5}$$

where Y_{zt} represents the entrepreneurial outcomes (SFR, EQI, RECPI and REAI) for ZIP code z in year t.[3] The dummy variables T_{zk} indicate whether a ZIP code is k periods away from the violent tornado, taking the value of 1 if ZIP code z is k periods from treatment, and 0 otherwise. For never-treated ZIP codes, these indicators are always 0.

The specification includes ZIP code fixed effects (ϕ_z) to control for time-invariant local characteristics and year fixed effects (γ_t) to account for common temporal shocks. Standard errors are clustered at the ZIP code level to account for serial correlation. The coefficients of interest, β_k, measure the treatment effects k periods before or after tornado exposure, relative to the year immediately before the tornado. In determining the event study window, I carefully select the period from 10 years before to 10 years after the tornado events (Deryugina, 2017).

In addition to a TWFE event study model, I also employ the Sun and Abraham (2021) event study approach. This method provides more reliable estimates by properly accounting for variation in treatment timing and avoiding contamination from already-treated units in the control group.

[3] I use log-transformed SFR, z-scored EQI, and log-transformed RECPI and REAI. EQI is standardized using z-scores because it contains extremely small values (mean = 0.000389) and represents an index measuring the actual level.

Some ZIP codes experienced multiple violent tornado events over the years.[4] To solve this issue, I created a system that detects violent tornadoes at the ZIP code level. If a ZIP code is hit by multiple violent tornadoes, I first compare the EF level, only keeping the one with the highest EF record. Secondly, if the EF levels are the same, I only consider the most recent one. By prioritizing the highest EF level tornado, I capture the most severe impact a location experienced. Using the most recent tornado when intensities are equal ensures up-to-date response data while avoiding recovery period overlaps. Notably, only around 5% of ZIP codes in my sample were hit by multiple violent tornadoes and required processing through this system. Others, such as Deryugina (2017), consider only the first hurricane within the sample period as the treatment. I adopt the same approach in my robustness check section.

In this research, I focus exclusively on tornadoes classified with an Enhanced Fujita score of 4 or 5 (Gallagher et al., 2023). When assessing tornado-related damage, surveyors compare the damage to a set of Damage Indicators (DIs) and Degrees of Damage (DoD) to estimate the range of wind speeds likely produced by the tornado (National Weather Service, 2024). The EF scale is an *estimated* value, not a directly measured one, and is based on both DIs and DoD.[5] However, DoD itself is influenced by multiple factors, such as population, buildings, and other variables. This makes the EF level highly endogenous, adding complexity to the selection of appropriate control units.

To address this challenge, I collect ZIP code-level population data for the year 2011 from the U.S. Census.[6] I define control units as ZIP codes with populations of more than 3,000 people that have never been impacted by an EF4/5 tornado during 1988 to 2016.[7] Since tornadoes

[4]For example, the City of Moore, Oklahoma, which endured violent tornadoes in 1999, 2003, 2010, and 2013 across multiple ZIP codes (73065, 73170, 73160, 73165), represents the type of location where this processing method was applied to ensure methodological consistency. Further robustness checks suggest there is no temporal sensitivity with or without this selection process.

[5]For example, the most recent EF5 tornado struck Moore, Oklahoma, on May 20, 2013, with peak winds of 200–210 mph (320–340 km/h). Just 11 days later, a tornado near El Reno reached radar-estimated winds of 313 mph (504 km/h) (Bluestein, Snyder, & Houser, 2015; Lyza, Flournoy, & Alford, 2024; National Weather Service, Norman, OK, 2013), yet was rated only EF3. The likely reason is exposure: Moore's urban density provided more structural damage evidence, while sparsely populated El Reno offered fewer indicators—suggesting EF ratings partly reflect population density and visibility of damage, not storm strength alone.

[6]Since the dataset spans from 2011 to 2023, I use 2011 data to identify control ZIP codes with a population greater than 3,000. These selected ZIP codes are then retained across all years, ensuring the analysis focuses only on these control units.

[7]A concern with using population thresholds is that disasters might alter local population, biasing estimates. To test this, I use IRS personal exemptions as a ZIP-level proxy and model the impact of violent tornadoes on population. I find no significant long-term changes, consistent with Raker (2020), who also report no net population

tend to cause more damage in urban areas than in rural regions, this difference in damage can indirectly affect the EF rating. To ensure the consistency of the results, I also consider using adjacent ZIP codes as control units in my robustness checks.

1.4 Baseline Results

As shown in Figure 4, immediately after violent tornadoes, SFR increases by around 22% in year 0, and this impact persists for 4 years. After year 4, the effects revert. The impact ranges from 15.12% to 21.07% according to a TWFE estimate, and from 16.61% to 22.77% according to the Sun and Abraham (2021) method. These similar coefficients across both methods demonstrate that SFR increases by approximately 20% following a violent tornado.

EQI does not exhibit a significant increase during the first five years following a tornado, although a gradual long-run improvement is observed in Figure 5. This suggests that while startup formation rises sharply in the short term, the quality of new businesses does not immediately improve. Instead, quality appears to increase over time as quantity accumulates. One possible explanation for this delayed effect is the low survival rate of new firms after natural disasters, as noted by Gallagher et al. (2023). Many newly established businesses fail in the short run, which may offset any immediate gains in average quality. Over time, however, as less viable firms exit the market and stronger ones persist, overall entrepreneurial quality gradually improves.

RECPI shows a significant increase. As RECPI is a composite measure combining quantity (SFR) and quality (EQI), and given that EQI does not change significantly in the short run, I can conclude that SFR is the main driver of the observed RECPI increase. RECPI rises by approximately 20% as well, with a pattern highly consistent with the SFR trends. Finally, REAI does not exhibit significant changes over the study period.

These event study graphs also support the parallel trend assumption. Average treatment effect on the treated (ATT) can be seen in Table A.1. The result indicates that violent tornadoes have an average increase of 10.38% on SFR. EQI does not show a significant effect, possibly due to the lagged impacts.

The identified 4-year persistence window represents a critical opportunity for policy inter-

shifts after severe tornadoes.

vention following violent tornadoes. Rather than implementing temporary relief efforts alone, this research suggests that sustained policy interventions spanning the full 4-year impact period could potentially enhance both the quantity of post-disaster entrepreneurship, with effective intervention, quality can be improved as well.

The surge in startup formation following violent tornados aligns with prior research on disaster-induced entrepreneurship (Bayar et al., 2025; Monllor & Murphy, 2017), which suggests that disasters can create market opportunities and necessitate new business creation to replace damaged establishments. The lack of quality improvement, however, indicates that disaster-induced entrepreneurship may be more necessity-driven than opportunity-driven, potentially leading to businesses with lower growth prospects and survival rates. Future research could explore interventions that not only stimulate post-disaster business formation but also enhance the quality and resilience of these new ventures.

1.5 Heterogeneity

This section examines how the impacts vary with tornado intensity.

Figure 6 includes two panels: panel (a) showcases the heterogeneity effects of EF4 and EF5 tornadoes using a TWFE estimate, while panel (b) shows the effects using the Sun and Abraham (2021) method. Both panels indicate that there are significantly different impacts between EF4 and EF5 tornadoes. EF4 tornadoes show an immediate increase in SFR of approximately 20% (ranging from 14% to 19.02% according to TWFE, and from 15.24% to 20.22% according to Sun and Abraham (2021)), with this impact disappearing after year 3, indicating a similar pattern to the combined EF4 and EF5 impacts on SFR discussed earlier. EF5 tornadoes, on the other hand, demonstrate much more dramatic impacts on SFR, resulting in approximately 40% increases (ranging from 27.07% to 44.71% according to TWFE, and from 29.83% to 48.35% using Sun and Abraham (2021)). Both TWFE and Sun and Abraham (2021) methods demonstrate highly similar patterns, with the key difference being that for EF5 tornadoes, the Sun and Abraham (2021) method shows longer-lasting impacts on SFR, suggesting that the effects of EF5 tornadoes could potentially extend to year 5 before normalizing.

These results demonstrate that EF5 tornadoes' impacts are substantially different from those of EF4 tornadoes, with EF5 tornadoes' impacts on SFR being approximately twice as large as those of EF4 tornadoes. This finding aligns with intuitive expectations given the catastrophic nature of EF5 events and further supports the causal model, indicating that the entrepreneurial responses to tornadoes are not coincidental. Additionally, it reinforces the theory that intensity matters in the creative destruction process, as more violent tornadoes cause deeper impacts on entrepreneurial activity.

The difference in entrepreneurial response between EF4 and EF5 tornadoes suggests that policymakers should develop intensity-calibrated support systems. Specifically, communities affected by EF5 tornadoes may require more substantial and longer-duration economic support programs to effectively channel the surge in entrepreneurship toward sustainable economic recovery. While both intensity categories stimulate startup formation, the approximately double impact of EF5 tornadoes indicates that these communities may need not just more resources, but potentially different types of entrepreneurial support programs tailored to address the more extensive destruction and subsequent rebuilding opportunities. Local governments and economic development agencies should consider implementing specialized entrepreneurship centers, targeted loan programs, and extended business development services in areas affected by the most severe (EF5) tornadoes to maximize the potential long-term benefits of post-disaster entrepreneurship while mitigating potential market instabilities caused by such dramatic shifts in the local business environment.

1.6 Mechanisms

This section examines the possible mechanisms behind the increased SFR after a violent tornado. First, I examine SBA Disaster Loan's impacts on entrepreneurial activity. Second, I explore changes in risk perception following existing literature. Finally, I examine violent tornadoes' impacts on establishments.

1.6.1 Disaster Assistance

Following a declared disaster, SBA provides critical disaster assistance through low-interest, long-term loans for damages *not* covered by insurance. These loans are available to businesses, nonprofits, homeowners, and renters, serving as a financial lifeline for affected communities (U.S. Small Business Administration, 2026).

Business Physical Disaster Loans: The SBA offers up to $2 million in disaster loans to businesses and nonprofits to cover uninsured losses, repair or replace damaged assets, and refinance mortgages when insurance proceeds must be applied to debt. Loans cannot fund business expansion unless required by building codes, but up to 20% of verified damage may be included to provide mitigation assistance.[8] Repayment starts after a 12-month deferral with no interest accruing during that period. Interest rates are capped at 4% for those lacking credit access and 8% otherwise.

Home and Personal Property Loans: Homeowners can borrow up to $500,000 to repair their primary residence, and both homeowners and renters may borrow up to $100,000 to replace personal property. Insurance proceeds reduce eligible loan amounts. As with business loans, up to 20% of verified damage may be included to provide mitigation assistance. Repayment also begins after a 12-month deferral with no interest in that period. Loans can extend up to 30 years, with collateral required above certain thresholds, though lack of collateral alone does not disqualify applicants.

The programs ease liquidity constraints through deferred payments and low interest rates, freeing resources for future entrepreneurship. They may also strengthen long-term resilience by providing mitigation assistance and refinancing options. SBA disaster loans not only aid recovery but can facilitate post-disaster startup formation in communities where necessity- and opportunity-driven entrepreneurship arise during rebuilding.

Using SBA data from 2000–2016 matched to FEMA tornado disaster declarations, I analyze how loan disbursements affect entrepreneurial activity. Immediately after violent tornadoes (year 0), SBA-approved business loans increase by approximately 210%, while home loans rise about

[8]Eligible SBA disaster loan borrowers may choose to receive expanded funding to help mitigate their home or business against future disasters (U.S. Small Business Administration, 2025b).

520%, as shown in Figure 7. The impacts differ by intensity: EF4 tornadoes lead to roughly 160% more business loans and 450% more home loans, while EF5 tornadoes produce much larger increases—520% for business loans and 1,080% for home loans, as shown in Figure 8. This pattern aligns with the observed intensity heterogeneity, confirming that EF5 tornadoes have effects at least twice as large as EF4 events.

Table 1.2 shows TWFE OLS estimates linking SBA loans to startup outcomes as a way to test if SBA loans are the mechanisms through which tornadoes affect entrepreneurship. A 1% increase in business loans correlates with a modest 0.005% rise in entrepreneurial quantity but a decline in entrepreneurial quality, suggesting these loans mainly spur necessity-driven, lower-quality ventures. In contrast, home loans have a stronger positive association: a 1% increase yields a 0.01% rise in SFR without harming business quality.

According to Table 1.3, the magnitude is substantial: the 520% surge in home loans corresponds to a 5.2% overall increase in SFR, with EF4 tornadoes contributing a 4.4% rise and EF5 events an 10.6% rise. Business loans account for smaller gains—about a 1.1% overall increase in SFR. Altogether, home loans explain around a quarter of the total observed increase in new business formation, while business loans account for about 5%.

Further analysis splits ZIP codes by income level (Table 1.4). Home loans have similar effects on startup formation in both low- and high-income regions, while business loans show no significant SFR impact in wealthier areas. In lower-income areas, business loans significantly reduce quality, consistent with necessity-driven entrepreneurship. Home loans do not show a negative quality effect.

Figure 9 highlights that SBA loan amounts are higher in wealthier regions, reflecting more valuable properties and businesses. Table 1.5 presents quartile regression results, showing business loans have a non-monotonic relationship with SFR—positive in lower-income regions, negative in middle-income areas, and strongly positive in the highest-income quartile. Home loans consistently boost startup formation, especially in middle-income areas. Regarding quality, business loans harm startup quality most in the poorest areas, while home loans have mixed effects—positive in Q1 but negative in Q2 and Q3.

In disadvantaged communities, restoring housing appears more effective for spurring new ventures than providing direct business capital. For policymakers, this underscores the need to prioritize residential recovery and ensure SBA loans are accessible and targeted to foster both housing security and higher-quality entrepreneurship.

1.6.2 Risk Perceptions

The psychological impact of disasters on risk perceptions offers a compelling framework for understanding the entrepreneurial response observed in this study. Two key studies provide particularly relevant insights:

Hanaoka, Shigeoka, and Watanabe (2018) find that men who experienced higher intensity earthquakes became more risk tolerant, with these effects persisting for five years after the event at almost the same magnitude. Their research demonstrated increased engagement in gambling activities among affected individuals, suggesting a fundamental shift in risk assessment following disaster exposure.

Similarly, Bernile, Bhagwat, and Rau (2017) examined how CEOs' early-life disaster experiences affect corporate risk-taking, finding that those who experienced fatal disasters without suffering extreme negative personal consequences became desensitized to risk, adopting more aggressive corporate policies.

These studies collectively illuminate the mechanisms potentially driving the response documented in my research on violent tornadoes. The approximately 20% increase in startup formation following EF4-5 tornadoes that persists for about 4 years likely reflects altered risk perceptions among residents in affected areas. Violent tornado survivors may be more willing to undertake the inherent risks of launching new businesses, particularly those who witnessed the destructive power but retained sufficient resources to start ventures.

1.6.3 Establishments

I also examine the impacts of violent tornadoes on existing establishments using data from the County Business Patterns (CBP) and the ZIP Code Business Patterns (ZBP) from the U.S. Census. First, I analyze the effects on the size, focusing on establishments with 1 to 99 employees. The results, presented in Figure A.2, indicate that violent tornadoes do not significantly alter the overall number of establishments.

Next, I examine the impacts of violent tornadoes on establishments by industry. I focus on six industries: construction, manufacturing, retail trade, wholesale trade, transportation, and professional services. The results show that most of these industries do not experience a significant change following violent tornadoes (see Figure A.3), However, the retail trade industry experiences an immediate decline of approximately 1.5% in overall establishments. This could indicate that retail businesses are particularly vulnerable to tornado disruptions, potentially due to physical damage, supply chain interruptions, or shifts in consumer demand.

It is important to distinguish between SFR and the total number of establishments. SFR measures the number of new business registrations, whereas establishments refer to the total number of active businesses in the market. The findings suggest that while SFR significantly increases after violent tornadoes, the overall number of establishments remains largely unchanged.[9] This aligns with the theory of creative destruction, where new businesses replace old ones rather than leading to a simple expansion of the market.[10]

1.7 Robustness Checks

This section documents comprehensive robustness checks validating the impact of violent tornadoes on entrepreneurship through five approaches: (1) intensity tests comparing EF4-5 versus EF0-3 tornadoes; (2) temporal sensitivity analyses with varied treatment timing; (3) spatial checks using adjacent ZIP codes as alternative controls; (4) methodological validation using Callaway and Sant'Anna (2021) estimator; and (5) standard placebo test.

1.7.1 Intensity Sensitivity

The first, and one of the most important robustness checks I have undergone is to replace EF4 and EF5 tornadoes with EF0, EF1, EF2, and EF3 tornadoes, to test if they would generate the

[9] One limitation of this analysis stems from the data. The ZBP dataset does not include information on the number of firms exiting the market, nor does SCP provide industry-specific details on startup formation. As a result, I can only capture the overall trend rather than the heterogeneity across industries. Additionally, the number of establishments serves only as a proxy measure, reflecting the broader market status rather than directly indicating startup formation and business closures.

[10] This may also suggest that some newly established firms exit almost immediately after entry.

same impact as EF4 and EF5 ones do. To achieve this goal, I randomly selected 600 EF0-3 tornadoes from the pool.[11] By repeating this process multiple times, the results show that EF0-3 tornadoes do not cause similar impacts as EF4-5 tornadoes as shown in Figure 10 . The overall impact on SFR appears to be statistically insignificant.

This result supports the statement that only if the intensity reaches a certain level will the creative process be realized. This can also provide an important distinction between EF0-3 and EF4-5 tornadoes for policy makers to aid and fund.

1.7.2 Temporal Sensitivity

In this section, I analyze the sensitivity to treatment time. Firstly, I intentionally delay the treatment year by 5 years to observe the trend. After postponing the treatment by 5 years, I find no significant change from year 0 to year 3 anymore. This strongly supports my finding that the increase is caused by tornadoes, not by coincidence.

Secondly, instead of using the original method—comparing the EF level and keeping only the most recent one—I only consider the first one during the time window by default (Deryugina, 2017).

After considering only the first treatment time, there is no significant change in this pattern, with coefficients remaining stable and reliable. This demonstrates that the finding of violent tornadoes increasing SFR by 20% is not dependent on specific treatment time criteria. These results also indicate that my current strategy does not bias the results.

1.7.3 Spatial Sensitivity

I identified all neighboring ZIP code units that did not get hit by violent tornadoes during 1988 to 2016, as seen in Figure 11.

First, I defined control units as the neighboring units that didn't get hit and have a population threshold of 3000 to make the analysis consistent with the major design. The result exhibits a highly consistent pattern with the main outcome: Violent tornadoes increase SFR by approxi-

[11]As the number of EF0-3 tornadoes is much larger than violent tornadoes, which only account for 1.1% of the overall tornadoes during 1988 to 2016 (see Figure 1)

mately 20%. Secondly, I only considered neighboring areas without considering the population threshold. The result indicates a similar pattern. Overall, the conclusion is still valid.

1.7.4 Alternative Method

In this section, I utilize the Callaway and Sant'Anna (2021) method to validate my primary findings, as illustrated in Figure 12. The results demonstrate that immediately following a violent tornado, SFR increases significantly in year 0, with the impact peaking at 27.7%—higher than the estimates from both TWFE and Sun and Abraham (2021) approaches. The effect gradually diminishes over time, with the overall impact ranging from 14.4% to 27.7%, indicating a wider impact interval than observed with the other methods. Notably, the Callaway and Sant'Anna (2021) approach reveals a more extended duration of impact, with statistically significant effects persisting for approximately 6 years, compared to the 4-year window identified by the alternative methods. Despite these differences in magnitude and duration, the estimates remain fundamentally consistent with my main results, reinforcing the central finding that violent tornadoes substantially increase entrepreneurial activity.

1.7.5 Placebo Test

Finally, I conduct a placebo test by randomly assigning synthetic treatment years to control units that were never affected by violent tornadoes. The results show no significant changes in startup formation rates following these fictitious tornado events. This effectively rules out the possibility that my main findings could be attributed to systematic temporal trends or statistical artifacts in the model specification, further strengthening the causal interpretation of the relationship between violent tornadoes and entrepreneurial activity.

1.8 Conclusion

My research builds on creative destruction theory by examining the effects of violent tornadoes on entrepreneurial activity from 1988 to 2016 across 18 states in the U.S.

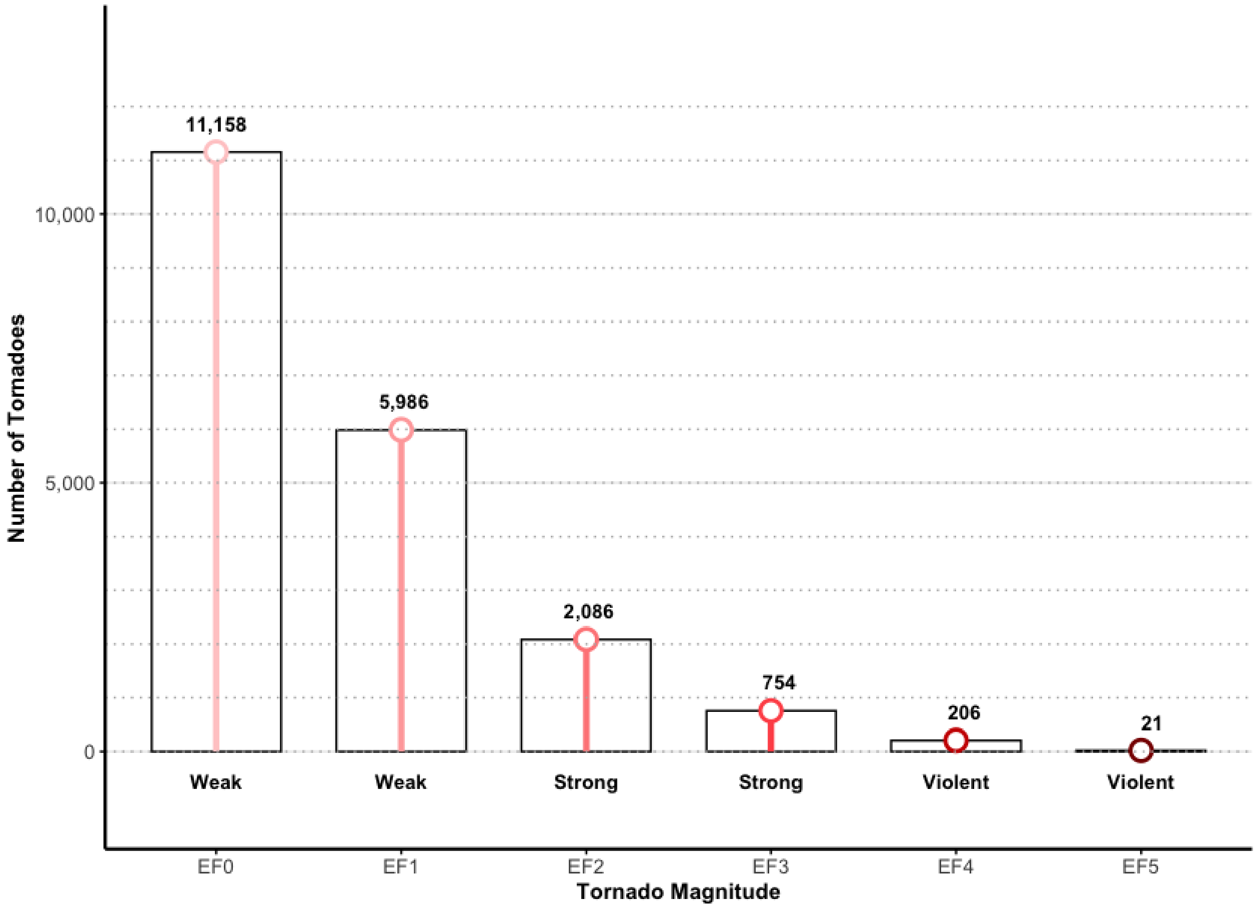
I find that ZIP codes impacted by violent tornadoes experience at least a 20% increase in startup formation. This effect persists for four years. Further heterogeneity analysis shows that EF5 tornadoes generate nearly twice the effect compared to EF4 tornadoes. While the quality of these businesses does not increase immediately, it exhibits a gradual improvement in the long run, suggesting a possible rise in quality through competition.

Additionally, my findings show that SBA disaster loan programs significantly stimulate entrepreneurial activity, with home loans playing a crucial role in post-tornado recovery.

My research expands the understanding of natural disasters and entrepreneurship, while also offering valuable policy implications. Future work should focus on firm-level data to reveal more granular effects often overlooked in disaster and entrepreneurship research.

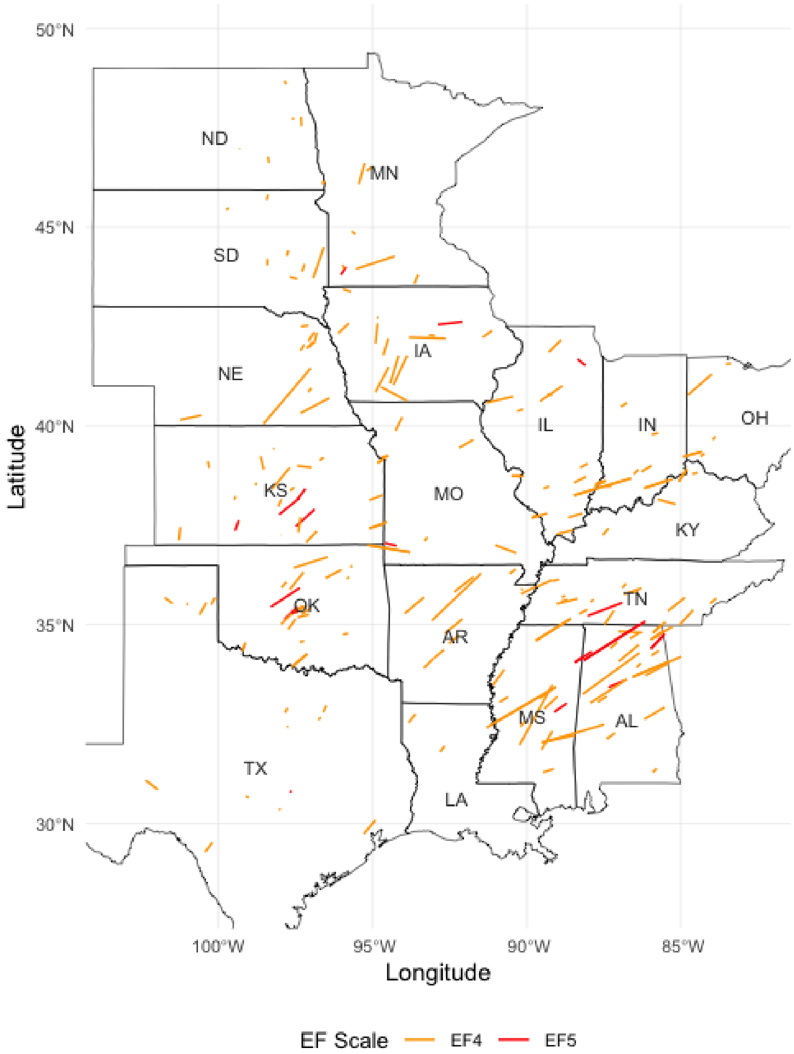
Figures and Tables

Figure 1: Distribution of Tornadoes by Enhanced Fujita (EF) Scale: 1988 - 2016



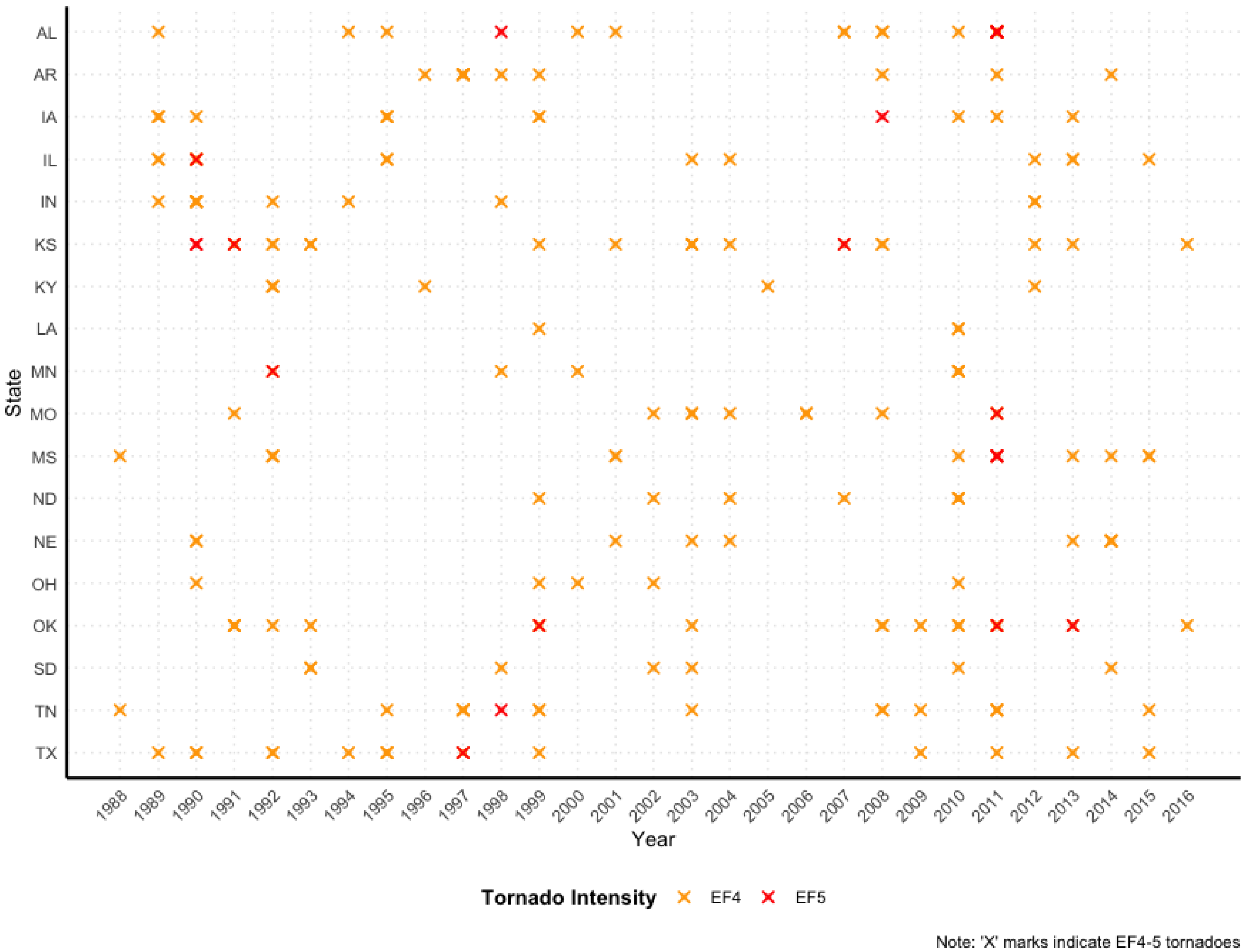
Note: This figure shows the categorical distribution of EF0-EF5 tornadoes from 1988 to 2016. The figure examines tornado occurrences across 18 states: Alabama, Arkansas, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Minnesota, Missouri, Mississippi, Nebraska, North Dakota, Ohio, Oklahoma, South Dakota, Tennessee, and Texas. The figure is created based on data from the National Weather Service.

Figure 2: Spatial Variation of Violent Tornadoes (EF4-5): 1988 - 2016



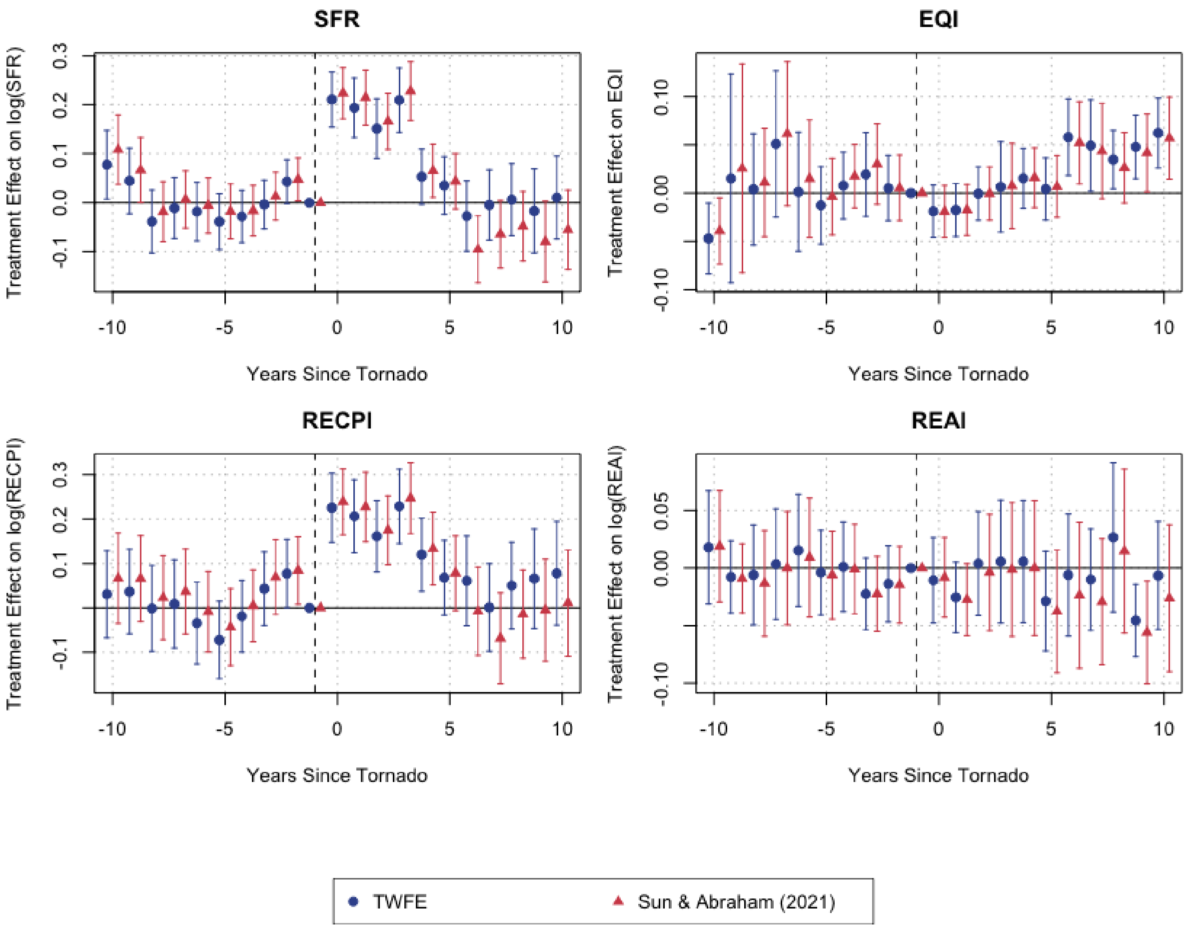
Note: This figure shows the spatial distribution of EF4-EF5 tornadoes from 1988 to 2016. The figure examines tornado occurrences across 18 states: Alabama, Arkansas, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Minnesota, Missouri, Mississippi, Nebraska, North Dakota, Ohio, Oklahoma, South Dakota, Tennessee, and Texas. The figure is created based on data from the National Weather Service.

