Essays on the Economics of Conservation Policy:

Impacts of Protected Areas, Wildfire Dynamics, and Species Delisting

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

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May 2025

DEDICATION

To my Grandfather, Grandmother, Mother, Uncles, Aunties, my Sister, and my Fur Angels—your boundless love and unwavering support have been the sanctuary of my soul. You have been my steadfast pillars, my guiding light, and the stars illuminating my path through the tempestuous seas of life.

As the Vedas proclaim, *"Matru Devo Bhava, Pitru Devo Bhava, Acharya Devo Bhava, Atithi Devo Bhava"*—revere the Mother, the Father, the Teacher, and all who grace our lives. To you, I offer my deepest reverence, for it is through your sacrifices and your wisdom that I have walked this journey.

This work is a tribute to you, whose love echoes the eternal truth spoken by Sri Sathya Sai Baba: *"Love lives by giving and forgiving; self lives by getting and forgetting."*

ACKNOWLEDGEMENTS

With profound humility and gratitude, I bow before the sanctity of life and the grace of those who have walked beside me on this journey. To my Family, who have gifted me the invaluable wisdom of learning, resilience, and the art of letting go, I echo the words of the Vedas: *"The wise see all beings in themselves, and themselves in all beings, and thus attain peace."* Your lessons have been the compass guiding me through the labyrinth of existence.

To Professor Charles Sims, a beacon of unwavering light who steadied me in moments of despair and doubt, I offer my eternal gratitude. Your belief in me, even when my own faith wavered, has been a testimony to the divine truth: *"There is no greater wealth than self-confidence, and no greater force than love."*

To Professors Ketki Sheth, Mohammed Mohsin, and Paul Armsworth, your counsel has been akin to the nurturing rain upon a parched earth. Your support and guidance have been instrumental in transforming this dream into a reality, and I am forever indebted to your wisdom.

My heart turns to Nature herself—Mother Earth, Father Sky, Grandfather Sun, and Grandmother Moon. To the rivers, mountains, forests, and all beings—Earthly and Celestial—you have been the silent witnesses and gentle teachers throughout this journey. *"The Earth is our mother; we are her children,"* says the Veda, and so, I offer my gratitude to the great family of life.

Finally, I bow before the Primordial Sound, the eternal vibration that resonates as **Aum, Amen, Ameen**—the source from which all creation flows. May this work honor that sacred vibration, which unites all beings in the infinite rhythm of existence.

DISCLOSURE STATEMENT

This dissertation, authored by Prubesh Lutchmunsing Balgobin, incorporates the use of artificial intelligence (AI) to enhance the research and writing process. Specifically, the AI model ChatGPT (developed by OpenAI, GPT-4) was employed in the following capacities:

- **Idea Generation and Refinement:** Assistance in brainstorming and structuring sections of the dissertation.
- **Technical Writing Support:** Clarification of complex concepts and assistance in drafting clear and concise descriptions of methodologies and findings.
- **Editing and Proofreading:** Suggestions for improving grammar, style, and coherence throughout the text.

The AI was used as a supplementary tool to support the author's independent research and writing efforts. All analytical content, original research, and conclusions presented in this document remain the sole responsibility of the author. The use of AI complies with the academic integrity guidelines established by the University of Tennessee, Knoxville.

ABSTRACT

This dissertation examines the multifaceted interactions between environmental conservation policies and economic dynamics through three distinct but interrelated studies spanning the contiguous United States from 1998 to 2018.

The first chapter focuses on the economic impacts of Protected Area Designations (PADs) on land-intensive sectors (LIS), such as agriculture, forestry, and construction. Using a Poisson Pseudo-Maximum Likelihood model with High-Dimensional Fixed Effects (PPMLHDFE), this study uncovers non-linear relationships between PAD coverage and business dynamics, including establishment births, exits, and relocations at both intra- and inter-state levels. Results emphasize the critical role of conservation stringency in shaping regional economies.

The second chapter evaluates the economic consequences of wildfires in California, analyzing the frequency and intensity of wildfires and their differential effects on LIS and non-land-intensive sectors (non-LIS). Findings reveal that wildfire frequency destabilizes LIS through increased establishment deaths and outward relocations, while wildfire intensity generates opportunities for recovery-oriented sectors like construction. This study provides actionable insights into disaster resilience and sectoral adaptation.

The third chapter examines the post-recovery economic impacts of delisting the Louisiana Black Bear under the Endangered Species Act. Using proprietary establishment-level data, it highlights the temporal and spatial dimensions of delisting effects on LIS and non-LIS, revealing trade-offs between economic growth and conservation recovery. Findings underscore the importance of monitoring post-delisting dynamics to align economic and environmental goals.

Together, these studies contribute to the fields of conservation economics, disaster economics, and land-use policy by offering a nuanced understanding of how conservation interventions

influence economic landscapes. Policymakers can leverage these insights to design adaptive, spatially targeted strategies that balance ecological preservation with economic development.

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INTRODUCTION

The intricate relationship between environmental conservation policies and economic development has become increasingly significant as societies strive to balance ecological preservation with sustainable growth. Conservation measures such as Protected Area Designations (PADs), disaster responses to climate-induced wildfires, and the recovery of endangered species highlight the multifaceted challenges and opportunities that arise at the intersection of environmental and economic goals.

This dissertation investigates these dynamics through three interrelated chapters, each addressing a critical aspect of conservation and its economic implications. The research spans the contiguous United States from 1998 to 2018, employing advanced econometric techniques and leveraging proprietary establishment-level data to provide robust insights.

Chapter 1 examines the economic impacts of PADs, focusing on land-intensive sectors (LIS) such as agriculture, forestry, and construction. It explores how varying levels of conservation stringency influence establishment births, exits, and relocations at intra- and inter-state levels. This chapter highlights the non-linear effects of PADs, emphasizing the trade-offs between ecological preservation and regional economic activity.

Chapter 2 shifts attention to the economic consequences of wildfires, with a particular focus on frequency and intensity measures. By analyzing the impacts on LIS and non-land-intensive sectors (non-LIS) in California, this chapter uncovers the vulnerabilities and adaptive capacities of different sectors. It also highlights the dual nature of wildfires, which both disrupt economic stability and create opportunities for recovery-focused industries like construction.

Chapter 3 delves into the post-recovery economic impacts of delisting the Louisiana Black Bear under the Endangered Species Act. This chapter investigates the temporal and spatial dimensions of delisting effects on LIS and non-LIS, providing insights into the economic trade-offs that emerge after species recovery. It underscores the need for long-term monitoring and adaptive policy measures to harmonize conservation outcomes with economic growth.

By integrating these three distinct but complementary studies, this dissertation advances our understanding of how conservation policies shape economic landscapes. The findings offer actionable recommendations for policymakers, emphasizing the importance of spatially targeted and sector-specific strategies to achieve sustainable development. As environmental challenges continue to evolve, this research provides a framework for aligning economic and ecological priorities in a rapidly changing world.

CHAPTER I: PRESERVATION AND PRODUCTION

INVESTIGATION INTO THE RELATIONSHIP BETWEEN PADS AND LAND INTENSIVE INDUSTRIAL ACTIVITY

Abstract

This chapter examines the economic effects of Protected Area Designations (PADs) on land-intensive sectors (LIS) at the county level across the contiguous United States from 1998 to 2018. Using a Poisson Pseudo-Maximum Likelihood model with High-Dimensional Fixed Effects (PPMLHDFE), we analyze the effects of PADs under two categories representing different levels of environmental stringency on establishment births, deaths, and relocations, including intra-state and inter-state movements.

Our results reveal non-linear relationships between PAD coverage and business location dynamics, with marginal effects varying in direction and magnitude depending on both the stringency of PAD restrictions and the existing level of PAD coverage within a county. For LIS, strict PADs initially reduce entries and increase exits, but beyond specific thresholds, ecological benefits stabilize business operations. Conversely, non-land-intensive sectors (non-LIS) leverage the ecological amenities associated with PADs to attract new business entries and enhance stability.

This chapter makes three key contributions: First, it provides robust evidence of the non-linear effects of PADs on business dynamics. Second, it highlights the differential effects of PADs based on their classification, reflecting varying levels of conservation stringency and associated land-use restrictions. Third, it extends the understanding of spatial economic dynamics by analyzing intra- and inter-state relocations in response to PAD coverage. These findings offer valuable insights for policymakers seeking to align conservation goals with sustainable economic development.

1.1 Introduction

Protected Area Designations (PADs) serve as vital instruments for biodiversity conservation and sustainable land-use management, influencing not only environmental outcomes but also regional economic dynamics by shaping land-use policies and regulatory frameworks. In the United States, the Gap Analysis Program (GAP) categorizes PADs into four levels of conservation intensity, providing a systematic approach to prioritize conservation goals based on permissible land uses and management objectives.

This study distinguishes between strict PADs (GAP 1 and 2) and broad PADs (GAP 1–4) to explore their economic implications. Strict PADs focus on ecological preservation, with GAP 1 ensuring the permanent protection of natural ecosystems through minimal human interference, and GAP 2 permitting limited, non-disruptive management to maintain essential ecological processes. Broad PADs include all GAP levels, incorporating GAP 3, which allows sustainable land-use practices without significant land cover alterations, and GAP 4, which encompasses lands with no explicit conservation mandates but indirect biodiversity contributions. These distinctions in regulatory intensity and flexibility provide a basis for investigating the trade-offs between conservation goals and economic activities.

Employing a Poisson Pseudo-Maximum Likelihood model with High-Dimensional Fixed Effects (PPMLHDFE), the study accounts for unobserved heterogeneity and provides robust estimates of PAD effects on business dynamics. Rather than focusing on causality, the analysis emphasizes non-linear marginal effects, illustrating how PAD coverage influences economic outcomes while acknowledging the complexities of PAD-related dynamics and potential unobserved factors. PAD effects are threshold-sensitive, with their magnitude and direction contingent upon the prevailing PAD levels within a county. For illustrative purposes, marginal effects are evaluated at the mean PAD levels (14.3% for broad PADs and 5.33% for strict PADs), offering policy-relevant insights into the economic implications of conservation measures without overinterpreting specific statistical patterns.

The primary objective of this chapter is to examine how PADs influence the location outcomes of businesses—specifically entries, exits, and relocations—within land-intensive sectors (LIS), such as agriculture, mining, utilities, and construction, which are especially sensitive to land-use restrictions due to their reliance on natural resources and physical landscapes. Strict PADs exhibit pronounced non-linear effects. They impose higher regulatory constraints, initially deterring entries and relocations while fostering long-term stability through reduced exits and inter-state relocations as businesses adapt to stringent conservation requirements. Broad PADs, in contrast, display more moderate non-linear effects, facilitating flexibility in economic adjustments by encouraging local retention and reducing inter-state outward relocations, though they also amplify intra-state relocations and exits in some contexts.

Sector-specific evaluations highlight these dynamics further: Agriculture benefits from increased entries and stabilized exits under both PAD definitions, showcasing adaptability to conservation-driven environments. Mining experiences stability under strict PADs, with reduced exits and outward relocations, despite marginal deterrence of new entries. Utilities face significant entry constraints under broad PADs but exhibit local retention as exits decline. Construction demonstrates heightened intra-state mobility under strict PADs while maintaining reduced total exits, reflecting its capacity for adaptation under stringent conservation measures.

To offer a broader perspective, the study also assesses the Manufacturing sector (NAICS 31–33) as a representative non-land-intensive sector (non-LIS), highlighting how the effects of PAD extend to industries with lesser reliance on land resources. Broad PADs encourage entries and relocations, reflecting moderate flexibility. However, these benefits are counterbalanced by increased outward mobility, underscoring the sector's sensitivity to conservation intensity. Strict PADs suppress entries and amplify outward relocations, presenting challenges for industries less reliant on land but subject to regulatory pressures.

The analysis of PADs' non-linear marginal effects provides a comprehensive understanding of how conservation policies influence business location outcomes. These findings highlight the importance of evaluating PAD effects based on existing coverage levels, enabling policymakers to balance ecological objectives with economic resilience effectively. These findings extend the Pollution Haven Hypothesis (PHH), which suggests that stringent regulations may prompt relocations to less-regulated areas, particularly for LIS industries, and the Porter Hypothesis (PH), which posits that stricter environmental regulations can drive innovation and long-term stability. By uncovering the nuanced economic effects of PADs, this research contributes to the broader literatures on conservation economics, land-use economics, environmental federalism, and industrial location.

Additionally, the results challenge assumptions about regulatory flight, demonstrating that conservation policies can encourage localized adaptations rather than inter-state mobility. This research underscores the need to balance conservation objectives with regional economic resilience, offering actionable insights for policymakers seeking to align ecological preservation with sustainable economic growth.

1.1.1 Research Objectives, Questions and Hypotheses

1.1.1.1 Research Objectives

This study aims to assess the relationship between PAD coverage and business location dynamics, focusing on the aggregate LIS. The primary objective is to analyze the non-linear associations between PAD coverage and key location outcomes—specifically, establishment births (entries), deaths (exits), and relocations (intra-state and inter-state)—and to determine how these relationships vary with existing PAD coverage levels.

On a secondary level, the research explores heterogeneity in these effects across specific LIS industries (agriculture, mining, utilities, and construction) and within the non-LIS (manufacturing). By integrating these perspectives, the study offers insights into the differential economic implications of conservation policies across sectors with varying levels of dependency on land resources.

1.1.1.2 Research Questions

Research Question 1 (Non-Linear PAD Effects): How do PADs affect establishment location outcomes—specifically births, deaths, and relocations (intra-state and inter-state)—of establishments, and are these effects non-linear, with marginal effects dependent on the existing level of PAD coverage?

Research Question 2 (Differential Effects by PAD Intensity): How do the effects of PADs on establishment location outcomes differ under the strict PAD definition (GAP 1-2) versus under the broad PAD definition (GAP 1–4)?

Research Question 3 (Relocation Dynamics): How do PADs influence the prevalence of intra-state versus inter-state relocations of establishments?

1.1.1.3 Hypotheses

Hypothesis 1 (Non-Linear Effect Hypothesis): The relationship between PAD coverage and establishment location outcomes—specifically births, deaths, and relocations—is statistically significant and non-linear, with the marginal effect of PAD coverage dependent on the existing PAD level within a county.

Hypothesis 2 (Differential Effect Hypothesis): Stricter PADs (GAP 1 and 2) have a more pronounced effect on establishment location outcomes compared to broader PADs (GAP 1–4), with stricter conservation measures imposing greater constraints on business dynamics.

Hypothesis 3 (Relocation Cost Hypothesis): Intra-state relocations of establishments are more prevalent than inter-state relocations, potentially due to lower relocation costs and familiarity with local regulatory environments.

1.1.2 Dissertation Structure

The chapter is structured as follows. Section 2 reviews the literature on PADs, conservation policies, and business dynamics. Section 3 describes the dataset, key variables, and descriptive statistics. Section 4 details the econometric methodology, focusing on the modeling approach and robustness checks. Section 5 presents the results, interpreting their implications for LIS and non-LIS sectors. Section 6 discusses the broader theoretical and policy contributions of the findings and offers recommendations for conservation strategy design. Section 7 provides the conclusion to this chapter. Appendices provide detailed regression tables and sector-specific results under broad and strict PAD definitions.

1.2 Literature Review

This literature review synthesizes insights from environmental federalism, capital mobility, industrial location, and conservation economics to examine the effects of PADs on establishment location decisions. It integrates theoretical frameworks and empirical findings, addressing key gaps in PAD-focused research while situating this study within the broader academic discourse.

1.2.1 Environmental Federalism and the Race to the Bottom

The environmental federalism literature examines how decentralized regulation can incentivize inter-jurisdictional competition, often leading to a "race to the bottom" as regions lower environmental standards to attract businesses (Oates & Schwab, 1988). Levinson (2003) finds that weaker environmental standards attract 5–10% more new establishments in pollution-intensive sectors, while Fredriksson and Millimet (2002) demonstrate that higher regulatory stringency reduces manufacturing establishment births by 12%. However, PADs differ fundamentally from emissions-based regulations. As federally mandated policies, PADs bypass the competitive dynamics observed in decentralized systems.

1.2.2 Capital Mobility and Economic Responses to Regulatory Changes

Capital mobility literature explores how businesses adjust to localized costs, including regulatory stringency. Establishment-level responses are particularly relevant, as they directly reflect location-specific factors. Coughlin et al. (1991) and Head et al. (1995) show that establishments are influenced by agglomeration economies and regulatory costs, with state-level tax increases reducing new establishment births by 6–10%.

Rosenthal and Strange (2004) emphasize that agglomeration benefits significantly offset regulatory deterrents, while Ellison and Glaeser (1997) demonstrate that agglomeration reduces business exit rates by 4–6%. These findings suggest that localized economic advantages play a critical role in moderating the effects of regulatory policies. We control for agglomeration economies in our study.

1.2.3 Impacts of Environmental Regulations on Establishment Dynamics

Research on environmental regulations predominantly focuses on emissions-based policies, such as the Clean Air Act (CAA). Greenstone (2002) and Becker and Henderson (2000) find that nonattainment designations reduce establishment births by 15–20% and increase closure rates by 10–12%. Levinson and Taylor (2008) highlight the pollution haven effect, where businesses relocate to less-regulated areas, while Berman and Bui (2001) provide evidence supporting the

Porter Hypothesis, showing that stricter air quality standards can drive productivity gains. In contrast, PADs extend beyond emissions controls, imposing land-use constraints that directly affect LIS.

The inclusion of lagged explanatory variables in our econometric models of establishment dynamics is supported by existing literature. For instance, Manjón-Antolín and Arauzo-Carod (2011) emphasize the role of past business activity in shaping current location choices, finding that previous exits and relocations influence new business births and movements. Similarly, Bartik (1985) and Greenstone (2002) discuss the importance of lagged variables in capturing adjustment processes in regional economies. These studies underscore that prior establishment dynamics, such as deaths or entries, provide valuable signals about market saturation, competition, and economic resilience, justifying their inclusion in models analyzing industrial location outcomes.

1.2.4 Related Fields in the Literature

Several related fields provide additional insights into PADs' economic impacts, including land-use economics, resource economics, and environmental justice.

Restrictive land-use policies, such as zoning laws, decrease business dynamism by limiting land availability. Gyourko and Molloy (2015) find that such policies reduce business growth by 10–15%, while Saiz (2010) shows that land-use constraints disproportionately affect land-intensive industries. Costanza et al. (1997) estimate that protected areas contribute $33 trillion annually in ecosystem services, providing long-term environmental and economic benefits. PADs enhance ecosystem services critical to LIS sectors, such as water filtration for agriculture and biodiversity preservation for recreation. Environmental justice research highlights the uneven distribution of conservation benefits and economic burdens. Morello-Frosch et al. (2002) and Pastor et al.

(2004) emphasize that lower-income regions often bear higher economic constraints from environmental policies.

By examining the nonlinear effects of PAD coverage on LIS dynamics and contrasting these with broader regulatory policies, this study contributes to multiple literatures, from environmental federalism to conservation economics. It offers new perspectives on how PADs affect LIS and non-LIS, further distinguishing between the non-linear marginal effects of strict versus broad PADs and how these effects depends upon the existing level of PAD within a region (county).

1.3 Data

This section focuses on the data, their sources, and the construction of variables employed in our econometric model. It also provides an overview of the summary and descriptive statistics of key variables used in the analysis. In the main text, we present the summary statistics specifically for the aggregate LIS sector, which combines NAICS sectors 11, 21, 22, and 23.

However, we do not comment on the summary statistics for individual LIS sectors (Agriculture, Mining, Utilities, and Construction) or the non-LIS sector (Manufacturing) within this section. These are instead provided in the Appendix document (**Table A28** and **Table A29**).

Additionally, we note that the socio-demographic, environmental, and economic explanatory variables across the specific sectors in their respective datasets exhibit similar characteristics as that of the aggregate LIS, and therefore, we do not provide separate summary statistics for these. To ensure the robustness of our analysis, we conducted variance inflation factor (VIF) tests, all of which yielded values below the standard threshold of 10, confirming no multicollinearity among variables. Correlation tests indicated low overlap between explanatory variables, and stepwise regression procedures validated the inclusion of only statistically significant predictors.

This comprehensive variable selection framework ensures the relevance and reliability of our data for subsequent analysis.

1.3.1 Outcome Variables

Research on business location decisions often relies on public datasets such as the County Business Patterns (CBP), Quarterly Census of Employment and Wages (QCEW), and Bureau of Labor Statistics (BLS). While these datasets are valuable, they frequently suppress data to protect confidentiality when establishments in small geographical regions, like counties, are sparse (Jarmin & Miranda, 2002; Abowd & Vilhuber, 2008). This suppression poses significant challenges for county-level analyses, as it limits observations on the annual number of establishment entries and exits, particularly in less densely populated counties.

To address these limitations, this study employs the proprietary Data Axle historical business dataset (formerly Infogroup). Unlike public datasets, Data Axle provides unsuppressed, establishment-level data with unique American Business Information (ABI) identifiers, enabling precise tracking of each businesses across years. It offers detailed information on geolocations, employment, sales, and NAICS classifications, making it particularly well-suited for county-level analyses of establishment dynamics. The dataset's granularity allows for a detailed examination of establishment location outcomes, including births, deaths, and relocations, further disaggregated into intra-state and inter-state movements.

Using this dataset, which spans from 1997 to 2019, we constructed annual sector-specific county-level measures of establishment location outcomes for the 1998–2018 period, listed below. The first and final years of the dataset (1997 and 2019) are excluded due to missing prior-year (1996) and subsequent-year (2020) data needed to compute exits in 1997 and entries in 2019, respectively. The sectors which we look at are NAICS 11, 21, 22, 23, and 31-33. We construct our location outcome variables for each of these NAICS sectors, then for the aggregate LIS sector, which consists of establishments from NAICS sectors 11, 21, 22, and 23.

Figure A1 (Location Decision Tree) illustrates the conceptual decision tree underlying establishment location dynamics, emphasizing the distinct pathways of entries (births and relocations) and exits (deaths and relocations). Below, are the exact definitions of each location outcome variable we constructed:

1. **Birth:** An establishment is considered "born" in county C in year T if it did not exist anywhere in the United States in the previous year (T-1).
2. **Inward Relocation:** An inward relocation occurs in county C in year T if, in the previous year (T-1), the establishment was located in a different county within the United States. Inward relocations are further categorized into either:

    2.1) Intra-State Inward Relocation: Occurs in county C, state S, in year T if the establishment was previously located in another county within the same state (S) in year T-1.

    2.2) Inter-State Inward Relocation: Occurs in county C, state S, in year T if the establishment was previously located in a county within a different state from state S in year T-1.
3. **Deaths:** An establishment is considered "dead" in county C in year T-1 if it no longer exists anywhere in the United States by year T.
4. **Outward Relocations:** An outward relocation occurs in county C in year T-1 if, in year T, the establishment moves to a different county within the United States. Outward relocations are further categorized into:

4.1) **Intra-State Outward Relocation:** Occurs in county C, state S, in year T-1 if, by year T, the establishment relocates to another county within the same state (S).

4.2) **Inter-State Outward Relocation:** Occurs in county C, state S, in year T-1 if, by year T, the establishment relocates to a different state from state S.

5. **Total Entries:** Total entries in county C for year T refer to the sum of establishment births and inward relocations (both intra-state and inter-state) into the county during that year.
6. **Total Exits:** Total exits in county C for year T refer to the sum of establishment deaths and outward relocations (both intra-state and inter-state) from the county during that year.

1.3.1.1 Justification for using count versus rate outcome variables

The choice of using counts for establishment location outcomes—such as entries, exits, and relocations—instead of rates is deliberate and methodologically sound. Counts preserve the absolute scale of business activity, capturing critical heterogeneity across counties with varying economic sizes. Entry or exit rates may obscure meaningful variations between small rural counties and large urban centers, where the scale of activity differs despite potentially similar rates.

Furthermore, including past establishment counts as explanatory variables accounts for path-dependence in business dynamics. For example, a high number of past exits may signal market opportunities created by reduced competition, influencing current entries. This approach ensures that the model captures the scale and feedback effects of past dynamics without the information loss associated with standardization to rates.

Count outcome variables are also well-suited to the Poisson Pseudo-Maximum Likelihood (PPML) framework employed in this study, which addresses the non-negative, discrete nature of these variables while accommodating overdispersion and heteroskedasticity.

1.3.1.2 Summary Statistics of Aggregate LIS Location Outcome Variables

The summary statistics for our LIS location outcome variables in **Table A1** provide a quantitative overview of business dynamics across U.S. counties. On average, business births average 69 establishments per county annually, closely mirrored by business deaths at 67, suggesting a stable but dynamic equilibrium. Total entries and exits align closely, averaging 72 and 70 establishments per county, reinforcing the balanced nature of LIS business activity. While relocations are less frequent compared to births and deaths, with intra-state movements dominating over inter-state relocations possibly due to lower relocation costs and better regulatory familiarity within states, these trends reflect the importance of localized factors.

The high variability across counties, reflected in the range of establishment births (0 to 12,469) and deaths (0 to 13,569), underscores heterogeneity driven by regional economic conditions, resource availability, and policy effects. Relocations remain minimal, signaling that land-intensive businesses are less mobile, possibly constrained by logistical and sector-specific land dependencies.

We now provide additional exploratory analyses in regards to our location outcome variables.

1.3.1.3 Trends in Aggregate LIS Entries and Exits

Figure A2 shows the annual trends in LIS entries and exits reflect the sector's sensitivity to macroeconomic cycles. Periods of economic growth, such as the early 2000s, show increased entries and reduced exits. Conversely, economic downturns like the 2008 financial crisis are marked by declining entries and surging exits, highlighting the vulnerability of LIS to financial shocks. The negative correlation between entries and exits throughout the study period underscores the cyclical nature of LIS dynamics.

1.3.1.4 Decomposition of Aggregate LIS Entries

In **Figure A3**, we see that births overwhelmingly drive entry trends in LIS, reflecting the importance of local entrepreneurship and regional business conditions. Intra-state and inter-state relocations remain consistently low throughout the study period, with limited mobility within states possibly due to economic and environmental constraints. Peaks in relocations, such as those observed in 2003 and 2007, likely correspond to external factors such as state-level policy changes or economic shifts.

1.3.1.5 Decomposition of Aggregate LIS Exits

In **Figure A4**, we see that exits in the LIS are predominantly driven by business closures (deaths), which far outnumber outward relocations. Significant spikes in closures, such as those in 2003 and 2007, coincide with periods of economic strain or regulatory pressures. Intra-state and inter-state outward relocations remain low and stable, with inter-state relocations slightly more frequent. This suggests that businesses facing restrictive conditions prefer local adaptation but may relocate out of state under extreme pressures.

1.3.2 Aggregate LIS location dynamics and PAD coverage levels

This section describes and presents graphically the relationship between PAD coverage, under the strict and broad definition, with our different aggregate LIS location outcome variables—entries, exits, and relocations. While the analyses presented here are descriptive, they offer key preliminary insights into the potential trends and non-linear effects of PAD coverage and LIS establishment location choices.

1.3.2.1 Aggregate LIS Entries and PAD Coverage

Figure A5 and **Figure A6** presents the relationship between PADs and aggregate LIS entries, suggesting potential non-linear effects. Across all PAD types, as shown in **Figure A5**, establishment entries decline with increasing PAD coverage, particularly up to 50%, possibly reflecting the challenges of operating under restricted land use. A slight increase is observed between 50% and 70% coverage, followed by another decline at higher PAD levels. In **Figure A6**, we see that Stricter PADs (GAP Status 1 and 2) show a sharper decline in entries, with sparse activity above 20% coverage. These findings possibly indicate that higher conservation stringency may pose additional barriers to new business formation.

1.3.2.2 Aggregate LIS Exits and PAD Coverage

From **Figure A7**, and **Figure A8**, under each PAD definition, we observe exits to be concentrated at low PAD coverage levels and generally decline as PAD coverage increases. Across all PAD types, as shown in **Figure A7**, exits become less frequent at higher PAD percentages. Stricter PADs reinforce this trend, as shown in **Figure A8**. Businesses may be thought to be adapting to stricter conservation measures or benefit from the enhanced predictability of protected environments.

1.3.2.3 Aggregate LIS Relocations and PAD Coverage

As shown in **Figure A9**, under the broad PAD definition, we find inward relocations to generally decline as PAD coverage levels increases. In **Figure A10**, stricter PADs show an even sharper drop-off at coverage levels above 20%**,** reflecting potential deterrents for relocating businesses. Under the broad PAD definitions, as shown in **Figure A11**, outward relocations decline slightly with higher PAD coverage. In **Figure A12**, we observe that stricter PADs reduce outward movements more significantly, suggesting that stringent protections may anchor establishments.

1.3.3 Explanatory Variables and Summary Statistics

The choice of explanatory variables in this study is guided by foundational works in industrial location choice and environmental federalism, including List (2001), Greenstone (2002), and Becker and Henderson (2000), which emphasize the importance of local economic, demographic, and regulatory factors in shaping establishment dynamics. In addition to the main explanatory variables, selected lagged versions of certain outcome variables—such as births, deaths, inward relocations, and outward relocations—are included in specific regression models to account for intertemporal dependencies. These lagged variables capture the influence of prior market dynamics on current outcomes and are described further in Section 4.

Table A3 provides the summary statistics on the key explanatory variables used in the analysis, across U.S. counties from 1998 to 2018.

1.3.3.1 Environmental Variables

1. Protected Area Designations (PADs)

PADs form the core environmental variable in this study, representing conservation intensity at the county level. Data were sourced from the PAD-US 3.0 database, the most comprehensive national dataset on protected lands in the United States. PADs classify regions based on their environmental or cultural protections, with varying levels of management and permissible activities defined by GAP status codes. These classifications inform policy and conservation strategies, guiding land use and resource management decisions. **Table A2** provides a complete description for PAD under each GAP status code.

Using GIS tools in ARCGIS Pro, we constructed annual county-level cumulative PAD coverage under two key definitions:

- **Broad PADs (GAP Status 1–4):** Captures all conservation levels and averages 14.3% of county land.
- **Strict PADs (GAP Status 1–2):** Focuses on the strictest protection measures, such as national parks and wilderness areas, and averages 5.33% of county land.

For each year in the study period (1998–2018), we calculated our PAD coverage variable by summing the acreage of all PADs in a county (under the strict and broad definitions) and dividing it by the total land area (in acres) of that county. On average, 5.33% of county land falls under GAP 1 and 2, which are the most strictly protected areas aimed at biodiversity conservation, where commercial use is generally prohibited. When including all GAP categories (which encompass varying levels of protection), the average protected land rises to 14.3%.

Data Adjustments for Overlaps and Outliers: To address anomalies in PAD-US 3.0, such as instances where PAD coverage exceeded 100% of county land due to overlapping designations, adjustments were made to ensure analytical reliability. Overlapping designations in PAD-US have been recognized as a source of inconsistency, complicating the assessment of conservation intensity and protection status (USGS, 2020).

Following best practices in spatial data analysis, counties with PAD coverage exceeding 88% were excluded, representing less than 1% of the dataset. This threshold was chosen to maintain the representativeness of the dataset while mitigating distortions caused by extreme outliers. Sensitivity analyses confirmed that the exclusion of these outliers did not affect regression outcomes on a statistical significance level, ensuring that the findings remained robust and reliable.

Evaluation of Flattened PAD-US Dataset: We also investigated the potential use of the Flattened PAD-US dataset, which addresses overlapping PAD designations. While this resolves issues of overlap, the dataset lacks temporal coverage, making it unsuitable for the spatio-temporal framework of this study. By using PAD-US 3.0, which retains temporal information, we are able to account for annual changes in PAD coverage.

Temporal Considerations: Approximately 33% of PADs in PAD-US 3.0 lack designation dates, presenting challenges in accurately determining the temporal sequence of protection. We improved upon the PAD-US dataset by incorporating supplemental data from the California Protected Areas Database (CPAD) shared by Professor Maria De Santos of Zurich University. Her dataset provided partial missing designation dates for PADs within California, which were then merged into the national PAD-US dataset.

Additionally, following phone consultations with a PAD-US representative, I was informed that the missing PAD dates predated the 1990s. Based on this information, we assumed that PADs without designation dates were established before the start of the study period (1997–2019). This assumption aligns with historical conservation trends, ensuring temporal consistency at the national scale.

By acknowledging these limitations, leveraging supplementary data, and adapting our approach to the available resources, this study addresses potential concerns about the temporal aspects of PAD designations while maintaining the robustness and relevance of the findings.

Lags, Leads, and Counterfactuals: For counterfactual analysis, we constructed lags and leads of PAD coverage under both the broad and strict definitions. These variables enabled the examination of pre- and post-designation effects on establishment location outcomes, offering insights into the dynamic effects of conservation policies.

2. Non-Attainment Status

Under the Clean Air Act (CAA), the EPA classifies counties as "in-attainment" or "out-of-attainment" for six criteria pollutants based on compliance with the National Ambient Air Quality Standards (NAAQS). These pollutants include Carbon Monoxide (CO), Lead (Pb), Ozone (O_3), Particulate Matter (PM 2.5), Sulfur Dioxide (SO_2), and Nitrogen Dioxide (NO_2), each with specific thresholds that when exceeded trigger stricter regulatory requirements. Counties out-of-attainment face heightened compliance costs, which can influence industrial location decisions by raising operating costs and deterring new establishments. We downloaded our data from the EPA's Greenbook website, and constructed county-non-attainment-status binary variables for each pollutant.

Prior research underscores the importance of non-attainment status in influencing business behavior (List et al., 2003; Kuminoff et al., 2013; Chay & Greenstone, 2005). The inclusion of non-attainment variables ensures that our results account for overlapping regulatory pressures, aligning with our objective to evaluate PAD effects while isolating the influence of broader environmental stringency.

1.3.3.2 Socio-Demographic and Economic Variables

The socio-demographic and economic variables used in this study were sourced from the U.S. Census Bureau, County Business Patterns, and American Community Survey. Their inclusion in our model aligns with prior research (Glaeser et al., 2001; Moretti, 2010; Ellison and Glaeser, 1997), highlighting the role of local economic conditions in shaping establishment location decisions. We now provide comments on each one of them. Note that some of these variables have been scaled, with their respective scaling factor written in parentheses (See **Table A3**).

Population Density: Population density serves as a proxy for urbanization and market size, averaging 0.004 (scaled by 100), with a maximum value of 1.16. Higher density regions provide access to larger consumer markets and agglomeration economies, attracting business entries. However, congestion, higher land costs, and intensified competition in densely populated counties may lead to elevated exit rates.

Unemployment Rate: The unemployment rate reflects local labor market conditions, with a mean of 6.1% and a maximum of 30.6%. High unemployment often signals weak demand, potentially deterring new establishments. However, regions with higher unemployment may attract cost-sensitive businesses due to reduced labor costs.

Median Household Income: Median household income, averaging $42,300, captures local purchasing power and labor costs. Higher-income counties may attract establishment seeking skilled labor and affluent markets. However, elevated income levels may deter labor-intensive or low-margin sectors due to increased wage pressures.

Housing Price Index: With a mean of 2.466 and a wide range (0.637–20.849), the Housing Price Index captures real estate and land costs. High housing prices often correlate with economic activity but may discourage new business entries in land-intensive sectors due to operational cost concerns.

Poverty Rate: The poverty rate averages 15.3%, with substantial variation (0–62%). High poverty rates can deter businesses reliant on local consumer demand but may attract low-cost industries. This variable also highlights economic disparities across counties, influencing business dynamics.

1.3.3.3 Aggregate LIS-Specific Explanatory Variables

This subsection highlights additional explanatory variables specific to the aggregate LIS, capturing economic, agglomeration, and mobility dynamics within counties. These variables provide insights into key factors influencing establishment location outcomes, such as entries, exits, and relocations, and help account for the regional disparities in business dynamics. Each variable reflects unique aspects of county-level economic activity, including agglomeration economies, business churn, and localized mobility trends, offering a comprehensive view of the aggregate LIS environment.

Localization Economies: Measured as the prior-year count of establishments in a county-sector, this variable reflects agglomeration economies. Higher localization supports establishment entries through reduced search costs for suppliers and labor and fosters innovation.

Employment Density: Employment density, with a mean of 0.191 and a high standard deviation (1.332), reflects the concentration of employment within counties. Higher density fosters productivity and supports establishment entries due to agglomeration effects. However, competitive pressures in densely employed regions can lead to increased establishment exits.

Sales Volume (t-1): The average sales volume is $621,662, with a high standard deviation of $2,267,050, indicating substantial disparities in economic scale across counties. The maximum value of $188 million underscores the presence of a few counties with extremely large businesses driving economic activity, while many counties experience much smaller sales volumes.

Births (t-1): Counties see an average of 68.34 establishment births per year, with a wide range (0 to 12,469). The high standard deviation (229.62) indicates significant variability, suggesting that certain counties exhibit substantial entrepreneurial activity, while others show minimal new business formation.

Deaths (t-1): Establishment deaths closely align with births, averaging 65.70 per year, with a similarly large range (0 to 13,569) and standard deviation (221.28). This near parity between births and deaths suggests a dynamic but balanced environment in most counties, with notable churn in business activity.

Relocation Variables (t-1): Total inward relocations average 2.85 annually per county, dominated by intra-state movements (2.83) compared to inter-state (0.016). This highlights a clear preference for localized relocations, possibly due to lower costs and greater regulatory familiarity. The minimal inter-state movements reflect limited mobility for businesses across state boundaries. Total outward relocations also average 2.85, mirroring inward relocations, with intra-state out-migrations (2.83) far outpacing inter-state out-migrations (0.016). The pattern underscores the importance of intra-state dynamics in shaping business mobility.

Total Entries (t-1): Total entries, encompassing both births and inward relocations, average 71.19 per year, with a substantial range (0 to 12,469) and standard deviation (243.13). This variability highlights regional disparities in growth opportunities.

Total Exits (t-1): Total exits, including deaths and outward relocations, align closely with total entries, averaging 70 per year, with a similarly wide range and standard deviation. This balance between entries and exits reinforces the dynamic equilibrium observed in many counties.

1.3.4 Conclusion

In summary, this data section establishes a comprehensive framework for analyzing the relationship between PAD coverage and establishment location outcomes across the LIS and non-LIS sectors. By integrating robust explanatory variables that capture environmental, socio-economic, and regulatory factors, the data preparation aligns closely with the study's research objectives. This foundation enables a nuanced evaluation of the interplay between conservation policies, business dynamics, and sectoral heterogeneities. The following section details the econometric approach employed to examine the non-linear effects of PAD coverage on establishment location outcomes.

1.4 Methodological Framework

This section outlines the econometric approach used to analyze the effects of PADs on the location decision choice of establishments from the LIS and non-LIS, emphasizing robustness against endogeneity and incorporating joint-significance tests to evaluate non-linear relationships.

1.4.1 Econometric Model

The analysis employs a Poisson Pseudo-Maximum Likelihood (PPML) estimator with High-Dimensional Fixed Effects (HDFE) to model count data outcomes, including business births, deaths, and relocations. The PPML-HDFE approach offers several advantages over traditional models such as OLS, Negative Binomial, and Zero-Inflated Poisson models:

1. **Resilience to Heteroskedasticity:** Unlike OLS, PPML produces consistent estimates under heteroskedasticity, ensuring robust results even in the presence of skewed data distributions (Santos Silva & Tenreyro, 2006; Correia et al., 2019).
2. **Handling of Fixed Effects:** High-dimensional fixed effects account for unobserved heterogeneity at multiple levels, enhancing the precision and interpretability of our coefficients (Fally, 2020).
3. **Flexibility for Count Data:** PPML is well-suited to datasets with excess zeros and variability across regions, common in business dynamics research (Cameron & Trivedi, 2013).

The model is specified as follows:

$$Y_{csnt} = \exp\left(\beta_0 + \beta_1 PAD_{cs,t-1} + \beta_2 PAD^2_{cs,t-1} + \sum \beta X_{csnt} + \gamma_c + \alpha_{s*t} + \delta_n\right) + \epsilon_{cstn}$$

Where,

- Y_{csnt}: Outcome variable for county *c*, state *s*, NAICS sector *n,* year *t*.
- $PAD_{cs,t-1}$: Lagged percentage of county land under PADs.
- $PAD^2_{cs,t-1}$: Quadratic PAD term modeling non-linear dynamics.
- $\gamma_c, \alpha_{s*t}, \delta_n$: County, state-year, and sector fixed effects, respectively.
- X_{csnt}: Vector of control variables.
- ϵ_{cstn}: Clustered error term at the county level.

Results from Hausman tests confirm the superiority of fixed effects over random effects, validating the inclusion of county, state-by-year, and sector fixed effects. These fixed effects isolate within-county temporal variations, mitigating confounding influences from time-invariant and state-level unobserved factors.

Our models incorporate socio-economic and environmental controls, scaled and lagged where appropriate. Additionally, to account for intertemporal dependencies and dynamic business responses, lagged outcome variables are selectively included in models for specific business location outcomes. This approach aligns with established literature (e.g., Brouwer et al., 2004; Arauzo-Carod, 2009; Greenstone, 2002), which emphasizes the influence of past dynamics on current decisions.

For establishment births, lagged total exits signal reduced competition or new market opportunities, encouraging entries. Inward relocations are influenced by prior births, which indicate local economic vitality, and past deaths, which highlight market vacancies, while lagged outward relocations reflect market dynamism shaping inflows. Similarly, lagged total exits suggest economic churn, spurring total entries. For establishment deaths, lagged entries capture market saturation or competitive pressures, increasing closure risks. Outward relocations are driven by prior births, which may create crowding effects, and past deaths, which signal instability, while lagged inward relocations underscore how inflows can trigger outflows. Finally, lagged total entries highlight market congestion, potentially leading to exits or relocations. This integration of lagged variables ensures that models capture the dynamic interplay between past and current business activities.

All our control variables capture broader temporal trends and local economic conditions. Variance Inflation Factor (VIF) tests indicate minimal multicollinearity, while AIC/BIC measures demonstrate improved model fit when these variables are included. This ensures that our controls significantly contribute to our models, in terms of explanatory power without overfitting, reinforcing the robustness and interpretability of the results. This econometric framework provides a robust foundation for analyzing the effects of PAD coverage on business location dynamics, setting the stage for the exploration of non-linear relationships in Section 4.2.

1.4.2 Decoding Non-linear Dynamics of PADs

To investigate threshold-sensitive effects, the model includes both linear and quadratic terms for PAD coverage:

- **Linear Term** ($\boldsymbol{PAD_{cs,t-1}}$)**:** Captures the initial directional effect of PADs, revealing whether coverage positively or negatively influences business outcomes at low levels.
- **Quadratic Term** ($\boldsymbol{PAD^2_{cs,t-1}}$)**:** Reflects threshold effects, where PAD effects shift from being constraints to catalysts (or vice versa) for economic activity.

1.4.2.1 Joint-Significance Tests

To examine the presence of non-linear effects of PAD coverage on the dependent variable (Y), we conduct joint-significance tests for the linear (PAD) and quadratic (PAD^2) terms. Specifically, we test the null hypothesis:

H_0: $\beta_1 = 0$ and $\beta_2 = 0$, against the alternative: H_a: $\beta_1 \neq 0$ or $\beta_2 \neq 0$,

where β_1 and β_2 represent the coefficients of the linear and quadratic PAD terms, respectively. Rejecting H_0 indicates that the two terms jointly and significantly contribute to explaining (Y), validating the presence of non-linear effects. (Y).

A statistically significant p-value for the joint test—determined at the 10% significance threshold—indicates the presence of non-linear effects. In such cases, the marginal effects of PAD coverage are interpreted as dependent on the level of existing PAD in a county. Conversely, if the joint test is statistically insignificant, we refrain from interpreting the coefficients of either the linear or quadratic PAD terms, even if they are individually significant. This approach follows econometric best practices, which caution against interpreting isolated coefficients in polynomial specifications without joint significance (Wooldridge, 2010; Greene, 2012).

Primary Test: Wald Test: The Wald test is the baseline approach employed to assess whether the estimated coefficients of PAD and PAD^2 are jointly significantly different from zero. The Wald test statistic is computed as: $W = \hat{\beta}' * Var\left(\hat{\beta}\right)^{-1} * \hat{\beta}$

Where $\hat{\beta} = (\beta_1, \beta_2)'$ is the vector of estimated coefficients, and $Var(\hat{\beta})$ is the variance-covariance matrix of the coefficients. This test is computationally efficient and commonly applied in high-dimensional fixed effects models. While computationally efficient and widely used, the Wald test has limitations. Its validity relies on large-sample properties, which may lead to inaccuracies in smaller datasets. Issues such as heteroskedasticity or over-dispersion, common in count data models like PPML, can affect reliability.

Stricter and Alternative Robustness Tests

Recognizing the potential limitations of the Wald test, we employ more stringent tests to ensure the robustness of our findings:

1) **Likelihood Ration (LR) Test:** This test compares the log-likehoods of models with and without the linear and quadratic PAD terms: $LR = -2 * [\ln(L_{restricted}) - \ln(L_{unrestricted})]$

This test is generally more reliable than the Wald test, particularly in finite samples, as it evaluates the joint explanatory power of the terms based on likelihood differences.

2) **Bootstrap-Based Wald Test**: The bootstrap-based Wald test mitigates small-sample biases by resampling the data and recalculating the test statistic across these samples. This approach strengthens inference under non-standard conditions.

3) **F-Test:** Commonly used in linear regression, the F-test compares the variance explained by the restricted and unrestricted models. While conceptually relevant, its direct application is limited in PPML models.

The joint significance of PAD and PAD^2 was consistently supported by the Wald test and confirmed by stricter alternatives, such as the LR and bootstrap-based Wald tests. These results bolster confidence in the non-linear effects of PAD coverage on Y. However, sensitivity analyses reveal some attenuation of results under the stricter tests. For instance, in certain specifications, the quadratic term (PAD^2) becomes statistically insignificant under the LR test. This suggests that the evidence for non-linear effects may depend on the specific econometric method employed. By transparently addressing these discrepancies, we ensure that our results are interpreted cautiously and robustly.

Where joint significance is established, the results validate the presence of non-linear dynamics in PAD's effect on Y. In these cases, marginal effects are evaluated at the mean PAD coverage levels for broad (14.3%) and strict (5.33%) definitions. This approach provides practical insights into the direction and magnitude of PAD effects under realistic conditions, while avoiding overinterpretation of imprecise estimates. However, in the absence of joint significance, we refrain from interpreting the marginal effects or asserting the presence of non-linear patterns.

1.4.2.2 Marginal Effects

Marginal effects quantify the relationship between changes in an independent variable and the dependent variable (Y), offering critical insights into how explanatory variables influence outcomes. For this analysis, marginal effects are calculated to capture the percentage change in Y for small changes in the explanatory variables, with a particular focus on PAD.

Marginal Effects in Non-Linear Models: In the PPML regression framework, the expected value of Y is modeled as: $E[Y \mid X] = exp\ (\beta_0 + \beta_1 \cdot PAD + \beta_2 \cdot PAD^2 + Z'\gamma)$

where β_1 and β_2 are the coefficients for the linear and quadratic terms of PAD, respectively, and $Z'\gamma$ represents other control variables.

The marginal effect of PAD is given by: $\frac{\partial E[Y|X]}{\partial PAD} = E[Y \mid X] \cdot (\beta_1 + 2 \cdot \beta_2 \cdot PAD)$

To simplify interpretation, we adopt the normalization $E[Y \mid X] = 1$, which transforms the marginal effect into: $\frac{\partial E[Y|X]}{\partial PAD} = \beta_1 + 2 \cdot \beta_2 \cdot PAD$

This assumption is standard in applied econometrics (Wooldridge, 2010; Cameron & Trivedi, 2013) and allows the marginal effect to be interpreted directly as the percentage change in Y for a small change in PAD. Without normalization, the interpretation of the marginal effect would require explicit computation of $E[Y \mid X]$, introducing unnecessary complexity without altering the relative interpretation of the coefficients.

Non-Linearity in PAD's Marginal Effects: The inclusion of quadratic terms (PAD^2) introduces non-linearity, meaning the marginal effect of PAD varies with the current level of PAD. At low levels of PAD, the linear term dominates, resulting in more pronounced impacts. At higher levels of PAD, the quadratic term moderates or reverses the effect.

For example, at the mean strict PAD level (5.33%): $Marginal\ Effect = \beta_1 + 2 \cdot \beta_2 \cdot PAD$

Using $\beta_1 = -2.435$ and $\beta_2 \ = \ 2.653$, the marginal effect is:

$Marginal\ Effect = -2.435 + 2 \cdot 2.653 \cdot 0.0533 = -2.1523$

This implies that a 1 percentage point increase in PAD (from 5.33% to 6.33%) reduces relocations by 2.15%. At higher PAD levels (for instance at 20%):

$Marginal\ Effect = -2.435 + 2 \cdot 2.653 \cdot 0.20 = -1.105$

This indicates a diminishing effect as PAD coverage increases.

Comparison with Non-PAD Variables: In contrast, non-PAD explanatory variables exhibit constant marginal effects because they are modelled linearly.

For these variables: $\frac{\partial E[Y|X]}{\partial X} = E[Y \mid X] \cdot \beta$

Where β is the coefficient on any of the non-PAD explanatory variable. This means a 1-unit increase in the variable produces the same percentage change in Y, regardless of the baseline level of the variable.

The non-linear marginal effects of PAD underscore the importance of accounting for baseline coverage levels in policymaking. For counties with low PAD coverage, small increases may have significant impacts, while in counties with high PAD coverage, the effects diminish. Conversely, the constant marginal effects of non-PAD variables simplify their interpretation, enabling more straightforward policy interventions. While the marginal effects of PAD demonstrate its non-linear relationship with Y, the interpretation of coefficients and marginal effects for other variables depends on whether they are scaled or unscaled, as discussed next.

1.4.2.3 Relevance of Scaled and Unscaled Variables

The PPMLHDFE model is designed to handle count-based dependent variables (e.g., business births, relocations, and exits) by modeling the conditional mean of the outcome variable Y as $exp(\beta' X)$. In this framework, the inclusion of both scaled and unscaled explanatory variables allows for precise interpretation of the marginal effects of key factors on business dynamics, aligning with best econometric practices (Bartik, 1985; Levinson, 1996).

- **Unscaled Variables:** Coefficients represent the percentage change in the outcome variable (Y) associated with a one-unit increase in the explanatory variable (X), ceteris paribus.
- **Scaled Variables:** Variables such as median household income, housing price index, or employment density are scaled (e.g., in 100s or 1,000s) to enhance interpretability. Coefficients for these variables reflect the percentage change in Y for a standardized change in X (e.g., a 100-unit or 1,000-unit increase).

Scaled coefficients offer intuitive insights into relationships without being overshadowed by differences in variable magnitudes. This nuanced approach underscores the importance of carefully constructed variables to control for confounding factors providing a comprehensive framework to assess and interpret the possible non-linear effects of PAD coverage on establishment location decision outcomes.

1.4.3 Addressing Biases and Validating Robustness

To ensure the reliability and robustness of the results, this study addresses potential biases arising from omitted variables, reverse causality, and measurement error. Additionally, rigorous robustness checks were conducted to validate the consistency of findings across alternative model specifications and assumptions, enhancing the credibility of the observed relationships between PAD coverage and business dynamics.

1.4.3.1 Addressing Endogeneity Concerns

1. Omitted Variable Bias: Unobserved factors influencing both PAD coverage and business dynamics could bias estimates. To address this, the analysis employs:

- **County Fixed Effects:** Control for time-invariant local characteristics, such as geography, historical land-use patterns, and political stability.
- **State-Year Fixed Effects:** Capture time-varying state-level factors, including economic shocks and policy changes, that might simultaneously affect PAD designations and business outcomes.
- **Sector Fixed Effects:** Account for industry-specific attributes, such as sectoral sensitivity to environmental regulations, ensuring comparability across industries.

These fixed effects isolate within-county variation over time, mitigating potential confounding influences and allowing for a robust examination of PAD effects.

2. Reverse Causality: To address concerns that business dynamics could influence PAD coverage. PAD coverage and several control variables were lagged to ensure that conservation policies precede observed changes in business activity. Dynamic models incorporated leads and lags up to four periods to assess whether businesses anticipated PAD designations or adjusted gradually over time. Results showed no significant anticipatory behavior, and lagged effects diminished after two to three years, as shown in counterfactual analyses.

3. Measurement Error: Potential inaccuracies in PAD coverage or business outcomes were mitigated through cross-referencing PAD data with alternative datasets, resolving spatial overlaps and inconsistencies in PAD boundaries for precise measurement, and excluding counties with extreme PAD coverage to test result stability, confirming that findings are not driven by outliers.

4. Clustering of Standard Errors: To account for within-county correlations in error terms over time, standard errors were clustered at the county level. This adjustment addresses potential heteroskedasticity and serial correlation, ensuring robust statistical inference.

1.4.3.2 Robustness Checks

1. Alternative Model Specifications: To test the sensitivity of results, models with and without quadratic terms were estimated to assess non-linear relationships. Joint-significance tests, as described in Section 4.2, were applied to confirm the presence of statistically significant non-linear effects of PAD coverage on business outcomes. Marginal effects were subsequently evaluated at mean PAD levels to illustrate how PAD effects vary depending on the level of existing PAD coverage within counties.

2. Counterfactual and Placebo Tests: Building on the endogeneity analyses in Section 4.3.1. Dynamic models incorporated lags to examine persistence in PAD effects over time. Results showed that PAD effects diminish after two to three years, reflecting business adaptation periods. Testing for anticipatory effects revealed no evidence of businesses pre-emptively adjusting to PAD designations, reducing simultaneity concerns. Varying PAD intensities confirmed that moderate PAD coverage stabilizes business dynamics, while excessive coverage imposes constraints. Randomly assigning PAD coverage to counties produced no significant effects, affirming that the observed relationships are not spurious.

3. Subsample Analyses: Subsample analyses were conducted to examine heterogeneity in PAD effects. Urban versus rural counties showed consistent patterns, confirming that PAD effects are not confined to specific geographic contexts. Separate analyses of each LIS sector and the non-LIS sector highlighted how PAD effects vary by industry. Comparing strict (GAP 1–2) and broad (GAP 1–4) PAD definitions revealed consistent trends, validating the robustness of findings across varying levels of conservation stringency.

1.4.3.3 Summary of Robustness Results

Overall, the robustness checks confirm that the core results of this study are stable and reliable. The significant non-linear effects of PADs on business entries, exits, and relocations across the LIS and non-LIS sectors remain consistent across various specifications, subsamples, and placebo tests. These analyses reinforce the validity of the findings and ensure that the relationships between PADs and business location dynamics are not artifacts of specific modelling choices or data limitations.

1.5 Results, Interpretation, and Discussion

This section evaluates the economic effects of PAD coverage, focusing on marginal effects evaluated at mean PAD levels for broad (14.3%) and strict (5.33%) PAD definitions. The marginal effects represent percentage changes in business outcomes (Y) resulting from a 1 percentage point increase in PAD coverage (see Section 4.2.2). These results are presented across establishment births, closures, entries, and exits, disaggregated by sector and location dynamics. This structure provides a nuanced understanding of how PADs influence business outcomes across various economic and geographic contexts.

The econometric framework employs Poisson Pseudo-Maximum Likelihood models with High-Dimensional Fixed Effects (PPMLHDFE), which account for unobserved heterogeneity, spatial correlation, and endogeneity. County, year, and state-by-year fixed effects are included to capture unobserved heterogeneity and policy shocks, while standard errors are clustered at the county level for robust inference. Joint significance tests validate the non-linear relationship between PAD coverage and economic outcomes, and marginal effects are interpreted within this framework.

We begin by addressing our primary research objective, examining the relationship between PAD coverage and the aggregate LIS, which comprises establishments from the Agriculture, Mining, Utilities, and Construction sectors. Next, we address the secondary objective by analyzing PAD effects on each of these four LIS sectors individually, uncovering the drivers behind aggregate trends. Finally, we analyze the Manufacturing sector, representing the non-LIS, to contrast PAD effects across distinct economic contexts.

1.5.1 Effects of PADs on the Aggregate LIS

The following subsections present the PPMLHDFE regression results in regards to our aggregate LIS, under each PAD definition, across each location outcome of interest. Full regression tables are provided in the Appendix section. **Table A4** and **Table A5** present the results on entry type LIS location outcomes under the broad and strict PAD definitions, respectively. **Table A6** and **Table A7** present the results on exit type LIS location outcomes under the broad and strict PAD definitions, respectively.

1.5.1.1 Effect of Broad PADs on Aggregate LIS Establishment Entries

The results, from **Table A4**, reveal no statistically significant effects of broad PADs on LIS business entries. Joint-significance tests confirm the absence of measurable non-linear relationships, indicating that moderate conservation policies under broad PADs do not substantially alter establishment births or inward relocations. Overall, broad PADs exhibit limited economic effects on LIS entries, reflecting their more flexible conservation mandates. These findings address Research Question 1, suggesting that broad PADs neither deter new establishments through regulatory constraints nor incentivize them via associated ecological benefits. This contradicts Hypothesis 1 (Non-Linear Effect Hypothesis) and aligns partially with Hypothesis 2 (Differential Effect Hypothesis), as broad PADs appear less influential compared to stricter PADs (see next section).