Figure 3: Temporal Variation of Violent Tornadoes (EF4-5): 1988 - 2016



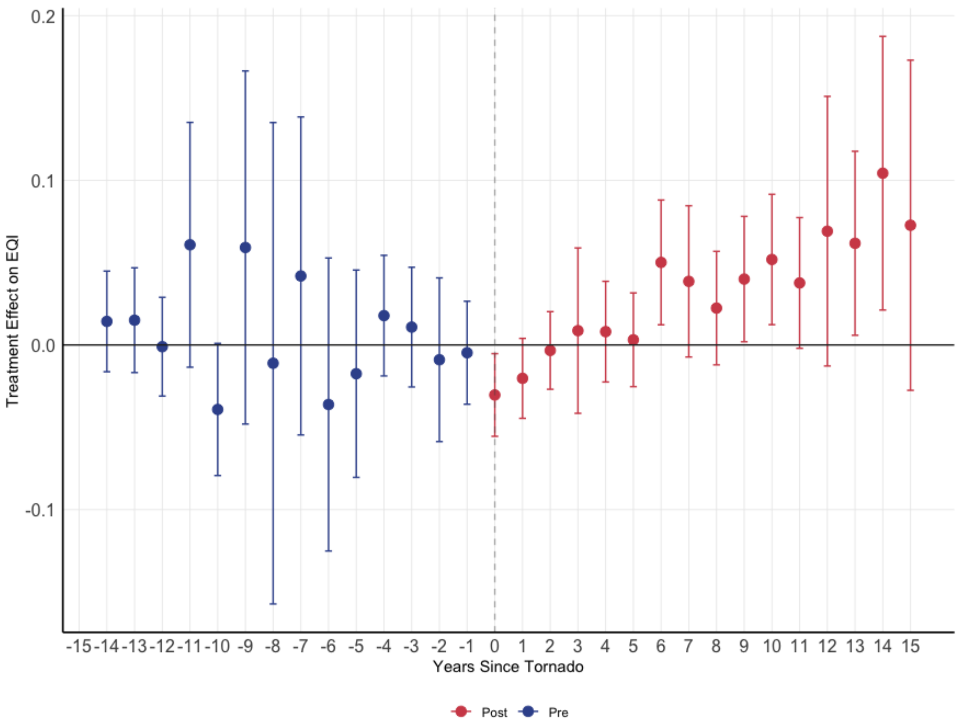
Note: This figure shows the temporal distribution of EF4-EF5 tornadoes from 1988 to 2016. The figure examines tornado occurrences across 18 states: Alabama, Arkansas, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Minnesota, Missouri, Mississippi, Nebraska, North Dakota, Ohio, Oklahoma, South Dakota, Tennessee, and Texas. The figure is created based on data from the National Weather Service.

Figure 4: Violent Tornadoes' Impacts on Entrepreneurial Statistics



Note: This figure shows the impact of EF4–EF5 tornadoes on startup formation rates (SFR, number of for-profit new business registrations within a given time and region); entrepreneurship quality index (EQI, measure of entrepreneurial quality); regional entrepreneurship cohort potential index (RECPI, inherent potential of a startup cohort within a region); and regional ecosystem acceleration index (REAI, realized number of growth events from that cohort). Estimation uses both TWFE and Sun and Abraham (2021) methods. The x-axis represents years relative to tornado occurrence, with dashed vertical line indicating the event year. Bars represent 95% confidence intervals.

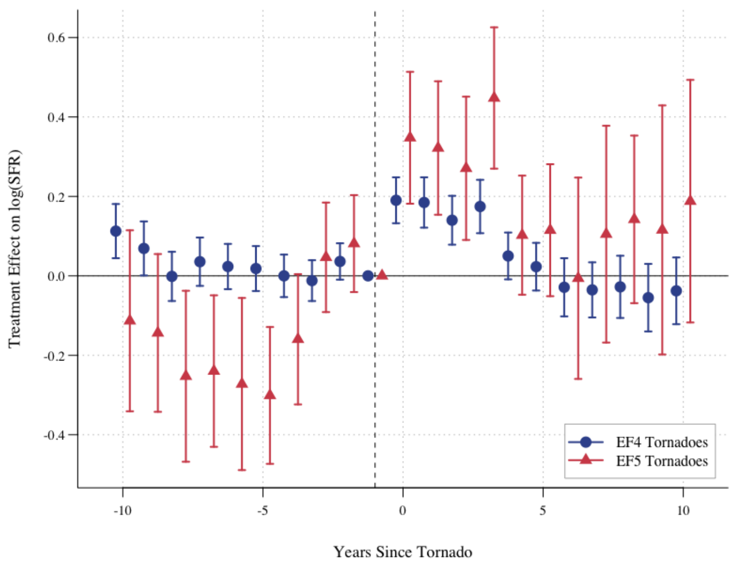
Figure 5: Violent Tornadoes' Impacts on Entrepreneurial Quality



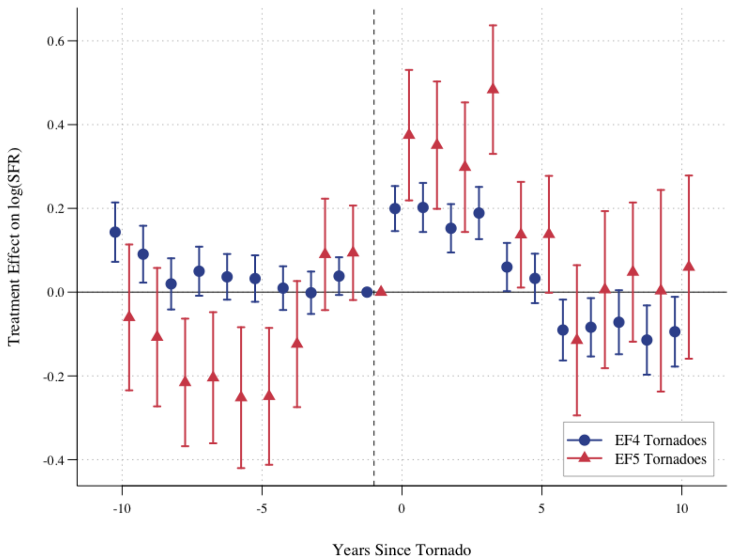
Note: This figure shows the impact of EF4-EF5 tornadoes on entrepreneurship quality index (EQI). Estimation uses Callaway and Sant'Anna (2021) methods. The x-axis represents years relative to tornado occurrence, with dashed vertical line indicating the event year. Bars represent 95% confidence intervals.

Figure 6: EF4 and EF5 Tornadoes Impacts on SFR

Panel (a): TWFE Estimate



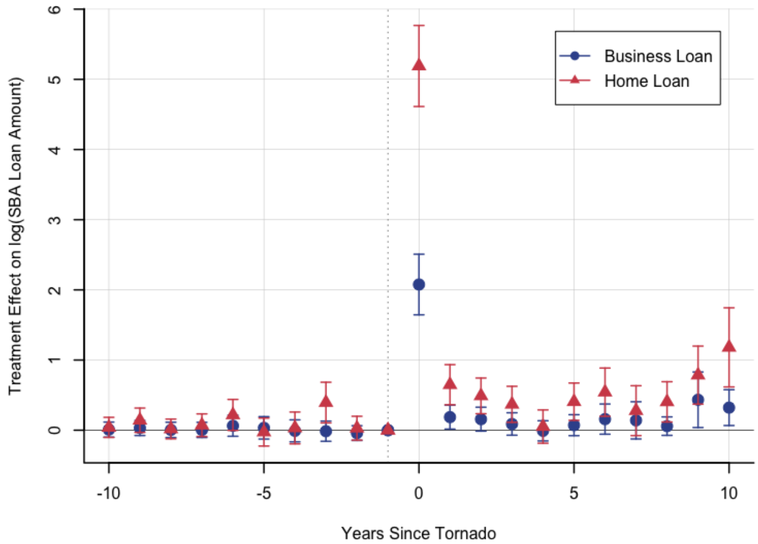
Panel (b): Sun and Abraham (2021) Estimate



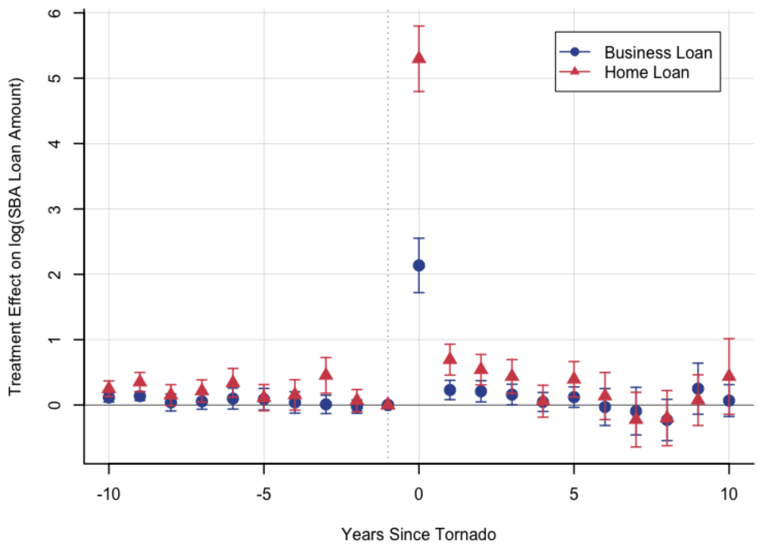
Note: This figure examines the separate impacts of EF4 and EF5 tornadoes on startup formation rates (SFR), illustrating the intensity gradient in entrepreneurial response. Both TWFE and Sun and Abraham (2021) estimation methods produce consistent results across intensity levels, confirming the robustness of these findings. The x-axis represents years relative to tornado occurrence, with the dashed vertical line indicating the event year. Bars represent 95% confidence intervals.

Figure 7: Overall Effects of Violent Tornadoes on SBA Loan Approvals

Panel (a): TWFE Estimate



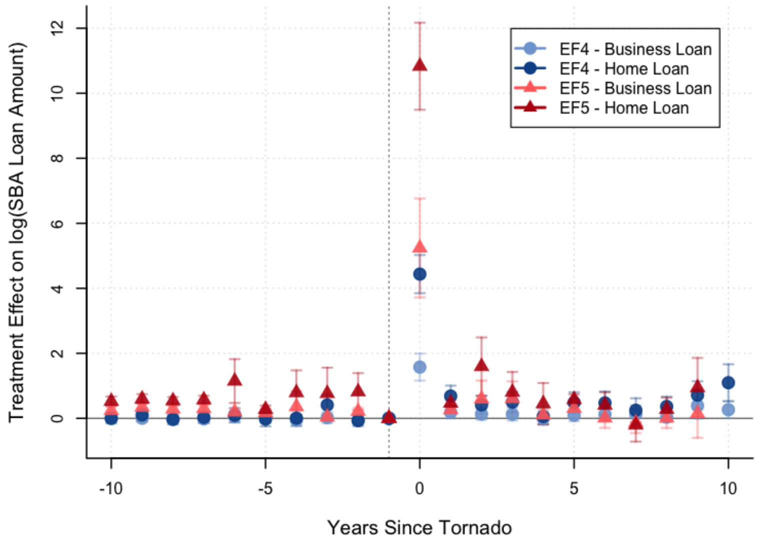
Panel (b): Sun and Abraham (2021) Estimate



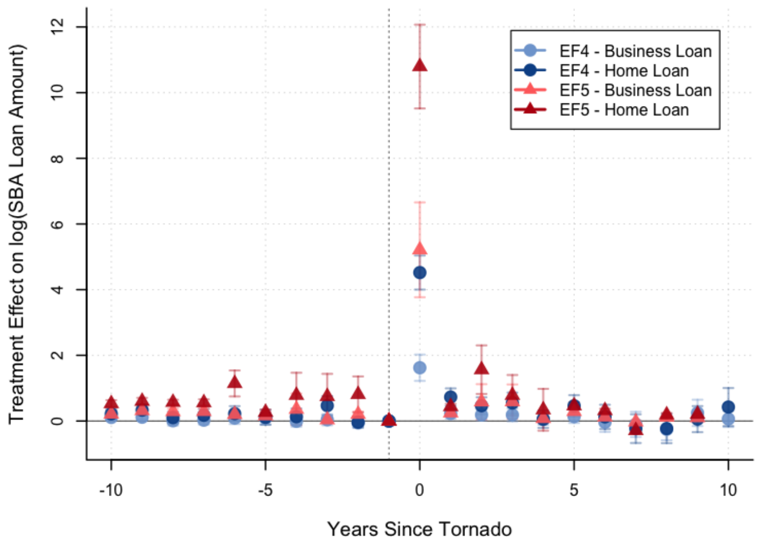
Note: This figure presents the overall effects of violent tornadoes on SBA loan approvals.

Figure 8: Effects of EF4 and EF5 Tornadoes on SBA Loan Approvals

Panel (a): TWFE Estimate



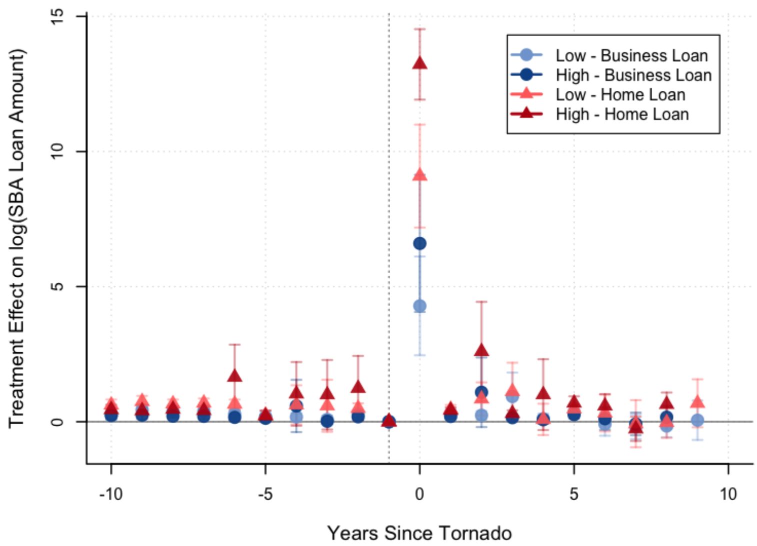
Panel (b): Sun and Abraham (2021) Estimate



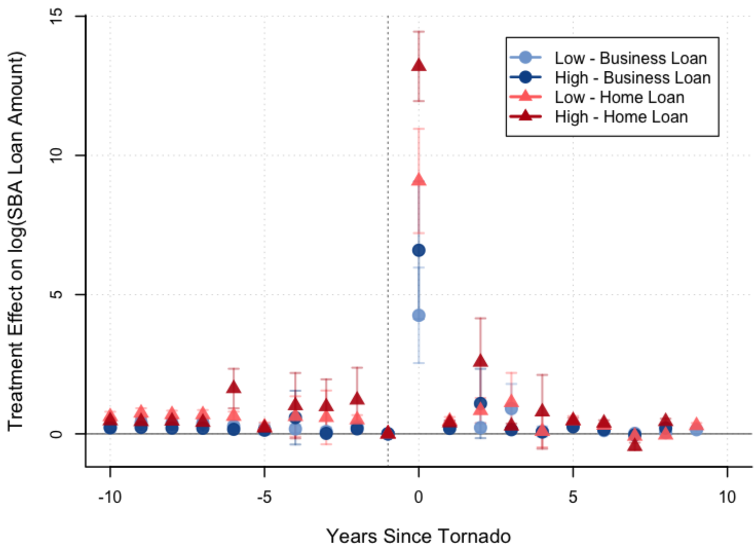
Note: This figure presents the effects of violent tornadoes on SBA loan approvals.

Figure 9: Effects of Household Income on SBA Loan Approvals

Panel (a): TWFE Estimate

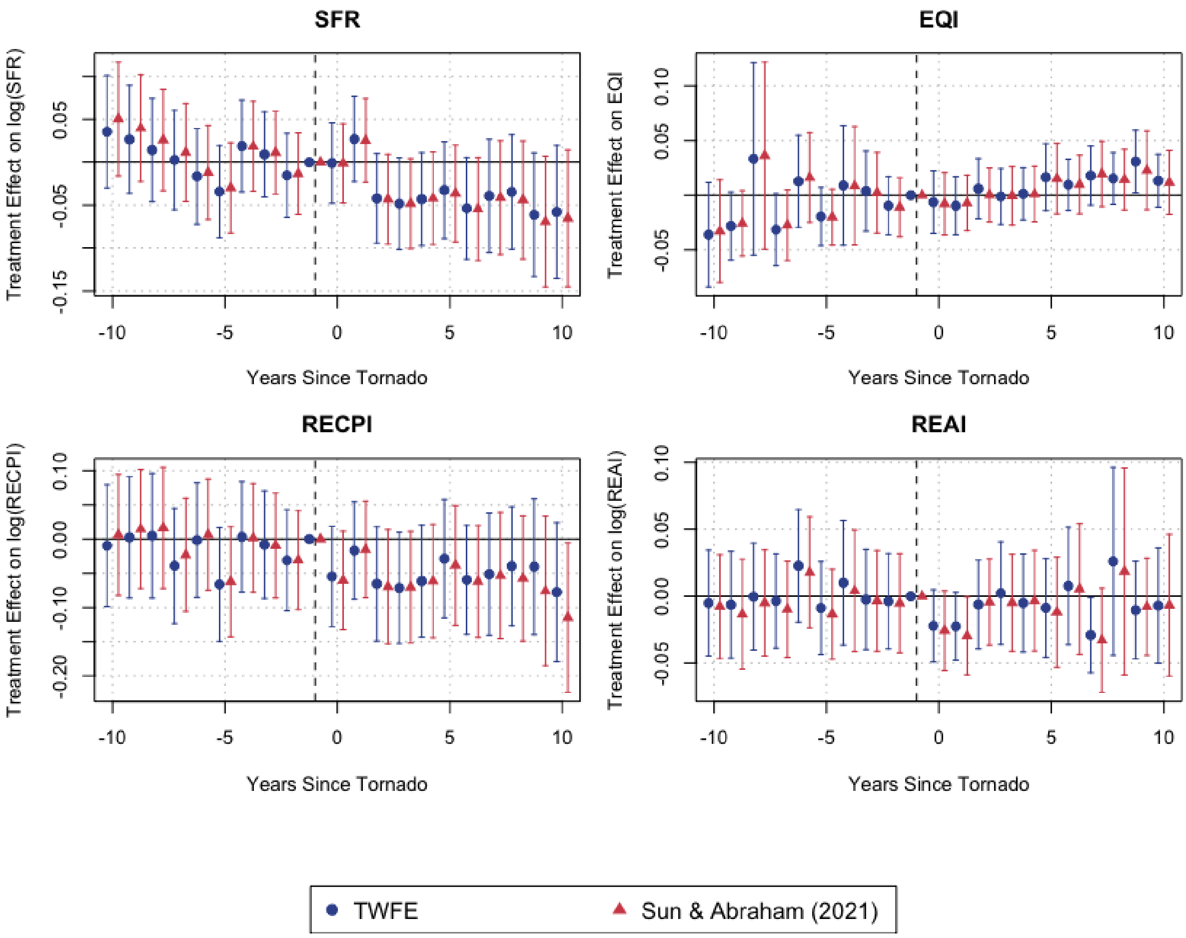


Panel (b): Sun and Abraham (2021) Estimate



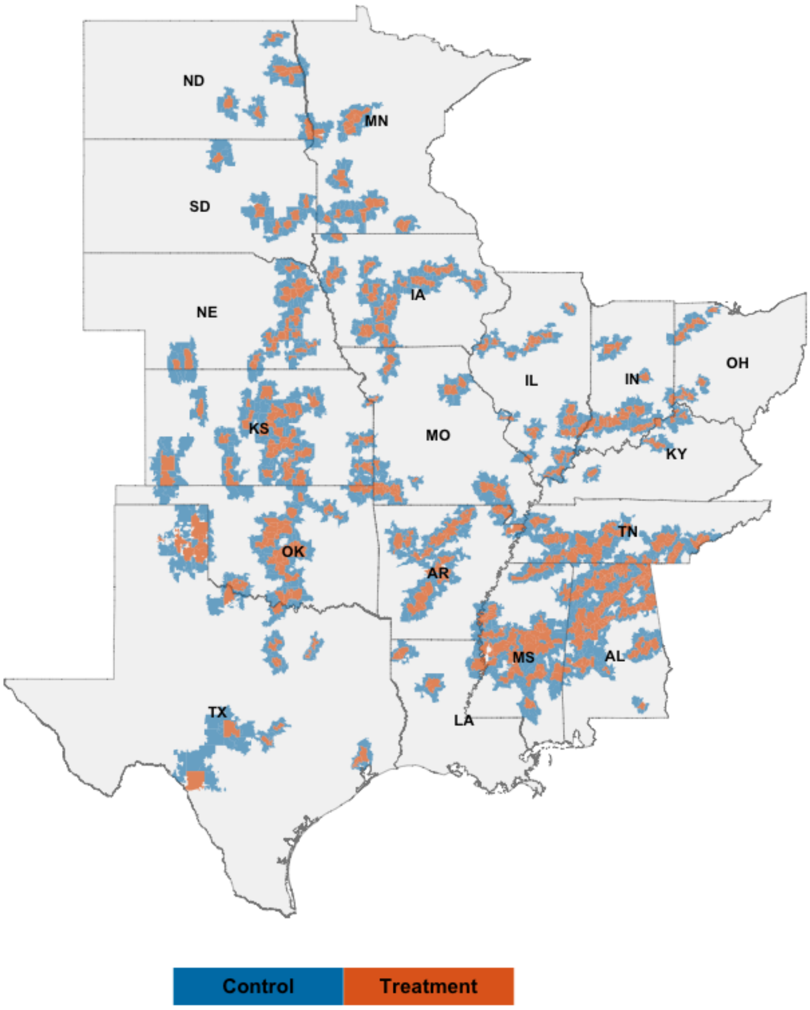
Note:This figure illustrates the impact of violent tornadoes on SBA loan approvals for business and home loans, comparing low-income and high-income regions.

Figure 10: Robustness Check: EF0 - EF3 Tornadoes Impacts on Entrepreneurial Quality Statistics



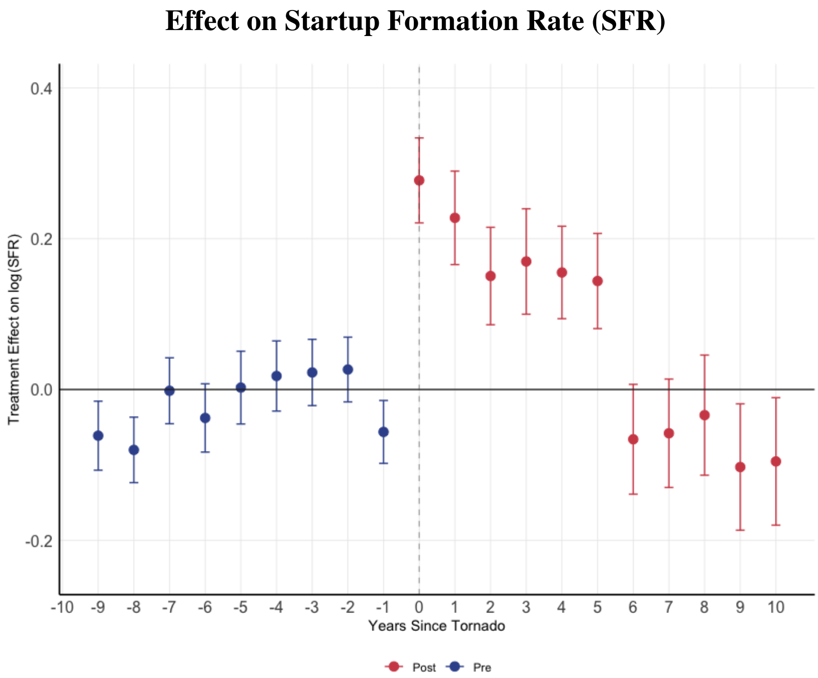
Note: This figure shows the impact of EF0–EF3 tornadoes on startup formation rates (SFR, number of for-profit new business registrations within a given time and region); entrepreneurship quality index (EQI, measure of entrepreneurial quality); regional entrepreneurship cohort potential index (RECPI, inherent potential of a startup cohort within a region); and regional ecosystem acceleration index (REAI, realized number of growth events from that cohort). Unlike violent tornadoes (EF4-5), lower-intensity tornadoes do not exhibit significant positive effects on entrepreneurial activity. Estimation uses both TWFE and Sun and Abraham (2021) methods. The x-axis represents years relative to tornado occurrence, with dashed vertical line indicating the event year. Bars represent 95% confidence intervals.

Figure 11: Distribution of Treatment and Adjacent (Control) ZIP Codes



*Note:*This figure displays the spatial distribution of treatment (EF4-5 tornado-affected) and control (neighboring) ZIP codes across 18 states. Treatment areas (orange) represent ZIP codes directly impacted by violent tornadoes, while control areas (blue) consist of adjacent ZIP codes that share similar geographic and socioeconomic characteristics but were not directly affected. This spatial matching approach helps control for regional heterogeneity while maintaining comparable baseline conditions between groups.

Figure 12: Robustness Check: Callaway and Sant'Anna (2021) Estimator



Note: This figure presents event study estimates of the effects of violent tornadoes using the Callaway and Sant'Anna (2021) difference-in-differences estimator for staggered treatment adoption. The panel shows effects on the startup formation rate (SFR). The x-axis represents time relative to tornado occurrence, with year 0 indicating the year of the tornado. Blue points and confidence intervals represent the pre-treatment period, while red points and confidence intervals show post-treatment effects. Error bars indicate 95% confidence intervals. The vertical dashed line at $t = 0$ marks the time of the tornado, and the horizontal dashed line at zero represents no effect.

Table 1.1: Summary Statistics

Variables	**Mean**	**Min**	**Max**	**StD**	**N(Obs)**
Panel A: Entrepreneurial Quality Statistics					
Entrepreneurship Quality Index (EQI)	0.000389	7.24E-06	0.0755	0.000673	166,884
Startup Formation Rate (SFR)	52.104	1.000	2,724.000	91.422	166,884
Regional Entrepreneurship Cohort Potential Index (RECPI)	0.021	7.24E-06	3.040	0.059	166,884
Regional Ecosystem Acceleration Index (REAI)	0.820	0.000	9,630.286	33.972	144,377
Panel B: Tornado Statistics					
Tornado Enhanced Fujita Score (EF)	4.155	4.000	5.000	0.362	227
Tornado Enhanced Fujita Score (EF) = 4					206
Tornado Enhanced Fujita Score (EF) = 5					21
Panel C: Business Pattern Statistics I					
Size: Overall	361.456	1.000	3,044.000	383.610	112,759
Size: 1–4 Employees	185.663	0.000	1,837.000	191.933	112,759
Size: 5–9 Employees	71.855	0.000	674.000	75.327	112,759
Size: 10–19 Employees	48.993	0.000	497.000	55.193	112,759
Size: 20–49 Employees	34.049	0.000	410.000	41.850	112,759
Size: 50–99 Employees	11.626	0.000	184.000	16.121	112,759
Panel D: Business Pattern Statistics II					
Industry: Construction	32.239	0.000	377.000	31.458	112,757
Industry: Manufacturing	16.705	0.000	549.000	21.929	112,757
Industry: Wholesale Trade	20.781	0.000	602.000	31.551	112,757
Industry: Retail Trade	57.228	0.000	567.000	62.628	112,757
Industry: Transportation and Warehousing	11.003	0.000	894.000	16.427	112,757
Industry: Professional, Scientific, Technical Service	36.001	0.000	1,133.000	61.217	112,757
Panel E: Disaster Loan Statistics					
Total Approved Business Loan Amount	375,942.2	1,100	26,050,800	1,506,320	1,045
Total Approved Home Loan Amount	336,549.1	300	38,717,700	1,592,880	3,117

Table 1.2: SBA Disaster Loan's Impacts on Entrepreneurial Quality Statistics

Dependent Variables:	**log(SFR)**			**EQI**			**log(RECPI)**			**log(REAI)**		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
log(Business Loan)	0.0053***	0.0052***	0.0056***	-0.0039***	-0.0037**	-0.0037**	0.0030	0.0026	0.0034	0.0007	0.0007	0.0007
	(0.0018)	(0.0018)	(0.0018)	(0.0015)	(0.0015)	(0.0015)	(0.0022)	(0.0022)	(0.0022)	(0.0017)	(0.0017)	(0.0017)
log(Home Loan)	0.0098***	0.0098***	0.0099***	-0.0011	-0.0011	-0.0012	0.0111***	0.0112***	0.0110***	-0.0006	-0.0006	-0.0006
	(0.0011)	(0.0011)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0014)	(0.0014)	(0.0014)	(0.0011)	(0.0011)	(0.0011)
Fixed-effects												
ZIP Code	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics												
Observations	101,652	101,394	100,033	101,652	101,394	100,033	101,652	101,394	100,033	78,356	78,178	77,074
Within R^2	0.00240	0.00236	0.00254	5.46×10^{-5}	5.18×10^{-5}	5.46×10^{-5}	0.00118	0.00117	0.00123	4.44×10^{-6}	4.39×10^{-6}	4.17×10^{-6}

Note: Columns (1)–(3) report the overall impact of SBA loans on startup formation rate (SFR), where (1) presents the general impact, (2) focuses on the effect of SBA loans following EF4 tornadoes, and (3) examines the effect after EF5 tornadoes. Columns (4)–(6), (7)–(9), and (10)–(12) follow the same structure but for different dependent variables: (4)–(6) analyze the impact on the entrepreneurship quality index (EQI), (7)–(9) evaluate the effects on regional entrepreneurship cohort potential index (RECPI), and (10)–(12) examine the impact on the regional ecosystem acceleration index (REAI). Clustered (ZIP code) standard errors are in parentheses, with significance levels denoted as *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

Table 1.3: SBA Loan Effects on Entrepreneurial Activity

		Loan Increase (%)		**SFR Impact (%)**	
Tornado Type	**Loan Type**	TWFE	Sun and Abraham (2021)	TWFE	Sun and Abraham (2021)
EF4&EF5	Business	207.6	213.6	1.10	1.13
	Home	519.0	529.8	5.09	5.19
EF4	Business	157.6	162.2	0.82	0.84
Only	Home	443.7	452.1	4.35	4.43
EF5	Business	524.1	521.3	2.93	2.92
Only	Home	1083.0	1079.0	10.72	10.68

Note: This table presents the impacts of SBA disaster loans on startup formation rate (SFR) following violent tornadoes. The loan increase percentages show the estimates from both TWFE and Sun and Abraham (2021) methods. The SFR impacts are calculated by multiplying the loan percentage increase by the elasticity coefficients (for example, 0.0053 for business loans and 0.0098 for home loans, I also consider intensity heterogeneity). Results demonstrate that home loans generate substantially stronger entrepreneurial responses than business loans across all tornado intensities, with EF5 tornadoes producing the largest effects. These findings suggest that housing stability plays a critical role in fostering post-disaster entrepreneurship. For example, following EF5 tornadoes, home loans increase by 1080%, which translates to a 10.6% increase in startup formation.

Table 1.4: SBA Disaster Loan's Impacts on Entrepreneurial Quality Statistics: Household Income

Dependent Variables:	**log(SFR)**		**EQI**		**log(RECPI)**		**log(REAI)**	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
log(Business Loan)	0.0073***	0.0033	-0.0062***	-0.0007	0.0033	0.0035	-0.0015	0.0036
	(0.0025)	(0.0026)	(0.0016)	(0.0026)	(0.0031)	(0.0031)	(0.0023)	(0.0026)
log(Home Loan)	0.0092***	0.0106***	0.0002	-0.0028	0.0113***	0.0104***	0.0003	-0.0018
	(0.0016)	(0.0015)	(0.0011)	(0.0018)	(0.0020)	(0.0019)	(0.0016)	(0.0014)
Fixed-effects								
ZIP Code	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	49,132	50,828	49,132	50,828	49,132	50,828	37,573	39,447
Within R^2	0.00247	0.00260	8.13×10^{-5}	4.78×10^{-5}	0.00118	0.00127	1.83×10^{-5}	4.18×10^{-5}

Note: This table presents the impact of SBA disaster loans on entrepreneurial activity in the aftermath of violent tornadoes, using data from the U.S. Census. The analysis distinguishes between ZIP codes based on household income levels. Specifically, columns (1), (3), (5), and (7) report the results for ZIP codes with lower household incomes, while columns (2), (4), (6), and (8) present the estimates for ZIP codes with higher household incomes. This segmentation allows for a comparative assessment of how SBA loans influence entrepreneurship in economically disadvantaged versus more affluent areas, highlighting potential disparities in access to financial resources and post-disaster business recovery trends.

Table 1.5: SBA Disaster Loan's Impacts on Entrepreneurial Quality Statistics: Income Quartile

Dependent Variables:	log(SFR)				EQI			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
log(Business Loan)	0.0078**	0.0071**	-0.0053*	0.0135***	-0.0086***	-0.0034**	0.0029	-0.0048
	(0.0034)	(0.0036)	(0.0032)	(0.0044)	(0.0028)	(0.0015)	(0.0034)	(0.0040)
log(Home Loan)	0.0094***	0.0087***	0.0139***	0.0074***	0.0029*	-0.0027**	-0.0041**	-0.0016
	(0.0021)	(0.0024)	(0.0023)	(0.0019)	(0.0017)	(0.0012)	(0.0017)	(0.0033)
Fixed-effects								
ZIP Code	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	24,990	24,990	24,990	24,990	24,990	24,990	24,990	24,990
Within R^2	0.00250	0.00237	0.00263	0.00357	0.00010	0.00013	0.00012	5.18×10^{-5}

Note: This table presents the results of a quartile regression analysis investigating how the effects of SBA loans differ across the income distribution. The dependent variables include startup formation rate (SFR), analyzed in Columns (1)–(4), and entrepreneurial quality index (EQI), examined in Columns (5)–(8). The quartiles are based on income levels, where Q1 represents the lowest income group, and Q4 represents the highest income group. This segmentation allows for a detailed examination of whether and how the impact of SBA loans varies for entrepreneurs across different income brackets.

Chapter 2

The Unexpected Effects of Place-Based Remote-Work Incentives: Evidence from the Tulsa Remote Program

2.1 Introduction

Place-based policies aim to improve economic outcomes in specific locations, often by promoting job creation and higher wages (Neumark & Simpson, 2015). These policies are highly heterogeneous, ranging from infrastructure investments and anchor-institution strategies to firm-level subsidies and incentives (Kline, 2010). They may target already competitive regions to amplify growth or focus on lagging areas facing structural constraints (Neumark & Simpson, 2015; Olfert et al., 2014).

A longstanding debate in regional science contrasts place-based and place-neutral approaches. Place-neutral policies emphasize supporting individuals rather than locations, relying on mobility and market adjustment to reduce regional disparities (Bolton, 1992). In contrast, place-based approaches argue that local context matters: economic outcomes depend on spatially embedded factors such as institutions, networks, and agglomeration forces that markets alone may not address (Barca, McCann, & Rodríguez-Pose, 2012). A growing empirical literature finds that, under appropriate conditions, targeted spatial interventions can generate meaningful and persistent economic effects (Aguilar, Akee, & Mykerezi, 2024; Busso, Gregory, & Kline, 2013; Isserman & Rephann, 1995).

This paper focuses on a specific subtype of place-based policy: individual-targeted relocation incentive programs. Conceptually, these programs resemble interregional mobility vouchers proposed in the literature (Glaeser, Kahn, & Rappaport, 2008; Moretti, 2012), which aim to reduce relocation frictions and facilitate labor mobility. However, unlike mobility vouchers—typically framed as place-neutral instruments—relocation incentive programs are explicitly geographic, seeking to attract workers to particular locations to advance local economic development objectives.