1.5.1.2 Effect of Strict PADs on Aggregate LIS Establishment Entries

In contrast, we find non-linear significant effects of strict PADs on inward relocations (**Table A5**). Specifically, a 1 percentage point increase in strict PAD coverage results in a 2.15% decrease in inward relocations and a 2.31% decrease in intra-state relocations, evaluated at the mean strict PAD level (5.33%). These results suggest that the effects of strict PADs on relocation outcomes are sensitive to existing PAD coverage levels.

While we do not specify the exact shape of the non-linear relationship, the varying marginal effects reflect the restrictive nature of stringent conservation policies, which reduce land availability and impose higher regulatory burdens. These findings address Research Question 1 and validate Hypothesis 1 by confirming the presence of non-linear effects of PAD coverage. The results also support Hypothesis 2, highlighting differential impacts of PAD coverage on entries under strict versus broad PADs.

1.5.1.3 Effect of Broad PADs on Aggregate LIS Establishment Exits

We find that broad PAD coverage has non-linear effects on establishment closures, intra-state outward relocations, and total exits, as evidenced by statistically significant joint tests of the linear and quadratic terms (**Table A6**). Evaluated at the mean Broad PAD level (14.3%), a 1 percentage point increase in broad PAD coverage is associated with a 0.54% increase in closures, a 17.8% reduction in inter-state outward relocations, and a 0.47% increase in total exits. These results confirm that broad PADs influence establishment exit-related outcomes, addressing Research Question 1. The observed decline in inter-state relocations aligns with the Relocation Cost Hypothesis (Hypothesis 3), suggesting that businesses adapt locally rather than incurring the costs and regulatory unfamiliarity associated with inter-state moves. However, the increase in closures and total exits underscores that broad PADs impose moderate pressures on business operations, reflecting the trade-offs between conservation policies and economic adaptability.

1.5.1.4 Effect of Strict PADs on Aggregate LIS Establishment Exits

Significant joint tests confirm the presence of non-linear effects of strict PAD coverage on business exits (see **Table A7**). Evaluated at the mean Strict PAD level (5.33%), a 1 percentage point increase in strict PAD coverage is associated with a 0.94% reduction in deaths, a 16.3% decline in inter-state relocations, and a 0.93% reduction in total exits. These results address Research Question 1 by demonstrating that strict PADs reduce business exits, with significant declines in deaths and inter-state relocations. This suggests that stricter conservation policies provide a stabilizing effect on local businesses, likely by creating a more predictable regulatory environment over time.

The differential effects of strict PADs, compared to broad PADs, align with Hypothesis 2, confirming that stricter conservation measures exert stronger regulatory effects on business dynamics. Furthermore, the decline in inter-state relocations supports the Relocation Cost Hypothesis (Hypothesis 3), indicating that businesses are more inclined to adapt locally under strict PAD coverage, likely due to the higher costs and challenges associated with moving across state lines.

1.5.1.5 Summary of LIS Results

The analysis of PAD effects on LIS establishments reveals key findings across business location outcomes. Broad PADs exert moderate effects, reducing inter-state relocations while slightly increasing closures and total exits. These outcomes suggest that businesses often prefer local adaptation over costly inter-state moves but may face operational pressures under broad conservation mandates. Strict PADs, on the other hand, demonstrate more pronounced regulatory effects. They reduce deaths, total exits, and inter-state relocations, indicating their stabilizing influence on local business dynamics. These findings suggest that strict PADs create a predictable regulatory environment that supports retention and mitigates broader economic disruptions.

The results confirm the non-linear effects of PAD coverage, as evidenced by significant joint tests of the linear and quadratic terms. Marginal effects vary based on existing PAD levels, underscoring the importance of accounting for coverage intensity when evaluating policy effects. These findings validate the Non-Linear Effect Hypothesis (Hypothesis 1). Moreover, the distinct effects of broad and strict PADs emphasize their differential effects, supporting Hypothesis 2. Lastly, the consistent decline in inter-state relocations under both PAD definitions aligns with the Relocation Cost Hypothesis (Hypothesis 3), highlighting businesses' preference for local adaptation in the face of regulatory stringency.

1.5.2 Summary of Sectoral Heterogeneity: Drivers of LIS Results

The results for the constituent sectors of the aggregate LIS—Agriculture (NAICS 11), Mining (NAICS 21), Utilities (NAICS 22), and Construction (NAICS 23)—offer critical insights into the varied responses of specific sectors to PADs. Similar to the previous section, marginal effects follow from statistically significant joint tests and are dependent upon the level of PAD coverage within a county. For illustrative purposes, we provide practical insights by evaluating these marginal effects at mean PAD level.

These sector-specific findings sheds light on the non-linear, differential, and relocation dynamics within the aggregate LIS. **Table A8** to **Table A17** present the results on births, inward relocations, intra-state inward relocations, inter-state inward relocations, total entries, deaths, outward relocations, intra-state outward relocations, inter-state outward relocations, and total exits, respectively, under the broad PAD definition. **Table A18** to **Table A27** present the results on those same outcome location variables, respectively, under the strict PAD definition. The column names in each table correspond a specific NAICS sector.

1.5.2.1 Agriculture, Forestry, Fishing, and Hunting (NAICS 11)

The Agriculture sector exhibits distinct responses to PAD coverage, with significant non-linear effects identified under both broad and strict PAD definitions. For broad PADs, a 1 percentage point increase in coverage leads to a 5.26% rise in births and a 5.06% increase in total entries, evaluated at the mean broad PAD level (14.3%). These effects suggest that broad PADs enhance establishment entries, likely due to the ecological benefits provided by less restrictive conservation policies.

Strict PADs similarly show significant positive effects on entries, where we find that a 1 percentage point increase in strict PAD coverage results in a 2.06% rise in births and a 2.03% increase in total entries, evaluated at the mean strict PAD level (5.33%). However, we find that Strict PADs also significantly reduce closures (1.85%) and total exits (1.76%), emphasizing their stabilizing role.

These findings confirm the presence of non-linear effects (Hypothesis 1), highlighting the sensitivity of agricultural establishments to conservation intensity. Broad PADs primarily facilitate new business formation, reflecting their flexibility in allowing land use while promoting ecological services. In contrast, strict PADs stabilize existing operations, fostering resilience by providing predictable regulatory environments. This differential effect supports Hypothesis 2, demonstrating the varying effects of strict versus broad PADs. However, relocation dynamics are not prominent in the Agriculture sector, rendering Research Question 3 less applicable.

1.5.2.2 Mining, Quarrying, Oil, and Gas Extraction (NAICS 21)

The Mining sector exhibits significant non-linear effects only under strict PAD coverage, with no statistically measurable effects observed for broad PADs. Strict PADs demonstrate a stabilizing influence on mining establishments, particularly by reducing exits and outward relocations. Evaluated at the mean strict PAD level (5.33%), a 1 percentage point increase in coverage leads to a 0.18% reduction in closures, a 15.9% decline in outward relocations, a 17.41% decrease in inter-state outward relocations, and a 0.353% reduction in total exits. These effects suggest that stringent conservation policies encourage mining businesses to remain operational locally rather than relocating, particularly across state boundaries.

However, strict PADs also appear to deter new establishment entries, reflecting the regulatory costs associated with operating under stricter conservation mandates. At the mean strict PAD level, a 1 percentage point increase in coverage is associated with only a modest increase of 0.21% in births and 0.12% in total entries, indicating that strict PADs primarily influence retention rather than new business formation.

These results confirm Hypotheses 1 and 2 by demonstrating the non-linear and differential effects of strict PADs compared to broad PADs. The significant reductions in inter-state outward relocations also address Research Question 3, aligning with the Relocation Cost Hypothesis. The findings emphasize that mining establishments, due to their reliance on localized resources, are particularly sensitive to the regulatory constraints and stabilization provided by strict PADs. While strict PADs discourage new entries, they foster long-term stability by reducing mobility pressures and exits.

1.5.2.3 Utilities (NAICS 22)

The Utilities sector demonstrates significant non-linear effects under broad PAD coverage, with additional PAD coverage negatively affecting establishment births, relocations, and entries. At the mean broad PAD level (14.3%), a 1 percentage point increase in broad PAD coverage is associated with a 7.43% decline in births, a 37.7% decrease in overall inward relocations, a 46.1% reduction in intra-state in-migrations, and a 7.47% decline in total entries. These results indicate that broad PADs impose constraints on new business activity, reflecting the sector's sensitivity to land-use restrictions. Additionally, broad PADs slightly increase establishment deaths (0.347%), suggesting heightened operational challenges. Total exits decline marginally (1.58%), reflecting a preference among existing establishments to adapt locally rather than relocate.

In contrast, strict PADs do not exhibit statistically significant effects on the Utilities sector. This indicates that the regulatory dynamics of broad PADs already encompass the relevant constraints and adaptation mechanisms for this sector, likely due to the nature of utility operations, which are typically site-specific and less mobile.

These findings align with Hypotheses 1 and 2, confirming the presence of non-linear effects and highlighting the differential effects of broad versus strict PADs. The observed reductions in relocations also support Hypothesis 3, underscoring the influence of relocation costs and regulatory familiarity in shaping business dynamics in the Utilities sector. Broad PADs, in particular, appear to discourage new activity while stabilizing existing operations, reflecting a complex interplay between conservation policies and economic adjustments.

1.5.2.4 Construction (NAICS 23)

The Construction sector exhibits marginal non-linear effects under both broad and strict PAD coverage, revealing its sensitivity to varying conservation intensities. Under broad PAD coverage, evaluated at the mean broad PAD level (14.3%), a 1 percentage point increase in coverage is associated with a 0.325% rise in closures and a 0.929% decline in total exits. These results indicate mixed pressures: while broad PADs increase business closures, they simultaneously reduce total exits, suggesting that businesses are more inclined to adapt locally rather than relocate.

In contrast, strict PAD coverage exhibits more pronounced effects. Evaluated at the mean strict PAD level (5.33%), a 1 percentage point increase in strict PAD coverage results in a 1.98% decline in inward relocations, a 1.94% decline in intra-state inward relocations, and reductions in closures (0.839%) and total exits (0.82%). Positive marginal effects are observed for outward relocations (3.0%) and intra-state outward relocations (3.26%), suggesting that while strict PADs stabilize overall exits, they also incentivize intra-state mobility.

These findings emphasize the Construction sector's adaptability to conservation intensity. Broad PADs impose moderate pressures, balancing closures with mitigated exits, while strict PADs exert stronger regulatory constraints that encourage intra-state mobility but stabilize total exits.

The results support Hypotheses 1 and 2, confirming the presence of non-linear effects and the more pronounced effects of strict PADs relative to broad PADs. Additionally, the observed relocation patterns align with Hypothesis 3, highlighting the sector's intra-state adjustments in response to regulatory and cost considerations.

1.5.3 Unveiling Sectoral Drivers of LIS Outcomes

The analysis of PAD effects on both the aggregate LIS and its constituent sectors (Agriculture, Mining, Utilities, and Construction) uncovers overarching trends and critical sector-specific heterogeneities. These insights provide a deeper understanding of how conservation policies influence LIS establishment location dynamics.

At the aggregate LIS level, strict PADs exhibit more pronounced regulatory constraints, initially deterring business activity but fostering stability over time through reductions in exits and inter-state relocations. However, disaggregated sector-specific results reveal the diverse mechanisms that drive these aggregate trends, emphasizing the importance of analyzing individual LIS sectors to capture the nuanced effects of PAD coverage.

Agriculture demonstrates a consistently positive response to additional PAD coverage under both broad and strict PAD definitions. Broad PADs enhance entries, reflecting ecological benefits that outweigh regulatory costs, while strict PADs stabilize operations by significantly reducing exits.

Mining benefits from stability under strict PADs, which deter exits and outward relocations while modestly increasing entries. These results suggest that stricter conservation measures create a more predictable operating environment for the sector.

Utilities face constraints under broad PADs, which reduce entries and relocations but promote local retention by lowering total exits. Strict PADs, however, show no significant effects, implying that the regulatory dynamics of broad PADs dominate in shaping outcomes for this sector. Construction exhibits the most pronounced intra-state mobility under strict PADs, reflecting adaptability to stringent conservation measures. Broad PADs impose moderate pressures, increasing closures but reducing overall exits, while strict PADs stabilize total exits despite encouraging some intra-state relocations.

This sectoral decomposition underscores the varying sensitivities of LIS to conservation policies. The results illustrate that aggregate trends emerge from the complex interplay of sector-specific responses to PAD coverage, highlighting the necessity of distinguishing between broad and strict PADs to understand their differential economic impacts.

1.5.4 Non-LIS Results: Insights from Manufacturing

This section evaluates the effects of PAD coverage on the Manufacturing sector (NAICS 31–33), representing non-LIS industries with lower land dependency. Manufacturing provides a comparative lens for understanding how conservation policies affect economic dynamics across diverse sectors, addressing the study's secondary objective.

Table A8 to **Table A17** present the results on births, inward relocations, intra-state inward relocations, inter-state inward relocations, total entries, deaths, outward relocations, intra-state outward relocations, inter-state outward relocations, and total exits, respectively, under the broad PAD definition. **Table A18** to **Table A27** present the results on those same outcome location variables, respectively, under the strict PAD definition. Refer to the last column in each table for the specific results in regards to the Manufacturing sector (NAICS 31-33).

The results for Manufacturing reveal distinct dynamics under broad and strict PAD definitions. Evaluated at the mean Broad PAD level (14.3%), a 1 percentage point increase in coverage corresponds to increases in births (0.619%), inward relocations (2.93%), intra-state in-migrations (4.10%), and total entries (0.614%). Meanwhile, exits show a mixed response, with reductions in deaths (0.87%) but increases in outward relocations (9.77%), intra-state outward relocations (9.73%), and total exits (1.35%). These results suggest that broad PADs support business mobility and new entries while imposing moderate pressures on existing establishments to exit. Evaluated at the mean Strict PAD level (5.33%), a 1 percentage point increase in coverage leads to declines in births (1.72%) and total entries (1.76%). Exits increase under strict PADs, with rises in outward relocations (3.40%), intra-state outward relocations (5.11%), and total exits (1.85%). These findings indicate that strict PADs impose higher regulatory burdens, deterring new activity and increasing exit pressures.

Our results reveal significant non-linear relationships between PAD coverage and business outcomes, addressing Research Question 1 and supporting Hypothesis 1. Our results further addresses Research Question 2 and validates Hypothesis 2, as broad PADs encourage positive dynamics such as increased births and relocations, whereas strict PADs impose stronger constraints on new activity and intensify relocations. Relocation dynamics further reveal that intra-state relocations are particularly responsive to PAD coverage under both PAD definitions, reflecting localized adjustments, while inter-state relocations show limited effects, aligning with the Relocation Cost Hypothesis (Hypothesis 3), as stricter PADs increase the costs and complexity of broader mobility.

1.5.5 Key Insights from Manufacturing

The Manufacturing sector (NAICS 31–33) provides valuable insights into how PAD coverage influences non-LIS industries, offering a critical contrast to the dynamics observed in LIS sectors. Addressing the study’s secondary objective, these results illustrate the broader adaptability of industries less dependent on land resources to conservation policies. Broad PADs exhibit flexibility by fostering entries and relocations, promoting positive business dynamics.

However, they also heighten outward mobility pressures, reflecting moderate regulatory impacts that balance conservation goals with economic activity. In contrast, strict PADs impose entry barriers and intensify exit pressures, revealing their more restrictive nature.

The inclusion of Manufacturing demonstrates how conservation policies affect sectors beyond LIS, enriching the narrative on PAD effects. These findings align with the Porter Hypothesis, suggesting that conservation policies can constrain activity while fostering stability depending on regulatory intensity. Manufacturing also provides a complementary perspective to LIS dynamics, illustrating how non-LIS sectors adapt to PAD coverage through increased mobility and responsiveness. This contrast highlights the importance of tailoring conservation policies to balance ecological objectives with economic resilience across diverse industrial contexts.

1.5.6 Validation of Key Findings

This section validates the robustness and reliability of the observed relationships between PAD coverage and business dynamics through comprehensive endogeneity checks and robustness tests. These efforts confirm the consistency of findings across alternative specifications, enhancing confidence in their relevance for economic and policy interpretation.

1.5.6.1 Addressing Biases

1. **Omitted Variable Bias:** The inclusion of high-dimensional fixed effects—county, state-year, and sectoral—effectively controlled for unobserved heterogeneity. For example, the non-linear effects of PADs remained significant even after accounting for county-specific geographic and historical conditions, affirming the robustness of the findings.
2. **Reverse Causality:** Lagged variables ensured that PAD coverage preceded observed changes in business outcomes, addressing simultaneity concerns. The lack of significant lead coefficients in dynamic models confirmed that businesses did not anticipate PAD

designations before implementation, further validating the temporal sequencing of observed PAD effects.

3. **Measurement Error:** Sensitivity analyses confirmed that measurement errors in PAD coverage or business outcomes did not bias results. Excluding extreme PAD coverage values did not alter key findings, demonstrating the stability of observed relationships.

1.5.6.2 Robustness and Dynamic Effects

1. **Alternative Specifications:** Models with quadratic terms captured non-linear dynamics, validating the relationship between PAD coverage and business outcomes without overinterpreting turning points. Marginal effects were consistently significant, even though turning points were not precisely estimated.
2. **Dynamic Effects:** PAD effects were shown to persist but diminish after two to three years, reflecting businesses' gradual adaptation to regulatory environments. For example, initial increases in closures due to PAD constraints stabilized as firms adjusted their operations to align with conservation policies.

1.5.6.3 Counterfactual and Placebo Results

1. **Counterfactual Scenarios:** Simulated PAD coverage levels confirmed that the observed dynamics are robust across varying policy intensities. Moderate PAD coverage promoted stability, while excessive coverage-imposed constraints, underscoring the importance of balanced conservation policies.
2. **Placebo Assignments:** Randomized PAD assignments yielded no significant effects, validating that the observed relationships are not driven by spurious correlations.

1.5.6.4 Implications for Results Interpretation

1. **Temporal Adaptation:** Businesses face initial adjustment costs following PAD implementation but stabilize over time, supporting the non-linear dynamics observed in entries, exits, and relocations.
2. **Sectoral Heterogeneity:** The differential effects across LIS and non-LIS sectors highlight the need for tailored conservation policies that consider sectoral dependencies on land use and adaptation capacities.
3. **Policy Design:** The findings emphasize the importance of threshold-sensitive PAD policies that balance regulatory intensity with economic resilience, ensuring conservation goals are achieved without destabilizing businesses.

1.6 Discussion

This section synthesizes the study's findings, aligning them with the research objectives, hypotheses, and broader theoretical frameworks. It emphasizes the non-linear, differential, and relocation dynamics of PADs on business outcomes across LIS and non-LIS sectors, offering insights into their sectoral implications. The discussion concludes with theoretical contributions, policy recommendations, limitations, and future research opportunities.

1.6.1 Primary Findings and Hypotheses Validation

The results validate the study's hypotheses, revealing nuanced PAD effects on establishment location outcomes, as follows:

Non-Linear Effects (Hypothesis 1): PAD effects are highly non-linear, with effects dependent on existing PAD coverage levels. Broad PADs impose moderate pressures, primarily influencing exits, while strict PADs stabilize operations over time by reducing exits and inter-state relocations. For example, in Agriculture, broad PADs enhance entries through ecological benefits, while strict PADs reduce closures, stabilizing long-term operations. In Manufacturing, non-linear effects reveal adaptability under broad PADs and constraints under strict PADs.

Differential Effects (Hypothesis 2): The intensity of PAD regulations shapes their differential effects. Broad PADs exhibit flexibility, encouraging entries and relocations while imposing moderate exit pressures. Strict PADs exert stronger constraints, deterring entries and relocations but fostering stability by reducing exits. For Mining, strict PADs stabilize operations but deter new entries due to compliance costs.

Relocation Dynamics (Hypothesis 3): PADs influence relocation patterns, with broad PADs supporting intra-state relocations and strict PADs deterring inter-state moves. This reflects localized adjustments under broad PADs and cost-driven retention under strict PADs. For Manufacturing, intra-state relocations dominate under both PAD definitions, while inter-state relocations remain less responsive.

1.6.2 Sectoral Insights

Sectoral heterogeneity highlights the diverse mechanisms through which PADs affect LIS and non-LIS industries.

For the Agriculture sector, Broad PADs enhance entries, leveraging ecological amenities, while strict PADs stabilize operations by reducing exits, reflecting adaptability to conservation-driven changes. For the Mining sector, Strict PADs reduce exits and relocations, stabilizing operations despite deterring new entries, emphasizing trade-offs between regulatory intensity and long-term resilience. For the Utilities sector, Broad PADs deter entries and relocations but reduce total exits, fostering localized adaptation. Strict PADs add minimal effects, indicating that broad policies sufficiently shape sectoral dynamics. For the Construction sector, mixed effects emerge under broad PADs, with closures increasing but total exits declining. Strict PADs intensify intra-state mobility while stabilizing overall exits, demonstrating resilience under heightened regulatory pressures.

For the non-LIS representative, i.e., the Manufacturing sector, Broad PADs promote entries and relocations, reflecting moderate regulatory flexibility, while strict PADs suppress entries and amplify outward relocations. This dual role highlights the constraints and stabilizing effects of conservation policies in non-LIS industries.

1.6.3 Theoretical Contributions

The findings offer significant contributions to the understanding of conservation policies and industrial dynamics across multiple theoretical domains. The threshold-sensitive effects of PADs reveal how moderate conservation measures can balance ecological and economic objectives, promoting adaptability and economic flexibility, while stricter measures provide long-term stability by reducing exits and inter-state relocations. These findings challenge conventional assumptions about regulatory flight, particularly in LIS sectors like Mining, where strict PADs encourage local retention and adaptive behavior rather than widespread mobility.

PADs simultaneously act as constraints and stabilizers, with broad PADs fostering innovation and economic adjustments, and strict PADs enhancing resilience through predictable operating environments. These dynamics align with the Porter Hypothesis, demonstrating its applicability across LIS and non-LIS, and highlighting how conservation policies can drive both short-term economic adjustments and long-term stability.

1.6.4 Policy Implications

The study provides actionable recommendations for policymakers designing conservation strategies. Policymakers should optimize PAD coverage to balance ecological goals with economic adaptability. Moderate PADs encourage entries and relocations, while strict PADs stabilize operations at higher thresholds.

Tailored incentives are necessary for Agriculture and Mining to enhance ecological benefits and mitigate compliance costs. Utilities and Construction require policies addressing mobility dynamics and operational constraints. Manufacturing policies should focus on reducing entry barriers and managing relocation pressures, particularly under strict PAD coverage. By fostering predictable regulatory environments, strict PADs support local retention and reduce disruptions, aligning conservation objectives with regional economic stability.

1.6.5 Summary

This discussion highlights the non-linear, differential, and relocation effects of PADs, underscoring their varied effects across LIS and non-LIS sectors. By validating key hypotheses, the study advances theoretical and policy debates, offering actionable insights for balancing conservation goals with economic resilience. Policymakers can leverage these findings to design nuanced strategies that align environmental objectives with sustainable growth across diverse industries.

1.7 Conclusion

This dissertation chapter investigates how Protected Area Designations (PADs), under varying levels of environmental stringency—broad (GAP 1–4) and strict (GAP 1–2)—influence business location dynamics. The analysis spans (i) the aggregate LIS, comprising establishments from NAICS sectors 11 (Agriculture), 21 (Mining), 22 (Utilities), and 23 (Construction); (ii) each LIS sector individually; and (iii) NAICS 31–33 (Manufacturing), which serves as a representative non-land-intensive sector (non-LIS). By utilizing a proprietary historical business dataset from Data Axle, this study evaluates establishment births, deaths, and inter- and intra-state relocations at the county level from 1998 to 2018 across the conterminous United States. These findings offer insights into the complex interactions between conservation policies and economic outcomes, contributing to debates in Conservation Economics, Land Use Economics, Environmental Federalism, Capital Mobility, and Industrial Location.

This study employs Poisson Pseudo-Maximum Likelihood with high-dimensional fixed effects (PPMLHDFE), a robust econometric framework well-suited for analyzing count data in the presence of heteroskedasticity. County fixed effects, state-by-year fixed effects, and year fixed effects control for unobservable heterogeneity across regions, state-specific shocks, and time trends, respectively. Standard errors are clustered at the county level to account for spatial correlation. To account for dynamic PAD effects, counterfactual analyses with leads and lags of PAD coverage were included, ensuring the robustness of the findings.

The joint significance test of linear and quadratic PAD terms establishes the presence of non-linear relationships between PAD coverage and business location outcomes. Importantly, these non-linear marginal effects are contingent on the level of existing PAD coverage in a county. Significant non-linear effects were evaluated at the mean PAD levels for both broad (14.3%) and strict (5.33%) PAD coverage, offering practical and interpretable insights.

The primary objective of this research was to assess how PADs influence the aggregate LIS. The findings reveal significant non-linear effects, underscoring that the effects of PADs vary with existing coverage levels. Broad PADs exert moderate pressures on LIS by increasing exits, with limited influence on entries. In contrast, strict PADs reduce exits and inter-state relocations, fostering long-term economic stability. These results validate Hypothesis 1 (Non-Linear Effect Hypothesis) by confirming that PAD effects are threshold-sensitive. Furthermore, Hypothesis 2 (Differential Effect Hypothesis) is supported by the stronger regulatory effects of strict PADs compared to broad PADs. Relocation dynamics, particularly the decline in inter-state relocations under strict PADs, partially confirm Hypothesis 3 (Relocation Cost Hypothesis), reflecting the role of regulatory familiarity and cost considerations.

Sector-specific analyses provide deeper insights into the heterogeneous effects of PADs. Within LIS, Agriculture benefits from both broad and strict PADs, leveraging ecological services to enhance entries and stabilize exits. Mining and Construction demonstrate resilience under strict PADs, with reduced relocations and exits. Utilities face challenges under broad PADs due to operational constraints that deter entries and relocations but stabilize total exits. In the non-LIS Manufacturing sector, broad PADs foster growth and stabilization by promoting entries and relocations, while strict PADs constrain entries and amplify outward relocations. These results underscore the adaptability of some sectors to conservation policies and the constraints faced by others.

The findings highlight important considerations for policymakers. First, the non-linear effects of PADs suggest that conservation policies should balance ecological goals with economic adaptability by targeting moderate coverage levels. Broad PADs encourage economic flexibility, while strict PADs stabilize operations at higher thresholds. Policymakers should implement tailored sectoral strategies: for example, supporting LIS subsectors like Agriculture and Mining to mitigate regulatory burdens while enhancing ecological benefits. For Manufacturing, policies should reduce entry barriers and address relocation pressures, particularly under strict PAD coverage.

From a methodological standpoint, this study underscores the importance of employing econometric methods that account for non-linear dynamics, spatial heterogeneity, and endogeneity concerns. Evaluating significant non-linear effects at mean PAD levels facilitates practical interpretation, while the inclusion of lagged and lead PAD terms strengthens the analysis by capturing temporal dynamics.

While this study provides valuable insights, it is not without limitations. The reliance on U.S.-specific data limits the generalizability of findings to other regulatory and economic contexts. Additionally, county-level analysis, while comprehensive, may overlook firm-level nuances in PAD responses. Future research could address these limitations by conducting international comparative studies, incorporating micro-level data, and exploring interactions between PADs and other regulatory instruments, such as zoning laws and fiscal policies.

This research demonstrates that PADs act as both constraints and stabilizers, creating complex and sector-specific economic dynamics. By distinguishing between broad and strict PADs, it offers actionable insights for designing conservation policies that align ecological objectives with economic resilience. Policymakers can leverage these findings to foster sustainable growth, encourage local retention, and support sectoral adaptation, ensuring that conservation policies contribute meaningfully to environmental preservation and economic stability.

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Appendix

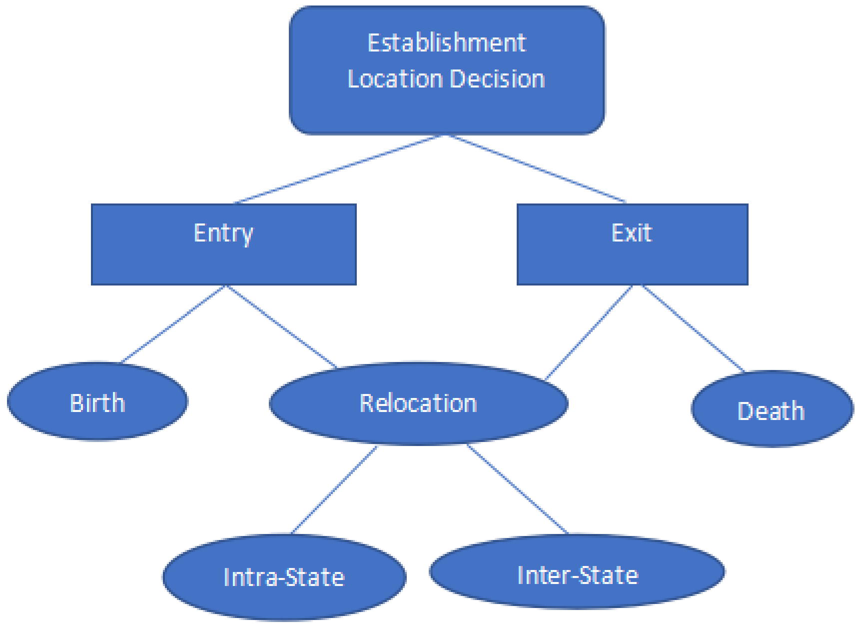

Figure A1: Location Decision Tree

This figure outlines the decision-making framework for establishment location dynamics. It categorizes entries into births and relocations (further divided into intra-state and inter-state) and exits into deaths and outward relocations. This framework supports the analysis of business dynamics across LIS and non-LIS.

Table A1: Summary Statistics of Aggregate LIS location variables – Entries and Exits

Variable	Mean	Std. Dev.	Min	Max
Births	69.3	228	0	12469
Inward Relocations	2.87	48.4	0	4410
Intra-State Inward Relocations	2.85	48.4	0	4410
Inter-State Inward Relocations	.019	.202	0	18
Total Entries	72.2	241	0	12469
Deaths	67.0	221	0	13568
Outward Relocations	2.89	50.2	0	4537
Intra-State Outward Relocations	2.87	50.2	0	4537
Inter-State Outward Relocations	.019	.196	0	23
Total Exits	69.9	234	0	13569

Table A1 provides descriptive statistics of key measures related to LIS establishment location dynamics across U.S. counties. It includes average counts, standard deviations, minimums, and maximums for establishment counts, entries (births and inward relocations), exits (deaths and outward relocations), and their intra- and inter-state components.

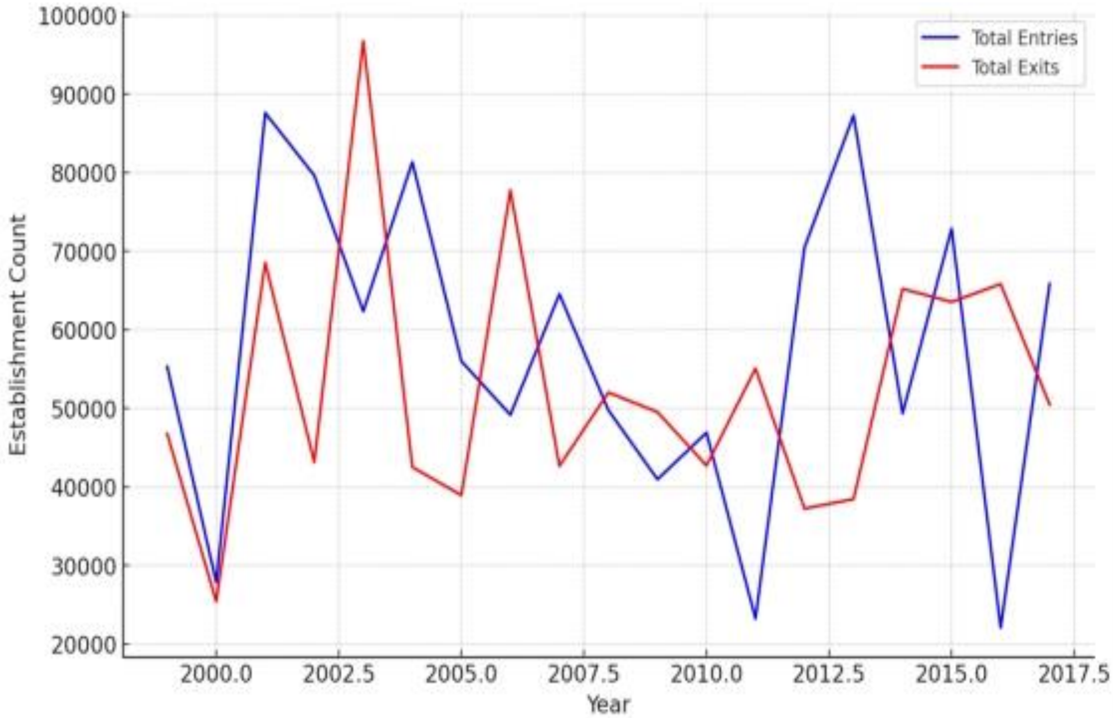

Figure A2: Trends in Aggregate LIS Entries and Exits Over Time

This figure illustrates the annual trends in establishment entries and exits for the LIS from 1998 to 2018. The blue line represents total entries, while the red line represents total exits. These trends highlight the dynamic nature of LIS business activity, influenced by macroeconomic cycles and external shocks, such as the 2008 financial crisis.

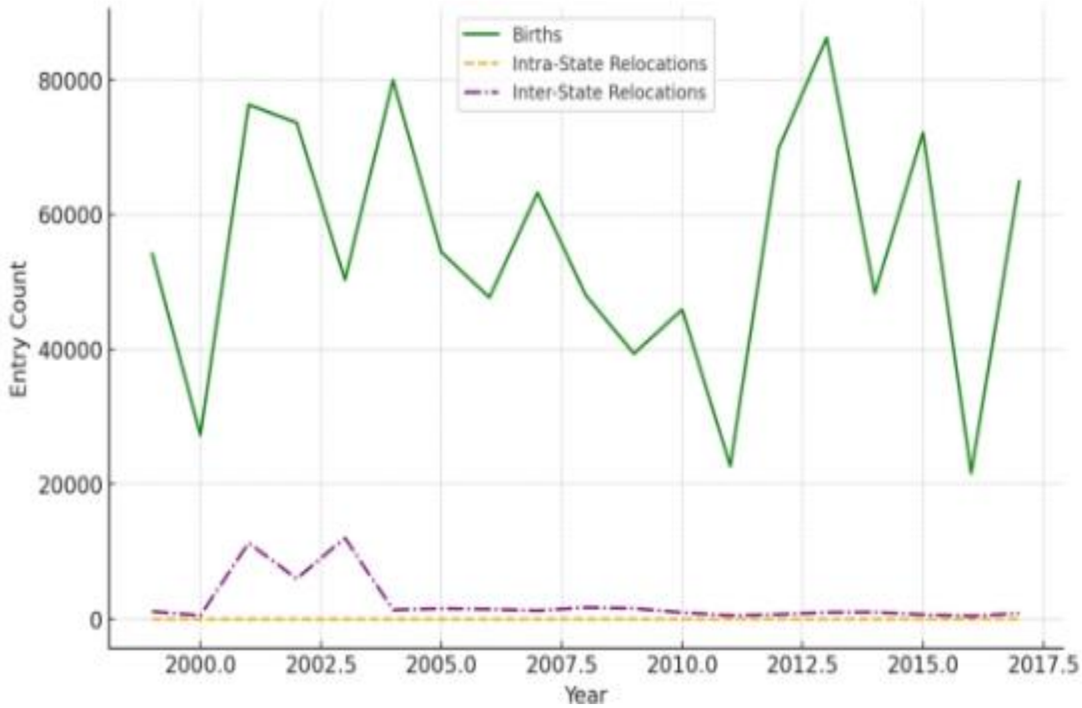

Figure A3: Trends in Aggregate LIS Entries Over Time

This figure depicts the decomposition of total establishment entries in the LIS over time (1998–2018). The green line represents establishment births, while the orange and purple lines represent intra-state and inter-state relocations, respectively. The trends reveal that births dominate total entries, with relocations (both intra- and inter-state) contributing a smaller and relatively stable share of total entries over the study period.

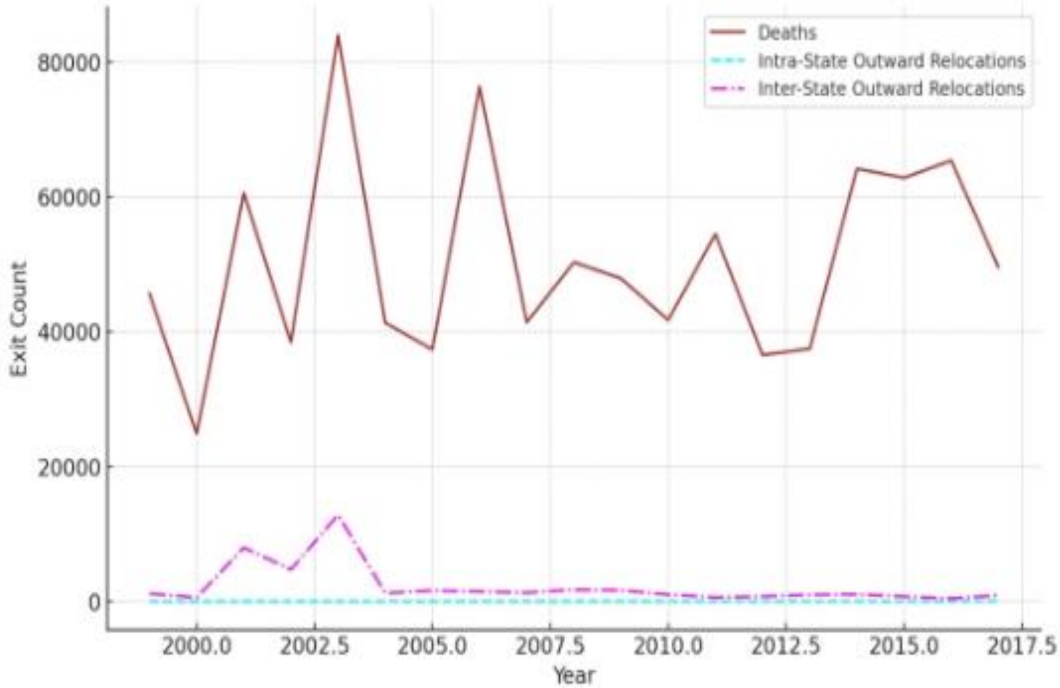

Figure A4: Trends in Aggregate LIS Exits Over Time

This figure illustrates the decomposition of total establishment exits in the LIS over time (1998–2018). The red line represents establishment deaths, while the pink and cyan lines indicate intra-state and inter-state outward relocations, respectively. Establishment deaths account for the majority of exits, with intra-state and inter-state relocations contributing smaller and relatively stable shares throughout the study period. Peaks in deaths, such as those observed during the 2008 financial crisis, highlight the sensitivity of LIS sectors to macroeconomic disruptions.

Table A2: GAP Definitions

GAP Status	Definition
0	No formal designation or protection. They might be open to various uses, such as resource extraction or development, without specific conservation measures. Such examples are undeveloped lands or regions in some countries that lack official protection, where construction, mining, or other activities can occur without restriction.
1	PADs with strict protection aimed at preserving biodiversity and natural processes. These areas generally prohibit activities like logging or mining and focus on conservation and research. Such examples are national parks with strict protection, wilderness areas, or nature reserves where only non-intrusive activities like hiking or birdwatching are allowed. These areas typically have rigorous management plans to maintain ecological integrity.
2	Moderately protected areas that permit some sustainable resource use. They are managed for conservation, but may allow limited activities such as controlled logging, grazing, or tourism. Such examples are wildlife management areas, some types of nature parks, or buffer zones around strictly protected regions. These areas might have zoning that allows for sustainable use while maintaining overall ecological health.
3	PADs with less stringent protection, where more varied activities are allowed but still follow some conservation principles. These areas might focus on sustainable resource use or community involvement. Such examples are national forests or designated multi-use zones. These regions may allow recreational activities, timber harvesting, or other resource-based activities under regulated guidelines to ensure sustainability.
4	These PADs have a focus on sustainable resource management, often with significant human activity. They are typically designated for multiple uses, balancing conservation with economic interests. Such examples are areas with resource management plans for agriculture, forestry, or fisheries. They may include zones for sustainable agriculture or other land-use activities that support local communities while maintaining ecological considerations.

Table A2 defines the conservation categories under the Gap Analysis Program (GAP), detailing the objectives and allowable land uses for each GAP status. GAP Status 1 and 2 reflect stricter conservation measures with limited human intervention, while GAP Status 3 and 4 represent more flexible land-use policies balancing conservation and economic activities. These classifications provide a framework for evaluating the impact of PADs on land-intensive and non-land-intensive business dynamics.

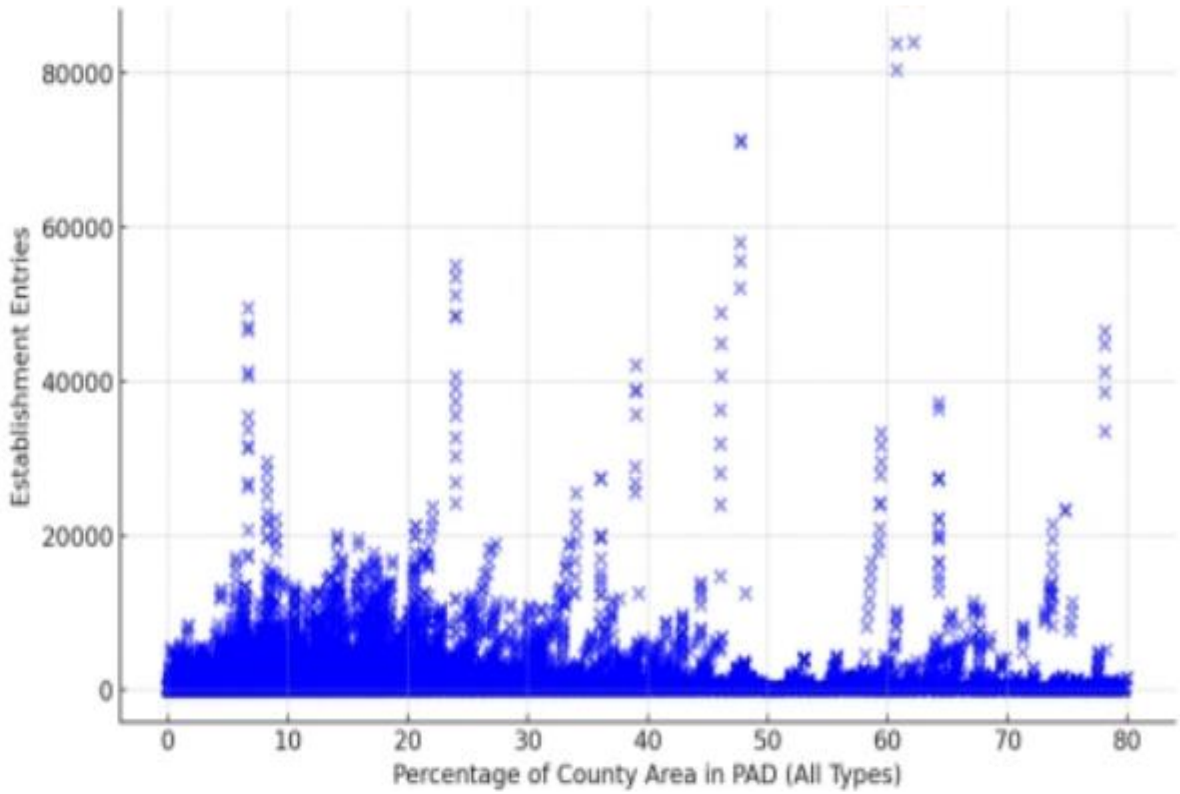

Figure A5: Aggregate LIS Entries vs. Broad PADs (GAP 1-4)

This scatter plot illustrates the relationship between establishment entries and the percentage of county area covered by all types of PADs. The plot highlights how varying levels of PAD coverage may influence the formation of new establishments across U.S. counties.

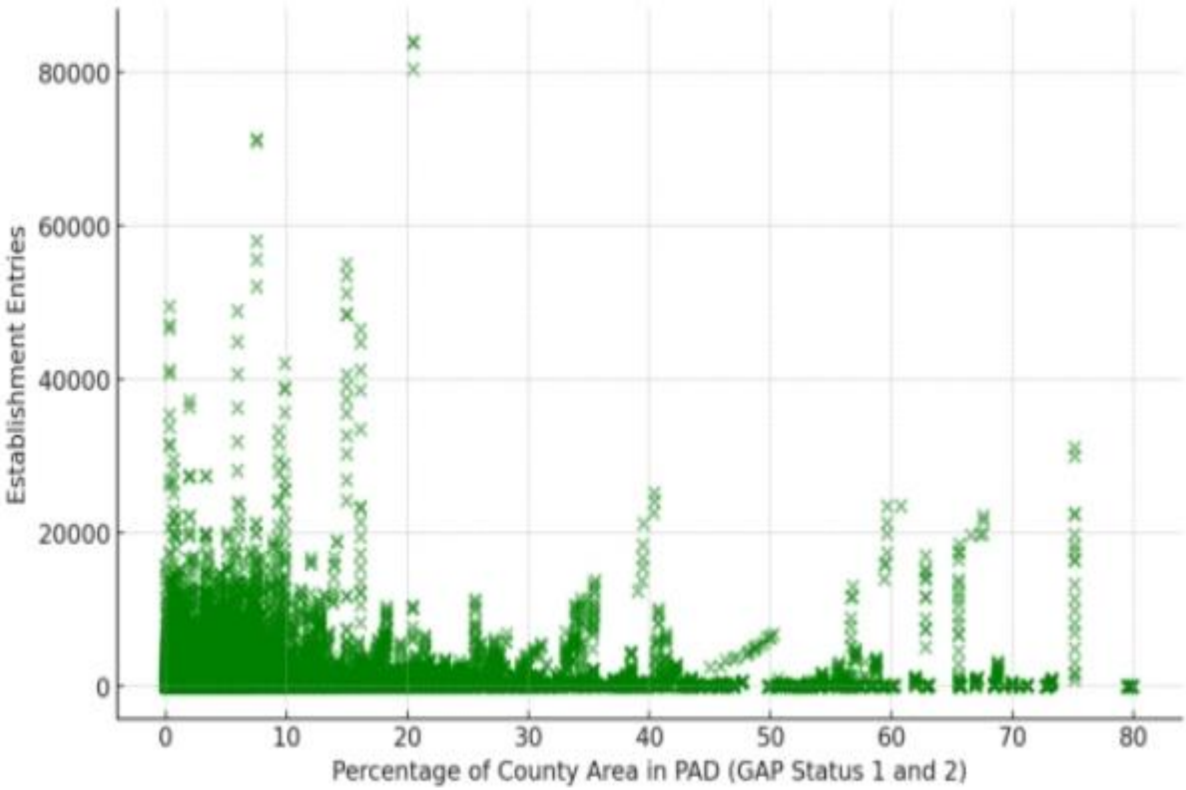

Figure A6: Aggregate LIS Entries vs. Strict PADs (GAP 1-2)

This figure highlights the relationship between establishment entries and the percentage of county area covered by PADs under GAP Status 1 and 2. These PADs represent stricter conservation measures aimed at preserving ecological integrity with minimal human intervention.

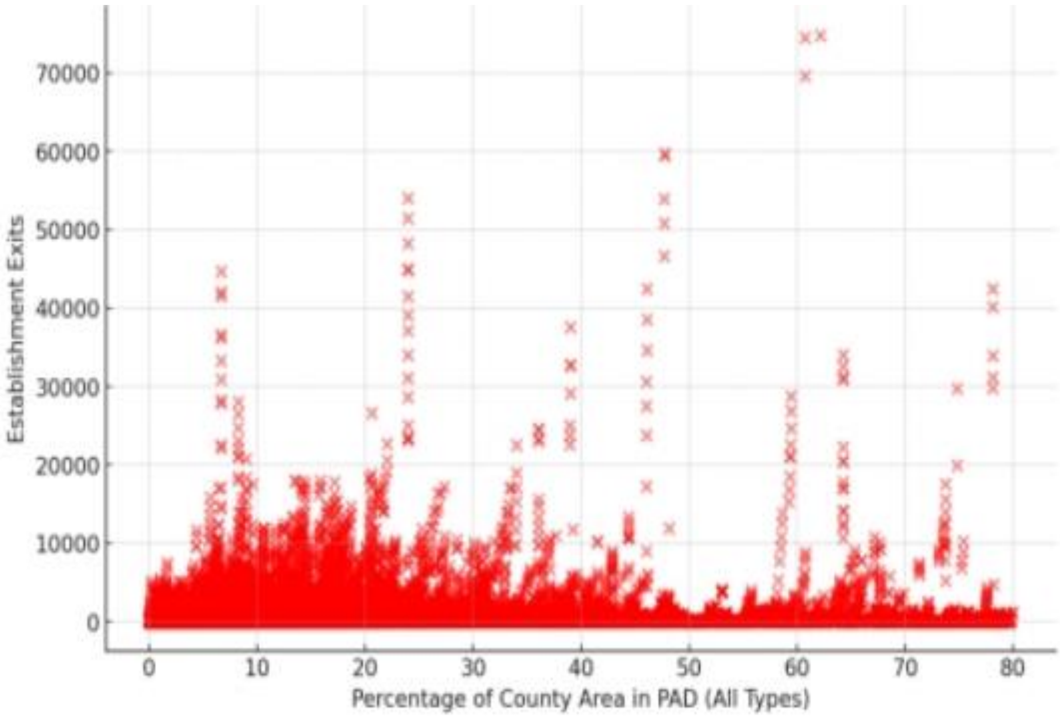

Figure A7: Aggregate LIS Exits vs. Broad PADs (GAP 1-4)

This figure illustrates the relationship between establishment exits and the percentage of county area covered by PADs under the broad PAD definition (GAP Status 1–4), encompassing all conservation intensities.

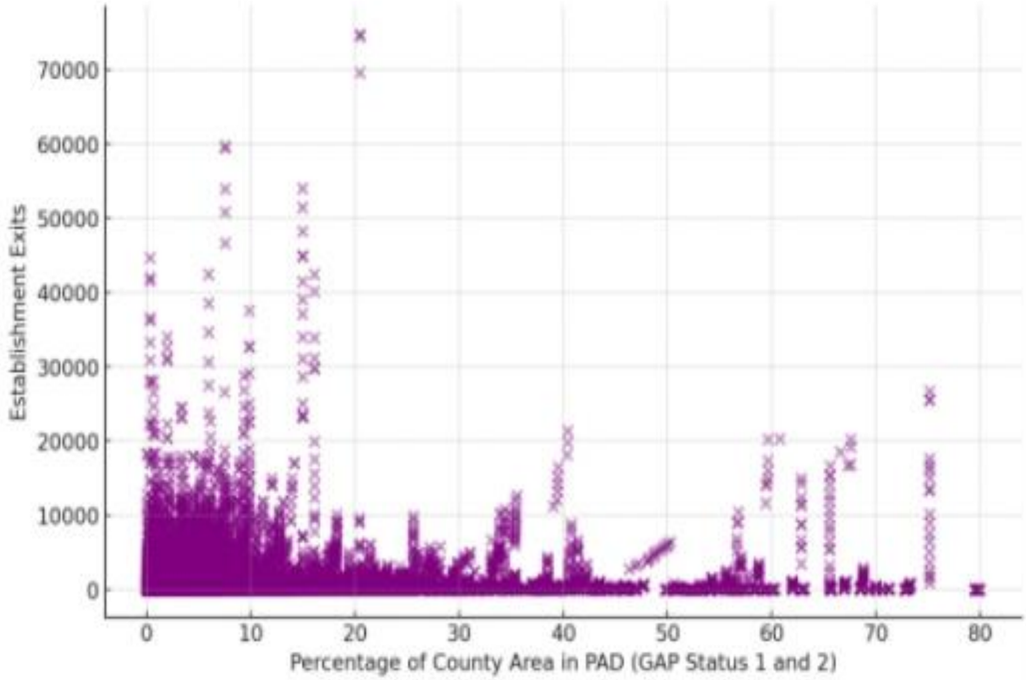

Figure A8: Aggregate LIS Exits vs. Strict PADs (GAP 1-2)
This figure demonstrates the relationship between establishment exits and the percentage of county area covered by stricter PADs under GAP Status 1 and 2, which emphasize the highest levels of conservation restrictions.

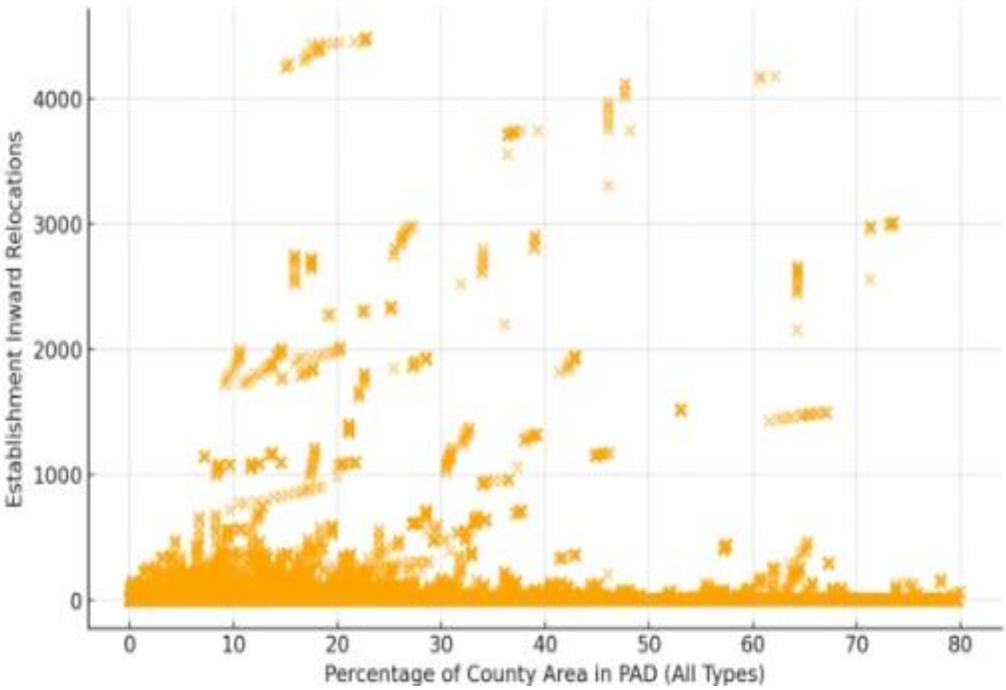

Figure A9: Aggregate LIS Inward Relocations vs. Broad PADs (GAP 1-4)
This figure illustrates the relationship between inward relocations of establishments and the percentage of county area covered by PADs across all GAP categories.

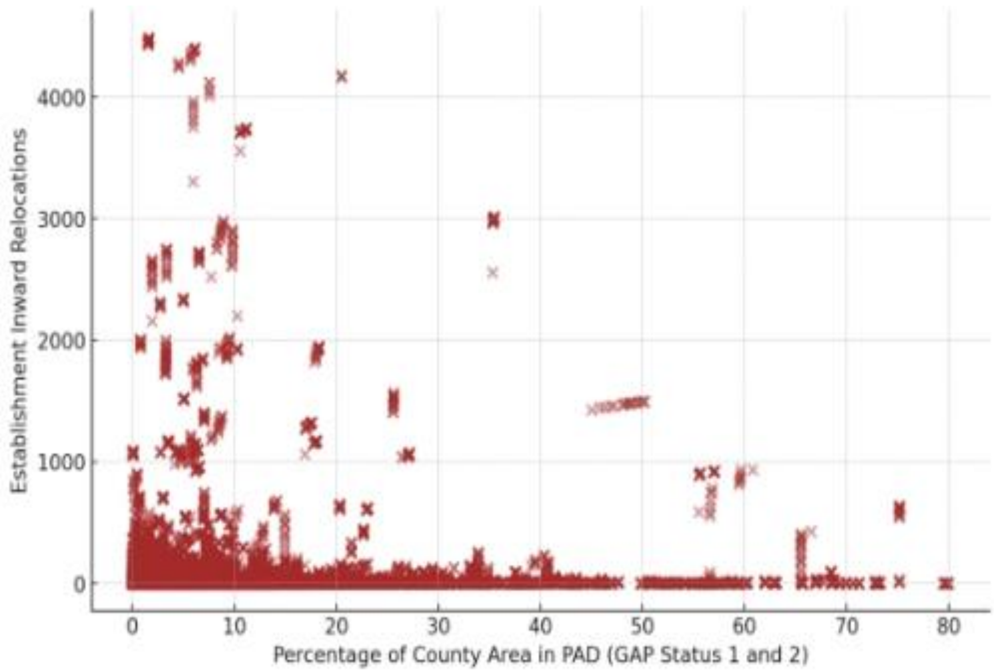

Figure A10: Aggregate LIS Inward Relocations vs. Strict PADs (GAP 1-2)
This scatter plot highlights the relationship between inward relocations of establishments and the percentage of county area covered by strictly protected PADs under GAP Status 1 and 2.

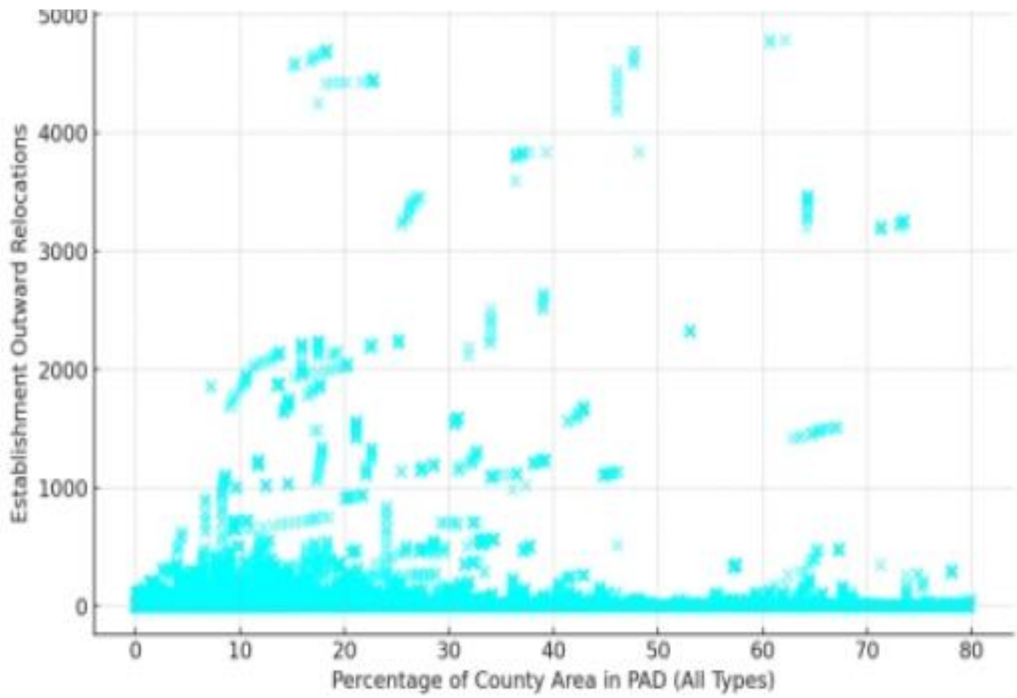

Figure A11: Aggregate LIS Outward Relocations vs. broad PADs (GAP 1-4)
This figure illustrates the relationship between outward relocations of establishments and the percentage of county area covered by PADs across all GAP status categories.

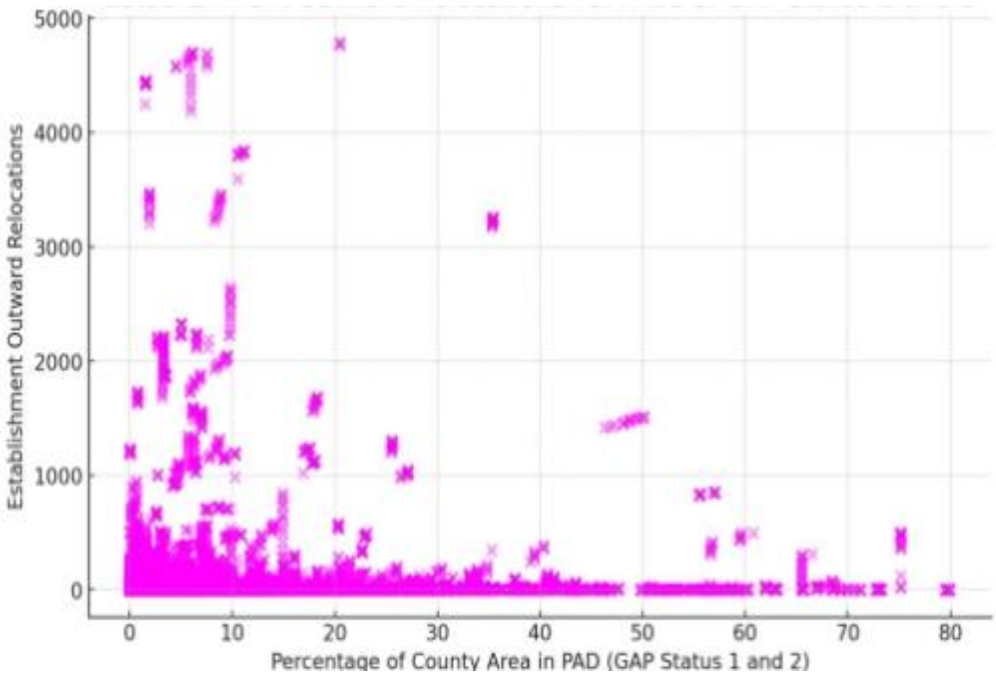

Figure A12: Aggregate LIS Outward Relocations vs. Strict PADs (GAP 1-2)
This scatter plot depicts outward relocations of establishments relative to PADs under GAP Status 1 and 2, representing stricter conservation measures.

Table A3: Summary Statistics of Explanatory Variables

Variable	Mean	Std. Dev.	Min	Max
PAD in GAP 1 and 2 (100s)	0.0533	0.0999	0	0.874
PAD in all GAPs (100s)	0.143	0.188	0	.88
Carbon Monoxide (CO) – 1985 std	.003	.043	0	1
Lead (Pb) – 2008 std	.002	.03	0	1
Ozone (O3) – 2015 std	.095	.329	0	1
Particulate Matter (PM) – 2012 std	.046	.238	0	1
Sulphur Dioxide (SO2) – 2010 std	.004	.048	0	1
Poverty rate (100s)	.153	.062	.017	.62
Unemployment rate (100s)	.061	.028	.007	.306
Median HH Income (100ks)	.423	.122	.099	1.40
Housing Price Index (100s)	2.47	1.57	.637	20.8
Percent African American (100s)	.096	.146	0	.858
Population Density (100s)	.004	.027	0	1.16
Employment Density	.191	1.33	0	63.3
Loc. Economies (t-1)	84.9	432	0	26029
Sales Volume (t-1)	621662	2267050	0	1.880e+08
Births (t-1)	68.3	230	0	12469
Entry Relocations (t-1)	2.85	48.4	0	4410
Total Entries (t-1)	71.2	243	0	12469
Deaths (t-1)	65.7	221	0	13568
Exit Relocations (t-1)	2.85	49.9	0	4537
Total Entries (t-1)	68.5	234	0	13569

Table A3 presents the summary statistics for the explanatory variables included in the analysis of the aggregate LIS. The variables are categorized into three groups: environmental, socio-demographic-economic, and aggregate LIS-specific explanatory variables. These statistics provide insights into the mean, standard deviation, minimum, and maximum values. Standard deviations highlight regional disparities, while minimum and maximum values capture extremes in economic, environmental, and business activity contexts.

Table A4: Regression Results of Broad PADs on Aggregate LIS Entries

Variable	Births	Inward Relocations (IR)	Intra-State IR	Inter-State IR	Total Entries
Broad PAD (t-1)	-2.322	1.040	1.412	9.399	-2.440
	(1.921)	(2.742)	(2.765)	(13.786)	(1.936)
Broad PAD Squared (t-1)	2.469	-1.947	-2.577	-8.909	2.586
	(2.011)	(2.544)	(2.551)	(12.704)	(2.033)
Loc. Economies (t-1) (10ks)	0.586***	0.916***	1.326***	-0.424*	0.584***
	(0.160)	(0.286)	(0.296)	(0.243)	(0.158)
Median HH Income (100ks)	-0.153	-0.202	-0.011	-4.162**	-0.152
	(0.177)	(0.317)	(0.321)	(1.833)	(0.174)
Housing Price Index (100s)	0.016	-0.002	-0.007	0.022	0.014
	(0.013)	(0.024)	(0.025)	(0.116)	(0.013)
Poverty rate (100s)	0.048	-0.234	-0.035	-1.554	0.057
	(0.329)	(0.596)	(0.600)	(4.369)	(0.329)
Avg annual wages (100k)	0.086***	0.106***	0.096***	0.143***	0.087***
	(0.011)	(0.011)	(0.010)	(0.027)	(0.011)
Attainment Status-CO (t-1)	0.455*	-0.471	-0.472		0.424*
	(0.256)	(0.849)	(0.869)		(0.238)
Attainment Status-Pb (t-1)	-0.061	-0.163	-0.163	0.217	-0.063
	(0.058)	(0.198)	(0.193)	(0.632)	(0.057)
Attainment Status-O3 (t-1)	0.097***	0.024	0.035	-0.145	0.095***
	(0.027)	(0.031)	(0.031)	(0.163)	(0.027)
Attainment Status-PM (t-1)	-0.018	-0.023	-0.019	-0.008	-0.019
	(0.013)	(0.026)	(0.027)	(0.141)	(0.013)
Attainment Status-SO2 (t-1)	0.001	-0.256	-0.285*	0.064	-0.006
	(0.042)	(0.159)	(0.158)	(0.508)	(0.041)
Density Employment	0.030	-0.077***	-0.082***	0.106	0.029
	(0.024)	(0.028)	(0.029)	(0.172)	(0.024)
Percent Black (100s)	0.537	-0.472	-0.261	-4.211	0.507
	(0.639)	(1.331)	(1.353)	(7.735)	(0.626)
Population count (1ms)	0.155	0.446	0.230	-2.592***	0.179
	(0.137)	(0.334)	(0.349)	(0.742)	(0.137)
Unemployment rate (100s)	1.504***	2.604*	2.289	4.020	1.577***
	(0.579)	(1.469)	(1.475)	(9.383)	(0.575)
Sales Volume (t-1)	3.172**	2.377	2.408*	-0.478	3.150**
	(1.269)	(1.673)	(1.439)	(4.761)	(1.273)
Total Exits (t-1) (1ks)	0.002				0.001
	(0.036)				(0.036)

Table A4: Continued

Variable	Births	Inward Relocations (IR)	Intra-State IR	Inter-State IR	Total Entries
Births (t-1) (1ks)		-0.026	-0.039	-0.017	
		(0.023)	(0.024)	(0.041)	
Deaths (t-1) (1ks)		-0.205***	-0.213***	0.097	
		(0.049)	(0.051)	(0.093)	
Outward Reloc. (t-1) (1ks)		3.103*	2.432	-6.690	
		(1.806)	(1.862)	(6.835)	
Constant	4.379***	0.144	0.114	2.764	4.384***
	(0.308)	(0.457)	(0.466)	(2.695)	(0.305)
Observations	77994	71576	71058	14051	77994
Pseudo R^2	0.908	0.594	0.594	0.317	0.909
Chi^2	397	181	177	116	407
Log Likelihood	-440378	-46384	-45293	-3414	-442318
Akaike's Criterion	880792	92809	90627	6866	884673
Bayesian Criterion	880959	92992	90810	7010	884840
County FE	Yes	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.4706	0.3220	0.1541	0.7812	0.4444

Table A4: PPMLHDFE regression results on aggregate LIS under broad PADs (GAP 1-4) are presented above. Column names correspond to specific entry-type location outcomes. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A5: Regression Results of Strict PADs on Aggregate LIS Entries

Variable	Births	Inward Relocations (IR)	Intra-State IR	Inter-State IR	Total Entries
Strict PAD (t-1)	0.080	-2.435**	-2.527**	1.304	0.088
	(0.568)	(0.981)	(1.199)	(5.778)	(0.564)
Strict PAD Sq. (t-1)	-0.456	2.653	2.073	-1.773	-0.498
	(0.944)	(2.015)	(2.700)	(18.342)	(0.950)
Loc. Economies (t-1) (10ks)	0.592***	0.866***	1.294***	-0.540*	0.590***
	(0.164)	(0.273)	(0.289)	(0.304)	(0.163)
Median HH Income (100ks)	-0.190	-0.319	-0.131	-3.953**	-0.194
	(0.191)	(0.311)	(0.316)	(1.778)	(0.189)
Housing Price Index (100s)	0.024*	0.001	-0.005	0.001	0.023*
	(0.013)	(0.024)	(0.025)	(0.111)	(0.013)
Poverty rate (100s)	-0.044	-0.340	-0.131	-1.649	-0.033
	(0.319)	(0.588)	(0.592)	(4.337)	(0.318)
Avg annual wages (100k)	0.090***	0.106***	0.099***	0.129***	0.090***
	(0.012)	(0.011)	(0.011)	(0.027)	(0.011)
Attainment Status-CO (t-1)	-0.382	-1.366	-0.909	-5.029***	-0.392
	(0.261)	(1.041)	(0.881)	(1.689)	(0.259)
Attainment Status-Pb (t-1)	-0.024	-0.157	-0.159	0.241	-0.026
	(0.051)	(0.198)	(0.192)	(0.623)	(0.050)
Attainment Status-O3 (t-1)	0.097***	0.032	0.045	-0.123	0.096***
	(0.027)	(0.031)	(0.031)	(0.164)	(0.027)
Attainment Status-PM (t-1)	-0.017	-0.025	-0.021	-0.007	-0.017
	(0.013)	(0.026)	(0.027)	(0.141)	(0.013)
Attainment Status-SO2 (t-1)	-0.021	-0.271*	-0.299*	0.056	-0.028
	(0.044)	(0.160)	(0.158)	(0.513)	(0.043)
Density Employment	0.019	-0.084***	-0.090***	0.109	0.018
	(0.022)	(0.028)	(0.029)	(0.165)	(0.021)
African-American (100s)	-0.102	-0.756	-0.567	-5.675	-0.135
	(0.806)	(1.326)	(1.347)	(7.659)	(0.796)
Population count (1ms)	0.191	0.532	0.269	-2.640***	0.217
	(0.164)	(0.331)	(0.341)	(0.747)	(0.165)
Unemployment rate (100s)	1.052*	2.455*	2.129	3.951	1.123*
	(0.592)	(1.424)	(1.424)	(8.849)	(0.587)
Sales Volume (t-1)	3.301***	1.901	2.158	-4.929	3.270**
	(1.265)	(2.147)	(1.646)	(6.608)	(1.271)
Total Exits (t-1) (1ks)	0.007				0.006
	(0.037)				(0.037)
Births (t-1) (1ks)		-0.023	-0.036	-0.008	

Table A5: Continued

Variable		Births	Inward Relocations (IR)	Intra-State IR	Inter-State IR	Total Entries
		(0.021)	(0.023)	(0.048)		
Deaths (t-1) (1ks)		-0.199***	-0.197***	0.071		
		(0.050)	(0.048)	(0.091)		
Outward Reloc. (t-1) (1ks)		3.131*	2.020	-0.426		
		(1.889)	(1.831)	(8.467)		
Constant	4.216***	0.395	0.435	4.296**	4.205***	
	(0.229)	(0.314)	(0.327)	(1.815)	(0.226)	
Observations	77389	71022	70522	14295	77389	
Pseudo R^2	0.911	0.597	0.598	0.312	0.912	

Chi^2	380	202	200	162	384
Log Likelihood	-445973	-46558	-45343	-3561	-447793
Akaike's Criterion	891982	93157	90727	7163	895622
Bayesian Criterion	892148	93340	90910	7314	895789
County FE	Yes	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.7598	0.0252	0.0178	0.9420	0.7263

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table A5: PPMLHDFE regression results on aggregate LIS under strict PADs (GAP 1-2) are presented above. Column names correspond to specific entry-type location outcomes. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A6: Regression Results of Broad PADs on Aggregate LIS Exits

Variable	Deaths	Outward Relocations (OR)	Intra-State OR	Inter-State OR	Total Exits
Broad PAD (t-1)	1.161	0.119	1.400	-21.726	1.061
	(1.232)	(2.676)	(2.926)	(15.446)	(1.215)
Broad PAD Sq. (t-1)	-2.168*	-0.830	-1.886	13.812	-2.074
	(1.317)	(3.246)	(3.501)	(13.032)	(1.301)
Loc. Economies (t-1) (10ks)	1.240***	0.760**	0.968***	0.025	1.238***
	(0.113)	(0.343)	(0.327)	(0.349)	(0.113)
Median HH Income (100ks)	-0.538**	-0.316	-0.327	1.105	-0.538***
	(0.178)	(0.309)	(0.306)	(1.824)	(0.175)
Housing Price Index (100s)	0.036**	0.039*	0.044*	-0.237**	0.035**
	(0.016)	(0.023)	(0.023)	(0.100)	(0.016)
Poverty rate (100s)	-0.518*	-1.971***	-1.911***	-2.254	-0.541*
	(0.293)	(0.581)	(0.584)	(3.347)	(0.290)
Avg annual wages (100k)	0.085***	0.083***	0.077***	0.113***	0.085***
	(0.010)	(0.011)	(0.011)	(0.025)	(0.010)
Attainment Status-CO (t-1)	0.113	0.770**	0.738**		0.139*
	(0.101)	(0.372)	(0.366)		(0.084)
Attainment Status-Pb (t-1)	-0.052	0.071	0.060	0.488	-0.050
	(0.061)	(0.149)	(0.150)	(0.749)	(0.060)
Attainment Status-O3 (t-1)	0.012	0.048	0.048	0.230	0.013
	(0.018)	(0.035)	(0.035)	(0.160)	(0.018)
Attainment Status-PM (t-1)	0.047**	-0.002	0.004	-0.136	0.047**
	(0.020)	(0.028)	(0.028)	(0.142)	(0.020)
Attainment Status-SO2 (t-1)	0.113*	0.121	0.119	-0.088	0.115*
	(0.059)	(0.112)	(0.112)	(0.609)	(0.059)
Density Employment	0.051**	0.046	0.014	0.298	0.050**
	(0.025)	(0.055)	(0.047)	(0.204)	(0.025)
Percent Black (100s)	1.047	-0.426	0.235	-11.146*	1.008
	(0.652)	(1.139)	(1.144)	(6.768)	(0.645)
Population count (1ms)	-0.474**	-0.378*	-0.564**	-0.962	-0.468**
	(0.210)	(0.193)	(0.220)	(0.679)	(0.206)
Unemployment rate (100s)	4.264***	1.002	1.332	-18.244**	4.223***
	(0.607)	(1.090)	(1.095)	(7.191)	(0.599)
Sales Volume (t-1)	3.284***	2.370	2.729*	-2.713	3.272***
	(1.175)	(1.652)	(1.560)	(4.513)	(1.179)
Total Entries (t-1) (1ks)	-0.072**				-0.071***
	(0.007)				(0.007)
Births (t-1) (1ks)		-0.034**	-0.042***	-0.050	
		(0.017)	(0.015)	(0.060)	
Deaths (t-1) (1ks)		-0.132*	-0.174***	0.107	
		(0.080)	(0.050)	(0.073)	
Inward relocations (t-1) (1ks)		10.726***	10.229***	-2.657	
		(1.926)	(1.945)	(10.264)	
Constant	4.713***	0.970***	0.843**	5.154*	4.739***

Table A6: Continued

Variable	Deaths	Outward Relocations (OR)	Intra-State OR	Inter-State OR	Total Exits
	(0.263)	(0.365)	(0.369)	(2.782)	(0.258)
Observations	78299	71834	71166	15062	78299
Pseudo R^2	0.928	0.609	0.609	0.310	0.928
Chi^2	565	193	222	85	571
Log Likelihood	-399154	-45872	-44698	-3620	-400365
Akaike's Criterion	798345	91785	89437	7278	800766
Bayesian Criterion	798511	91968	89620	7423	800932
County FE	Yes	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes	Yes
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.0220	0.8528	0.8637	0.0443	0.0217

Table A6: PPMLHDFE regression results on aggregate LIS under broad PADs (GAP 1-4) are presented above. Column names correspond to specific exit-type location outcomes. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A7: Regression Results of Strict PADs on Aggregate LIS Exits

Variable	Deaths	Outward Relocations (OR)	Intra-State OR	Inter-State OR	Total Exits
Strict PAD (t-1)	-1.005**	0.846	2.325	-20.678***	-0.999**
	(0.417)	(1.704)	(1.565)	(5.609)	(0.416)
Strict PAD Sq. (t-1)	0.601	-1.257	-4.436	40.992**	0.609
	(0.963)	(4.868)	(4.503)	(16.941)	(0.960)
Loc. Economies (t-1) (10ks)	1.238***	0.718**	0.937***	-0.084	1.236***
	(0.117)	(0.333)	(0.322)	(0.363)	(0.116)
Median HH Income (100ks)	-0.537***	-0.242	-0.234	0.462	-0.537***
	(0.176)	(0.306)	(0.303)	(1.745)	(0.173)
Housing Price Index (100s)	0.041***	0.045**	0.047**	-0.153	0.041***
	(0.016)	(0.022)	(0.022)	(0.099)	(0.016)
Poverty rate (100s)	-0.523*	-1.952***	-1.871***	-4.093	-0.545*
	(0.293)	(0.579)	(0.583)	(3.327)	(0.289)
Avg annual wages (100k)	0.090***	0.085***	0.083***	0.102***	0.090***
	(0.010)	(0.011)	(0.011)	(0.025)	(0.010)
Attainment Status-CO (t-1)	-0.326**	0.340	0.791**	-0.406	-0.316**
	(0.130)	(0.378)	(0.332)	(1.189)	(0.129)
Attainment Status-Pb (t-1)	-0.041	0.036	0.010	0.706	-0.040
	(0.059)	(0.144)	(0.142)	(0.690)	(0.058)
Attainment Status-O3 (t-1)	0.015	0.047	0.047	0.308**	0.016
	(0.018)	(0.034)	(0.035)	(0.156)	(0.018)
Attainment Status-PM (t-1)	0.047**	-0.001	0.006	-0.128	0.047**
	(0.020)	(0.029)	(0.029)	(0.141)	(0.020)
Attainment Status-SO2 (t-1)	0.125**	0.132	0.131	-0.043	0.126**
	(0.059)	(0.113)	(0.115)	(0.605)	(0.059)
Density Employment	0.053**	0.047	0.017	0.222	0.053**
	(0.025)	(0.054)	(0.047)	(0.193)	(0.026)
Percent Black (100s)	1.465**	0.119	0.704	-11.265*	1.423**
	(0.709)	(1.144)	(1.146)	(6.754)	(0.701)
Population count (1ms)	-0.623***	-0.339	-0.573**	-1.117	-0.613***
	(0.240)	(0.218)	(0.258)	(0.708)	(0.236)
Unemployment rate (100s)	4.252***	0.938	1.243	-18.372***	4.216***
	(0.602)	(1.092)	(1.096)	(6.912)	(0.593)
Sales Volume (t-1)	3.382***	2.090	2.720	-6.047	3.366***
	(1.182)	(1.926)	(1.659)	(5.416)	(1.186)
Total Entries (t-1) (1ks)	-0.071***				-0.070***
	(0.006)				(0.006)
Births (t-1) (1ks)		-0.031*	-0.037***	-0.064	

Table A7 Continued

Variable	Deaths	Outward Relocations (OR)	Intra-State OR	Inter-State OR	Total Exits
		(0.016)	(0.014)	(0.081)	
Deaths (t-1) (1ks)		-0.136*	-0.175***	0.109	
		(0.074)	(0.045)	(0.083)	
Inward relocations (t-1) (1ks)		10.457***	9.484***	5.018	
		(1.950)	(1.970)	(11.191)	
Constant	4.960***	0.743**	0.751**	3.127**	4.967***
	(0.252)	(0.292)	(0.307)	(1.544)	(0.248)
Observations	77694	71154	70470	15639	77694
Pseudo R^2	0.930	0.610	0.611	0.307	0.931
Chi^2	591	178	213	91	596
Log Likelihood	-404787	-45998	-44690	-3777	-405881
Akaike's Criterion	809611	92036	89420	7595	811799
Bayesian Criterion	809777	92220	89604	7748	811966
County FE	Yes	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes	Yes
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.0022	0.8158	0.2507	0.0001	0.0022

Table A7: PPMLHDFE regression results on aggregate LIS under strict PADs (GAP 1-2) are presented above. Column names correspond to specific exit-type location outcomes. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A8: Regression Results of Broad PADs on Entries by Sector

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
Broad PAD (t-1)	6.666***	0.476	-10.448***	-0.089	1.204
	(2.001)	(4.033)	(3.450)	(1.208)	(1.176)
Broad PAD Sq.(t-1)	-4.933**	0.604	10.536***	0.350	-2.044*
	(2.048)	(3.661)	(3.026)	(1.159)	(1.059)
Loc. Economies (t-1) (10ks)	-43.446***	-9.471**	-132.327***	-0.466***	-0.653
	(7.102)	(4.666)	(39.101)	(0.164)	(0.472)
Median HH Income (100ks)	-0.142	1.112***	0.291	0.275*	-0.248
	(0.315)	(0.401)	(0.441)	(0.165)	(0.195)
Housing Price Index (100s)	0.100***	0.073**	-0.050	0.015	0.034***
	(0.030)	(0.034)	(0.032)	(0.013)	(0.012)
Poverty rate (100s)	-0.391	-1.303*	0.995	-0.075	-0.480*
	(0.510)	(0.666)	(0.705)	(0.296)	(0.256)
Avg annual wages (100k)	0.020	0.002	-0.008	0.002	-0.012
	(0.013)	(0.006)	(0.012)	(0.011)	(0.008)
Attain. Status - CO (t-1)	-0.020	0.591	1.939***	0.682**	0.028
	(0.320)	(0.752)	(0.699)	(0.313)	(0.214)
Attain. Status - Pb (t-1)	0.014	0.044	-0.150	0.065	-0.082
	(0.111)	(0.124)	(0.155)	(0.063)	(0.053)
Attain. Status - O3 (t-1)	0.126***	0.146***	0.131***	0.113***	0.099***
	(0.037)	(0.038)	(0.047)	(0.029)	(0.024)
Attain. Status - PM (t-1)	-0.030	-0.048	0.123***	-0.035***	-0.011
	(0.022)	(0.031)	(0.034)	(0.014)	(0.016)
Attain. Status - SO2 (t-1)	0.062	-0.126	0.100	0.057	-0.005
	(0.119)	(0.136)	(0.151)	(0.044)	(0.032)
Density Employment	0.322	-0.054	-0.224	0.023	0.017
	(0.219)	(0.071)	(0.181)	(0.024)	(0.020)
Percent Black (100s)	-0.751	0.514	-2.332	2.690***	1.474**
	(1.664)	(2.610)	(2.242)	(0.720)	(0.655)
Population count (1ms)	0.766*	0.230*	-0.017	0.835***	0.211
	(0.420)	(0.134)	(0.248)	(0.186)	(0.134)
Unemployment rate (100s)	1.951**	0.100	-2.243*	1.578***	2.489***
	(0.844)	(1.472)	(1.359)	(0.528)	(0.561)
Sales Volume (t-1)	-4.402	0.705	-0.289	-22.076*	0.092
	(3.742)	(0.434)	(0.341)	(12.269)	(0.099)
Prior Total Exits (1ks)	0.941	2.961***	6.624**	0.061	0.107
	(0.862)	(0.483)	(3.096)	(0.047)	(0.088)
Constant	1.100***	0.911	3.555***	3.873***	3.938***
	(0.367)	(0.619)	(0.618)	(0.305)	(0.251)
Observations	15357	10049	14425	26430	26355
Pseudo R^2	0.653	0.648	0.482	0.948	0.923
Chi^2	184	158	99	139	114
Log Likelihood	-34774	-14852	-19853	-114632	-69021
Akaike's Criterion	69585	29740	39742	229301	138078
Bayesian Criterion	69722	29870	39878	229448	138226
County FE	Yes	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes	Yes

Table A8 Continued

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.0001	0.3887	0.0007	0.6688	0.0173

Table A8: PPMLHDFE regression results on establishment births under broad PADs (GAP 1-4) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A9: Regression Results of Broad PADs on Entries by Sector

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
Broad PADs (t-1)	3.724	-1.781	-56.040	-0.687	4.837
	(13.699)	(17.286)	(37.882)	(3.337)	(4.271)
Broad PADs Sq. (t-1)	4.049	6.155	64.222*	-0.462	-6.663
	(12.931)	(15.637)	(34.569)	(3.111)	(4.065)
Loc. Economies (t-1) (10ks)	-16.322	-12.050	-372.402***	0.041	-0.615
	(44.389)	(16.579)	(112.264)	(0.314)	(0.765)
Median HH Income (100ks)	-1.860	-0.315	0.151	-0.024	-0.153
	(2.048)	(2.280)	(2.791)	(0.354)	(0.540)
Housing Price Index (100s)	0.224	-0.225	-0.008	-0.007	-0.030
	(0.142)	(0.184)	(0.223)	(0.028)	(0.041)
Poverty rate (100s)	5.396	0.275	1.686	-0.994	1.499
	(3.335)	(4.361)	(5.731)	(0.668)	(1.015)
Avg annual wages (100k)	0.172*	0.057***	-0.068	0.036	-0.011
	(0.099)	(0.017)	(0.088)	(0.026)	(0.022)
Attain. Status - CO (t-1)	4.219			-0.822	-1.519
	(2.738)			(0.755)	(1.892)
Attain. Status - Pb (t-1)	-2.996**	-0.814	-2.111	-0.043	-0.080
	(1.324)	(0.639)	(1.332)	(0.160)	(0.160)
Attain. Status - O3 (t-1)	0.168	0.273	0.184	0.032	0.030
	(0.246)	(0.231)	(0.313)	(0.034)	(0.048)
Attain. Status - PM (t-1)	-0.272	0.351	0.412	-0.007	0.025
	(0.210)	(0.281)	(0.286)	(0.028)	(0.041)
Attain. Status - SO2 (t-1)	-0.854	-1.191	0.234	-0.243	-0.234
	(0.944)	(0.847)	(0.855)	(0.157)	(0.180)
Density Employment	1.015	0.909**	-1.682	-0.152***	0.005
	(1.094)	(0.374)	(1.356)	(0.043)	(0.071)
Percent Black (100s)	-5.070	-6.068	-13.044	0.052	-0.375
	(9.258)	(11.106)	(14.498)	(1.370)	(2.005)
Population count (1ms)	-1.327	0.427	2.334	1.145***	0.660**
	(1.611)	(0.768)	(1.712)	(0.417)	(0.332)
Unemployment rate (100s)	1.023	2.809	13.463	2.196	2.205
	(6.089)	(9.064)	(11.520)	(1.463)	(1.875)
Sales Volume (t-1)	5.009	-16.218**	5.966	26.724	0.995
	(16.958)	(7.349)	(4.699)	(17.110)	(0.679)
Prior Births (1ks)	0.944	1.400*	54.551***	0.004	-0.050
	(4.740)	(0.723)	(17.005)	(0.034)	(0.123)
Prior Deaths (1ks)	3.830	0.885	-16.626	-0.165**	-0.210**
	(6.404)	(1.848)	(12.233)	(0.072)	(0.101)
Outward Reloc. (t-1) (1ks)	65.735	86.987***	-23.187	3.435*	3.191
	(57.144)	(33.378)	(237.946)	(1.999)	(4.329)
Constant	-2.877	-1.162	5.634	0.769	-0.161
	(2.357)	(2.916)	(5.196)	(0.550)	(0.728)
Observations	4756	2310	1911	22529	17082
Pseudo R^2	0.147	0.328	0.141	0.579	0.500
Chi^2	26	29	25.	46	38
Log Likelihood	-2256	-1290	-912	-24152	-13087
Akaike's Criterion	4552	2618	1863	48345	26214
Bayesian Criterion	4682	2728	1968	48505	26369
County FE	Yes	Yes	Yes	Yes	Yes

Table A9 Continued

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
State by Year FE	Yes	Yes	Yes	Yes	Yes
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.2679	0.6095	0.0068	0.4438	0.0856

Table A9: PPMLHDFE regression results on establishment inward relocations under broad PADs (GAP 1-4) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A10: Regression Results of Broad PADs on Exits by Sector

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
Broad PADs (t-1)	5.683	10.270	-66.631	-0.343	6.515
	(13.678)	(33.273)	(41.837)	(3.345)	(4.917)
Broad PADs Sq. (t-1)	2.461	-1.319	71.929*	-0.754	-8.441*
	(12.932)	(27.466)	(38.516)	(3.114)	(4.543)
Loc. Economies (t-1) (10ks)	-14.555	5.561	-378.470***	0.251	-1.313
	(46.318)	(22.651)	(128.112)	(0.334)	(1.092)
Median HH Income (100ks)	-1.654	1.169	0.685	0.171	-0.101
	(2.061)	(2.493)	(3.150)	(0.356)	(0.588)
Housing Price Index (100s)	0.193	-0.288	-0.036	-0.010	-0.011
	(0.146)	(0.249)	(0.241)	(0.029)	(0.043)
Poverty rate (100s)	5.510	-0.306	1.515	-0.772	1.559
	(3.351)	(5.033)	(5.934)	(0.673)	(1.092)
Avg annual wages (100k)	0.167*	0.067***	-0.054	0.033	-0.008
	(0.100)	(0.018)	(0.096)	(0.026)	(0.025)
Attain. Status - CO (t-1)	4.146			-0.876	-1.481
	(2.762)			(0.760)	(1.907)
Attain. Status - Pb (t-1)	-2.867**	-0.898	-2.170	-0.075	-0.146
	(1.321)	(0.833)	(1.401)	(0.160)	(0.162)
Attain. Status - O3 (t-1)	0.147	0.464*	0.294	0.042	0.055
	(0.247)	(0.263)	(0.323)	(0.036)	(0.052)
Attain. Status - PM (t-1)	-0.280	0.626**	0.516	-0.003	0.033
	(0.213)	(0.311)	(0.324)	(0.029)	(0.044)
Attain. Status - SO2 (t-1)	-0.968	-2.549**	0.076	-0.255	-0.345*
	(0.996)	(1.155)	(1.075)	(0.155)	(0.180)
Density Employment	1.064	1.131	-2.035	-0.160***	-0.109*
	(1.097)	(0.701)	(1.626)	(0.041)	(0.056)
Percent Black (100s)	-2.939	-8.640	-14.508	0.156	-0.295
	(9.385)	(12.360)	(17.654)	(1.425)	(2.037)
Population count (1ms)	-1.722	0.671	5.458***	1.015**	0.294
	(1.879)	(1.160)	(1.964)	(0.461)	(0.327)
Unemployment rate (100s)	1.396	2.796	14.549	1.967	3.479*
	(6.155)	(9.635)	(11.825)	(1.494)	(2.026)
Sales Volume (t-1)	4.732	-24.027**	7.318	21.128	0.975
	(17.156)	(9.381)	(4.676)	(16.160)	(0.713)
Prior Births (1ks)	2.274	0.648	59.373***	-0.010	0.160
	(4.828)	(0.819)	(20.650)	(0.035)	(0.120)
Prior Deaths (1ks)	3.951	2.200	-22.316	-0.177**	-0.297**
	(6.754)	(2.481)	(14.666)	(0.074)	(0.130)
Outward Reloc. (t-1) (1ks)	45.110	134.179**	5.638	2.875	7.203*
	(58.866)	(55.445)	(242.931)	(2.035)	(4.315)
Constant	-3.231	-3.094	4.556	0.665	-0.235
	(2.338)	(3.758)	(5.680)	(0.558)	(0.793)
Observations	4694	1941	1740	22344	16503
Pseudo R^2	0.147	0.256	0.130	0.577	0.476
Chi^2	24	45	23	50	51
Log Likelihood	-2215	-1042	-825	-23821	-12141
Akaike’s Criterion	4470	2123	1688	47682	24323
Bayesian Criterion	4599	2229	1792	47843	24477
County FE	Yes	Yes	Yes	Yes	Yes

Table A10 Continued

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
State by Year FE	Yes	Yes	Yes	Yes	Yes
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.2403	0.6176	0.0324	0.4779	0.0434

Table A10: PPMLHDFE regression results on establishment intra-state inward relocations under broad PADs (GAP 1-4) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A11: Regression Results of Broad PADs on Exits by Sector

Variable	NAICS 21	NAICS 23	NAICS 31-33
Broad PADs (t-1)	68.224	-1.863	2.109
	(66.050)	(19.950)	(15.256)
Broad PADs Sq. (t-1)	-61.981	1.963	-3.372
	(61.862)	(17.774)	(14.448)
Loc. Economies (t-1) (10ks)	-70.277*	-3.993**	2.121
	(38.677)	(1.666)	(1.328)
Median HH Income (100ks)	-10.713**	-5.975**	-0.507
	(5.302)	(2.516)	(1.460)
Housing Price Index (100s)	0.506*	0.037	-0.010
	(0.307)	(0.191)	(0.102)
Poverty rate (100s)	6.576	-4.894	3.010
	(11.617)	(6.523)	(3.100)
Avg annual wages (100k)	0.060	0.318	-0.071
	(0.069)	(0.260)	(0.070)
Attain. Status - Pb (t-1)	0.184	1.882**	0.722**
	(1.088)	(0.951)	(0.347)
Attain. Status - O3 (t-1)	-0.746	-0.107	0.001
	(0.731)	(0.207)	(0.146)
Attain. Status - PM (t-1)	0.025	0.023	-0.033
	(0.628)	(0.145)	(0.109)
Attain. Status - SO2 (t-1)	2.535	-0.602	0.338
	(2.681)	(0.593)	(0.475)
Density Employment	0.540	0.178	0.315**
	(0.541)	(0.281)	(0.151)
Percent Black (100s)	82.873**	-1.972	-3.339
	(41.007)	(10.571)	(4.846)
Population count (1ms)	-3.411**	-0.945	-1.710**
	(1.693)	(1.480)	(0.705)
Unemployment rate (100s)	8.901	8.517	-10.264*
	(41.819)	(14.644)	(5.294)
Sales Volume (t-1)	23.157	107.989	-0.054
	(16.284)	(106.539)	(5.916)
Prior Births (1ks)	14.311**	0.236	-0.648**
	(6.234)	(0.144)	(0.310)
Prior Deaths (1ks)	-2.731	0.310	0.146
	(3.627)	(0.411)	(0.254)
Prior outward relocations (1ks)	-85.248	20.366*	-8.567
	(66.685)	(11.058)	(10.186)
Constant	-11.303	2.787	2.080
	(14.655)	(3.696)	(2.471)
Observations	425	2581	4905
Pseudo R^2	0.325	0.270	0.302
Chi^2	41	28	32
Log Likelihood	-279	-1360	-2742
Akaike's Criterion	597	2759	5523
Bayesian Criterion	674	2870	5646
County FE	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes

Table A11 Continued

Variable	NAICS 21	NAICS 23	NAICS 31-33
NAICS FE	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.5823	0.9927	0.8402

Table A11: PPMLHDFE regression results on establishment inter-state inward relocations under broad PADs (GAP 1-4) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A12: Regression Results of Broad PADs on Total Entries

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
Broad PADs (t-1)	6.376***	0.250	-10.505***	-0.240	1.208
	(2.042)	(4.045)	(3.411)	(1.216)	(1.153)
Broad PADs Sq. (t-1)	-4.603**	0.775	10.603***	0.507	-2.077**
	(2.087)	(3.668)	(2.965)	(1.177)	(1.037)
Loc. Economies (t-1) (10ks)	-43.350***	-9.450**	-131.002***	-0.470***	-0.680
	(7.003)	(4.787)	(38.821)	(0.163)	(0.471)
Median HH Income (100ks)	-0.173	1.074***	0.310	0.283*	-0.254
	(0.315)	(0.404)	(0.433)	(0.161)	(0.190)
Housing Price Index (100s)	0.099***	0.067**	-0.053*	0.013	0.032***
	(0.030)	(0.033)	(0.032)	(0.013)	(0.012)
Poverty rate (100s)	-0.363	-1.211*	1.004	-0.069	-0.444*
	(0.512)	(0.662)	(0.693)	(0.293)	(0.253)
Avg annual wages (100k)	0.022*	0.005	-0.009	0.003	-0.012
	(0.013)	(0.006)	(0.012)	(0.010)	(0.008)
Attain. Status - CO (t-1)	0.089	0.602	1.648***	0.632**	-0.007
	(0.323)	(0.756)	(0.635)	(0.288)	(0.196)
Attain. Status - Pb (t-1)	-0.048	-0.032	-0.187	0.066	-0.083
	(0.120)	(0.124)	(0.149)	(0.062)	(0.052)
Attain. Status - O3 (t-1)	0.125***	0.147***	0.131***	0.111***	0.097***
	(0.037)	(0.037)	(0.046)	(0.029)	(0.024)
Attain. Status - PM (t-1)	-0.033	-0.045	0.126***	-0.035***	-0.011
	(0.023)	(0.031)	(0.033)	(0.013)	(0.016)
Attain. Status - SO2 (t-1)	0.026	-0.131	0.091	0.048	-0.010
	(0.132)	(0.130)	(0.145)	(0.043)	(0.032)
Density Employment	0.327	-0.045	-0.221	0.020	0.017
	(0.220)	(0.066)	(0.179)	(0.023)	(0.019)
Percent Black (100s)	-0.907	0.104	-2.401	2.607***	1.411**
	(1.655)	(2.518)	(2.195)	(0.703)	(0.630)
Population count (1ms)	0.787*	0.211	-0.009	0.858***	0.231*
	(0.412)	(0.135)	(0.258)	(0.185)	(0.132)
Unemployment rate (100s)	2.117**	0.129	-1.657	1.644***	2.532***
	(0.864)	(1.463)	(1.331)	(0.518)	(0.548)
Sales Volume (t-1)	-4.448	0.645	-0.218	-21.775*	0.102
	(3.543)	(0.408)	(0.318)	(12.004)	(0.103)
Prior Total Exits (1ks)	0.933	2.894***	6.397**	0.057	0.106
	(0.860)	(0.484)	(3.072)	(0.047)	(0.087)
Constant	1.134***	1.041*	3.526***	3.896***	3.950***
	(0.369)	(0.612)	(0.608)	(0.304)	(0.246)
Observations	15357	10054	14433	26430	26355
Pseudo R^2	0.652	0.654	0.482	0.949	0.924
Chi^2	187	141	102	143	111
Log Likelihood	-34910	-14987	-19983	-115116	-69329
Akaike’s Criterion	69857	30011	40003	230269	138695
Bayesian Criterion	69994	30141	40139	230416	138842
County FE	Yes	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes	Yes

Table A12 Continued

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA ^{2} Joint Test p-value	0.0001	0.4328	0.0004	0.6279	0.0127

Table A12: PPMLHDFE regression results on total establishment entries under broad PADs (GAP 1-4) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A13: Regression Results of Broad PADs on Establishment Deaths

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
Broad PADs (t-1)	-0.491	5.628	1.368	0.933	-1.639
	(2.034)	(5.294)	(3.763)	(1.533)	(1.152)
Broad PADs Sq. (t-1)	-0.267	-4.707	-3.570	-2.127	2.677**
	(1.773)	(5.416)	(3.539)	(1.665)	(1.088)
Loc. Economies (t-1) (10ks)	81.567***	49.349***	269.946***	1.381***	1.810***
	(11.166)	(7.224)	(50.494)	(0.303)	(0.540)
Median HH Income (100ks)	-0.007	-2.051**	0.266	-0.222	-0.393**
	(0.247)	(0.920)	(0.422)	(0.182)	(0.173)
Housing Price Index (100s)	-0.021	0.011	-0.072**	0.035*	0.048***
	(0.021)	(0.060)	(0.030)	(0.019)	(0.014)
Poverty rate (100s)	0.197	-0.683	0.257	-0.408	-0.202
	(0.396)	(1.068)	(0.682)	(0.372)	(0.264)
Avg annual wages (100k)	-0.017	0.001	0.014	0.005	-0.023***
	(0.014)	(0.016)	(0.010)	(0.011)	(0.009)
Attain. Status - CO (t-1)	0.107	-0.560	0.330	0.241**	-0.356**
	(0.142)	(0.682)	(0.449)	(0.115)	(0.170)
Attain. Status - Pb (t-1)	-0.071	-0.008	-0.273**	-0.174***	0.096
	(0.116)	(0.220)	(0.130)	(0.065)	(0.074)
Attain. Status - O3 (t-1)	-0.043	0.152***	0.023	0.016	-0.044**
	(0.032)	(0.047)	(0.043)	(0.022)	(0.019)
Attain. Status - PM (t-1)	0.129***	0.067*	0.081***	0.044**	0.052**
	(0.032)	(0.038)	(0.030)	(0.020)	(0.021)
Attain. Status - SO2 (t-1)	-0.236**	0.123	0.005	0.101	0.125***
	(0.099)	(0.154)	(0.138)	(0.063)	(0.041)
Density Employment	-0.076	0.216***	0.161	0.042**	0.017
	(0.056)	(0.067)	(0.108)	(0.021)	(0.024)
Percent Black (100s)	-2.831*	0.599	-3.274	2.229***	0.300
	(1.569)	(2.792)	(2.029)	(0.764)	(0.632)
Population count (1ms)	-0.554**	-0.169	-1.627***	-0.113	-0.137*
	(0.235)	(0.243)	(0.451)	(0.184)	(0.083)
Unemployment rate (100s)	2.205***	-3.286	3.653***	4.474***	3.713***
	(0.855)	(2.475)	(1.338)	(0.686)	(0.579)
Sales Volume (t-1)	3.916	-0.024	-0.293	-36.536**	-0.134
	(2.925)	(0.799)	(0.283)	(16.439)	(0.087)
Prior Total Entries (1ks)	-1.741**	-0.766**	-4.962***	-0.049***	0.004
	(0.761)	(0.319)	(1.828)	(0.009)	(0.039)
Constant	2.359***	2.059**	1.771***	4.734***	4.504***
	(0.333)	(0.927)	(0.631)	(0.266)	(0.294)
Observations	15414	10283	15163	26638	26791
Pseudo R^2	0.635	0.700	0.550	0.956	0.935
Chi^2	153	197	103	143	115
Log Likelihood	-32727	-16763	-21486	-116388	-72174
Akaike's Criterion	65491	33562	43009	232813	144384
Bayesian Criterion	65629	33692	43146	232961	144531
County FE	Yes	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes	Yes

Table A13 Continued

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA ^{2} Joint Test p-value	0.3910	0.3420	0.0160	0.0938	0.0050

Table A13: PPMLHDFE regression results on establishment deaths under broad PADs (GAP 1-4) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A14: Regression Results of Broad PADs on Outward Relocations

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
Broad PADs (t-1)	42.013*	-13.858	7.712	1.200	12.576**
	(23.619)	(32.655)	(26.760)	(2.728)	(4.990)
Broad PADs Sq. (t-1)	-40.751*	10.742	-14.048	-0.782	-9.799**
	(21.845)	(29.064)	(25.849)	(3.101)	(4.825)
Loc. Economies (t-1) (10ks)	60.746*	5.484	493.152**	0.983***	0.514
	(32.306)	(11.920)	(229.731)	(0.274)	(0.760)
Median HH Income (100ks)	3.963*	-2.837	1.718	-0.504	-0.071
	(2.161)	(2.361)	(3.137)	(0.331)	(0.543)
Housing Price Index (100s)	-0.207	-0.095	-0.318	0.082***	-0.021
	(0.140)	(0.177)	(0.213)	(0.024)	(0.036)
Poverty rate (100s)	-5.315	-5.526	-7.803	-1.922***	-0.292
	(3.707)	(3.985)	(5.148)	(0.646)	(1.032)
Avg annual wages (100k)	-0.062	-0.010	0.084	0.007	-0.018
	(0.117)	(0.021)	(0.087)	(0.024)	(0.022)
Attain. Status - CO (t-1)	3.398			0.449	1.077*
	(2.340)			(0.429)	(0.592)
Attain. Status - Pb (t-1)	1.136	-0.529	2.920	0.006	0.057
	(0.966)	(0.752)	(1.778)	(0.142)	(0.177)
Attain. Status - O3 (t-1)	0.258	0.252	0.319	0.041	0.072
	(0.205)	(0.204)	(0.296)	(0.037)	(0.059)
Attain. Status - PM (t-1)	0.205	0.232	0.062	0.013	0.007
	(0.182)	(0.183)	(0.253)	(0.029)	(0.038)
Attain. Status - SO2 (t-1)	0.076	0.273	-0.022	0.160	-0.163
	(0.765)	(0.699)	(1.085)	(0.129)	(0.183)
Density Employment	0.514	0.674	0.442	0.049	0.058
	(0.431)	(0.430)	(0.708)	(0.054)	(0.050)
Percent Black (100s)	-6.465	-4.694	1.280	0.374	-0.337
	(10.184)	(14.547)	(14.600)	(1.248)	(2.309)
Population count (1ms)	-2.286**	0.956	-4.453	-0.544*	-0.332
	(1.096)	(0.863)	(3.327)	(0.302)	(0.437)
Unemployment rate (100s)	10.348*	-8.394	0.819	-0.445	0.197
	(6.157)	(8.112)	(9.711)	(1.247)	(2.026)
Sales Volume (t-1)	-17.723	-3.152	1.159	-3.414	-1.531
	(20.139)	(6.373)	(4.876)	(18.849)	(1.245)
Prior Births (1ks)	-4.408	1.090	-47.133**	-0.049*	-0.031
	(4.311)	(1.097)	(21.206)	(0.027)	(0.147)
Prior Deaths (1ks)	5.376	0.823	13.525	-0.242***	0.104
	(5.565)	(1.700)	(14.573)	(0.048)	(0.094)
Inward Relocations (1ks)	64.782	64.695*	299.630**	6.749***	18.447***
	(51.991)	(35.918)	(128.040)	(1.722)	(4.752)
Constant	-5.512	2.881	-0.162	1.591***	-0.412
	(3.412)	(4.527)	(4.309)	(0.401)	(0.865)
Observations	4688	2234	2080	22256	16581
Pseudo R^2	0.170	0.278	0.129	0.604	0.542
Chi^2	33	42	21	87	48
Log Likelihood	-2259	-1316	-971	-23564	-12441
Akaike's Criterion	4559	2670	1980	47169	24923
Bayesian Criterion	4688	2779	2087	47329	25077
County FE	Yes	Yes	Yes	Yes	Yes

Table A14 Continued

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
State by Year FE	Yes	Yes	Yes	Yes	Yes
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA ^{2} Joint Test p-value	0.1751	0.8947	0.4644	0.8431	0.0034

Table A14: PPMLHDFE regression results on establishment outward relocations under broad PADs (GAP 1-4) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A15: Regression Results of Broad PADs on Intra-State Outward Relocations

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
Broad PADs (t-1)	44.625*	-36.008	28.460	1.431	12.283**
	(24.293)	(62.821)	(31.092)	(2.742)	(5.805)
Broad PADs Sq. (t-1)	-42.575*	9.568	-35.457	-0.973	-8.934
	(22.289)	(44.121)	(31.009)	(3.106)	(5.608)
Loc. Economies (t-1) (10ks)	58.820*	0.355	451.718	1.028***	-0.140
	(32.632)	(13.949)	(278.974)	(0.273)	(0.838)
Median HH Income (100ks)	4.184*	-2.575	4.576	-0.483	-0.155
	(2.188)	(2.760)	(3.328)	(0.337)	(0.582)
Housing Price Index (100s)	-0.257*	0.218	-0.373	0.083***	0.006
	(0.142)	(0.222)	(0.252)	(0.025)	(0.040)
Poverty rate (100s)	-5.203	-1.659	-7.500	-2.016***	-0.327
	(3.736)	(4.692)	(5.809)	(0.648)	(1.097)
Avg annual wages (100k)	-0.078	-0.010	0.085	0.013	-0.021
	(0.123)	(0.027)	(0.093)	(0.024)	(0.023)
Attain. Status - CO (t-1)	3.181			0.381	1.125*
	(2.256)			(0.427)	(0.683)
Attain. Status - Pb (t-1)	1.130	0.690	2.780	-0.001	-0.128
	(0.963)	(0.872)	(1.846)	(0.146)	(0.193)
Attain. Status - O3 (t-1)	0.275	0.285	0.218	0.041	0.091
	(0.213)	(0.217)	(0.321)	(0.037)	(0.059)
Attain. Status - PM (t-1)	0.224	0.230	0.650*	0.023	0.013
	(0.187)	(0.269)	(0.338)	(0.029)	(0.041)
Attain. Status - SO2 (t-1)	0.118	-0.174	0.646	0.153	-0.172
	(0.796)	(1.014)	(1.128)	(0.126)	(0.195)
Density Employment	0.341	-0.880	0.951	0.015	0.021
	(0.502)	(1.356)	(0.914)	(0.051)	(0.052)
Percent Black (100s)	-5.951	-2.495	-2.509	1.180	-1.125
	(10.635)	(18.005)	(17.055)	(1.243)	(2.419)
Population count (1ms)	-2.166*	1.613	-4.534	-0.629**	-0.593
	(1.114)	(1.154)	(4.141)	(0.318)	(0.573)
Unemployment rate (100s)	12.406**	-8.852	-5.197	-0.394	-0.510
	(6.265)	(9.155)	(10.478)	(1.258)	(2.154)
Sales Volume (t-1)	-16.516	3.494	2.453	-4.242	-2.016
	(20.753)	(8.189)	(5.187)	(19.654)	(1.595)
Prior Births (1ks)	-3.150	1.246	-37.392	-0.051*	0.073
	(4.579)	(0.820)	(24.285)	(0.026)	(0.144)
Prior Deaths (1ks)	6.424	-3.775*	11.385	-0.244***	0.080
	(5.656)	(2.157)	(14.734)	(0.046)	(0.102)
Prior inward relocations (1ks)	56.262	94.534**	332.598**	6.054***	21.274***
	(51.480)	(46.669)	(139.914)	(1.696)	(5.123)
Constant	-5.917*	4.157	-3.001	1.485***	-0.018
	(3.515)	(6.922)	(4.890)	(0.400)	(0.964)
Observations	4595	1809	1840	22109	15908
Pseudo R^2	0.171	0.238	0.139	0.602	0.517
Chi^2	32	42	24	84	50
Log Likelihood	-2209	-1008	-839	-23228	-11568
Akaike's Criterion	4459	2054	1717	46497	23177
Bayesian Criterion	4588	2159	1822	46657	23330
County FE	Yes	Yes	Yes	Yes	Yes

Table A15 Continued

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
State by Year FE	Yes	Yes	Yes	Yes	Yes
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.1606	0.3006	0.3512	0.7978	0.0049

Table A15: PPMLHDFE regression results on establishment intra-state outward relocations under broad PADs (GAP 1-4) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A16: Regression Results of Broad PADs on Inter-State Outward Relocations

Variable	NAICS 21	NAICS 23	NAICS 31-33
Broad PADs (t-1)	-39.132	6.251	14.612
	(45.420)	(27.099)	(17.521)
Broad PADs Sq. (t-1)	34.100	-3.689	-13.598
	(39.329)	(26.430)	(16.097)
Loc. Economies (t-1) (10ks)	58.850*	2.089	3.610**
	(32.650)	(1.845)	(1.838)
Median HH Income (100ks)	-7.335	1.900	-0.096
	(5.056)	(2.393)	(1.568)
Housing Price Index (100s)	-0.266	-0.320**	-0.131
	(0.380)	(0.163)	(0.100)
Poverty rate (100s)	-30.812**	5.755	-0.162
	(12.143)	(4.585)	(3.444)
Avg annual wages (100k)	-0.034	0.047	-0.015
	(0.075)	(0.196)	(0.051)
Attain. Status - Pb (t-1)	-3.011	0.554	1.391***
	(1.942)	(0.677)	(0.465)
Attain. Status - O3 (t-1)	0.286	0.171	-0.057
	(0.534)	(0.189)	(0.146)
Attain. Status - PM (t-1)	0.403	-0.288	0.058
	(0.472)	(0.186)	(0.116)
Attain. Status - SO2 (t-1)	-0.450	0.272	0.140
	(1.952)	(0.908)	(0.368)
Density Employment	0.088	0.372	0.320***
	(0.625)	(0.328)	(0.105)
Percent Black (100s)	-34.921	-21.161**	2.049
	(29.235)	(9.775)	(6.513)
Population count (1ms)	-0.869	-0.561	-1.268
	(2.724)	(1.292)	(0.796)
Unemployment rate (100s)	-17.337	-10.891	8.912
	(32.220)	(10.372)	(5.756)
Sales Volume (t-1)	-21.048	1.160	-1.076
	(38.476)	(135.635)	(2.129)
Prior Births (1ks)	-6.264	-0.001	-0.448
	(5.431)	(0.260)	(0.369)
Prior Deaths (1ks)	8.019	-0.538	0.256
	(5.791)	(0.449)	(0.224)
Prior inward relocations (1ks)	-14.056	16.764	1.722
	(66.712)	(10.973)	(14.115)
Constant	21.477**	1.395	-2.290
	(9.276)	(3.937)	(3.032)
Observations	540	2797	4563
Pseudo R^2	0.252	0.272	0.308
Chi^2	31	24	46
Log Likelihood	-319	-1457	-2623
Akaike's Criterion	676	2953	5284
Bayesian Criterion	757	3065	5406
County FE	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes

Table A16 Continued

Variable	NAICS 21	NAICS 23	NAICS 31-33
NAICS FE	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.6850	0.9163	0.6999

Table A16: PPMLHDFE regression results on establishment inter-state outward relocations under broad PADs (GAP 1-4) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A17: Regression Results of Broad PADs on Establishment Exits