Launched in November 2018, Tulsa Remote is a prominent example of this approach. The program offers $10,000 in cash incentives along with community amenities such as coworking access, networking opportunities, and wellness benefits to remote workers who relocate to Tulsa, Oklahoma. In this sense, Tulsa Remote lies at the intersection of people-based and place-based frameworks: it reduces individual relocation barriers while pursuing spatially grounded goals including economic revitalization, tax base expansion, and community transformation.

Tulsa Remote (2024) reports over 3,500 participants as of 2025, of which 76% remained in Tulsa after the first year. The present analysis focuses on the 2019-2021 period, during which approximately 1,400 individuals participated. The program has been credited with generating cultural benefits, new jobs, and tax revenue. Bartik (2025) estimates that between 58% and 70% of participants would not have relocated to Tulsa without the financial incentive, while Yoo (2024) finds that the program attracted remote workers, boosted the service sector, and modestly improved welfare, though rising rents and sectoral shifts posed challenges.

This research makes several contributions. Building on the framework proposed by Bartik (2019a, 2019b), I evaluate place-based incentives by examining not only whether Tulsa Remote attracts migrants, but also its displacement patterns, associated costs and benefits, and distributional implications. In addition, the analysis provides evidence on the types of individuals most responsive to such programs, offering practical insights for policymakers and program administrators aiming to improve targeting and outreach.

This study estimates U.S. county-to-county migration inflows and outflows related to the Tulsa Remote implementation using Internal Revenue Service (IRS) data (2011-2021), a synthetic control model, and a gravity model. [1] The Integrated Public Use Microdata Series' Current Population Survey (IPUMS CPS) for the Tulsa metropolitan area (2010–2024) is used in an

[1]For the synthetic control method, this paper employs the generalized synthetic control approach (GSYNTH), which is described in detail in the empirical section.

individual-level logistic regression to assess how personal characteristics affect the likelihood of relocating.

The synthetic control estimates indicate that the Tulsa Remote Program is associated with higher adjusted interstate inflows into Tulsa County, accompanied by declining intrastate inflows and modest increases in intrastate outflows. These patterns are suggestive of a replacement or re-sorting dynamic in migration flows rather than a uniform expansion of total in-migration.

Scaled by program participation, the estimates imply that while Tulsa Remote is effective in attracting out-of-state movers and improving overall resident retention, these gains are partially offset by adjustments within intrastate migration. One plausible interpretation is that the arrival of higher-income remote workers increases housing demand and local competition, which may discourage potential in-state movers and induce some existing residents to relocate elsewhere within Oklahoma. This interpretation is consistent with evidence from Yoo (2024), who documents housing price pressures following the inflow of remote workers, and with the gentrification literature, which shows that rising housing costs tend to reduce in-migration opportunities for lower-income households while generating only modest direct displacement (Freeman, 2005).

I also estimate a gravity model using IRS county-to-county migration flow data to examine factors associated with migration to Tulsa. The results indicate that migration flows are closely correlated with cost-of-living differences, particularly housing prices and wage gaps. These cost-related factors appear more salient in the post–Tulsa Remote period, suggesting that relative affordability may interact with program incentives. Complementary individual-level evidence indicates that Tulsa Remote participants are disproportionately married, middle-aged individuals with some college education, moderate incomes, and origins in higher-cost metropolitan areas.

These patterns point to a compositional shift in Tulsa's population, in which new arrivals reshape local mobility not through direct displacement, but by altering migration incentives and perceptions. Place-based incentive programs like Tulsa Remote can therefore affect spatial equilibria by attracting remote workers from higher-cost regions while simultaneously generating adjustment pressures for local residents. Policymakers should account for these trade-offs when designing similar programs to ensure that economic gains are balanced against community stability.

The paper proceeds as follows. Section 2.2 provides background, Sections 2.3 and 2.4 describe the data and methodology, Section 2.5 presents the results, Section 2.6 discusses policy implications, and Section 2.7 concludes.

2.2 Background

2.2.1 Tulsa Remote Program

The Tulsa Remote Program was launched in November 2018 as part of a broader strategy to stimulate economic growth in Tulsa, Oklahoma.[2] The program emerged as part of the city's broader place-based development strategy outlined in its 2010 Comprehensive Plan, which sought to attract talent, revitalize the economy, and strengthen institutions. Tulsa is the second largest city in Oklahoma, with a population of 411,867 as of July 2022 (U.S. Census Bureau, 2022). The program offers a $10,000 cash incentive to attract remote workers residing outside the state, encouraging them to relocate to Tulsa while continuing their existing employment.

Unlike traditional relocation incentives that require participants to secure new local jobs, Tulsa Remote specifically targets individuals whose work is location-independent. This approach seeks to import income into the local economy without displacing existing workers, thereby preserving the local labor market. The program's broader objective is to attract skilled residents who can contribute to Tulsa's growth and community development.

Tulsa Remote has become a model for similar efforts across the country, inspiring a rapid proliferation of Remote Work Incentive (RWI) programs. There were 54 such initiatives nationwide as of December 2021 and more than 160 programs operating in over 30 states as of September 2025, illustrating the rapid adoption of this policy instrument as cities seek to attract remote workers and revitalize their economies. [3]

[2]Some information of this section is obtained from my interview with Tulsa Remote Program Director Justin Harlan and the Data Analyst, Jake Cronin. I am thankful to their help.

[3]Data from MakeMyMove, a consulting firm specializing in designing and promoting remote worker incentive programs. See `https://www.makemymove.com`.

2.2.1.1 Eligibility and Participation Requirements

Applicants must satisfy several eligibility criteria:

- Be at least 18 years of age,
- Be a U.S. citizen or green card holder legally eligible to work in the United States,
- Be fully employed with the flexibility to work from anywhere, or self-employed outside Oklahoma,
- Commit to a one-year residency,
- Have lived outside Oklahoma for at least one year prior to applying.[4]

Once an application is submitted, the program's recruitment team reviews and selects candidates. According to Justin Harlan, the program's Managing Director, application volume has varied significantly over time. In 2020 and 2021, approximately 20,000 applications were received annually. After implementing stricter eligibility criteria in 2022, applications declined to around 10,000 that year. By 2023, the program had received a cumulative total of approximately 50,000 applications, resulting in about 2,500 relocations. As of 2025, the program has relocated more than 3500 individuals.

2.2.1.2 Philanthropic Funding and Institutional Structure

A defining feature of the Tulsa Remote Program is its philanthropic funding structure. Unlike many place-based incentive programs that rely primarily on public funding, Tulsa Remote is largely financed by private philanthropic sources, most notably the George Kaiser Family Foundation (GKFF). GKFF is a Tulsa-based private foundation with a long-standing mission focused on early childhood education, economic mobility, and regional economic development. [5]

[4] This residency requirement was added after the program's initial launch.

[5] The George Kaiser Family Foundation (GKFF) is a Tulsa-based private foundation focused on early childhood education, economic mobility, and regional economic development. See `https://www.gkff.org/` for additional institutional background.

The foundation has played a central role not only in financing the program's cash incentives but also in supporting complementary investments such as coworking infrastructure, community-building activities, and participant engagement initiatives. By leveraging private capital, Tulsa Remote operates with greater flexibility than traditional publicly funded incentive programs, allowing it to scale rapidly and adapt eligibility criteria and program design over time.

This philanthropic model has important implications for both program sustainability and external validity. While private funding reduces fiscal pressure on local governments, it also raises questions about replicability in regions without comparable philanthropic capacity. As such, Tulsa Remote represents a hybrid institutional model that blends place-based economic development goals with privately funded, people-targeted incentives.

2.2.1.3 Compliance and Monitoring

Since Tulsa Remote does not maintain an official system for continuous residency monitoring, the program requires participants to adhere to specific terms and conditions:

- Maintain a 12-month lease in Tulsa,
- Meet with a designated program representative within the first 90 days of relocation,
- Refrain from monetizing their residence (e.g., via Airbnb),
- Remain physically present in Tulsa.

Failure to comply may result in removal from the program and repayment of incentive funds. According to the program's management, instances of non-compliance have been rare, with fewer than five removals since the program began (as of February 2023).

2.2.1.4 Broader Reach and Promotion

The visibility of Tulsa Remote has been amplified through sustained marketing efforts and widespread media coverage. Figure 1 presents Google Trends data illustrating search interest in the term "Tulsa Remote" before and after the program's launch.[6] Related search queries include

[6] The data is collected through Google Trends.

"incentives," "grant money," "entry-level job," and "Vermont,"[7] reflecting broader public interest in relocation incentive programs.

Tulsa Remote employs a diverse mix of promotional channels, including Facebook,[8] Twitter,[9] Instagram,[10] and LinkedIn.[11] The George Kaiser Family Foundation, in partnership with local organizations, has led much of the program's outreach, ensuring consistent visibility to potential applicants nationwide.

2.2.1.5 Participant Demographics and Origins

Table 2.2 shows that prominent feeder regions include the Greater New York City MSA, Los Angeles MSA, Dallas–Fort Worth MSA, and more (Newman et al., 2021). Figure 2(a) shows that California, Texas, and New York account for approximately 45.2% of all participants. Figure 2(b) illustrates that the most common industries represented are Information Technology (26%), Computer Software (22%), and Financial Services (13%) (Tulsa Remote, 2025b).

2.2.2 Remote Work and Migration

The rise of remote work—particularly the shift from work-from-home (WFH) to work-from-anywhere (WFA)—has significantly influenced migration behavior. WFH offers temporal flexibility but often still requires proximity to a central office. In contrast, WFA eliminates geographic constraints, granting workers full autonomy over their residential choices (Choudhury, Foroughi, & Larson, 2021). This added flexibility increases the likelihood of relocation, as individuals can better align work with personal or family needs (J. A. Evans, Kunda, & Barley, 2004).

Survey data support this trend. During the COVID-19 pandemic, 1 in 5 U.S. tech workers and 1 in 10 in the UK expressed interest in relocating (Remote Technology, Inc., 2020). Tan, Fang, and Lester (2023) found that 53% of high-tech workers in the Bay Area had moved or

[7] In 2018, the State of Vermont launched the country's first RWI program, offering reimbursement grants of up to $7,500 to eligible newcomers.
[8] Facebook: `https://www.facebook.com/tulsaremote/`
[9] Twitter: `https://twitter.com/tulsaremote`
[10] Instagram: `https://www.instagram.com/tulsaremote/`
[11] LinkedIn: `https://www.linkedin.com/company/tulsaremote/`

intended to, while Ozimek (2020) estimated that remote work could prompt 14–23 million Americans to consider relocating, potentially tripling historical migration rates.

As for where people move, patterns vary. Many prefer short-distance moves within their region—Tan et al. (2023) reported a median potential move of 33.7 km—while others consider long-distance migration. Ozimek (2020) found that 55% of respondents considered relocating beyond typical commuting distances. Cost of living is a key driver: states like Florida and Texas saw large inflows in 2022, while California and New York experienced net outflows (Evangelou, 2023). International studies similarly show remote workers relocating to more affordable and less dense areas (Akan, 2022).

Remote work, especially WFA, affects both the likelihood and destination of migration. The decoupling of residence from workplace is expanding geographic flexibility, with cost of living emerging as a central factor in relocation decisions.

Recent narratives surrounding remote work suggest substantial evolution since the early pandemic period. While remote work expanded rapidly in 2020–2021, emerging evidence indicates a re-optimization characterized by return-to-office mandates and the rise of hybrid work arrangements (Aksoy et al., 2023; Barrero et al., 2021, 2023). These trends appear to reflect not the disappearance of remote work, but rather a stabilization around a narrower subset of workers with sustained geographic flexibility.

Tulsa Remote is designed to target this specific group: individuals whose employment arrangements remain fully remote or sufficiently flexible to permit long-distance relocation. Notably, the program was launched in November 2018, prior to the COVID-19 pandemic, when remote work was relatively uncommon. Its continued operation through pre-pandemic, pandemic, and post-pandemic labor market regimes provides a unique opportunity to assess the migration effects of relocation incentives across differing remote work environments. As such, the analysis speaks to the viability of individual-targeted relocation incentives under varying degrees of remote work prevalence, rather than being tied to a single, transitory period.

2.3 Data

2.3.1 SOI Tax Stats - Migration Data

As the main data source of this research, Internal Revenue Service (IRS) - Survey of Income (SOI) provides aggregate county-level migration information through out each tax year, the information include the county identifier for origins and destinations, number of people flowing from the origins to destinations, number of tax returns received and gross income. Migration data for the United States are based on year-to-year address changes reported on individual income tax returns filed with the IRS. They present migration patterns by state or by county for the entire United States and are available for inflows—the number of new residents who moved to a state or county and where they migrated from, and outflows—the number of residents leaving a state or county and where they went (Internal Revenue Service, 2025).

The IRS SOI Migration data stands out with notable advantages when compared to other migration datasets in the U.S. (Molloy, Smith, & Wozniak, 2011). Firstly, it offers specific information regarding counties and states, catering to diverse requirements within the internal migration literature and facilitating the current research. Secondly, its provision of yearly data is a distinct benefit in contrast to the US Census, which presents migration data on a yearly aggregate basis. Additionally, the IRS data provides a dynamic perspective as it captures the flow from origins to destinations. [12]

For this study, I employ the dataset spanning from 2011 to 2021. The IRS SOI Migration dataset includes two key migration variables: the "number of returns" and the "number of exemptions." These variables play a crucial role in understanding migration dynamics. The "number of returns" represents the count of individual tax returns filed by households or individuals. It serves as a quantification of the movement of individuals from one location to another, enabling the tracking of migration flows over time. Conversely, the "number of exemptions" signifies the total number of individuals, including both primary taxpayers and their dependents, claimed on tax returns. This measure offers insights into population mobility,

[12] One limitation of this approach stems from the data source: IRS migration data are only available at the county level and are released with considerable delay, resulting in a relatively short post-treatment window.

considering not only the primary taxpayers but also their accompanying family members. In this study, I utilize the "number of exemptions" variable to analyze migration trends following the implementation of the Tulsa Remote Program.

2.3.2 Time-Varying Variables

The dataset includes county-level population, gender ratio (calculated as the male population divided by the female population), racial demographics (white and black) for the years 2011-2021, obtained from the US Census. These variables are essential for building the county-to-county gravity model, as different counties exhibit distinct characteristics that influence migration patterns and other socio-economic dynamics.

Industry shares, including construction, manufacturing, and professional service, and average weekly wage data are sourced from the Bureau of Labor Statistics.

Data on median housing prices are obtained from the U.S. Census.[13] Median housing prices serve as a proxy for long-term housing affordability and broader cost-of-living differences across counties. To capture more immediate housing expenses, I also include Fair Market Rents (40th percentile rents) from HUD's Office of Policy Development and Research (PD&R), which better reflect short-run rental market conditions.

Employment and unemployment data are obtained from the U.S. Department of Agriculture (USDA).

County-level GDP data is obtained from Bureau of Economic Analysis (BEA).

2.3.3 Integrated Public Use Microdata Series (IPUMS) CPS Data

The data on individual migration behavior is gathered from IPUMS CPS. Control variables encompass individuals' racial identifications, genders, ages, household structures, incomes, and other pertinent factors.

IPUMS CPS provides harmonized microdata from the monthly U.S. labor force survey, covering 1962 to the present [14]. This dataset encompasses demographic information, comprehen-

[13] I would like to thank Riley Wilson for his assistance in accessing this dataset.

[14] IPUMS offers various branches, such as IPUMS USA. However, it's important to note that Tulsa County (FIPS: 40143) is missing from the IPUMS USA data, as indicated on the website: For IPUMS USA, which provides

sive employment statistics, and supplementary information on various topics including fertility, tobacco use, volunteer activities, voter registration, computer and internet use, food security, and more .

I use metro level data in CPS of Tulsa metro (Metro Code 6580) from 2010 to 2024, which includes seven Oklahoma Counties: Creek, Okmulgee, Osage, Pawnee, Rogers, Tulsa, and Wagoner. By utilizing the variable "migration status," I can differentiate individuals based on whether they moved within the same state, across different states, or did not move at all. This variable allows for the categorization of individuals into three distinct groups, enabling a more nuanced analysis of migration behavior and its impacts.

2.4 Empirical Framework

2.4.1 County-Level Estimates

Given that Tulsa County is the only treated unit in this study, traditional difference-in-differences (DiD) approach faces limitations in constructing an appropriate counterfactual. DiD requires parallel trends across treated and control groups, which is difficult to assess with a single treated unit. Synthetic control methods address these limitations by constructing a weighted combination of control units that closely replicates the treated unit's pre-treatment trajectory (Abadie et al., 2010).

The traditional Synthetic Control Method selects weights to minimize the distance between the treated unit's characteristics X_1 and the weighted average of control units X_0W, as shown in Equation 2.1, subject to $w_j \geq 0$ and $\sum_j w_j = 1$:

$$\|X_1 - X_0W\|_V = \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)} \tag{2.1}$$

U.S. Census data, counties are identifiable in public use data prior to 1950, but not after. This is due to the "72-year" rule, which restricts the U.S. government from releasing personally identifiable information until 72 years after it was collected for the Census. Identifying individual records by all counties in the U.S. runs the risk of breaching this confidentiality requirement. Experienced IPUMS USA users will note, however, that some counties are actually identifiable in post-1950 IPUMS USA samples. This is because some counties are able to be recovered by using other geographic identifiers–such as, in recent years, Public Use Microdata Area (PUMA) . Not all counties are available, however, and this spreadsheet details which counties are available in which post-1950 samples. For Tulsa County (Fip: 40143), IPUMS USA provides 1% of 1950, 5% state in 1990 and 1% unweighted. For data that has a high demand: 10% of 2010 ACS and 2012 on-ward, the data is missing.

This study employs the Generalized Synthetic Control Method (GSYNTH) (Xu, 2017), which extends this approach by incorporating interactive fixed effects. The GSYNTH estimator is defined as:

$$Y_{it} = \delta_{it} D_{it} + \mathbf{X}_{it}' \boldsymbol{\beta} + \boldsymbol{\lambda}_i' \mathbf{f}_t + \varepsilon_{it} \tag{2.2}$$

where Y_{it} is the outcome for unit i at time t, and D_{it} is the treatment indicator that equals 1 if unit i has been exposed to treatment prior to time t and 0 otherwise. The parameter δ_{it} represents the heterogeneous treatment effect on unit i at time t. $\mathbf{X}_{it}$ is a $(k \times 1)$ vector of observed time-varying covariates, and $\boldsymbol{\beta} = [\beta_1, \ldots, \beta_k]'$ is a $(k \times 1)$ vector of unknown parameters. $\mathbf{f}_t = [f_{1t}, \ldots, f_{rt}]'$ is an $(r \times 1)$ vector of unobserved common factors, and $\boldsymbol{\lambda}_i = [\lambda_{i1}, \ldots, \lambda_{ir}]'$ is an $(r \times 1)$ vector of unknown factor loadings. The term ε_{it} represents unobserved idiosyncratic shocks with zero mean.

This empirical framework estimates five outcome variables: (1) log of interstate inflow, (2) log of intrastate inflow, (3) log of adjusted interstate inflow (calculated as overall interstate inflow minus the population of participants), (4) log of interstate outflow, and (5) log of intrastate outflow. The analysis includes county and year fixed effects to assess migration trends before and after program implementation.

The model assumes that treated and control units are affected by the same set of factors, with the number of factors r fixed during the observed period (i.e., no structural breaks). Unlike traditional SCM's weighted-average approach, GSYNTH uses this factor model to flexibly capture unobserved confounders that vary across both units and time. This is particularly advantageous for our setting, where treatment effects may be heterogeneous and parallel trends may not hold after conditioning on observables alone (Xu, 2017).

I include pre-treatment covariates capturing demographic characteristics, labor market conditions, industrial composition, and overall economic activity at the county level. These variables are measured strictly prior to program implementation and are commonly used in regional policy evaluations to ensure pre-treatment comparability and avoid post-treatment bias. The choice of covariates follows established practice in the literature (e.g., R. Wilson (2022)).

To ensure robustness, I examine migration flows separately for interstate (cross-state) and intrastate (within-state) patterns using multiple donor pool specifications: (1) all mainland U.S. counties (excluding Alaska and Hawaii, as well as counties with zero time variation in the outcome variables), and (2) only Metropolitan Statistical Area (MSA) counties in Oklahoma and its neighboring states. In addition, I conduct placebo tests by applying the synthetic control method to non-treated metropolitan counties in neighboring states.

One limitation of the analysis is that the post-treatment period is relatively short due to the update lag in the IRS SOI migration data. However, this constraint is less problematic when using the generalized synthetic control method. Unlike traditional SCM, which relies heavily on extrapolating treated-unit pre-trends into the post-treatment period, GSYNTH estimates counterfactual outcomes through latent interactive fixed effects using information from the full panel. As a result, the approach is less sensitive to a limited post-treatment horizon and remains suitable for this setting.

2.4.2 County-to-County Estimates

I use a Poisson Pseudo-Maximum Likelihood (PPML) gravity model to analyze county-to-county migration flows, with the aim of understanding the characteristics of origin counties from which people move to Tulsa following the launch of the program. The outcome variable, n, captures migration counts, including many zeros—cases where no migration occurs between a given origin and destination in a specific year. As recommended by Silva and Tenreyro (2006), the PPML estimator is well-suited for this context because it accommodates zero flows and provides consistent estimates even under heteroskedasticity.

$$\mathbb{E}[n_{it}] = \exp\left[\alpha_i + \gamma_t + \mathbf{Z}'_{it}\beta + (Post_t \times \mathbf{Z}'_{it})\,\theta + \mathbf{X}'_{it}\delta\right] \tag{2.3}$$

Equation 2.3 presents the specification of the model, where the dependent variable is the migration flow from U.S. counties to Tulsa County. The analysis focuses on origin counties across 37 states, including Oklahoma. [15] The vector $\mathbf{Z}_{it}$ contains time-varying origin-specific

[15] The gravity analysis focuses on Tulsa-bound migration flows (origin $\rightarrow$ Tulsa). The sample includes all counties with at least one recorded migrant to Tulsa during 2011–2021; for these counties, all years are retained, including zero-flow years. Counties with no Tulsa-bound migration throughout the sample period are excluded as structural zeros. Routes not involving Tulsa fall outside the analysis scope, consistent with standard gravity model practice (Head & Mayer, 2014; Larch, Shikher, & Yotov, 2025; Silva & Tenreyro, 2006).

covariates, including the House gap, GDP per capita gap, rent gap, and wage gap—each calculated as the difference between Tulsa's value and that of the origin county, capturing relative cost or income differentials that may drive migration decisions.

The terms α_i and γ_t denote origin county and year fixed effects, respectively, absorbing time-invariant unobserved heterogeneity and national-level shocks.

The interaction terms with the post-treatment indicator $Post$ capture changes in migration flows after 2019, following the launch of Tulsa Remote in November 2018.

$\mathbf{X}'_{it}$ denotes a set of control variables, including differences in industry employment shares, gender ratios, racial composition, and labor market statistics between origin counties and Tulsa County.

With this model, I am able to identify the characteristics and economic indicators—such as median housing price, rent, and GDP per capita—of the counties from which people are moving to Tulsa.

2.4.3 Individual Relocation Behaviors

In this section, I examine the factors influencing individuals' decisions to relocate to the Tulsa Metropolitan Statistical Area (MSA). [16] The analysis focuses on identifying key demographic, socioeconomic, and motivational characteristics associated with migration to Tulsa. The goal is to better understand the target populations most responsive to the Tulsa Remote program. These insights are intended to inform both program administrators and policymakers in Tulsa, as well as other cities seeking to replicate similar initiatives.

The logistic regression depicted in Equation 2.4, inspired by Borjas (2017), models the individual-level likelihood of relocating to the Tulsa metropolitan area. The dependent variable on the left-hand side is a binary indicator, taking the value of 1 if individual i resides in Tulsa in year t, and 0 otherwise. The model uses a logistic specification to estimate the log-odds of this outcome.

$$\text{logit}\left(P(\text{Tulsa}_{it} = 1)\right) = \boldsymbol{X}'_{it}\beta + Post_t \cdot \boldsymbol{Z}'_{it}\gamma \tag{2.4}$$

[16] My aim is not to show that policy causally changed the demographic characteristics of the in-migrants. My aim is instead to show how migration composition changed after the policy.

In the model, the vector of individual-level covariates $\boldsymbol{X}_{it}$ includes age, age squared, race (White), gender (Male), household head status, marital status (Married), college education, logged income, and stated migration reasons. A reduced vector $\boldsymbol{Z}_{it}$ is also used, which excludes age and age squared but retains race, gender, household head status, marital status, college education, logged income, and migration reasons. $Post_t$ is a binary indicator equal to one for observations after the year 2019—corresponding to the launch of the Tulsa Remote program—and zero otherwise. The coefficients $\boldsymbol{\gamma}$ capture how the impact of the policy varies across these groups.

2.5 Baseline Results

2.5.1 County-Level Migration

I investigate the impacts of the Tulsa Remote Program on county-level migration dynamics. I employ a GSYNTH model to estimate the average treatment effect on the treated (ATT) for the log of inflow, adjusted inflow[17], and outflow.

Figure 3 illustrates the pattern of interstate migration inflows following the implementation of the Tulsa Remote Program.[18] The estimated ATT increases immediately following the program's launch, reaching approximately 0.21 by 2021. This pattern indicates that observed interstate inflows into Tulsa County exceed the synthetic counterfactual by roughly this magnitude over time. When restricting the control units to neighboring states, the estimated deviation from the synthetic counterfactual is smaller in magnitude but remains positive throughout the post-treatment period.

By contrast, Figure 4 shows a declining pattern in intrastate migration. Following the program's introduction, in-state migration into Tulsa County declines by approximately 0.12 by

[17]Adjusted inflow is defined as total observed migration inflow minus the number of officially reported Tulsa Remote participants in each year. According to Vinopal (2023), the program attracted approximately 60–70 remote workers in 2019, around 400 in 2020, and 937 individuals in 2021.

[18]The ATT figures are estimated using a generalized synthetic control framework and are interpreted descriptively. Formal confidence intervals for aggregate county-level ATT estimates are not reported because recent prediction-interval approaches for single-treated-unit designs (Cattaneo, Feng, & Titiunik, 2021; Cattaneo et al., 2025) yield degenerate intervals in this setting due to extremely limited pre-treatment variation. Accordingly, the GSYNTH-based estimates are used to characterize post-treatment patterns rather than to establish statistically significant causal effects.

2021. This downward trend is consistent across alternative donor pool specifications.

I then re-estimate the model using adjusted interstate inflow as the dependent variable to examine potential spillover effects. As shown in Figure 5, the estimated deviation based on adjusted inflow is smaller in magnitude: by 2021, migration inflows exceed the synthetic counterfactual by approximately 0.10. This pattern is suggestive of migration responses beyond directly enrolled program participants.

Figure 6 displays a decline in interstate outflows from Tulsa County following the program's implementation, which is consistent with a potential retention mechanism.[19] In contrast, Figure 7 shows an increase of more than 0.08 in intrastate outflows over the post-treatment period. This pattern is consistent with a possible replacement effect, whereby incoming remote workers may alter local conditions in ways that encourage some residents to relocate elsewhere within Oklahoma.

The results obtained from the GSYNTH model are highly consistent with those calculated using absolute number levels, as shown in Table 2.3. In absolute terms, the program is associated with an increase of approximately 635 interstate in-migrants per year, alongside a decline of about 1,025 intrastate in-migrants and a modest increase in intrastate out-migration, magnitudes that are economically meaningful yet plausible given baseline migration volumes.

Using a descriptive normalization, the estimates imply that each Tulsa Remote participant is associated with approximately 1.35 additional interstate migrants and the retention of about 2.84 residents who might otherwise have left Tulsa during the post-treatment period. At the same time, each participant is associated with roughly 1.69 residents relocating to other parts of Oklahoma and about 2.19 fewer potential intrastate movers choosing Tulsa. [20]

Notably, the implied inflow patterns align closely with the program's own characterization of

[19]For some outcomes, particularly interstate outflows, there is evidence of modest pre-treatment divergence. Interstate outflows also exhibit substantially greater year-to-year volatility than inflows at the county level, reflecting sensitivity to short-run housing market conditions, firm-level relocation decisions, and broader macroeconomic shocks. In particular, the COVID-19 period introduced nationwide disruptions to mobility patterns that disproportionately affected out-migration.

[20]The calculations are descriptive and proceed as follows. For each outcome, I first compute the average pre-treatment level over 2016–2018 and the average post-treatment level over 2019–2021 for both Tulsa County and its synthetic control. I then calculate the implied treatment effect as the difference-in-differences in levels between the post- and pre-treatment periods. To express these changes on a per-participant basis, I divide the average annual treatment effect by the average annual number of Tulsa Remote participants (1,407 participants over 2019–2021, divided by three). These back-of-the-envelope calculations are intended to provide an intuitive interpretation of the magnitude of the estimated effects rather than causal per-participant impacts.

a “multiplier” or “magnet mover” effect, whereby Tulsa Remote participants attract additional residents through social and family networks, including immediate and extended family members as well as friends and acquaintances. The Tulsa Remote Economic Impact Report documents that the city gains 3 additional residents for every 2 program participants, a pattern that closely aligns with the magnitudes observed here (Tulsa Remote, 2023). [21]

The displacement patterns are consistent with housing market adjustments as documented by Yoo (2024). The influx of high-income remote workers increased housing demand, raising rents and property values. This price escalation creates barriers for lower-income Oklahomans attempting to move to Tulsa—potential in-state migrants face affordability constraints that did not exist pre-program. Freeman (2005) demonstrates similar dynamics in gentrifying neighborhoods: rising costs reduce in-migration opportunities for lower-income households while direct displacement remains modest. The modest outflow increases likely reflect some residents seeking more affordable housing elsewhere in Oklahoma. Retention effects may stem from positive spillovers—service sector growth, enhanced amenities, and improved labor market conditions documented by Yoo (2024), though these mechanisms remain more speculative without individual-level data and may partly reflect broader pandemic-era mobility reductions.

The robustness checks show that the estimated patterns are stable across alternative donor pool specifications. Results from the baseline and controls display similar post-program deviations relative to their synthetic counterfactuals, suggesting that the findings are not sensitive to a particular control group definition.

Placebo tests applied to non-treated metropolitan counties in Oklahoma and neighboring states exhibit heterogeneous post-period behavior. Some placebo counties show little deviation from their synthetic controls, while others display temporary or modest deviations, likely reflecting concurrent local economic development activities or broader regional dynamics. Figures B.1–B.3 display the placebo ATT paths, and Table B.1 summarizes the corresponding inference results.

[21] Note that there are no known eligibility criteria that restrict the program to single individuals (i.e., participants without families).

2.5.2 County-to-County Flow

Table 2.4 summarizes the findings from the PPML gravity models. Panel A includes all states, including Oklahoma, while Panel B exclude origin counties within Oklahoma, focusing solely on the remaining 36 states. Column 1 examine models using housing price gaps; Column 2 uses rent gaps; Column 3 examine models using GDP per capita gaps; and Column 4 focus on weekly wage gaps. Each specification is estimated separately to avoid multicollinearity among the four key explanatory variables. [22]

Housing affordability plays a central role in shaping migration decisions to Tulsa. When in-state migration is included, a one log unit increase in Tulsa's housing price relative to the origin county—meaning housing is about 2.72 times more expensive—is associated with a 48% drop in migration flows. Following the launch of Tulsa Remote, the estimated association becomes stronger: the same housing price gap leads to a 62.7% decrease in migration. This suggests that while the program offers financial incentives, they are not sufficient to fully offset concerns about high housing costs.

When focusing only on out-of-state movers, this pattern becomes even more pronounced. Prior to the program, a one log unit housing price gap corresponds to an 87.6% decline in migration, and this figure rises to 92.1% after the program was introduced. These results indicate that out-of-state migrants are particularly sensitive to housing cost differentials during the post-program period.

Rent affordability shows a similar shift after the implementation of Tulsa Remote. Before the program, the rent gap between Tulsa and origin counties does not significantly affect migration. However, once the program began, a one log unit increase in rent is associated with a 49.2% decrease in migration, indicating that Rent differentials appear more strongly associated with migration flows in the post-program period. Among out-of-state counties, the rent gap

[22] The gravity model estimates are interpreted descriptively rather than causally. These regressions characterize how migration flows to Tulsa are associated with housing costs, wages, and other origin–destination differentials, and how these associations differ before and after the launch of Tulsa Remote. The post-treatment interaction terms should not be interpreted as causal effects of the program on migration behavior. Instead, they reflect changes in the composition and sorting of migrants during the post-2018 period, including the expansion of remote work and heightened cost-of-living sensitivity. As such, the gravity results complement the generalized synthetic control estimates by clarifying who is more likely to move to Tulsa, rather than identifying the causal impact of the program itself.

continues to be insignificant before the program, but the interaction term after the program is both significant and larger in magnitude, suggesting a 59.4% decrease in migration flows. This implies that relatively high rent in Tulsa dampens the program's pull, especially for people from more affordable states.

Differences in economic development, as measured by GDP per capita, also influence migration patterns. When in-state migration is included, the interaction between GDP per capita gap and the post-treatment period is significant and negative: a one log unit higher GDP in Tulsa compared to the origin county leads to a 13.4% drop in migration after the program begins. This suggests that individuals from lower-GDP areas may be discouraged by the perceived cost or economic barriers of relocating to a more affluent city. However, when excluding in-state movers, the GDP gap itself is significant even before the program and remains so, while the post-treatment interaction becomes insignificant. This indicates that Tulsa Remote did not change the underlying reluctance of people in lower-GDP counties to move to Tulsa.

Wage differences present one of the strongest deterrents to migration. When including Oklahoma counties, a one log unit wage gap before the program is associated with a 78% decline in migration. After the program, this increases to 87.2%. When limiting the analysis to out-of-state counties, the reduction is even larger: 88.3% before the program and 93.5% after. These results imply that higher wages in Tulsa do not necessarily attract people from lower-wage counties—possibly due to concerns about cost of living, skill mismatches, or perceived barriers to entry.

The combined results align closely with Tulsa Remote's internal statistics, which show that the top three origin metropolitan areas for participants are New York City, Los Angeles–Long Beach–Anaheim, and Dallas–Fort Worth–Arlington. In contrast, nearby low-cost states such as Missouri, Arkansas, and Kansas contribute relatively few participants (see Table 2.2).

The results are consistent with Tulsa Remote aligning with existing location preferences among cost-sensitive remote workers. The program did not fundamentally alter individuals' preferences regarding housing costs. Rather, by reducing relocation frictions through financial incentives and community support, it enabled cost-conscious individuals to act on pre-existing preferences. Future place-based incentive programs like Tulsa Remote might benefit from focusing outreach and marketing efforts on major urban centers with high living costs. Emphasizing Tulsa's affordability and quality of life may be especially persuasive to individuals in those areas who are looking for a more sustainable and comfortable lifestyle.

2.5.3 Individual Relocation Behavior

Table 2.5 summarizes the findings across three specifications: all migrations to Tulsa MSA (Column 1), interstate migration only (Column 2), and intrastate migration only (Column 3). [23]

Several demographic factors significantly predict migration to Tulsa in the overall sample (Column 1). College-educated individuals are substantially less likely to move to Tulsa, with a coefficient of -0.36, translating to 30.3% lower odds compared to those without college degrees.