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
Broad PADs (t-1)	-1.991***	-1.091	-2.827*	-0.762	2.149**
	(0.535)	(1.411)	(1.477)	(0.603)	(1.015)
Broad PADs Sq. (t-1)	2.196*	6.922**	4.357	-0.583	-2.788*
	(1.178)	(3.069)	(3.215)	(1.040)	(1.516)
Loc. Economies (t-1) (10ks)	74.274***	48.585***	259.295***	1.359***	1.866***
	(9.476)	(8.255)	(44.504)	(0.299)	(0.610)
Median HH Income (100ks)	-0.057	-2.377**	0.391	-0.216	-0.338*
	(0.247)	(0.982)	(0.421)	(0.176)	(0.173)
Housing Price Index (100s)	-0.021	0.024	-0.085***	0.043**	0.046***
	(0.020)	(0.052)	(0.027)	(0.018)	(0.013)
Poverty rate (100s)	0.008	-0.645	0.177	-0.387	-0.222
	(0.387)	(1.139)	(0.672)	(0.364)	(0.259)
Avg annual wages (100k)	-0.012	0.005	0.014	0.006	-0.021**
	(0.013)	(0.016)	(0.009)	(0.011)	(0.009)
Attain. Status - CO (t-1)	0.254	0.160	0.542	-0.317*	-0.326***
	(0.172)	(0.282)	(0.354)	(0.171)	(0.099)
Attain. Status - Pb (t-1)	-0.017	0.011	-0.211*	-0.165***	0.103
	(0.112)	(0.175)	(0.118)	(0.062)	(0.069)
Attain. Status - O3 (t-1)	-0.034	0.144***	0.046	0.018	-0.043**
	(0.031)	(0.050)	(0.041)	(0.022)	(0.018)
Attain. Status - PM (t-1)	0.137***	0.067*	0.074**	0.045**	0.054***
	(0.032)	(0.038)	(0.030)	(0.020)	(0.020)
Attain. Status - SO2 (t-1)	-0.219**	0.119	-0.022	0.119*	0.135***
	(0.096)	(0.145)	(0.131)	(0.062)	(0.042)
Density Employment	-0.063	0.252***	0.177	0.042**	0.022
	(0.051)	(0.063)	(0.112)	(0.021)	(0.026)
Percent Black (100s)	-2.241	1.299	-3.942**	2.586***	0.971
	(1.649)	(2.662)	(1.906)	(0.772)	(0.769)
Population count (1ms)	-0.637***	-0.327	-1.759***	-0.223	-0.110
	(0.215)	(0.277)	(0.482)	(0.201)	(0.094)
Unemployment rate (100s)	2.389***	-1.435	4.398***	4.627***	3.271***
	(0.791)	(2.619)	(1.300)	(0.683)	(0.581)
Sales Volume (t-1)	4.507*	0.109	-0.288	-37.352**	-0.147*
	(2.608)	(0.727)	(0.288)	(15.355)	(0.084)
Prior Total Entries (1ks)	-1.704**	-0.745**	-4.314***	-0.046***	-0.005
	(0.671)	(0.304)	(1.640)	(0.009)	(0.034)
Constant	2.448***	2.661***	2.094***	4.895***	4.193***
	(0.211)	(0.862)	(0.363)	(0.231)	(0.269)
Observations	15287	10129	15133	26461	26612
Pseudo R^2	0.648	0.708	0.560	0.958	0.938
Chi^2	155	161	127	188	114
Log Likelihood	-32963	-16354	-21825	-116941	-72734
Akaike's Criterion	65963	32744	43687	233919	145505
Bayesian Criterion	66101	32874	43824	234066	145652
County FE	Yes	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes	Yes

Table A17 Continued

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.3122	0.4009	0.0130	0.0922	0.0055

Table A17: PPMLHDFE regression results on total establishment exits under broad PADs (GAP 1-4) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A18: Regression Results of Strict PADs on Births

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
Strict PAD(t-1)	2.274***	-0.270	1.516	0.359	-2.115***
	(0.632)	(1.336)	(1.185)	(0.573)	(0.754)
Strict PAD Sq. (t-1)	-2.048*	4.545	-1.234	-0.573	3.668***
	(1.157)	(2.957)	(2.130)	(0.966)	(1.279)
Loc. Economies (t-1) (10ks)	-42.973***	-10.724**	-133.185***	-0.457***	-0.664
	(6.400)	(4.764)	(35.270)	(0.165)	(0.480)
Median HH Income (100ks)	-0.018	0.999**	0.375	0.250	-0.176
	(0.310)	(0.415)	(0.460)	(0.177)	(0.189)
Housing Price Index (100s)	0.080***	0.068**	-0.035	0.025*	0.032***
	(0.026)	(0.032)	(0.030)	(0.014)	(0.011)
Poverty rate (100s)	-0.266	-1.548**	1.092	-0.270	-0.419*
	(0.546)	(0.696)	(0.711)	(0.292)	(0.253)
Avg annual wages (100k)	0.018	0.005	-0.008	-0.005	-0.011
	(0.013)	(0.006)	(0.012)	(0.011)	(0.008)
Attain. Status - CO (t-1)	-0.739	-0.199	-0.710	-0.089	-0.045
	(0.501)	(0.292)	(1.011)	(0.256)	(0.096)
Attain. Status - Pb (t-1)	0.023	0.036	-0.161	0.083	-0.067
	(0.108)	(0.131)	(0.155)	(0.061)	(0.052)
Attain. Status - O3 (t-1)	0.105***	0.132***	0.132***	0.116***	0.100***
	(0.036)	(0.037)	(0.046)	(0.029)	(0.024)
Attain. Status - PM (t-1)	-0.032	-0.034	0.121***	-0.034**	-0.011
	(0.022)	(0.031)	(0.034)	(0.014)	(0.016)
Attain. Status - SO2 (t-1)	0.050	-0.123	0.106	0.039	-0.008
	(0.120)	(0.133)	(0.152)	(0.046)	(0.032)
Density Employment	0.345	-0.055	-0.228	0.012	0.017
	(0.233)	(0.075)	(0.182)	(0.023)	(0.020)
Percent Black (100s)	-1.312	0.039	-1.073	2.183**	1.439**
	(1.676)	(2.483)	(2.313)	(0.859)	(0.636)
Population count (1ms)	0.768**	0.269*	0.203	0.876***	0.201
	(0.380)	(0.138)	(0.269)	(0.185)	(0.135)
Unemployment rate (100s)	1.736**	0.071	-3.103**	1.337**	2.132***
	(0.815)	(1.504)	(1.410)	(0.594)	(0.564)
Sales Volume (t-1)	-4.465	0.677	-0.403	-27.793**	0.091
	(3.748)	(0.436)	(0.382)	(12.470)	(0.101)
Prior Total Exits (1ks)	0.812	2.664***	5.353*	0.063	0.106
	(0.869)	(0.524)	(2.774)	(0.046)	(0.084)
Constant	1.939***	1.097***	1.920***	3.994***	4.148***
	(0.278)	(0.425)	(0.419)	(0.254)	(0.212)
Observations	15227	9866	14362	26206	26170
Pseudo R^2	0.666	0.654	0.491	0.950	0.926
Chi^2	201	137	93	177	119
Log Likelihood	-34915	-14498	-20077	-115492	-69224
Akaike's Criterion	69867	29032	40190	231021	138484
Bayesian Criterion	70004	29162	40326	231168	138631
County FE	Yes	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes	Yes

Table A18 Continued

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.0001	0.0349	0.1648	0.8110	0.0128

Table A18: PPMLHDFE regression results on establishment births under strict PADs (GAP 1-2) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A19: Regression Results of Strict PADs on Inward Relocations

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
Strict PAD(t-1)	-21.262*	12.649	12.083	-2.100	-2.626
	(11.319)	(9.435)	(9.820)	(1.306)	(2.495)
Strict PAD Sq. (t-1)	46.301*	-12.254	-19.470	1.172	0.260
	(23.692)	(17.399)	(14.321)	(2.722)	(4.715)
Loc. Economies (t-1) (10ks)	-30.742	-8.578	-241.635**	-0.095	-0.329
	(40.710)	(16.556)	(107.516)	(0.311)	(0.663)
Median HH Income (100ks)	-2.425	-1.442	-0.125	-0.085	-0.242
	(2.065)	(2.173)	(2.880)	(0.345)	(0.527)
Housing Price Index (100s)	0.099	-0.144	0.088	-0.002	-0.042
	(0.132)	(0.172)	(0.216)	(0.027)	(0.040)
Poverty rate (100s)	4.985	-1.150	1.335	-0.946	1.614
	(3.349)	(4.736)	(5.687)	(0.661)	(1.005)
Avg annual wages (100k)	0.156	0.051***	-0.030	0.035	-0.018
	(0.100)	(0.017)	(0.086)	(0.026)	(0.023)
Attain. Status - CO (t-1)	3.448	-2.704		-1.259	0.058
	(2.414)	(1.939)		(0.840)	(1.069)
Attain. Status - Pb (t-1)	-2.354**	-0.751	-1.826	-0.036	-0.067
	(1.199)	(0.589)	(1.310)	(0.158)	(0.156)
Attain. Status - O3 (t-1)	0.068	0.387	0.015	0.041	0.040
	(0.241)	(0.244)	(0.300)	(0.035)	(0.048)
Attain. Status - PM (t-1)	-0.278	0.237	0.415	-0.007	0.022
	(0.202)	(0.283)	(0.277)	(0.028)	(0.040)
Attain. Status - SO2 (t-1)	-0.893	-1.242	0.206	-0.245	-0.233
	(0.907)	(0.853)	(0.882)	(0.157)	(0.178)
Density Employment	1.047	0.718**	-1.945	-0.157***	0.015
	(1.014)	(0.313)	(1.401)	(0.044)	(0.069)
Percent Black (100s)	-11.387	-14.691	-8.204	0.153	-0.308
	(10.256)	(11.415)	(15.087)	(1.383)	(1.989)
Population count (1ms)	0.290	0.136	1.765	1.229***	0.701**
	(1.777)	(0.795)	(1.735)	(0.399)	(0.302)
Unemployment rate (100s)	4.687	3.430	15.524	1.732	2.346
	(6.058)	(9.086)	(11.502)	(1.411)	(1.827)
Sales Volume (t-1)	-0.014	-17.718**	6.735	15.928	0.621
	(20.440)	(7.582)	(4.888)	(16.489)	(0.784)
Prior Births (1ks)	-1.093	1.213*	36.230**	0.015	-0.129
	(4.483)	(0.721)	(15.503)	(0.034)	(0.139)
Prior Deaths (1ks)	0.122	0.440	-6.327	-0.128*	-0.226**
	(6.663)	(1.988)	(12.721)	(0.068)	(0.092)
Prior outward relocations (1ks)	47.581	101.410***	-30.927	2.864	3.405
	(58.598)	(33.302)	(220.218)	(1.919)	(4.240)
Constant	-0.336	0.523	-1.318	0.756**	0.531
	(1.660)	(2.316)	(2.642)	(0.379)	(0.518)
Observations	4769	2219	1942	22340	17084
Pseudo R^2	0.148	0.343	0.139	0.584	0.507
Chi^2	27	32	19	58	40
Log Likelihood	-2266	-1264	-923	-24176	-13211
Akaike's Criterion	4572	2568	1884	48393	26462
Bayesian Criterion	4701	2682	1990	48553	26617
County FE	Yes	Yes	Yes	Yes	Yes

Table A19 Continued

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
State by Year FE	Yes	Yes	Yes	Yes	Yes
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.1352	0.3293	0.3923	0.0817	0.1143

Table A19: PPMLHDFE regression results on establishment inward relocations under strict PADs (GAP 1-2) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A20: Regression Results of Strict PADs on Intra-State Inward Relocations

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
Strict PAD(t-1)	-18.609*	16.505	12.860	-2.034	-2.735
	(11.125)	(11.890)	(8.962)	(1.404)	(2.779)
Strict PAD Sq. (t-1)	39.515*	-20.639	-21.238	0.905	0.640
	(21.684)	(20.325)	(13.346)	(2.980)	(5.246)
Loc. Economies (t-1) (10ks)	-32.292	10.163	-246.029**	0.115	-0.842
	(43.151)	(23.319)	(121.164)	(0.333)	(0.985)
Median HH Income (100ks)	-2.102	-0.553	0.777	0.102	-0.250
	(2.080)	(2.337)	(3.263)	(0.347)	(0.572)
Housing Price Index (100s)	0.058	-0.167	0.063	-0.004	-0.021
	(0.136)	(0.244)	(0.237)	(0.028)	(0.042)
Poverty rate (100s)	5.192	-4.301	2.195	-0.734	1.871*
	(3.361)	(5.492)	(5.859)	(0.665)	(1.082)
Avg annual wages (100k)	0.153	0.062***	-0.021	0.032	-0.016
	(0.101)	(0.018)	(0.093)	(0.026)	(0.025)
Attain. Status - CO (t-1)	3.801	-2.692		-1.128	-0.461
	(2.396)	(1.938)		(0.786)	(1.437)
Attain. Status - Pb (t-1)	-2.268*	-0.863	-2.077	-0.068	-0.128
	(1.209)	(0.778)	(1.451)	(0.157)	(0.156)
Attain. Status - O3 (t-1)	0.049	0.634**	0.099	0.051	0.065
	(0.243)	(0.280)	(0.307)	(0.036)	(0.051)
Attain. Status - PM (t-1)	-0.276	0.460	0.542*	-0.003	0.030
	(0.206)	(0.308)	(0.316)	(0.029)	(0.042)
Attain. Status - SO2 (t-1)	-0.979	-2.656**	0.105	-0.257*	-0.341*
	(0.954)	(1.207)	(1.107)	(0.155)	(0.177)
Density Employment	1.107	0.621	-2.010	-0.168***	-0.099*
	(1.034)	(0.668)	(1.466)	(0.042)	(0.055)
Percent Black (100s)	-8.612	-16.138	-7.916	0.171	0.013
	(10.394)	(13.095)	(18.235)	(1.429)	(2.006)
Population count (1ms)	-0.119	0.419	4.279**	1.094**	0.357
	(2.027)	(1.226)	(1.834)	(0.440)	(0.320)
Unemployment rate (100s)	4.815	1.085	14.635	1.513	3.561*
	(6.115)	(10.348)	(11.756)	(1.434)	(1.984)
Sales Volume (t-1)	-0.346	-26.828***	7.613	10.675	0.594
	(20.830)	(9.838)	(4.939)	(15.951)	(0.818)
Prior Births (1ks)	0.363	0.276	38.987**	0.001	0.072
	(4.573)	(1.298)	(18.260)	(0.035)	(0.123)
Prior Deaths (1ks)	-0.318	2.234	-10.315	-0.138*	-0.310***
	(7.121)	(2.862)	(15.209)	(0.070)	(0.117)
Prior outward relocations (1ks)	28.423	161.218***	-24.628	2.253	7.355*
	(60.754)	(56.009)	(242.253)	(1.951)	(4.172)
Constant	-0.578	0.138	-3.925	0.714*	0.601
	(1.651)	(2.404)	(3.005)	(0.390)	(0.554)
Observations	4694	1823	1784	22155	16503
Pseudo R^2	0.148	0.264	0.130	0.582	0.485
Chi^2	25	48	18	59	49
Log Likelihood	-2219	-988	-831	-23838	-12234
Akaike's Criterion	4478	2017	1701	47717	24508
Bayesian Criterion	4607	2127	1805	47877	24663
County FE	Yes	Yes	Yes	Yes	Yes

Table A20 Continued

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
State by Year FE	Yes	Yes	Yes	Yes	Yes
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.1859	0.3731	0.2799	0.0958	0.1638

Table A20: PPMLHDFE regression results on establishment intra-state inward relocations under strict PADs (GAP 1-2) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A21: Regression Results of Strict PADs on Inter-State Inward Relocations

Variable	NAICS 21	NAICS 23	NAICS 31-33
Strict PAD(t-1)	29.340	0.879	-6.584
	(20.886)	(10.394)	(5.634)
Strict PAD Sq. (t-1)	-51.025*	0.880	17.709
	(28.547)	(28.046)	(14.209)
Loc. Economies (t-1) (10ks)	-86.054**	-3.939**	2.181*
	(38.992)	(1.698)	(1.311)
Median HH Income (100ks)	-6.195	-5.939**	0.034
	(5.342)	(2.486)	(1.468)
Housing Price Index (100s)	0.314	0.061	-0.035
	(0.290)	(0.184)	(0.104)
Poverty rate (100s)	14.020	-3.907	2.644
	(12.337)	(6.527)	(3.070)
Avg annual wages (100k)	0.068	0.329	-0.078
	(0.058)	(0.254)	(0.066)
Attain. Status - Pb (t-1)	-0.246	1.873*	0.710**
	(0.852)	(0.962)	(0.356)
Attain. Status - O3 (t-1)	-0.786	-0.063	0.005
	(0.719)	(0.206)	(0.145)
Attain. Status - PM (t-1)	-0.080	0.040	-0.025
	(0.586)	(0.145)	(0.109)
Attain. Status - SO2 (t-1)	2.636	-0.571	0.321
	(2.688)	(0.588)	(0.475)
Density Employment	0.618	0.193	0.322**
	(0.542)	(0.278)	(0.149)
Percent Black (100s)	45.833	-0.813	-3.972
	(40.322)	(10.675)	(4.872)
Population count (1ms)	-3.523**	-1.383	-1.548**
	(1.583)	(1.575)	(0.665)
Unemployment rate (100s)	19.218	6.762	-10.986**
	(34.193)	(14.694)	(5.247)
Sales Volume (t-1)	27.364*	89.792	1.962
	(15.410)	(109.324)	(6.255)
Prior Births (1ks)	13.547**	0.223	-0.694**
	(6.525)	(0.147)	(0.326)
Prior Deaths (1ks)	-4.872	0.241	0.096
	(3.214)	(0.426)	(0.291)
Prior outward relocations (1ks)	-70.030	20.929*	-9.247
	(64.827)	(10.735)	(10.234)
Constant	-0.457	2.469	2.228
	(7.984)	(2.714)	(1.383)
Observations	488	2573	4996
Pseudo R^2	0.335	0.265	0.297
Chi^2	34	30	35
Log Likelihood	-317	-1378	-2818
Akaike's Criterion	673	2795	5676
Bayesian Criterion	753	2906	5807
County FE	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes

Table A21 Continued

Variable	NAICS 21	NAICS 23	NAICS 31-33
NAICS FE	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.2024	0.9736	0.4522

Table A21: PPMLHDFE regression results on establishment inter-state inward relocations under strict PADs (GAP 1-2) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A22: Regression Results of Strict PADs on Total Entries

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
Strict PAD(t-1)	2.226***	-0.435	1.638	0.399	-2.151***
	(0.634)	(1.306)	(1.177)	(0.571)	(0.747)
Strict PAD Sq. (t-1)	-1.854	5.178*	-1.599	-0.678	3.655***
	(1.156)	(2.963)	(2.103)	(0.969)	(1.248)
Loc. Economies (t-1) (10ks)	-42.961***	-10.549**	-131.344***	-0.462***	-0.696
	(6.343)	(4.980)	(35.008)	(0.164)	(0.480)
Median HH Income (100ks)	-0.059	0.928**	0.378	0.256	-0.184
	(0.310)	(0.418)	(0.454)	(0.173)	(0.185)
Housing Price Index (100s)	0.080***	0.064**	-0.035	0.023*	0.030***
	(0.026)	(0.031)	(0.030)	(0.014)	(0.011)
Poverty rate (100s)	-0.247	-1.494**	1.083	-0.255	-0.380
	(0.546)	(0.691)	(0.701)	(0.288)	(0.250)
Avg annual wages (100k)	0.019	0.007	-0.009	-0.004	-0.011
	(0.013)	(0.006)	(0.012)	(0.011)	(0.007)
Attain. Status - CO (t-1)	-0.665	-0.464*	-0.827	-0.105	-0.034
	(0.541)	(0.249)	(0.955)	(0.250)	(0.098)
Attain. Status - Pb (t-1)	-0.037	-0.038	-0.196	0.083	-0.068
	(0.117)	(0.132)	(0.149)	(0.060)	(0.050)
Attain. Status - O3 (t-1)	0.103***	0.135***	0.130***	0.114***	0.098***
	(0.036)	(0.036)	(0.046)	(0.029)	(0.024)
Attain. Status - PM (t-1)	-0.036	-0.033	0.124***	-0.034**	-0.011
	(0.022)	(0.031)	(0.033)	(0.013)	(0.016)
Attain. Status - SO2 (t-1)	0.013	-0.130	0.098	0.031	-0.013
	(0.132)	(0.127)	(0.146)	(0.045)	(0.032)
Density Employment	0.350	-0.048	-0.229	0.010	0.018
	(0.234)	(0.070)	(0.180)	(0.022)	(0.019)
Percent Black (100s)	-1.512	-0.531	-1.107	2.114**	1.369**
	(1.664)	(2.403)	(2.267)	(0.839)	(0.611)
Population count (1ms)	0.801**	0.232*	0.196	0.902***	0.221*
	(0.371)	(0.140)	(0.279)	(0.183)	(0.133)
Unemployment rate (100s)	1.901**	0.094	-2.534*	1.393**	2.181***
	(0.831)	(1.482)	(1.382)	(0.582)	(0.548)
Sales Volume (t-1)	-4.560	0.615	-0.325	-27.566**	0.097
	(3.534)	(0.411)	(0.352)	(12.206)	(0.104)
Prior Total Exits (1ks)	0.796	2.609***	5.150*	0.060	0.104
	(0.869)	(0.520)	(2.763)	(0.046)	(0.083)
Constant	1.950***	1.258***	1.894***	3.993***	4.163***
	(0.274)	(0.417)	(0.411)	(0.248)	(0.206)
Observations	15227	9871	14370	26206	26170
Pseudo R^2	0.665	0.660	0.491	0.950	0.927
Chi^2	198	131	95	177	116
Log Likelihood	-35043	-14625	-20206	-115920	-69520
Akaike's Criterion	70123	29286	40448	231877	139076
Bayesian Criterion	70261	29416	40584	232024	139223
County FE	Yes	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes	Yes

Table A22 Continued

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.0001	0.0232	0.1744	0.7607	0.0105

Table A22: PPMLHDFE regression results on total establishment entries under strict PADs (GAP 1-2) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A23: Regression Results of Strict PADs on Deaths

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
Strict PAD(t-1)	-2.088***	-0.360	-2.843*	-0.776	2.105**
	(0.532)	(1.446)	(1.509)	(0.611)	(1.015)
Strict PAD Sq. (t-1)	2.268**	5.105*	4.399	-0.587	-2.774*
	(1.118)	(3.023)	(3.247)	(1.051)	(1.522)
Loc. Economies (t-1) (10ks)	74.679***	49.540***	258.043***	1.356***	1.874***
	(9.391)	(8.488)	(43.652)	(0.301)	(0.615)
Median HH Income (100ks)	-0.085	-2.327**	0.409	-0.216	-0.328*
	(0.246)	(0.999)	(0.423)	(0.180)	(0.176)
Housing Price Index (100s)	-0.021	0.022	-0.083***	0.043**	0.048***
	(0.020)	(0.053)	(0.027)	(0.019)	(0.013)
Poverty rate (100s)	0.050	-0.496	0.271	-0.358	-0.215
	(0.382)	(1.157)	(0.674)	(0.370)	(0.262)
Avg annual wages (100k)	-0.011	0.005	0.014	0.006	-0.021**
	(0.013)	(0.016)	(0.010)	(0.011)	(0.009)
Attain. Status - CO (t-1)	0.221	0.189	0.664*	-0.324*	-0.344***
	(0.143)	(0.295)	(0.389)	(0.172)	(0.101)
Attain. Status - Pb (t-1)	-0.042	0.027	-0.241**	-0.169***	0.105
	(0.112)	(0.193)	(0.117)	(0.062)	(0.071)
Attain. Status - O3 (t-1)	-0.037	0.143***	0.043	0.017	-0.043**
	(0.031)	(0.051)	(0.042)	(0.022)	(0.019)
Attain. Status - PM (t-1)	0.136***	0.068*	0.074**	0.045**	0.053***
	(0.032)	(0.037)	(0.030)	(0.020)	(0.021)
Attain. Status - SO2 (t-1)	-0.217**	0.107	-0.003	0.118*	0.138***
	(0.099)	(0.150)	(0.135)	(0.062)	(0.043)
Density Employment	-0.076	0.243***	0.175	0.043**	0.020
	(0.055)	(0.066)	(0.109)	(0.021)	(0.025)
Percent Black (100s)	-2.002	1.650	-3.956**	2.649***	1.060
	(1.647)	(2.706)	(1.968)	(0.785)	(0.788)
Population count (1ms)	-0.534**	-0.338	-1.735***	-0.216	-0.112
	(0.216)	(0.287)	(0.461)	(0.204)	(0.094)
Unemployment rate (100s)	2.341***	-1.357	4.438***	4.695***	3.314***
	(0.792)	(2.658)	(1.313)	(0.694)	(0.589)
Sales Volume (t-1)	4.620*	0.113	-0.295	-38.466**	-0.137
	(2.698)	(0.735)	(0.289)	(15.830)	(0.088)
Prior Total Entries (1ks)	-1.689**	-0.782**	-4.088**	-0.047***	-0.008
	(0.677)	(0.319)	(1.631)	(0.009)	(0.034)
Constant	2.387***	2.544***	2.043***	4.870***	4.160***
	(0.211)	(0.880)	(0.366)	(0.235)	(0.272)
Observations	15287	10123	15131	26461	26608
Pseudo R^2	0.648	0.705	0.561	0.958	0.938
Chi^2	157	144	126	185	115
Log Likelihood	-32843	-16251	-21685	-116596	-72447
Akaike's Criterion	65723	32538	43406	233228	144931
Bayesian Criterion	65860	32668	43543	233376	145078
County FE	Yes	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes	Yes

Table A23 Continued

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.0001	0.0499	0.1545	0.0040	0.1089

Table A23: PPMLHDFE regression results on establishment deaths under strict PADs (GAP 1-2) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A24: Regression Results of Strict PADs on Outward Relocations

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
Strict PAD(t-1)	40.502**	-21.223***	-13.488	3.707**	3.543*
	(19.981)	(5.623)	(12.676)	(1.677)	(1.809)
Strict PAD Sq. (t-1)	-94.042*	50.288***	32.571	-6.656	-1.326
	(49.930)	(7.429)	(42.759)	(4.528)	(4.266)
Loc. Economies (t-1) (10ks)	49.069*	11.596	491.848**	0.937***	0.773
	(28.375)	(12.770)	(218.560)	(0.265)	(0.748)
Median HH Income (100ks)	2.839	-4.726**	0.564	-0.369	0.047
	(2.235)	(2.344)	(2.937)	(0.330)	(0.530)
Housing Price Index (100s)	-0.134	0.077	-0.353*	0.081***	-0.036
	(0.142)	(0.160)	(0.197)	(0.024)	(0.034)
Poverty rate (100s)	-7.695**	-7.782*	-8.027	-1.989***	-0.291
	(3.790)	(4.219)	(5.190)	(0.645)	(1.009)
Avg annual wages (100k)	-0.068	-0.005	0.068	0.002	-0.014
	(0.120)	(0.020)	(0.087)	(0.024)	(0.023)
Attain. Status - CO (t-1)	2.328	1.374		0.426	-0.095
	(2.162)	(1.009)		(0.341)	(0.676)
Attain. Status - Pb (t-1)	0.915	-0.333	2.841	-0.049	0.016
	(1.013)	(0.667)	(1.771)	(0.137)	(0.170)
Attain. Status - O3 (t-1)	0.305	0.093	0.199	0.049	0.067
	(0.208)	(0.216)	(0.299)	(0.037)	(0.059)
Attain. Status - PM (t-1)	0.145	0.126	0.125	0.016	0.003
	(0.183)	(0.178)	(0.252)	(0.030)	(0.037)
Attain. Status - SO2 (t-1)	-0.078	0.794	-0.039	0.172	-0.158
	(0.772)	(0.701)	(1.074)	(0.131)	(0.178)
Density Employment	0.493	0.521	0.576	0.050	0.047
	(0.432)	(0.390)	(0.673)	(0.054)	(0.050)
Percent Black (100s)	-7.510	-0.469	1.966	0.713	-1.234
	(10.513)	(14.248)	(14.575)	(1.273)	(2.339)
Population count (1ms)	-3.136**	0.536	-4.533	-0.515	-0.425
	(1.446)	(0.856)	(3.048)	(0.327)	(0.445)
Unemployment rate (100s)	9.652	-4.728	-1.083	-0.432	0.119
	(6.328)	(8.003)	(9.914)	(1.236)	(1.946)
Sales Volume (t-1)	-15.461	-0.791	3.042	-6.761	-1.390
	(21.243)	(5.538)	(4.974)	(18.594)	(1.277)
Prior Births (1ks)	-5.537	0.885	-45.662**	-0.039	0.019
	(4.027)	(1.065)	(20.722)	(0.026)	(0.140)
Prior Deaths (1ks)	1.414	0.667	11.319	-0.240***	0.116
	(5.471)	(1.593)	(14.152)	(0.051)	(0.087)
Prior inward relocations (1ks)	68.596	82.933**	182.467	5.944***	17.849***
	(53.501)	(38.306)	(122.018)	(1.709)	(4.709)
Constant	-0.813	2.034	1.738	1.515***	1.210*
	(1.867)	(2.314)	(2.797)	(0.345)	(0.638)
Observations	4610	2080	2076	22232	16601
Pseudo R^2	0.174	0.289	0.131	0.606	0.544
Chi^2	30	137	23	85	47
Log Likelihood	-2228	-1264	-977	-23660	-12583
Akaike's Criterion	4496	2569	1993	47360	25207
Bayesian Criterion	4624	2681	2100	47520	25361
County FE	Yes	Yes	Yes	Yes	Yes

Table A24 Continued

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
State by Year FE	Yes	Yes	Yes	Yes	Yes
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA² Joint Test p-value	0.1222	0.0000	0.4867	0.0569	0.0047

Table A24: PPMLHDFE regression results on establishment outward relocations under strict PADs (GAP 1-2) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A25: Regression Results of Strict PADs on Intra-State Outward Relocations

Variable	NAICS 11	NAICS 22	NAICS 23	NAICS 31-33
Strict PAD(t-1)	43.118**	-12.010	4.065**	5.649**
	(21.068)	(12.468)	(1.653)	(2.196)
Strict PAD Sq. (t-1)	-98.964*	30.845	-7.511*	-5.094
	(51.929)	(39.173)	(4.522)	(5.350)
Loc. Economies (t-1) (10ks)	45.434	432.855*	0.982***	0.303
	(28.698)	(250.532)	(0.264)	(0.832)
Median HH Income (100ks)	2.905	2.952	-0.337	-0.009
	(2.263)	(3.143)	(0.336)	(0.570)
Housing Price Index (100s)	-0.176	-0.441*	0.082***	-0.010
	(0.145)	(0.233)	(0.025)	(0.037)
Poverty rate (100s)	-7.411*	-8.381	-2.055***	-0.224
	(3.826)	(5.833)	(0.648)	(1.070)
Avg annual wages (100k)	-0.084	0.061	0.010	-0.017
	(0.130)	(0.093)	(0.025)	(0.024)
Attain. Status - CO (t-1)	2.155		0.720	0.672
	(2.103)		(0.531)	(0.523)
Attain. Status - Pb (t-1)	0.897	2.742	-0.058	-0.165
	(1.014)	(1.853)	(0.141)	(0.183)
Attain. Status - O3 (t-1)	0.326	0.065	0.048	0.088
	(0.217)	(0.327)	(0.037)	(0.059)
Attain. Status - PM (t-1)	0.149	0.739**	0.026	0.014
	(0.188)	(0.343)	(0.030)	(0.040)
Attain. Status - SO2 (t-1)	-0.075	0.609	0.165	-0.157
	(0.803)	(1.146)	(0.128)	(0.190)
Density Employment	0.363	1.143	0.016	0.006
	(0.514)	(0.858)	(0.051)	(0.051)
Percent Black (100s)	-7.672	-1.628	1.449	-2.026
	(10.948)	(16.966)	(1.267)	(2.456)
Population count (1ms)	-3.020**	-4.609	-0.619*	-0.710
	(1.457)	(3.704)	(0.340)	(0.583)
Unemployment rate (100s)	11.170*	-5.699	-0.357	-0.889
	(6.460)	(10.923)	(1.243)	(2.061)
Sales Volume (t-1)	-14.822	4.457	-7.998	-1.857
	(21.894)	(5.440)	(19.388)	(1.691)
Prior Births (1ks)	-4.476	-36.652	-0.040	0.117
	(4.190)	(22.768)	(0.025)	(0.136)
Prior Deaths (1ks)	2.346	5.878	-0.241***	0.095
	(5.407)	(14.481)	(0.050)	(0.094)
Prior inward relocations (1ks)	60.299	208.454	5.187***	19.921***
	(52.393)	(132.701)	(1.688)	(5.120)
Constant	-0.856	1.400	1.436***	1.492**
	(1.930)	(3.034)	(0.348)	(0.736)
Observations	4524	1843	22035	15967
Pseudo R^2	0.173	0.140	0.603	0.521
Chi^2	27	23	83	55
Log Likelihood	-2183	-849	-23308	-11682
Akaike's Criterion	4406	1737	46656	23405
Bayesian Criterion	4534	1842	46816	23559
County FE	Yes	Yes	Yes	Yes

Table A25 Continued

Variable	NAICS 11	NAICS 22	NAICS 23	NAICS 31-33
State by Year FE	Yes	Yes	Yes	Yes
NAICS FE	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.1174	0.6220	0.0307	0.0011

Table A25: PPMLHDFE regression results on establishment intra-state outward relocations under strict PADs (GAP 1-2) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A26: Regression Results of Strict PADs on Inter-State Outward Relocations

Variable	NAICS 21	NAICS 23	NAICS 31-33
Strict PAD(t-1)	-25.269**	3.174	-2.088
	(12.524)	(12.154)	(4.086)
Strict PAD Sq. (t-1)	73.752***	-12.923	4.083
	(19.141)	(25.635)	(12.797)
Loc. Economies (t-1) (10ks)	93.497***	2.297	3.402**
	(34.654)	(1.874)	(1.708)
Median HH Income (100ks)	-8.096*	1.137	-0.092
	(4.823)	(2.364)	(1.531)
Housing Price Index (100s)	0.082	-0.260	-0.157
	(0.313)	(0.161)	(0.097)
Poverty rate (100s)	-34.220***	3.644	-1.551
	(11.974)	(4.674)	(3.404)
Avg annual wages (100k)	-0.068	0.048	-0.015
	(0.079)	(0.196)	(0.048)
Attain. Status - CO (t-1)	-2.143	21.989***	-2.961**
	(1.632)	(1.993)	(1.358)
Attain. Status - Pb (t-1)	-2.295	0.589	1.316***
	(1.798)	(0.674)	(0.462)
Attain. Status - O3 (t-1)	0.546	0.255	-0.088
	(0.495)	(0.186)	(0.146)
Attain. Status - PM (t-1)	0.252	-0.292	0.039
	(0.412)	(0.185)	(0.116)
Attain. Status - SO2 (t-1)	0.309	0.208	0.087
	(1.698)	(0.904)	(0.368)
Density Employment	-0.242	0.303	0.321***
	(0.587)	(0.326)	(0.105)
Percent Black (100s)	-37.992	-20.954**	-0.011
	(29.692)	(10.061)	(6.264)
Population count (1ms)	-2.243	-0.620	-1.224*
	(2.630)	(1.271)	(0.729)
Unemployment rate (100s)	-5.649	-12.610	10.411*
	(26.188)	(10.273)	(5.500)
Sales Volume (t-1)	-25.017	16.837	-1.244
	(38.027)	(139.134)	(2.132)
Prior Births (1ks)	-5.219	-0.028	-0.385
	(4.903)	(0.256)	(0.363)
Prior Deaths (1ks)	7.335	-0.532	0.222
	(5.522)	(0.414)	(0.229)
Prior inward relocations (1ks)	19.008	17.297	4.075
	(71.295)	(11.070)	(13.372)
Constant	15.783***	2.799	0.309
	(5.894)	(2.188)	(1.492)
Observations	633	2867	4668
Pseudo R^2	0.268	0.269	0.303
Chi^2	76	15034	70
Log Likelihood	-372	-1493	-2717
Akaike's Criterion	784	3027	5474
Bayesian Criterion	873	3146	5603
County FE	Yes	Yes	Yes

Table A26 Continued

Variable	NAICS 21	NAICS 23	NAICS 31-33
State by Year FE	Yes	Yes	Yes
NAICS FE	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.0000	0.8436	0.8694

Table A26: PPMLHDFE regression results on establishment inter-state outward relocations under strict PADs (GAP 1-2) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A27: Regression Results of Strict PADs on Total Exits

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
Strict PAD(t-1)	-1.991***	-1.091	-2.827*	-0.762	2.149**
	(0.535)	(1.411)	(1.477)	(0.603)	(1.015)
Strict PAD Sq. (t-1)	2.196*	6.922**	4.357	-0.583	-2.788*
	(1.178)	(3.069)	(3.215)	(1.040)	(1.516)
Loc. Economies (t-1) (10ks)	74.274***	48.585***	259.295***	1.359***	1.866***
	(9.476)	(8.255)	(44.504)	(0.299)	(0.610)
Median HH Income (100ks)	-0.057	-2.377**	0.391	-0.216	-0.338*
	(0.247)	(0.982)	(0.421)	(0.176)	(0.173)
Housing Price Index (100s)	-0.021	0.024	-0.085***	0.043**	0.046***
	(0.020)	(0.052)	(0.027)	(0.018)	(0.013)
Poverty rate (100s)	0.008	-0.645	0.177	-0.387	-0.222
	(0.387)	(1.139)	(0.672)	(0.364)	(0.259)
Avg annual wages (100k)	-0.012	0.005	0.014	0.006	-0.021**
	(0.013)	(0.016)	(0.009)	(0.011)	(0.009)
Attain. Status - CO (t-1)	0.254	0.160	0.542	-0.317*	-0.326***
	(0.172)	(0.282)	(0.354)	(0.171)	(0.099)
Attain. Status - Pb (t-1)	-0.017	0.011	-0.211*	-0.165***	0.103
	(0.112)	(0.175)	(0.118)	(0.062)	(0.069)
Attain. Status - O3 (t-1)	-0.034	0.144***	0.046	0.018	-0.043**
	(0.031)	(0.050)	(0.041)	(0.022)	(0.018)
Attain. Status - PM (t-1)	0.137***	0.067*	0.074**	0.045**	0.054***
	(0.032)	(0.038)	(0.030)	(0.020)	(0.020)
Attain. Status - SO2 (t-1)	-0.219**	0.119	-0.022	0.119*	0.135***
	(0.096)	(0.145)	(0.131)	(0.062)	(0.042)
Density Employment	-0.063	0.252***	0.177	0.042**	0.022
	(0.051)	(0.063)	(0.112)	(0.021)	(0.026)
Percent Black (100s)	-2.241	1.299	-3.942**	2.586***	0.971
	(1.649)	(2.662)	(1.906)	(0.772)	(0.769)
Population count (1ms)	-0.637***	-0.327	-1.759***	-0.223	-0.110
	(0.215)	(0.277)	(0.482)	(0.201)	(0.094)
Unemployment rate (100s)	2.389***	-1.435	4.398***	4.627***	3.271***
	(0.791)	(2.619)	(1.300)	(0.683)	(0.581)
Sales Volume (t-1)	4.507*	0.109	-0.288	-37.352**	-0.147*
	(2.608)	(0.727)	(0.288)	(15.355)	(0.084)
Prior Total Entries (1ks)	-1.704**	-0.745**	-4.314***	-0.046***	-0.005
	(0.671)	(0.304)	(1.640)	(0.009)	(0.034)
Constant	2.448***	2.661***	2.094***	4.895***	4.193***
	(0.211)	(0.862)	(0.363)	(0.231)	(0.269)
Observations	15287	10129	15133	26461	26612
Pseudo R^2	0.648	0.708	0.560	0.958	0.938
Chi^2	155	161	127	188	114
Log Likelihood	-32963	-16354	-21825	-116941	-72734
Akaike's Criterion	65963	32744	43687	233919	145505
Bayesian Criterion	66101	32874	43824	234066	145652
County FE	Yes	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes	Yes

Table A27 Continued

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33
NAICS FE	Yes	Yes	Yes	Yes	Yes
PA-PA^2 Joint Test p-value	0.0002	0.0223	0.1439	0.0037	0.0970

Table A27: PPMLHDFE regression results on total establishment exits under strict PADs (GAP 1-2) are presented above. Column names correspond to a specific NAICS sector. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. p-values of joint-tests on linear and quadratic PAD terms are shown in the last row.

Table A28: Summary Statistics of Additional Sectoral Explanatory Variables

NAICS Sector	Variables	Mean	SD	Min	Max
11	Births (t-1)	4.84	8.96	0	290
-	Inward Relocations (t-1)	.171	4.18	0	630
Agriculture, Forestry,	Total Entries (t-1)	5.01	10.5	0	866
Fishing,	Deaths (t-1)	4.35	8.09	0	291
and Hunting	Outward Relocations (t-1)	.171	4.32	0	695
	Total Exits (t-1)	4.52	9.74	0	867
	Sales Volume (t-1)	32427	127806	0	11548636
	Loc. Economies (t-1)	25.8	34.6	0	874
21	Births (t-1)	1.35	6.44	0	627
–	Inward Relocations (t-1)	.049	.818	0	140
Mining, Quarrying, and	Total Entries (t-1)	1.4	6.65	0	627
Oil and Gas Extraction	Deaths (t-1)	1.40	6.71	0	620
	Outward Relocations (t-1)	.049	.824	0	140
	Total Exits (t-1)	1.45	6.92	0	621
	Sales Volume (t-1)	45035	695120	0	79516648
	Loc. Economies (t-1)	6.82	32.5	0	1416
22	Births (t-1)	1.52	3.66	0	129
-	Inward Relocations (t-1)	.035	.299	0	26
Utilities	Total Entries (t-1)	1.56	3.72	0	129
	Deaths (t-1)	1.35	3.36	0	124
	Outward Relocations (t-1)	.035	.315	0	32
	Total Exits (t-1)	1.38	3.42	0	124
	Sales Volume (t-1)	97903	322095	0	20420646
	Loc. Economies (t-1)	7.89	12.7	1	420
23	Births (t-1)	60.7	219	0	12223
-	Inward Relocations (t-1)	2.56	46.2	0	4225
Construction	Total Entries (t-1)	63.3	231	0	12223
	Deaths (t-1)	58.7	211	0	13257
	Outward Relocations (t-1)	2.60	47.7	0	4520
	Total Exits (t-1)	61.3	223	0	13258
	Sales Volume (t-1)	456758	1642687	0	1.058e+08
	Loc. Economies (t-1)	289	812	0	26029
31-33	Births (t-1)	29.0	133	0	9539
-	Inward Relocations (t-1)	1.05	22.4	0	3159
Manufacturing	Total Entries (t-1)	30.5	141	0	12580
	Deaths (t-1)	30.9	141	0	10206
	Outward Relocations (t-1)	1.05	22.9	0	3575
	Total Exits (t-1)	32.0	149	0	11862
	Sales Volume (t-1)	986241	3946004	0	1.99e+08
	Loc. Economies (t-1)	148	570	1	27802

Table A28: Summary statistics (mean, standard deviation, minimum, and maximum) for lagged sector-specific explanatory variables across individual LIS sectors (NAICS 11, 21, 22, and 23) and the representative non-LIS sector (NAICS 31–33). The variables include lagged establishment dynamics (e.g., births, deaths, total entries and exits, and relocations by type) and key economic indicators (e.g., sales volume and localization economies). These variables capture intertemporal dependencies in business location outcomes, contributing to the robustness of econometric models. Values are based on county-level observations between 1998 and 2018.

Table A29: Summary Statistics of Sector Outcome Variables

NAICS Sector	Variables	Mean	SD	Min	Max
11	Births	4.95	9.08	0	290
-	Inward Relocations	.165	4.08	0	630
Agriculture, Forestry,	Intra-state Inward Relocations	.164	4.08	0	630
Fishing, and Hunting	Inter-state Inward Relocations	.001	.024	0	2
	Total Entries	5.12	10.6	0	866
	Deaths	4.49	8.13	0	291
	Outward Relocations	.165	4.22	0	695
	Intra-State Outward Relocations	.164	4.22	0	695
	Inter-State Outward Relocations	.001	.026	0	2
	Total Exits	4.66	9.71	0	867
21	Births	1.34	6.36	0	627
–	Inward Relocations	.048	.799	0	140
Mining, Quarrying, and Oil	Intra-state Inward Relocations	.043	.786	0	140
and Gas Extraction	Inter-state Inward Relocations	.005	.098	0	7
	Total Entries	1.39	6.57	0	627
	Deaths	1.39	6.66	0	620
	Outward Relocations	.048	.805	0	140
	Intra-State Outward Relocations	.043	.795	0	140
	Inter-State Outward Relocations	.005	.089	0	6
	Total Exits	1.44	6.86	0	621
22	Births	1.49	3.60	0	129
-	Inward Relocations	.034	.293	0	26
Utilities	Intra-state Inward Relocations	.033	.29	0	26
	Inter-state Inward Relocations	.001	.04	0	4
	Total Entries	1.52	3.65	0	129
	Deaths	1.38	3.40	0	124
	Outward Relocations	.034	.309	0	32
	Intra-State Outward Relocations	.033	.306	0	32
	Inter-State Outward Relocations	.001	.037	0	2
	Total Exits	1.42	3.45	0	124
23	Births	59.9	215	0	12223
-	Inward Relocations	2.52	45.1	0	4225
Construction	Intra-state Inward Relocations	2.50	45.1	0	4225
	Inter-state Inward Relocations	.012	.145	0	17
	Total Entries	62.4	228	0	12223
	Deaths	58.1	208	0	13257
	Outward Relocations	2.52	46.6	0	4520
	Intra-State Outward Relocations	2.50	46.6	0	4520
	Inter-State Outward Relocations	.012	.147	0	19
	Total Exits	60.6	220	0	13258
31-33	Births	29.0	131	0	9539
-	Inward Relocations	1.01	21.9	0	3159
Manufacturing	Intra-state Inward Relocations	.974	21.9	0	3158
	Inter-state Inward Relocations	.04	.306	0	35
	Total Entries	30	139	0	12580
	Deaths	30.2	138	0	10206
	Outward Relocations	1.01	22.4	0	3575
	Intra-State Outward Relocations	.974	22.4	0	3574

Table A29 Continued

NAICS Sector	Variables	Mean	SD	Min	Max
	Inter-State Outward Relocations	.04	.318	0	40
	Total Exits	31.3	146	0	11862

Table A29: Summary statistics (mean, standard deviation, minimum, and maximum) for sector-specific outcome variables across individual LIS sectors (NAICS 11, 21, 22, and 23) and the representative non-LIS sector (NAICS 31–33). Outcome variables include establishment births, deaths, total entries and exits, and relocations (categorized as intra-state and inter-state, inward and outward). Sales volume is also included as a key economic indicator. These statistics summarize the variation in business location dynamics at the county level between 1998 and 2018, providing foundational context for econometric analysis.

CHAPTER 2: NAVIGATING THE INFERNO

UNDERSTANDING THE ECONOMIC IMPACTS OF CALIFORNIA WILDFIRES: AN EMPIRICAL STUDY ON SECTOR-SPECIFIC INDUSTRIAL LOCATION CHOICES, ESTABLISHMENT PERFORMANCE AND LABOR MARKET OUTCOMES.

Abstract

Wildfires, escalating in frequency and intensity, pose significant economic challenges to industries and regional development. This study examines the impacts of wildfire frequency (annual fire count) and intensity (proportion of county area burned) on establishment dynamics, employment, and sales performance across land-intensive sectors (LIS)—including Agriculture, Mining, Utilities, and Construction—and the Manufacturing sector in California from 1998 to 2018. Using establishment-level data aggregated at the county level and wildfire exposure metrics, we employ a Poisson Pseudo-Maximum Likelihood (PPML) regression model with high-dimensional fixed effects to estimate the nonlinear effects of wildfire risks.

The results reveal that wildfire frequency increases establishment deaths (+0.94%) and outward relocations (+14%), destabilizing local economies. Wildfire intensity suppresses establishment births (-1.75%) but boosts sales performance in recovery-focused sectors like Construction (+2.01%) and Utilities (+1.90%). Sectoral heterogeneity is evident: Agriculture experiences substantial declines in employment (-2.74%) and births due to its reliance on stable land conditions, while Manufacturing demonstrates resilience by leveraging recovery demand, despite production disruptions.

These findings underscore the dual nature of wildfire impacts, exposing vulnerabilities in land-dependent sectors while highlighting opportunities for recovery-oriented industries. This research advances understanding in disaster economics, industrial organization, and climate adaptation, offering actionable insights for enhancing economic resilience and supporting policy design in wildfire-prone regions.

2.1 Introduction

The economic consequences of natural disasters have garnered increasing attention due to climate change, which has intensified their frequency, scale, and unpredictability (Deryugina et al., 2018). While extensive research has explored the impacts of hurricanes, floods, and earthquakes on business dynamics and labor markets (Cavallo & Noy, 2010; Kousky, 2014), the economic implications of wildfires remain underexplored. This gap is particularly critical as wildfires have become more frequent and severe, with California emerging as a global hotspot. Understanding how wildfires reshape local economies is essential for designing strategies to enhance resilience and adaptive capacity in vulnerable regions.

This study investigates the economic impacts of wildfires in California from 1998 to 2018, analyzing how wildfire frequency (measured as annual fire count) and intensity (measured as the proportion of county land area burned by wildfires) affect establishment dynamics, employment, and sales performance. By incorporating both temporal and spatial dimensions of wildfire risks, the analysis provides a nuanced understanding of how recurring and severe wildfires disrupt local economies and catalyze sector-specific adaptation strategies.

The study focuses on Land-Intensive Sectors (LIS), including Agriculture, Mining, Utilities, and Construction, alongside Manufacturing as a representative non-LIS sector. These sectors exhibit varying degrees of dependency on land, operational flexibility, and exposure to wildfire risks, making them ideal for analyzing the heterogeneity of wildfire impacts. Six key economic outcomes are assessed: establishment births, deaths, inward relocations, outward relocations, employment, and sales performance. These outcomes capture the broad spectrum of wildfire-induced disruptions, from business creation and closures to labor market stability and recovery-driven economic activity.

To achieve these objectives, this research utilizes a novel dataset combining wildfire metrics from the California Department of Forestry and Fire Protection (CAL FIRE) with socio-economic data from the U.S. Census Bureau and Bureau of Labor Statistics (BLS). Proprietary establishment-level data from Data Axle's historical business dataset enhances the granularity of the analysis. The Poisson Pseudo-Maximum Likelihood (PPML) regression model with high-dimensional fixed effects (HDFE) is employed to account for unobserved heterogeneity, ensuring robust and interpretable estimates of the economic impacts of wildfire frequency and intensity.

We define the marginal effects as a 100-fire increase in wildfire frequency and a 1% increase in county area burned. The findings reveal distinct and measurable economic impacts. For the aggregate LIS, a 100-fire increase raises establishment deaths by 0.94% and outward relocations by 14.0%, demonstrating the destabilizing effects of recurring wildfires. Simultaneously, a 1% increase in burned area reduces establishment births by 0.84% but boosts sales performance by 2.26%, driven by post-disaster reconstruction demand. Sectoral analyses highlight Agriculture's acute vulnerability, with a 1% increase in burned area reducing births by 1.75% and a 100-fire increase cutting employment by 2.74%. In contrast, Utilities and Construction exhibit resilience, benefiting from recovery-driven demand. Wildfire frequency raises Utilities' employment by 4.09% and sales by 7.31%, while intensity increases sales in Utilities (+1.90%) and Construction (+2.01%). Manufacturing, the sole non-LIS sector analyzed, reflects resilience in sales performance (+1.47% under wildfire intensity) but faces challenges such as employment declines (-0.34%).

These results underscore the dual nature of wildfires: while recurring and severe wildfires disrupt business continuity and labor markets, they also create short-term recovery-driven opportunities in certain sectors. The pronounced vulnerability of Agriculture highlights the need for targeted climate adaptation policies, including land restoration and fire-resilient farming practices. Conversely, the resilience demonstrated by Utilities and Construction underscores their critical roles in stabilizing regional economies after wildfires.

This study makes three major contributions to the literature. First, it advances disaster economics by isolating the differential impacts of wildfire frequency and intensity, capturing both their destructive and recovery-driven dimensions. Second, it enhances understanding of sectoral heterogeneity by linking resource dependencies, operational flexibility, and exposure to wildfire risks to sector-specific responses. Third, by including Manufacturing as a non-LIS comparison, the study broadens the scope of wildfire economics, demonstrating how less land-reliant sectors adapt to and recover from wildfire disruptions. Together, these contributions provide actionable insights for policymakers, including prioritizing investments in fire-resistant infrastructure, supporting recovery-focused sectors, and fostering climate resilience in wildfire-prone economies.

2.1.1 Research Objectives, Research Questions, and Hypotheses

2.1.1.1 Research Objectives

The increasing frequency and intensity of wildfires in California present significant challenges for regional economies, particularly for land-intensive sectors (LIS) such as Agriculture (NAICS 11), Mining (NAICS 21), Utilities (NAICS 22), and Construction (NAICS 23). These sectors are heavily reliant on natural resources and physical land use, making them highly vulnerable to wildfire-induced disruptions. Together, these industries constitute the aggregate LIS, which is analyzed as a composite grouping to capture overarching trends, as well as in their individual sectors to uncover subsector-specific dynamics.

In addition, this study includes Manufacturing (NAICS 31–33) as the non-LIS representative sector. Manufacturing, while less dependent on land, is critical for supply chains, labor-intensive production processes, and post-disaster recovery, providing a counterpoint to LIS in terms of resilience and adaptability to wildfire risks.

This study investigates the impacts of wildfire frequency (measured as the annual fire count) and intensity (measured as the annual proportion of county land area burned) on six key economic outcomes:

Establishment dynamics: Births, deaths, inward relocations, and outward relocations.

Employment levels: Labor market stability and job losses.

Sales performance: Business revenue and market activity.

By focusing on the aggregate LIS, its individual subsectors, and Manufacturing, this study captures a comprehensive view of how wildfires reshape business activity, labor market dynamics, and revenue streams across vulnerable and resilient industries. These insights aim to inform evidence-based policies to mitigate economic risks, stabilize at-risk industries, and foster regional resilience.

2.1.1.2 Research Questions

The following two research questions guide the analysis:

RQ1: Wildfire Impacts on Economic Outcomes: How do wildfire frequency and intensity affect establishment births, deaths, inward relocations, outward relocations, employment, and sales performance in the Aggregate LIS?

RQ2: Sectoral Differences: How do wildfire frequency and intensity affect these six economic outcomes across the individual LIS subsectors (NAICS 11, 21, 22, and 23), and the non-LIS sector (NAICS 31–33)?

2.1.1.3 Hypotheses

H1: Wildfire frequency and intensity negatively affect establishment births and positively affect establishment deaths.

Rationale: Wildfires create uncertainty, infrastructure damage, and resource loss, deterring new business formation while increasing closures (Moritz et al., 2014; Kunreuther & Pauly, 2019). This is particularly severe for LIS subsectors like Agriculture, where land degradation directly affects productivity, and Mining, where operational disruptions are costly to resolve. In contrast, Manufacturing may face indirect disruptions, such as supply chain bottlenecks, rather than direct losses, potentially reducing the magnitude of these impacts.

H2: Wildfire frequency and intensity positively influence establishment outward relocations and negatively affect inward relocations.

Rationale: Businesses in wildfire-prone areas incur increased costs (e.g., insurance premiums, labor shortages) and heightened risks, prompting relocations to safer regions (Hsiang et al., 2017). This effect is magnified for sectors like Construction, where proximity to affected areas is essential, and Utilities, which may relocate assets to ensure operational continuity. Manufacturing, with more centralized operations, may experience lower relocation rates but still face regional disruptions.

H3: Wildfire frequency and intensity reduce employment levels, particularly in LIS sectors.

Rationale: Employment losses result from temporary shutdowns, worker displacement, and longer-term closures (Bayham et al., 2022). The aggregate LIS experiences pronounced effects, as outdoor labor in Agriculture and Construction is highly exposed to fire risks. Utilities may show resilience due to their role in recovery, while Manufacturing's employment impacts may be mitigated by its ability to adopt remote work or automation.

H4: Wildfire intensity negatively affects sales performance across sectors, particularly in LIS.

Rationale: Wildfires disrupt sales through supply chain interruptions, damaged infrastructure, and reduced consumer demand (Prestemon et al., 2020). Agriculture and Forestry are acutely affected by destroyed resources, while Construction may see temporary gains during recovery phases. Manufacturing’s sales impacts may be mitigated by diversified markets and increased demand for recovery-related goods.

H5: The impacts of wildfire frequency and intensity on establishment dynamics, employment, and sales performance vary across the aggregate LIS, its individual subsectors, and Manufacturing.

Rationale: Resource reliance, exposure to wildfire risks, and operational flexibility drive sectoral differences. Agriculture and Mining exhibit higher vulnerability due to direct dependence on land, while Utilities and Construction benefit from increased post-disaster demand. Manufacturing demonstrates adaptability through diversification and supply chain resilience (Calkins et al., 2021; Deryugina et al., 2018).