However, migration patterns shifted following program implementation year (set to 2019) through several key mechanisms. The interaction term for married individuals indicates that post-2019, married people experienced a 91.9% increase in the odds of moving to Tulsa relative to unmarried individuals. Conversely, the income interaction effect suggests that higher-income individuals became relatively less likely to migrate, with each 1% increase in income associated with a 17.9% decrease in migration odds post-implementation.

Cross-state migration exhibits distinct age patterns, with the positive age coefficient and negative age-squared term indicating that younger adults are most likely to relocate across state lines to Tulsa. The most striking finding concerns marital status effects. Before 2019, married individuals were 60.8% less likely to engage in interstate migration to Tulsa. However, the massive interaction effect reveals that after 2019, married individuals became over ten times more likely to move to Tulsa compared to unmarried individuals. This reversal supports the program's family-friendly design and multiplier effects.

Within-state migration to Tulsa follows different demographic patterns. Age exhibits a negative effect, consistent with traditional migration theory where older individuals are less

[23] The CPS-based logistic regression results are interpreted descriptively rather than causally. The CPS does not contain individual-level indicators of Tulsa Remote participation or eligibility, so the analysis captures aggregate compositional changes among individuals moving to Tulsa rather than isolating program participants. In addition, the post-period partially coincides with the COVID-19 pandemic, which substantially altered migration and labor market behavior, making it infeasible to disentangle program-specific effects from broader pandemic-era dynamics. Accordingly, these estimates are intended to characterize shifts in the demographic composition of movers rather than identify the causal impact of Tulsa Remote. They complement the causal county-level synthetic control analysis and the descriptive gravity model by providing individual-level context.

mobile. White individuals show lower propensity for intrastate migration, while college-educated individuals are significantly less likely to relocate within Oklahoma . The income interaction effect is particularly pronounced for intrastate migration, suggesting that the city primarily attracted middle- and lower-income residents from within Oklahoma.

Additionally, after 2019, environmental motivations were slightly more prevalent among interstate migrants, while relationship-based motivations were substantially less common among intrastate migrants. This pattern is consistent with the program attracting quality-of-life seekers from other states while potentially crowding out family-motivated moves within Oklahoma.

Combined results indicate that post-2019 migrants to Tulsa were more likely to be married, middle-aged, have some college education, and originate from counties with high housing prices, high rents, and metropolitan areas with higher wages. These patterns may inform the design of future relocation incentive programs by identifying demographic profiles and origin characteristics associated with program participation.

2.6 Discussion

2.6.1 External Validity and Generalizability

Tulsa Remote benefits from several distinctive features that may limit direct replicability. The George Kaiser Family Foundation provides substantial philanthropic backing, enabling $10,000 incentives plus extensive programming and community support—resources that government-funded or chamber-backed programs may lack (Dong & Rogers, 2026). Additionally, Tulsa's size as a metropolitan area provides diverse neighborhoods, employment opportunities, and amenities that smaller or rural communities cannot replicate (Dong & Rogers, 2026). While Tulsa's affordability is central to its appeal, this is not unique, nearly all cities operating remote work attraction programs have relatively low costs of living, suggesting cost differentials relative to expensive coastal metros are a common and important feature.

Despite these characteristics, the program's experience offers valuable lessons. Northwest Arkansas's Life Works Here received over 66,000 applications, and Ascend West Virginia offers $12,000 incentives, demonstrating that other cities can implement effective programs by strategically leveraging their own advantages. My findings are most directly applicable to mid-size cities with: (1) low to moderate costs of living relative to major metros, (2) sufficient urban amenities and infrastructure to attract families and professionals, and (3) capacity to sustain multi-year funding commitments.

The findings may generalize less well to very small or rural communities lacking urban amenities, already-expensive metros where cost differentials work against attraction, or cities unable to sustain meaningful incentive levels. However, the displacement and housing market mechanisms I document—rising costs discouraging in-state migrants, modest outflows of existing residents—remain important considerations for any city implementing relocation incentive programs, regardless of size or context. Policymakers should carefully evaluate these tradeoffs against potential benefits when designing similar initiatives.

2.6.2 COVID-19 Timing and Identification

A critical identification concern is distinguishing program effects from pandemic-era migration dynamics. The timing of effects provides strong evidence for program-specific impacts. Tulsa Remote launched in November 2018, and treatment effects emerge clearly in 2019—well before COVID-19's onset in March 2020.

In early 2020, the pandemic initially suppressed mobility nationwide, and work-from-home did not immediately translate to work-from-anywhere. The "Great Reshuffle" and widespread remote work adoption occurred later in 2020-2021. Since Tulsa's migration patterns shifted in 2019, before these broader trends, the observed effects cannot be solely attributed to pandemic-induced migration dynamics.

The GSYNTH provides additional protection against pandemic confounding. Control counties were exposed to the same macroeconomic shocks, labor market disruptions, and remote work trends as Tulsa. The synthetic control comparison isolates Tulsa-specific deviations from these shared pandemic experiences. While the pandemic may have amplified program effects—making relocation easier for remote workers and increasing interest in affordable cities—the 2019 pre-pandemic evidence demonstrates that the program generated measurable impacts independent of COVID-19.

Nevertheless, I acknowledge that complete separation of program and pandemic effects remains challenging, particularly for 2020-2021 estimates. The treatment effect averages reported span both pre-pandemic (2019) and pandemic (2020-2021) periods. Estimates should therefore be interpreted as program effects operating within a pandemic-era context rather than effects that would occur in normal times. The key takeaway is that 2019 evidence validates program-specific impacts, while 2020-2021 patterns reflect these impacts potentially amplified by pandemic-era remote work trends.

2.6.3 Cost Analysis

As Bartik (2019b) emphasizes in the context of business incentives, the true cost of place-based programs must account for displacement effects and opportunity costs, rather than focusing solely on headline expenditures.

The fiscal implications of the Tulsa Remote program can be illustrated using a back-of-the-envelope accounting exercise that relates estimated migration deviations to program participation. Normalizing average annual treatment effects by average annual program participation, the implied migration adjustments associated with each Tulsa Remote participant include approximately 1.35 additional interstate in-migrants, 2.84 fewer interstate out-migrants (retention), 2.19 fewer intrastate in-migrants, and 1.69 additional intrastate out-migrants. These components imply an approximate net gain of 1.31 residents per participant.

Under this descriptive accounting, a nominal \$10,000 cash incentive corresponds to an implied cost of approximately \$7,634 per net additional resident (\$10,000 divided by 1.31). This reflects the fact that the incentive is paid to participants, while the estimated net population change incorporates both direct participation and indirect migration responses. Moreover, the nominal \$10,000 cash payment per participant understates the program's full cost. In addition to cash incentives, Tulsa Remote provides substantial in-kind benefits, including a multi-year coworking membership, organized networking and volunteer events, and wellness benefits through platforms such as Benepass. Accounting for these non-cash components, the total program investment per participant likely exceeds \$13,000, implying a cost per net new resident closer to \$10,000 rather than \$7,634.

These figures are intended as descriptive benchmarks rather than precise fiscal or welfare estimates. They highlight that the effectiveness of relocation incentives depends not only on participant counts, but also on broader migration spillovers and retention dynamics, alongside the opportunity cost of alternative policy uses of public funds.

2.6.4 Spatial Equilibrium, General Equilibrium Effects, and Policy Tradeoffs

The migration responses documented in this paper can be interpreted through the lens of spatial equilibrium theory (Roback, 1982; Rosen, 1979), in which individuals choose locations by trading off wages, housing costs, and local amenities. Recent extensions of this framework emphasize that remote work weakens the traditional wage–rent trade-off by decoupling job location from residential choice, allowing workers to retain high wages while relocating to lower-cost areas (Brueckner, Kahn, & Lin, 2023). From this perspective, Tulsa Remote can be viewed as temporarily amplifying the utility gains from such spatial cost arbitrage by reducing relocation frictions for remote workers.

At the same time, these migration responses should be interpreted in light of broader general equilibrium considerations. Inflows of relatively high-income remote workers may increase local housing demand and place upward pressure on rents and property prices, even in the absence of large differences in housing supply elasticities (Louie, Mondragon, & Wieland, 2025; Yoo, 2024). Although this paper does not directly estimate housing price or amenity effects, the observed reduction in intrastate in-migration and increase in intrastate out-migration are consistent with housing market adjustment mechanisms operating through affordability rather than direct displacement.

In addition, following the framework emphasized by Bartik (2019b), the fiscal implications of relocation incentives extend beyond headline subsidy amounts.

Finally, individual-targeted relocation incentives raise important distributional concerns. Programs such as Tulsa Remote disproportionately subsidize higher-income, highly mobile workers, while potential costs—through housing market pressures or labor market adjustments—may be borne by lower-income or less mobile residents (Yoo, 2024).

2.7 Conclusion

This study shows that individual-targeted place-based remote-work incentives, exemplified by the Tulsa Remote program, are associated with meaningful changes in migration dynamics in the United States. By offering targeted financial incentives, Tulsa is observed to attract individuals from high-cost metropolitan areas, particularly married, middle-aged, college-educated individuals with moderate incomes. These patterns suggest that migration responses are shaped not only by financial incentives but also by broader lifestyle considerations, such as affordability, community fit, and family-related factors.

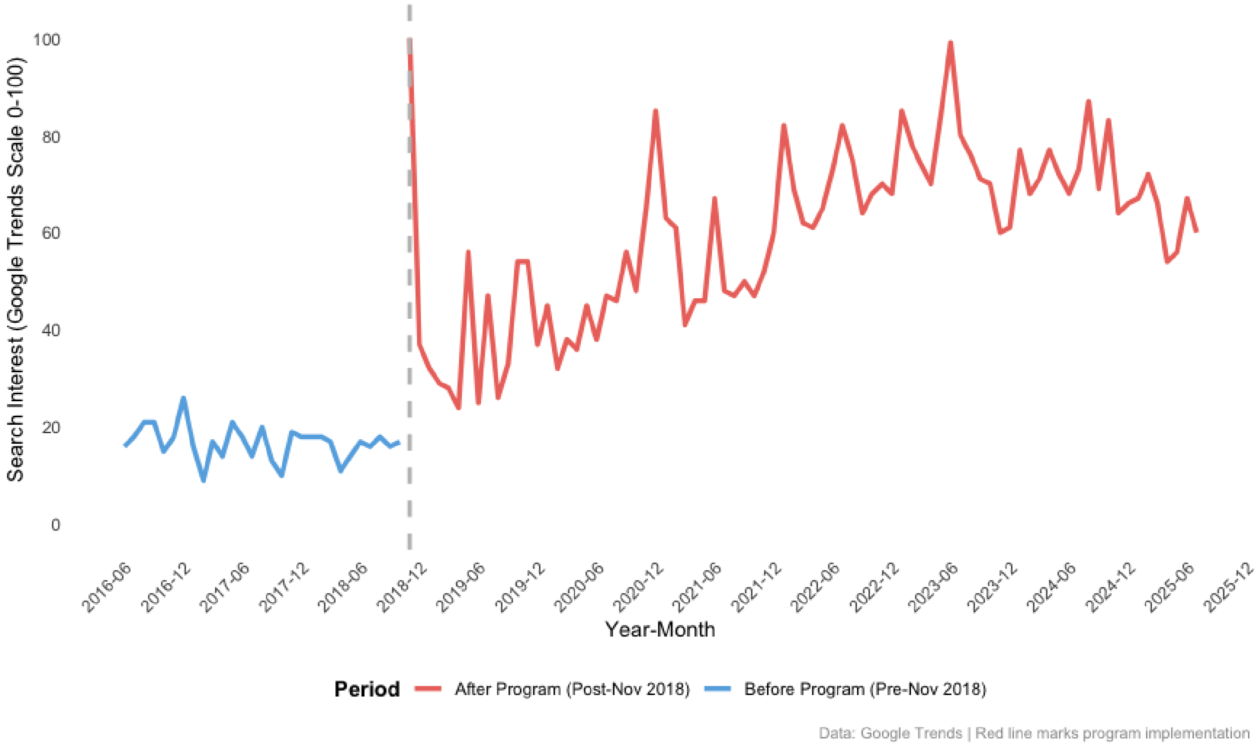
At the same time, the results highlight important and sometimes unexpected trade-offs.

While Tulsa Remote coincides with increased interstate migration inflows, it is also associated with reduced intrastate inflows and increased outflows, pointing to potential compositional shifts in the local population. These patterns underscore that place-based interventions may generate complex spatial adjustments beyond their immediate objectives.

For policymakers, these findings offer two key insights. First, programs that focus on attracting remote workers from high-cost urban centers—where cost-of-living pressures are most salient—appear more likely to coincide with larger migration responses. Second, combining monetary incentives with broader narratives around quality of life, community, and long-term opportunity may enhance program appeal. Overall, the Tulsa Remote experience illustrates how place-based policies can be aligned with remote work trends to influence domestic migration patterns, while also emphasizing the importance of monitoring unintended effects to avoid potential tensions between economic development goals and community stability.

Figures and Tables

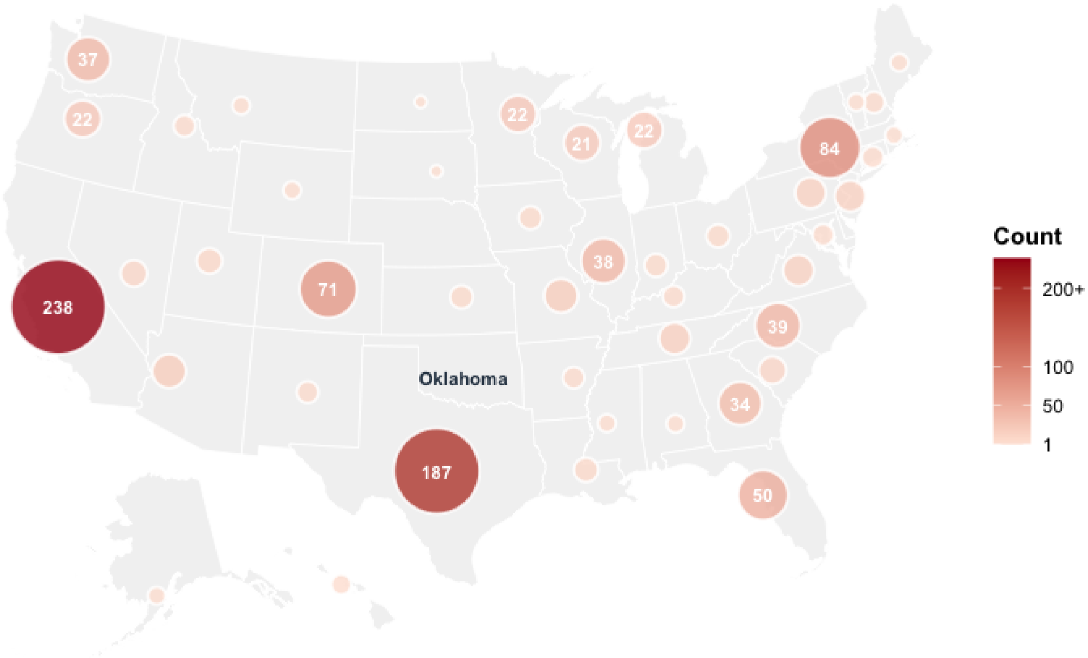
Figure 1: Google Trend Analysis



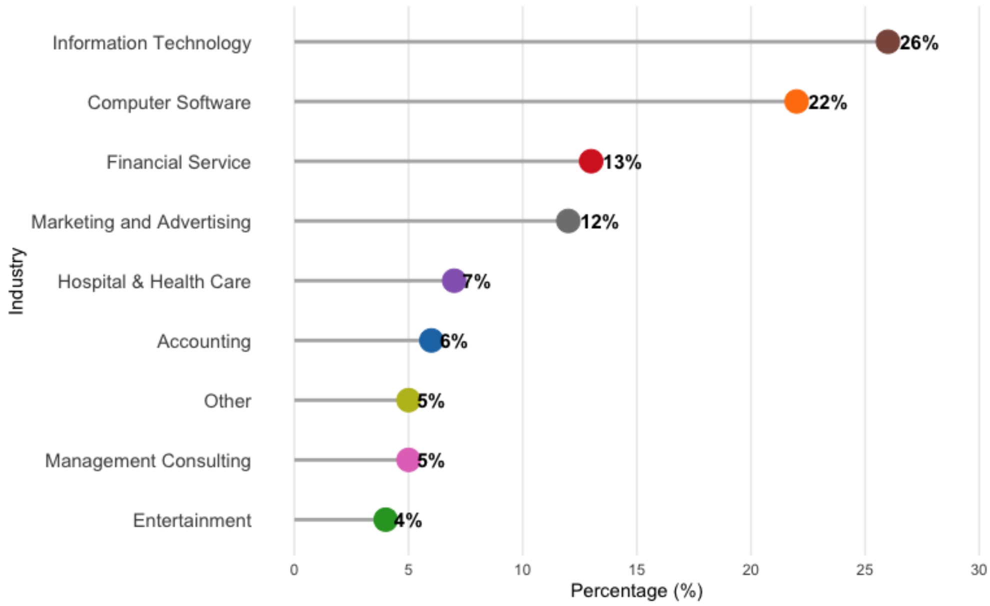
Source: Google Trends, search term "Tulsa Remote"

Note: Search interest spikes only after program launch, indicating the program was unforeseen and not a response to pre-existing trends.

Figure 2: Participants of Tulsa Remote Program



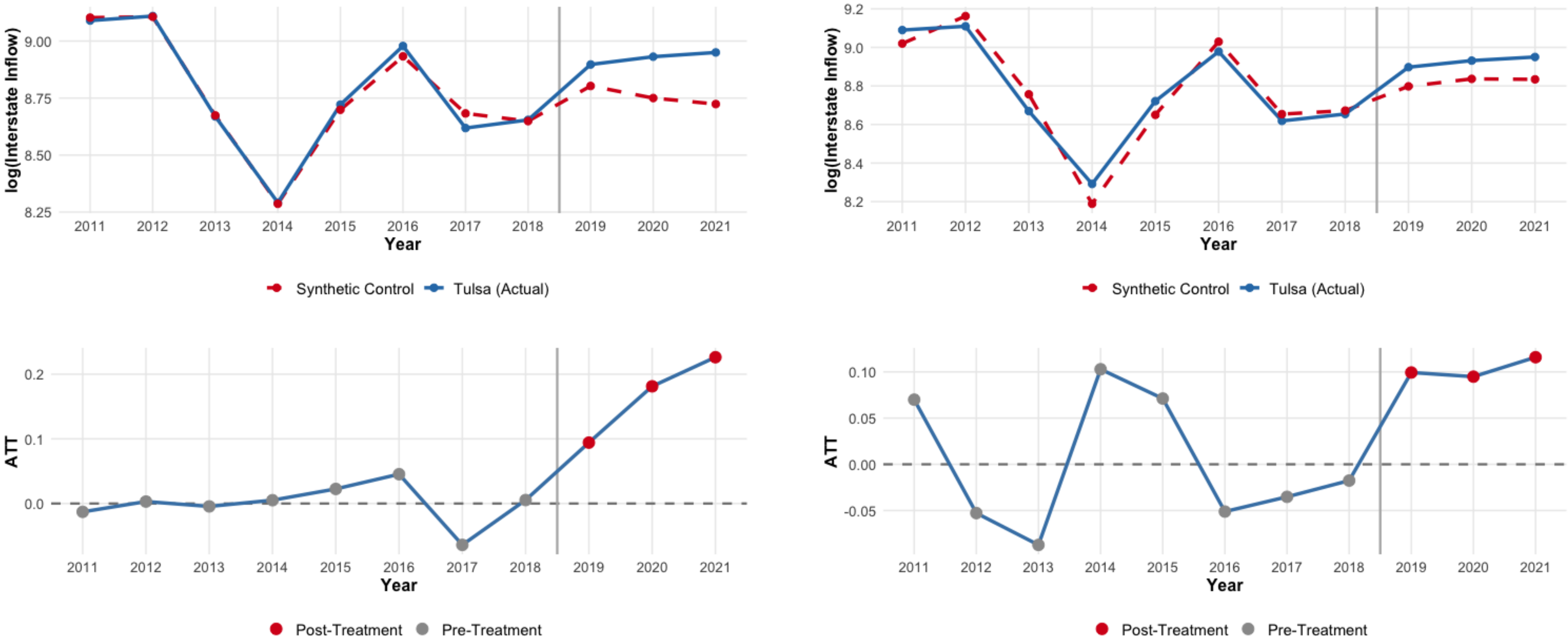
(a) Geographical Distribution



(b) Industry Share

Source: `https://www.tulsaremote.com/program-details`

Figure 3: Treatment Effects on Interstate Inflow: Baseline vs. Robustness

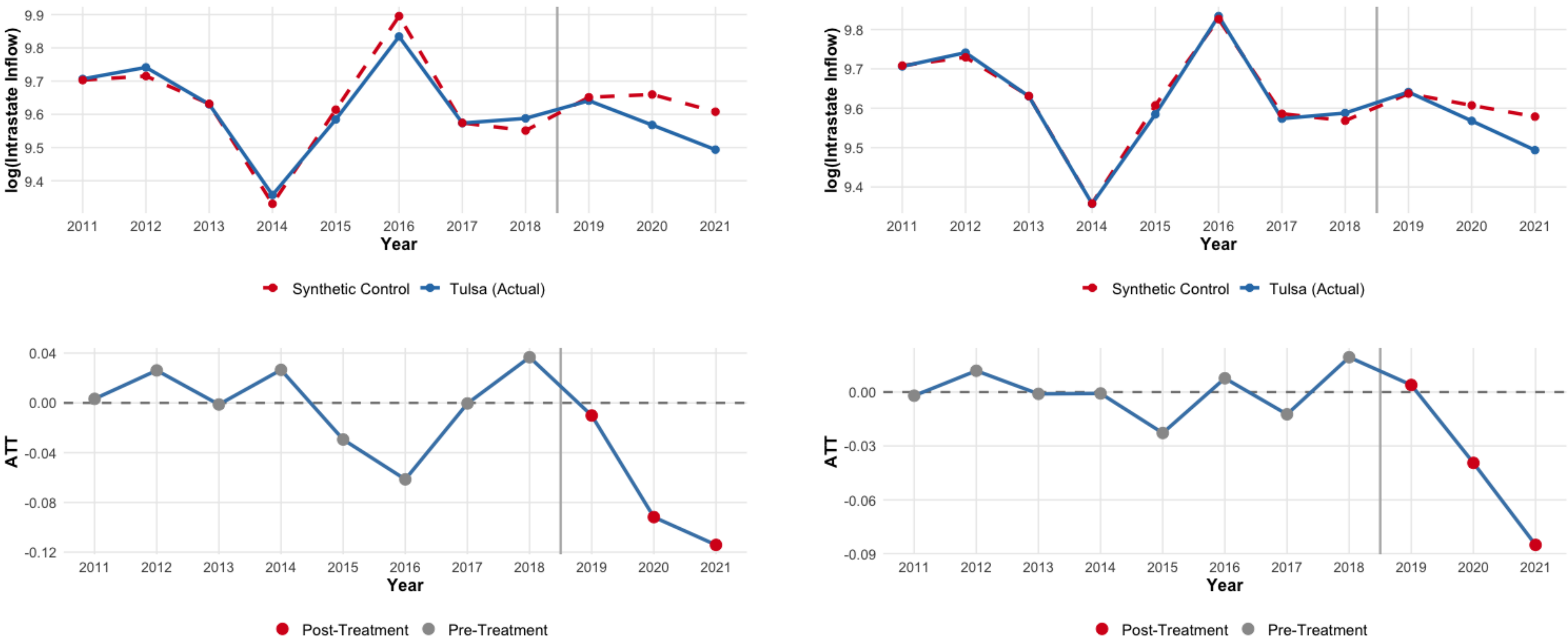


(a) All US Counties

(b) Neighboring MSA Counties

Note: Panel (a) uses all mainland US counties as control units (N=1,262); panel (b) restricts to MSA counties from Oklahoma and six neighboring states (Texas, Kansas, Arkansas, Missouri, Colorado, New Mexico; N=53). Both specifications exclude counties with zero variation over time. In each panel, the upper figure shows actual versus synthetic control trajectories; the lower figure shows the average treatment effect (ATT). The vertical line indicates program launch in November 2018.

Figure 4: Treatment Effects on Intrastate Inflow: Baseline vs. Robustness

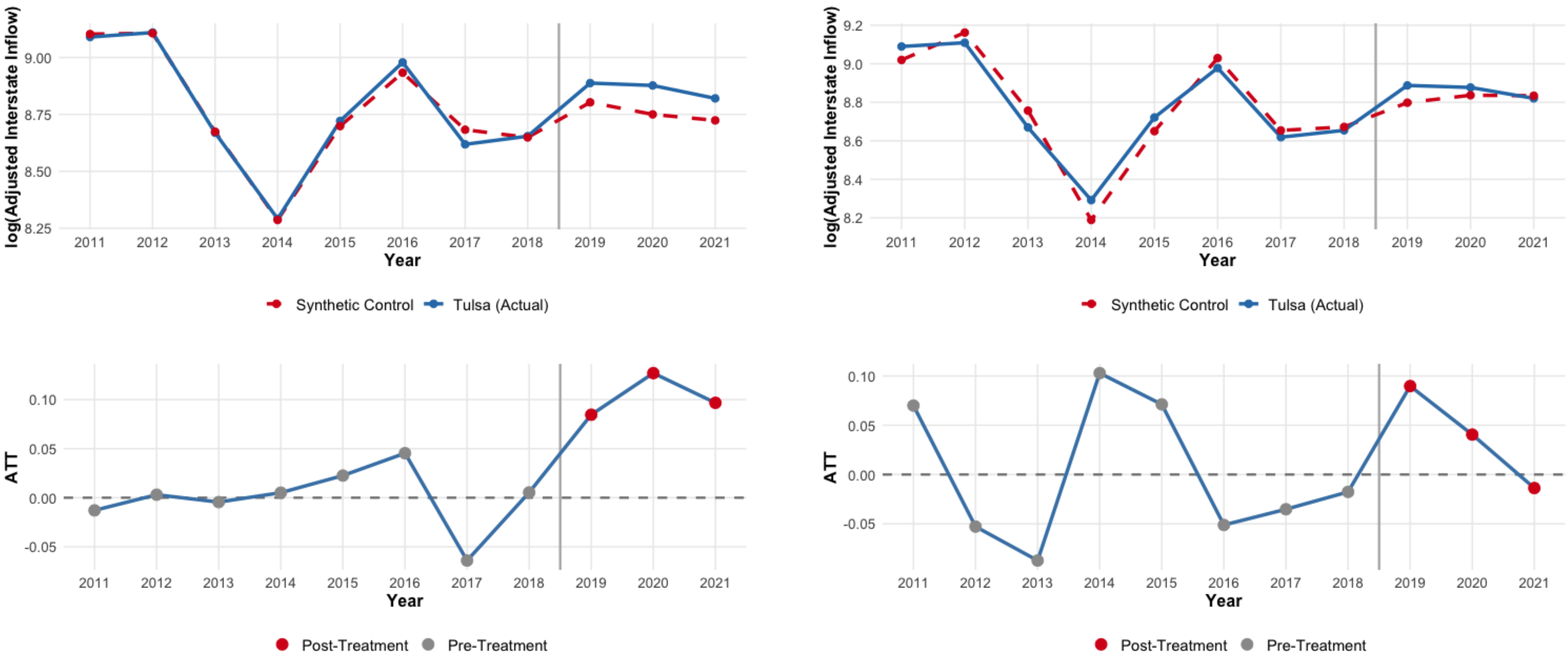


(a) All US Counties

(b) Neighboring MSA Counties

Note: Panel (a) uses all mainland US counties as control units (N=1,262); panel (b) restricts to MSA counties from Oklahoma and six neighboring states (Texas, Kansas, Arkansas, Missouri, Colorado, New Mexico; N=53). Both specifications exclude counties with zero variation over time. In each panel, the upper figure shows actual versus synthetic control trajectories; the lower figure shows the average treatment effect (ATT). The vertical line indicates program launch in November 2018.

Figure 5: Treatment Effects on Adjusted Interstate Inflow: Baseline vs. Robustness

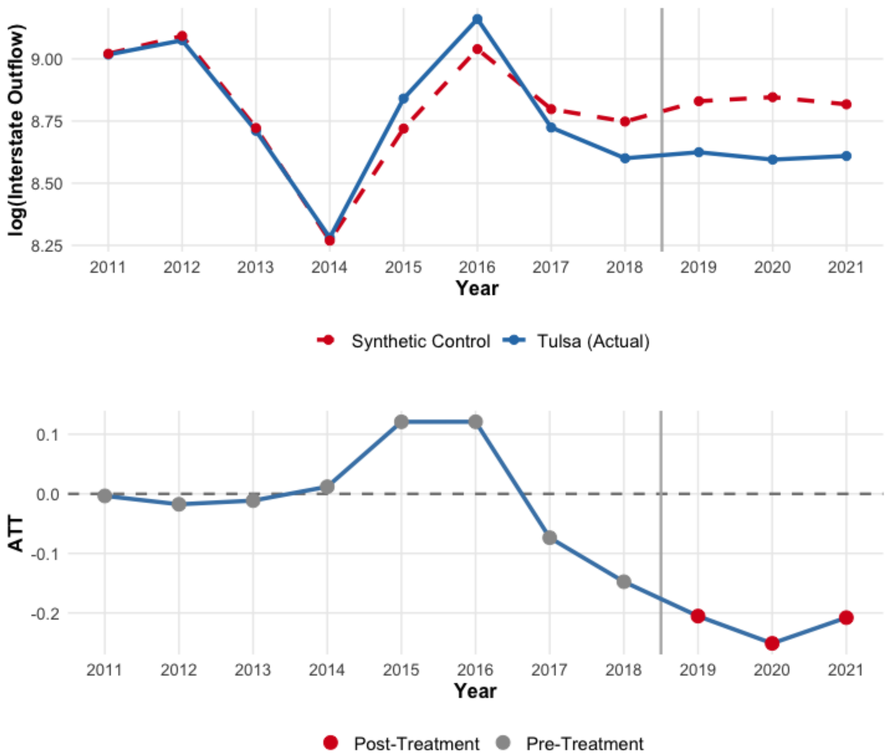


(a) All US Counties

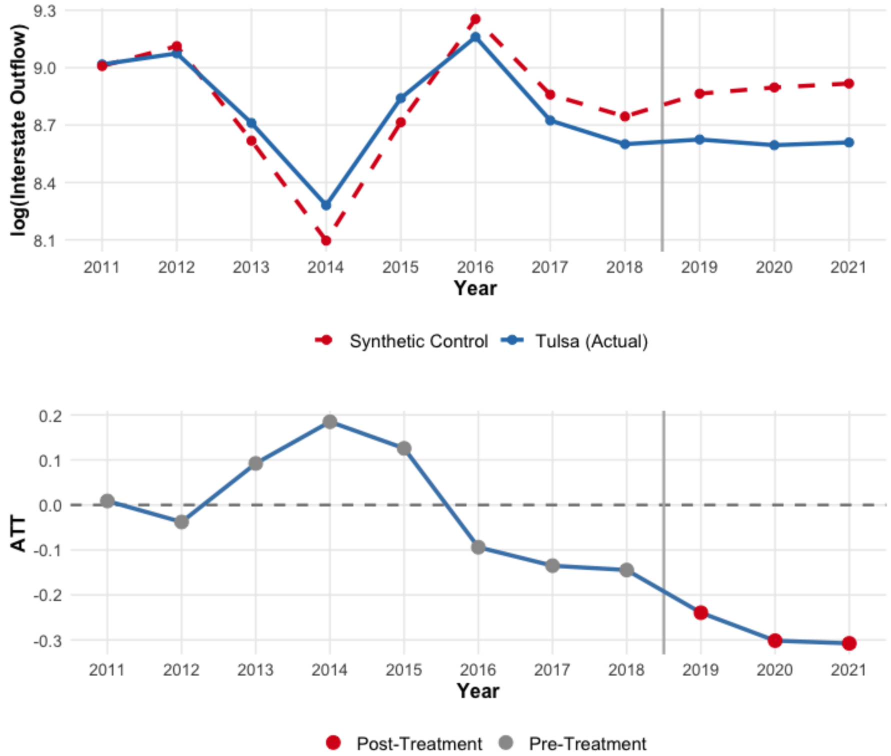
(b) Neighboring MSA Counties

Note: Panel (a) uses all mainland US counties as control units (N=1,262); panel (b) restricts to MSA counties from Oklahoma and six neighboring states (Texas, Kansas, Arkansas, Missouri, Colorado, New Mexico; N=53). Both specifications exclude counties with zero variation over time. In each panel, the upper figure shows actual versus synthetic control trajectories; the lower figure shows the average treatment effect (ATT). The vertical line indicates program launch in November 2018.

Figure 6: Treatment Effects on Interstate Outflow: Baseline vs. Robustness



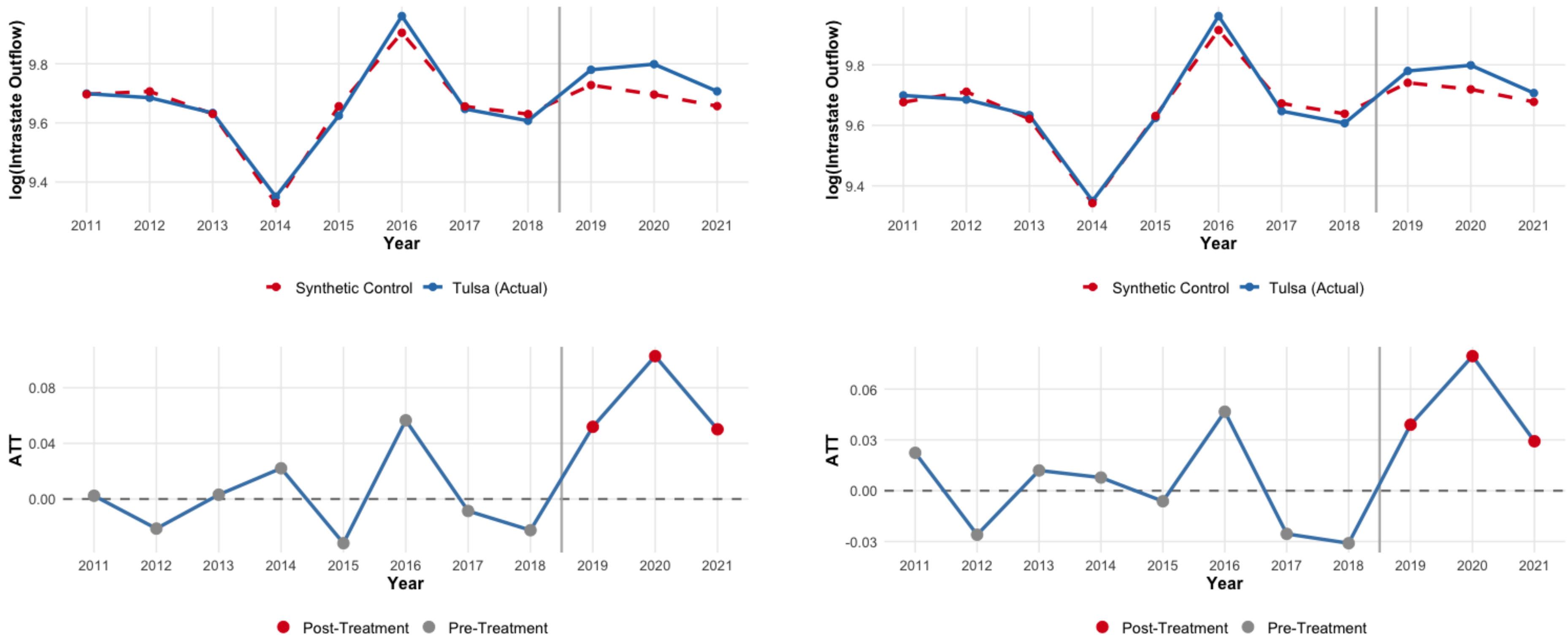
(a) All US Counties



(b) Neighboring MSA Counties

Note: Panel (a) uses all mainland US counties as control units (N=1,262); panel (b) restricts to MSA counties from Oklahoma and six neighboring states (Texas, Kansas, Arkansas, Missouri, Colorado, New Mexico; N=53). Both specifications exclude counties with zero variation over time. In each panel, the upper figure shows actual versus synthetic control trajectories; the lower figure shows the average treatment effect (ATT). The vertical line indicates program launch in November 2018.