This section outlines the research objectives, questions, and hypotheses that underpin the study's analysis of wildfire-induced economic impacts. By integrating the aggregate LIS, its individual subsectors, and Manufacturing, the study offers a detailed examination of sectoral heterogeneity in vulnerability and resilience. These findings contribute to the literature on disaster economics, industrial organization, and regional resilience, while providing actionable insights for policymakers seeking to stabilize at-risk industries and foster long-term economic recovery.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature, situating this study within the broader fields of disaster economics, industrial organization, and regional economic resilience. Section 3 describes the data sources and presents the descriptive statistics, highlighting the key metrics and explanatory variables used in the analysis. Section 4 outlines the methodological framework, detailing the Poisson Pseudo-Maximum Likelihood (PPML) regression approach and the inclusion of high-dimensional fixed effects to address endogeneity concerns. Section 5 presents the results and interpretation, analysing the impacts of wildfire frequency and intensity on establishment dynamics, employment, and sales performance across sectors. Section 6 discusses the findings, drawing out their theoretical implications and offering actionable policy recommendations. Section 7 concludes with a summary of the study's contributions and suggestions for future research, followed by the comprehensive reference list in Section 8.

2.2 Literature Review

The economic consequences of natural disasters, particularly wildfires, have been a significant focus of empirical and theoretical research, with studies exploring impacts on municipal finances, labor markets, sectoral dynamics, and regional economies. This study integrates these themes to bridge gaps in understanding the specific economic consequences of wildfires on business establishments and sectoral performance.

Theoretical foundations emphasize the dual nature of disasters as both disruptive and transformational events. Hallegatte (2014) introduces resilience pathways, demonstrating how disaster-affected regions adjust their recovery trajectories. Albala-Bertrand (1993) posits that disasters create opportunities for economic renewal, particularly in sectors aligned with recovery and reconstruction. Boustan et al. (2020), leveraging a century of disaster data, find that severe events reduce local productivity and labor demand, leading to out-migration and declining property values, particularly when disasters convey heightened risk information. These theoretical insights underscore the localized and heterogeneous nature of disaster impacts.

Empirical studies provide robust evidence of the economic effects of wildfires across multiple domains. Liao and Kousky (2022), using a difference-in-differences (DiD) framework and municipal finance data from California, identify that wildfires result in increased property tax revenues due to reassessment laws, alongside elevated spending on public safety and community development. However, these benefits are outweighed by net fiscal deficits, challenging the fiscal resilience of municipalities. Nielsen-Pincus et al. (2014), focusing on the Western U.S., show that wildfires temporarily boost employment during suppression efforts but cause significant disruptions in leisure, hospitality, and natural resource sectors, with lingering adverse effects on local employment for up to two years.

Sector-specific research further elaborates on the economic heterogeneity of wildfire impacts. Borgschulte et al. (2019) employ satellite-derived wildfire smoke data linked with labor market outcomes to reveal that wildfire smoke exposure reduces annual labor income by 1.26%, lowers labor force participation, and increases Social Security claims. These findings highlight the spillover effects of wildfires beyond immediate zones of destruction. Similarly, Meier et al. (2023), focusing on Southern Europe, use satellite data on burned areas and Eurostat economic indicators to quantify wildfire-induced GDP losses ranging from €13–21 billion annually. They document negative employment effects in retail and tourism sectors but offsetting gains in insurance and real estate, emphasizing sectoral vulnerability and adaptation.

Tourism and outdoor recreation, as highly wildfire-sensitive sectors, have received detailed attention. Gellman et al. (2022), analyzing campground visitation data in the Western U.S., estimate that wildfires and smoke reduce visitor-days by up to 1 million annually. They find that while smoke does not significantly deter visitors from public lands, it imposes welfare losses through health risks. Otrachshenko and Nunes (2021), focusing on Portugal, demonstrate that increased wildfire activity substantially reduces both domestic and inbound tourist arrivals, with projected annual costs to tourism rising fourfold by 2050 under climate change scenarios. These findings illustrate the compounded economic risks posed by wildfires to regions reliant on tourism.

The indirect effects of wildfires on supply chains and regional economies have been explored in studies like Wang et al. (2021). Using input-output models, they estimate that California's 2018 wildfires caused $148.5 billion in economic losses, of which 59% were indirect, stemming from supply chain disruptions and regional interdependencies. Their study emphasizes the far-reaching economic footprint of wildfires, extending well beyond the directly affected areas. Jia et al. (2022) provide complementary insights into disaster-induced risk effects, showing that increased flood risk—analogous to wildfire risks—reduces firm entry and employment, reshaping local economic geography.

Lastly, Alves et al. (2022) investigate the resilience of businesses to disasters through the lens of subsidized credit policies. Their study on the 2011 Rio de Janeiro landslides demonstrates that while credit programs prevented business closures, they were less effective in preserving employment, highlighting the limitations of financial interventions in disaster recovery. Similarly, Liao and Kousky (2022) argue that wildfire impacts on municipal budgets may discourage local investments in risk mitigation, given the asymmetric burden-sharing between local and federal governments in wildfire management.

This study makes key contributions to these strands of literature. By focusing on wildfire-specific impacts, it addresses gaps in generalized disaster studies that often obscure the unique economic dynamics of wildfires. Furthermore, it extends the understanding of sectoral heterogeneity, particularly in land-intensive sectors. Methodologically, the use of advanced econometric techniques, such as PPML, enhances the precision of impact estimates, aligning with recent advancements in disaster economics research. These findings contribute actionable insights for policymakers to enhance resilience and mitigate the economic fallout of wildfires.

2.3 Data and descriptive statistics

2.3.1 Dependent variable: Establishment Data

Analysing business location decisions requires granular establishment-level data. While public datasets such as the County Business Patterns (CBP), Quarterly Census of Employment and Wages (QCEW), and Bureau of Labor Statistics (BLS) offer valuable insights, they often suppress data to protect confidentiality, particularly in sparsely populated counties (Jarmin & Miranda, 2002; Abowd & Vilhuber, 2008). This suppression limits observations on establishment entries and exits, presenting challenges for county-level analyses.

To address these issues, this study utilizes the proprietary Data Axle historical business dataset (formerly Infogroup). This dataset provides unsuppressed, annual establishment-level data for U.S. businesses from 1997 to 2019, including geolocation, employment count, sales volume, and NAICS sector classifications. Each establishment is uniquely identified with an American Business Information (ABI) code, and tracked annually.

Using this dataset, county-level, sector-specific measures of the outcome variables were constructed for California’s 58 counties over the 1998–2018 period. This period aligns with available socio-economic, demographic, and environmental data. The analysis focuses on

Agriculture, Forestry, Fishing and Hunting (NAICS 11); Mining, Quarrying, and Oil and Gas Extraction (NAICS 21); Utilities (NAICS 22); and Construction (NAICS 23), collectively forming the aggregate Land-Intensive Sector (LIS). Additionally, Manufacturing (NAICS 31–33) is included as the representative non-LIS in the analysis. Data from 1997 and 2019 were excluded due to missing prior-year (1996) and subsequent-year (2020) data needed to compute establishment entries and exits for 1997 and 2019, respectively.

2.3.1.1 Definition of Outcome Variables

Following conventions in the industrial location literature (Neumark et al., 2005), the dependent variables were defined as follows:

- **Births**: An establishment is present in a California county C in year T but absent in any California county in $T - 1$.
- **Inward Relocations**: An establishment is present in county C in T but located in a different California county in $T - 1$.
- **Deaths**: An establishment is present in county C in $T - 1$ but absent in any California county in T.
- **Outward Relocations**: An establishment is present in county C in $T - 1$ but located in a different California county in T.
- **Employment**: The total number of employees within a sector in a California county.
- **Sales Volume**: The total sales volume for a specific sector in a California county.

County-level aggregates of these six variables were computed annually for each of the five NAICS sectors, as well as for the aggregate LIS sector which is composed of establishments from NAICS 11, 21, 22, 23. Additional outcome variables include:

2.3.1.2 Summary Statistics of Dependent Variables

Table A30 provides summary statistics for the dependent variables across five key sectors (NAICS 11, 21, 22, 23, and 31-33), aggregated at the county-year level. The dataset covers 58 California counties over a 21-year period (1998–2018), offering a comprehensive view of sectoral economic activity, including sales volume, employment, and establishment dynamics (births, deaths, inward relocations, and outward relocations). Observations with zero sales volume or employees reflect establishments that were temporarily closed, inactive, or had incomplete data. These are included to account for the full range of economic outcomes, capturing downturns or inactivity relevant to understanding sectoral resilience.

In regards to NAICS 11, Agriculture shows modest levels of average sales volume ($288,897 per county-year), with relatively low employment (1,833 employees on average). Establishment dynamics are steady, with moderate levels of births and relocations, reflecting the sector's low mobility and dependence on regional natural resources. In regards to NAICS 21, Mining has the lowest average sales volume ($125,771) and employment (305 employees), indicative of its niche focus and high capital intensity. Establishment births and relocations are infrequent, reflecting the sector’s static nature due to high entry costs and location-specific resource constraints. In regards to NAICS 22, Utilities report the highest mean sales volume ($340,319), underscoring their role as critical infrastructure providers. Employment levels are moderate (813 employees on average), and establishment relocations are rare, consistent with the sector's infrastructure-driven stability.

In regards to NAICS 23, Construction shows high sales volume ($2,596,628) and employment (12,400 employees on average), driven by its pivotal role in economic development and disaster recovery. Construction demonstrates the highest establishment births (338 per county-year) and relocation activity, reflecting its responsiveness to economic cycles and post-wildfire rebuilding efforts. In regards to NAICS 31-33, Manufacturing ranks second in sales volume ($4,809,024) and leads in employment (23,981 employees on average), emphasizing its importance to California’s economy. The sector also shows notable relocation activity, driven by supply chain demands and competitive regional dynamics.

Through the comparative lenses, we find that Utilities and Manufacturing dominate sales, reflecting their substantial economic contributions, while Agriculture and Mining represent smaller-scale sectors. Manufacturing and Construction lead in workforce size, whereas Agriculture and Mining show smaller, more localized employment structures. Construction exhibits the most dynamic establishment activity, possibly reflecting its flexibility and responsiveness to demand surges, particularly during recovery periods. In contrast, Utilities and Mining show greater stability, probably due to fixed infrastructure and sector-specific constraints.

These summary statistics reveal significant sectoral variations in economic activity, workforce composition, and establishment dynamics, which are critical for understanding sectoral vulnerabilities and resilience to wildfire risks. For instance, sectors like Construction and

Manufacturing, with high establishment mobility, may be more adaptable to disruptions, while those with fixed infrastructure, such as Utilities and Mining, may face greater challenges. These insights are essential for designing targeted policy interventions to enhance resilience and mitigate economic losses in wildfire-prone regions.

2.3.2 Control Variables

To address potential confounding factors influencing establishment location decisions, labor market outcomes, and establishment performance, a comprehensive set of control variables was incorporated at the county level. These include wildfire-related metrics, socio-economic and demographic indicators, and environmental variables, drawing on methodologies established in prior research (e.g., List, 2001; Greenstone, 2002; Bollinger et al., 2018; Kim et al., 2019; Moretti, 2011). **Table A31** summarizes the descriptive statistics for these control variables, measured annually at the county level over the 1998–2018 period.

2.3.2.1 Wildfire Data

Historical wildfire data was sourced from the California Department of Forestry and Fire Protection (CAL FIRE), and cross-checked it with the National Interagency Fire Center (NIFC), and the US Geological Survey (USGS). Our compiled Wildfire dataset included detailed information on each wildfire, such as unique identifiers, reporting agencies, fire names, fire years, causes (e.g., natural or human-induced), discovery and suppression dates, locations, and acres burned (CalFire, 2021; NIFC, 2021; USGS, 2021).

For the purpose of our analysis, we used ARCGIS Pro to construct our two county-level wildfire variables which served as measures for the frequency and intensity of wildfires. Firstly, the annual count of wildfires within each county and secondly the annual total proportion of county land area burned by wildfires. For descriptive purposes, we present the trends and patterns in wildfire-related variables for the 1998-2018 period, as shown in **Figure A13** and **Figure A14**.

Figure A13 illustrates the geographic distribution of establishments (top panel) and wildfires (bottom panel) across California from 1997 to 2018, color-coded by year. This visualization provides a clear depiction of the spatial and temporal dynamics of economic activity and wildfire exposure during the study period.

Geographic Distribution of Establishments: Establishments are densely clustered in major urban centers such as the Bay Area, Los Angeles, and San Diego, reflecting California's urban-centric economy. Over time, there is evidence of gradual expansion toward inland regions, driven by urban sprawl, regional diversification, and economic growth. Despite this outward diffusion, urban clusters remain dominant, underscoring the importance of market accessibility, infrastructure, and labor availability in shaping business location decisions.

Geographic Distribution of Wildfires: Wildfires are widespread, with higher concentrations in northern and central California, particularly in forested and mountainous regions like the Sierra Nevada and coastal ranges. Their persistent presence throughout the study period reflects the chronic nature of wildfire risks, driven by climate variability, vegetation accumulation, and land management practices.

Intersection of Economic Activity and Wildfire Risk: The proximity of establishments to wildfire-prone regions highlights the intersection of economic vulnerability and environmental risk. Many businesses are located near wildfire hotspots, particularly in areas with dense vegetation and complex topography. This spatial overlap suggests that businesses in these regions face elevated risks of disruption, property damage, and operational challenges, influencing location and investment decisions.

Possible Implications for Economic and Policy Outcomes: The spatial patterns observed have significant implications for economic outcomes. Businesses in high-risk areas are more likely to experience negative impacts such as increased costs, closures, or relocations, directly affecting local economies. At the same time, recovery-focused sectors, such as construction, may experience temporary benefits from post-wildfire rebuilding efforts. These insights underscore the need for strategic interventions, such as enhancing fire management, investing in fire-resistant infrastructure, and supporting vulnerable sectors, to safeguard local economies and foster long-term resilience.

Figure A14 illustrates the annual total acreage burned by wildfires in California from 1998 to 2018, highlighting significant variability and a clear upward trend in recent years. The peaks in 2008 and 2018 are particularly notable. In 2008, widespread wildfires in Northern California, exacerbated by lightning storms and dry conditions, drove a dramatic increase in acreage burned. The 2018 peak, the highest in the study period, reflects catastrophic events like the Camp Fire and Woolsey Fire, which caused substantial damage near urban areas.

The rising trend in total acreage burned over time aligns with evidence linking climate change to intensifying wildfire activity through higher temperatures, prolonged droughts, and reduced humidity. Although annual fluctuations occur due to varying weather patterns, fuel availability, and fire suppression efforts, the growing severity of wildfires underscores their potential to disrupt local economies. This trend is central to the study's focus on quantifying the economic impacts of wildfires, particularly on business dynamics, employment, and regional economic performance.

2.3.2.2 Wildfire Variables (Frequency and Intensity)

We employ two core wildfire-related variables: Fires (1000s) (Count) (t-1) and % County Area Burned (t-1). Fire count captures the frequency of wildfire events within a county, while burned area measures their intensity and scale by assessing the proportion of land impacted. Together, these variables provide a nuanced understanding of wildfire disruptions, enabling an analysis of how both frequent smaller fires and large, destructive events contribute to economic impacts (Otrachshenko & Nunes, 2022).

Frequent fires can lead to cumulative effects, such as increased suppression costs and diminished investment confidence, while larger fires that burn significant portions of land may result in immediate, widespread economic losses, including damage to infrastructure, disruptions to labor markets, and reduced property values. By combining these measures, the study evaluates the dual dimensions of wildfire activity—frequency and severity—and their implications for regional economic resilience and business dynamics.

Fires (1000s) (Count) (t-1): This variable measures the number of wildfires in a county during the preceding year, scaled by 1,000. Referring to **Table A31**, the mean of 0.161 indicates an average annual wildfire count of 161 fires, with a maximum of 7,902 fires in the most affected counties. The standard deviation of 0.433 highlights significant variation in wildfire frequency across counties. Frequent wildfires, even if individually small, can cumulatively degrade air quality, increase suppression costs, and diminish regional investment confidence. However, frequency alone does not fully capture the economic impacts of wildfires, necessitating additional measures to account for the severity of these events.

% County Area Burned (t-1): This variable measures the percentage of a county's land burned in the prior year, scaled by 100, reflecting the severity of wildfire events. Referring to **Table A31**, the mean of 0.007 (0.7%) and the maximum of 0.199 (19.9%) demonstrate substantial variability in fire severity, while the standard deviation of 0.02 (2%) highlights the localized nature of large-scale fire impacts. This measure is particularly useful for capturing the lasting disruptions caused by significant fires, such as reduced property values, delayed business openings, increased insurance costs, and prolonged recovery efforts. Large fires that burn substantial portions of a county's land area often have far-reaching economic and social consequences, particularly in rural and land-intensive regions.

2.3.2.3 Other Environmental Variables

% $\boldsymbol{CPAD}$ $(\mathbf{100}\boldsymbol{s})$ $(\boldsymbol{t}-\mathbf{1})$**:** This variable captures the percentage of land area under Protected Area Designation (PAD), under all GAP status codes, for each California county in the previous year, scaled by 100. Shapefiles were downloaded from the California Protected Areas Database (CPAD) website. The variable was constructed using GIS tools in ArcGIS Pro, summing protected area acreage for each county annually and dividing it by the county's total land area. The inclusion of this conservation variable aligns with prior research in environmental federalism and land conservation, as validated in the first dissertation chapter.

To address anomalies in CPAD data, where overlaps led to inflated percentages, counties with PAD coverage exceeding 88% were excluded from the analysis. This adjustment affected less than 1% of the dataset, and sensitivity analyses confirmed that these exclusions did not affect the statistical robustness of the results. Supplemental data was provided by Professor Maria de Santos from the University of Zurich to partially fill in missing designation dates for some PADs within California, improving temporal accuracy. Remaining CPADs without recorded designation dates were assumed to have been established before the study period, based on consultations with CPAD representatives.

While the PAD variable was included in both linear and quadratic forms in the first and third dissertation chapters, where the analysis spanned all counties in the conterminous United States, diagnostic tests specific to the California-focused analysis in this chapter indicated that the quadratic form did not add explanatory power. Model selection criteria, including goodness-of-fit measures and regression diagnostics, consistently demonstrated that the linear form alone sufficiently captured the relationship between protected areas and the dependent variables. Consequently, only the linear form of % CPAD is included in this analysis to maintain model parsimony while reflecting the geographic specificity of the data.

This metric serves as a core environmental control, reflecting conservation intensity. Referring to **Table A31**, the mean percentage of protected land area is 42.9%, with a standard deviation of 23.4%, ranging from a minimum of 1.2% to a maximum of 87.0%. These figures underscore significant variability in conservation coverage across California counties, highlighting the diverse environmental profiles that shape local economic and land-use dynamics.

Non-Attainment Status: Air quality indicators based on the National Ambient Air Quality Standards (NAAQS) capture regulatory stringency across California counties. These were downloaded from on EPA's Greenbook website. After careful tests (VIF, stepwise, and correlation tests), we retained county attainment status data only on two criteria pollutants, namely Ozone (O_3) and Particulate Matter (PM). Approximately 59.4% of counties meet O_3 attainment standards, while 44.8% meet PM standards. Counties in non-attainment face stricter regulatory oversight, which may influence business operations and location decisions by increasing compliance costs. We included the prior year's county attainment status vis a vis these two criteria pollutants in our model.

2.3.2.4 Socio-Economic and Demographic Variables

The socio-economic controls were sourced from the County Business Patterns (CBP) and American Community Survey (ACS), reflecting local economic conditions and population characteristics.

Housing Price Index (100s): The mean housing price index of 6.324 (scaled by 100) reflects significant variation in property values, ranging from 1 to 20.849. Higher values often indicate economic vitality but may also suggest greater vulnerability to declines after wildfires.

Poverty Rate and Median Household Income (100s): The mean poverty rate is 14.7% (0.147), while median household income averages $51,000 (0.51, scaled by 100s). These indicators capture economic resilience and vulnerability, influencing how communities cope with wildfire disruptions and recovery efforts.

Population Density (100s): With a mean of 0.11 (scaled by 100s), this variable reflects the diverse population distribution across California, spanning dense urban centers and sparsely populated rural areas. Urban areas often see higher fire ignition rates due to human activity, while rural regions are more exposed to large-scale fires.

2.3.2.5 Weather-Climate Controls

This study incorporates precipitation and temperature as critical weather-related controls to analyse how broader climatic variability influences wildfire dynamics, establishment location decisions, labor markets, and sectoral performance. These variables capture both direct and indirect pathways through which environmental conditions shape economic outcomes, complementing the primary wildfire variables—Fire Count and Proportion of County Land Burned.

Precipitation plays a dual and paradoxical role in wildfire dynamics and economic systems. Higher rainfall reduces short-term fire risks by increasing soil and fuel moisture, but it also fosters vegetation growth, heightening fuel loads during subsequent dry periods. This cyclic vulnerability, as highlighted by Abatzoglou and Williams (2016), exacerbates wildfire risks over time. Precipitation also directly affects agricultural productivity, water availability for hydropower, and the viability of water-dependent industries (Lobell et al., 2011). For example, insufficient rainfall can impair businesses reliant on agriculture and forestry, while excess precipitation may cause flooding and logistical disruptions. Across California counties, annual precipitation varies significantly, with a mean of 27.3 inches and a range of 0.62 to 112 inches, reflecting substantial geographic variability in exposure.

Temperature similarly influences wildfire and economic outcomes. Higher temperatures amplify wildfire risks by drying vegetation, reducing soil moisture, and creating conditions conducive to ignition and rapid-fire spread. Beyond wildfire dynamics, temperature impacts labor productivity, particularly in outdoor sectors such as agriculture and construction, as noted by Deschênes and Greenstone (2011). Furthermore, Burke et al. (2015) find that prolonged high temperatures negatively affect crop yields and raise operational costs for temperature-sensitive industries. The annual mean temperature across California counties is 57.8°F, with a range from 41.6°F to 76.5°F, highlighting the varied climatic challenges faced by different regions. Incorporating precipitation and temperature as control variables ensures that broader climatic influences on economic outcomes are accounted for, minimizing potential confounding effects when analysing the economic impacts of wildfire frequency and intensity. The inclusion of these variables complements the explanatory power of wildfire metrics while reducing the risk of multicollinearity.

Trends in precipitation and temperature, as shown in **Figure A15**, reveal their inverse relationship over the study period (1998–2018), with critical climatic events such as severe droughts in 2014 and 2018 coinciding with heightened wildfire activity. Wetter years like 2010 mitigated wildfire risks but increased vulnerabilities for flood-sensitive sectors. Conversely, drier, hotter years, such as 2018, exacerbated wildfire activity and its associated economic disruptions.

By including precipitation and temperature in the analysis, this study provides a more comprehensive understanding of how climatic variability interacts with wildfire behaviour and economic outcomes across California’s diverse sectors. These variables enable the isolation of wildfire impacts on outcomes such as establishment births, deaths, relocations, employment, and sales volume, while accounting for broader environmental influences.

2.3.2.6 Additional Sector-Specific Controls

To improve the explanatory power of the regression models, additional variables were included to account for localized economic dynamics and establishment interactions. Across all location outcome variables—births, inward relocations, deaths, and outward relocations—a measure of localization economies, represented by the number of establishments in the prior period, was added. This variable captures the influence of agglomeration economies, where a higher density of businesses fosters knowledge spillovers, supply chain efficiencies, and labor pooling, ultimately affecting establishment decisions (Glaeser et al., 1992; Henderson, 1997).

For entry-type outcomes, such as births and inward relocations, the number of prior-year establishment exits was included as an explanatory variable. Prior exits can signal opportunities for new entrants by freeing resources like market share, infrastructure, and labor, as shown by Schumpeter's (1942) "creative destruction" hypothesis and empirical evidence from Meltzer et al. (2020). Conversely, for exit-type outcomes, including deaths and outward relocations, the number of prior-year establishment entries was added to account for potential market congestion and competitive displacement. Carlton (1983) and Dunne et al. (1989) document how increased competition from new entrants can destabilize less resilient firms, leading to exits or relocations.

These variables ensure the models capture dynamic relationships within regional business ecosystems, allowing for a more precise analysis of how external factors, such as wildfire activity and climatic conditions, influence establishment outcomes.

2.3.3 Conclusion of the Data and Descriptive Section

This study's descriptive analysis highlights the escalating severity of wildfire activity in California and its profound economic implications. By integrating wildfire frequency and intensity measures alongside socio-economic and weather-related controls, our dataset aims to provide a nuanced understanding of how these variables influence economic outcomes, in the aggregate LIS, its constituent sectors, and the non-LIS. These insights lay the groundwork for the econometric modelling detailed in the next section, where a Pseudo-Poisson Maximum Likelihood framework with high-dimensional fixed effects is employed to quantify the economic impacts of wildfires.

2.4 Methodology

2.4.1 Conceptual Model

Wildfires in California act as external shocks, disrupting businesses, workers, and economic systems. To understand how wildfire frequency (annual fire counts) and intensity (proportion of county area burned) shape economic outcomes, this study employs a conceptual model grounded in economic and disaster resilience theory. The model provides a structured framework to analyze the pathways through which wildfires affect establishment dynamics, employment, and sales performance.

Wildfire frequency captures the recurrence of fire events, while intensity reflects the severity and scale of damage. These variables represent external disturbances that directly and indirectly impact businesses by altering operational costs, risk perceptions, and decision-making processes (Helmers et al., 2020; Keeley & Syphard, 2016). Frequent or severe wildfires often deter new investments, encourage closures, and prompt relocations, particularly in sectors heavily reliant on land or natural resources (Prestemon et al., 2019). Businesses evaluate wildfire risks in the context of market accessibility, labor availability, infrastructure quality, and resource dependencies, creating sector-specific patterns of vulnerability and resilience.

This study focuses on six key outcomes to capture wildfire-induced disruptions across economic systems:

Establishment Dynamics: Births, deaths, inward relocations, and outward relocations.

Employment Levels: A measure of workforce participation in affected regions.

Sales Volume: A proxy for business performance and regional economic vitality.

These outcomes are examined at the aggregate LIS level and across its constituent subsectors—Agriculture, Mining, Utilities, and Construction—along with Manufacturing as a representative non-LIS sector. The model explicitly accounts for business mobility, capturing adaptive strategies in mobile sectors like Construction through relocation metrics, while identifying prolonged disruptions in less mobile, resource-dependent sectors like Agriculture.

The mediating role of financial resources, local policy responses, and infrastructure conditions shapes how wildfires affect these outcomes. For instance, businesses with greater mobility or access to recovery funding may adapt by reallocating resources to safer locations, while fixed-resource enterprises, such as farms, may endure prolonged economic losses (Calkins et al., 2021; Radeloff et al., 2018).

By linking wildfire impacts to establishment dynamics, labor markets, and sales performance, this model enables the identification of vulnerabilities and resilience mechanisms within and across sectors. Understanding these dynamics is essential for designing targeted interventions to stabilize regional economies, support recovery efforts, and enhance resilience in wildfire-prone areas.

2.4.2 Model Specification

Analyzing the economic impacts of wildfires requires a model that accommodates nonlinearity, count data characteristics, and zero-inflated distributions. The Pseudo-Poisson Maximum Likelihood (PPML) regression model with high-dimensional fixed effects (HDFE) addresses these challenges effectively. The model is specified as:

$$Y_{its} = \exp\left(\beta_0 + \beta_1 Fire\ Count_{i,t-1} + \beta_2 Burned\ Areas_{i,t-1} + \beta_3 Z_{is,t-1} + \sum_{k=1}^{N} \beta_k X_{kit} + \alpha_i + \lambda_t + \gamma_s\right) + \epsilon_{it}$$

Where:

- Y_{its}: Economic outcome (e.g., Establishment Births, Deaths, Inward Relocations, Outward Relocations, Employment, Sales Volume) in sector s, county i, year t.
- $Fire\ Count_{i,t-1}$: Number of wildfires in prior year.
- $Burned\ Areas_{i,t-1}$: Proportion of county area burned by wildfires in prior year.
- $\alpha_i, \lambda_t, \gamma_s$: Fixed effects controlling for county, year, and sector-specific unobserved heterogeneity.
- X_{kit}: Vector of socio-economic explanatory variables.

- $Z_{is,t-1}$: Lagged sector-specific controls.
- ϵ_{it}: Error term

Coefficient Interpretations: The coefficients (β_k) are semi-elasticities, indicating the percentage change in Y_{its} for a one-unit change in X_{kit}, holding all else constant.

- **Scaled Variable:** The fire count variable is scaled by 1,000. If the coefficient (β_1) on the Fire Count variable is -0.05, this implies that a one-unit increase in the Fire Count variable translates to a 1,000 increase in wildfire count which altogether corresponds to a 5% decrease in the dependent variable
- **Unscaled Variable:** Lagged establishment exits is an unscaled control. If its coefficient is 0.2, then we would interpret that a 1-unit increase in that variable, which corresponds to an additional exit count in the prior period, will translate into an increase of 20% in the outcome variable.

Advantages of the PPMLHDFE Model: The PPMLHDFE model, based on the foundational work of Santos Silva and Tenreyro (2006) and Correia, Guimarães, and Zylkin (2020), offers several key advantages that make it ideal for this study:

1. **Zero-Inflated Data:** The model handles zero-heavy distributions, common in economic outcomes like establishment births and relocations. Unlike linear models, PPML provides consistent and unbiased estimates in such contexts.
2. **Nonlinear Relationships:** Wildfire impacts are often nonlinear—minor increases in fire frequency may have negligible effects, while large-scale wildfires induce

disproportionate disruptions. PPML accommodates these dynamics by modeling outcomes in multiplicative terms, aligning with real-world complexities.

3. **Heteroskedasticity Robustness:** PPML inherently accounts for heteroskedasticity, a frequent issue in datasets with varied scales of economic activity, ensuring consistent coefficient estimation.
4. **High-Dimensional Fixed Effects (HDFE):** Correia et al. (2020) enhanced PPML to integrate fixed effects across multiple dimensions efficiently. This feature allows robust control over county-specific, year-specific, and sector-specific unobserved heterogeneity, isolating the true effects of wildfire frequency and intensity.
5. **Interpretability and Policy Relevance:** Coefficients are directly interpretable as percentage changes, offering clear, actionable insights for policymakers. For example, understanding the exact percentage drop in employment due to a 1% increase in burned area provides critical information for disaster preparedness and economic stabilization efforts.

This methodology leverages the strengths of PPMLHDFE to produce robust, policy-relevant insights into the economic impacts of wildfires. By accommodating the intricacies of count data, heterogeneity, and nonlinear dynamics, this model ensures rigorous analysis aligned with the study's objectives.

2.4.3 Variable Selection and Multicollinearity

The selection of explanatory variables was informed by economic theory, prior research, and diagnostic testing to ensure robustness and interpretability. After identifying an initial set of variables, diagnostic measures—including correlation analysis, Variance Inflation Factor (VIF) tests, and stepwise regression (forward and backward)—were conducted. Model refinement was further guided by Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), ensuring a balance between explanatory power and parsimony.

The correlation heatmap (**Figure A16**, Appendix) illustrates pairwise relationships among the explanatory variables. All correlations are below 0.6, indicating a low-to-moderate level of association among the predictors and minimizing concerns about multicollinearity. Median Household Income and Housing Price Index (HPI), with a correlation just below 0.6, show a moderate relationship, reflecting common economic dynamics between income levels and housing markets. Both variables were retained in the model due to their distinct theoretical relevance—HPI represents housing market fluctuations, while Median Household Income captures broader economic well-being.

Fire Count is negatively correlated with Protected Areas and Precipitation, consistent with expectations that regions with higher environmental protections or greater rainfall experience fewer wildfires. These negative correlations align with established wildfire literature, reinforcing the importance of environmental characteristics in wildfire risk assessment. % County Burned, representing wildfire intensity, exhibits low correlations with other variables, confirming its independent contribution to the model. Socio-demographic variables such as Population Density, Poverty Rate, and Median Household Income exhibit modest correlations, reflecting their typical interconnectedness in regional economic contexts.

The VIF tests confirm that no variables exhibit problematic levels of multicollinearity, with all VIF values remaining well below standard thresholds. By ensuring that each variable provides unique and meaningful insights, the final econometric model captures the multi-dimensional impacts of wildfire frequency and intensity on establishment dynamics, employment, and sales performance while maintaining stability and interpretability.

2.5 Results and Interpretation

This section presents the results of the PPMLHDFE regression models, which assess the economic impacts of wildfires on six key outcomes: establishment births, deaths, inward relocations, outward relocations, employment, and sales volume performance. Our focus is on the interpretation of results for the two primary wildfire variables: wildfire frequency (measured as the annual fire count, scaled by 1,000) and wildfire intensity (measured as the proportion of county land area burned, bounded between 0 and 1). Results for non-wildfire variables are discussed in detail in the Appendix for conciseness.

To ensure the robustness and interpretability of the results, the analysis adopts the normalization assumption $E[Y|X]$=1, standard in PPML regression models. This assumption enhances theoretical rigor and simplifies interpretation, enabling coefficients to be understood as semi-elasticities, representing percentage changes in the dependent variable in response to one-unit changes in the independent variable, holding other factors constant. This approach aligns with econometric best practices as outlined by Cameron and Trivedi (2013) and Wooldridge (2010). Additional details on the normalization assumption and its theoretical justification are provided in the Appendix.

Interpretation Framework

To facilitate intuitive and meaningful interpretation:

For wildfire frequency (Fire Count (t-1) (1000s)), a one-unit increase corresponds to an additional 1,000 fires. If the coefficient for this variable is estimated at 0.10, it implies that an additional 1,000 fires are associated with a 10% increase in the dependent variable. For more realistic increments, such as a 100-fire increase, the effect would be proportional, yielding a 1% increase in the dependent variable.

For wildfire intensity (% County Burned (t-1) (100s)), a one-unit increase corresponds to a 100% increase in county land area burned. For instance, if the coefficient for this variable is estimated at -0.842, it implies that a 100% increase in the burned area is associated with an 84.2% decrease in the dependent variable. For a more realistic increment of a 1% increase in county area burned, the effect would be proportional, resulting in a 0.842% decrease in the dependent variable.

To ensure clarity, comparability, and relevance to observed wildfire activity, the results are consistently interpreted using increments of an additional 100 fires for frequency and a 1% increase in county area burned for intensity. These standard increments are applied throughout this section to highlight the practical implications of the findings for stakeholders and policymakers.

Results Overview

The following subsections detail the regression results, beginning with the Aggregate Land-Intensive Sector (LIS), followed by the four LIS subsectors (Agriculture, Mining, Utilities, and Construction), and concluding with the non-LIS representative sector, Manufacturing. Each subsection emphasizes the key economic outcomes, the differential impacts of wildfire frequency and intensity, and their broader implications for resilience, adaptation, and sectoral heterogeneity.

2.5.1 Land-Intensive Sector

The aggregate LIS is composed of establishments from NAICS 11, 21, 22, and 23, all of which are heavily reliant on land and natural resources, and as such are highly sensitive to wildfire disruptions. **Table A32** presents summarized regression results on the coefficients of the wildfire variables only. The full regression results are available in **Table A35**.

2.5.1.1 Wildfire Frequency (Fire Count)

Our results (**Table A32** and **Table A35**) indicate that wildfire frequency significantly affects business continuity and mobility in the LIS:

Establishment Deaths: A 100-fire increase leads to a 0.94% increase in establishment deaths. While the magnitude appears modest, the result highlights the cumulative toll of recurring wildfires on business closures, consistent with disaster economics literature (Hallegatte, 2014). This supports H1, emphasizing the vulnerability of land-intensive industries to frequent environmental disturbances.

Outward Migrations: A 100-fire increase results in a 14.0% increase in outward relocations, demonstrating the substantial role of wildfire frequency in driving businesses to relocate. These findings align with theories of "environmental mobility," where recurring ecological risks prompt businesses to seek safer operational environments (Black et al., 2011). This supports H2, underscoring the challenges of business retention in wildfire-prone regions.

Births and Inward Relocations: Unlike deaths and outward migrations, wildfire frequency does not significantly affect establishment births or inward relocations at the aggregate LIS level. This indicates that businesses are more likely to react to wildfire frequency by exiting affected regions rather than new businesses avoiding entry.

Our findings in regards to wildfire frequency support H1 (positive relationship between wildfire frequency and establishment deaths), H2 (positive relationship between wildfire frequency and outward relocations), and provide partial support for the absence of significant effects on births and inward relocations.

2.5.1.2 Wildfire Severity (Burned Areas)

Our results (**Table A32** and **Table A35**) reveal that wildfire intensity has distinct and significant effects on establishment births and sales performance in the LIS:

Establishment Births: A 1% increase in burned areas leads to a 0.842% decrease in establishment births. This substantial deterrent effect reflects how visible environmental degradation discourages entrepreneurship, consistent with research on environmental uncertainty and its impact on business formation (Turner et al., 1994). This finding supports H1, highlighting the risks posed by severe wildfires to new business creation.

Sales Performance: Conversely, a 1% increase in burned areas leads to a 2.26% increase in sales performance. This result underscores the temporary economic boost possibly driven by post-wildfire reconstruction activities, particularly in recovery-focused industries such as Construction (Comerio, 1998). This supports H4, which posits that while wildfires generally disrupt economic activity, they can create opportunities in certain sectors.

Deaths, Relocations, and Employment: Unlike wildfire frequency, burned area does not significantly affect establishment deaths, relocations, or employment at the aggregate LIS level. This distinction underscores how wildfire frequency and intensity exert differing pressures on business dynamics, with intensity more closely tied to localized recovery opportunities.

Overall findings in regards to wildfire intensity support H1 (negative effect of wildfire intensity on establishment births) and H4 (dual nature of wildfire impacts, with reduced births offset by temporary boosts in sales performance).

2.5.1.3 Contribution to Research Objectives

The results for the aggregate LIS demonstrate how wildfire frequency and intensity distinctly impact establishment dynamics and economic outcomes, fulfilling key components of the study's research objectives:

Addressing RQ1: Wildfire frequency significantly increases establishment deaths and outward relocations, confirming the hypothesized disruptions to business continuity and mobility (H1, H2). Wildfire intensity reduces establishment births while boosting sales performance, reflecting both the destructive and recovery-driven dimensions of wildfire impacts (H1, H4).

Advancing Hypotheses Testing: Our findings confirm hypothesized relationships (H1, H2, H4) while highlighting areas where frequency and intensity exhibit divergent impacts, particularly in terms of establishment dynamics. This detailed interpretation lays the groundwork for the sector-specific analysis in Section 5.2, where sectoral heterogeneity within the LIS is explored, as well as identifying the main drivers behind our Aggregate LIS results.

2.5.2 Sector-Specific Impacts Across LIS

The LIS, comprising Agriculture (NAICS 11), Mining (NAICS 21), Utilities (NAICS 22), and Construction (NAICS 23), reveals significant heterogeneity in responses to wildfire frequency and intensity. The summarized regression results are presented in **Table A33** and **Table A34**, with full regression results available from **Table A36** to **Table A39**.

2.5.2.1 Similarities Across LIS Subsectors

Deaths (H1): A 100-fire increase significantly increases deaths in Agriculture (+1.56%) and Utilities (+3.59%), reflecting heightened vulnerability to recurring wildfires. These results align with H1, indicating how operational disruptions and infrastructure damage exacerbate establishment closures. Results are located in **Table A33**, **Table A36**, **Table A37**, and **Table A38**.

Outward Migrations (H2): A 100-fire increase significantly increases outward migrations in Mining (+29.2%) and Construction (+6.59%), showcasing "environmental mobility" as businesses migrate to mitigate risks. This supports H2 and highlights the shared adaptive strategies of relocation in wildfire-affected regions. Results are located in **Table A33**, **Table A37**, and **Table A39**.

Sales Performance (H4): A 1% increase in county land area burned by wildfires boost sales performance in Utilities (+1.90%) and Construction (+2.01%) possibly due to post-wildfire reconstruction demands. These similarities underscore the critical roles of both sectors in disaster recovery efforts, aligning with H4 and the disaster economics literature (Cavallo & Noy, 2010). Results are located in **Table A34**, **Table A38**, and **Table A39**.

2.5.2.2 Differences Across LIS Subsectors

Births (H1): A 1% increase in county land area burned significantly reduce establishment births in Agriculture (-1.75%) and Construction (-0.746%) but increase births in Mining (+2.28%). Agriculture's vulnerability reflects the adverse effects of degraded land and heightened risks (Turner et al., 1994), while Mining possibly benefits from post-disaster resource demand and investment opportunities. Results are located in **Table A34**, **Table A36**, **Table A37**, and **Table A39**.

Employment (H3): Employment outcomes diverge sharply across subsectors. For every 100 additional fires, Agriculture suffers a decline in jobs (-2.74%) possibly due to destroyed crops and disrupted labor markets, while Utilities experience a notable employment increase (+4.09%), probably driven by emergency repairs and operational demands. Results are located in **Table A33**, **Table A36**, and **Table A38**.

Deaths (H1): Under wildfire intensity, we find that a 1% increase in county land area burned by wildfires results in significant reduction in establishment deaths in the Mining (-2.06%) and Utilities (-2.35%) sectors, likely reflecting pre-emptive relocations and proactive mitigation strategies. These findings contrast with Agriculture, where no significant reductions are observed, underscoring its limited resilience to severe wildfires. Results are located in **Table A5**, **Table A7**, **Table A8** and **Table A9**.

Conclusion

Our results demonstrate that wildfire frequency and intensity impact LIS subsectors in both similar and divergent ways, addressing RQ2. Substantial heterogeneity across subsectors supports H5, reflecting varying levels of vulnerability, reliance on land, and post-disaster resilience. Furthermore, the findings validate hypotheses H1–H4, showing how recurring and severe wildfires disrupt establishment dynamics and employment while driving demand-driven recovery in Utilities and Construction. These insights provide critical evidence for policymakers aiming to tailor climate adaptation strategies to sector-specific needs.

2.5.2.3 Main Drivers of Aggregate LIS Results

The aggregate LIS results reflect the combined effects of its constituent sectors. Analyzing the drivers clarifies which subsectors dominate observed trends.

Wildfire Frequency (100-Fire Count Increase): The 0.94% increase in Aggregate LIS deaths is driven primarily by Utilities (+3.59%) and Agriculture (+1.56%), as both sectors face heightened vulnerability to wildfire frequency. The 14.0% increase in Aggregate LIS outward migrations stems largely from Mining (+29.2%) and Construction (+6.59%), reflecting their reliance on relocation as a key adaptive response.

Wildfire Intensity (1% Increase in County Area Burned): The 0.842% decline in births is predominantly influenced by Agriculture (-1.75%) and Construction (-0.746%), which face significant barriers to new business formation. Positive sales performance (+2.26%) is primarily driven by Utilities (+1.90%) and Construction (+2.01%), underscoring their pivotal roles in post-disaster recovery efforts.

2.5.3 Manufacturing as the Representative Non-LIS

Manufacturing (NAICS 31–33) is chosen as the representative non-LIS sector due to its lower land dependency and distinct role in production, supply chains, and post-disaster recovery. The inclusion of Manufacturing allows for a comparative analysis of wildfire impacts across sectors with differing land reliance. The summarized regression results for wildfire frequency and intensity are provided in **Table A33** and **Table A34**, while the full regression results are detailed in **Table A40**.

2.5.3.1 Wildfire Frequency

We find the following impact, for every 100-count increase in Wildfires:

Births (H1): Manufacturing births increase by 1.22%, reflecting growth opportunities in the aftermath of wildfires, possibly driven by heightened demand for durable goods in recovery efforts.

Outward Migrations (H2): Wildfire frequency significantly drives relocations (+16.4%), indicating operational challenges similar to those seen in Mining and Construction.

Deaths and Employment (H3): Deaths increase modestly (+0.71%), while employment rises slightly (+0.70%), suggesting resilience through increased production demands but also exposure to operational risks.

2.5.3.2 Wildfire Intensity

We find the following impact, for every 1% increase in county land area burned:

Deaths (H1): We find an increase of 0.788% in establishment deaths. This result aligns with H1, indicating how operational disruptions and infrastructure damage exacerbate establishment closures.

Outward Migrations (H2): Wildfire intensity drives substantial relocations (+8.27%), highlighting the sensitivity of Manufacturing to severe disruptions.

Employment (H3): Employment declines (-0.344%), reflecting operational disruptions and workforce displacement in the face of severe wildfires.

Sales Performance (H4): Sales performance improves significantly (+1.47%), likely fuelled by post-disaster reconstruction demands, mirroring trends in Utilities and Construction.

2.5.4 Addressing Research Questions and Hypotheses

This section integrates our findings in addressing our study's research questions and hypotheses. By comparing wildfire frequency and intensity, our results reveal the distinct mechanisms through which recurring and severe wildfires impact economic outcomes.

2.5.4.1 Research Questions

RQ1: Wildfire Impacts on Economic Outcomes: The aggregate LIS results demonstrate that wildfire frequency significantly increases establishment deaths and outward relocations. These findings highlight the disruptive nature of recurring wildfires on business continuity and mobility, supporting the hypothesized relationships in H1 and H2. Similarly, burned areas reduce establishment births and enhance sales performance, illustrating the dual nature of wildfire intensity, where long-term deterrents to new business formation are offset by short-term recovery-driven demand, particularly in sectors like Utilities and Construction. These results directly address RQ1 by quantifying the distinct economic effects of wildfire frequency and intensity at the aggregate level.

RQ2: Sectoral Differences: Sub-sectoral analysis reveals significant heterogeneity within the LIS, as well as key differences between LIS and Manufacturing. Agriculture exhibits the greatest vulnerability, with substantial declines in births and employment due to land degradation and disrupted labor markets. In contrast, Utilities and Construction demonstrate resilience, with employment and sales performance bolstered by post-disaster reconstruction efforts. Mining and Manufacturing, while similarly affected by outward relocations, capitalize on opportunities for resource extraction and durable goods production, respectively, reflecting sector-specific adaptations. These findings address RQ2 by showcasing the differential impacts of wildfire frequency and intensity across LIS subsectors and the representative non-LIS sector.

2.5.4.2 Hypotheses

H1: Births and Deaths: The findings support H1, as wildfire frequency and intensity reduce establishment births and increase deaths in vulnerable LIS subsectors. For instance, Agriculture and Construction experience significant reductions in births, while wildfire frequency increases deaths in sectors like Utilities and Agriculture. These results validate the predicted effects of wildfire-related disruptions on establishment dynamics.

H2: Relocations: The results confirm H2, as wildfire frequency and intensity significantly drive outward relocations in Mining, Construction, and Manufacturing. These findings highlight mobility as a key adaptive strategy in wildfire-prone regions, reflecting the increased costs and risks faced by businesses in these sectors.

H3: Employment: The evidence partially supports H3, as wildfire frequency and intensity reduce employment in vulnerable sectors like Agriculture and Manufacturing while increasing employment in Utilities. These mixed effects demonstrate that labor market responses to wildfires depend on sectoral roles in recovery and operational resilience.

H4: Sales Performance: The results provide partial support for H4, as sales performance declines in Agriculture but rises significantly in Utilities, Construction, and Manufacturing. These increases align with the hypothesized recovery-driven demand, showcasing how wildfires create temporary economic opportunities for certain sectors.

H5: Sectoral Heterogeneity: The findings strongly support H5, revealing substantial variability in wildfire impacts across LIS subsectors and between LIS and Manufacturing. Sectoral differences are possibly driven by variations in resource reliance, operational flexibility, and exposure to wildfire risks. For instance, Utilities and Construction demonstrate resilience through recovery-focused demand, while Agriculture and Mining exhibit heightened vulnerability due to their dependence on land and resource extraction.

2.5.5 Conclusion

This refined analysis highlights the complex and differential impacts of wildfire frequency and intensity across the LIS and non-LIS. The results underscore the significant heterogeneity in responses, with Utilities and Construction emerging as drivers of resilience within LIS due to their roles in post-disaster recovery. In contrast, Agriculture faces disproportionate challenges from recurring and severe wildfires, reflecting its reliance on degraded natural resources and limited adaptive capacity. Manufacturing mirrors the resilience of Utilities and Construction, possibly benefiting from increased demand for durable goods during recovery efforts, but also experiences labor market disruptions and relocations.

These findings directly address the study’s research questions, validating key hypotheses regarding the disruptive and adaptive effects of wildfires on economic outcomes. By quantifying the mechanisms through which wildfire frequency and intensity reshape establishment dynamics, employment, and sales performance, this study provides actionable insights for policymakers. Targeted strategies to mitigate wildfire risks, enhance resilience, and support recovery efforts can be designed by prioritizing the unique needs of vulnerable sectors like Agriculture, while leveraging the recovery-driven roles of Utilities, Construction, and Manufacturing.

2.6 Robustness Checks

To ensure the reliability and validity of the findings, this study conducted a series of robustness checks and sensitivity analyses. These analyses validate the consistency of the results across alternative specifications, varied assumptions, and counterfactual tests, reinforcing the soundness of the empirical approach.

First, a counterfactual analysis incorporating leads and lags of wildfire variables (Fire Count and Burned Areas) was performed to address potential temporal dynamics and causality concerns. Lagged variables, up to three periods revealed that wildfire impacts persist over time, with significant delayed effects on establishment dynamics, employment, and outward relocations. In contrast, leads up to two periods served as placebo tests and demonstrated no significant effects, confirming the absence of anticipatory behavior or reverse causation.

Second, alternative model specifications, including Zero-Inflated Poisson (ZIP) and Negative Binomial regressions, were employed to account for overdispersion and zero inflation in the count data. The results were consistent with the Poisson Pseudo-Maximum Likelihood (PPML) approach, further validating the choice of PPML as the preferred model for analyzing wildfire impacts on establishment dynamics and economic outcomes.

Third, placebo tests using randomized wildfire events—either by assigning wildfire occurrences to unaffected counties or by randomly altering wildfire timing—were conducted. These placebo tests yielded insignificant coefficients, confirming that the observed impacts are directly attributable to actual wildfire events and not driven by spurious correlations.

Fourth, interaction terms were introduced between wildfire variables and socio-demographic factors, such as income and population density, to assess heterogeneous effects. The results revealed that wildfire impacts were more pronounced in lower-income and densely populated counties, while higher-income regions exhibited greater resilience in establishment births and employment.

Finally, the inclusion of additional weather control variables (e.g., precipitation, temperature) in the regressions confirmed that the primary wildfire variables maintained their statistical significance, indicating that the observed economic impacts of wildfires are distinct and not confounded by broader climate trends.

Together, these robustness checks provide strong evidence that the findings are reliable, robust, and consistent across a range of alternative assumptions and model specifications. These analyses reinforce the credibility of the observed impacts of wildfire frequency and intensity on establishment dynamics, employment, and sales performance.

2.7 Discussion and Policy Implications

2.7.1 Summary of Findings and Contributions

This study examines the economic impacts of wildfire frequency (fire count) and intensity (burned area) on establishment dynamics and economic performance across California's LIS sectors (NAICS 11, 21, 22, 23) and non-LIS (NAICS 31–33). By addressing the research objectives and validating the hypotheses, the findings reveal that wildfires disrupt business continuity, mobility, and employment, while simultaneously creating temporary, recovery-driven economic opportunities. These results contribute to multiple fields, including disaster economics, sectoral resilience, and land-use policy.

Contributions to Literature

1. **Wildfire Frequency as a Disruptor of Economic Stability:** Recurring wildfires significantly increase establishment deaths and outward relocations, underscoring the risks of cumulative environmental disturbances. These findings validate H1 and H2, contributing to theories of business disruption (Hallegatte, 2014) and "environmental mobility" (Black et al., 2011).
2. **Dual Nature of Wildfire Intensity:** Intense wildfires discourage new business formation in Agriculture for instance but boost sales in recovery-focused sectors, such as Construction. This duality aligns with H4 and complements disaster recovery literature by demonstrating how reconstruction activities stimulate temporary economic growth (Albala-Bertrand, 1993).
3. **Sectoral Heterogeneity and Resilience Patterns:** Agriculture emerges as the most vulnerable LIS subsector, with significant declines in births and employment, while Utilities and Construction display adaptive resilience through positive employment and sales outcomes. These results extend H5 and provide empirical support for sectoral differentiation frameworks in disaster economics (Abatzoglou & Williams, 2016).

4. **Broadening Disaster Economics with Manufacturing Insights:** As a non-LIS sector, Manufacturing mirrors LIS trends, with increased relocations and boosted sales during recovery phases. These findings reinforce the universality of wildfire impacts, enriching cross-sectoral analyses (Venn & Quiggin, 2007).

2.7.2 Addressing Research Questions and Hypotheses

Research Question 1: What are the impacts of wildfire frequency and intensity on establishment births, deaths, relocations, employment, and sales in the aggregate LIS?

Wildfire frequency disrupts business continuity through increased establishment deaths and outward relocations. Wildfire intensity suppresses establishment births but temporarily boosts sales in recovery-focused sectors. These findings validate H1, H2, and H4, illustrating both the disruptive and adaptive dynamics of wildfires at the aggregate level.

Research Question 2: How do these impacts vary across LIS subsectors?

The sub-sectoral analysis reveals substantial heterogeneity in responses to wildfire risks. Agriculture emerges as highly vulnerable, with significant declines in establishment births and employment, reflecting its dependence on stable land conditions and environmental predictability. In contrast, Utilities demonstrate resilience, with positive employment and sales driven by heightened demand during recovery efforts. Mining and Construction exhibit substantial outward relocations, underscoring mobility as a key adaptive strategy in response to wildfire risks. These findings strongly support H5, emphasizing sectoral differences in vulnerability and adaptive capacity to wildfire-induced disruptions.

2.7.3 Theoretical Implications

2.7.3.1 Disaster Economics and Environmental Mobility

This study contributes to the disaster economics literature by demonstrating how wildfire frequency disrupts business stability and drives relocations, validating theories of "environmental mobility" (Black et al., 2011). The findings expand on location theory (Fujita et al., 1999) by showing that recurring wildfires amplify operational costs and uncertainty, pushing businesses toward safer regions.

2.7.3.2 Sectoral Vulnerability and Resilience Frameworks

The results advance sectoral vulnerability frameworks by identifying Agriculture as highly sensitive to wildfires due to its dependency on stable environmental conditions, while Utilities leverage post-disaster demand to build resilience. These insights align with Dillon et al. (2011) and extend understanding of sector-specific adaptive capacities.

2.7.3.3 Dual Impacts of Wildfires on Economic Dynamics

The study highlights the dual nature of wildfire impacts, where intense fires disrupt establishment births but simultaneously create recovery-driven sales opportunities. This finding aligns with disaster recovery economics (Albala-Bertrand, 1993) and emphasizes the need for policies that balance immediate recovery with long-term sustainability.

2.7.4 Policy Implications

The findings of this study provide a foundation for targeted policies to mitigate wildfire-induced economic disruptions and enhance resilience in affected sectors. By addressing the distinct impacts of wildfire frequency and intensity, these recommendations focus on actionable strategies aligned with the empirical results.

2.7.4.1 Strengthening Resilience in Vulnerable Sectors

Agriculture: As the sector most vulnerable to wildfires, Agriculture experiences significant declines in establishment births and employment due to land degradation, environmental instability, and reduced soil fertility. Wildfires can exacerbate desertification, especially in regions with arid or semi-arid climates, where vegetation loss leads to soil erosion, reduced water retention, and long-term declines in land productivity (D'Odorico et al., 2013). Policymakers should promote climate-resilient farming practices, such as drought-resistant crops, improved irrigation systems, and sustainable land management, to mitigate these risks and improve adaptive capacity.

Monoculture farming systems, which dominate in some wildfire-prone regions, increase vulnerability by reducing biodiversity and ecosystem resilience. These systems create homogenous landscapes that can accelerate the spread and intensity of wildfires while diminishing the soil's ability to recover after fire events (Pausas & Keeley, 2021). Encouraging a transition to regenerative agriculture, which includes practices such as crop rotation, cover cropping, and agroforestry, can enhance soil health, boost biodiversity, and reduce wildfire risks. Regenerative practices not only improve ecosystem resilience but also offer economic benefits by increasing the sustainability and profitability of agricultural operations (Lal, 2020).

Land restoration programs play a critical role in rehabilitating degraded areas post-wildfire. Restoring native vegetation, stabilizing soil, and improving water management can prevent further soil erosion and foster ecological recovery. These initiatives are essential for economic recovery, encouraging new business formation in agricultural regions, and mitigating the long-term impacts of wildfires. Integrating these strategies into regional climate adaptation plans can bolster the resilience of agricultural communities in wildfire-prone regions, ensuring sustainable livelihoods while reducing exposure to future risks.

Construction: Given its pivotal role in post-wildfire recovery, Construction requires policy support to enhance resilience and sustainability. Enforcing fire-resistant building codes, incentivizing the use of sustainable materials, and investing in advanced construction technologies can help reduce future wildfire risks while supporting recovery efforts.

Utilities: Utilities demonstrate resilience under wildfire intensity, benefiting from recovery-driven demand for emergency and restoration services. To strengthen this sector's adaptive capacity, policymakers should prioritize investments in resilient infrastructure, such as underground power lines and wildfire-resistant grid systems, which can minimize service disruptions and reduce economic losses.

2.7.4.2 Reducing Outward Migrations and Supporting Business Retention

Business Retention Incentives: Wildfire frequency drives outward relocations, particularly in Mining, Construction, and Manufacturing, as businesses seek safer operational environments. Policymakers should offer tax incentives, grants, and subsidies to encourage investments in fire-resistant technologies and infrastructure, reducing the economic pressures that lead to relocation.

Risk Mitigation Programs: Public-private risk-sharing mechanisms, such as subsidized insurance premiums or wildfire recovery loans, can offset the costs of disruptions for businesses, making it more feasible for them to remain in high-risk areas.

Improved Risk Communication: Transparent communication of wildfire risks and preparedness measures is essential to restoring confidence in wildfire-prone regions. Policymakers can establish centralized platforms to provide real-time updates, risk assessments, and guidance on recovery efforts, enabling businesses to plan more effectively and remain operational.

2.7.4.3 Promoting Recovery and Workforce Adaptation

Job Training and Workforce Mobility: Wildfires disrupt employment in vulnerable sectors like Agriculture while creating opportunities in recovery-focused industries such as Construction and Utilities. Job training programs should target displaced workers, equipping them with skills in construction technology, utility restoration, and disaster management. This can help fill labor gaps in recovery-driven sectors while mitigating unemployment in wildfire-affected areas.

Equitable Recovery Strategies: Recovery efforts must prioritize support for disadvantaged communities and small businesses disproportionately affected by wildfires. Targeted grants and microloans, combined with technical assistance programs, can ensure that these groups have equitable access to recovery resources, reducing long-term economic disparities in fire-prone regions.

Balancing Recovery with Sustainability: While recovery activities generate temporary economic boosts, overreliance on post-disaster rebuilding can perpetuate vulnerabilities.

Policymakers should balance immediate recovery investments with strategies that reduce future risks, such as fire-resilient land-use planning, sustainable resource management, and integrated community-led preparedness programs.

2.7.4.4 Coordinating Cross-Sectoral Collaboration

Effective resilience strategies require coordination between public and private stakeholders, academic researchers, and community organizations. Public-private partnerships can drive large-scale infrastructure improvements, such as wildfire-resistant grids and regional firebreak systems. Academic contributions can inform evidence-based policy design, ensuring that resilience measures align with the latest empirical findings. Localized initiatives, including participatory planning and citizen-led recovery programs, can enhance community preparedness and ensure recovery efforts are inclusive and impactful.

2.7.5 Limitations

This study provides valuable insights into the economic impacts of wildfire frequency and intensity across California's LIS sectors and non-LIS. However, certain limitations must be acknowledged. First, the use of county-level data may obscure important intra-county variations in wildfire impacts, particularly for large or geographically diverse counties. Second, the analysis primarily focuses on immediate impacts, leaving longer-term recovery trajectories and structural economic adjustments unexplored. Third, while the study examines wildfire impacts at the 2-digit NAICS Supersector level, analyzing more granular 3-, 4-, and 5-digit NAICS subsectors could yield deeper insights into within-sector variations, such as specific vulnerabilities or resilience strategies in subindustries. Finally, the sectoral scope, while comprehensive for the

LIS and Manufacturing, excludes other potentially affected sectors, such as Retail, Tourism, and Healthcare, which could exhibit distinct responses to wildfire risks.

2.7.6 Conclusion

This study provides empirical evidence on how wildfire frequency and intensity reshape economic outcomes across California's land-intensive sectors (LIS) and the representative non-LIS sector, Manufacturing. By disentangling the disruptive impacts of recurring wildfires from the recovery-driven opportunities associated with severe burned areas, the findings offer important contributions to disaster economics and resilience policy.

Wildfire frequency emerges as a persistent disruptor, significantly increasing establishment deaths and outward relocations at both the aggregate LIS level and across its subsectors. Wildfire intensity, while suppressing establishment births, drives sales growth in recovery-oriented sectors such as Construction and Utilities. Agriculture stands out as the most vulnerable sector, suffering sharp declines in births and employment due to its dependency on stable environmental conditions. In contrast, Utilities and Construction exhibit resilience by leveraging recovery demand to support employment and sales, while Mining and Manufacturing adopt mobility-driven adaptations to mitigate wildfire risks.

This research advances disaster economics by validating theories of environmental mobility and resilience, demonstrating how wildfires disrupt business continuity while catalyzing recovery-driven economic activity. It also highlights sectoral heterogeneity, linking resource dependency and recovery roles to adaptive capacity. Finally, it provides policymakers with actionable insights for mitigating wildfire-induced economic risks, emphasizing the need for tailored strategies that enhance resilience in vulnerable sectors while supporting recovery-driven industries.

These findings underscore the necessity of balancing immediate recovery efforts with sustainable long-term strategies. Addressing the dual nature of wildfire impacts and focusing on sector-specific vulnerabilities and opportunities equips policymakers with evidence-based tools to strengthen regional economies in the face of escalating climate challenges.

The final section synthesizes these insights, situates them within the broader literature, and outlines the path forward for translating this evidence into effective policies to enhance economic resilience and sustainability in wildfire-prone regions.

2.8 Conclusion

This study rigorously examines the economic impacts of wildfire frequency and intensity on California's land-intensive sectors (LIS) and Manufacturing, providing empirical evidence on how wildfires reshape establishment dynamics, employment, and sales performance. By employing Poisson Pseudo-Maximum Likelihood (PPML) with high-dimensional fixed effects, the analysis disentangles the disruptive effects of recurring wildfires from the recovery-driven opportunities created by severe burned areas, addressing key research objectives.

The findings reveal that wildfire frequency destabilizes local economies by increasing establishment deaths (+0.94%) and outward relocations (+14%), particularly in Agriculture and Mining, which depend on stable environmental conditions and physical resources. Wildfire intensity, while suppressing establishment births (-1.75% in Agriculture), stimulates sales growth in recovery-oriented sectors such as Construction (+2.01%) and Utilities (+1.90%), demonstrating the dual nature of wildfires as both disruptors and drivers of localized recovery. Sectoral heterogeneity emerges as a defining feature of wildfire impacts. Agriculture is the most vulnerable sector, experiencing sharp declines in births and employment due to land degradation and environmental instability. In contrast, Utilities and Construction exhibit resilience, leveraging recovery-driven demand to achieve employment and sales gains. Manufacturing mirrors some LIS trends, including relocations and recovery-driven sales growth, but faces unique challenges such as production disruptions and workforce displacement under intense wildfires. These insights confirm the sector-specific dynamics outlined in the research objectives and advance understanding of the differential impacts of wildfires.

This research makes significant contributions to multiple literatures. In disaster economics, it validates theories of environmental mobility and resilience by illustrating how wildfires disrupt traditional business stability while fostering recovery-driven growth. It also advances industrial organization and location theory by showing how wildfire risks reshape business location decisions, with capital mobility playing a central role in adaptation. In land-use economics, the findings provide empirical evidence on the interplay between environmental degradation and economic activity, emphasizing the role of resource dependency in shaping sectoral vulnerability and resilience.

The policy implications are clear and actionable. Climate-resilient farming practices, such as regenerative agriculture and land restoration programs, not only mitigate economic losses in Agriculture but also reduce wildfire risks, enhance ecosystem resilience, and support sustainable recovery. Investments in fire-resistant infrastructure and advanced technologies for Utilities and Construction can stabilize regional economies, minimize disruptions, and prepare for future wildfire events. Business retention policies, including risk-sharing mechanisms, tax incentives, and improved risk communication, are essential for reducing outward relocations and fostering economic stability in fire-prone regions. These strategies should be complemented by equitable recovery efforts that prioritize vulnerable communities and small businesses.

In sum, this study provides a robust framework for understanding the transformative economic impacts of wildfires, bridging gaps in disaster economics by linking disruption with recovery-driven growth. By highlighting sector-specific vulnerabilities, recovery opportunities, and adaptive strategies, it equips policymakers, businesses, and stakeholders with evidence-based insights to foster resilient, adaptive economies in an era of intensifying climate risks. These findings underscore the importance of integrating resilience-building measures into broader climate adaptation plans, ensuring that recovery efforts address both immediate needs and long-term sustainability.

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Appendix

Table A30: Summary Statistics of Dependent Variables by Sector

NAICS Sector	Variables	N	Mean	SD	Min	Max
11-Agriculture, Forestry, Fishing & Hunting	Sales Volume	1218	288897	640594	0	11548636
	Number of employees	1218	1833	2422	0	16874
	Establishment births	1218	24.4	28.9	0	236
	Establishment inward relocations	1218	3.01	28.3	0	630
	Establishment deaths	1218	22.8	25.2	0	214
	Establishment outward relocation	1218	3.02	29.4	0	695
21 – Mining, Quarrying, and Oil and Gas Extraction	Sales Volume	1218	125771	459297	0	4979810
	Number of employees	1218	305	974	0	7025
	Establishment births	1218	3.82	8.34	0	95
	Establishment inward relocations	1218	.329	5.53	0	140
	Establishment deaths	1218	3.81	8.01	0	67
	Establishment outward relocation	1218	.336	5.56	0	140
22 - Utilities	Sales Volume	1208	340319	730293	0	9280034
	Number of employees	1208	813	1557	2	14619
	Establishment births	1208	4.72	8.43	0	85
	Establishment inward relocations	1208	.136	1.10	0	26
	Establishment deaths	1207	4.14	7.43	0	90
	Establishment outward relocation	1207	.138	1.18	0	32
23 - Construction	Sales Volume	1218	2596628	5646244	0	51644632
	Number of employees	1218	12401	24107	0	178507
	Establishment births	1218	338	700	0	8564
	Establishment inward relocations	1218	26.4	192	0	3048
	Establishment deaths	1218	319	623	0	6224
	Establishment outward relocation	1218	26.4	201	0	3447
31-33 - Manufacturing	Sales Volume	1207	4809024	14164407	0	1.360e+08
	Number of employees	1207	23982	62595	0	536899
	Establishment births	1207	200	582	0	9421
	Establishment inward relocations	1207	13.9	129	0	3159
	Establishment deaths	1208	211	616	0	8287
	Establishment outward relocation	1208	14.0	133	0	3575

Table A30: Descriptive statistics for key dependent variables across five sectors: Agriculture, Forestry, Fishing, and Hunting (NAICS 11); Mining, Quarrying, and Oil and Gas Extraction (NAICS 21); Utilities (NAICS 22); Construction (NAICS 23); and Manufacturing (NAICS 31-33). Variables include sales volume, number of employees, establishment births, inward relocations, deaths, and outward relocations. Data represent county-year aggregates. Zero values for sales volume and employees indicate inactive or temporarily closed establishments.

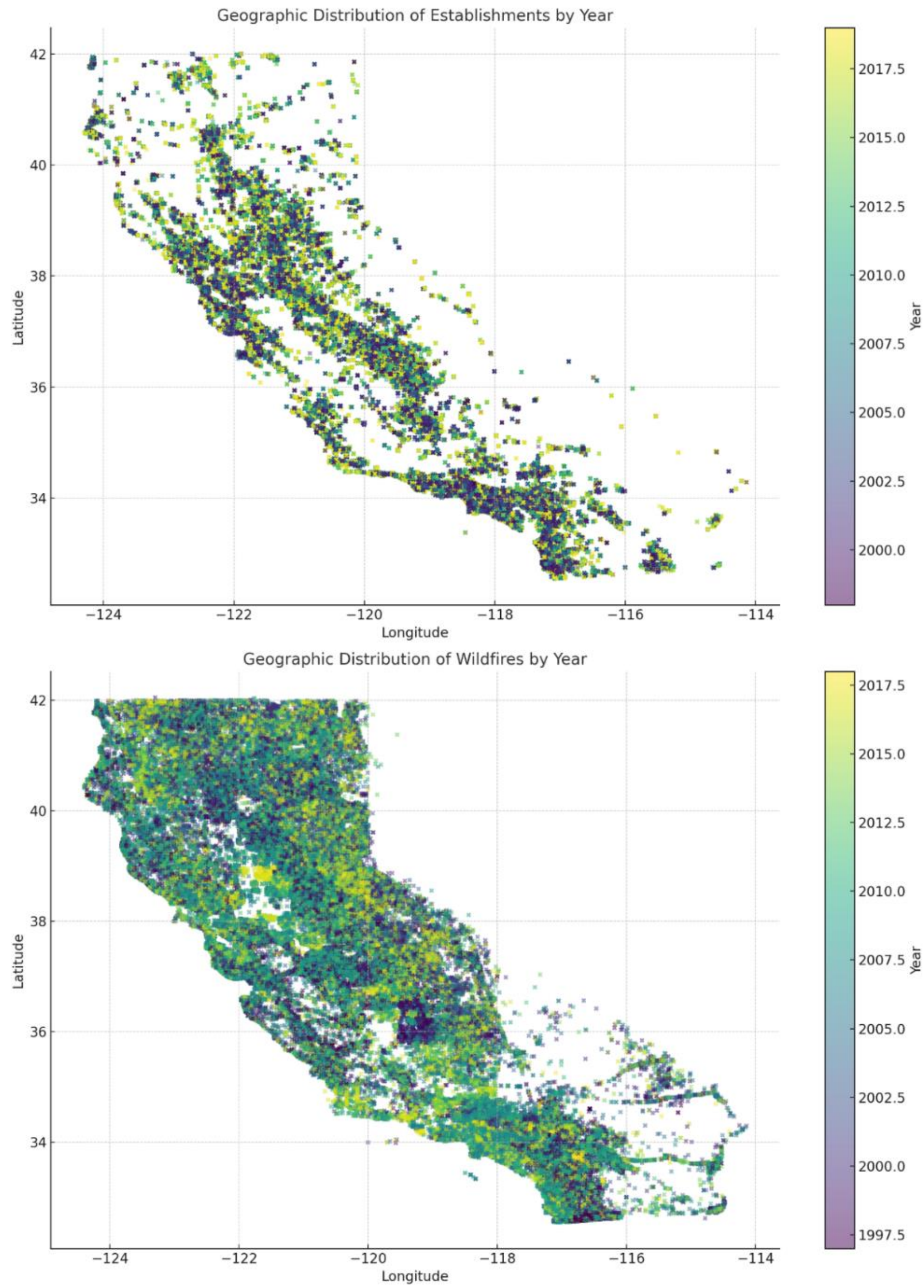

Figure A13: Spatial-Temporal Distribution of Establishments and Wildfires

Description: The top panel depicts the geographic distribution of establishments across California by year, illustrating spatial and temporal trends in business activity from 1998 to 2018. The bottom panel presents the geographic distribution of wildfires across California by year over the same period, highlighting the intensity and frequency of wildfire events in affected regions.

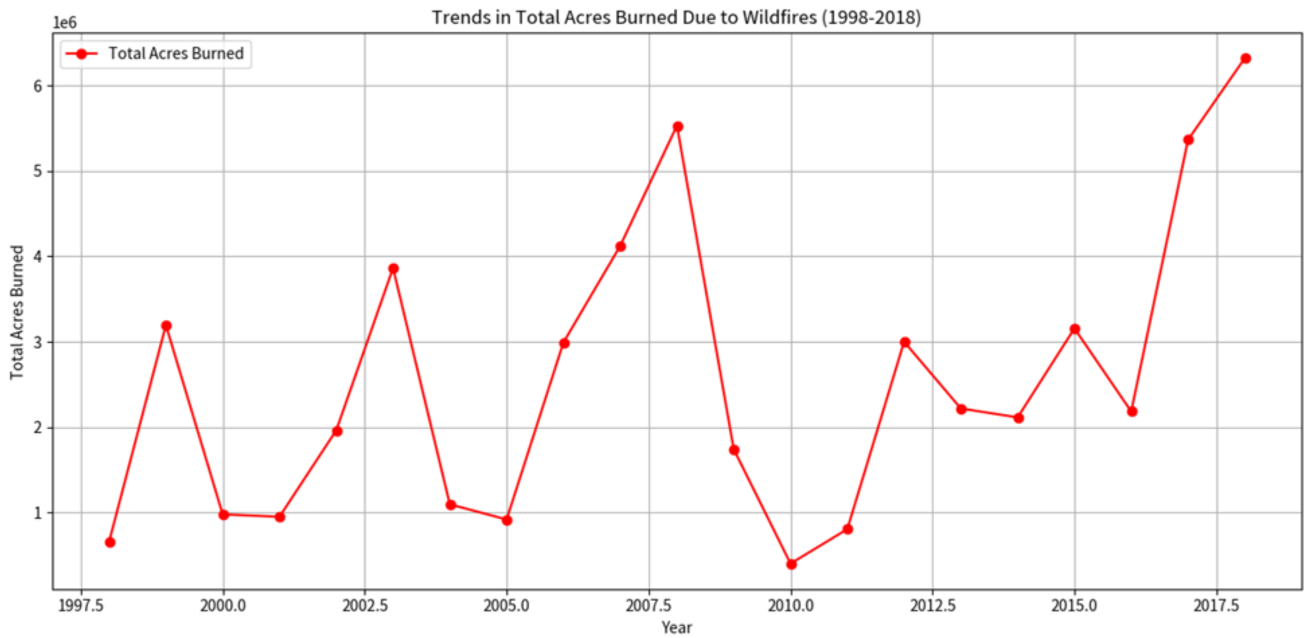

Figure A14: Total Acres Burned Due to Wildfires (1998–2018)
Description: The red line illustrates the annual total acres burned in California due to wildfires from 1998 to 2018. The data captures trends in wildfire activity over time, indicating fluctuations in fire severity and spatial extent.

Table A31: Summary Statistics for Explanatory Variables (1998-2018)

Variable	Obs	Mean	Std. Dev.	Min	Max
Fires (1000s) (Count) (t-1)	1130	.161	.433	.001	7.90
% County area burned (t-1) (100s)	941	.007	.02	0	.199
% CPAD (100s) (t-1)	1218	.429	.234	.012	0.87
Housing Price Index (100s)	1218	6.32	3.66	1	20.8
Poverty rate (100s)	1218	.147	.049	.051	.319
Median HH Income (100ks)	1218	.51	.156	.244	1.26
O3 - Attainment Status (t-1)	1218	.594	.611	0	1
PM - Attainment Status (t-1)	1218	.448	.712	0	1
Population Density (100s)	1218	.01	.036	0	.294
Precipitation (Inches)	1218	27.3	18.2	.62	112
Temperature (Fahrenheit)	1218	57.8	5.81	41.6	76.5

Table A31: Descriptive statistics for the explanatory variables used in the analysis. Wildfire metrics include wildfire frequency (Fires), measured in thousands of annual fire counts, and wildfire intensity (% County Area Burned, scaled by 100), representing the proportion of county land burned by wildfires in the previous year (t-1). Socio-economic variables include Housing Price Index (scaled by 100s), Poverty Rate (scaled by 100s), and Median Household Income (scaled by 100,000s). Environmental and demographic controls include % CPAD (percentage county area in protected area designations, scaled by 100), attainment status for ozone (O3) and particulate matter (PM), population density (scaled by 100s), average annual precipitation (in inches), and average annual temperature (in Fahrenheit). Observations (Obs), means, standard deviations (Std. Dev.), and ranges (Min and Max) are reported for all variables.

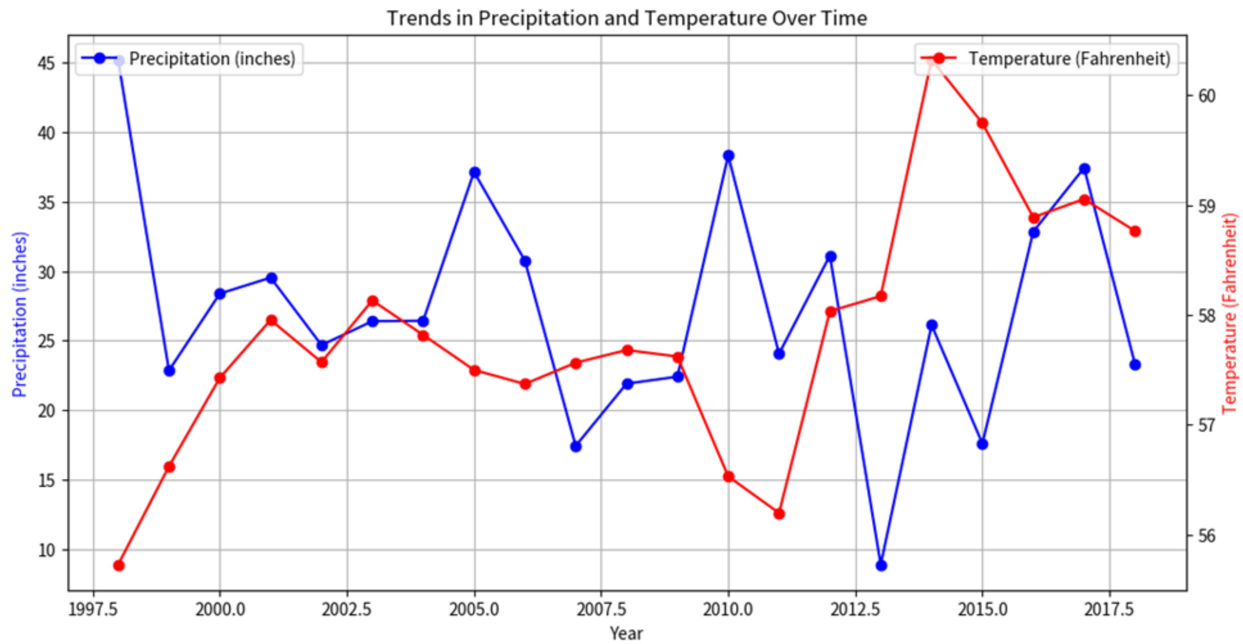

Figure A15: Annual Trends in Precipitation and Temperature (1998–2018)

Description: This figure illustrates the annual trends in precipitation (inches) and temperature (Fahrenheit) across California counties from 1998 to 2018. The blue line represents precipitation levels, while the red line reflects temperature trends. The graph highlights the variability in climatic conditions over time, which serves as key explanatory factors in wildfire risk and economic outcomes.

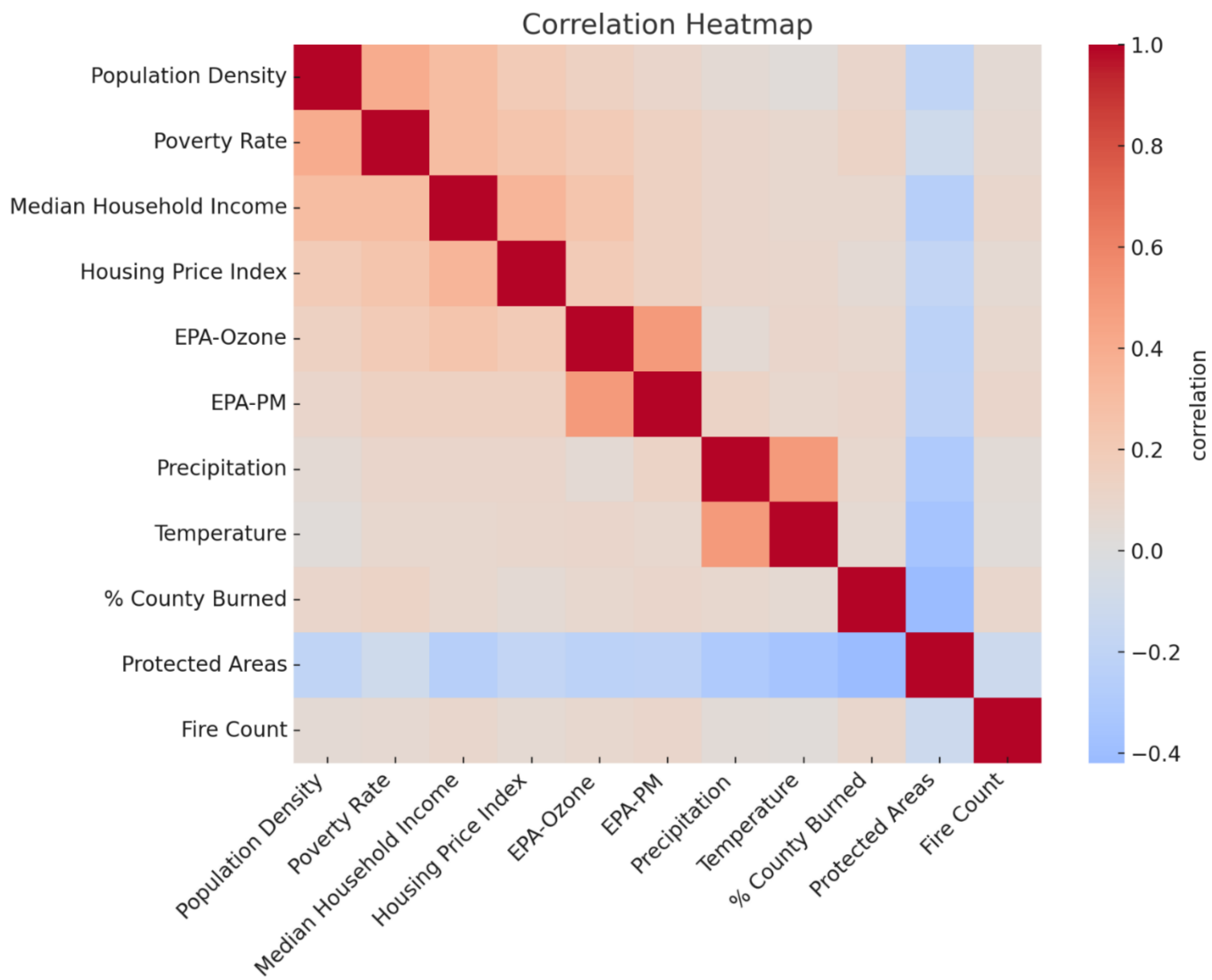

Figure A16: Correlation Heatmap of Explanatory Variables
Description: This heatmap shows the pairwise correlations among explanatory variables used in the analysis. The correlation coefficients range from -0.4 to 1.0, with strong positive correlations shown in red and strong negative correlations in blue. The variables include socio-demographic factors (e.g., Population Density, Median Household Income, Housing Price Index), environmental conditions (e.g., Precipitation, Temperature, Protected Areas, EPA-Ozone, EPA-PM), and wildfire-related metrics (e.g., % County Burned, Fire Count). The heatmap highlights potential multicollinearity and the relationships among predictors, which are critical for model interpretation.

Table A32: Summary of LIS Regression Results: Wildfire Frequency and Intensity

Dependent Variable	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$
Births	+	-0.842**
Inward Migrations	+	-
Deaths	0.094***	-
Outward Migrations	1.40***	+
Employment Numbers	+	+
Sales Performance	+	2.26***

Table A32: Summary of the regression results showing the effects of wildfire frequency (Fire Count) and wildfire intensity (Burned Areas) on establishment births, deaths, inward relocations, outward relocations, employment numbers, and sales performance within the Aggregate Land-Intensive Sectors (LIS) (NAICS 11, 21, 22, 23). Coefficients $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ correspond to the coefficients on the Fire Count and Burned Areas variables, respectively. The coefficients are semi-elasticities, indicating the percentage change in the dependent variable for a one-unit change in the explanatory variable, holding all else constant. For e.g., a 1-unit increase in the Fire count variable (which corresponds to a 1000 increase in Fire Count) corresponds to a 9.4% increase in establishment deaths; Similarly, a 1-unit increase in the Burned Area Variable (which corresponds to 100% increase of county area being burned) corresponds to a decrease of 84.2% in establishment births. For practical purposes, we interpret the effect of 0.1-unit change in our Fire Count variable (i.e., 100-fire count change) and a 0.01-unit change in the Wildfire Intensity measure variable (i.e., a 1% change in county area burned). This would then correspond to an increase of 0.94% increase in deaths, and a 0.842% decrease in births. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Full regression results are provided in Table A35 for further reference.

Table A33: Sector-Specific Regression Results: Wildfire Frequency

NAICS Sector	Births	Inward Migrations	Deaths	Outward Migrations	Employment Numbers	Sales Performance
11	0 (NS)	- (NS)	+0.156***	+ (NS)	-0.274**	-0.870***
21	- (NS)	+ (NS)	-0.203*	+2.92 ***	- (NS)	- (NS)
22	+ (NS)	- (NS)	+0.359***	- (NS)	+0.409***	+0.731***
23	- (NS)	+ (NS)	+ (NS)	+0.659*	+ (NS)	+ (NS)
31-33	+0.122**	- (NS)	+0.071*	+1.64***	+0.070***	- (NS)

Table A33: Summarizes the regression results of the coefficients on the Fire Count variable (*Fire Count (t-1) (1000s)*) on establishment births, deaths, inward relocations, outward relocations, employment numbers, and sales performance across five sectors: Agriculture, Forestry, Fishing, and Hunting (NAICS 11); Mining, Quarrying, and Oil and Gas Extraction (NAICS 21); Utilities (NAICS 22); Construction (NAICS 23); and Manufacturing (NAICS 31–33). Statistically significant coefficients are denoted by asterisks at the following levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The coefficients are semi-elasticities, indicating the percentage change in Y for a one-unit change in X, holding all else constant. For e.g., a 1-unit increase in the wildfire intensity variable (which corresponds to a 100% increase in county area burned in the previous year) will result in an increase of 15.6% in establishment deaths in the current year. For practical purposes, in our results and interpretation section, we interpret effects of 0.01-unit increases, that is, 1% increases in county area burned (which would then correspond to a 0.156% increase in deaths). Full regression results for each sector are provided in Tables A36–A40.

Table A34: Sector-Specific Regression Results: Wildfire Intensity

NAICS Sector	Births	Inward Migrations	Deaths	Outward Migrations	Employment Numbers	Sales Performance
11	-1.75**	+ (NS)	- (NS)	+ (NS)	- (NS)	- (NS)
21	+2.28***	+ (NS)	-2.06**	+18.7**	- (NS)	- (NS)
22	- (NS)	- (NS)	-2.35***	- (NS)	- (NS)	+1.90*
23	-0.746**	- (NS)	- (NS)	- (NS)	- (NS)	+2.01**
31-33	+ (NS)	- (NS)	+0.788**	+8.27***	-0.344***	+1.47**

Table A34: Regression results for the effects of wildfire intensity (*% County Burned (t-1) (100s)*) on establishment births, deaths, inward relocations, outward relocations, employment numbers, and sales performance across five sectors: Agriculture, Forestry, Fishing, and Hunting (NAICS 11); Mining, Quarrying, and Oil and Gas Extraction (NAICS 21); Utilities (NAICS 22); Construction (NAICS 23); and Manufacturing (NAICS 31–33). The wildfire intensity measures the proportion of county area burned by wildfires. The results capture differentiated sectoral responses to wildfire intensity, reflecting both positive and negative impacts based on sector characteristics. Statistically significant coefficients, denoted by asterisks, represent percentage changes associated with a one-unit increase in Burned Areas. Asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1. Full regression results for each sector can be found in Tables A36–A40.

Table A35: Regression Results for the Aggregate LIS

Variable	Births	In-Migrations	Deaths	Out-Migrations	Employment	Performance
Fire Count (t-1) (1000s)	0.038	0.114	0.094***	1.40***	0.019	0.073
	(0.051)	(0.485)	(0.034)	(0.494)	(0.025)	(0.087)
% County Burned (t-1) (100s)	-0.842**	-32.3	-0.128	5.06	-0.052	2.26***
	(0.345)	(29.0)	(0.350)	(5.07)	(0.121)	(0.770)
Precipitation (t-1) (10s)	0.030	-0.394	-0.008	0.918***	-0.003	-0.140***
	(0.021)	(0.687)	(0.019)	(0.308)	(0.012)	(0.044)
Temperature (t-1) (10s)	0.035	-4.24	-0.124	-4.44	0.568***	-1.20
	(0.411)	(6.59)	(0.321)	(4.13)	(0.209)	(0.827)
CPAD (t-1) (100s)	0.188	1.43	-0.457**	2.12	-0.003	0.233
	(0.270)	(2.59)	(0.206)	(4.17)	(0.122)	(0.397)
Housing Price Index (100s)	-0.069**	-0.143	-0.054**	-0.122	-0.001	-0.071***
	(0.019)	(0.213)	(0.013)	(0.173)	(0.010)	(0.026)
Poverty rate (100s)	-0.435	-37.6**	0.611	3.72	-0.603	1.89
	(1.13)	(15.3)	(0.799)	(11.9)	(0.525)	(2.84)
Median HH Income (100ks)	1.86***	0.126	0.548*	5.58	0.063	2.16***
	(0.497)	(5.68)	(0.309)	(4.39)	(0.260)	(0.701)
O3-Attainment Status (t-1)	0.022	0.258	0.005	-0.049	-0.019	-0.052
	(0.057)	(0.408)	(0.051)	(0.271)	(0.027)	(0.112)
PM-Attainment Status (t-1)	0.064*	-0.750*	0.022	-0.270	-0.038**	-0.192
	(0.035)	(0.424)	(0.025)	(0.392)	(0.016)	(0.121)
Population Density (100s)	3.53***	53.4**	2.36*	17.4	1.11	4.92
	(1.30)	(25.7)	(1.30)	(19.5)	(1.10)	(4.02)
Prior Estab. Count (10ks)	0.777***	-0.433	0.794***	0.075		
	(0.143)	(0.664)	(0.199)	(1.31)		
Prior Exits	-0.033*	0.213				
	(0.019)	(0.284)				
Prior Entries			0.002	0.515***		
			(0.012)	(0.113)		
Observations	3509	3463	3514	3419	3534	3534
Pseudo R2	0.962	0.856	0.969	0.908	0.926	0.859
Chi2	325	57.5	74.2	52.2	47.4	84.9
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A35: PPMLHDFE regression estimates for the effects of wildfire frequency (Fire Count) and wildfire intensity (Burned Areas) on establishment dynamics (births, deaths, inward relocations, outward relocations), employment, and sales performance for the Aggregate Land-Intensive Sectors (NAICS 11, 21, 22, 23). Standard errors (in parentheses) are clustered at the county level to account for spatial heterogeneity. County fixed effects (FE) and year fixed effects (FE) are included in all specifications. Coefficients represent percentage changes associated with a one-unit increase in the explanatory variables. Asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

The regression results in **Table A35** above provide a comprehensive analysis of the aggregate Land-Intensive Sectors (LIS), capturing the overall patterns and relationships across multiple sub-sectors. The interpretation focuses on how socio-economic, environmental, and policy factors influence key outcome variables, offering broad insights into the dynamics of establishment births, migrations, deaths, employment, and sales performance in land-intensive industries:

Births: The Housing Price Index (HPI) negatively affects establishment births, suggesting that higher property values deter new businesses by raising entry costs, consistent with findings from Meltzer et al. (2020). PM Attainment Status positively impacts births, indicating that environmental compliance and better air quality can attract new establishments (Currie et al., 2015). Population Density and Prior Establishment Count positively influence births, reflecting the agglomeration economies where higher density and localized economic activity foster business formation (Glaeser et al., 1992). Prior Exits negatively affect births, supporting Schumpeter's (1942) concept of "creative destruction," where instability from recent exits discourages new ventures.

Inward Relocations: Poverty Rate negatively affects inward relocations, suggesting that areas with higher poverty levels lack the economic infrastructure and demand to attract relocating businesses (Henderson, 1997). Similarly, the negative impact of PM Attainment Status indicates that compliance with stricter particulate matter regulations may discourage firms from relocating to these areas (Currie et al., 2015). Conversely, Population Density positively impacts relocations, reflecting the benefits of concentrated infrastructure, skilled labor, and network effects (Glaeser et al., 1992).

Deaths: Protected Areas (% CPAD t-1) exhibit a negative relationship with deaths, implying that establishments near protected lands benefit from stable operations, potentially tied to ecosystem services or tourism demand (Radeloff et al., 2018). The Housing Price Index negatively affects deaths, suggesting that higher property values sustain demand and reduce firm closures (Meltzer et al., 2020). Median Household Income shows a positive association, consistent with the idea that competitive pressures in wealthier regions increase business turnover (Carlton, 1983). Population Density and Prior Establishment Count positively impact deaths, highlighting the role of competition and saturation in driving closures (Dunne et al., 1989).

Outward Relocations: Precipitation positively impacts outward relocations, likely reflecting operational disruptions in high-precipitation areas, particularly for land-intensive sectors dependent on stable weather conditions (Lobell et al., 2011). Prior Entries also positively affect relocations, suggesting that increased competition from new entrants forces some firms to relocate (Schumpeter, 1942).

Employment: Temperature positively affects employment, indicating increased labor demand to manage heat-related disruptions or adaptations in land-intensive sectors (Deschênes & Greenstone, 2011). PM Attainment Status negatively impacts employment, likely reflecting compliance costs and operational constraints associated with air quality regulations (Currie et al., 2015).

Sales Volume Performance: Precipitation negatively impacts sales volume, consistent with weather-induced disruptions to production and supply chains (Lobell et al., 2011). The Housing Price Index also negatively affects sales performance, indicating that higher costs erode profitability in land-intensive sectors (Meltzer et al., 2020). Conversely, Median Household Income positively impacts sales, supporting findings that stronger local economic conditions boost consumer demand and business revenues (Glaeser et al., 1992).

Table A36: Regression Results for Agriculture (NAICS 11)

Variable	Births	In-Migrations	Deaths	Out-Migrations	Employment	Performance
Fire Count (t-1) (1000s)	-0.057	-0.786	0.156***	0.096	-0.274**	-0.870***
	(0.110)	(1.20)	(0.055)	(1.69)	(0.119)	(0.242)
% County Burned (t-1) (100s)	-1.75**	4.24	0.208	-0.558	-0.212	-0.147
	(0.882)	(5.76)	(0.530)	(6.40)	(0.516)	(1.08)
Precipitation (t-1) (10s)	0.005	-0.549	-0.001	0.079	-0.011	-0.006
	(0.028)	(0.595)	(0.023)	(0.376)	(0.016)	(0.059)
Temperature (t-1) (10s)	0.018	-4.88	0.352	-8.31	0.156	0.412
	(0.581)	(5.73)	(0.484)	(5.52)	(0.514)	(1.01)
CPAD (t-1) (100s)	-0.127	1.79	-0.634**	-4.56	-0.880**	-1.17
	(0.425)	(4.55)	(0.266)	(6.67)	(0.400)	(0.825)
Housing Price Index (100s)	-0.028	-0.002	-0.074***	-0.412**	-0.003	0.001
	(0.021)	(0.223)	(0.016)	(0.201)	(0.020)	(0.045)
Poverty rate (100s)	-1.03	-16.8	-0.761	12.2	-0.770	-0.226
	(1.84)	(16.9)	(1.06)	(15.4)	(1.39)	(2.71)
Median HH Income (100ks)	1.59***	-0.659	0.911	3.95	1.41**	1.59
	(0.595)	(10.2)	(0.653)	(6.35)	(0.712)	(1.45)
O3-Attainment Status (t-1)	-0.064	-0.047	-0.055	0.016	-0.054	0.081
	(0.066)	(0.652)	(0.038)	(0.529)	(0.052)	(0.200)
PM-Attainment Status (t-1)	0.076	-0.714	0.061*	-0.996*	-0.015	0.030
	(0.046)	(0.737)	(0.034)	(0.529)	(0.040)	(0.116)
Population Density (100s)	-5.42	-0.593	-3.86	86.5***	-4.49	-20.4
	(4.93)	(68.1)	(2.78)	(19.3)	(6.53)	(16.9)
Prior Estab. Count (10ks)	2.17	-49.6***	34.8***	165***		
	(2.56)	(8.71)	(4.41)	(25.9)		
Prior Exits	-0.371	3.37**				
	(0.228)	(1.36)				
Prior Entries			-0.365*	-7.67***		
			(0.202)	(1.18)		
Observations	880	795	880	773	885	885
Pseudo R2	0.762	0.917	0.779	0.931	0.933	0.849

Table A36: Continued

Chi2	33.0	125	221	117	30.9	19.2
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A36: PPMLHDFE regression results for the effects of wildfire frequency (Fire Count) and wildfire intensity (Burned Areas) on establishment births, deaths, inward relocations, outward relocations, employment, and sales performance in the Agriculture, Forestry, and Fishing sector (NAICS 11). Standard errors (in parentheses) are clustered at the county level to account for spatial heterogeneity. County fixed effects (FE) and year fixed effects (FE) are included in all specifications. Coefficients represent percentage changes associated with a one-unit increase in the explanatory variables. Asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A36 above presents the regression results for the Agriculture, Forestry, and Fishing sector, emphasizing how explanatory variables shape business and economic outcomes in resource-dependent activities. The interpretations reveal the unique sensitivities of these industries to factors such as income, environmental regulations, and market dynamics, providing insights into their operational challenges and opportunities:

Births: Median Household Income shows a positive association with establishment births, consistent with findings by Glaeser et al. (1992), who emphasize that higher income levels reflect stronger local demand and consumer spending, which attract new businesses. Wealthier counties likely provide better infrastructure and higher labor productivity, making them appealing for new agricultural and forestry ventures.

Inward Relocations: Prior Establishment Count and Prior Exits negatively affect relocations. Higher establishment density signals market saturation, discouraging new entrants (Carlton, 1983). Similarly, recent exits may reflect underlying economic instability or sector-specific risks, making the region less attractive for inward relocations (Meltzer et al., 2020).

Deaths: The negative effect of CPAD(t-1) suggests that protected areas constrain business operations by limiting access to natural resources, consistent with Radeloff et al. (2018). The negative relationship with the Housing Price Index aligns with the idea that higher costs force closures, particularly in cost-sensitive agricultural sectors (Henderson, 1997). Conversely, the positive effect of PM Attainment Status might indicate compliance costs or stricter regulations driving exits (Currie et al., 2015). Prior Establishment Count positively affects deaths, reflecting market competition, while Prior Entries negatively affect them, suggesting market stabilization effects after new businesses enter (Dunne et al., 1989).

Outward Relocations: Higher Housing Price Index discourages outward relocations, likely because firms in high-cost areas have made significant investments, reducing mobility (Meltzer et al., 2020). PM Attainment Status also negatively influences relocations, indicating that regions with better air quality compliance provide a more favorable environment for businesses to remain (Currie et al., 2015). Population Density's positive effect suggests congestion pressures, pushing some establishments to relocate (Glaeser et al., 1992). Prior Establishment Count and Prior Entries also positively affect relocations, reflecting intensified competition and market churn.

Employment: The positive impact of Median Household Income is expected, as wealthier areas often sustain stronger labor demand, fostering job growth (Henderson, 1997). Conversely, CPAD(t-1) negatively affects employment, indicating that land-use restrictions in protected areas limit job creation in resource-intensive activities.

Table A37: Regression Results for Mining (NAICS 21)

Variable	Births	In-Migrations	Deaths	Out-Migrations	Employment	Performance
Fire Count (t-1) (1000s)	-0.116	1.13	-0.203*	2.91***	-0.074	-0.238
	(0.117)	(1.02)	(0.106)	(1.13)	(0.180)	(0.383)
% County Burned (t-1) (100s)	2.27***	6.85	-2.05**	18.6**	-0.490	0.910
	(0.653)	(7.38)	(0.854)	(8.11)	(1.08)	(0.997)
Precipitation (t-1) (10s)	0.153**	0.736	-0.092*	-0.078	0.027	0.211*
	(0.063)	(0.782)	(0.054)	(0.647)	(0.075)	(0.109)
Temperature (t-1) (10s)	2.31**	7.42	1.41*	6.49	-1.16	-1.45
	(1.03)	(8.90)	(0.808)	(7.68)	(1.56)	(2.22)
CPAD (t-1) (100s)	2.15***	6.84	0.986**	0.983	-0.576	1.36
	(0.691)	(6.21)	(0.479)	(8.91)	(0.613)	(1.19)
Housing Price Index (100s)	-0.044	-0.235	-0.038	-0.807**	0.076	-0.123
	(0.032)	(0.348)	(0.036)	(0.338)	(0.051)	(0.083)
Poverty rate (100s)	-2.33	-33.3	-3.00	-6.96	3.45**	9.17**
	(2.29)	(24.4)	(2.74)	(32.5)	(1.64)	(4.00)
Median HH Income (100ks)	1.25	-0.527	-1.38	9.41	0.011	5.70*
	(0.865)	(17.3)	(0.967)	(12.9)	(1.59)	(2.95)
O3-Attainment Status (t-1)	-0.095	-2.26**	-0.217*	-0.981	0.101	0.078
	(0.102)	(1.11)	(0.119)	(1.10)	(0.145)	(0.337)
PM-Attainment Status (t-1)	0.032	-1.73*	0.122	-2.07*	-0.040	-0.350**
	(0.104)	(0.947)	(0.113)	(1.06)	(0.114)	(0.142)
Population Density (100s)	2.07	63.8	5.42	18.6	9.39*	16.8*
	(5.11)	(50.9)	(5.60)	(34.1)	(4.93)	(10.2)
Prior Estab. Count (10ks)	-24.6*	-170**	141***	356***		
	(13.2)	(80.6)	(14.7)	(135)		
Prior Exits	-0.258	16.5				
	(1.20)	(14.9)				
Prior Entries			-3.13**	-9.68		
			(1.32)	(8.81)		
Observations	868	292	868	324	873	873
Pseudo R2	0.729	0.894	0.732	0.885	0.948	0.906

Table A37: Continued

Chi2	47.1	2059	511	202	85.6	182
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A37: PPMLHDFE regression results estimating the effects of wildfire frequency (Fire Count) and wildfire intensity (Burned Areas) on establishment births, deaths, inward relocations, outward relocations, employment, and sales performance in the Mining, Quarrying, and Oil & Gas Extraction sector (NAICS 21). Standard errors (in parentheses) are clustered at the county level to account for spatial heterogeneity. County fixed effects (FE) and year fixed effects (FE) are included in all specifications. Coefficients represent percentage changes associated with a one-unit increase in the explanatory variables. Statistical significance is denoted as follows: ***p < 0.01, **p < 0.05, *p < 0.1.

The regression results in **Table A37** above examine the Mining, Quarrying, and Oil & Gas Extraction sector, highlighting the effects of explanatory variables on key economic outcomes. These findings shed light on how capital-intensive and resource-driven industries respond to socio-economic, policy, and environmental conditions:

Births: Precipitation positively impacts establishment births, highlighting the reliance of this sector on water availability for extraction processes and environmental stabilization, as noted by Lobell et al. (2011). Temperature also shows a positive relationship, suggesting that favorable weather conditions contribute to resource accessibility and operational efficiency in mining and quarrying activities (Burke et al., 2015). CPAD(t-1) positively influences births, likely reflecting demand for mining services near protected areas where resource availability and ecological tourism overlap. Conversely, Prior Establishment Count negatively affects births, indicating that regions with higher business density experience market saturation, discouraging new entries (Carlton, 1983).

Inward Relocations: Negative coefficients for both Ozone and Particulate Matter Attainment Status suggest that stricter environmental regulations deter relocations into areas that comply with these standards, as compliance imposes additional costs on firms in this sector (Currie et al., 2015). Prior Establishment Count also has a negative effect, indicating that higher density discourages relocations due to intensified competition for resources and markets (Henderson, 1997).

Deaths: Precipitation negatively impacts deaths, underscoring the stabilizing role of adequate rainfall in sustaining extraction activities and mitigating operational risks. In contrast, higher temperatures positively influence deaths, reflecting operational challenges and increased production costs associated with extreme heat (Burke et al., 2015). CPAD(t-1) positively affects deaths, potentially reflecting the operational limitations imposed near protected areas due to regulatory constraints. Negative effects of Ozone Attainment Status further emphasize the role of regulatory burdens in reducing viability. Prior Establishment Count positively affects deaths, reflecting competitive pressures in densely concentrated markets, while Prior Entries negatively impact deaths, consistent with findings that recent entrants can stabilize markets by signaling economic recovery (Dunne et al., 1989).

Outward Relocations: The Housing Price Index negatively affects outward relocations, suggesting that higher property values anchor firms in place by increasing sunk costs (Meltzer et al., 2020). Particulate Matter Attainment Status also negatively affects relocations, indicating that regions meeting stricter air quality standards retain firms by providing a healthier and more stable operational environment (Currie et al., 2015). Prior Establishment Count positively impacts relocations, reflecting heightened competition in saturated markets, which pushes some firms to relocate (Carlton, 1983).

Employment: The Poverty Rate positively affects employment, suggesting that mining and quarrying activities thrive in economically disadvantaged areas where labor costs are lower, consistent with Henderson (1997). Population Density also has a positive effect, likely reflecting the sector's need for readily available labor and infrastructure in densely populated areas (Glaeser et al., 1992).

Sales Volume Performance: Precipitation positively affects sales volume, highlighting the importance of stable water supply for extraction processes and overall production. Similarly, Poverty Rate and Median Household Income positively impact performance, reflecting the sector's responsiveness to both low-cost labor availability and local economic demand (Henderson, 1997). Conversely, Particulate Matter Attainment Status negatively affects sales, likely due to the costs of compliance and operational adjustments required to meet regulatory standards (Currie et al., 2015). Population Density positively impacts sales, emphasizing the role of concentrated demand and infrastructure in supporting sectoral performance (Glaeser et al., 1992).

Table A38: Regression Results for Utilities (NAICS 22)

Variable	Births	In-Migrations	Deaths	Out-Migrations	Employment	Performance
Fire Count (t-1) (1000s)	0.086	-0.278	0.359***	-1.351	0.409***	0.731***
	(0.093)	(1.34)	(0.091)	(1.58)	(0.115)	(0.215)
% Burned (t-1) (100s)	-0.067	-50.7	-2.34***	-3.49	-0.279	1.89*
	(0.828)	(34.0)	(0.719)	(8.51)	(0.707)	(1.09)
Precipitation (t-1) (10s)	-0.012	-0.146	0.032	0.536	-0.114***	-0.352***
	(0.048)	(0.421)	(0.047)	(0.524)	(0.034)	(0.064)
Temperature (t-1) (10s)	0.174	-8.74	-0.724	-0.114	-0.326	-1.60
	(0.708)	(6.65)	(0.677)	(7.32)	(0.602)	(1.17)
CPAD (t-1) (100s)	-0.743**	4.90	0.336	8.15**	-0.241	0.016
	(0.376)	(3.00)	(0.300)	(3.47)	(0.492)	(0.375)
Housing Price Index (100s)	-0.021	0.256	-0.188**	-0.188	-0.066***	-0.111***
	(0.036)	(0.257)	(0.045)	(0.272)	(0.023)	(0.042)
Poverty rate (100s)	0.510	-14.5	-3.46	-0.222	4.41*	9.24**
	(2.27)	(18.7)	(2.90)	(22.8)	(2.46)	(3.80)
Median HH Income (100ks)	1.87**	-4.67	2.02*	-1.47	2.98**	2.22
	(0.942)	(5.83)	(1.15)	(8.02)	(1.46)	(1.76)
O3-Attainment Status (t-1)	-0.022	-1.15	-0.061	-0.598	0.207	0.193
	(0.130)	(1.147)	(0.132)	(0.900)	(0.171)	(0.190)
PM-Attainment Status (t-1)	0.218**	-0.053	0.142*	-0.241	-0.117	-0.377**
	(0.087)	(0.544)	(0.082)	(0.468)	(0.105)	(0.189)
Population Density (100s)	-5.53	33.2	-1.72	34.5	-6.15	2.88
	(4.66)	(33.3)	(3.84)	(33.5)	(5.17)	(6.64)
Prior Estab. Count (10ks)	-53.7***	-365***	44.3***	279*		
	(9.77)	(83.1)	(15.8)	(149)		
Prior Exits	5.96***	69.2**				
	(1.64)	(31.1)				
Prior Entries			7.46***	50.8***		
			(2.85)	(12.8)		
Observations	869	417	863	504	879	879
Pseudo R2	0.663	0.544	0.666	0.586	0.949	0.864
Chi2	96.0	67.7	261	85.6	45.9	52.1

Table A38: Continued

County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A38: PPMLHDFE regression estimates examining the effects of wildfire frequency (Fire Count) and wildfire intensity (Burned Areas) on establishment births, deaths, inward relocations, outward relocations, employment, and sales performance in the Utilities sector (NAICS 22). Standard errors (in parentheses) are clustered at the county level to account for spatial heterogeneity. County fixed effects (FE) and year fixed effects (FE) are included in all specifications. Coefficients represent percentage changes associated with a one-unit increase in the explanatory variables. Statistical significance is denoted as follows: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A38 above details the regression results for the Utilities sector, exploring the impact of socio-economic and environmental factors on this critical infrastructure industry. The interpretations underscore how regulatory frameworks, population density, and income levels influence establishment dynamics, employment, and sales performance within utilities:

Births: Protected Areas (% CPAD t-1) negatively affect establishment births, suggesting that restrictions on land use near protected areas hinder infrastructure development for utilities, consistent with Radeloff et al. (2018). Median Household Income positively impacts births, indicating that wealthier regions provide stronger demand for utility services, encouraging new establishment creation (Henderson, 1997). The positive effect of Particulate Matter (PM) Attainment Status implies that compliance with air quality standards enhances attractiveness by ensuring a healthier environment (Currie et al., 2015). However, Prior Establishment Count negatively impacts births, reflecting market saturation, while Prior Exits positively affect births, supporting Schumpeter’s (1942) concept of "creative destruction," where closures create opportunities for new entrants.

Inward Relocations: Prior Establishment Count negatively impacts inward relocations, reflecting the deterrent effect of saturated markets (Carlton, 1983). Conversely, Prior Exits positively influence relocations, as the availability of resources and infrastructure from exiting establishments attracts relocating firms, consistent with Meltzer et al. (2020).

Deaths: The Housing Price Index negatively affects deaths, suggesting that higher property values provide stability by supporting consistent demand for utility services (Meltzer et al., 2020). Median Household Income positively impacts deaths, reflecting competitive pressures in wealthier regions that may push out less competitive firms (Carlton, 1983). PM Attainment Status positively affects deaths, likely due to compliance costs associated with maintaining air quality standards (Currie et al., 2015). Prior Establishment Count and Prior Entries both positively influence deaths, indicating increased competition and market churn in regions with higher density and new entrants (Dunne et al., 1989).

Outward Relocations: CPAD(t-1) positively impacts outward relocations, suggesting that regulatory and operational challenges near protected areas may prompt firms to relocate. Both Prior Establishment Count and Prior Entries positively influence relocations, reflecting market competition and pressures in regions with higher density and business turnover (Glaeser et al., 1992).

Employment: Precipitation negatively impacts employment, likely due to operational disruptions caused by excessive rainfall (Lobell et al., 2011). The Housing Price Index also negatively affects employment, suggesting that higher costs constrain labor demand (Meltzer et al., 2020). Conversely, Poverty Rate and Median Household Income positively affect employment. The positive effect of Poverty Rate reflects the sector's reliance on lower-cost labor available in economically disadvantaged regions (Henderson, 1997), while Median Household Income indicates that wealthier regions sustain stronger labor demand.

Sales Volume Performance: Precipitation negatively affects sales volume, reflecting the disruptive impacts of extreme weather on utility operations (Lobell et al., 2011). Similarly, the Housing Price Index negatively impacts sales, consistent with cost pressures in high-value property areas. The positive effect of Poverty Rate indicates that utility demand remains resilient even in economically disadvantaged areas due to the essential nature of utility services (Henderson, 1997). However, PM Attainment Status negatively impacts sales volume, reflecting compliance costs associated with meeting air quality standards (Currie et al., 2015).

Table A39: Regression Results for Construction (NAICS 23)

Variable	Births	In-Migrations	Deaths	Out-Migrations	Employment	Performance
Fire Count (t-1) (1000s)	-0.006	0.532	0.059	0.659*	0.003	0.029
	(0.050)	(0.616)	(0.041)	(0.365)	(0.033)	(0.067)
% Burned (t-1) (100s)	-0.746**	-6.50	-0.156	-0.754	-0.184*	2.00***
	(0.296)	(8.21)	(0.400)	(4.13)	(0.108)	(0.693)
Precipitation (t-1) (10s)	0.031	-0.270	-0.004	0.411	0.001	-0.132***
	(0.021)	(0.417)	(0.021)	(0.263)	(0.014)	(0.050)
Temperature (t-1) (10s)	0.421	5.26	-0.052	-10.1***	0.617***	-2.13***
	(0.417)	(6.31)	(0.351)	(3.90)	(0.214)	(0.713)
CPAD (t-1) (100s)	0.647**	6.41**	-0.282	-1.826	0.058	0.379
	(0.301)	(2.71)	(0.219)	(3.68)	(0.147)	(0.442)
Housing Price Index (100s)	-0.036**	0.014	-0.033**	-0.504***	-0.009	-0.103***
	(0.018)	(0.172)	(0.016)	(0.114)	(0.010)	(0.025)
Poverty rate (100s)	-1.79	-25.4**	0.129	12.3	-0.991	-0.108
	(1.20)	(11.2)	(0.830)	(12.6)	(0.647)	(3.27)
Median HH Income (100ks)	1.15***	-1.89	0.152	12.5***	-0.163	2.28***
	(0.435)	(5.44)	(0.357)	(2.70)	(0.267)	(0.695)
O3-Attainment Status (t-1)	-0.005	0.379	0.000	-0.031	-0.030	-0.087
	(0.045)	(0.363)	(0.050)	(0.402)	(0.035)	(0.136)
PM-Attainment Status (t-1)	0.019	-0.738	-0.001	-0.215	-0.010	-0.143
	(0.044)	(0.511)	(0.025)	(0.375)	(0.019)	(0.112)
Population Density (100s)	8.28***	91.6***	4.49***	-17.2	1.89	8.25**
	(1.36)	(28.4)	(1.16)	(15.0)	(1.19)	(4.09)
Prior Estab. Count (10ks)	0.130	-7.31***	0.551***	8.37***		
	(0.105)	(1.61)	(0.191)	(2.00)		
Prior Exits	-0.027*	0.409*				
	(0.016)	(0.231)				
Prior Entries			0.008	0.139		
			(0.011)	(0.187)		
Observations	880	848	880	856	885	885
Pseudo R2	0.968	0.886	0.975	0.935	0.991	0.919
Chi2	201	170	68.9	324	43.7	114

Table A39: Continued

County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A39: PPMLHDFE regression results analyzing the effects of wildfire frequency (Fire Count) and wildfire intensity (Burned Areas) on establishment births, deaths, inward relocations, outward relocations, employment, and sales performance in the Construction sector (NAICS 23). Standard errors (in parentheses) are clustered at the county level to account for spatial heterogeneity. County fixed effects (FE) and year fixed effects (FE) are included in all specifications. Coefficients represent percentage changes associated with a one-unit increase in the explanatory variables. Statistical significance is denoted as follows: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A39 presents the regression results for the Construction sector, illustrating the relationship between explanatory variables and establishment outcomes in this labor-intensive and highly localized industry. The analysis highlights how market conditions and environmental factors interact to shape business performance and employment trends:

Births: Protected Areas (% CPAD t-1) positively affect establishment births, suggesting that proximity to protected areas creates demand for construction projects related to infrastructure development or residential expansion, consistent with findings by Radeloff et al. (2018). Conversely, the Housing Price Index negatively impacts births, indicating that high property costs serve as a barrier to new entrants in the construction sector (Meltzer et al., 2020). Median Household Income positively influences births, as higher income levels signify stronger demand for housing and commercial projects (Glaeser et al., 1992). Similarly, Population Density positively affects births, reflecting the increased need for construction services in densely populated areas (Henderson, 1997). Prior Exits negatively impact births, aligning with Schumpeter’s (1942) concept of "creative destruction," where instability from recent closures discourages new business formation.