Figure 7: Treatment Effects on Intrastate Outflow: Baseline vs. Robustness



(a) All US Counties

(b) Neighboring MSA Counties

Note: Panel (a) uses all mainland US counties as control units (N=1,262); panel (b) restricts to MSA counties from Oklahoma and six neighboring states (Texas, Kansas, Arkansas, Missouri, Colorado, New Mexico; N=53). Both specifications exclude counties with zero variation over time. In each panel, the upper figure shows actual versus synthetic control trajectories; the lower figure shows the average treatment effect (ATT). The vertical line indicates program launch in November 2018.

Table 2.1: Statistical Summary

Panel A: County-Level Analysis					
Variables	Mean	Min	Max	St.D	N
Year	2016	2011	2021	3.16	17,853
Total Inflow	6,201	0	219,386	14,196	17,853
Total Cross-state Inflow	1,897	0	152,834	6,608	17,853
Adjusted Inflow	6,201	0	219,386	14,196	17,853
Adjusted Cross-state Inflow	1,897	0	152,834	6,608	17,853
Total Outflow	6,183	0	327,679	15,780	17,853
Total Cross-state Outflow	1,870	0	133,822	6,632	17,853
Total Population	177,004	2,560	10,094,865	437,414	17,853
White Race (%)	83.9	14.5	98.9	14.8	17,853
Black Race (%)	10.1	0.07	82.4	14.0	17,853
Gender Ratio	0.990	0.821	1.97	0.069	17,853
Weekly Wage ($)	810	436	3,563	194	17,853
Construction Share (%)	10.5	0.51	30.6	3.32	17,853
Manufacturing Share (%)	4.63	0.35	19.9	2.15	17,853
Transportation Share (%)	23.3	4.67	50.5	4.70	17,853
Professional Services Share (%)	14.1	2.17	36.6	4.74	17,853
Employed	82,272	1,140	4,917,685	204,595	17,853
Unemployment Rate (%)	5.93	1.1	29.3	2.52	17,853
Employment to Population Ratio	45.0	21.7	99.7	6.13	17,853
Housing Value ($)	153,578	42,003	1,605,225	100,213	17,853
GDP Value ($)	10,263,898	66,016	841,953,895	31,777,534	17,853
Panel B: Individual-Level Analysis					
Post	0.271	0	1	0.444	42,046
Family Head	0.529	0	1	0.499	42,046
Age	37.810	15	85	15.561	42,046
Male	0.498	0	1	0.500	42,046
White (Non-Hispanic)	0.763	0	1	0.425	42,046
Married	0.458	0	1	0.498	42,046
College	0.391	0	1	0.488	42,046
Total Income	44,585	2	1,420,999	61,656	42,046
Tulsa (All)	0.005	0	1	0.074	42,046
Tulsa (Cross-state)	0.002	0	1	0.040	42,046
Tulsa (Within-state)	0.004	0	1	0.062	42,046

Notes: Panel A reports county-level variables used in the generalized synthetic control (GSYNTH) and PPML gravity model analyses. Panel B reports individual-level variables aggregated at the metropolitan level and used in the logistic regression analysis of migration behavior.

Table 2.2: Geographic Origins of Tulsa Remote Program Members

Panel A: Top 14 Metro Areas	Share	**Panel B: Top 14 States**	Share
New York-Newark-Jersey City, NY-NJ-PA	9.9%	California	21.9%
Los Angeles-Long Beach-Anaheim, CA	9.6%	Texas	14.5%
Dallas-Fort Worth-Arlington, TX	7.2%	New York	8.8%
San Francisco-Oakland-Hayward, CA	4.9%	Colorado	5.4%
Washington-Arlington-Alexandria, DC-MD-VA	4.9%	Florida	3.6%
Denver-Aurora-Lakewood, CO	4.1%	Illinois	2.8%
Atlanta-Sandy Springs-Roswell, GA	2.9%	Virginia	2.6%
Austin-Round Rock, TX	2.9%	Massachusetts	2.2%
Houston-The Woodlands-Sugar Land, TX	2.7%	Missouri	2.2%
San Diego-Carlsbad, CA	2.6%	Washington	2.2%
Chicago-Naperville-Elgin, IL-IN-WI	2.4%	D.C.	2.1%
Boston-Cambridge-Newton, MA-NH	2.1%	New Jersey	1.9%
Kansas City, MO-KS	1.9%	Arizona	1.8%
Portland-Vancouver-Hillsboro, OR-WA	1.8%	Oregon	1.8%

Source: Analysis of EIG-HBS survey data (Newman et al., 2021)

Table 2.3: Treatment Effects on Migration Flows: Tulsa County vs. Synthetic Control

	Adjusted Interstate Inflow	
	Average (per year)	Δ from Baseline
Actual Tulsa (2016–2018)	6,398	
Actual Tulsa (2019–2021)	7,059	+660 (+10.3%)
Synthetic Tulsa (2016–2018)	6,341	
Synthetic Tulsa (2019–2021)	6,366	+25 (+0.4%)
Treatment Effect (ATT)		**+635 (+10.0%)**
	Intrastate Inflow	
	Average (per year)	Δ from Baseline
Actual Tulsa (2016–2018)	15,874	
Actual Tulsa (2019–2021)	14,318	-1,556 (-9.8%)
Synthetic Tulsa (2016–2018)	15,891	
Synthetic Tulsa (2019–2021)	15,360	-531 (-3.3%)
Treatment Effect (ATT)		**-1,025 (-6.5%)**
	Interstate Outflow	
	Average (per year)	Δ from Baseline
Actual Tulsa (2016–2018)	7,030	
Actual Tulsa (2019–2021)	5,484	-1,547 (-22.0%)
Synthetic Tulsa (2016–2018)	7,055	
Synthetic Tulsa (2019–2021)	6,842	-213 (-3.0%)
Treatment Effect (ATT)		**-1,334 (-19.0%)**
	Intrastate Outflow	
	Average (per year)	Δ from Baseline
Actual Tulsa (2016–2018)	17,178	
Actual Tulsa (2019–2021)	17,369	+191 (+1.1%)
Synthetic Tulsa (2016–2018)	16,814	
Synthetic Tulsa (2019–2021)	16,210	-604 (-3.6%)
Treatment Effect (ATT)		**+794 (+4.6%)**

Note: This table reports average annual migration flows for Tulsa County (actual) and its synthetic control over the three-year periods before (2016–2018) and after (2019–2021) program implementation. Treatment effects (ATT) are computed using a difference-in-differences framework: $\left(\text{Tulsa}_{post} - \text{Tulsa}_{pre}\right) - \left(\text{Synthetic}_{post} - \text{Synthetic}_{pre}\right)$. The gsynth model uses U.S. counties with complete data after applying sample restrictions as control units ($N = 1{,}262$). Positive values indicate increases, while negative values indicate decreases.

Table 2.4: Determinants of Migration to Tulsa

Panel A: Include Oklahoma				
Dependent Variable:	Migration to Tulsa			
Model:	(1)	(2)	(3)	(4)
House Gap	-0.6550***			
	(0.1817)			
Rent Gap		-0.1399		
		(0.2368)		
GDP Per Capita Gap			-0.2111	
			(0.1294)	
Wage Gap				-1.513***
				(0.2923)
Post × House Gap	-0.3305***			
	(0.0430)			
Post × Rent Gap		-0.6754***		
		(0.0924)		
Post × GDP Per Capita Gap			-0.1438***	
			(0.0429)	
Post × Wage Gap				-0.5465***
				(0.0955)
Origin County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Unique Counties	229	229	229	229
Observations	2,519	2,519	2,519	2,519
Pseudo R^2	0.94732	0.94663	0.94537	0.94629
Panel B: Exclude Oklahoma				
House Gap	-2.090***			
	(0.3222)			
Rent Gap		-0.2766		
		(0.4096)		
GDP Per Capita Gap			-0.9354*	
			(0.4999)	
Wage Gap				-2.142***
				(0.8075)
Post × House Gap	-0.4521***			
	(0.0677)			
Post × Rent Gap		-0.9015***		
		(0.1636)		
Post × GDP Per Capita Gap			-0.1307	
			(0.1162)	
Post × Wage Gap				-0.5891***
				(0.1983)
Origin County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Unique Counties	179	179	179	179
Observations	1,969	1,969	1,969	1,969
Pseudo R^2	0.80921	0.80081	0.79572	0.79779

Notes: Dependent variable is the number of migrants from origin counties to Tulsa. Gaps are log differences between Tulsa and each origin county. Post indicates years after program implementation. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2.5: Determinants of Migration to Tulsa

Dependent Variable:	Moved to Tulsa		
Model:	All Migrants (1)	Interstate (2)	Intrastate (3)
Post	1.495	-2.644	3.031***
	(0.954)	(2.029)	(1.159)
Age	-0.006	0.114**	-0.051*
	(0.025)	(0.052)	(0.029)
Age^2	-0.00002	-0.001**	0.0004
	(0.0003)	(0.001)	(0.0003)
White	-0.291*	-0.151	-0.358*
	(0.171)	(0.305)	(0.207)
College	-0.360**	0.038	-0.578**
	(0.179)	(0.294)	(0.226)
Married	-0.257	-0.937***	0.036
	(0.167)	(0.310)	(0.200)
Male	-0.108	0.161	-0.246
	(0.158)	(0.275)	(0.193)
Head of Household	-0.029	0.043	-0.074
	(0.158)	(0.279)	(0.192)
log(Income)	0.103	-0.062	0.204**
	(0.064)	(0.088)	(0.087)
Housing Reason	-0.233	-0.362	-0.162
	(0.206)	(0.351)	(0.255)
Relationship Reason	0.149	-0.150	0.289
	(0.189)	(0.338)	(0.230)
Environment Reason	0.010	-0.215	0.114
	(0.346)	(0.619)	(0.417)
Post × White	0.283	0.211	0.319
	(0.346)	(0.723)	(0.397)
Post × College	-0.219	-0.163	-0.174
	(0.347)	(0.631)	(0.425)
Post × Married	0.652**	2.363***	0.148
	(0.311)	(0.743)	(0.359)
Post × Male	0.101	-0.462	0.313
	(0.311)	(0.627)	(0.361)
Post × Head	-0.077	-0.347	0.089
	(0.308)	(0.614)	(0.359)
Post × log(Income)	-0.197**	0.067	-0.318***
	(0.092)	(0.184)	(0.113)
Post × Housing Reason	0.380	-0.682	0.423
	(0.381)	(1.209)	(0.425)
Post × Relationship Reason	-0.665	1.004	-1.497**
	(0.450)	(0.809)	(0.607)
Post × Environment Reason	0.465	1.830*	-0.100
	(0.534)	(0.985)	(0.662)
Observations	40,471	40,471	40,471
AIC	2,829.2	1,030.6	2,079.1

Notes: Logistic regressions predicting migration to Tulsa. Sample includes only individuals who moved within the last year. Columns (2) and (3) indicate whether the migration was interstate or intrastate.

Chapter 3

Attracting Remote Workers: Overview of Programs in the US

3.1 Introduction

This article reviews the evolving landscape of remote worker attraction (RWA) programs offered by urban and rural communities across the United States. The rapid diffusion of these programs reflects broader labor market shifts triggered by the COVID-19 pandemic (Schnoke, Yochum, Frantz, et al., 2022). The pandemic created unprecedented opportunities for employees to engage in remote work (Barton, 2022; Schnoke et al., 2022). [1] CPS data show that in the first quarter of 2024, 22.9% of the workforce engaged in hybrid or fully remote work, with 47.9% of that group working entirely off-site (Borkowski & Kaynas, 2025). Robert Half (2025) reports stabilization in job postings, with roughly 24% hybrid and 13% remote. According to Apollo Technical (2025), approximately 16% of companies operate fully remote without physical offices.

Remote and hybrid work arrangements continue to reshape workforce dynamics and local economies, including control over work environment, commuting costs, and commercial office space demand (Aksoy et al., 2025; Barrero et al., 2023; Gajendran & Harrison, 2007; Gallardo & Whitacre, 2018; Gupta, Mittal, & Van Nieuwerburgh, 2022). Remote work differs fundamentally from hybrid models by severing the link between job site and residential location, giving workers

[1] Telework and remote work indicate jobs that are not performed in-person at a job location. Telework is the historic term. Hybrid work includes some on-site hours.

unprecedented geographic flexibility (Choudhury et al., 2021). Employers gain access to a wider talent pool, and employees experience expanded job opportunities, which could improve labor market matching. Remote workers have a greater ability to optimize their preferences for public goods and taxation levels, potentially moving spatial equilibrium outcomes closer to optimal levels via Tiebout sorting mechanisms (Jansen, Ascani, Faggian, et al., 2024; Tiebout, 1956).

The emergence of "footloose" remote workers has reinforced interest in place-based approaches to economic development. Place-based approaches focus on building local capacity, exploiting comparative advantages, and providing attractive bundles of public goods (Barca et al., 2012; Bolton, 1992). RWA programs offer monetary and non-monetary benefits, often linked to local amenities, for remote workers who relocate to a state or city. Bringing in new workers with non-local employment income departs from traditional employer-focused incentives. Instead of incentivizing employers to create or retain new jobs, which might largely go to new workers (Bartik, 1993), RWA programs directly incentivize workers with remote jobs. This plays on the "jobs follow people" driver of economic development (Hoogstra, van Dijk, & Florax, 2017). If people follow remote workers, who prefer high-amenity places, then amenities become even more important drivers of economic growth (Partridge, 2010). RWA programs can enhance the attraction of rural communities with natural amenities and low cost of living.

The pioneering RWA programs, Think Vermont and Tulsa Remote set the baseline for the hundreds of programs that followed. There is no central clearing house for information on RWA programs. MakeMyMove.com serves as a clearinghouse and provides details on programs that subscribe to their service. Approximately 60% of the 158 programs listed are offered in nonmetropolitan counties. [2] Nonmetropolitan counties that are not adjacent to metropolitan areas are represented in the RWA program list at the same rate (29%) as in the overall U.S. county distribution. Nonmetropolitan, metropolitan adjacent counties are slightly less representative of the US county distribution (28.4% versus 33.27%).

RWA programs continue to be implemented despite a lack of evidence demonstrating their effectiveness (Lusoli, 2022; Schnoke et al., 2022; Teodorovicz, Choudhury, & Starr, 2023).

[2]As of December 1, 2025, 158 programs were listed on MakeMyMove.com. We summarize programs based on their primary location using 2023 Rural-Urban Continue codes published by the U.S. Department of Agriculture, Economic Research Service (2024).

The scarcity of empirical analyses can be attributed to many factors, including the lack of comprehensive data on programs, limited post-implementation observation periods, and nuanced implementation environments. There is little guidance for communities considering RWA programs. We address this gap.

We build on previous research that classifies and summarizes programs (Barton, 2022; Lusoli, 2022; PFM, 2021; Schnoke et al., 2022). Our database includes more programs and more current information than previous research. Specifically, we assemble comprehensive information from various sources for 27 major RWA programs across 21 states. [3] We characterize heterogeneity across communities implementing RWA programs and program design. We also establish connections between RWA programs and dynamic economic channels, such as self-selection into internal migration, highlighting intensive and external margins.

Our discussion provides practical insights for communities that already implement RWA programs as well as those considering doing so. The market for remote workers is competitive and can be costly; leading programs offer upwards of $10,000 per worker. Some communities try to leverage natural amenity advantages. The economic benefit of attracting a remote worker is unclear. The main benefit of an RWA program, particularly for small, rural communities, may arise from marketing and information dissemination about the community through social media platforms.

3.2 RWA Programs, Tiebout Sorting, Migration, and Interjurisdictional Competition

The rise of remote work enhances Tiebout sorting and interjurisdictional competition in public finance. In the classic Tiebout (1956) model, mobile households "vote with their feet" by selecting among communities that offer distinct bundles of local public goods, services, and tax prices. Remote work causes a structural shift that addresses several of the Tiebout model's most restrictive assumptions. Interjurisdictional competition becomes more operational in practice. By enhancing mobility, reducing informational frictions, and increasing the salience of fiscal

[3] We include programs with links to program websites.

and amenity tradeoffs, remote work approximates the conditions under which Tiebout sorting can approach efficiency.

Remote work alters job-market conditions, increasing the empirical plausibility of the Tiebout framework. First, by severing the spatial link between employment and residence, remote work expands the feasible choice set of households, reducing mobility constraints that previously limited sorting. Second, advances in digital and AI-based platforms, and the MakeMyMove.com clearinghouse, increase access to detailed data on local tax regimes, government services, amenities, and RWA programs. It is more plausible that households possess sufficient information to evaluate alternatives effectively. Third, geographic flexibility heightens the likelihood that households will locate in jurisdictions that most closely match their preferences, enhancing the allocative efficiency of sorting mechanisms. Of the canonical assumptions, only the issue of interjurisdictional spillovers remains fundamentally unchanged, as external economies and diseconomies continue to complicate the efficiency of local public finance equilibria.

The ability of remote workers to sort across a wider range of communities amplifies the role of both fiscal- and amenity-based competition. Households evaluate not only the quality of public goods but also the associated tax burdens (Cebula, 2009; Tullock, 1971). Empirical work has demonstrated the sensitivity of migration to state and local tax policies (Koşar, Ransom, & Van der Klaauw, 2022; Moretti & Wilson, 2017). Remote work expands opportunities for cross-border tax arbitrage, where workers may earn income from employers in one jurisdiction while residing in another.

Local amenities, long recognized as drivers of migration (Partridge, 2010), are even more influential in the location decisions of remote workers. RWA program incentives address the financial costs of relocating and, in many cases, the challenge of making new community connections. Communities respond to increased mobility through quality-of-life investments, including upgrading transportation systems, increasing affordable housing supply, and developing recreational activities.

Remote work also impacts the political economy context of interjurisdictional competition. Yardstick competition arises when voters compare local government performance with neighboring jurisdictions (Besley & Case, 1995; Shleifer, 1985; Tang & Zeng, 2018). Cities or regions with strong performance, characterized by low taxes and high-quality public services, can attract residents from adjacent areas (Salmon, 2019). With the rise of remote work opportunities and the promotion of RWA programs on digital platforms like MakeMyMove.com, the relevant comparison distance expands to a national and global context. The yardstick is transformed into an infinity stick with an expanded intensive spatial margin for migration.

The drive to outperform the competition pushes local governments to optimize public service provision, which could ultimately benefit the community (Tiebout, 1956). Alternatively, spending scarce resources to attract remote workers could be counterproductive, much like tax cuts financed through reduced public expenditures can be wasteful (J. D. Wilson, 1999). It is unclear whether attracting remote workers accelerates economic growth.

3.3 Overview of RWA Programs

The earliest RWA programs pre-dated the pandemic by a few years. Vermont launched its Think Vermont program in 2018 and Tulsa followed quickly with the well-known Tulsa Remote program. [4] The diffusion of RWA programs accelerated after the pandemic with the rise of remote work opportunities. According to MakeMyMove, there were 54 RWA programs in place by December 2021, 108 by September 2023, and over 150 as of September 2025. [5] Figure 1 shows the number of RWA programs in place as of September 2025. The RWA programs are predominantly concentrated in the Midwest and central regions of the United States. Indiana leads with 51 programs, followed by Kansas (21) and Kentucky (16). Twelve states have only one program each: California, Hawaii, Montana, Missouri, Wisconsin, Maine, Vermont, Alabama, Louisiana, Mississippi, South Carolina, and New Mexico. Given the monumental task of collecting comprehensive data on all RWA programs currently offered across the US, we focus on 27 major programs for which we could gather comprehensive information. Our list of major programs includes all 19 programs discussed by Barton (2022), 16 of the programs in Schnoke et al. (2022), 12 of the 15 programs in Lusoli (2022), and 10 of the 18 programs listed

[4] For details see https://thinkvermont.com/wp-content/uploads/2021/10/Worker-Relocation-Grant-Program-FAQs.pdfandhttps://tulsaremote.com

[5] Data was retrieved from https://www.makemymove.com/get-paid.

in PFM (2021). The overlaps are shown in Appendix Table C.1. We highlight similarities and differences in the programs to illustrate the range of RWA programs across the US.

Table 3.1 lists the names of the major programs ordered by month and year of adoption. Most program names include the program delivery location, especially the common “Move to X” format. Some program names are less transparent, including Life Works Here (Northwest Arkansas), Technology Workforce Initiative (Savannah, GA), 218 Relocate (Bemidji, MN), and Shift South (Natchez and Adams County, MS). Throughout the paper, we use program names and provide descriptive locations when the names are not self-explanatory. Figure 2 illustrates the timeline of the major programs included in our analysis. The major programs span 17 states, including four in Indiana (out of the 36 RWA programs offered in the state) and two each in Kentucky, Tennessee, and West Virginia.

Table 3.2 provides demographic information for the program city or the primary location if programs span multiple jurisdictions. There is considerable heterogeneity among RWA program communities by population size, median income, median age, median housing prices, and unemployment rates. Small and large, rural and urban communities use RWA programs. Even cities with low unemployment rates (West Lafayette and Noblesville, Indiana) offer RWA programs.

The earliest RWA programs set important precedents for later initiatives. Think Vermont offers remote workers up to $10,000 to cover moving expenses and related costs when establishing residency in Vermont. Tulsa Remote offers a $10,000 cash incentive plus complimentary access to co-working spaces and various exclusive perks and events. RWA Programs that followed the pioneers also primarily rely on cash incentives and offer various supplemental non-cash benefits.

In many cases, RWA programs evolved from pre-existing programs. The Shoals Area in Alabama introduced the Remote Shoals program in 2019. It mirrored the Think Vermont and Tulsa Remote programs by offering $10,000 to remote workers living outside of Colbert and Lauderdale Counties. Choose Topeka, also adopted in 2019, was inspired by Tulsa Remote. Not limited to remote workers, it requires employers to pay incentives that are reimbursed by the city/county joint economic development organization after the new hire has lived in Topeka/Shawnee County for a year. It offers up to $10,000 for rent and up to $15,000 to purchase a home in Topeka or Shawnee County, paid throughout the year. [6]

The Covid-19 pandemic had an unprecedented impact on the United States starting in 2020. Five new major RWA programs were launched, showcasing a diverse range of offerings compared to their predecessors. Two programs offered financial incentives on par with earlier programs. Life Works Here Initiative in Northwest Arkansas offered $10,000 in financial support plus a mountain bike. Move to Michigan went even further, providing $15,000 towards a new home purchase valued at $200,000 or more, plus a choice of over $5,000 in supplementary perks where individuals could pick two from a list including car service, annual rail pass, athletic club membership, economic club membership, golf driving range membership, co-working space, VIP passes to the local PGA championship, or an annual park pass. [7]

Three programs implemented in 2020 offered considerably smaller monetary incentives. Remote Tucson provided a small package including $1,000 for relocation, an additional $1,000 in Airbnb credit, and access to co-working spaces. The Technology Workforce Incentive applied a more targeted recruitment approach by focusing on qualified technology professionals living outside of Savannah, Georgia. The program reimbursed up to $2,000 for individual moving expenses. Finally, Honolulu, Hawaii, adopted the creatively named Movers & Shakas program, which covers airfare and hotel costs for remote workers to participate in an island culture experience in hopes of luring former residents and non-residents to move back to the island. The increased variety of approaches and the shift away from the $10,000 cash-incentive benchmark was notable.

As the COVID-19 pandemic persisted in 2021, there was a notable surge in RWA-program adoption. This was accompanied by an increasingly diverse array of monetary and non-monetary offerings and geographic locations. Table 3.1 describes twelve major RWA programs adopted in 2021. Ascend West Virginia offered the most generous monetary incentive, $12,000, for relocations to the eastern panhandle, Greenbrier Valley, Morgantown, and Lewisburg, WV. Including various non-monetary benefits, the total benefits are valued at $20,000 or more. Three programs adopted in 2021 offered $10,000 monetary benefits following the pioneer programs, and the rest offered monetary incentives between $2,500 and $6,000.

[6] For details see Yarborough (2019).
[7] For details see `https://movetomichigan.org/`.

The six major programs adopted in 2022 had a range of monetary benefits. One replicated the pioneer programs, four provided \$5,000, and one offered \$2,000. These programs offered various non-monetary benefits, most tied to local community amenities.

As shown in Table 3.1, \$10,000 is the cap for cash incentives among the major RWA programs, excluding Ascend West Virginia. Many factors determine moving costs. Estimates of long-distance costs to move the contents of a three-bedroom home fall in the \$4,000 to \$8,000 range (Greenhalgh & Auer, 2023). Moving also entails rental deposits, mortgage down payments, utility deposits, and storage costs. \$10,000 would cover most direct relocation costs over a long distance. RWA programs offering considerably less would only cover costs for shorter moves.

Figure 3 plots the total value of RWA program incentives and the natural amenity rank for the primary county in which each program is located. The Economic Research Service natural amenity scale combines six environmental measures, including warm weather, winter sun, temperate summer, low summer humidity, topographic variation, and water area for counties in the 48 contiguous US states (McGranahan, 1999). The scale represents deviations from the mean, where: 0 is -3 to -2 deviations from the mean and 7 is over 3 deviations above the mean. The RWA program counties all rank between 3 (-1 to 0 standard deviations from the mean) and 4 (0 to 1 standard deviations from the mean), except for Remote Tucson, which has a rank of 5 (1–2 standard deviations from the mean). Remote Tucson has the highest ranking and the lowest RWA Program incentive. There is no apparent relationship for the remaining major RWA programs.

3.4 RWA Program Eligibility Requirements

This section provides additional details about key eligibility requirements for program applicants. There is notable heterogeneity across programs, reflecting desirable targets.

Generally, RWA programs are designed to entice remote workers to relocate. Some programs also offer incentives to non-remote workers. Three of the major programs we reviewed have mixed programs. Think Vermont provides grants for relocating remote workers and new remote workers. The eligibility criteria differ. Newly relocating workers must move to Vermont, become full-time residents, and secure full-time employment with a Vermont-based employer. New remote workers must work remotely full-time for an out-of-state employer from a home office or coworking space in Vermont. Similarly, Choose Topeka is designed to attract on-site and remote workers who wish to live in Shawnee County. Qualified applicants must secure employment with a local employer. The Fremont Remote Worker Grant Program (OH) also targets remote and relocating workers.

3.4.1 Delivery Location/Relocation Requirements

The second column of Table 3.1 highlights significant diversity when it comes to eligible geographic areas covered by RWA programs. RWA delivery locations can include all or part of a city or county, multiple cities or counties, a single county, or an entire state. Work from Purdue covers designated neighborhoods in the city. Programs encompassing city-wide locations include Technology Workforce Incentive (GA), 218 Relocate (MN), Johnson City Remote (TN), Beckley Remote (WV), Move to Paducah (KY), Shift South (MS), Welcome to Ruston (LA), Choose Ketchikan (AK), Fremont RW Grant (OH), Move to Mattoon (IL), Noblesville RW (IN), and Greater ROC Remote (NY). Move to Michigan and Ascend West Virginia serve multiple cities. Move to Michigan, for example, covers nine cities in southwest Michigan. County-wide programs are offered by Tulsa Remote, Choose Topeka, Movers & Shakas, Remote Tucson, Bloomington Remote, Move to Rutherford County, Choose Southern Indiana, EKY Remote (KY), Remote Shoals (AL), and Life Works Here in Northwest Arkansas cover multiple counties. Two small states, Vermont and Maine, offer statewide RWA incentives.

The geographic limitations on the delivery area are important for determining inter- and intra-state competition for remote workers between communities. Statewide programs increase the relative competitiveness of localities compared with cities outside the state. In contrast, sub-state-level programs create competition between neighborhoods and cities within and across states.

3.4.2 Origin Location Requirements

RWA incentive programs exhibit significant diversity concerning the targeted origin of applicants. The most common restriction is that applicants must reside outside the program state to qualify. Table 3.3 shows that 16 major programs impose this constraint, including programs that have substate delivery areas, such as Tulsa Remote (city only), Ascend West Virginia (multiple cities), and EKY Remote (multiple counties). Movers & Shakas requires participants to live in the continental US. The out-of-state eligibility requirement mitigates the likelihood of poaching potential new remote workers from neighboring communities in the state. In theory, intra-state moves are less costly and less risky for remote workers than inter-state relocations.

Programs also impose more localized exclusions. Four programs require applicants to reside outside of the county in which the RWA operates: Choose Topeka (KS), Remote Tucson (AZ), Move to Rutherford County (TN), and Shift South (Natchez, MS). Three programs require applicants to live outside the city where RWA incentives are offered — Technology Workforce Incentive (Savannah, GA), Johnson City Remote (TN), and Welcome to Ruston (LA). Four RWA programs require candidates to be outside a certain radius which transcends administrative boundaries. 218 Remote (Bemidji, MN) sets a 60-mile radius, Move to Paducah (KY) and Move to Mattoon (IL) both set a 100-mile radius, which would allow in-state relocations as long as they are not close. In contrast, Greater ROC Remote (Rochester, NY) sets a 300-mile radius for in-state relocations and has no minimum distance for out-of-state applicants.

3.4.3 Minimum Age Requirements

Table 3.3 shows information on age restrictions for RWA program applicants. Many of the major programs do not set age requirements. Most of the programs with age requirements set the minimum at 18. A few programs set higher age minimums: Move to Paducah (KY) and Welcome to Ruston (LA) set the minimum at 21 and Move to Rutherford County (TN) sets the minimum at 24. The age restrictions are merely a screen and do not indicate the selection criteria used by RWA program administrators.

3.4.4 Income Requirements

As shown in Table 3.3, most of the RWA programs do not have specific income requirements. Among the programs with income thresholds, requirements range from a low of $45,000 (Move to Mattoon) to a high of $80,000 (Noblesville Remote Worker), with $50,000 being the most common. Vermont requires a minimum hourly wage of $13.39, which equates to $26,780 annually for 2,000 hours of work.

There is no clear relationship between the minimum income requirements and the median income in the RWA Program locations. Figure 4 shows the $50,000 minimum is above the median income in all the major locations except Muscle Shoals. Noblesville Remote has the highest minimum income requirement and the highest median income among the major programs. Remote Tucson and EKY Remote (KY) set the minimum eligibility requirements above their median incomes.

RWA programs apply other work-related criteria. Two major programs require work experience to qualify: Life Works Here (NW Arkansas) and Technology Workforce Incentive (GA) require at least 2 and 3 years, respectively. Additionally, certain programs may exhibit preferences for specific professions among remote workers. For example, the Technology Workforce Incentive (GA) explicitly targets technology workers. In contrast, Life Works Here (NW Arkansas) is more inclusive and highlights a particular demand for STEAM (Science, Technology, Engineering, Arts, and Mathematics) professionals and entrepreneurs.

The income and job-related requirements serve as initial filters for applicants. The median income of those selected for the programs reflects a combination of factors including the income distribution among the applicant pool, previous experience, and targeted skills/industries.

The eligibility criteria are reflected in the RWA program participants. For instance, the median income for participants in the Tulsa Remote program was $85,000, with an average income slightly surpassing $104,600 (Newman et al., 2021). This is well above the $49,425 average wage in Tulsa (ZipRecruiter, 2023). Ascend West Virginia participants earned $105,000 on average, which is over four times higher than the local wage. [8] The inaugural cohort of Life

[8] For additional information see "Meet the 2021 Ascend Morgantown Class," posted at `https://ascendwv.com/ascend-morgantown-class/` last accessed August 26, 2024.

Works Here in NW Arkansas includes an executive chef and a James Beard Foundation Impact Fellow hailing from Atlanta, a digital marketing manager from Denver, a music producer and creative community curator based in Los Angeles, a gaming producer also from Los Angeles, and a cloud technology manager with roots in San Francisco (Northwest Arkansas Council, 2021). The average annual income of participants in Choose Topeka was $89,000 (Hrenchir, 2022). In contrast, the hourly wage of $23.56 corresponds to about $49,116.80 annually (U.S. Bureau of Labor Statistics, 2021). Starting in 2021, 40 individuals from 19 US states and one foreign country participated in the Bloomington Remote program. These individuals collectively exhibit an impressive average household income of $155,000, which is three times higher than Bloomington's average income (East, 2023).

3.4.5 Eligibility: Residency Requirements to Retain RWA Participants

Programs use various strategies to deter remote workers from leaving after collecting benefits. Incremental disbursement of funds is a common strategy. For instance, Ascend West Virginia disburses payments monthly, spreading the initial $10,000 over 12 months and the remaining $2,000 after the participant's second year of residence in West Virginia. Ascend WV participants collect their scheduled checks in person at the designated coworking space. The small, nonmetropolitan town of Ruston, Louisiana, spreads $10,000 incentives over three years.

As shown in Table 3.3, many programs have minimum residency requirements. Choose Topeka, Move to Paducah (KY), and Greater ROC Remote (NY) require at least one year of residency. The programs with 2-year residency requirements are Ascend WV, Technology Workforce Incentive (GA), Choose Southern Indiana, and Move to Mattoon (IL).

Move to Michigan does not have a residency requirement but does require participants to purchase or build a home worth at least $200,000. Choose Topeka offers $15,000 towards the purchase of a home or $10,000 for rent within the first year of being hired or relocating through its employer match program. It also requires participation in an immersion program. Tying incentives to home purchase or lease serves a dual purpose: it incentivizes investment in the local economy and demonstrates the participant's commitment to the community. This policy also adds separation costs if a participant leaves the community later.

Some programs, such as Think Vermont, do not specify a minimum stay and, instead, emphasize the need for participants to be “full-time residents” or pay taxes in the state. Some of these programs may require individuals to obtain a local driver’s license as evidence of their committed residency.

3.5 RWA Program Funding Sources

Table 3.4 provides information on the funding sources for the major RWA programs. The sources fall into three categories: public, private, or a public-private mix. Only two programs are funded entirely by private foundations. The George Kaiser Family Foundation funds Tulsa Remote as well as other major projects in Tulsa including the Gathering Place, a 100-acre park that offers numerous activities, play structures, sports facilities, and community experiences (Padilla, 2022). The Walton Family Foundation funds the Life Works Here program in northwest Arkansas. Most communities, however, fund RWA programs using public funds.

Three small communities are the sole funders of their programs. The City of Paducah, Kentucky, with a population of a little over 26,000 people, funds its RWA program from its city budget. It seeks to attract 25 remote workers and their families with a $2,500 cash incentive, plus tax waivers and working space. Ruston, Louisiana, a town of about 22,000, allocated funds to recruit 25 participants to receive $10,000 from its city budget which was experiencing a surplus from sales tax revenue growth and American Rescue Act funds (LeBoeuf, 2021). The even smaller town of Fremont, Ohio, with a population of just under 16,000, allocated $20,000 for its RWA program (Carson, 2021).