Inward Relocations: CPAD(t-1) positively affects inward relocations, indicating that protected areas create opportunities for firms relocating to meet infrastructure or development needs near these regions (Radeloff et al., 2018). Poverty Rate negatively impacts relocations, suggesting that economically disadvantaged areas are less attractive to construction firms due to limited market demand (Henderson, 1997). In contrast, Population Density positively influences relocations, as urban areas with higher population concentrations provide better opportunities for construction firms (Glaeser et al., 1992). Prior Establishment Count negatively impacts relocations, likely due to market saturation or intense competition. However, Prior Exits positively affect relocations, suggesting that business closures free up resources or market opportunities that attract new firms (Meltzer et al., 2020).

Deaths: The Housing Price Index negatively impacts deaths, indicating that higher property values provide a stabilizing effect by ensuring consistent demand for construction services (Meltzer et al., 2020). Population Density positively affects deaths, reflecting competitive pressures in densely populated areas that push out less competitive firms (Glaeser et al., 1992). Prior Establishment Count also positively influences deaths, consistent with findings that higher business density increases competition and market churn (Dunne et al., 1989).

Outward Relocations: Temperature negatively affects outward relocations, suggesting that construction firms are less likely to leave areas with favorable climate conditions that support year-round operations (Burke et al., 2015). The Housing Price Index also negatively impacts relocations, as high property values create sunk costs that deter firms from moving. Conversely, Median Household Income positively influences relocations, as wealthier areas may generate competitive pressures or higher costs that incentivize some firms to relocate (Carlton, 1983). Prior Establishment Count positively affects outward relocations, indicating that high competition in dense markets can drive firms to seek less saturated locations (Henderson, 1997).

Employment: Temperature positively impacts employment, reflecting the increased demand for labor in warmer climates, where year-round construction activity is more feasible (Deschênes & Greenstone, 2011).

Sales Volume Performance: Precipitation negatively impacts sales volume, as weather-related disruptions reduce construction activity and delay project completion (Lobell et al., 2011). Similarly, Temperature negatively affects sales, reflecting the operational challenges posed by extreme heat. The Housing Price Index also negatively impacts sales, as high property values may constrain profitability due to increased costs (Meltzer et al., 2020). Conversely, Median Household Income positively influences sales, as wealthier areas provide stronger demand for construction projects (Glaeser et al., 1992). Population Density positively impacts sales, reflecting the increased demand for construction services in urban and densely populated regions (Henderson, 1997).

Table A40: Regression Results for Manufacturing (NAICS 31–33)

Variable	Births	In-Migrations	Deaths	Out-Migrations	Employment	Performance
Fire Count (t-1) (1000s)	0.122**	-0.079	0.071*	1.64***	0.070***	-0.014
	(0.049)	(0.524)	(0.039)	(0.538)	(0.023)	(0.103)
% County Burned (t-1) (100s)	-0.310	-0.120	0.788*	8.26**	-0.344***	1.47**
	(0.351)	(4.47)	(0.427)	(3.82)	(0.134)	(0.618)
Precipitation (t-1) (10s)	0.067**	0.573*	0.019	0.287	0.024	0.059
	(0.032)	(0.348)	(0.024)	(0.302)	(0.017)	(0.084)
Temperature (t-1) (10s)	0.144	-1.53	0.161	-0.910	0.189	-1.47
	(0.446)	(5.34)	(0.313)	(4.45)	(0.359)	(1.00)
CPAD (t-1) (100s)	0.581*	0.154	-0.034	0.334	-0.358**	0.092
	(0.330)	(4.02)	(0.264)	(4.49)	(0.145)	(0.614)
Housing Price Index (100s)	-0.080***	-0.675***	0.004	0.216	-0.094***	-0.225***
	(0.024)	(0.143)	(0.016)	(0.169)	(0.015)	(0.044)
Poverty rate (100s)	0.363	-5.49	-3.72***	-14.6	0.261	2.06
	(1.27)	(14.8)	(0.773)	(15.4)	(0.711)	(3.27)
Median HH Income (100ks)	1.91***	12.4***	-0.683**	-4.90	1.74***	4.56***
	(0.567)	(4.12)	(0.317)	(3.97)	(0.213)	(0.642)
O3-Attainment Status (t-1)	0.004	-0.956*	0.039	0.346	-0.004	-0.073
	(0.051)	(0.563)	(0.037)	(0.574)	(0.030)	(0.162)
PM-Attainment Status (t-1)	-0.011	-0.527	0.049	-0.324	0.033	-0.054
	(0.039)	(0.410)	(0.039)	(0.347)	(0.029)	(0.078)
Population Density (100s)	0.697	35.5**	1.52	18.1	1.02	7.71
	(2.07)	(14.1)	(1.30)	(19.9)	(0.991)	(5.470)
Prior Estab. Count (10ks)	0.204***	-2.31*	0.629***	-0.611		
	(0.075)	(1.34)	(0.179)	(2.44)		
Prior Exits	0.011**	-0.025				
	(0.004)	(0.157)				
Prior Entries			0.004	0.322*		
			(0.020)	(0.194)		
Observations	864	807	873	736	878	808
Pseudo R2	0.981	0.902	0.984	0.917	0.994	0.926

Table A40: Continued

Chi2	304	337	684	64.4	179	357
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A40: PPMLHDFE regression estimates of wildfire impacts on establishment dynamics, employment, and sales performance in the Manufacturing sector, representing the non-LIS group. Standard errors (in parentheses) are clustered at the county level to account for spatial heterogeneity. County fixed effects (FE) and year fixed effects (FE) are included in all specifications. Coefficients represent percentage changes associated with a one-unit increase in the explanatory variables. Statistical significance is denoted as follows: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A40 provides regression results for the Manufacturing sector, focusing on how socio-economic, policy, and environmental variables influence this diverse and innovation-driven industry. The interpretations offer insights into how manufacturing establishments navigate market competition, regulatory constraints, and economic opportunities:

Births: Precipitation positively impacts establishment births, indicating that stable water availability supports manufacturing operations, particularly those reliant on water-intensive processes, as suggested by Lobell et al. (2011). $CPAD(t-1)$ also positively affects births, reflecting the stabilizing influence of proximity to protected areas that can provide resources or buffer economic fluctuations (Radeloff et al., 2018). Conversely, the Housing Price Index negatively impacts births, suggesting that high property costs deter new manufacturing establishments by increasing operational costs (Meltzer et al., 2020). Median Household Income positively influences births, as higher income levels reflect stronger consumer demand for manufactured goods (Glaeser et al., 1992). Similarly, Prior Establishment Count and Prior Exits both positively impact births, highlighting the role of agglomeration economies and opportunities created by business turnover (Dunne et al., 1989; Schumpeter, 1942).

Inward Relocations: Precipitation positively impacts inward relocations, emphasizing the sector's dependence on stable climatic conditions for operations. However, the Housing Price Index negatively affects relocations, indicating that higher property costs discourage firms from relocating to high-cost regions (Carlton, 1983). Median Household Income positively influences relocations, as wealthier areas provide a supportive consumer base and infrastructure (Henderson, 1997). Ozone Attainment Status negatively impacts relocations, reflecting the additional regulatory burdens in areas meeting stricter air quality standards (Currie et al., 2015). Population Density positively impacts relocations, as urban areas offer labor pools and supply chain advantages (Glaeser et al., 1992). Conversely, Prior Establishment Count negatively impacts relocations, reflecting saturation effects in regions with dense manufacturing clusters.

Deaths: Poverty Rate negatively impacts deaths, suggesting that manufacturing establishments in economically disadvantaged areas benefit from lower costs and reduced competition (Henderson, 1997). Conversely, Median Household Income negatively affects deaths, indicating that wealthier areas experience greater competitive pressures, leading to higher exit rates among less competitive firms (Carlton, 1983). Prior Establishment Count positively impacts deaths, reflecting market saturation and competitive pressures in regions with high business density (Dunne et al., 1989).

Outward Relocations: Prior Entries positively influence outward relocations, suggesting that increased competition from new entrants forces some existing firms to relocate to less saturated regions (Schumpeter, 1942).

Employment: $CPAD(t-1)$ negatively impacts employment, indicating that restrictions on land use in protected areas limit opportunities for job creation in manufacturing activities. Similarly, the Housing Price Index negatively impacts employment, reflecting the cost pressures associated with operating in high-value property areas (Meltzer et al., 2020). Conversely, Median Household Income positively affects employment, as wealthier regions can support higher labor demand and wages (Henderson, 1997).

Sales Volume Performance: The Housing Price Index negatively affects sales volume, consistent with findings that high property costs reduce profitability in cost-sensitive manufacturing sectors (Meltzer et al., 2020). Median Household Income positively impacts sales, reflecting the role of consumer demand in wealthier regions in sustaining manufacturing output (Glaeser et al., 1992).

Marginal Impact Calculation, Normalization, and Interpretation

The PPML-HDFE model, used to estimate the nonlinear economic impacts of wildfire frequency and intensity, expresses results as semi-elasticities. This approach simplifies interpretation by representing percentage changes in the dependent variable due to unit changes in independent variables. This section provides a detailed explanation of the marginal impact calculation and the normalization procedure applied in this chapter.

Model Specification

In this study, the dependent variables are count data (e.g., the number of establishments). The relationship between the outcome variable (Y) and the explanatory variables is modeled using the following specification:

$$Y_{its} = \exp\left(\beta_0 + \beta_1 Fire\ Count_{i,t-1} + \beta_2 Burned\ Areas_{i,t-1} + \beta_3 Z_{is,t-1} + \sum_{k=1}^{N} \beta_k X_{kit} + \alpha_i + \lambda_t + \gamma_s\right) + \epsilon_{it}$$

This specification emphasizes that the dependent variable (Y_{its}) is a count variable and incorporates the error term (ε_{it}) to capture deviations from the model.

Transition to the Expected Value Representation

To estimate the relationships and interpret results, we focus on the expected value of Y_{its}, denoted $E[Y_{its}]$, instead of the observed Y_{its} . The observed counts Y_{its} are assumed to follow a Poisson distribution, where the mean (μ_{its}) is modeled as: $E[Y_{its} \mid Covariates] = \mu_{its}$

The Poisson assumption links the observed Y_{its} to its expected value. The expected value of Y_{its} is expressed as:

$$E[Y_{its} \mid Covariates] = exp\ (\beta_0 + \beta_1 FireCount_{i,t-1}\ + \beta_2 BurnedAreas_{i,t-1} + \cdots\ )$$

The exponential function ensures the expected value is non-negative, which is consistent with the count nature of Y_{its}. The error term (ε_{it}) is implicitly absorbed into the quasi-likelihood estimation framework of PPML, where the estimation focuses on the expected value ($E[Y]$) rather than modeling the error explicitly. This is a standard feature of the PPML approach. The transition leads to the final expected value formulation:

$E[Y_{its}] = exp\ (\beta_0 + \beta_1 FireCount_{i,t-1}\ + \beta_2 BurnedAreas_{i,t-1} + \cdots + \alpha_i + \lambda_t + \gamma_s)$

Marginal Impact Calculation

(a) Marginal Effect for Fire Count

The marginal effect of $FireCount_{i,t-1}$ on $E[Y_{its}]$ is: $\frac{\partial E[Y_{its}|Covariates]}{\partial FireCount_{i,t-1}} =$

$E[\,Y_{its}\mid Covariates\,] * \beta_1$

After normalization ($E[Y_{its}] = 1$): $\frac{\partial E[Y_{its}|Covariates]}{\partial FireCount_{i,t-1}} = \beta_1$

Interpretation:

- A 1-unit increase in $FireCount$ (scaled by 1,000 fires) results in a $\beta_1 * 100\%$ change in $E[Y_{its}]$.
- For a smaller increment of 0.1 units (representing 100 fires), the marginal effect is $0.1 * \beta_1$.

(b) Marginal Effect for Burned Area

The marginal effect of $Burned\ Areas_{i,t-1}$ is: $\frac{\partial E[Y_{its}|Covariates]}{\partial Burned\ Areas_{i,t-1}} = E[\,Y_{its}\mid Covariates\,] * \beta_2$

After normalization ($E[Y_{its}] = 1$): $\frac{\partial E[Y_{its}|Covariates]}{\partial Burned\ Areas_{i,t-1}} = \beta_2$

Interpretation:

- A 1-unit increase in $Burned\ Areas$ (100% increase in area burned) results in a $\beta_2 * 100\%$ change in $E[Y_{its}]$.
- For a smaller increment of 0.01 units (1% increase in area burned), the marginal effect is $0.1 * \beta_2$.

What Is Normalization in the Context of Marginal Effects?

Normalization in the context of marginal effects refers to the simplification of the scaling factor $E[Y \mid X]$ (the expected value of the dependent variable) by assuming $E[Y \mid X] = 1$. This is a common practice in econometric analysis to focus on relative changes in the dependent variable (Y) rather than its absolute level.

Theoretical Justification

Normalization involves setting $E[Y] = 1$ to simplify the interpretation of marginal effects. This is standard in econometrics for non-linear models like the PPML model and supported by:

Cameron & Trivedi (2013): Emphasize that normalization simplifies semi-elasticity interpretations, allowing marginal effects to represent percentage changes directly.

Greene (2012): States that normalization avoids the need to scale results by the level of Y, ensuring consistent interpretation across different dependent variable levels.

Wooldridge (2010): Suggests normalizing $E[Y \mid X]$ to align with multiplicative models and facilitate direct interpretability of marginal effects as elasticities. Hence the Normalization procedure aligns with common practices in the econometrics literature (Wooldridge, 2010; Greene, 2012; Cameron & Trivedi, 2013).

CHAPTER III: FROM ENDANGERED TO RECOVERED

ECONOMIC EFFECTS OF SPECIES DELISTING WITH EVIDENCE FROM THE LOUISIANA BLACK BEAR

Abstract

This study examines the economic impacts of delisting the Louisiana Black Bear, providing one of the first rigorous empirical analyses of post-delisting effects on regional economies. Using data across multiple sectors and three key outcome variables—establishment count, job count, and sales volume—this dissertation chapter investigates the delisting impact on land-intensive and non-land-intensive sector outcomes. The analysis captures both immediate impacts and the temporal evolution of these effects. The results reveal significant heterogeneity in economic responses: LIS experience large and persistent declines, driven by their reliance on fixed land resources and infrastructure, while non-LIS demonstrate resilience and growth, benefiting from increased economic opportunities. For example, agriculture sees a 12.5% immediate decline in establishments, compounded annually, whereas construction shows a positive 8.7% immediate increase with further annual growth. This study makes several contributions to the literature on Conservation Economics, Land Use Economics, and Industrial Organization. First, it integrates spatial and temporal dimensions, providing a more nuanced understanding of delisting impacts. Second, it highlights sectoral heterogeneity, emphasizing the role of land dependency and economic flexibility in shaping outcomes. Finally, it offers practical policy recommendations, including targeted support for vulnerable industries, spatially differentiated interventions, and sustainable conservation management. This research advances the understanding of post-delisting trade-offs and provides policymakers with actionable insights to harmonize species recovery and economic development goals.

3.1 Introduction

The Endangered Species Act (ESA) has played a pivotal role in preventing species extinction, yet it remains a subject of debate due to its perceived economic implications. Critics argue that land-use restrictions imposed by the ESA disrupt economic activity, particularly in Land-Intensive Sectors (LIS) such as agriculture and mining. Proponents, on the other hand, emphasize its success in preserving biodiversity and ecosystem health. However, the economic dynamics following species delisting—when protections are lifted—remain poorly understood. This gap in understanding is critical, as delisting represents a transition point where regulatory constraints are removed, creating potential for both economic recovery and ecological risk.

This study examines the economic impacts of species delisting using the case of the Louisiana Black Bear, which was removed from the ESA list in 2016 following decades of conservation efforts. Employing county-level data from 1998 to 2019 across 118 counties within the bear's historical range, this analysis leverages a Poisson Pseudo-Maximum Likelihood (PPML) framework to evaluate changes in establishment counts, employment, and sales volumes. The study integrates spatial (species range overlap), temporal (time since delisting), and sectoral (LIS vs. non-LIS) dimensions, providing a comprehensive assessment of delisting's economic consequences.

The findings reveal significant heterogeneities in how sectors respond to delisting. LIS such as agriculture and mining experience persistent declines, reflecting structural dependencies on land resources and slower adaptation to regulatory changes. In contrast, non-LIS like construction and real estate exhibit robust growth, capitalizing on reduced regulatory barriers. Temporally, LIS exhibit immediate disruptions and cumulative declines, while non-LIS demonstrate steady growth over time. Spatially, counties with greater habitat overlap face delayed recovery in LIS but realize substantial long-term gains in adaptable industries. These results highlight the importance of understanding sectoral vulnerabilities, spatial variation, and temporal adjustments to develop effective conservation and economic policies.

This study contributes to the literature on conservation economics, land use, and regional development by addressing the economic trade-offs associated with species delisting. It advances methodological precision through the integration of spatial and temporal dimensions, offering a nuanced perspective that balances ecological and economic considerations. The findings inform policymakers on strategies to support vulnerable sectors while leveraging growth opportunities in adaptable industries, underscoring the importance of post-delisting monitoring, targeted interventions, and dynamic conservation policies.

The structure of this chapter is as follows: Section 2 reviews the existing literature on the economic implications of ESA regulations. Section 3 provides an overview of the ESA and the specific case of the Louisiana Black Bear. Section 4 details the research objectives, questions, and hypotheses. Section 5 describes the dataset, variables, and data sources, along with summary statistics. Section 6 presents the econometric methodology employed. Section 7 discusses the empirical results and their interpretation. Section 8 examines policy implications and broader relevance, while Section 9 concludes by summarizing key insights and outlining directions for future research.

3.2 The Endangered Species Act (ESA), and the Louisiana Black Bear

3.2.1 The Endangered Species Act (ESA)

The ESA of 1973 is a cornerstone of U.S. conservation policy, providing legal protections for species at risk of extinction. Protections include restrictions on land use within designated Critical Habitat Designations (CHDs) and species ranges, which facilitate recovery but often constrain land-intensive industries. Of the 1,732 species listed under the ESA, only 3% have recovered (PERC, 2023). While the economic costs of listing have been extensively studied, the economic effects of delisting remain underexplored. This chapter addresses this gap by analyzing the delisting of the Louisiana Black Bear, following decades of successful conservation efforts.

3.2.2 The Louisiana Black Bear: Listing and Delisting

The Louisiana Black Bear (Ursus americanus luteolus) was listed as threatened under the ESA in 1992 due to habitat loss and population decline. The species' large, connected habitat needs significantly impacted land use in its range, spanning Louisiana, Mississippi, and Texas. After decades of habitat restoration and population recovery, the bear was delisted in 2016, lifting ESA-imposed restrictions and creating an opportunity to evaluate the economic consequences of delisting. The Louisiana Black Bear serves as an ideal case study for this research due to the following reasons.

First, mammals like the Louisiana Black Bear require large habitats, amplifying the economic consequences of both listing and delisting, especially for LIS. Second, few mammals have been delisted, and even fewer provide sufficient post-delisting data for rigorous analysis, making the Louisiana Black Bear a rare and valuable subject. Third, Historical range data from reliable sources such as the U.S. Fish and Wildlife Service and the Databasin platform enable robust spatial analysis of economic outcomes. Fourth, the bear's range overlaps with key LIS like agriculture, forestry, and construction, as well as non-land-intensive industries like real estate and tourism, allowing for sectoral comparisons. Lastly, the proprietary Data Axle Historical Business Database (1997–2019) aligns closely with the bear's 2016 delisting, enabling robust empirical analysis of spatial, temporal, and sectoral impacts.

3.2.3 Range as the Primary Measure

This study uses the Louisiana Black Bear's range as the primary measure of regulatory impact, as it aligns with the research objectives to analyze spatial, temporal, and sectoral economic outcomes.

The Range is defined using two complementary measures:

1. **Binary Measure**: This variable indicates whether any part of a county overlaps with the Louisiana Black Bear's range (1 = within range, 0 = outside range). The binary measure enables categorical comparisons of economic outcomes between counties directly and indirectly affected by regulatory protections.
2. **Continuous Measure**: This variable captures the percentage of a county's land area within the bear's range. The continuous measure allows for nuanced analyses of spatial variation and intensity of habitat overlap, offering insights into how economic impacts vary with the extent of range coverage.

These dual definitions provide flexibility in capturing both the presence and magnitude of the species' range within counties, enhancing the ability to evaluate spatial heterogeneity in economic impacts. The choice of Range over Critical Habitat Designations (CHDs) further supports the study's objectives. In terms of spatial coverage, the range encompasses all counties associated with the species, reflecting the full extent of regulatory impacts during and after listing. In contrast, CHDs are limited to specific areas and provide a narrower geographic scope. In terms of temporal relevance post-delisting, CHDs were removed alongside the bear's delisting in 2016, limiting their applicability for understanding post-delisting adjustments. The range remains relevant for analyzing economic impacts and their evolution.

In terms of sectoral insights, the range intersects both LIS (e.g., agriculture, forestry) and non-LIS (e.g., real estate, tourism). This allows the study to evaluate sectoral heterogeneity more effectively than CHDs. In terms of policy context, even after delisting, the range reflects ongoing economic and conservation dynamics, including state regulations and voluntary conservation agreements that influence land use and industry adjustments. This makes the range a more effective proxy for capturing how delisting continues to shape economic activity. By prioritizing the species Range and employing dual definitions, this study ensures a robust and comprehensive analysis of delisting's economic impacts, capturing spatial breadth, temporal evolution, and sectoral variation.

3.3 Research Objectives, Questions, and Hypotheses

3.3.1 Research Objectives

The primary objective of this chapter is to quantify the economic impacts of delisting the Louisiana Black Bear under the Endangered Species Act (ESA). Specifically, the study examines how delisting influences economic outcomes—establishment counts, employment, and sales volumes—across spatial, temporal, and sectoral dimensions. Spatially, it evaluates differences in economic impacts between counties within the bear's range and those outside. Temporally, it investigates how these impacts evolve over time following the delisting decision. Sectorally, it analyzes variations in impacts between land-intensive industries and non-land-intensive industries. Together, these objectives provide a comprehensive framework to assess the economic adjustments driven by delisting, offering insights into the broader interplay between conservation policies and regional economic dynamics.

3.3.2 Research Questions and Hypotheses

The study addresses three core research questions (RQs) and hypotheses (H):

RQ1: Spatial Impacts: How does the delisting of the Louisiana Black Bear affect economic outcomes (establishments, employment, and sales) in counties within the bear's range compared to those outside?

H1: Counties within the bear's range experience significant differences in economic outcomes compared to counties outside the range.

RQ2: Temporal Dynamics: How do the economic impacts of delisting vary over time in counties within the bear's range?

H2: The interaction between the bear's range and the time since its delisting explains the evolution of economic impacts, with effects either growing, stabilizing, or diminishing over time.

RQ3: Sectoral Variation: How do the impacts of delisting differ between land-intensive and non-LIS?

H3: LIS experience more pronounced economic impacts than non-LIS, especially in counties with higher habitat coverage.

3.3.3 Model Linkage and Applications

The econometric framework (detailed in Section 6) directly addresses the research questions and hypotheses by integrating the dual definitions of Range:

Spatial Impacts (RQ1): The binary and continuous measures of Range allow for spatial analysis at different levels of granularity. The binary measure facilitates comparisons between counties within and outside the Range, while the continuous measure captures the intensity of habitat overlap and its economic effects.

Temporal Dynamics (RQ2): Interaction terms incorporating the Time Since Delisting (TSD) variable are applied to both Range measures. This approach tracks the evolution of economic outcomes over time and assesses whether impacts grow, stabilize, or diminish following delisting.

Sectoral Variation (RQ3): Sector-specific regressions (based on NAICS industry categories) utilize the Range definitions to examine heterogeneity in economic impacts. Land-intensive and non-land-intensive industries are evaluated for differential responses based on their dependency on land access and regulatory relief.

By employing these dual definitions within the econometric framework, this study ensures robust testing of the spatial, temporal, and sectoral hypotheses, offering deeper insights into the economic consequences of delisting.

3.3.4 Summary

This chapter develops a structured approach to quantify the economic impacts of delisting the Louisiana Black Bear. By addressing spatial, temporal, and sectoral dimensions, the study aims to identify patterns of economic adjustment and their implications for regional development. The framework ensures alignment with the research objectives, focusing on measurable economic outcomes while informing policy strategies to balance conservation goals with economic opportunities.

3.4 Literature Review

3.4.1 Introduction

This section synthesizes key research examining the economic implications of the U.S. Endangered Species Act (ESA) and its regulations. The reviewed literature focuses on how ESA-related policies, including species listing and critical habitat designation (CHD), affect land use, economic activity, and labor markets. These studies inform this dissertation's exploration of the economic consequences of delisting the Louisiana Black Bear, with particular emphasis on spatial, temporal, and sectoral variations.

3.4.2 Economic Impacts of ESA Regulations

Research demonstrates that ESA-imposed land use restrictions significantly influence agricultural and labor markets. Melstrom (2020) employed a hedonic pricing model to examine the effects of ESA restrictions on agricultural land values, profits, and revenues. The study found that dryland areas—regions with less than 1% of agricultural land under irrigation—experienced a 4% decline in land values and profitability post-listing. Irrigated areas, in contrast, showed no measurable impact, underscoring the heterogeneous economic burdens of ESA compliance. Similarly, Melstrom (2016) assessed the labor market consequences of the ESA listing of the lesser prairie chicken. Using a difference-in-differences framework with county-level employment data, the study identified a 1% decline in employment in counties with prairie chicken habitats. The magnitude of the impact was proportional to the extent of habitat coverage, suggesting that areas with larger habitats faced greater economic disruption.

3.4.3 Critical Habitat Designation and Development

Critical Habitat Designation (CHD) is another contentious aspect of the ESA, with significant implications for development activities. Zabel and Paterson (2006) investigated the effect of CHD on California's housing market by analyzing permit issuance data over a 13-year period. Their fixed-effects regression analysis revealed a 23.5% reduction in housing permits in the short term and a 37% decline in the long term. These findings suggest that CHD increases development costs and acts as a deterrent to construction activities, thereby affecting housing supply and local economic dynamics.

3.4.4 Behavioral Responses to ESA Policies

Regulatory uncertainty often triggers unintended economic and environmental consequences. Zhang (2007) explored the behavioral responses of timberland owners to the potential listing of the red-cockaded woodpecker. The study found that landowners preemptively clear-cut forests to avoid future restrictions, thereby undermining conservation objectives. Using econometric models, Zhang demonstrated the counterproductive effects of ESA-induced regulatory uncertainty on private land management (Zhang, 2007). In contrast, Sims et al. (2019) provided evidence that land protection under the ESA can have neutral or even positive local economic effects. Their quasi-experimental analysis of employment and housing permits in New England showed modest increases in employment without significant changes in housing development or median incomes. This study underscores the complexity of balancing conservation and economic objectives, suggesting that well-managed land protection policies can support local economies.

3.4.5 Broader Regional and Sectoral Impacts

Several studies have examined the broader economic impacts of ESA policies across regions and sectors. Ferris et al. (2021) analyzed the labor market effects of the Northern Spotted Owl's listing, which led to extensive logging restrictions in the Pacific Northwest. Using spatial data and control group comparisons, the study estimated long-run employment declines of 13.9% regionally and 28.1% nationally in the timber sector. Areas with larger shares of federally protected timberland experienced the most significant job losses, highlighting the localized costs of conservation policies. Aillery et al. (1996) evaluated the economic consequences of salmon recovery measures in the Pacific Northwest. The study estimated annual agricultural losses of $4 to $35 million due to reduced irrigation and increased transportation costs. Despite these losses, the study emphasized the ecological and recreational benefits of salmon recovery, including improved fishery health and ecosystem services. This dual perspective illustrates the complex trade-offs between economic costs and environmental gains.

3.4.6 Contribution of This Research

This dissertation makes a significant and novel contribution to the existing literature on the economic impacts of conservation policies under the ESA. While previous studies have extensively examined the effects of species listing and critical habitat designation (e.g., Melstrom, 2020; Zabel & Paterson, 2006; Ferris et al., 2021), no research to date has empirically investigated the economic implications of *delisting* a species. By focusing on the Louisiana Black Bear, this study addresses a critical gap in the literature, shifting the focus from the restrictive impacts of ESA policies to the economic dynamics of their reversal.

The findings provide robust evidence on the heterogeneous effects of delisting across spatial, temporal, and sectoral dimensions, highlighting the differential impacts on land-intensive and non-land-intensive industries. Moreover, the study's methodological approach—leveraging high-dimensional fixed effects and longitudinal data—adds a new layer of rigor to the empirical analysis of conservation policies. This research not only informs the broader debate on balancing conservation and economic development but also offers actionable insights for policymakers navigating post-delisting transitions.

By filling this unexplored niche, the study establishes a foundation for future research on delisting decisions and their socio-economic consequences, extending the literature on conservation economics to a domain previously overlooked.

3.5 Data, and Data Source

3.5.1 Introduction

This section outlines the data sources, variables, and summary statistics used to evaluate the economic impacts of delisting the Louisiana Black Bear. The analysis is based on a county-year panel dataset covering 3,246 counties in the contiguous United States from 1998 to 2019. The study investigates the effects of delisting on three primary economic outcomes—establishment count, employment, and sales volume—across land-intensive and non-LIS. The explanatory variables include species-specific measures of habitat and temporal changes post-delisting, as well as a robust set of socio-economic, demographic, and environmental controls.

3.5.2 Outcome Variables

3.5.2.1 Establishment Count

Establishment count refers to the number of operational businesses in a sector, county, and year. This variable reflects business dynamics in response to regulatory changes and is commonly used in studies of industrial location and economic adjustment to policy interventions (Henderson, 1988; Ferris and Frank, 2021). Delisting is expected to lower entry barriers for new establishments, particularly in LIS.

3.5.2.2 Employment

Employment measures the total number of jobs within a sector, county, and year.
As a core indicator of economic activity, employment captures the labor market effects of delisting-induced changes in land use and regulatory constraints (Gerber, 2016; Sims et al., 2019). Increased land access and reduced compliance costs post-delisting are hypothesized to drive employment growth in affected industries.

3.5.2.3 Sales Volume

Sales volume refers to the total revenue generated by businesses in a sector, county, and year. Sales volume captures sectoral economic output and provides insights into revenue shifts following delisting. Prior research highlights its importance in assessing the economic spillovers of environmental regulations (Zhang, 2007; Melstrom et al., 2016).

Together, these outcome variables offer a comprehensive view of the economic impacts, capturing changes in business activity, labor markets, and sectoral performance.

3.5.3 Key Explanatory Variables

3.5.3.1 Species Range

The range of the Louisiana Black Bear is a key explanatory variable in this study, capturing the spatial dimensions of delisting's economic impacts. To provide a robust and nuanced analysis, the species range is measured using two definitions: binary and continuous. These complementary approaches ensure that the study captures both broad patterns and finer spatial variations in economic outcomes.

The binary definition is a categorical measure that identifies whether a county overlaps with any portion of the Louisiana Black Bear's range. Counties within the range are assigned a value of 1, while those outside the range are assigned a value of 0. This measure simplifies the spatial analysis, enabling clear comparisons between counties that are directly affected by delisting and those that are not. The binary approach is particularly useful for identifying broad, immediate impacts of habitat presence on economic activities.

In contrast, the continuous definition quantifies the percentage of a county's land area that overlaps with the bear's range. This measure provides a more granular understanding of how varying levels of habitat overlap influence economic outcomes. By accounting for differences in habitat coverage, the continuous definition captures spatial heterogeneity, allowing for more precise analysis of marginal effects. This approach is particularly valuable in identifying how economic impacts scale with increasing habitat overlap.

These dual definitions align with established methodologies in conservation economics, such as those employed by Zabel and Paterson (2006). By incorporating both binary and continuous measures, this study ensures a comprehensive evaluation of delisting's spatial impacts, accommodating varying levels of habitat overlap and their associated economic effects.

3.5.3.2 Time Since Delisting (TSD)

Time Since Delisting (TSD) measures the number of years since the Louisiana Black Bear was removed from the Endangered Species Act (ESA) list in 2016. This variable is bounded below by zero, reflecting only the post-delisting period. It is instrumental in capturing the temporal evolution of economic impacts as industries adapt to regulatory changes associated with the delisting decision.

TSD provides a framework for analyzing how economic outcomes develop over time following the removal of federal protections. Immediate responses to delisting may be observed in industries that are highly sensitive to regulatory changes, while gradual adjustments may characterize sectors requiring time to adapt operations or reallocate resources. The interaction between TSD and the species range measures allows the study to distinguish between immediate impacts (β1) and evolving temporal effects (β2), capturing the dynamic nature of sectoral responses to delisting.

The data availability in this study extends from 1998 to 2019, with the delisting event occurring in 2016. This temporal range ensures robust pre-delisting observations, facilitating a clear baseline for identifying shifts in economic outcomes post-delisting. However, the limited three-year window (2016–2019) available for post-delisting analysis imposes constraints on capturing long-term trends. While this window is sufficient for identifying initial and immediate responses, it may not fully capture extended sectoral adjustments, particularly for industries requiring longer periods to adapt to reduced regulatory constraints.

The inclusion of TSD in this analysis aligns with the approaches employed in prior studies, such as Melstrom et al. (2016), which emphasize the importance of temporal variables in assessing the impacts of species conservation policies. By integrating TSD with the spatial measures of range, this study provides a multi-dimensional perspective on the economic implications of delisting, balancing immediate and temporal effects within the available data constraints.

3.5.4 Control Variables

A comprehensive set of control variables is included to account for socio-economic, demographic, and environmental factors that influence economic outcomes. These controls are widely recognized in the literature as determinants of industrial performance and location decisions (Greenstone, 2002; Levinson, 2003; List, 2001).

Socio-Economic and Demographic Controls: Poverty rate is included as it reflects regional economic conditions affecting labor supply and demand. Unemployment Rate serves as a measure of labor market slack, influencing industrial activity. As a proxy for regional economic health and purchasing power, we include the median household income. To capture market size and urbanization effects on economic activity, we include population density. To account for property value changes over time, housing price index is included serving as an indicator of regional economic health and land-use dynamics. To control for localization economies, accounting for agglomeration effects and pre-existing economic activity, we include the number of business establishments in the prior period.

Environmental Controls: We include measures of protected area designations (PADs), in particular the percentage of county land under conservation restrictions, which can influence land availability for industrial use. We also control for air quality attainment status, including binary indicators for EPA-regulated pollutants (e.g., SO_2, O_3, CO, PSM, Pb, NO_2), capturing regulatory compliance and environmental quality effects on businesses.

3.5.5 Data Sources

3.5.5.1 Species-Specific Data

This study relies on species-specific data sourced from the Environmental Conservation Online System (ECOS), maintained by the U.S. Fish and Wildlife Service (FWS). ECOS is a comprehensive platform that consolidates data on species listings, critical habitat designations, conservation plans, and range maps. Shapefiles of the Louisiana Black Bear's range were downloaded from ECOS and cross-verified with data from the Databasin platform, an additional resource providing species-specific spatial information. The range data focus on counties and parishes where the Louisiana Black Bear is known to occur, based on field surveys, expert reports, and habitat modelling conducted by the FWS. These data were processed using ArcGIS Pro, where shapefiles of the species range were overlaid with county boundary maps (FIPS codes) to calculate the percentage of each county's land area that overlaps with the bear's range. **Figure A17** presents a visual map of the Louisiana Black Bear's range to illustrate the geographic distribution of the species across the study area. The year of delisting (2016) was verified using the official FWS website and corresponding Federal Register documents, which detail the legal and procedural context for the bear's removal from the Endangered Species List. This verification ensures that the temporal dimensions of the study, including the Time Since Delisting (TSD) variable, align accurately with the regulatory timeline. By combining detailed spatial data with rigorous processing methods, this study ensures that the constructed range variables are accurate and suitable for examining the economic impacts of delisting across counties.

3.5.5.2 Socio-Economic, Demographic and Environmental Data

The three county-level outcome variables, namely the count of establishments, employment count, and sales volume, were constructed from Data Axle's Historical Business Database, which provides annual establishment-level data on each sector-specific business establishment from 1997 to 2019 within the USA. As detailed in Chapter 1, this proprietary dataset overcomes the suppression limitations of public datasets, offering granular insights critical for this study. Socio-Economic and Demographic Variables were sourced from the Bureau of Labor Statistics (BLS) and from the County Business Patterns (CBP). The environmental county attainment status variables were extracted from the EPA's Greenbook and data on PADs were downloaded from the Protected Areas Database website (PAD-US 3.0). Refer to Chapter 1 for more details on the construction of the PAD variable.

3.5.6 Summary Statistics

3.5.6.1 Explanatory Variables

The summary statistics presented in **Table A41** provide an overview of county-level explanatory variables, encompassing socio-economic, demographic, and environmental indicators that are significant determinants of regional economic outcomes and policy impacts. Most of the variables have been scaled, where the scaling factor is written in parentheses.

Socio-Economic and Demographic Variables: The poverty rate exhibits a mean of 15.36%, with a standard deviation of 6.24%, indicating moderate variability across counties. Its minimum value of 1.7% and maximum of 62% reflect substantial socio-economic disparities between counties. Similarly, the unemployment rate averages 5.96% with a standard deviation of 2.76%, suggesting relatively consistent employment conditions across most counties, although the range (0.7% to 30.6%) highlights significant variation in labor market conditions. Median household income averages $42,770, with a standard deviation of $12,630, reflecting notable income inequality across counties. Income levels range from $9,860 to $151,810, indicating a mix of low-income rural areas and affluent urban regions.

The housing price index, which measures changes in property values, has a mean of 2.47 and a standard deviation of 1.58, indicating considerable variability in housing market dynamics. Property values range from 0.64 to 21.17, suggesting the presence of both highly rural and urbanized counties with divergent housing market trends. Population density, measured per 100 units, has a low mean of 0.004 and a standard deviation of 0.0281, underscoring the predominance of rural areas in the dataset, although some counties reach higher urbanization levels, as reflected by the maximum value of 1.1655.

Environmental Variables: EPA County Attainment Status: For sulphur dioxide (SO_2), the mean value of 0.0041 reflects that most counties are in non-attainment, with limited regions achieving compliance. For particulate suspended matter (PSM), the mean is 0.0457, while for ozone (O_3), it is 0.1005, both suggesting widespread non-attainment. Attainment for nitrogen dioxide (NO_2) is minimal, indicating pervasive non-attainment, and similarly low attainment is observed for lead (Pb), with a mean of 0.0017, and for carbon monoxide (CO), with a mean of 0.1417. The standard deviations for these variables, such as 0.2377 for PSM and 0.1866 for CO, highlight considerable regional variation in compliance status.

Lastly, the percentage of county land designated as protected, measured by the Protected Area Designation (PAD) variable, has a mean of 14.1% (0.1417), with a standard deviation of 18.66%, reflecting substantial variation across counties. Some counties have no protected land, while others have up to 88% of their area designated as protected. This diversity highlights the differing conservation priorities and land-use policies across counties, which are critical for understanding the spatial heterogeneity in economic outcomes related to environmental protections.

Range of Bear: The summary statistics in **Table A42** provide insights into the subset of 118 counties within the range of the Louisiana Black Bear, which are mainly located in Louisiana, Texas and Mississippi. Among the 118 counties in the range, the mean percentage is 35.63%, indicating that, on average, over one-third of the land area in these counties overlaps with the bear’s range. The standard deviation of 12.81%, with a minimum of 5.55% and a maximum of 63.69%, highlights significant spatial variability in the extent of habitat overlap.

3.5.6.2 Outcome Variables

The summary statistics of the outcome variables across each sector is presented in **Table A43**.

LIS: LIS exhibit lower average establishment counts but significantly higher economic output per establishment. Establishments in agriculture, mining, utilities, and construction (mean counts ranging from 7 to 301) show considerable variability across counties. Employment figures reflect the labor and capital intensity of these industries, with averages ranging from 122 employees in mining (NAICS 21) to over 2,200 in construction (NAICS 23). Sales volumes are disproportionately high, particularly in utilities (NAICS 22, $98.6M average), reflecting the critical infrastructure and capital requirements of this sector. These sectors’ strong reliance on land access underscores their vulnerability to regulatory constraints and their substantial capacity for economic recovery once those constraints are removed.

Non-LIS: Non-LIS, including manufacturing, real estate, and arts, entertainment, and recreation, demonstrate greater variability in scale and output. Manufacturing (NAICS 31-33) stands out for its substantial employment (average of 4,428 employees) and sales volumes (average $1.05B), reflecting the presence of both small-scale operations and large industrial hubs. Real estate (NAICS 53) and arts and recreation (NAICS 71) have smaller establishment counts on average but still contribute significantly to sales and employment. These sectors benefit indirectly from broader economic recovery, though they are less directly influenced by changes in land use.

General Observations: Across sectors, the variability in establishment count, employment count, and sales volumes highlights the diversity of county-level economic activity. This preliminary analysis reinforces the importance of distinguishing between land-intensive and non-land-intensive industries when evaluating the economic impacts of species delisting.

3.6 Methodology

This section outlines the econometric framework used to analyze the economic impacts of delisting the Louisiana Black Bear, integrating spatial, temporal, and sectoral dimensions. Given the diversity of economic responses observed across regions and industries, the methodology is designed to capture both immediate and evolving effects of delisting. We employ the Pseudo Poisson Maximum Likelihood (PPML) with High-Dimensional Fixed Effects (HDFE) which offers several advantages. Regarding heteroskedasticity, the PPML provides consistent estimates even when the variance of the outcome variable (Y) is not constant. Also, many observations involve zero establishment counts, and PPML models these appropriately without transformation. Last, coefficients are interpreted as semi-elasticities, meaning they reflect percentage changes in the expected outcome ($E[Y \mid X]$) for a unit change in explanatory variables.

The analysis focuses on three key outcome variables—establishment count, employment, and sales volume—across land-intensive and non-LIS, with the Range and Time Since Delisting serving as the primary explanatory variables. By incorporating socio-economic, demographic, and environmental controls, this section lays the foundation for a rigorous exploration of post-delisting economic dynamics.

3.6.1 Model Specification

The model specification is:

$Y_{cstn} = \exp\left(\beta_0 + \beta_1 Range_{cst} + \beta_2 Range_{cst} * TSD_t + \beta_3 X_{cstn} + \alpha_c + \gamma_s + \rho_t + \epsilon_{cst}\right)$

Where:

- $\boldsymbol{Y_{cstn}}$: Dependent variable capturing economic outcomes at the county (c), state (s), year (t), and NAICS sector (n) levels.
- $\boldsymbol{\beta_0}$: Intercept term
- $\boldsymbol{Range_{cst}}$: Explanatory variable representing the species range, constructed as either a binary indicator (1 = within range, 0 = outside range) or a continuous measure (percentage of county land within the range).
- $\boldsymbol{TSD_t}$: Time Since Delisting, capturing the number of years since the Louisiana Black Bear's delisting in 2016.
- $\boldsymbol{Range_{cst} * TSD_t}$: Interaction term to measure how the spatial impacts of the range evolve over time post-delisting.
- $\boldsymbol{X_{csti}}$: Vector of control variables including socio-economic, demographic, environmental , and sectoral factors.
- $\boldsymbol{\alpha_c, \gamma_s, \rho_t}$: County fixed effects (Controlling for unobserved, time-invariant heterogeneity across counties), State fixed effects (Controls for unobserved heterogeneity across states), Year fixed effects (To capture time-specific shocks or trends), respectively.
- $\boldsymbol{\epsilon_{csti}}$: Error term. Standard errors have been clustered at the county-level.

3.6.2 Justification for Excluding Standalone TSD

The standalone Time Since Delisting (TSD) variable is excluded for the following reasons. First, including both TSD and the interaction term $(Range \times TSD)$ introduces perfect collinearity, as TSD is implicitly captured in the fixed effects (e.g., year effects) and through the interaction term. Second, excluding TSD focuses the analysis on spatial and interaction effects, providing a cleaner interpretation of how habitat overlap and delisting jointly influence economic outcomes. Third, empirical tests show identical results whether TSD is included or excluded, demonstrating its redundancy. Fourth, **s**implifying the model by excluding TSD improves parsimony, aligning with econometric best practices. This approach ensures that the effects of delisting are captured through meaningful variables $(Range\ and\ Range \times TSD)$, avoiding unnecessary complexity.

3.6.3 Key Variables

3.6.3.1 Outcome Variables

The model assesses three key economic outcomes across land-intensive and non-LIS. First, establishment count which measures business presence and entry/exit dynamics. Second, employment count which tracks labor market effects across industries. Third, sales volume which captures the sectoral economic output and revenue changes. These outcomes collectively provide a comprehensive picture of how delisting affects regional economic activity.

3.6.3.2 Independent Variables

Main Explanatory Variables

1. **Range (Binary and Continuous):** First as binary, it indicates whether a county overlaps with the bear's range (1 = yes; 0 = no). Secondly, as continuous, it measures the percentage of county land within the bear's range, capturing spatial heterogeneity.
2. **Interaction Term ($\boldsymbol{Range} \times \boldsymbol{TSD}$):** Explains how the spatial impact of range evolves over time as regulatory constraints are lifted.

Other Control Variables: Socio-Economic-Demographic and Environmental Controls (X_{csti}): Include poverty rate, unemployment rate, population density, median household income, housing price index, county attainment status vis a vis the criteria pollutants Sulphur dioxide (SO_2), particulate suspended matter (PSM), ozone (O_3), nitrogen dioxide (NO_2), lead (Pb), carbon monoxide (CO), protected area designation, and prior year sector specific establishment count.

3.6.4 Joint-Significance Tests

To assess the joint contribution of $Range_{cst}$ and its interaction with TSD_t on establishment outcomes, joint significance tests are conducted. These tests evaluate the null hypothesis:

$H_0: \beta_1 = 0 \; and \; \beta_2 = 0$ vs $H_a: \beta_1 \neq 0 \; or \; \beta_2 \neq 0$,

Where $\beta_1$is the baseline effect of $Range_{cst}$ on establishment outcomes, and β_2 shows how the effect of $Range_{cst}$ evolves (annually) with time since delisting (TSD), through the interaction term $Range_{cst} * TSD_t$. It is essential to examine whether both β_1 and β_2 are jointly significant. Even if one of these coefficients (say β_1) is significant individually, but β_2 is not, interpreting them separately may lead to misleading conclusions. In such cases, the joint test will determine if, together, the coefficients contribute significantly to explaining variations in the dependent variable. If both β_1 and β_1 are jointly significant, we can confidently say that the effect of $Range_{cst}$ on outcomes depends on the time since delisting (TSD). If the joint test is not significant (i.e., H_0 is not rejected), it implies that the interaction between $Range_{cst}$ and TSD_t does not add substantial explanatory power beyond the individual effect of $Range_{cst}$.

Methodologies for Joint Tests

1. **Wald Test**: Assesses H_0 using the estimated coefficients $(\widehat{\beta_1}, \widehat{\beta_2})$ and their covariance matrix. The test statistic is computed as: $W = \hat{\beta}' * Var(\hat{\beta})^{-1} * \hat{\beta}$

   Where $\hat{\beta} = [\widehat{\beta_1}, \widehat{\beta_2}]'$ is the vector of estimated coefficients, and$Var(\hat{\beta})$ is the covariance matrix of $\hat{\beta}$. The Wald statistic follows a chi-square distribution with degrees of freedom equal to the number of restrictions (2 in this case).

2. **Likelihood Ratio (LR) Test**: The LR test compares the goodness-of-fit of the unrestricted model (including β_1 and β_2) to the restricted model (excluding β_1 and β_2). The test statistic is given by: $LR = -2 * [\ln(L_{restricted}) - \ln(L_{unrestricted})]$

   Where $L_{restricted}$is the Log-likelihood of the model excluding the variables of interest and $L_{unrestricted}$ is the Log-likelihood of the model including the variables of interest. The LR statistic also follows a chi-square distribution with 2 degrees of freedom.

3. **Bootstrap Wald Test**: To address potential heteroskedasticity or small-sample biases, a bootstrap-based Wald test is employed. This involves resampling the data to estimate the sampling distribution of the Wald statistic, providing robust inference.

We report the p-values from the Wald tests for joint significance in the regression tables. This choice ensures brevity and clarity in presenting results while maintaining alignment with standard regression reporting formats. Notably, the results of the Wald and Likelihood Ratio (LR) tests are generally consistent; however, some deviations arise when applying more stringent tests or alternative robustness checks. In such cases, we prioritize results where the Wald and LR tests align, ensuring the reliability of the findings. While the joint significance tests provide an essential basis for interpreting the main and interaction terms, it is important to acknowledge that these methods represent standard, though not exhaustive, approaches for evaluating joint contributions.

Additional tests, such as robustness checks across alternative model specifications or more restrictive hypothesis tests, can further validate the findings. Incorporating these alternative approaches enhances transparency and strengthens the robustness of the conclusions, even if certain results are attenuated under more stringent tests. By combining joint significance tests with robustness checks, the analysis adheres to best practices in econometric research (Cameron & Trivedi, 2013; Wooldridge, 2010). This approach ensures that the conclusions drawn are both theoretically grounded and empirically validated, providing a reliable foundation for interpreting the interactive and non-linear effects of the explanatory variables.

3.6.5 Marginal Effects and Their Interpretation

Building on the results of the joint significance tests (Section 6.3), this section explores the marginal effects of the explanatory variables $\boldsymbol{Range_{cst}}$ and $\boldsymbol{TSD_t}$ on establishment outcomes. These marginal effects reveal the incremental impact of these variables while accounting for their dynamic, interactive relationships. This section also addresses normalization, scaling, and practical considerations for interpretation.

3.6.5.1 From the Model to Marginal Effects

Transitioning from our PPML specification, the expected outcome is given by:

$E[Y|X] = \exp\,(\beta_0 + \beta_1 Range_{cst} + \beta_2 Range_{cst} * TSD_t + \beta_3 {X'}_{cst})$

which links the explanatory variables directly to the expected value of Y. The marginal effects quantify the expected percentage change in the outcome variable (Y) given a unit change in an explanatory variable. For this chapter, the marginal effects of interest are:

The marginal effect of $Range_{cst}$, is expressed as: $\frac{\partial E[Y|X]}{\partial Range_{cst}} = E[\,\mathrm{Y} \mid X\,] * (\beta_1 + \beta_2 * TSD_t)$,

where β_1 captures the baseline effect of $Range_{cst}$ on establishment outcomes. β_2 reflects how the effect of $Range_{cst}$ evolves over time through its interaction with TSD_t, where TSD_t is the time since delisting.

The marginal effect of TSD_t, which is given by: $\frac{\partial E[Y|X]}{\partial TSD_t} = E[\,\mathrm{Y} \mid X\,] * (\beta_2 * Range_{cst})$, where β_2 captures the temporal dynamics and $Range_{cst}$ moderates the effect.

3.6.5.2 Normalization for Simplification

In PPML models, the marginal effects are scaled by the expected value of the dependent variable ($E[Y \mid X]$). To simplify this, normalization assumes $E[Y \mid X] = 1$, allowing coefficients and marginal effects to be interpreted as semi-elasticities. Normalization standardizes the marginal effects, ensuring they are independent of the expected level of Y. After normalization, coefficients represent the percentage change in $\boldsymbol{Y}$ for a unit change in an explanatory variable.

This approach is widely adopted in count data models and ensures comparability across observations and models. Therefore, with normalization:

$Marginal\ Effect_{Range} = \beta_1 + \beta_2 * TSD_t$ and $Marginal\ Effect_{TSD} = \beta_2 * Range_{cst}$

This allows coefficients to be interpreted as semi-elasticities, whereβ_1 represents the percentage change in Y for a one-unit increase in $Range_{cst}$ (e.g., moving from 0 to 1 in the binary case or a 1-percentage-point increase in the proportional case). And β_2 represents the percentage change in Y for a one-unit increase in TSD_t, moderated by $Range_{cst}$.

3.6.5.3 Context-Specific Interpretation

When $Range_{cst}$ is binary (1 = within range, 0 = outside range), β_1 measures the baseline spatial effect of being within the bear's range, and β_2 captures how the baseline effect evolves over time as $\boldsymbol{TSD_t}$ increases. The total effect of $Range_{cst}$ is $\beta_1 + \beta_2 * TSD_t$, which reflects the immediate and dynamic adjustments associated with habitat overlap.

When $Range_{cst}$ is proportional (e.g., 10% overlap = 0.1), β_1 represents the percentage change in Y for a 1-percentage-point increase in $Range_{cst}$. For example, if $\beta_1 = 0.05$, a 1-percentage-point increase in $Range_{cst}$ leads to a 0.05% change in Y. β_2 scales the temporal evolution of impacts, proportional to the percentage of habitat overlap.

The practical Marginal Effect being: $Marginal\ Effect_{Range} = \frac{\beta_1 + \beta_2 \cdot TSD_t}{100}$,

ensures that small changes (e.g., 1-percentage-point increases) are interpreted accurately.

3.6.5.4 Conclusion

In conclusion, the marginal effects analysis provides a nuanced understanding of the dynamic relationships between Range, TSD, and establishment outcomes. By transitioning from the Poisson model to the expected outcomes framework, we demonstrate how spatial and temporal factors jointly shape the economic impacts of delisting policies. Normalization ensures that coefficients and marginal effects are interpreted as semi-elasticities, simplifying their practical application while maintaining theoretical rigor. The distinction between percentage-point and percentage changes is particularly critical for proportional variables like Range, enabling accurate and contextually relevant interpretations of small, incremental changes in habitat overlap. These insights highlight the dual importance of understanding baseline spatial effects and their temporal evolution, especially when evaluating policies with long-term ecological and economic implications. By integrating joint tests, normalization, and carefully scaled marginal effects, this analysis provides a robust framework for assessing the spatial-temporal dynamics underlying policy impacts on economic outcomes.

3.6.6 Robustness Checks and Model Validation

To ensure the reliability and robustness of the econometric results, the analysis incorporates a series of robustness checks and validation exercises:

Alternative Fixed Effects Specifications: The baseline model does not include fixed effects. Our preferred model includes high-dimensional fixed effects to account for unobserved heterogeneity at the county, state, and year levels. To test the robustness of these specifications, alternative fixed effects (e.g., state-year and county-year combinations) are incorporated to verify the stability of key coefficients (β_1 and β_2).

Alternative Range Definitions: Both binary and continuous measures of Range are employed in the analysis. Comparing results across these definitions ensures that findings are not sensitive to the choice of spatial variable.

Lagged Dependent Variable: The inclusion of lagged outcome variables (e.g., establishment count, employment) helps control for autocorrelation and pre-existing trends in economic activity.

Robustness to Outliers: The model's sensitivity to outlier observations (e.g., counties with extremely high or low levels of habitat overlap or economic outcomes) is assessed through trimming and winsorization of key variables.

Heteroskedasticity Robustness: The PPML approach inherently accounts for heteroskedasticity in count data. Additional robustness checks involve re-estimating models using alternative techniques, such as Ordinary Least Squares (OLS) with robust standard errors, to confirm the consistency of key results.

Placebo Tests: Placebo tests are conducted by simulating "pseudo-delisting" years before 2016 to verify that the observed temporal dynamics are attributable to the actual delisting event and not spurious trends.

These robustness checks provide confidence in the validity and generalizability of the findings, ensuring that the estimated effects of $Range$ and TSD are credible and not driven by modeling assumptions.