Most of the programs use multiple funding sources with a heavy reliance on local economic development organizations. For example, Johnson City Remote receives sponsorship from the Northeast Tennessee Regional Economic Partnership, Northeast Tennessee Tourism Association, VISIT Johnson City, and other local collaborators. Similarly, the Think Vermont program is jointly funded by The State of Vermont, the University of Vermont, and the Vermont Student Assistance Corporation. Work from Purdue combines university funding (i.e., Purdue Research Foundation) and public funding, including the City of West Lafayette and the Indiana Economic

Development Corporation.

The source of funds is an important factor for cost-benefit analysis of programs. Funding from private foundations reduces the opportunity costs of using public funding for RWA programs. Of course, there are still opportunity costs because the funds could go towards other possible projects. In contrast, when public funds are used there could be crowd-out, crowd-in, and opportunity costs due to budget constraints. These are important factors for assessing the economic impacts of RWA programs.

3.6 Promotion of RWA Programs

A key aspect of RWA programs concerns the ability to recruit applicants. Administrators promote their programs using diverse online avenues, including digital job boards, social media platforms, and focused digital campaigns. MakeMyMove provides an online clearing house that receives fees based on leads and relocations. It also offers consulting services regarding designing and marketing incentive programs (Orr, 2022). Not all communities list their programs on the MakeMyMove platform.

Table 3.5 lists the promotional forms used by the major programs. Four programs have dedicated social media accounts on LinkedIn, Facebook, Instagram, Twitter, and YouTube. All except three RWA programs—Move to Rutherford, RW Welcome (ME) and EKY Remote (KY)—have dedicated Facebook accounts. Instagram is the second most-used platform with 18 dedicated sites. Sixteen programs use Twitter and YouTube. LinkedIn is the least popular with only 12 dedicated sites. The reliance on Facebook reflects the huge popularity of this platform.

RWA programs also forge partnerships with official entities such as city websites and chambers of commerce. For instance, the Shift South Program is promoted by the Natchez Inc., an economic development organization with a presence on platforms like Facebook, Twitter, and Instagram. Purdue University, the City of West Lafayette, and the Indiana Development Corporation promote the Work From Purdue program.

The multifaceted promotional efforts to recruit participants advertise community features to individuals who would otherwise know little about a given community. According to Northwest

Arkansas Council President and CEO Nelson Peacock, “The Northwest Arkansas region offers a unique opportunity to create balance for those eager to move from congested and expensive larger cities and suburbs ... We’re not seen, necessarily, as a place to relocate to from the coasts. We need that visibility like these targeted incentives to get people here with the right skills to add value to our ecosystem” (Gatling, 2020).

Many program adoptions generated media reports in major publications across the country. The New York Times, Fox Business, CNN, TIME magazine, and other outlets reported the approval of the Choose Topeka program within 48 hours of the announcement. Stephen Colbert mentioned that “The city of Topeka will pay you up to $15,000 just to move there” in his Late Show monologue (Yarborough, 2019). The MakeMyMove website includes many articles about RWA programs published in various outlets including The LA Times and USA Today. Remote worker programs may also improve a state or community’s public image through branding (Lusoli, 2022). Vermont’s Agency of Commerce and Community Development (ACCD) reports the interest generated from national and international media coverage of the state’s RWA program. ACCD’s 2018 annual report estimated the value of the media coverage of the 2018 Program at over $7 million (PFM, 2021).

3.7 RWA Program Applicants and Recipients

The attraction of RWA programs is evident in the number of applicants and program participants. Table 3.6 gives information about the major RWA programs based on responses provided by program managers. [9] More generous incentives are expected to attract more applicants, holding other factors constant; however, this does not always hold. The Movers & Shakas cultural immersion program received the highest number of applicants (over 90,000) within one year. [10] It is currently not accepting new applicants. The two privately supported programs received overwhelming numbers of applicants. Life Works Here (NW Arkansas) and Tulsa Remote reported 66,000 and 50,000 applicants, respectively. Ascend West Virginia, which offers the

[9] Blank cells represent missing information. Contact information was available from local chambers of commerce and program websites. We thank Choose Southern Indiana, Remote Shoals Program, Tulsa Remote, SEDA, and Fremont Remote Worker Grant Program staff for their time, and support.

[10] Reported on the program website.

most monetary incentives, reported 20,000 applicants. In contrast, Welcome to Ruston, which offered $10,000 in benefits, only received 200 applicants. The programs offering less than $5,000 in cash incentives attracted many fewer applicants. Fremont Remote Worker Grant received only 12 applicants between 2021 and 2022. Move to Paducah received 65 applicants. The number of individuals who applied to multiple programs is not known.

The number of recipients reflects the applicant pool and available funding. Tulsa Remote has recorded more than 3,500 recipients since its inception in 2018. Tulsa Remote consistently stands out as the most successful program in attracting remote workers. A few programs funded a small number of remote worker relocations: Choose Ketchikan, Move to Mattoon, and Fremont RW Grant reported 2, 5, and 7 recipients, respectively.

Locations may be attractive to footloose remote workers regardless of RWA programs. Cities with fewer amenities may face greater challenges in attracting remote workers. As discussed above, the ERS natural amenity rankings indicate that the major RWA programs fell within one standard deviation of the mean score, except for Tucson, Arizona, which was between 1 and 2 standard deviations higher. Median-sized cities like Tulsa and Tucson may appeal more to remote workers due to their lower cost of living and increased community engagement. Conversely, college towns attract young professionals. Morgantown, WV, home to the West Virginia University, and West Lafayette, IN, with Purdue University, are prime examples.

Population growth can indicate a community's attractiveness. Figures 5–7 show population growth for the primary cities hosting RWA Programs. [11] Figure 5 includes cities larger than 100,000. Honolulu, Tucson, and Rutherford all experienced population growth in the decade before RWA program adoption. The remaining communities, Tulsa, Rochester, Savannah, and Topeka, had stagnating population growth. Figure 6 shows that five of the eight medium-sized cities with major RWA programs experienced robust population growth between 2000 and 2010. Morgantown, WV, Paducah, KY, and Ruston, LA had flat growth during the period. In Figure 7, only 218 Relocate, which lies in the most rural type of county, stands out by having notable population growth between 2000 and 2010. The remaining small cities had flat or declining population growth. Population growth trends were mixed: growing and stagnating cities adopted

[11] Population data are from World Population Review "World Population by Country (live) 2024," available at www.worldpopulationreview.com

RWA programs.

3.8 RWA Program Efficacy Research

Retention and spillover effects are important, but less well-documented, measures of RWA program success. RWA programs are too new to assess the long-term residency of participants. A survey of Tulsa Remote participants offers insights regarding retention. Newman et al. (2021) report a retention rate of 87.5 percent for the 450 Tulsa Remote participants who arrived before 2021 (p. 55). Tulsa Remote participants indicated how likely they were to remain in Tulsa for the next five years. The responses varied by age. The youngest cohort (under 30) was the least likely to remain for five years (43.5%), followed by the 30–39 age cohort (55.2%), the 50 and over cohort (62.3%), with the 40–49 cohort being the most likely to remain for five years (62.3%) (Newman et al., 2021, p. 52). This suggests that younger workers are more challenging to retain.

Choudhury et al. (2021) also use surveys to evaluate lessons that Tulsa Remote might offer to other communities. They compare program participants who were accepted and relocated ("Tulsa Remoters"), those who were accepted but had not yet relocated ("Near-Tulsa Remoters"), and those who applied but were rejected from the program. The first two recruitment waves in 2019 and 2020 generated over 20,000 applicants, of which 2,700 were invited to participate and 763 ultimately relocated. The low response rate among rejected applicants (1.9%) highlights the challenge of conducting RWA program evaluations.

A few studies that assess economic impacts typically use IMPLAN-type projection models. Newman et al. (2021) report projected impacts of Tulsa Remote participants in 2021 and 2025. Their estimates suggest that the 394 new remote worker jobs in 2021 led to an additional 198 induced full-time equivalent jobs in Tulsa, generating an estimated $62.0 million in new labor income for the local economy. To put this in perspective, the estimated 592 jobs represent about 0.19% of employment, and $62 million amounts to 36% of the total annual payroll in Tulsa County in 2021. These estimates do not seem plausible.

PFM (2021) use IMPLAN to estimate the impacts of the Think Vermont program. Surveys of program participants indicate that the incentives materially influenced the relocation decision for approximately 60% of respondents in the 2018 cohort and 47% in the 2019 cohort. Outdoor recreational opportunities were identified as a leading factor, with incentives described as "the icing on the cake." PFM reports both low and high impact scenarios: the low range reflects only the income of the grantee, while the high range reflects aggregate household income. For the 2019 program, the minimum estimate of induced new jobs was 5 and the maximum was 105, with the likely effect falling between these bounds (p. 52). They estimate an induced impact of 63 new jobs and approximately $3 million in labor income resulting from new household spending associated with program grantees (p. 53). In contrast, Newman et al. (2021) estimate labor income impacts of $130,000 per remote worker grantee, compared with PFM's estimate of roughly $19,000. The disparity highlights the sensitivity of IMPLAN projections to underlying assumptions. Differences in program design further complicate cross-program comparisons.

A recent analysis of the Tulsa Remote program finds unexpected results (Dong, 2026). While the program attracted new residents to Tulsa, it also generated replacement effects. On average, each Tulsa Remote participant attracted approximately 1.4 additional out-of-state movers and helped retain 2.8 existing residents who might otherwise have left. It also indirectly led to about 1.7 residents relocating to other parts of Oklahoma and discouraged approximately 2.2 potential in-state movers from choosing Tulsa. These patterns suggest a broader shift in the city's population composition. Dong (2026) concludes that the program is particularly effective in attracting middle-aged, married individuals with moderate incomes from expensive, high-income metropolitan areas, suggesting that generous cash incentives influence both the volume and characteristics of remote worker migration.

There is also skepticism regarding the success of RWA programs. Cost-effectiveness is a primary concern (Cline, 2022; Davis, 2023; Robinson-Puche, 2023; Walczak, 2021). Key considerations include long-term retention rates, the extent to which participants would have relocated without incentives, and the magnitude of spillover effects.

A second concern is that RWA programs may exacerbate economic inequality. Such initiatives could unintentionally contribute to socioeconomic stratification and rural brain drain (Johanson, 2021; Maynard, 2021). The influx of skilled individuals into selected regions raises concerns about weakened development prospects in origin areas. Host communities must also contend with housing affordability pressures (G. Evans, 2022; Johanson, 2021). Increased demand from remote workers and their families can drive up housing prices. Moreover, critics, including Schnoke et al. (2022), point to limited transparency regarding participant selection procedures and safeguards for minority communities. Lusoli (2022) argues that RWA programs extend class-based initiatives that replicate the exclusionary logic of creative-class strategies. Finally, concerns persist about transparency and accountability more broadly, as collecting systematic data on applicants, recipients, and outcomes remains challenging.

3.9 Conclusion and Discussion

RWA programs have gained traction across U.S. cities, particularly with the surge in remote work adoption in the post–COVID-19 environment. Given substantial gaps in the existing literature (Lusoli, 2022; Schnoke et al., 2022; Teodorovicz et al., 2023), economists and policymakers remain uncertain about the overall impact and broader implications of these emerging initiatives. Remote work incentives affect both the extensive margin of migration decisions and the spatial intensive margin through monetary payments that offset relocation costs. By increasing geographic flexibility in residential choice, remote work reduces the importance of commuting constraints. States, cities, and economic development professionals therefore compete to attract increasingly footloose workers. In doing so, remote work strengthens the practical relevance of Tiebout sorting mechanisms by decoupling employment location from residential choice.

Tulsa Remote is notable as an early and highly visible program offering generous monetary incentives. Its funding from a well-resourced private foundation distinguishes it from many other initiatives. The cost of relocating 2,500 Tulsa Remote participants exceeds $25 million (Tulsa Remote, 2025a). These outcomes may not generalize to smaller or more resource-constrained communities with fewer quality-of-life amenities. Larger programs may also benefit from greater selectivity in participant screening and potential economies of scale associated with building sizable remote-worker cohorts. Moreover, Padilla (2022) argues that private funding enabled Tulsa Remote administrators to avoid some public scrutiny regarding return on investment. As Lusoli (2022) note, programs can attract national media attention despite generating only modest economic effects. RWA programs offering relatively small monetary or non-monetary benefits are unlikely to significantly influence migration decisions on either the internal or external margin.

As RWA programs continue to proliferate, competition for a finite pool of remote workers is likely to intensify. Although monetary incentives have not escalated as dramatically as those offered to large corporations, the overall value of incentive packages continues to increase. As more jurisdictions enter the competition and package values rise, the marginal benefit of attracting an additional remote worker may decline. Rural communities may struggle to achieve the scale necessary to provide competitive public services and ecosystem amenities desired by remote workers. For smaller communities with limited natural amenities, RWA programs may function primarily as place-marketing tools rather than transformative economic development strategies.

Future research should further evaluate the causal impacts of RWA programs, particularly in relation to other economic development initiatives. Understanding their effects on internal migration patterns and potential spillovers will clarify their role in shaping regional dynamics, rural development, and interjurisdictional competition.

Figures and Tables

Figure 1: Count of RWA Programs by State as of September 2025

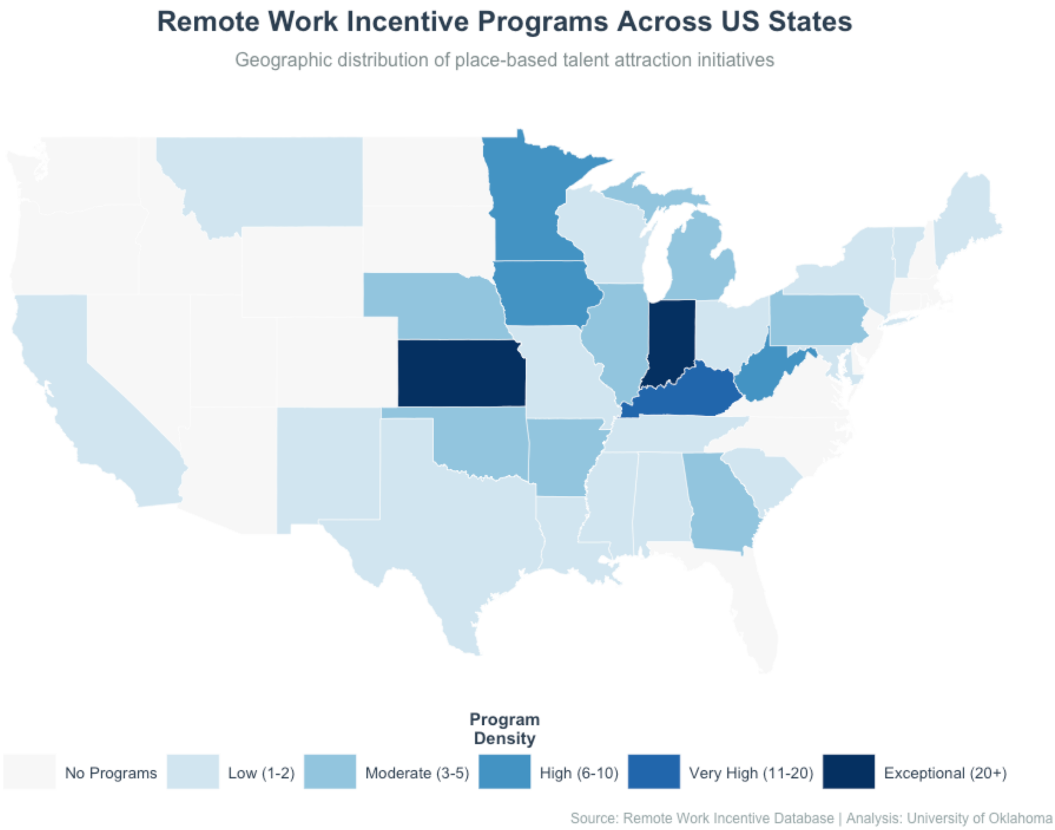


Figure 2: Timeline of Major RWA Programs

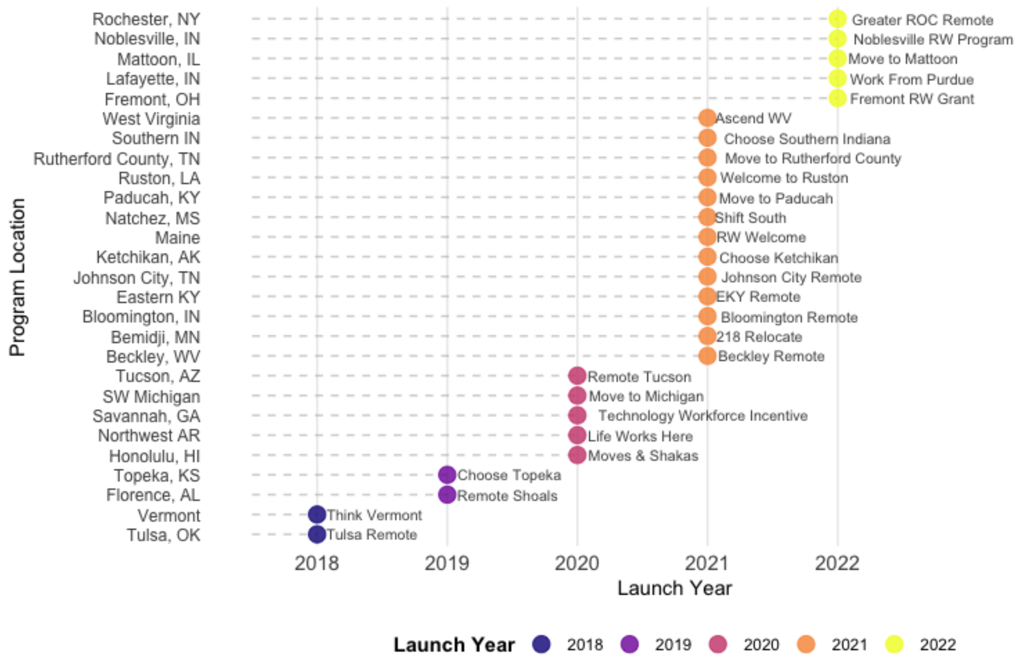


Figure 3: Total RWA Program Value and Natural Amenity Score

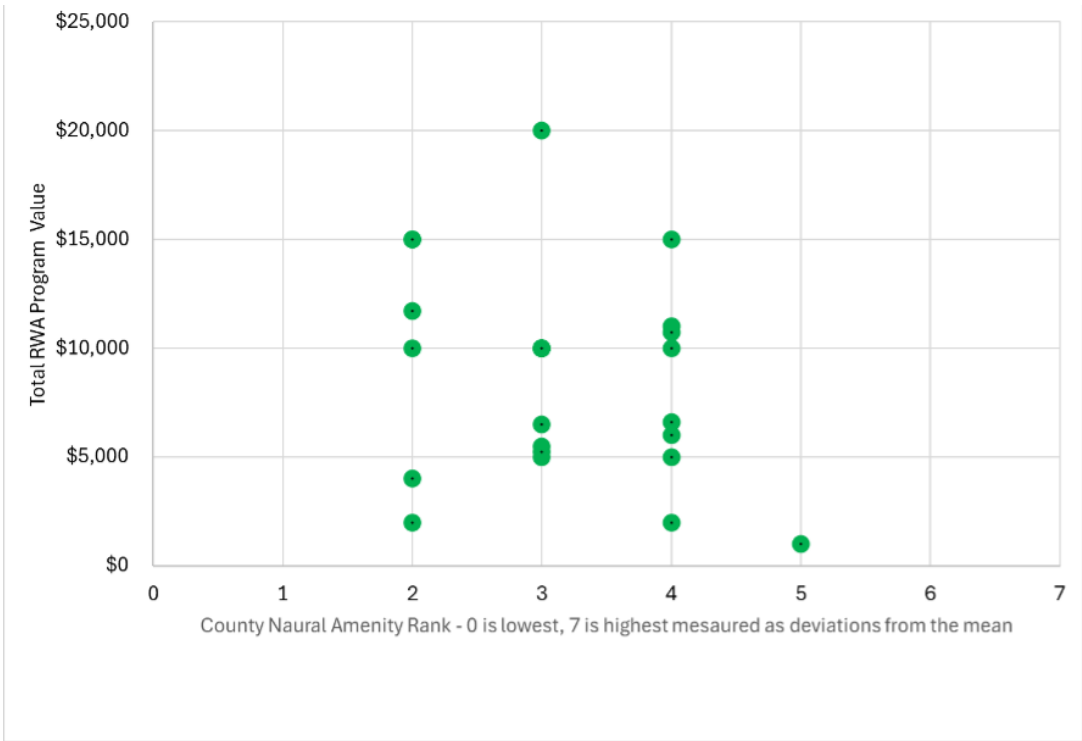


Figure 4: RWA Program Income Requirements and Local Median Income 2023

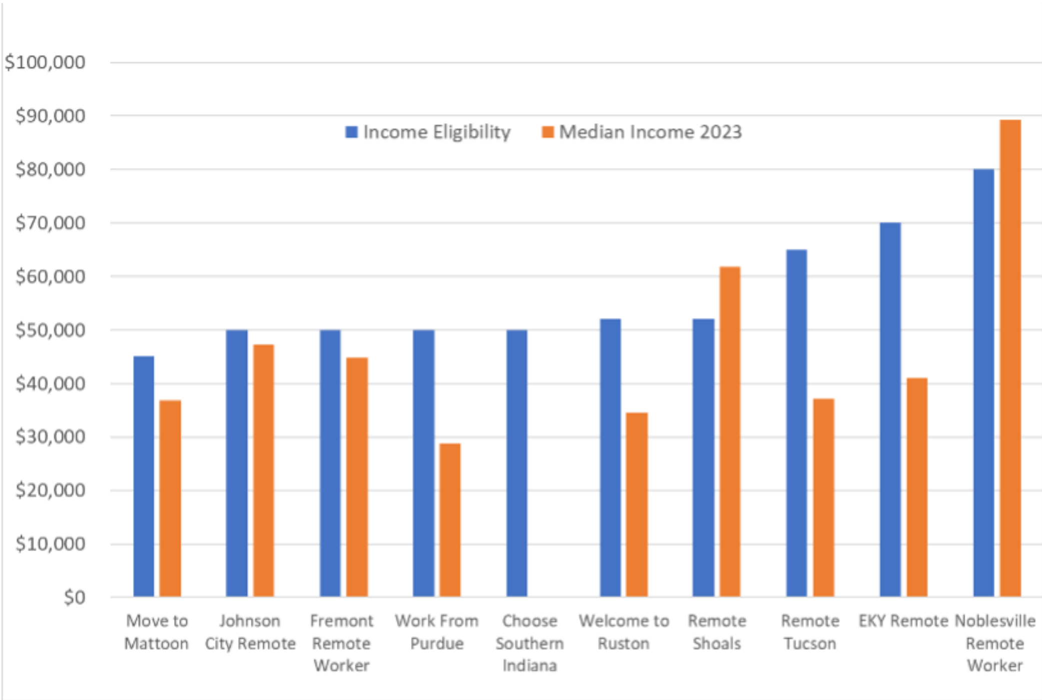


Figure 5: Population in Large RWA Program Cities

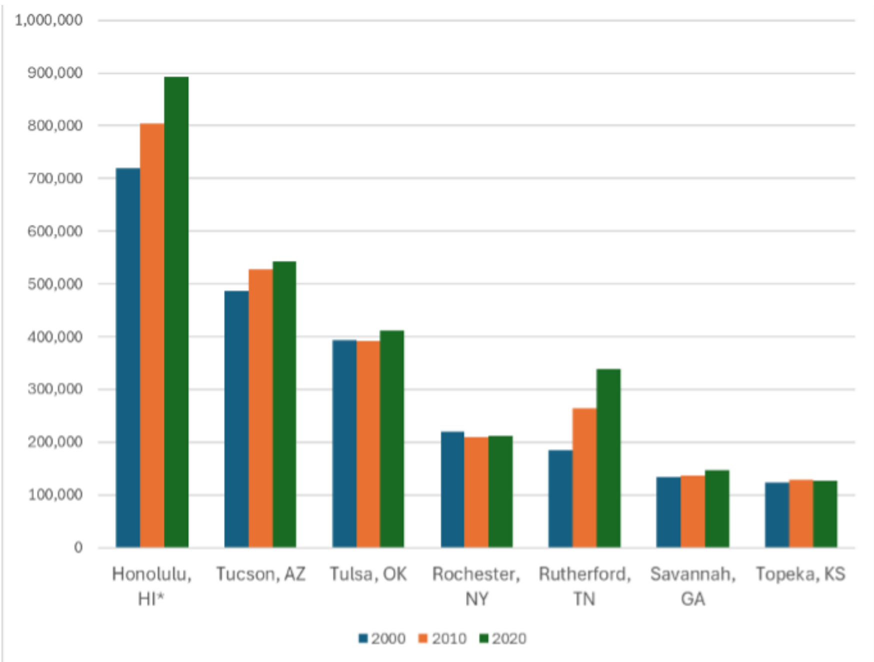
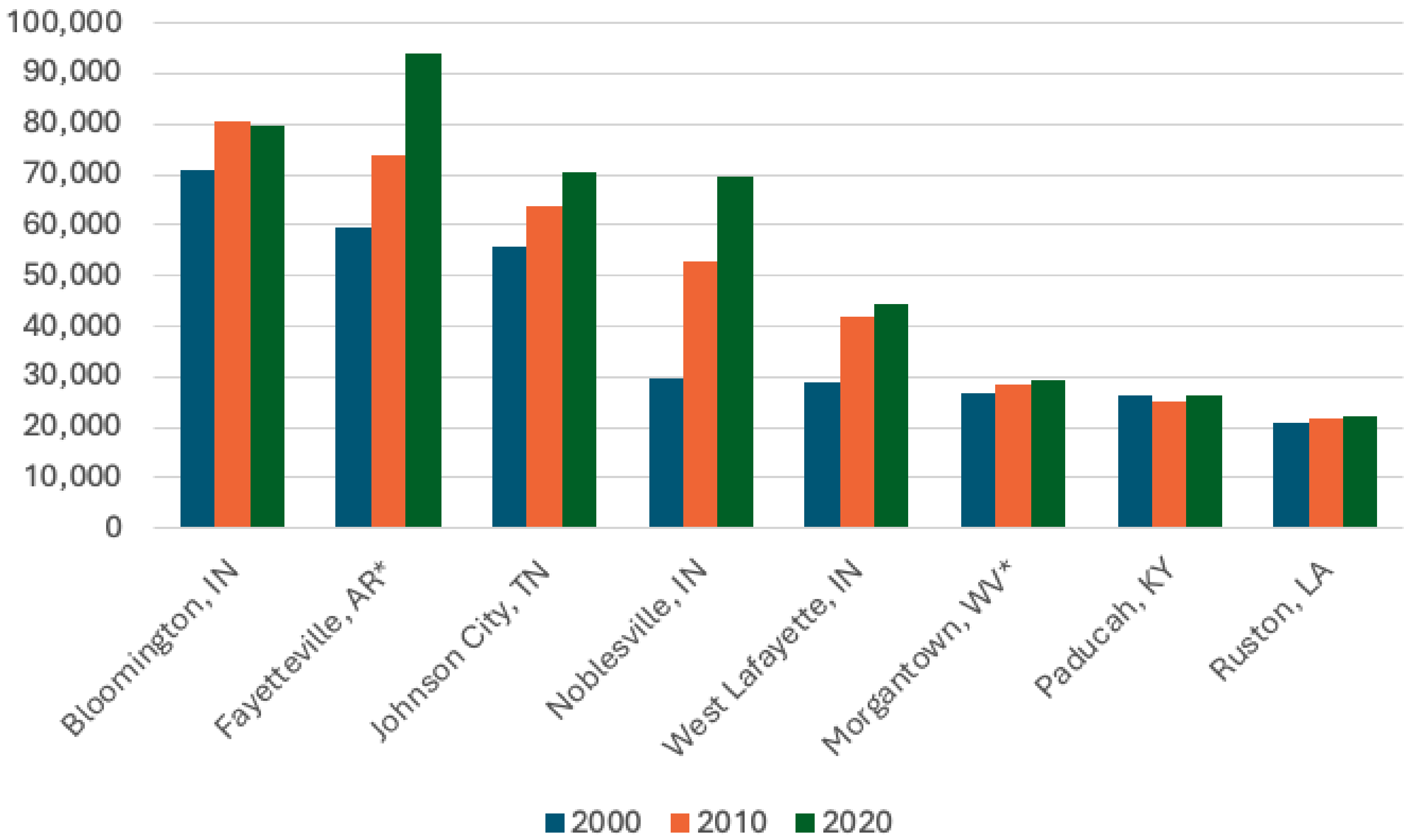
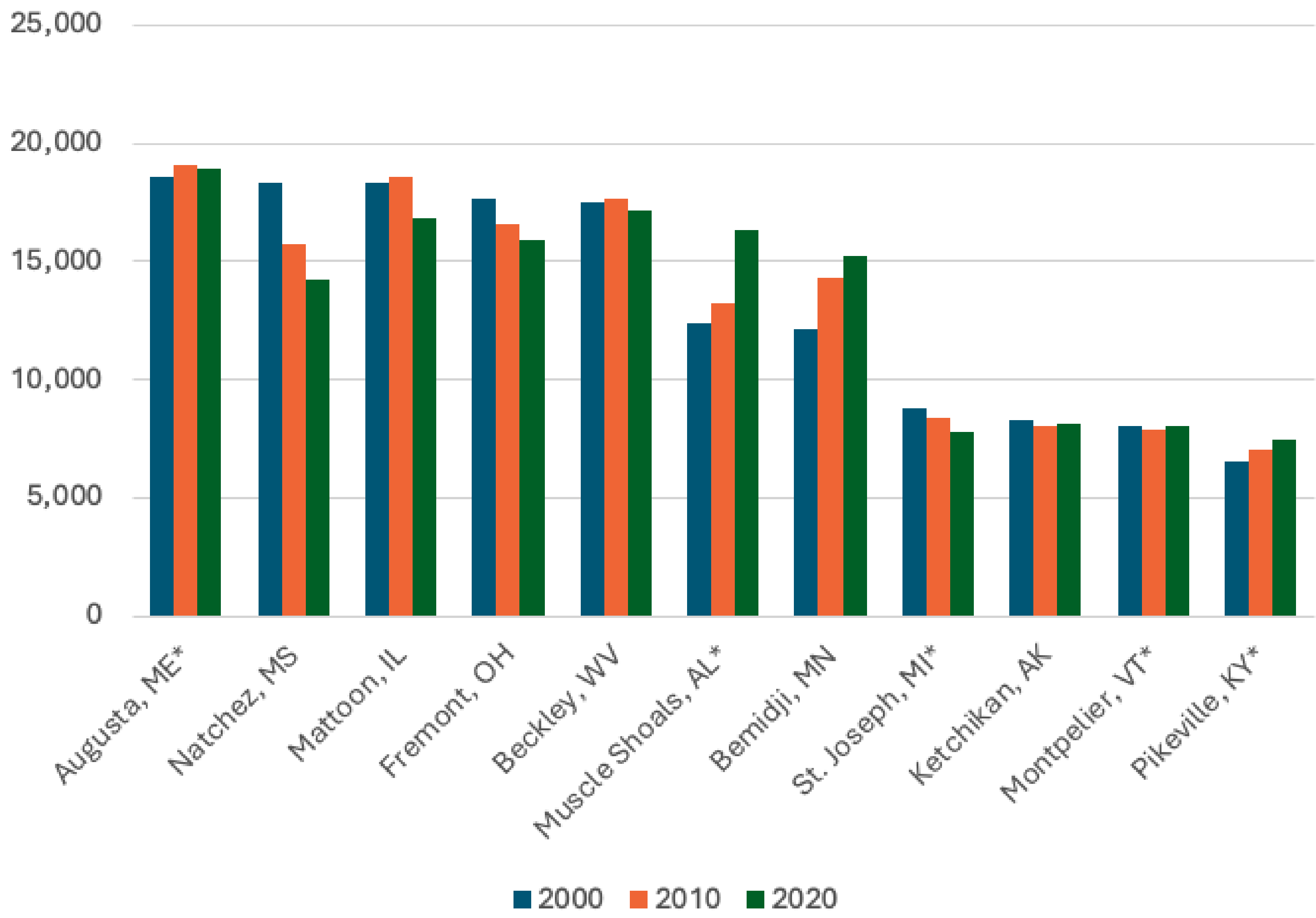


Figure 6: Population in Medium RWA Program Cities



Notes: * For programs delivered over multiple cities or counties, data for the primary city is reported.
Source: World Population Review (2024).

Figure 7: Population in Small RWA Program Cities



Notes: * For programs delivered over multiple cities or counties, data for the primary city is reported.
Source: World Population Review (2024).

Table 3.1: Major RWA Programs (as of Sep. 2023)

Programs	Delivery Locations	Year	Total Value	Monetary	Non-Monetary Incentives
Think Vermont	State of Vermont	2018	$15,000+	$10,000	
Tulsa Remote	Tulsa, OK	2018	$10,000+	$10,000	Free desk space; exclusive perks and events
Choose Topeka	Topeka, KS	2019	$11,000+	$10,000	Free Jimmy John's (as listed)
Remote Shoals	Florence, Muscle Shoals, Sheffield, Tuscumbia, AL	2019	$10,000+	$10,000	
Life Works Here Initiative	Northwest AR	2020	$10,750+	$10,000	Mountain bike
Move to Michigan	9 cities in SW Michigan	2020	$15,000+	$10,000	If a child attends a public school: $5,000
Movers & Shakas	Honolulu, HI	2020	$2,500+		Discounted airfare; hotel stays; etc.
Remote Tucson	Tucson, AZ	2020	$1,000+		Airbnb credits; gig membership; discounted mortgage; etc.
Technology Workforce Incentive	Savannah, GA	2020	$2,000+	$2,000	
218 Relocate	Bemidji, MN	2021	$4,000+	$2,500	Internet service; membership; etc.
Ascend West Virginia	Eastern Panhandle, Greenbrier Valley, Morgantown, Lewisburg, WV	2021	$20,000+	$12,000	Outdoor recreation experiences; free coworking; social programming; professional development resources
Bloomington Remote	Bloomington, IN	2021	$6,600+		Coworking; local perks

Continued on next page

Table 3.1 – continued from previous page

Programs	Delivery Locations	Year	Total Value	Monetary	Non-Monetary Incentives
Choose Southern Indiana	Daviess, Orange, Martin, Greene County, IN	2021	$5,500+	$5,000	State park pass; benefits
Johnson City Remote	Johnson City, TN	2021	$5,000+	$2,500	Spa credit; bike discount, etc
Beckley Remote	Beckley, WV	2021	$5,000+	$5,000	Outdoor recreation; coworking; social programming
Move to Paducah	Paducah, KY	2021	$6,500+	$2,500	Internet subsidy; city social pass; coworking space (first 6 months free)
Move to Rutherford County	Rutherford County, TN	2021	$10,000+	$10,000	
Remote Worker Welcome	Maine	2021	$10,000+	$10,000	
Shift South	Natchez & Adams County, MS	2021	$6,000+	$6,000	
Welcome to Ruston	Ruston, LA	2021	$10,000+	$10,000	Alumni foundation membership
Choose Ketchikan Program	Ketchikan, AK	2021	$2,000+	$2,000	3 months of free home internet
EKY Remote	Pike, Floyd, Johnson, Letcher County, KY	2022	$5,250+	$5,000	Welcome package; spouse bonus
Fremont Remote Worker Grant	Fremont, OH	2022	$2,000+	$2,000	

Continued on next page

Table 3.1 – continued from previous page

Programs	Delivery Locations	Year	Total Value	Monetary	Non-Monetary Incentives
Move to Mattoon	Mattoon, IL	2022	$11,707+	$5,000	Local restaurant vouchers; coworking space; YMCA membership
Noblesville Remote Worker Program	Noblesville, IN	2022	$15,000+	$5,000	Chamber membership; concert experience
Work From Purdue	Greater Lafayette, IN	2022	$10,000+	$5,000	Purdue library membership; campus benefits
Greater ROC Remote	Greater Rochester, NY	2022	$10,000+	$10,000	$9,000 in home grants

Table 3.2: RWA Program Host City Demographic Information 2023

	Population	Median Income	Median Age	Median Housing Price	Unemployment Rate	Average Commute Time
United States	329,725,481	$53,482	37.4	$338,100	6.0%	26.38
Montpelier, VT*	8,082	$71,163	44.7	$303,600	2.8%	17.78
Tulsa, OK	410,652	$41,957	35.0	$179,100	4.7%	18.39
Topeka, KS	126,802	$41,412	36.2	$169,700	3.9%	17.01
Muscle Shoals, AL*	15,969	$61,772	38.0	$221,100	3.6%	19.96
Fayetteville, AR*	92,070	$37,350	27.7	$332,200	3.9%	19.47
St. Joseph, MI*	7,868	$62,156	42.9	$263,200	5.8%	13.23
Urban Honolulu, HI*	351,554	$76,495	42.1	$778,600	7.6%	23.43
Tucson, AZ	538,167	$37,149	33.3	$303,400	7.4%	22.24
Savannah, GA	147,930	$49,832	33.2	$260,000	5.4%	20.19
Bemidji, MN	15,114	$33,197	28.7	$180,500	5.1%	14.25
Morgantown, WV*	29,316	$32,400	23.7	$257,900	4.4%	16.17
Bloomington, IN	80,064	$28,660	23.5	$293,800	4.3%	16.14
Johnson City, TN	69,521	$47,242	35.3	$233,400	4.7%	17.99
Beckley, WV	17,261	$39,845	41.1	$106,500	6.4%	16.92
Paducah, KY	26,248	$42,024	43.7	$163,200	6.2%	18.69

Continued on next page

Table 3.2 (continued)

	Population	Median Income	Median Age	Median Housing Price	Unemployment Rate	Average Commute Time
Rutherford, TN	1,196	$38,047	38.2	$105,100	5.1%	25.68
Augusta, ME*	18,895	$40,438	45.0	$236,300	5.0%	17.47
Natchez, MS	14,435	$26,853	40.2	$116,200	9.7%	14.92
Ruston, LA	22,286	$34,554	24.1	$195,100	4.7%	14.2
Ketchikan, AK	8,150	$68,125	37.7	$379,900	8.8%	13.4
Pikeville, KY*	7,376	$41,094	35.3	$236,500	7.0%	13.46
Fremont, OH	15,954	$44,832	36.6	$138,800	4.7%	17.6
Mattoon, IL	16,982	$36,803	39.0	$96,400	5.6%	16.04
Noblesville, IN	68,885	$89,258	34.4	$341,200	3.2%	26.05
West Lafayette, IN	44,515	$28,744	21.5	$306,000	2.9%	15.63
Rochester, NY	211,100	$30,784	31.2	$130,900	9.8%	20.06

Notes: * For programs delivered over multiple cities or counties, data for the primary city is reported.

Source: Best Places (2024).

Table 3.3: RWA Program Eligibility

Programs	Origin Location	Age Eligibility	Income Eligibility	Experience Requirements	Housing Eligibility	Year Eligibility
Think Vermont	Out-of-State		\$13.39/hour			Full-time residency
Tulsa Remote	Out-of-State	18				$\geq$ 1 year
Choose Topeka	Out-of-County				Purchase/Rent	
Remote Shoals	Out-of-State	18	\$52,000			
Life Works Here	Out-of-State	24		2 years		
Move to Michigan	Out-of-State				Purchase/Build ($\geq \$200,000$)	Full-time residency
Movers & Shakas	Out-of-State	18				$\geq$ 30 days
Remote Tucson	Out-of-County	18	\$65,000			
Technology Workforce Incentive	Out-of-City			3 years		$\geq$ 2 years
218 Relocate	Out-of-Radius (60 mi)					
Ascend WV	Out-of-State	18				$\geq$ 2 years
Bloomington Remote	Out-of-State	18				

Continued on next page

Table 3.3 (continued)

Programs	Origin Location	Age Eligibility	Income Eligibility	Experience Requirements	Housing Eligibility	Year Eligibility
Choose Southern Indiana	Out-of-State	18	\$50,000			$\geq$ 2 years
Johnson City Remote	Out-of-City	24	\$50,000			
Beckley Remote	Out-of-State	18				
Move to Paducah	Out-of-Radius (100 mi)	21				$\geq$ 1 year
Move to Rutherford County	Out-of-County	24				
RW Welcome	Out-of-State					
Shift South	Out-of-County					
Welcome to Ruston	Out-of-City	21	\$52,000			$\geq$ 3 years
Choose Ketchikan	Out-of-State	18				
EKY Remote	Out-of-State	18	\$70,000			
Fremont RW Grant	Out-of-State	18	\$50,000			
Move to Mattoon	Out-of-Radius (100 mi)		\$45,000			$\geq$ 2 years
Noblesville RW	Out-of-State	18	\$80,000			

Continued on next page

Table 3.3 (continued)

Programs	Origin Location	Age Eligibility	Income Eligibility	Experience Requirements	Housing Eligibility	Year Eligibility
Work From Purdue	Out-of-State	18	\$50,000			$\geq$ 1 year
Greater ROC Remote	Out-of-Radius (300 mi)/State	18				

Table 3.4: RWA Program Funding

Programs	Funding Source
Think Vermont	The State of Vermont; University of Vermont; the Vermont Student Assistance Corporation
Tulsa Remote	George Kaiser Family Foundation
Choose Topeka	The JEDO Board
Remote Shoals	Shoals Economic Development Authority
Life Works Here	Walton Family Foundation
Move to Michigan	Cornerstone Alliance
Movers & Shakas	Private group of CEOs
Remote Tucson	City of Tucson; Marshall Foundation; Main Gate Square; Tucson Electric Power; Pima County; etc.
Technology Workforce Incentive	The Savannah Economic Development Authority
218 Relocate	Greater Bemidji, Inc.
Ascend WV	Brad & Alys Smith Outdoor Economic Development Collaborative
Bloomington Remote	The Mill, City of Bloomington
Choose Southern Indiana	Radius Indiana Economic Development
Johnson City Remote	Northeast Tennessee Regional Economic Partnership (NeTREP); Northeast Tennessee Tourism Association; VISIT Johnson City; and other local partners
Beckley Remote	The New River Gorge Regional Development Authority (NRGRDA)

Continued on next page

Table 3.4 (continued)

Programs	Funding Source
Move to Paducah	City of Paducah
Move to Rutherford	Rutherford Chamber of Commerce
RW Welcome Program	Department of Economic and Community Development
Shift South	Natchez, Inc.
Welcome to Ruston	City budget funding and RPA funds
Choose Ketchikan	Ketchikan Chamber of Commerce
EKY Remote	SOAR and Kentucky Innovation
Fremont RW Grant	City of Fremont
Move to Mattoon	Community businesses and the Mattoon Chamber of Commerce
Noblesville RW Program	Indiana Economic Development Corporation; City of Noblesville
Work From Purdue	Purdue Research Foundation; City of West Lafayette; Indiana Economic Development Corp.
Greater ROC Remote	ROC2025 from private sources

Table 3.5: RWA Program Promotion Platforms as of Sept. 2023

	Promotion Platform				
Programs	LinkedIn	Facebook	Twitter	Instagram	YouTube
Think Vermont		Y	Y	Y	Y
Tulsa Remote	Y	Y	Y	Y	Y
Choose Topeka		Y	Y	Y	Y
Remote Shoals	Y	Y	Y	Y	Y
Life Works Here	Y	Y	Y	Y	Y
Move to Michigan		Y			
Movers & Shakas	Y	Y	Y	Y	Y
Remote Tucson	Y	Y		Y	Y
Technology Workforce Incentive	Y	Y	Y	Y	
218 Relocate	Y	Y		Y	Y
Ascend WV	Y	Y	Y	Y	Y
Bloomington Remote		Y	Y	Y	
Choose Southern Indiana	Y	Y	Y	Y	
Johnson City Remote		Y	Y	Y	Y
Beckley Remote		Y			
Move to Paducah		Y			
Move to Rutherford County					
RW Welcome					
Shift South		Y	Y	Y	
Welcome to Ruston		Y			Y
Choose Ketchikan		Y	Y	Y	Y
EKY Remote					Y
Fremont RW Grant		Y	Y	Y	Y
Move to Mattoon	Y	Y			
Noblesville RW*		Y			

Continued on next page

Table 3.5 (continued)

	Promotion Platform				
Programs	LinkedIn	Facebook	Twitter	Instagram	YouTube
Work From Purdue	Y	Y	Y	Y	Y
Greater ROC Remote	Y	Y	Y	Y	Y

Note: * suggests if the program is advertised by MakeMyMove.com. This information is approximate. I include programs that (1) have their own platforms (e.g., LinkedIn, Twitter, Facebook, Instagram, and YouTube), and (2) are advertised by cities, chambers of commerce, or related entities.

Source: Individually selected.

Table 3.6: RWA Program Applicants and Recipients

Programs	Implemented Year	Reported Year	Applicants*	Recipients*
Think Vermont	2018			
Tulsa Remote	2018	2023	50,000	2,500
Choose Topeka	2019	2022	7,000	70
Remote Shoals	2019	2023	8,000	118
Life Works Here	2020	2023	66,000	100
Move to Michigan	2020	2022	3,603	21
Movers & Shakas	2020	2021	90,000	50
Remote Tucson	2020	2022	1,177	23
Technology Workforce Incentive	2020			
218 Relocate	2021	2021		18
Ascend WV	2021	2022	20,000	143
Bloomington Remote	2021	2022	665	35
Choose Southern Indiana	2021	2023	3,080	95
Johnson City Remote	2021	2022	240	40
Beckley Remote	2021			
Move to Paducah	2021	2022	65	20
Move to Rutherford County	2021			
RW Welcome	2021			
Shift South	2021	2022		24
Welcome to Ruston	2021	2022	200	25
Choose Ketchikan	2021	2022	198	2
EKY Remote	2022			
Fremont RW Grant	2022	2023	12	7
Move to Mattoon	2022	2023	250	5
Noblesville RW	2022	2022	3,512	15
Work From Purdue	2022			
Greater ROC Remote	2022	2022	2,500	51

Notes: * This information is approximate. Not every program reports the information, and the report year varies.
Source: Phone interviews, Barton (2022), program websites, and news.

Bibliography

Abadie et al. (2010). Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. Journal of the American statistical Association, 105(490), 493–505.

Acs, Z. J., & Audretsch, D. B. (1988). Innovation in large and small firms: an empirical analysis. The American economic review, 678–690.

Aguilar, J. A., Akee, R., & Mykerezi, E. (2024). Place-based economic development and long-run firm employment and sales: Evidence from american indian reservations (Tech. Rep.). National Bureau of Economic Research.

Akan, D. (2022). Remote working and relocation after covid-19. the case studies of istanbul and milan.

Aksoy, C. G., Barrero, J. M., Bloom, N., Davis, S. J., Dolls, M., & Zarate, P. (2025, July). The global persistence of work from home. Proceedings of the National Academy of Sciences.

Aksoy et al. (2023). Working from home around the globe: 2023 report.

Andrews et al. (2019). The Startup Cartography Project. Harvard Dataverse. Retrieved from `https://doi.org/10.7910/DVN/BMRPVH` doi: 10.7910/DVN/BMRPVH

Apollo Technical. (2025). Statistics on remote workers that will surprise you. Apollo Technical, LLC. Retrieved from `https://www.apollotechnical.com/statistics-on-remote-workers/` (Accessed 22 January 2025)

Barca, F., McCann, P., & Rodríguez-Pose, A. (2012). The case for regional development intervention: place-based versus place-neutral approaches. Journal of regional science, 52(1), 134–152.

Barrero et al. (2021). Why working from home will stick (Tech. Rep.). National Bureau of Economic Research.

Barrero et al. (2023). The evolution of work from home. Journal of Economic Perspectives, 37(4), 23–49.

Bartik, T. J. (1993). Who benefits from local job growth: Migrants or the original residents? Regional Studies, 27(4), 297–311. doi: 10.1080/00343409312331347575

Bartik, T. J. (2019a). Making sense of incentives: Taming business incentives to promote prosperity. WE Upjohn Institute.

Bartik, T. J. (2019b). Should place-based jobs policies be used to help distressed communities? (Tech. Rep.). Upjohn Institute Working Paper.

Bartik, T. J. (2025). The effects of tulsa remote on inducing moves to tulsa: Estimates and implications.

Barton, S. (2022). Economic development plans: Creating remote worker incentive programs (MPA/MPP/MPFM Capstone Project, University of Kentucky). Retrieved from https://uknowledge.uky.edu/mpampp_etds/409

Baumol, W. J. (2014). The free-market innovation machine: Analyzing the growth miracle of capitalism.

Bayar, O., Boudreaux, C., & Yarbrough, T. R. (2025). Natural disasters and economic dynamism: Evidence from us entrepreneurial activity. Contemporary Economic Policy.

Bernile, G., Bhagwat, V., & Rau, P. R. (2017). What doesn't kill you will only make you more risk-loving: Early-life disasters and ceo behavior. The Journal of Finance, 72(1), 167–206.

Besley, T., & Case, A. (1995). Incumbent behavior: Vote seeking, tax setting, and yardstick competition. American Economic Review, 85(1), 25–45.

Best Places. (2024). Compare cities. BestPlaces.net. Retrieved from https://www.bestplaces.net/compare-cities (Accessed 24 August 2024)

Bluestein, H. B., Snyder, J. C., & Houser, J. B. (2015). A multiscale overview of the el reno, oklahoma, tornadic supercell of 31 may 2013. Weather and Forecasting, 30(3), 525–552.

Bolton, R. (1992). 'place prosperity vs people prosperity' revisited: An old issue with a new angle. Urban Studies, 29(2), 185–203.

Borjas, G. J. (2017). The labor supply of undocumented immigrants. Labour Economics, 46, 1–13.

Borkowski, C., & Kaynas, R. (2025). Telework trends. Beyond the Numbers: Employment & Unemployment, U.S. Bureau of Labor Statistics, 14(20).

Brueckner, J. K., Kahn, M. E., & Lin, G. C. (2023). A new spatial hedonic equilibrium in the emerging work-from-home economy? American Economic Journal: Applied Economics, 15(2), 285–319.

Bureau of Labor Statistics. (2023, July). North American Industry Classification System (NAICS) [Government Website]. Retrieved from `https://www.bls.gov/bls/naics.htm` (Last modified July 25, 2023. Accessed on April 29, 2026)

Busso, M., Gregory, J., & Kline, P. (2013). Assessing the incidence and efficiency of a prominent place based policy. American Economic Review, 103(2), 897–947.

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. Journal of econometrics, 225(2), 200–230.

Carson, D. (2021, September). Fremont hopes to attract, keep workers with new relocation program. Fremont News-Messenger. Retrieved from `https://www.thenews-messenger.com/story/news/local/2021/09/18/fremont-population-worker-shortage-could-helped-grant-program/8365841002/`

Cattaneo, M. D., Feng, Y., & Titiunik, R. (2021). Prediction intervals for synthetic control methods. Journal of the American Statistical Association, 116(536), 1865–1880.

Cattaneo et al. (2025). Uncertainty quantification in synthetic controls with staggered treatment adoption. Review of Economics and Statistics, 1–46.

Cebula, R. J. (2009). Migration and the Tiebout-Tullock hypothesis revisited. American Journal of Economics and Sociology, 68(2), 541–551.

Choudhury, P., Foroughi, C., & Larson, B. (2021). Work-from-anywhere: The productivity effects of geographic flexibility. Strategic Management Journal, 42(4), 655–683.

Cline, A. (2022). Should N.H. pay people to move here? The Josiah Bartlett Center for

Public Policy. Retrieved from https://jbartlett.org/2022/03/should-n-h-pay-people-to-move-here/

Crespo Cuaresma, J., Hlouskova, J., & Obersteiner, M. (2008). Natural disasters as creative destruction? evidence from developing countries. Economic inquiry, 46(2), 214–226.

Davis, R. (2023, February). Get paid up to $10,000 to move? that's great for remote workers, but economists say it's not a good investment for the cities footing the bill. Business Insider.

Deryugina, T. (2017). The fiscal cost of hurricanes: Disaster aid versus social insurance. American Economic Journal: Economic Policy, 9(3), 168–198.

Dong, B. (2026). The unexpected effects of place-based remote-work incentives: Evidence from the Tulsa Remote program. Retrieved from https://sites.google.com/view/boweidonecon/research (Unpublished working paper, University of Oklahoma)

Dong, B., & Rogers, C. (2026). Attracting remote workers: Overview of programs in the united states. (Working paper)

East, P. (2023, July). It's your business: Bloomington Remote has 2 years of success in attracting remote workers. The Herald-Times.

Ellson, R. W., Milliman, J. W., & Roberts, R. B. (1984). Measuring the regional economic effects of earthquakes and earthquake predictions. Journal of regional science, 24(4).

Evangelou, N. (2023). Where people moved in 2022 [Blog post]. Retrieved from https://www.nar.realtor/blogs/economists-outlook/where-people-moved-in-2022 (Accessed July 30, 2025)

Evans, G. (2022). Topeka relocation subsidy isn't working. Kansas Policy Institute. Retrieved from https://kansaspolicy.org/topeka-relocation-subsidy-isnt-working/

Evans, J. A., Kunda, G., & Barley, S. R. (2004). Beach time, bridge time, and billable hours: The temporal structure of technical contracting. Administrative Science Quarterly, 49(1), 1–38.

Fazio et al. (2019). The startup cartography project: measuring and mapping entrepreneurial ecosystems. Research Policy.

FEMA. (2020). OpenFEMA Dataset: Disaster Declaration Summaries [Government Dataset]. Retrieved from https://www.fema.gov/about/openfema/Datasets-disaster-declaration-summaries (Accessed on April 29, 2026)

Freeman, L. (2005). Displacement or succession? residential mobility in gentrifying neighborhoods. Urban affairs review, 40(4), 463–491.

Gajendran, R. S., & Harrison, D. A. (2007). The good, the bad, and the unknown about telecommuting: Meta-analysis of psychological mediators and individual consequences. Journal of Applied Psychology, 92(6), 1524–1541.

Gallagher, J., Hartley, D., & Rohlin, S. (2023). Weathering an unexpected financial shock: the role of federal disaster assistance on household finance and business survival. Journal of the Association of Environmental and Resource Economists, 10(2), 525–567.

Gallardo, R., & Whitacre, B. (2018). 21st century economic development: Telework and its impact on local income. Regional Science Policy & Practice, 10(2), 103–124. doi: 10.1111/rsp3.12117

Gatling, P. (2020). Want an extra 10,000? consider relocating to northwest arkansas. TalkBusiness.net. Retrieved from https://talkbusiness.net/2020/11/want-an-extra-10000-consider-relocating-to-northwest-arkansas/

Glaeser, E. L., Kahn, M. E., & Rappaport, J. (2008). Why do the poor live in cities? the role of public transportation. Journal of urban Economics, 63(1), 1–24.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. Journal of econometrics, 225(2), 254–277.

Greenhalgh, B., & Auer, E. (2023, June). How much does it cost to move? BobVila.com. Retrieved from https://www.bobvila.com/articles/how-much-does-it-cost-to-move

Gupta, A., Mittal, V., & Van Nieuwerburgh, S. (2022). Work from home and the office real estate apocalypse (Working Paper No. 30526). National Bureau of Economic Research.

Hallegatte, S., & Dumas, P. (2009). Can natural disasters have positive consequences? investigating the role of embodied technical change. Ecological economics, 68(3), 777–786.

Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2013). Who creates jobs? small versus large versus young. Review of Economics and Statistics, 95(2), 347–361.

Hanaoka, C., Shigeoka, H., & Watanabe, Y. (2018). Do risk preferences change? evidence from the great east japan earthquake. American Economic Journal: Applied Economics, 10(2), 298–330.

Head, K., & Mayer, T. (2014). Gravity equations: Workhorse, toolkit, and cookbook. In Handbook of international economics (Vol. 4, pp. 131–195). Elsevier.

Hoogstra, G. J., van Dijk, J., & Florax, R. J. G. M. (2017). Do jobs follow people or people follow jobs? a meta-analysis of Carlino–Mills studies. Spatial Economic Analysis, 12, 357–378. doi: 10.1080/17421772.2017.1340663

Hrenchir, T. (2022, February). Average annual salary is $89,000 for those who relocated here as part of Choose Topeka initiative. Topeka Capital-Journal. Retrieved from https://www.cjonline.com/story/news/2022/02/10/relocation-program-proves-rewarding-participants-who-choose-topeka/6700854001/

Huesler, J. (2024). The impact of tornadoes and damaging winds on county-level income growth in the united states. International Journal of Disaster Risk Science, 15(6), 906–918.

Internal Revenue Service. (2025). Soi tax stats - migration data. Retrieved from https://www.irs.gov/statistics/soi-tax-stats-migration-data (Accessed July 30, 2025)

Isserman, A., & Rephann, T. (1995). The economic effects of the appalachian regional commission: An empirical assessment of 26 years of regional development planning. Journal of the American Planning Association, 61(3), 345–364.

Jansen, T., Ascani, A., Faggian, A., et al. (2024). Remote work and location preferences: A study of post-pandemic trends in Italy. Annals of Regional Science, 73, 897–944. doi: 10.1007/s00168-024-01295-w

Johanson, M. (2021). The 'zoom towns' luring remote workers to rural enclaves. BBC. Retrieved from https://www.bbc.com/worklife/article/20210604-the-zoom-towns-luring-remote-workers-to-rural-enclaves

Kates et al. (2006). Reconstruction of new orleans after hurricane katrina: a research perspective. Proceedings of the national Academy of Sciences, 103(40), 14653–14660.

Kline, P. (2010). Place based policies, heterogeneity, and agglomeration. American Economic Review, 100(2), 383–387.

Koşar, G., Ransom, T., & Van der Klaauw, W. (2022). Understanding migration aversion using elicited counterfactual choice probabilities. Journal of Econometrics, 231, 123–147.

Kukeli, A. (2025). The effects and the macroeconomic dynamics of natural disaster damages: investigation of local evidence. Regional Studies, Regional Science, 12(1), 5–22.

Larch, M., Shikher, S., & Yotov, Y. V. (2025). Estimating gravity equations: Theory implications, econometric developments, and practical recommendations. Review of International Economics.

LeBoeuf, S. (2021, July). City of Ruston will offer $10k to LA Tech, Grambling graduates if they move back. The Monroe News-Star.

Loayza et al. (2012). Natural disasters and growth: Going beyond the averages. World Development, 40(7), 1317–1336.

Louie, S., Mondragon, J. A., & Wieland, J. (2025). Supply constraints do not explain house price and quantity growth across us cities (Tech. Rep.). National Bureau of Economic Research.

Lusoli, A. (2022). Live, work, play: Exploring the rhetorical dimension of remote work attraction incentives programs. International Journal of Communication, 16, 23.

Lyza, A. W., Flournoy, M. D., & Alford, A. A. (2024). Comparison of tornado damage characteristics to low-altitude wsr-88d radar observations and implications for tornado intensity estimation. Monthly Weather Review, 152(8), 1689–1710.

Maynard, J. (2021, October). Remote work incentives are a scam. Protean Magazine.

McGranahan, D. (1999, October). Natural amenities drive rural population change (Tech. Rep. No. AER-781). Economic Research Service, United States Department of Agriculture.

Molloy, R., Smith, C. L., & Wozniak, A. (2011). Internal migration in the united states. Journal of Economic perspectives, 25(3), 173–196.

Monllor, J., & Murphy, P. J. (2017). Natural disasters, entrepreneurship, and creation after destruction: A conceptual approach. International Journal of Entrepreneurial Behavior & Research, 23(4), 618–637.

Moretti, E. (2012). The new geography of jobs. Houghton Mifflin Harcourt.

Moretti, E., & Wilson, D. J. (2017). The effect of state taxes on the geographical location of top earners: Evidence from star scientists. American Economic Review, 107, 1858–1903.

National Weather Service. (2013, May). May 20, 2013 EF-5 tornado path and LandScan population. Image. Retrieved from https://www.weather.gov/oun/events-20130520 (Retrieved May 24, 2013, from archived version of October 16, 2011)

National Weather Service. (2024). The enhanced fujita scale (ef scale). Retrieved from https://www.weather.gov/oun/efscale

National Weather Service. (2025a). Tornado classification and safety. Retrieved 2024-03-04, from https://www.weather.gov/mkx/taw-tornado_classification_safety

National Weather Service. (2025b). Violent tornadoes in the united states. Retrieved 2024-03-04, from https://www.weather.gov/lmk/violent_tornadoes (Louisville, KY Weather Forecast Office)

National Weather Service, Norman, OK. (2013). The may 31, 2013 el reno, ok tornado. https://www.weather.gov/oun/events-20130531. Retrieved from https://www.weather.gov/oun/events-20130531 (Archived from the original on June 5, 2021. Retrieved June 5, 2021)

Neumark, D., & Simpson, H. (2015). Place-based policies. In Handbook of regional and urban economics (Vol. 5, pp. 1197–1287). Elsevier.

Newman et al. (2021). How tulsa remote is harnessing the remote work revolution to spur local economic growth: Lessons from a leading remote work incentive in tulsa, oklahoma. Economic Innovation Group.

Northwest Arkansas Council. (2021, February). First round of Northwest Arkansas 'Life Works Here' incentive program recipients announced. Northwest Arkansas Council. Retrieved from https://nwacouncil.org/2021/02/22/first-round-of-northwest-arkansas-life-works-here-incentive-program

-recipients-announced/ (Accessed 26 August 2024)

Olfert et al. (2014). Places for place-based policy. Development Policy Review, 32(1), 5–32.

Orr, S. (2022, December). MakeMyMove secures $2m investment. Indianapolis Business Journal.

Ozimek, A. (2020). Remote workers on the move. Available at SSRN 3790004.

Padilla, K. J. (2022). An analysis of the strengths and weaknesses of the Tulsa Remote program, as an effective economic development strategy (Master's Thesis). Portland State University.

Partridge, M. D. (2010). The duelling models: NEG vs amenity migration in explaining US engines of growth. Papers in Regional Science, 89(3), 513–536.

Paudel, J. (2022). Deadly tornadoes and racial disparities in energy consumption: Implications for energy poverty. Energy Economics, 114, 106316.

PFM. (2021). Study of effectiveness of incentive programs in attracting new workers: Act 51, Sec. 2b., new relocating workers; study (Report to the General Assembly). Department of Financial Regulation, Vermont.

Raker, E. J. (2020). Natural hazards, disasters, and demographic change: The case of severe tornadoes in the united states, 1980–2010. Demography, 57(2), 653–674.

Remote Technology, Inc. (2020). Global workforce revolution report 2020: How remote work is transforming the tech workforce [Research Report]. Retrieved from https://f.hubspotusercontent00.net/hubfs/7405301/Global-Workforce-Revolution-Report.pdf (Accessed July 30, 2025)

Roback, J. (1982). Wages, rents, and the quality of life. Journal of political Economy, 90(6), 1257–1278.

Robert Half. (2025). Remote work statistics and trends for 2025. Robert Half Inc. Retrieved from https://www.roberthalf.com/us/en/insights/research/remote-work-statistics-and-trends

Robinson-Puche, M. (2023, July). Should you take the money? why it probz isn't the best move to go to a town that wants to pay you. Money Scoop, Morning Brew. Retrieved from https://www.morningbrew.com/money-scoop/stories/2023/07/13/

should-you-take-the-money

Rosen, S. (1979). Wage-based indexes of urban quality of life. Current issues in urban economics, 74–104.

Salmon, P. (2019). Yardstick competition among governments: Accountability and policymaking when citizens look across borders. Oxford University Press.

Schnoke, M., Yochum, J., Frantz, F., et al. (2022). An examination of incentive programs to attract remote workers (Tech. Rep.). Center for Economic Development, Cleveland State University.

Schumpeter, J. A. (1934). The theory of economic development. Cambridge, MA: Harvard.

Schumpeter, J. A. (1942). Capitalism, Socialism, and Democracy, 1942. UK: George Allen & Unwin Ltd.

Shleifer, A. (1985). A theory of yardstick competition. The RAND Journal of Economics, 319–327.

Silva, J. S., & Tenreyro, S. (2006). The log of gravity. The Review of Economics and statistics, 641–658.

Skidmore, M., & Toya, H. (2002). Do natural disasters promote long-run growth? Economic inquiry, 40(4), 664–687.

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of econometrics, 225(2), 175–199.

Tan, S., Fang, K., & Lester, T. W. (2023). Post-pandemic relocation preferences of remote tech workers. Findings.

Tang, T., & Zeng, K. (2018). Evolution of government's performance through yardstick competition in the spatial game of gubernatorial elections. Journal of Artificial Societies and Social Simulation, 21.

Tartari, V., & Stern, S. (2021). More than an ivory tower: The impact of research institutions on the quantity and quality of entrepreneurship (Tech. Rep.). National Bureau of Economic Research.

Teodorovicz, T., Choudhury, P., & Starr, E. (2023). Location specificity and geographic competition for remote workers (Technology & Operations Management Unit Working

Paper No. 23-071). Harvard Business School.

Tiebout, C. M. (1956). A pure theory of local expenditures. Journal of Political Economy, 64, 416–424.

Tullock, G. (1971). Public decisions as public goods. Journal of Political Economy, 79, 913–918.

Tulsa Remote. (2023). Economic impact report: Building a knowledge economy, one worker at a time. Tulsa Remote. Retrieved from https://23811891.fs1.hubspotusercontent-na1.net/hubfs/23811891/Tulsa%20Remote%20Economic%20Impact%20Report.pdf

Tulsa Remote. (2024). Tulsa remote economic impact report 2024 (Tech. Rep.). Tulsa Remote. Retrieved from https://23811891.fs1.hubspotusercontent-na1.net/hubfs/23811891/Tulsa%20Remote%20Assets%20%2B%20Files/Tulsa%20Remote%20Impact%20Reports/2024%20Tulsa%20Remote%20Economic%20Impact%20Report.pdf (Accessed: April 29, 2026)

Tulsa Remote. (2025a). Economic impact report: Building a knowledge economy, one worker at a time. TulsaRemote.com.

Tulsa Remote. (2025b). Our community. Retrieved from https://www.tulsaremote.com/our-community (Accessed July 30, 2025)

U.S. Bureau of Labor Statistics. (2021). Occupational employment and wages in Topeka — May 2021. U.S. Bureau of Labor Statistics. Retrieved from https://www.bls.gov/regions/mountain-plains/news-release/occupationalemploymentandwages_topeka.html (Accessed 25 August 2024)

U.S. Census Bureau. (2022). Quickfacts: Tulsa city, oklahoma. Retrieved from https://www.census.gov/quickfacts/fact/table/tulsacityoklahoma/PST045222 (Accessed July 30, 2025)

U.S. Census Bureau. (2023a). Table b01003: Total population. American Community Survey 5-Year Estimates. Retrieved 2025-08-13, from https://data.census.gov/table/ACSDT5Y2023.B01003?t=Population+Total&g=010XX00US$8600000

(2019-2023 5-Year Estimates)

U.S. Census Bureau. (2023b). Table s1901: Income in the past 12 months (in 2023 inflation-adjusted dollars). American Community Survey 5-Year Estimates Subject Tables. Retrieved 2025-08-13, from https://data.census.gov/table/ACSST5Y2023.S1901?q=Income+by+Zip+code+tabulation+area (2019-2023 5-Year Estimates)

U.S. Department of Agriculture, Economic Research Service. (2024, January). Rural-urban continuum codes. USDA Economic Research Service.

U.S. Small Business Administration. (2025a). Disaster assistance. Website. Retrieved 2025-08-13, from https://www.sba.gov/funding-programs/disaster-assistance (Information on SBA low-interest disaster loans for homeowners, renters, and businesses recovering from declared disasters)

U.S. Small Business Administration. (2025b). Mitigation assistance. Website. Retrieved 2025-08-25, from https://www.sba.gov/funding-programs/disaster-assistance/mitigation-assistance#about-mitigation-assistance (Information on SBA disaster loan increases up to 20% for building upgrades to mitigate future disaster damage)

U.S. Small Business Administration. (2026). Disaster loan data. Retrieved from https://data.sba.gov/dataset/disaster-loan-data (Accessed: 2026/04/22)

Vinopal, C. (2023, June 22). Five years after tulsa started paying remote workers to move there, most haven't left. HR Brew. Retrieved from https://www.hr-brew.com/stories/2023/06/22/most-tulsa-remote-workers-haven-t-left (Accessed July 30, 2025)

Walczak, J. (2021). These states will pay you to move. does that strategy make sense? Tax Foundation. Retrieved from https://taxfoundation.org/blog/states-will-pay-you-to-move-there/

Wang et al. (2021). Economic footprint of california wildfires in 2018. Nature Sustainability, 4(3), 252–260.

Wennekers, S., & Thurik, R. (1999). Linking entrepreneurship and economic growth. Small business economics, 13, 27–56.

Wilson, J. D. (1999). Theories of tax competition. National tax journal, 52(2), 269–304.

Wilson, R. (2022). The isolated states of america: Home state bias, state identity, and the impact of state borders on mobility.

World Population Review. (2024). World population by country (live) 2024. WorldPopulationReview.com. Retrieved from `http://www.worldpopulationreview.com/` (Accessed 15 August 2024)

Xu, Y. (2017). Generalized synthetic control method: Causal inference with interactive fixed effects models. Political Analysis, 25(1), 57–76.

Yarborough, I. (2019, December). Another first for Topeka. Topeka Capital-Journal.

Yoo, H. (2024). The welfare consequences of incoming remote workers for local residents. Available at SSRN 5288300.

ZipRecruiter. (2023). Average salary in Tulsa, OK. ZipRecruiter. Retrieved from `https://www.ziprecruiter.com/Salaries/-in-Tulsa,OK` (Accessed 15 July 2024)

Appendix

A.1 Chapter 1

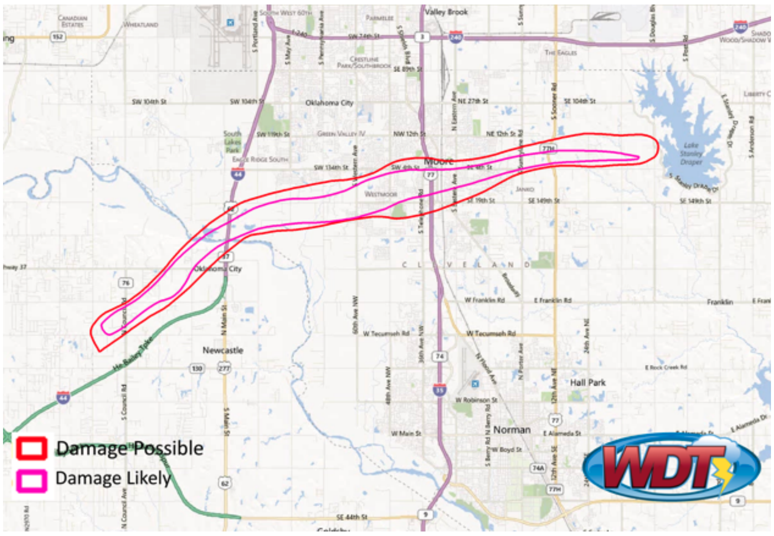
Table A.1: Violent Tornado Impacts on Entrepreneurship

Dependent Variables:	log(SFR)	EQI	log(RECPI)	log(REAI)
Model:	(1)	(2)	(3)	(4)
Variables				
FE4/5 $\times$ Post	0.1038***	0.0063	0.1305***	-0.0063
	(0.0278)	(0.0159)	(0.0312)	(0.0081)
Fixed-effects				
ZIP Code	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	166,884	166,884	166,884	144,377
Within R^2	0.00064	1.78×10^{-6}	0.00054	3.17×10^{-6}

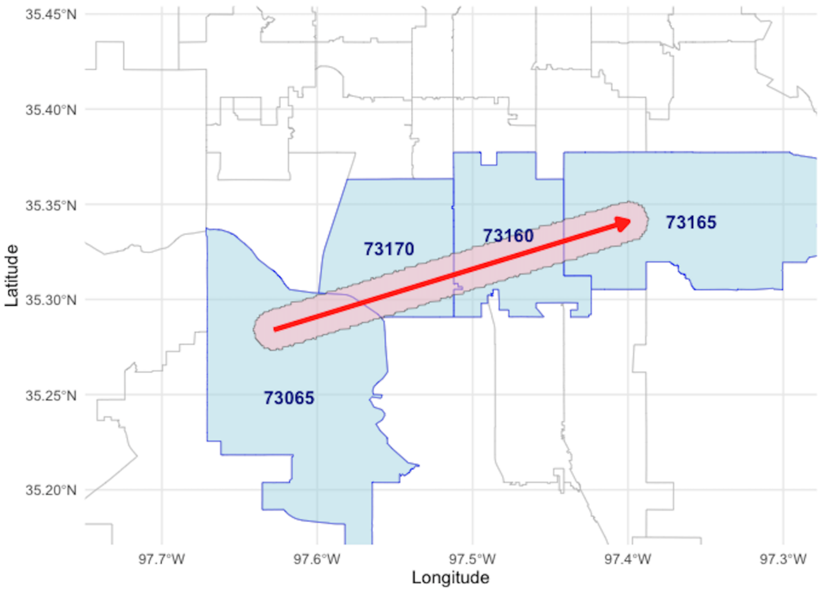
Note: This table shows the impact of violent tornadoes on startup formation rates (SFR, number of for-profit new business registrations within a given time and region); entrepreneurship quality index (EQI, a measure of entrepreneurial quality); regional entrepreneurship cohort potential index (RECPI, the inherent potential of a startup cohort within a region); and regional ecosystem acceleration index (REAI, the realized number of growth events from that cohort). Estimation uses difference-in-difference (DiD) to capture the average treatment effect on the treated (ATT). Standard errors are clustered at the ZIP code level. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

Figure A.1: Comparison of the 2013 Moore Tornado Track and the Generated Map

Panel (a): Preliminary Track of 2013 Moore Tornado

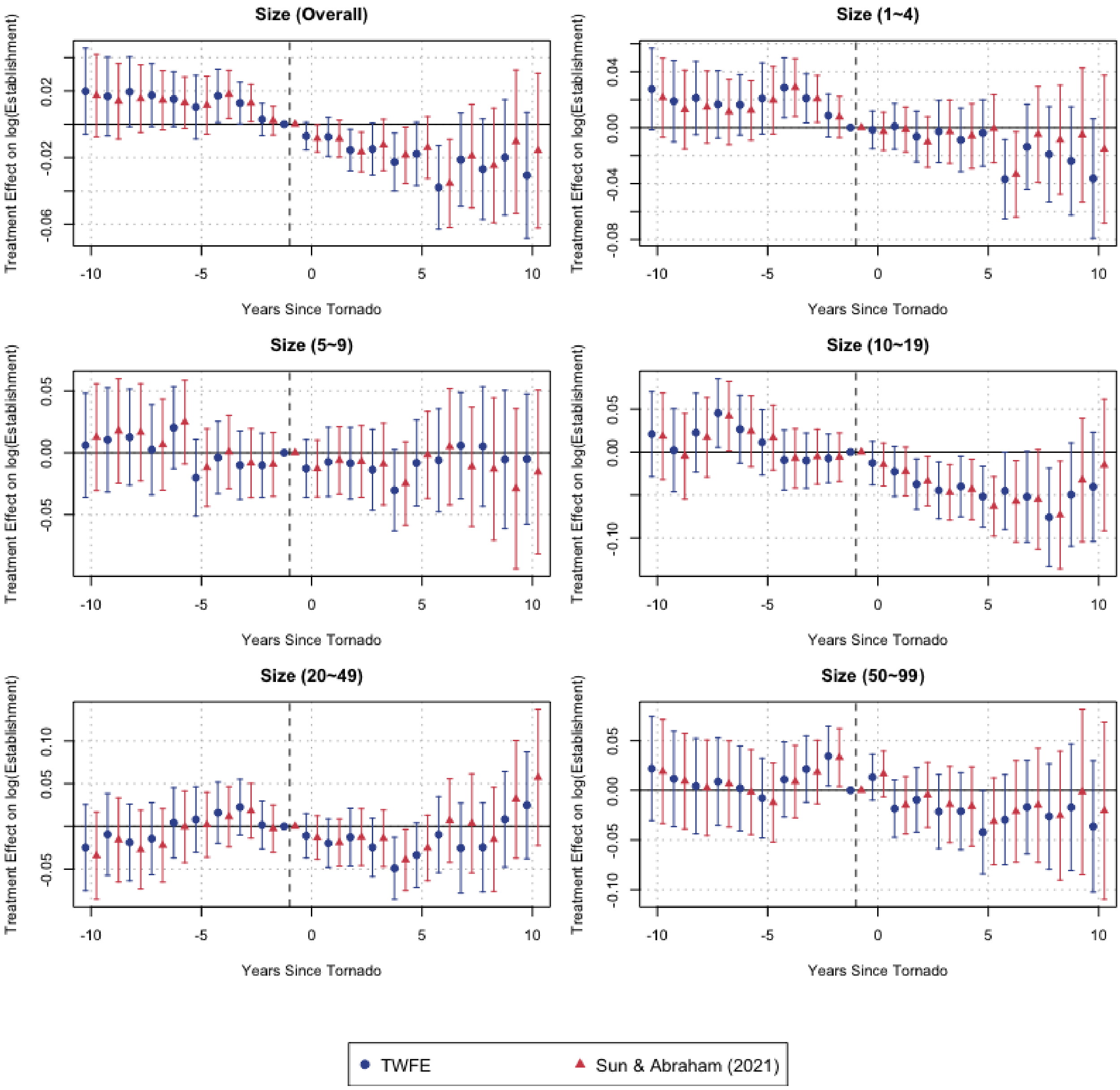


Panel (b): Generated Map with Tornado Path and ZIP codes



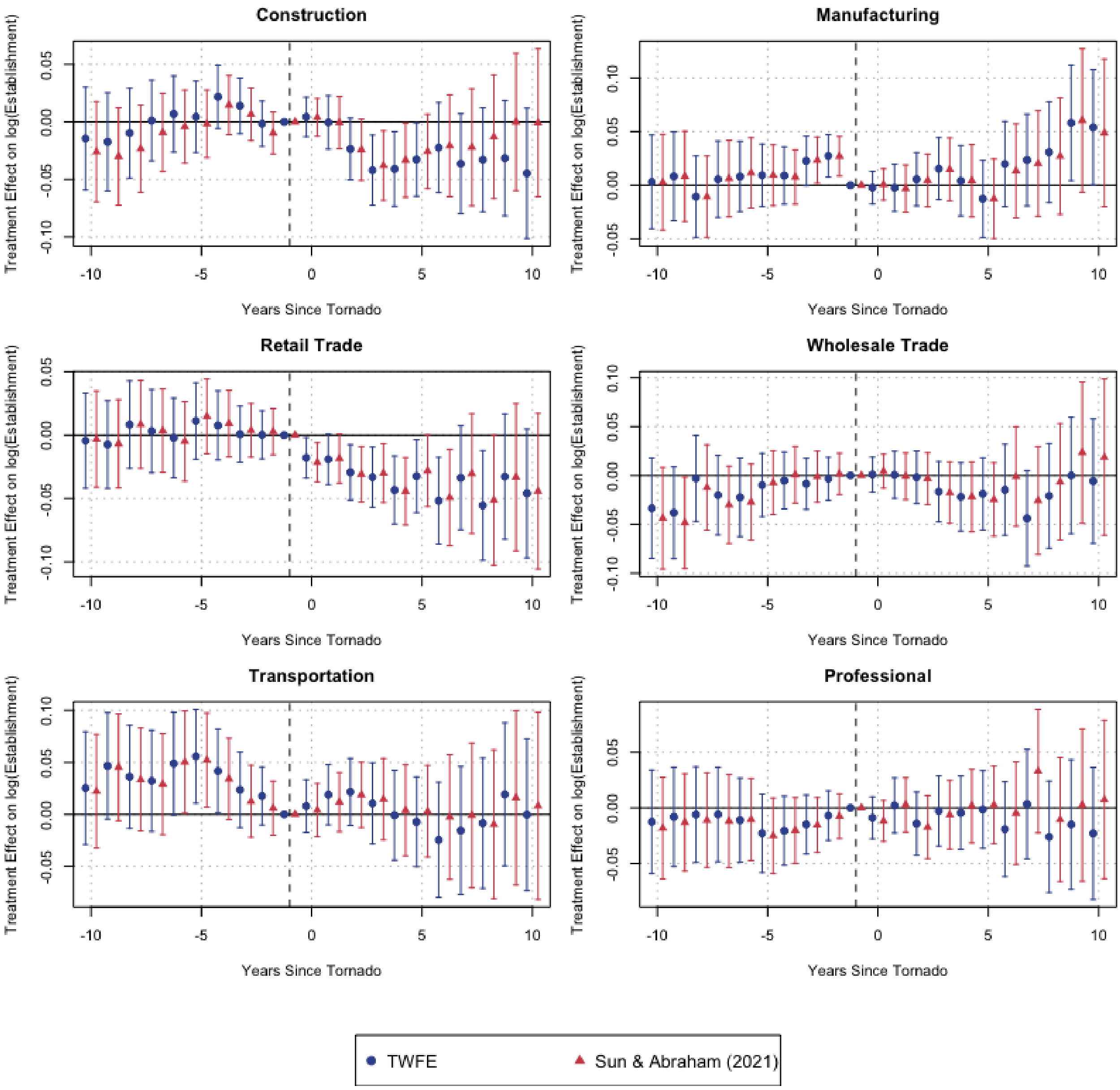
Note: These figures compare the actual tornado path with the author-generated path. Panel (a) is sourced from the Moore, Oklahoma, 2013 tornado analysis (credit: WeatherForensics). Panel (b) is created based on data from the National Weather Service.

Figure A.2: Violent Tornadoes' Impacts on Establishments with 1-99 Employees



Note: This figure shows the impact of EF4-EF5 tornadoes on establishments. The data includes establishments ranging from 1 to 1,000+ employees. However, I present only establishments with 1 to 99 employees, as tornadoes are less likely to impact large establishments. Estimation uses both TWFE and Sun and Abraham (2021) methods. The x-axis represents years relative to tornado occurrence, with dashed vertical line indicating the event year. Bars represent 95% confidence intervals. Data is obtained from US Census.

Figure A.3: Violent Tornadoes' Impacts on Establishments of Selected Industries



Note: This figure shows the impact of EF4-EF5 tornadoes on the 6 selected industries. There are more industries in the data; for readability, I present only 6. Estimation uses both TWFE and Sun and Abraham (2021) methods. The x-axis represents years relative to tornado occurrence, with dashed vertical line indicating the event year. Bars represent 95% confidence intervals. Data is obtained from US Census.

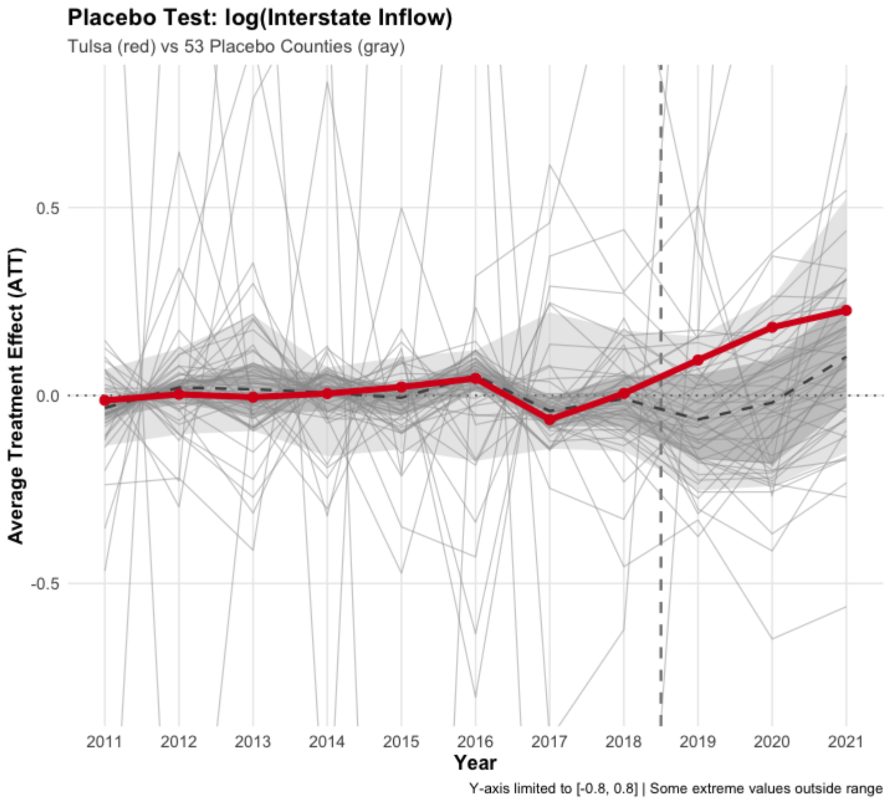
B.1 Chapter 2

Placebo Tests

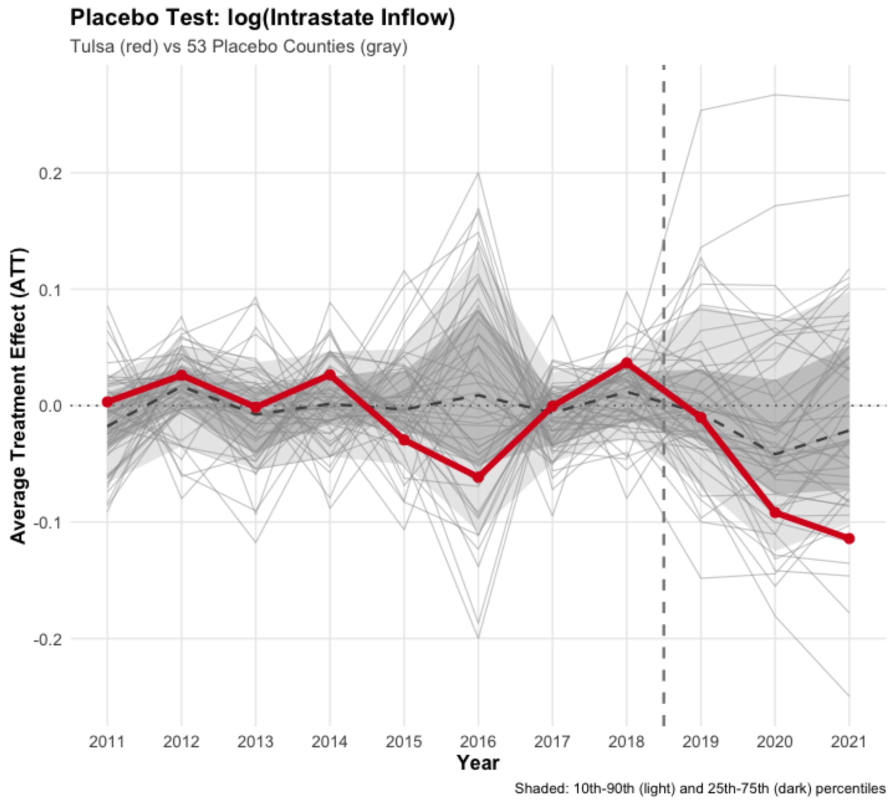
This section presents additional figures and tables from placebo tests designed to assess the robustness of the empirical findings. In these tests, all eligible mainland U.S. counties satisfying the sample selection criteria—including complete covariate information and non-zero variation in outcome variables—are used as the donor pool. Placebo treatments are sequentially assigned to 53 metropolitan counties located in Oklahoma and neighboring states. Four counties in Oklahoma or neighboring states (FIPS codes 40051, 40081, 40113, and 8014) are excluded from the placebo analysis due to zero variation in the relevant outcome variables over the sample period. For each placebo county, synthetic control estimates are constructed using the same specification as in the main analysis. The resulting placebo ATT paths are displayed in the figures, while corresponding inference statistics based on the placebo distribution are summarized in the accompanying table.

An important observation from Table B.1 is that the placebo distribution means are surprisingly close to—or in some cases exceed—Tulsa's estimated treatment effects. For example, the Interstate Inflow placebo mean (0.119) is only slightly below Tulsa's estimate (0.167), while for Adjusted Interstate Inflow, the placebo mean (0.119) actually exceeds Tulsa's estimate (0.103). This pattern is driven by the presence of extreme values among the 53 placebo counties. The substantial variation in the placebo distribution—with standard deviations ranging from 0.063 to 0.539—indicates that some placebo counties experienced large positive migration shocks during 2019–2021, unrelated to any place-based policy treatment. These extreme positive values pull the placebo mean and median upward, making them closer to Tulsa's estimates than would be expected in the absence of such outliers. Without these extreme placebo values, we would anticipate a larger difference between Tulsa's treatment effects and the placebo distribution center, potentially yielding stronger statistical evidence of treatment effects. This highlights an important limitation of the placebo inference approach during the 2019–2021 period: the COVID-19 pandemic and associated remote work transition created substantial migration volatility across all metropolitan areas, increasing the variability of placebo effects and making it more difficult to detect Tulsa Remote's specific impact against this noisy counterfactual.

Figure B.1: Placebo Tests for Migration Inflows: Interstate and Intrastate



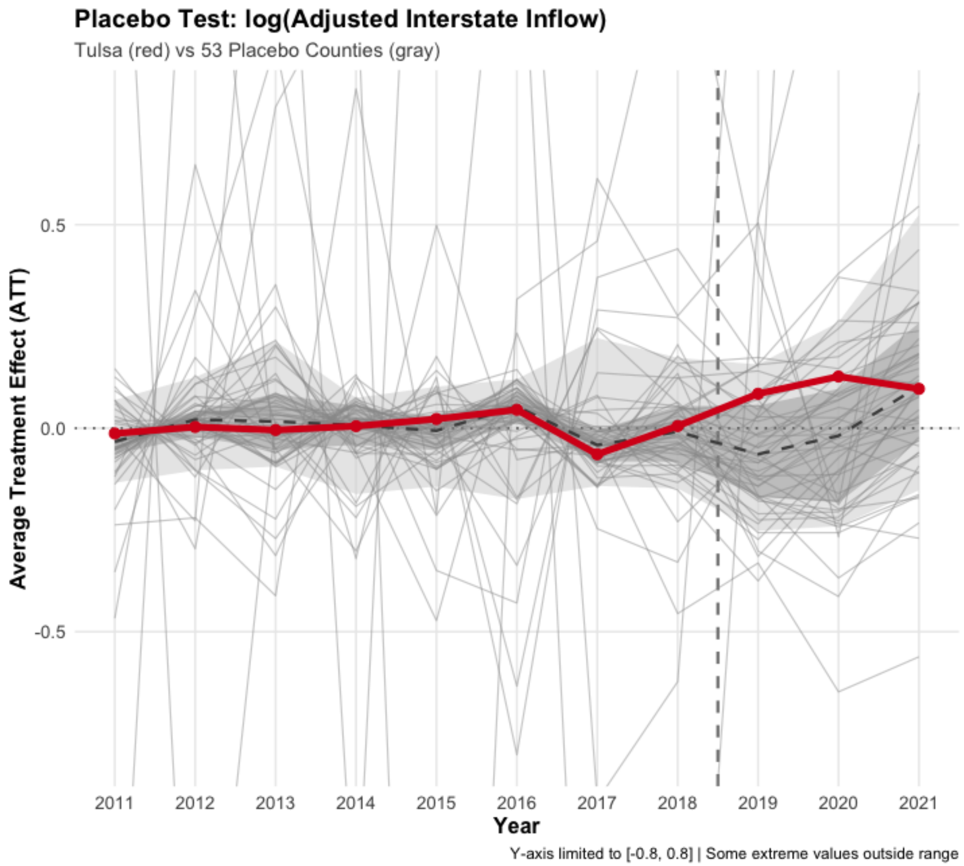
(a) Interstate Inflow



(b) Intrastate Inflow

Note: This figure presents placebo test results for interstate and intrastate migration inflow using the synthetic control method. The red solid line represents Tulsa County's estimated average treatment effect (ATT), while the gray lines show ATT paths for 53 placebo counties selected from MSAs in neighboring states (Oklahoma, Texas, Kansas, Arkansas, Missouri, Colorado, and New Mexico). The dark gray shaded area indicates the interquartile range (25th–75th percentiles) of the placebo distribution, and the light gray area shows the 10th–90th percentile range. The dashed gray line represents the median placebo effect. The vertical dashed line marks the treatment onset in 2019. For visual clarity, the y-axis in panel (a) is limited to [-0.8, 0.8]; some extreme placebo values outside this range are not displayed but are included in the statistical inference. Each placebo county is treated as if it received the treatment in 2019, using the same synthetic control specification: two-way fixed effects with $r = 2$ factors and a donor pool consisting of all mainland U.S. counties satisfying the sample selection criteria.

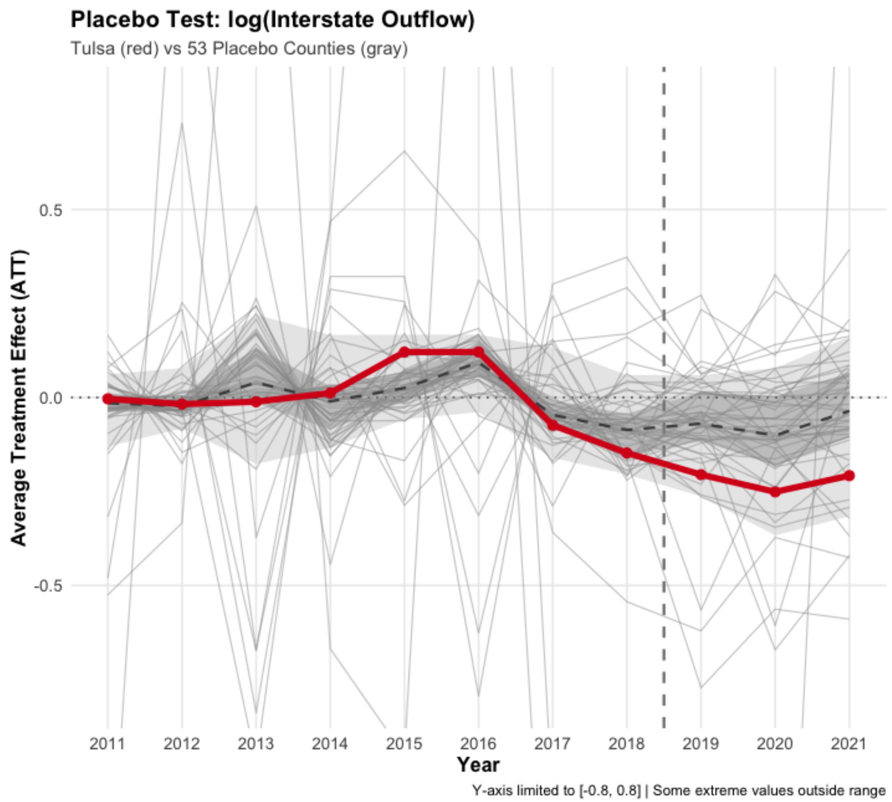
Figure B.2: Placebo Test for Adjusted Interstate Inflow



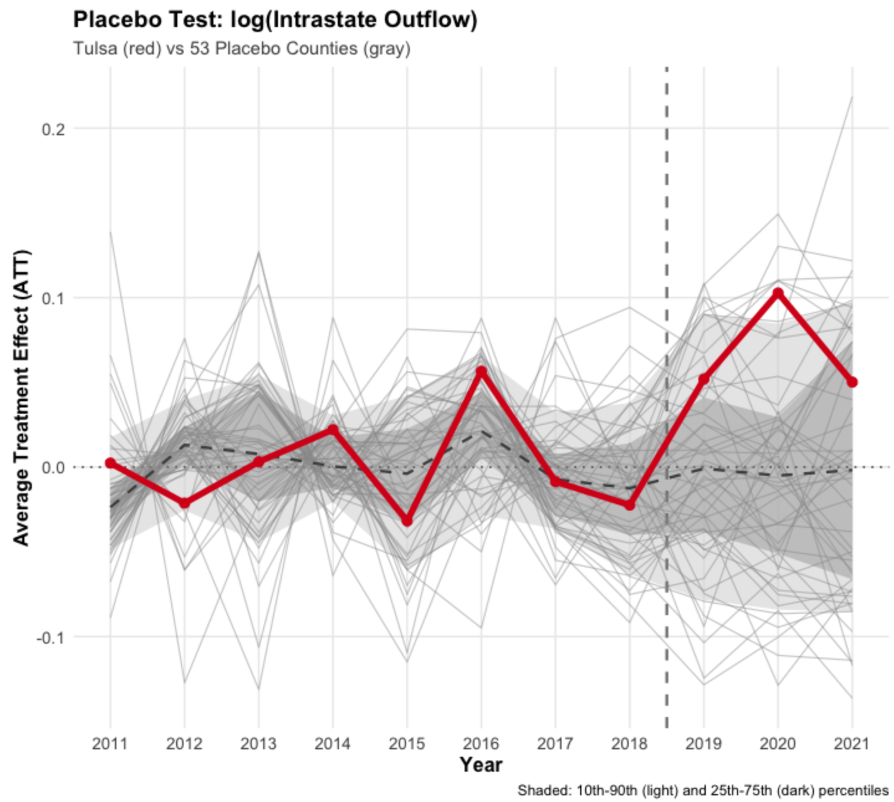
(a) Adjusted Interstate Inflow

Note: This figure presents placebo test results for adjusted interstate migration inflow. The red solid line represents Tulsa County's estimated average treatment effect (ATT), while the gray lines show ATT paths for 53 placebo counties selected from MSAs in neighboring states (Oklahoma, Texas, Kansas, Arkansas, Missouri, Colorado, and New Mexico). The dark gray shaded area indicates the interquartile range (25th–75th percentiles) of the placebo distribution, and the light gray area shows the 10th–90th percentile range. The dashed gray line represents the median placebo effect. The vertical dashed line marks the treatment onset in 2019. For visual clarity, the y-axis is limited to [-0.8, 0.8]; some extreme placebo values outside this range are not displayed but are included in the statistical inference. Placebo specification: two-way fixed effects with $r = 2$ factors and a donor pool consisting of all mainland U.S. counties satisfying the sample selection criteria.

Figure B.3: Placebo Tests for Migration Outflows: Interstate and Intrastate



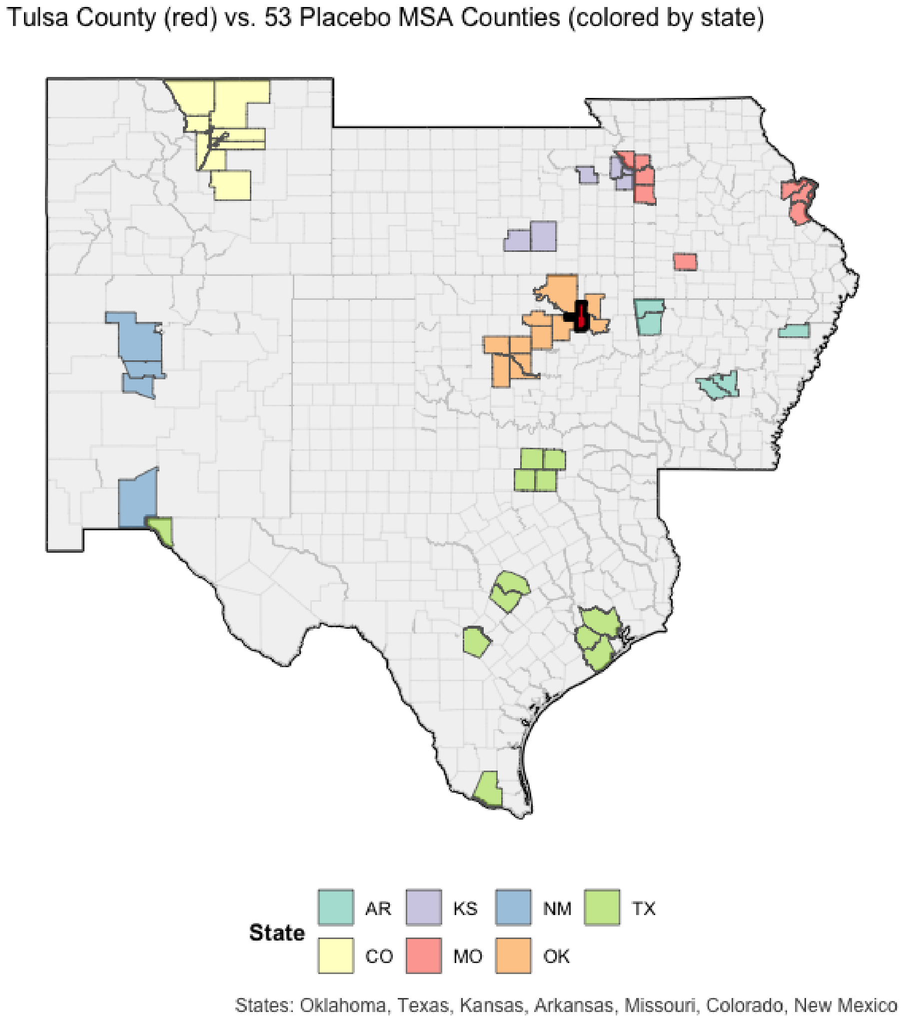
(a) Interstate Outflow



(b) Intrastate Outflow

Note: Placebo test results for migration outflow outcomes. The red solid line shows Tulsa County's estimated ATT, and the gray lines represent the 53 placebo counties from neighboring states' MSAs. The dark gray shaded area indicates the 25th–75th percentile range, and the light gray area shows the 10th–90th percentile range of the placebo distribution. The dashed gray line represents the median placebo path. The vertical dashed line marks the treatment onset in 2019. The y-axis in panel (a) is limited to [-0.8, 0.8] to improve readability; extreme placebo values outside the displayed range are included in all statistical calculations. Placebo specification identical to previous figures: two-way fixed effects with $r = 2$ factors, mainland U.S. donor pool.

Figure B.4: Geographic Distribution of Placebo Counties



Notes: This figure displays the geographic distribution of Metropolitan Statistical Areas (MSAs) used in placebo inference. Panel (a) shows Tulsa MSA (red) within the seven-state region. Panel (b) highlights the 54 MSA counties (1 treated + 53 placebos). Panel (c) shows distribution by state.
MSAs included: Tulsa (treated); Oklahoma City, Lawton; Dallas-Fort Worth, Houston, San Antonio, Austin, El Paso; Kansas City, Wichita; Little Rock, Fayetteville-Springdale-Rogers, Fort Smith; St. Louis; Denver, Colorado Springs, Boulder, Fort Collins; Albuquerque, Santa Fe.
Each placebo MSA is analyzed as if receiving treatment in 2019, using synthetic control with two-way fixed effects and mainland U.S. donor pool.

Table B.1: Placebo Inference Tests

	Post-Treatment Average Treatment Effect (2019–2021)					
	Tulsa	Placebo Distribution			Tulsa	
Outcome	Estimate	Mean	SD	Median	Percentile	N
Panel A: Migration Inflows						
Interstate	0.167	0.119	0.539	−0.005	62.3	53
Intrastate	−0.072	−0.011	0.075	−0.022	69.8	53
Adjusted Interstate	0.103	0.119	0.539	−0.005	47.2	53
Panel B: Migration Outflows						
Interstate	−0.221	−0.114	0.255	−0.071	83.0	53
Intrastate	0.068	−0.001	0.063	−0.009	66.0	53

Notes: This table reports placebo inference tests comparing Tulsa County's treatment effects to a distribution of placebo effects from 53 MSA counties in neighboring states (Oklahoma, Texas, Kansas, Arkansas, Missouri, Colorado, New Mexico). Column (1) shows Tulsa's estimated average treatment effect for 2019–2021. Columns (2)–(4) characterize the placebo distribution through the mean, standard deviation, and median. Column (5) reports Tulsa's percentile rank within the placebo distribution. The placebo distribution statistics are identical for Interstate Inflow and Adjusted Interstate Inflow because the adjustment only affects Tulsa County's own migration flows—it subtracts the participants of Tulsa Remote. Since no other counties in the placebo sample experienced treatment, their interstate flows remain unchanged by this adjustment, resulting in identical placebo distributions. All estimates use synthetic control methods with two-way fixed effects (r=2 factors), pre-treatment period 2011–2018, and a donor pool of mainland U.S. counties satisfying sample selection criteria.

C.1 Chapter 3

Table C.1: Comparison of RWA Programs Included in Recent Studies

Program	Dong & Rogers (2026)	Barton (2022)	Lusoli (2022)	PFM (2021)	Schnoke et al. (2022)
Think Vermont	Y	Y	Y		
Tulsa Remote	Y	Y	Y	Y	Y
Choose Topeka	Y		Y	Y	Y
Remote Shoals	Y	Y	Y	Y	Y
Life Works Here Initiative*	Y	Y	Y	Y	Y
Move to Michigan	Y	Y	Y	Y	
Movers & Shakas	Y				
Remote Tucson	Y	Y		Y	Y
Technology Workforce Incentive*	Y	Y	Y	Y	Y
218 Relocate	Y	Y	Y	Y	Y
Ascend West Virginia	Y	Y	Y	Y	Y
Bloomington Remote	Y	Y	Y		
Choose Southern Indiana	Y				Y
Johnson City Remote	Y	Y			Y
Beckley Remote	Y	Y			
Move to Paducah	Y	Y		Y	Y
Move to Rutherford County	Y				
Remote Worker Welcome Program*	Y		Y		
Shift South	Y	Y			Y
Welcome to Ruston	Y	Y			Y
Choose Ketchikan Program	Y	Y			
EKY Remote	Y				
Fremont Remote Worker Grant Program	Y				
Move to Mattoon	Y	Y			Y
Noblesville Remote Worker Program	Y				
Work From Purdue	Y	Y	Y		Y
Greater ROC Remote	Y	Y			Y

* Program names differ across sources.