3.6.7 Limitations and Scope

While the econometric framework is robust and the data comprehensive, several limitations must be acknowledged. County-level data may mask finer spatial or temporal variations in economic outcomes, particularly in large or heterogeneous counties. Although fixed effects capture time-invariant heterogeneity, some dynamic unobserved factors (e.g., local policy changes, environmental shocks) could influence results. The distinction between land-intensive and non-LIS assumes uniform behavior within each category, which may not fully account for sub-sectoral heterogeneity. While the methodology accounts for confounders and uses robust interaction terms, the results remain correlational due to the observational nature of the data. Despite these limitations, the approach offers a rigorous and nuanced analysis of the economic impacts of species delisting.

3.6.8 Conclusion

This section outlined the econometric methodology employed to analyze the economic impacts of delisting the Louisiana Black Bear. By leveraging a PPMLHDFE framework, the analysis integrates spatial, temporal, and sectoral dimensions, capturing both baseline effects (β_1) and their evolution over time (β_2). The inclusion of binary and continuous Range definitions enhances the ability to measure spatial heterogeneity, while interaction terms ($Range \times TSD$) reveal dynamic temporal patterns. A robust set of controls and fixed effects ensures the validity of the results, and planned robustness checks address potential concerns about model assumptions and data reliability. This methodological framework lays a solid foundation for interpreting the results in Section 7, where spatial and temporal dynamics will be systematically evaluated to provide actionable insights into the economic consequences of species delisting.

3.7 Results and Interpretation

3.7.1 Introduction

This section investigates the economic impacts of the delisting of the Louisiana Black Bear, focusing on three key outcome variables: establishment count, job count, and sales volume. These analyses are conducted across land-intensive and non-LIS to assess how delisting policies interact with economic outcomes in distinct industry contexts. The primary emphasis is on interpreting the coefficients of the species-related explanatory variables, particularly Range (spatial overlap with the bear's habitat) and Time Since Delisting (TSD), along with their interaction.

To address concerns about clarity and interpretation, we explicitly define TSD as capturing time elapsed since delisting, bounded at zero to ensure the results focus solely on post-delisting dynamics. The interaction between Range and TSD (β_2) captures how the baseline spatial effects (β_1) evolve over time, providing a comprehensive view of spatial-temporal dynamics. Acknowledging the limited post-delisting data (three years), we interpret the results cautiously, noting that longer time horizons may reveal more pronounced patterns. Furthermore, the results incorporate both binary and continuous definitions of Range. The binary definition indicates the presence or absence of habitat overlap (Range = 0 or 1), measuring the immediate effects of being within the bear's range. Whereas the continuous definition quantifies the proportion of a county's land overlapping with the habitat, enabling a more detailed understanding of spatial heterogeneity.

The marginal effects of Range and TSD are central to the interpretation. For binary Range, β_1 reflects the baseline spatial effect of habitat overlap, while $\beta_2 * TSD$ measures how this effect changes over time. For continuous Range, marginal effects are interpreted in terms of percentage-point changes in habitat overlap, explicitly distinguishing them from percentage changes. For example, a 1-percentage-point increase in habitat overlap corresponds to a marginal effect scaled by $\beta_1 + \beta_2 \cdot TSD$. We acknowledge instances of counter-intuitive findings, such as negative coefficients for β_2 in some sectors. These are interpreted as evidence of diminishing spatial impacts over time, possibly due to sector-specific constraints or delayed regulatory adaptation. Where applicable, we also highlight the importance of joint significance tests in guiding the interpretation of these coefficients. The results of Wald and LR tests are consistent in most cases, and for brevity, we report the Wald test results in regression tables.

The regression results are organized as follows. Our summarized results are presented as from **Table A44** to **Table A57** providing an overview of key findings. Our detailed results are presented as from **Table A58** to **Table A69** offer comprehensive regression outputs, including joint significance tests and marginal effects evaluations. This section begins by presenting the results for aggregate impacts across all sectors, distinguishing between LIS and non-LIS. Subsections 7.2 and 7.3 provide deeper insights into LIS and non-LIS sectors, respectively, focusing on the spatial-temporal dynamics of Range and TSD. Section 7.4 delves into robustness checks, highlighting how alternative specifications validate key findings. Finally, Section 7.5

discusses broader policy implications, tying the results back to research questions and the role of delisting policies in shaping economic outcomes.

Together, these subsections provide a comprehensive analysis of how delisting policies affect economic dynamics across sectors, offering insights into the interplay between conservation policies and economic adjustments.

3.7.2 Land Intensive Sectors

This section examines the impacts of delisting on LIS, including Agriculture, Mining, Utilities, and Construction. The results reflect both spatial and temporal dynamics, captured through Range (binary and continuous definitions) and Time Since Delisting (TSD). Key findings highlight the importance of land availability, sector-specific adaptation capacities, and regulatory constraints in shaping economic outcomes.

3.7.2.1 Agriculture, Forestry, Fishing, and Hunting (NAICS 11)

The Agriculture sector demonstrates significant and consistent declines across all economic outcomes, driven by its structural dependency on land availability and vulnerability to habitat-related constraints. Both immediate and temporal effects are evident, highlighting the sustained negative impacts of delisting-related dynamics. These effects are observed under both binary and continuous definitions of Range.

Establishment Counts: Under the binary range definition (**Table A44**), counties within the bear's range experience an immediate 12.5% decline in establishment counts, which worsens further over time with an additional 20.5% annual decline. These results emphasize the broad and severe disruptions faced by range counties. Under the continuous range definition (**Table**

A45), a 1-percentage-point increase in habitat overlap leads to an immediate 0.1% decline in establishment counts, followed by an additional 0.17% annual reduction. These findings highlight that the negative effects scale proportionally with habitat overlap, offering a more nuanced understanding of spatial heterogeneity compared to the binary definition.

Employment: The binary range definition (**Table A44**) indicates an annual 12.1% decline in employment in range counties, reflecting cumulative workforce losses over time. The continuous definition (**Table A45**) reveals smaller, incremental effects, with a 1-percentage-point increase in habitat overlap leading to an annual 0.097% reduction in job counts. These gradual and compounding declines underscore the challenges faced by agricultural employment in adapting to habitat-related restrictions, particularly in counties with higher habitat coverage.

Sales Volume: Sales volume also exhibits significant declines. Under the binary range definition (**Table A44**), counties within the bear's range experience a 21% immediate contraction in sales volume, signaling abrupt revenue losses. Continuous measures (**Table A45**) reveal worsening declines over time, with each 1-percentage-point increase in habitat overlap contributing to both immediate and compounding reductions in revenue. These results reflect both the direct and cascading economic impacts of delisting.

These findings indicate that agriculture's limited capacity for adaptation makes it particularly vulnerable to regulatory changes stemming from delisting. The observed declines likely arise from a combination of reduced production areas, increased compliance costs, and heightened investment risks in range counties. These results align with the literature on Land Use Economics, where habitat protection often disrupts agricultural efficiency and capital allocation

(Irwin & Wrenn, 2010). The cumulative nature of these declines underscores the sector's struggle to respond to delisting-related challenges, revealing significant economic vulnerabilities in range counties.

3.7.2.2 Mining, Quarrying, and Oil and Gas Extraction (NAICS 21)

The Mining sector experiences significant declines across all outcomes, reflecting the sector's sensitivity to habitat-related constraints and its reliance on stable regulatory environments. Both binary and continuous definitions of Range highlight these adverse effects, which manifest as gradual but persistent contractions over time.

Establishment Counts: The binary range definition (**Table A46**) reveals a 10.4% annual decline in establishment counts for counties within the bear's range. This broad trend captures the disruptive effects of delisting-related policies on mining activities. Under the continuous range definition (**Table A47**), each 1-percentage-point increase in habitat overlap results in an incremental 0.1% annual reduction in establishment counts. The continuous measure demonstrates the scaling nature of the impact, where counties with greater habitat overlap experience proportionately larger declines. These results underscore the increasing regulatory and operational constraints faced by mining establishments as habitat overlap intensifies.

Employment: Employment in the mining sector also exhibits significant declines. The binary measure (**Table A46**) indicates a 17.2% annual decline in job counts for range counties, reflecting substantial workforce contractions over time. The continuous measure (**Table A47**) provides a more detailed picture, revealing both immediate and compounding effects. Each 1-percentage-point increase in habitat overlap leads to an immediate 0.22% decline in jobs, followed by an additional 0.14% annual reduction. These findings emphasize the gradual erosion of mining employment, driven by long-term challenges in land access, operational restrictions, and regulatory uncertainty.

The distinct patterns of immediate and annual declines highlight the mining sector's reliance on long-term investment cycles and stable land access. Unlike agriculture, which responds immediately to habitat-related constraints, mining's response unfolds gradually, reflecting the sector's reliance on large-scale infrastructure, lengthy project timelines, and complex regulatory processes. These persistent effects likely stem from increased compliance costs, heightened uncertainties, and reduced investment incentives in counties with significant habitat overlap. These findings align with the Industrial Organization literature, particularly Dixit and Pindyck's (1994) work on Investment Under Uncertainty, which underscores the importance of policy stability in enabling resource-dependent industries to plan extraction schedules and allocate capital effectively. The observed declines in both establishments and employment emphasize the need for predictable regulatory frameworks to mitigate economic disruptions in mining and ensure long-term sectoral viability.

3.7.2.3 Utilities (NAICS 22)

The Utilities sector experiences significant negative impacts across key outcomes, reflecting its reliance on fixed infrastructure and capital-intensive operations. Both binary and continuous range definitions highlight the adverse effects of delisting-related constraints, with evidence of both immediate disruptions and gradual, compounding declines over time.

Establishment Counts: Under the binary range definition (**Table A48**), establishment counts decline by 6.1% annually in counties within the bear's range. This broad spatial effect reflects the sector's sensitivity to land-use restrictions. The continuous measure (**Table A49**) reveals a smaller, incremental decline, with each 1-percentage-point increase in habitat overlap reducing establishment counts by 0.045% annually. These results demonstrate that greater habitat overlap intensifies these negative effects over time, though the impacts are less pronounced than in other LIS.

Employment: Utilities face sharp job losses immediately post-delisting. Under the binary range definition (**Table A48**), job counts decline by 16.3% immediately, indicating significant workforce contractions. The continuous measure (**Table A49**) shows more gradual effects: each 1-percentage-point increase in habitat overlap leads to 0.16% immediate reductions in jobs, with an additional 0.08% annual decline. These results suggest that while utilities face immediate employment shocks, the cumulative effects of increasing habitat overlap exacerbate these challenges over time.

Sales Volume: Sales revenue in the Utilities sector also experiences substantial declines. The binary measure (**Table A48**) indicates a 33.9% immediate reduction in sales volume for counties within the bear's range, reflecting sharp revenue losses. Under the continuous range definition (**Table A49**), each 1-percentage-point increase in habitat overlap results in an immediate 0.39% reduction, with further annual declines of 0.085%. These findings highlight the compounding nature of revenue losses in counties with greater habitat overlap, driven by both direct constraints and operational inefficiencies.

The pronounced impacts observed in the Utilities sector can be attributed to its reliance on fixed infrastructure, such as power lines, pipelines, and treatment facilities, which are costly to relocate or adapt to habitat constraints. Habitat protection measures likely impede the expansion of essential infrastructure, restricting the sector's ability to scale operations in high-overlap counties. Furthermore, the sector's immobility limits its capacity to adapt to delisting-related challenges, as fixed assets cannot easily be reallocated to less constrained locations.

These results align with Capital Immobility theory (Jorgenson, 1963), which posits that sectors reliant on immobile, capital-intensive infrastructure are disproportionately affected by regulatory changes that restrict land use. The immediate and incremental revenue and employment losses observed in utilities underscore the sector's vulnerability to habitat-related constraints, highlighting the need for targeted policy interventions to mitigate these economic disruptions.

3.7.2.4 Construction (NAICS 23)

Unlike other LIS, the construction industry experiences significant and positive impacts post-delisting, demonstrating its capacity to capitalize on reduced regulatory barriers and increased land-use opportunities. Both binary and continuous range definitions highlight the sector's adaptability and ability to benefit from delisting policies.

Establishment Counts: The binary range definition (**Table A50**) shows an 8.7% immediate increase in establishment counts for counties within the bear's range, with further 2.8% annual growth over time. The continuous measure (**Table A51**) reveals a more incremental effect: each 1-percentage-point increase in habitat overlap leads to an immediate 0.078% increase in establishment counts, followed by 0.027% annual growth. These findings underscore the sector's ability to leverage eased habitat restrictions to spur new business formation.

The positive impacts on establishment counts highlight the construction sector's inherent flexibility and its ability to rapidly respond to changes in land-use policies. As habitat restrictions are lifted, construction activities such as housing developments, infrastructure projects, and commercial construction are likely to accelerate, contributing to broader economic growth in counties with habitat overlap.

The results align with Churning Dynamics theory (Davis & Haltiwanger, 1999), which emphasizes the reallocation of economic activity toward sectors with fewer constraints following regulatory changes. Construction's positive response to delisting underscores its role as a key driver of economic adjustment, with benefits concentrated in areas where regulatory relief enables increased land development and investment.

3.7.3 Non-LIS

Non-LIS—Manufacturing (NAICS 31-33), Real Estate (NAICS 53), and Arts, Entertainment, and Recreation (NAICS 71)—exhibit more favorable responses to delisting compared to their land-intensive counterparts. Unlike sectors heavily dependent on land resources, these industries rely less on fixed land inputs, enabling greater adaptability to the economic shifts brought about by delisting policies. The observed impacts are predominantly immediate (β_1), with relatively fewer significant temporal effects (β_2), suggesting that these sectors undergo rapid adjustments with limited long-term evolution.

The differences between land-intensive and non-LIS highlight the role of resource flexibility in shaping economic outcomes post-delisting. Non-land-intensive industries benefit from their ability to reallocate resources and adapt operationally without being heavily constrained by habitat-related regulations. This flexibility allows them to capitalize on the economic opportunities associated with reduced regulatory oversight.

In subsequent subsections, we examine the specific responses of Manufacturing, Real Estate, and Arts and Recreation sectors, focusing on establishment counts, employment, and sales volume. These analyses underscore how the spatial-temporal dynamics of Range and TSD differ between non-land-intensive and land-intensive industries, revealing insights into the broader implications of delisting for economic resilience and sectoral heterogeneity.

3.7.3.1 Manufacturing (NAICS 31-33)

The Manufacturing sector demonstrates strong positive impacts on sales volume following delisting, highlighting its resilience and ability to adapt to economic changes with minimal reliance on land resources. These results suggest that manufacturing firms capitalize on market opportunities generated by delisting without requiring significant expansions in workforce or physical infrastructure.

Sales Volume: Under the binary range definition (**Table A52**), sales volume increases immediately by 77% in counties within the bear's range relative to those outside. The continuous range definition (**Table A53**) reveals that each 1-percentage-point increase in habitat overlap leads to an immediate 0.57% increase in sales volume. These significant revenue gains suggest that delisting creates favorable conditions for manufacturing output, likely driven by heightened demand or improved economic activity in range counties.

Establishment and Job Counts: Results for establishment count and job count remain statistically insignificant under both range definitions. This indicates that the observed revenue increases are more likely attributable to productivity improvements or operational efficiencies rather than physical expansions or workforce growth. Manufacturing firms may achieve these gains by leveraging existing resources more effectively, reflecting the sector's scalability and flexibility.

The positive outcomes in manufacturing highlight its ability to benefit indirectly from delisting-related economic adjustments, such as increased demand for manufactured goods stemming from upstream construction activities. Additionally, the sector's relatively lower dependency on land resources allows it to capitalize on these opportunities without being constrained by habitat-related regulations.

These findings align with the Industrial Organization literature (Syverson, 2011), which emphasizes the role of productivity and operational efficiency in driving sectoral resilience. Manufacturing firms' ability to scale production without significant new investments in land or infrastructure reflects their capacity to adapt quickly to changes in economic conditions, further reinforcing the sector's role as a stabilizing force in range counties post-delisting.

3.7.3.2 Real Estate, Rental, and Leasing (NAICS 53)

The Real Estate sector experiences modest but statistically significant gains in establishment counts following delisting, reflecting improved investor confidence and reduced regulatory uncertainty. However, the absence of significant impacts on job count or sales volume suggests that these gains may represent early-stage developments rather than fully realized economic activity.

Establishment Counts: Under the binary range definition (**Table A54**), establishment counts increase immediately by 4.6% in counties within the bear's range relative to those outside. The continuous range definition (**Table A55**) indicates that each 1-percentage-point increase in habitat overlap leads to an immediate 0.028% increase in establishment counts. These results suggest modest but steady growth in real estate establishments, driven by the easing of regulatory constraints and improved investor confidence.

Job Count and Sales Volume: Results for job count and sales volume remain statistically insignificant under both range definitions. This lack of significant impacts indicates that while delisting encourages the establishment of new real estate firms, these gains may not yet translate into substantial employment growth or revenue generation. The observed establishment increases may reflect early-stage developments, speculative investments, or enhanced property leasing and development activities.

The positive impacts on real estate align with Location Dynamics theory (Glaeser et al., 2008), which emphasizes the role of reduced regulatory uncertainty in unlocking investment opportunities. By easing land-use restrictions, delisting likely facilitates property development, leasing activities, and speculative ventures in range counties. However, the limited scope of economic activity beyond establishment growth highlights the sector's gradual adjustment to delisting-related changes, suggesting that more substantial impacts on jobs and sales may materialize over time as real estate projects mature and market conditions stabilize.

3.7.3.3 Arts, Entertainment, and Recreation (NAICS 71)

The Arts, Entertainment, and Recreation sector emerges as a significant beneficiary of delisting, with positive and statistically significant impacts observed across establishment counts, employment, and sales volume. These results underscore the sector's ability to capitalize on improved economic conditions and increased consumer spending following delisting, highlighting its adaptability and lower dependency on fixed land resources.

Establishment Counts: Immediate growth in establishment counts under the binary range definition (**Table A56**) is approximately 3.9%, indicating that businesses in this sector respond swiftly to improved economic conditions in range counties. The continuous range measure (**Table A57**) reveals that each 1-percentage-point increase in habitat overlap leads to an immediate 0.023% increase in establishment counts. These findings suggest that greater habitat overlap correlates with a gradual but steady increase in the number of recreational establishments, reflecting the sector's flexibility and responsiveness.

Employment: The sector experiences substantial labor demand as recreational businesses expand operations. Under the binary range definition (**Table A56**), employment increases by 59.4%, highlighting strong and immediate workforce growth. The continuous range definition (**Table A57**) shows that each 1-percentage-point increase in habitat overlap leads to an immediate 0.37% increase in job counts. These results demonstrate the sector's ability to absorb labor efficiently and meet the rising demand for leisure and entertainment services.

Sales Volume: Sales revenue in the sector also experiences robust growth. Under the binary range definition (**Table A56**), sales volume increases immediately by 31.9%, reflecting increased consumer spending. The continuous range definition (**Table A57**) shows that each 1-percentage-point increase in habitat overlap leads to an immediate 0.23% increase in sales volume. These findings indicate that the sector benefits significantly from post-delisting economic adjustments, driven by heightened demand for recreational activities and services.

The positive impacts across all three outcome variables highlight the sector's ability to thrive in improved economic conditions, leveraging increased consumer spending and tourism opportunities in range counties. Greater habitat overlap appears to enhance recreational and leisure activities, creating spillover effects that benefit the local economy. These results align with insights from Welfare Economics and labor market studies (Moretti, 2010), which emphasize how improved economic conditions stimulate demand for recreational services and support local economic growth.

The sector's responsiveness also reflects its lower barriers to entry compared to land-intensive industries. Recreational businesses, such as entertainment venues, tourism services, and leisure activities, can adapt quickly to shifting economic conditions without being constrained by fixed infrastructure or extensive regulatory requirements. This flexibility enables the Arts, Entertainment, and Recreation sector to capitalize on delisting-related changes more effectively than other industries.

3.7.4 Overall Conclusions: Integrating Findings

The findings of this study provide a comprehensive and nuanced understanding of the economic impacts of delisting the Louisiana Black Bear. By analyzing results under both binary (presence/absence) and continuous range definitions (proportion of habitat overlap), this study reveals significant differences in how these two measures capture spatial and temporal effects. This section synthesizes the key findings, contrasts the outcomes across land-intensive and non-LIS, and highlights the broader implications for addressing the research questions, hypotheses, and policy considerations.

3.7.4.1 Key Findings and Comparative Insights

The results reveal clear distinctions between the binary and continuous range definitions, offering complementary perspectives that together enhance the understanding of delisting's impacts.

Binary Range Definition: The binary measure simplifies the interpretation by dividing counties into two clear groups—those with and without bear range. The impacts captured under this definition reflect the average immediate effect of habitat presence. For example: In NAICS 11 (Agriculture), establishment counts decline by 12.5% immediately (**Table A44**), reflecting broad disruptions in range counties. Similarly, utilities experience sharp immediate declines in job counts and sales volumes, underscoring the structural rigidity of LIS. The binary measure is particularly useful for identifying the overall spatial impact of delisting across sectors and is highly interpretable for policymakers seeking general insights into affected areas.

Continuous Range Definition: The continuous measure refines the analysis by capturing the marginal effects of incremental increases in habitat overlap. This allows for a more granular understanding of how the intensity of habitat presence affects economic outcomes. For instance: In NAICS 11 (Agriculture), establishment counts decrease by 0.1% for every 1% increase in land overlap, compounding annually with a further 0.17% reduction (**Table A45**). In NAICS 21 (Mining), cumulative reductions in establishment counts and job losses scale proportionately with increasing habitat coverage. These results emphasize the scaling nature of the impacts, which binary definitions cannot capture. Continuous measures are particularly valuable for identifying variation across counties with differing levels of range overlap, making them ideal for designing targeted interventions.

Temporal Dynamics: The coefficient on the interaction variable (β_2) reveals how impacts evolve over time, adding another layer of complexity. The results highlight two key trends: LIS (e.g., agriculture, mining, and utilities) exhibit cumulative annual declines, with negative effects worsening over time. These trends underscore the rigidity and slow adjustment of industries reliant on fixed land and infrastructure. In contrast, sectors such as construction and arts and recreation demonstrate positive cumulative effects or immediate stabilization, reflecting their greater adaptability to shifting economic conditions.

The combination of binary and continuous definitions, along with temporal dynamics, provides a more complete and realistic view of delisting's economic impacts. This nuanced comparison ensures that the analysis is not oversimplified, a limitation common in other studies.

3.7.4.2 Sectoral Heterogeneity and Key Patterns

The findings reveal stark differences in how sectors respond to delisting, driven by their land dependency, adaptability, and exposure to economic spillovers:

LIS: Agriculture, mining, and utilities face significant and persistent declines across establishment counts, employment, and sales volume. These sectors exhibit both immediate impacts and cumulative declines, reflecting their structural reliance on land resources and fixed infrastructure. Similarly, mining experiences proportional declines in job counts and establishments as habitat overlap increases, with effects worsening annually. Construction stands out as a notable exception, with establishment counts growing immediately and continuing to increase over time. The sector benefits from reduced regulatory barriers, which facilitate new development and infrastructure projects.

Non-LIS: Non-LIS, such as manufacturing, real estate, and arts and recreation, demonstrate more favorable outcomes. Manufacturing sees substantial increases in sales volume, likely driven by productivity improvements and spillover effects from construction activity. Real Estate experiences modest establishment growth, reflecting improved investor confidence and reduced land-use uncertainty. Arts, Entertainment, and Recreation emerges as a major beneficiary, with gains in establishments, employment, and sales volume. These results highlight the sector's sensitivity to economic recovery and consumer demand.

The divergent responses between land-intensive and non-LIS underscore the importance of sectoral adaptability. Industries with fixed land requirements face greater challenges, while those with operational flexibility can respond quickly to improved economic conditions.

3.7.4.3 Key Findings and Comparative Insights

The analysis highlights distinct strengths and limitations of binary and continuous range definitions, with each capturing unique dimensions of delisting's impacts:

Binary Range Definition: The binary measure divides counties into those with and without bear range, capturing average immediate effects of habitat presence. This approach is straightforward and highly interpretable for policymakers needing broad insights into delisting's spatial impacts. For instance, in NAICS 11 (Agriculture), establishment counts decline 12.5% immediately in range counties (**Table A44**), reflecting significant disruptions in production and workforce stability. In Utilities (NAICS 22), sharp 16.3% declines in employment and 33.9% reductions in sales volume (**Table A48**) illustrate the structural rigidity of land-intensive industries. The binary definition is particularly useful for identifying broad patterns and understanding the spatial scope of delisting's effects across sectors.

Continuous Range Definition: The continuous measure refines the analysis, capturing the marginal effects of incremental increases in habitat overlap. This allows for a more granular understanding of how habitat intensity influences economic outcomes. For example, in NAICS 11 (Agriculture), a 1-percentage-point increase in habitat overlap results in an immediate 0.1% decline in establishment counts, compounded annually by an additional 0.17% reduction (**Table A45**). In NAICS 21 (Mining), job and establishment losses scale proportionately with habitat overlap, with cumulative annual declines reflecting the sector's dependency on land stability and long-term planning (**Table A47**). Continuous measures are particularly valuable for targeting interventions in areas with varying levels of habitat overlap, offering actionable insights for policy design.

Temporal Dynamics: The coefficient on the interaction term (β_2) captures how impacts evolve over time, revealing two overarching trends. LIS such as agriculture, mining, and utilities experience cumulative annual declines as negative effects worsen over time. This reflects the rigidity of sectors reliant on land and fixed infrastructure, which are slow to adjust to regulatory and market changes. On the other hand, non-LIS such as construction and arts and recreation show immediate stabilization or positive cumulative effects, reflecting their operational flexibility and ability to capitalize on shifting economic conditions.

By combining these approaches, the analysis provides a multi-dimensional perspective of delisting's impacts, overcoming the limitations of relying on a single measure. This comprehensive framework ensures a more accurate and policy-relevant interpretation of spatial and temporal dynamics.

3.7.4.4 Sectoral Heterogeneity and Key Patterns

The findings reveal stark differences in sectoral responses to delisting, driven by variation in land dependency, adaptability, and exposure to economic spillovers:

1. LIS: For Agriculture, Mining, and Utilities, these sectors face significant and persistent declines across establishment counts, employment, and sales volume. Immediate impacts, compounded by annual declines, reflect their structural reliance on land resources and fixed infrastructure. For example, mining exhibits 17.2% annual declines in job counts (**Table A46**), and utilities suffer incremental declines in establishments and sales revenue as habitat overlap intensifies (**Table A49**). In contrast, construction stands out as a positive exception. Establishment counts grow by 8.7% immediately, with further 2.8% annual growth (**Table A50**). The sector benefits from reduced regulatory barriers, which facilitate new development and infrastructure projects, highlighting its capacity to capitalize on delisting policies.

2. Non-LIS: The manufacturing sector shows significant gains in sales volume, with an immediate 77% increase under the binary measure (**Table A52**). These gains are driven by productivity improvements and spillover effects from upstream construction activities, rather than workforce or establishment expansion. The Real Estate sector shows modest but steady establishment growth reflects improved investor confidence and reduced regulatory uncertainty. Establishment counts increase by 4.6% immediately under the binary definition (**Table A54**), though impacts on job counts and sales volume remain insignificant. The Arts, Entertainment, and Recreation sector emerges as a key beneficiary, with gains across all three outcome variables. Establishment counts increase by 3.9% immediately, while employment rises by 59.4%, and sales volume grows by 31.9% (**Table A56**). These gains reflect increased consumer demand and tourism opportunities post-delisting.

The divergence between LIS and non-LIS underscores the importance of sectoral adaptability. LIS face structural challenges tied to fixed land resources and immobile infrastructure, which limit their ability to respond to economic shifts. Non-LIS leverage their operational flexibility to adapt quickly to delisting-related changes, benefiting from improved market conditions and consumer demand.

3.7.4.5 Addressing the Research Questions and Hypotheses

The findings systematically address the research questions (RQs) and hypotheses (H) outlined in this study, with clear insights into the spatial, sectoral, and temporal dimensions of delisting's economic impacts:

1. Research Question 1 (H1: Non-Linear Effects Across Sectors): The results confirm significant non-linear effects across sectors, with LIS (e.g., agriculture, mining, utilities) experiencing large and persistent negative impacts. These sectors' reliance on fixed land and infrastructure limits their ability to adjust to delisting-related constraints, leading to cumulative declines in establishment counts, employment, and sales volume. Non-LIS (e.g., arts, recreation, manufacturing) exhibit stable or positive responses, reflecting their adaptability and lower dependency on land resources. This divergence underscores the importance of sectoral heterogeneity in understanding delisting's economic implications.

2. Research Question 2 (H2: Temporal Dynamics of Impacts): Temporal dynamics, captured by β_2, reveal key patterns: cumulative declines in LIS and immediate stabilization or growth in non-LIS. For example, construction demonstrates sustained positive growth in establishments, benefiting from reduced regulatory barriers and increased development opportunities. While the negative β_2 coefficients in some cases, such as utilities, appear counter-intuitive, they reflect worsening conditions in the immediate years following delisting (2016–2019). This result likely stems from the short post-delisting observation window, which limits the ability to capture longer-term recovery trends. This finding highlights the importance of extending future analyses to include a longer post-delisting period to validate these temporal effects.

3. Research Question 3 (H3: Structural and Resilience Challenges): The evidence strongly supports H3, highlighting the structural challenges faced by LIS and the resilience of non-LIS. Sectors like agriculture and mining struggle with regulatory and operational constraints, while adaptable sectors, such as arts and recreation, thrive on improved economic conditions and consumer demand.

These findings collectively provide a nuanced understanding of delisting's economic impacts, validating the hypotheses and addressing the study's research objectives.

3.7.5 Conclusion

This study integrates spatial, sectoral, and temporal analyses to provide a comprehensive understanding of the economic impacts of delisting the Louisiana Black Bear. By addressing the core research questions and hypotheses, the study highlights key contributions to Conservation Economics, Land Use Economics, and Industrial Organization:

1. Interpretation of Coefficients ($\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$): The immediate effects (β_1) capture the direct impact of habitat overlap on economic outcomes, distinguishing between counties with and without bear range (binary) or incremental increases in habitat overlap (continuous). Temporal effects (β_2) provide insight into how impacts evolve over time, with negative values in LIS reflecting short-term economic adjustments post-delisting. These values, though initially counter-intuitive, underscore the boundedness of TSD, which measures only the years post-delisting (2016–2019). The limited observation window highlights the need for extended analyses to capture long-term recovery trends.

2. Methodological Contributions: The use of binary and continuous range definitions ensures a multi-dimensional analysis of delisting impacts, offering complementary perspectives. The binary measure simplifies spatial impacts, while the continuous measure captures marginal effects of habitat overlap, providing granular insights into spatial heterogeneity. Temporal interaction terms further enrich the analysis by distinguishing immediate impacts from cumulative trends, addressing the dynamic nature of sectoral adjustments.

3. Key Findings and Policy Implications: LIS face significant and persistent economic challenges, underscoring the need for targeted policies to support sectors like agriculture, mining, and utilities. These policies should address structural constraints and facilitate adaptation to changing regulatory landscapes. Non-LIS benefit from improved market conditions, highlighting the potential for delisting to spur growth in adaptable industries like manufacturing, real estate, and recreation. Policymakers should consider sector-specific interventions that balance conservation goals with economic resilience, leveraging delisting decisions to foster sustainable development while mitigating adverse impacts.

4. Acknowledgment of Limitations: The study acknowledges the short post-delisting observation window (2016–2019), which limits the ability to capture longer-term sectoral adjustments. Future research should extend the temporal scope to better understand the evolving economic impacts of delisting. By combining rigorous econometric methods with a focus on spatial, temporal, and sectoral heterogeneity, this study provides actionable insights for policymakers and contributes to the broader understanding of the economic trade-offs inherent in species conservation decisions.

3.8 Discussion and Policy Implications

3.8.1 Introduction

The findings of this study provide significant empirical evidence on the economic consequences of delisting the Louisiana Black Bear, revealing sharp contrasts across LIS and non-LIS. The study captures the nuanced spatial and temporal effects of habitat regulatory changes. This dual approach highlights critical patterns often overlooked in similar studies, offering actionable insights for policymakers and advancing the broader field of conservation economics.

3.8.2 Reconciling Economic Recovery with Conservation Objectives

The results underscore the tension between economic recovery and species persistence, a central concern in post-delisting scenarios. LIS such as agriculture, mining, and utilities experience significant and persistent declines, particularly in counties with high habitat overlap. These findings align with literature on the economic costs of environmental regulations, where fixed land dependencies heighten vulnerabilities (Ferris & Frank, 2021; Melstrom, 2020). Sectors like construction and non-LIS, including arts and real estate, show immediate or incremental gains. This outcome reflects the capacity of certain industries to capitalize on regulatory relief, particularly when operational flexibility and market adaptability are high. For example, the arts sector's 31.9% increase in sales volume mirrors findings by Sims et al. (2019), where tourism and recreation industries benefited from eased restrictions.

3.8.3 Policy Recommendations

This study highlights actionable strategies to balance economic recovery and habitat protection following delisting.

First, post-delisting monitoring programs should track habitat quality and species populations, particularly in high-overlap counties where cumulative declines in LIS are most pronounced. Monitoring can provide early warnings of habitat degradation and enable timely interventions. Second, spatially targeted interventions are crucial for addressing localized pressures. High-overlap counties require conservation resources and tailored economic support to mitigate habitat and economic vulnerabilities. The study's findings reveal that economic impacts scale proportionally with habitat overlap, emphasizing the need for localized solutions. Third, incentives for sustainable practices can align economic activities with conservation goals. Programs promoting sustainable agriculture, responsible mining, and habitat-sensitive development can reduce ecological disruptions while supporting economic resilience. Finally, adaptive conservation policies should evolve based on monitoring outcomes.

These dynamic strategies can address immediate shocks and accommodate long-term adjustments, reflecting the study's temporal findings of gradual sectoral changes. Flexible policies ensure effective responses to shifting economic and ecological conditions.

3.8.4 Contributions to the Literature and Policy Discourse

This study makes significant contributions by integrating spatial, temporal, and sectoral analyses to evaluate delisting's economic impacts. The dual range definitions (binary and continuous) advance understanding by capturing both broad spatial patterns and the marginal effects of habitat overlap. Temporal dynamics, captured through interaction terms, reveal evolving impacts over time, underscoring the importance of adaptability in conservation and economic policy. The distinction between LIS and non-LIS highlights critical heterogeneities. LIS face persistent declines due to structural dependencies on land resources, while non-LIS exhibit resilience, leveraging improved economic conditions post-delisting. Importantly, this study challenges the assumption that conservation policies and economic growth are incompatible. The findings demonstrate that delisting can stimulate growth in adaptable sectors while identifying the need for safeguards in vulnerable industries. These insights inform balanced policy strategies that promote both economic recovery and conservation objectives.

3.9 Conclusion

This study provides a comprehensive empirical analysis of the economic impacts of delisting the Louisiana Black Bear, addressing critical gaps in the literature on species conservation and regional economic development. By evaluating three primary outcomes—establishment count, job count, and sales volume—across land-intensive (LIS) and non-land-intensive sectors (non-LIS), the research offers nuanced insights into the spatial, temporal, and sectoral dimensions of delisting. The hypotheses were systematically tested, revealing that delisting creates significant economic impacts that vary spatially and temporally, with profound sectoral differences driven by land dependency, regulatory relief, and adaptability.

This research makes pivotal contributions to Conservation Economics, Land Use Economics, and Industrial Organization. First, it advances methodological precision by integrating spatial and temporal frameworks. The dual use of binary and continuous range definitions captures both broad spatial patterns and incremental sensitivities to habitat overlap, providing a robust understanding of how delisting impacts evolve over time and space. Temporal dynamics, captured through the Time Since Delisting (TSD) variable, highlight the interplay between immediate impacts and longer-term adjustments, with results reflecting the limited three-year post-delisting observation window.

Second, the study emphasizes sectoral heterogeneity, revealing how land-intensive sectors like agriculture, mining, and utilities face persistent economic challenges due to fixed capital constraints and dependency on land resources. In contrast, adaptable sectors like construction and arts experience significant growth post-delisting, capitalizing on reduced regulatory barriers and improved market conditions. These findings underscore the importance of differentiating sectoral responses when analyzing conservation policy impacts.

Third, the study provides real-world policy relevance, challenging the assumption that species delisting universally benefits local economies. Instead, the findings reveal trade-offs between economic growth and conservation objectives, emphasizing the need for sector-specific policies. Industries like agriculture and mining require targeted interventions, including sustainable land-use practices and financial support, to mitigate compounding economic losses. Simultaneously, adaptable sectors like construction and arts should be supported through infrastructure investments, workforce development, and tourism promotion to foster economic resilience.

The results carry clear policy implications. Continuous range measures emphasize the need for localized interventions in counties with high habitat overlap, where economic and habitat pressures are most acute. Monitoring programs and adaptive policies are critical for balancing economic recovery with long-term species conservation, reducing the risk of habitat encroachment and potential relisting. The study reinforces the importance of integrating economic foresight into conservation planning, bridging the gap between ecological and economic objectives.

This study challenges policymakers to move beyond simplistic narratives, advocating for nuanced, evidence-based strategies that balance economic recovery with ecological sustainability. By capturing sectoral heterogeneity, spatial nuances, and temporal dynamics, it offers a realistic and balanced understanding of how delisting decisions impact regional economies. These findings contribute to broader discussions on Environmental Federalism (Oates, 1999) and Dynamic Conservation Policies (Ando & Shah, 2014), providing actionable insights for policymakers and conservation managers.

In conclusion, this research serves as a foundation for future studies and policy innovations, offering a blueprint for harmonizing economic growth with species conservation. It underscores that successful conservation policies require not only ecological sensitivity but also strategic flexibility and economic foresight. As species conservation and land-use decisions grow increasingly complex, this study provides critical insights for designing policies that support both sustainable development and biodiversity recovery.

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Appendix

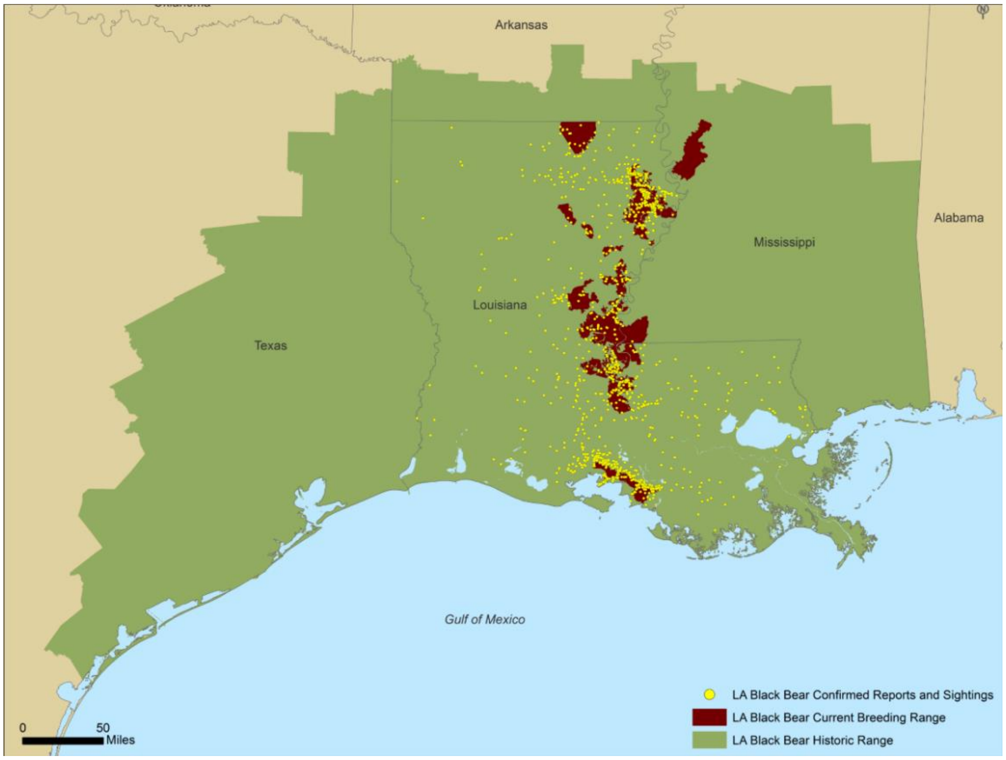

Figure A17: Habitat Range of the Louisiana Black Bear
Source: https://ecos.fws.gov/ecp/species/8552

The map in **Figure A17** above illustrates the spatial distribution of the Louisiana Black Bear's habitat, highlighting three distinct areas: the historic range, current breeding range, and confirmed reports and sightings. The historic range (light green) represents the broader area where the species was historically found, while the current breeding range (dark red) identifies areas with active populations. Yellow dots denote confirmed bear sightings, emphasizing the species' spatial presence and recovery efforts. Data sourced from the U.S. Fish and Wildlife Service (ECOS).

Table A41: Summary Statistics for County-Level Explanatory Variables

Variable	Mean	Std. Dev.	Min	Max
Poverty rate (100s)	.154	.0624	.017	.62
Unemployment rate (100s)	.0596	.0276	.007	.306
Median HH Income (100ks)	.428	.126	.0986	1.52
Housing Price Index (100s)	2.47	1.58	.637	21.2
Population Density (100s)	.004	.0281	0	1.17
SO2 - Attain. Status (t-1)	.0041	.0496	0	1
PSM - Attain. Status (t-1)	.0457	.238	0	1
O3 - Attain. Status (t-1)	.101	.338	0	1
NO2 - Attain. Status (t-1)	0	.0044	0	1
Pb - Attain. Status (t-1)	.0017	.0303	0	1
CO - Attain. Status (t-1)	.0032	.0474	0	1
PAD - All GAPs (t-1)	.142	.187	0	.88

Table A41: Summary statistics of socio-economic, demographic, and environmental variables across counties, including poverty rate, unemployment rate, and air quality attainment status for pollutants. The Protected Area Designation (PAD) variable highlights variation in conservation land use, while housing price index and population density capture regional economic dynamics.

Table A41 above presents the descriptive statistics for key explanatory variables used in the analysis, covering socio-economic, demographic, and environmental factors at the county level. Variables include poverty rate, unemployment rate, median household income, housing price index, and population density. Environmental indicators, such as air quality attainment status for pollutants (e.g., SO_2, PSM, O_3, NO_2, Pb, and CO) and PAD, capture regional regulatory and conservation contexts. Mean, standard deviation, minimum, and maximum values highlight the variability across counties, providing insights into the spatial and economic heterogeneity of the dataset.

Table A42: Summary Statistics for Bear Range

Variable	N	Mean	Std. Dev.	Min	Max
Bear - Range Indicator	118	1.00	0.00	1.00	1.00
Bear - % County in range	118	35.63	12.81	5.55	63.69

Table A42: Summary statistics for counties within the range of the Louisiana Black Bear. This includes the percentage of county land in the bear's range and an indicator of whether the county is within the range.

Table A42 above provides summary statistics for counties within the range of the Louisiana Black Bear. The Bear - Range Indicator is a binary variable indicating whether a county is within the species' range (1 = yes, 0 = no). The Bear - % County in Range captures the percentage of each county's land area that overlaps with the bear's range, highlighting spatial variation among counties. The mean percentage of overlap is 35.63%, with a minimum of 5.55% and a maximum of 63.69%.

Table A43: Summary Statistics of Outcome Variables

NAICS Sector	Variable	Mean	SD	Min	Max
11 – Agriculture, Forestry, Fishing, and Hunting	Establishment Count	27	33	0.00	874
	Employment Count	188	511	0.00	1687
	Sales Volume	32668	128178	0.00	11548636
21 – Mining, Quarrying, and Oil and Gas Extraction	Establishment Count	7	33	0.00	1416
	Employment Count	122	1188	0.00	108030
	Sales Volume	48050	736002	0.00	79516648
22 - Utilities	Establishment Count	7	12	1.00	420
	Employment Count	196	664	0.00	32869
	Sales Volume	98613	323305	0.00	20420646
23 - Construction	Establishment Count	301	829	0.00	26029
	Employment Count	2214	7002	0.00	180952
	Sales Volume	468517	1654091	0.00	105773792
53 – Real Estate, Rental, and Leasing	Establishment Count	193	692	0.00	36535
	Employment Count	1186	4972	0.00	159344
	Sales Volume	202151	960384	0.00	40728208
71 – Arts, Entertainment, and Recreation	Establishment Count	66	206	1.00	7733
	Employment Count	781	3265	0.00	127463
	Sales Volume	68090	330876	0.00	24991232
31-33 - Manufacturing	Establishment Count	148	574	1.00	27803
	Employment Count	4428	14484	0.00	536899
	Sales Volume	1056941	4108503	0.00	199494336

Table A43: Summary Statistics, including the mean, standard deviation, and range for the outcome variables—Establishment Count, Employment Count, and Sales Volume—across NAICS sectors. The data illustrate economic variability in land-intensive sectors (e.g., agriculture, mining) and non-land-intensive sectors (e.g., real estate, manufacturing), providing insights into sectoral responses to delisting.

Table A44: Summary of NAICS 11 Regression Results – Binary Range Indicator

Variable	Establishment Count		Job Count		Sales Volume	
Range	-.02026	-.12552***	-.15822**	-.10657	-.08914	-.21062*
	(.0383)	(.0357)	(.06791)	(.07043)	(.0765)	(.12038)
TSD * Range	-.28491***	-.205***	-.06013	-.12129***	-.31045***	-.19488***
	(.02307)	(.02097)	(.04282)	(.03778)	(.07212)	(.06694)
Joint Test (p-value)	0.0000	0.0000	0.0127	0.0019	0.0000	0.0017
State FE	-	Yes	-	Yes	-	Yes
Year FE	-	Yes	-	Yes	-	Yes
County FE	-	Yes	-	Yes	-	Yes

Table A44: Summary of PPMLHDFE Regression results for agriculture, forestry, fishing, and hunting sectors, using a binary range indicator. Results display the spatial, temporal, and combined impacts of delisting on Establishment Count, Job Count, and Sales Volume, with fixed effects at the state, year, and county levels. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A45: Summary of NAICS 11 Regression Results – Continuous Range Indicator

Variable	Establishment Count		Job Count		Sales Volume	
Range	-.00056	-.00104***	-.00202***	-.00069	-.00164**	-.00166
	(.00043)	(.00035)	(.00068)	(.00065)	(.00069)	(.00123)
TSD * Range	-.00159***	-.00171***	-.00094**	-.00097**	-.00114	-.00116
	(.0002)	(.00021)	(.00044)	(.00045)	(.00076)	(.00075)
Joint Test (p-value)	0.0000	0.0000	0.0001	0.0305	0.0046	0.0874
State FE	-	Yes	-	Yes	-	Yes
Year FE	-	Yes	-	Yes	-	Yes
County FE	-	Yes	-	Yes	-	Yes

Table A45: Regression results for the same sector using the continuous range indicator (% of county land in range). The table highlights spatial variability in economic outcomes and tracks the temporal evolution post-delisting. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A46: Summary of NAICS 21 Regression Results – Binary Range Indicator

Variable	Establishment Count		Job Count		Sales Volume	
Range	.94455***	-.0117	.57236***	-.17837	.90743***	-.09349
	(.14219)	(.05206)	(.15853)	(.15281)	(.1837)	(.17135)
TSD * Range	-.45443***	-.10357***	-.29202***	-.17156**	-.37055***	-.11754
	(.04937)	(.02409)	(.06251)	(.07054)	(.09762)	(.11099)
Joint Test (p-value)	0.0000	0.0001	0.0000	0.0378	0.0000	0.5196
State FE	-	Yes	-	Yes	-	Yes
Year FE	-	Yes	-	Yes	-	Yes
County FE	-	Yes	-	Yes	-	Yes

Table A46: Results for the mining and resource extraction sector, with binary range measures. Key findings include the direct and time-dependent effects of delisting on sectoral outcomes. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A47: Summary of NAICS 21 Regression Results – Continuous Range Indicator

Variable	Establishment Count		Job Count		Sales Volume	
Range	.00783***	-.00029	.00515***	-.00223*	.0072***	-.0017
	(.00115)	(.00046)	(.00128)	(.00115)	(.00141)	(.00137)
TSD * Range	.00046	-.00099***	-.00074	-.00135**	-.00026	-.00095
	(.00053)	(.00021)	(.00071)	(.00063)	(.00131)	(.00109)
Joint Test (p-value)	0.0000	0.0000	0.0003	0.0357	0.0000	0.4026
State FE	-	Yes	-	Yes	-	Yes
Year FE	-	Yes	-	Yes	-	Yes
County FE	-	Yes	-	Yes	-	Yes

Table A47: Results for the mining sector using the continuous range indicator. The interaction between range overlap and time since delisting provides insights into the dynamic adjustments in economic activity. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A48: Summary of NAICS 22 Regression Results – **Binary Range Indicator**

Variable	**Establishment Count**		**Job Count**		**Sales Volume**	
Range	.4058***	-.03869	.09534	-.16301*	.08406	-.33931*
	(.04939)	(.02703)	(.1099)	(.0917)	(.10063)	(.2016)
TSD * Range	-.07804***	-.06071***	-.05026	-.05257	-.19853***	-.0309
	(.02448)	(.01801)	(.05524)	(.05143)	(.05828)	(.05723)
Joint Test (p-value)	0.0000	0.0024	0.5447	0.1148	0.0030	0.1919
State FE	-	Yes	-	Yes	-	Yes
Year FE	-	Yes	-	Yes	-	Yes
County FE	-	Yes	-	Yes	-	Yes

Table A48: Regression outputs for utilities, showcasing the effects of delisting on economic outcomes, with county-level spatial variation and fixed effects. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A49: Summary of NAICS 22 Regression Results – Continuous Range Indicator

Variable	**Establishment Count**		**Job Count**		**Sales Volume**	
Range	.00313***	-.00039	.00104	-.00157**	.00058	-.00394**
	(.0005)	(.00025)	(.00108)	(.00071)	(.00093)	(.002)
TSD * Range	.00027	-.00045**	0	-.0008**	-.00023	-.00085*
	(.00024)	(.00018)	(.00043)	(.0004)	(.0005)	(.00049)
Joint Test (p-value)	0.0000	0.0219	0.6128	0.0010	0.7891	0.0152
State FE	-	Yes	-	Yes	-	Yes
Year FE	-	Yes	-	Yes	-	Yes
County FE	-	Yes	-	Yes	-	Yes

Table A49: Results for utilities with continuous range indicators, reflecting the proportional economic impacts relative to habitat overlap and temporal evolution. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A50: Summary of NAICS 23 Regression Results – Binary Range Indicator

Variable	**Establishment Count**		**Job Count**		**Sales Volume**	
Range	.29576**	.08674***	.41283***	-.01046	.42199***	.03021
	(.13021)	(.01606)	(.14327)	(.03381)	(.14316)	(.0466)
TSD * Range	-.15051***	.02823**	-.10711***	.02717**	-.26636***	-.00234
	(.03579)	(.01434)	(.02569)	(.01355)	(.02772)	(.02296)
Joint Test (p-value)	0.0001	0.0000	0.0000	0.0961	0.0000	0.8100
State FE	-	Yes	-	Yes	-	Yes
Year FE	-	Yes	-	Yes	-	Yes
County FE	-	Yes	-	Yes	-	Yes

Table A50: Results for construction, illustrating the spatial and temporal economic impacts of delisting, with binary range measures. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A51: Summary of NAICS 23 Regression Results – Continuous Range Indicator

Variable	Establishment Count		Job Count		Sales Volume	
Range	.00339***	.00078***	.00455***	-.00003	.00456***	.00009
	(.00114)	(.00009)	(.00121)	(.00027)	(.0012)	(.0004)
TSD * Range	.00002	.00027**	.00013	.00013	-.00021	-.00009
	(.00029)	(.00012)	(.00025)	(.00015)	(.00032)	(.00023)
Joint Test (p-value)	0.0074	0.0000	0.0003	0.5830	0.0003	0.9149
State FE	-	Yes	-	Yes	-	Yes
Year FE	-	Yes	-	Yes	-	Yes
County FE	-	Yes	-	Yes	-	Yes

Table A51: Continuous range analysis for construction, highlighting heterogeneity in outcomes as a function of habitat overlap and time since delisting. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A52: Summary of NAICS 31-33 Regression Results – Binary Range Indicator

Variable	Establishment Count		Job Count		Sales Volume	
Range	.15801	.00242	.01546	.01187	.50622***	.7738**
	(.14644)	(.02083)	(.14577)	(.04566)	(.1641)	(.36275)
TSD * Range	-.1549***	.01431	-.13996***	-.02041	-.04711	.04009
	(.03775)	(.01452)	(.03061)	(.02061)	(.08541)	(.0734)
Joint Test (p-value)	0.0002	0.5926	0.0000	0.4731	0.0046	0.0198
State FE	-	Yes	-	Yes	-	Yes
Year FE	-	Yes	-	Yes	-	Yes
County FE	-	Yes	-	Yes	-	Yes

Table A52: Regression results for manufacturing, using binary range measures. Captures the sector's indirect economic responses to delisting. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A53: Summary of NAICS 31-33 Regression Results – Continuous Range Indicator

Variable	Establishment Count		Job Count		Sales Volume	
Range	.0025*	-.00011	.00094	-.00011	.00559***	.00571**
	(.0013)	(.00021)	(.00134)	(.00048)	(.0013)	(.00261)
TSD * Range	.00003	.00012	-.00017	-.00014	.00083	.0005
	(.00037)	(.00011)	(.0003)	(.00022)	(.00085)	(.00067)
Joint Test (p-value)	0.1424	0.4266	0.7151	0.8048	0.0001	0.0111
State FE	-	Yes	-	Yes	-	Yes
Year FE	-	Yes	-	Yes	-	Yes
County FE	-	Yes	-	Yes	-	Yes

Table A53: Results for manufacturing with continuous range measures, emphasizing nuanced spatial and temporal responses post-delisting. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A54: Summary of NAICS 53 Regression Results – Binary Range Indicator

Variable	Establishment Count		Job Count		Sales Volume	
Range	.28434*	.04629**	.26674	.05747	.25466	.05793
	(.16094)	(.01986)	(.2023)	(.03704)	(.19769)	(.04243)
TSD * Range	-.07786*	-.00171	-.083***	.0065	-.24489***	-.02113
	(.0425)	(.02202)	(.02879)	(.01795)	(.03173)	(.02103)
Joint Test (p-value)	0.0971	0.0540	0.0109	0.2238	0.0000	0.1900
State FE	-	Yes	-	Yes	-	Yes
Year FE	-	Yes	-	Yes	-	Yes
County FE	-	Yes	-	Yes	-	Yes

Table A54: Regression results for real estate and leasing, showing how spatial proximity to the range affects economic outcomes post-delisting. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A55: Summary of NAICS 53 Regression Results – Continuous Range Indicator

Variable	Establishment Count		Job Count		Sales Volume	
Range	.00321**	.00028**	.00331**	.00009	.00337**	.00023
	(.00137)	(.00014)	(.00166)	(.00028)	(.00163)	(.00035)
TSD * Range	.00109**	-.00007	.00058**	-.00007	.00022	-.00016
	(.00055)	(.00016)	(.00029)	(.00014)	(.00039)	(.0002)
Joint Test (p-value)	0.0021	0.1147	0.0183	0.7188	0.1020	0.5826
State FE	-	Yes	-	Yes	-	Yes
Year FE	-	Yes	-	Yes	-	Yes
County FE	-	Yes	-	Yes	-	Yes

Table A55: Continuous range results for real estate and leasing, demonstrating the proportional influence of habitat overlap on sectoral outcomes. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A56: Summary of NAICS 71 Regression Results – Binary Range Indicator

Variable	Establishment Count		Job Count		Sales Volume	
Range	.19922	.03915**	.25905	.59429**	.38819**	.31859**
	(.15091)	(.0179)	(.18332)	(.26945)	(.18785)	(.15913)
TSD * Range	-.05783	.02357	.04284	-.04691	.12682	.03687
	(.04578)	(.02603)	(.04496)	(.0346)	(.1028)	(.09621)
Joint Test (p-value)	0.3006	0.0659	0.2498	0.0046	0.0753	0.0441
State FE	-	Yes	-	Yes	-	Yes
Year FE	-	Yes	-	Yes	-	Yes
County FE	-	Yes	-	Yes	-	Yes

Table A56: Regression outputs for arts and entertainment using binary range measures, capturing sectoral economic adjustments post-delisting. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A57: Summary of NAICS 71 Regression Results – Continuous Range Indicator

Variable	Establishment Count		Job Count		Sales Volume	
Range	.00279**	.00023**	.0045***	.00369*	.00557***	.00234**
	(.00128)	(.0001)	(.0016)	(.00201)	(.00155)	(.00107)
TSD * Range	.00067*	.00012	.0002	-.0003	.00091	.00059
	(.00036)	(.00019)	(.00042)	(.00033)	(.00091)	(.00077)
Joint Test (p-value)	0.0016	0.0906	0.0179	0.0468	0.0015	0.0465
State FE	-	Yes	-	Yes	-	Yes
Year FE	-	Yes	-	Yes	-	Yes
County FE	-	Yes	-	Yes	-	Yes

Table A57: Continuous range analysis for arts and entertainment, illustrating spatial heterogeneity and temporal dynamics in economic outcomes post-delisting. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A58: Regression Results on Establishment Count – Binary Range Indicator

Variable	**NAICS 11**	**NAICS 21**	**NAICS 22**	**NAICS 23**	**NAICS 31-33**	**NAICS 53**	**NAICS 71**
Range Ind.	-.126***	-.012	-.039	.087***	.002	.046**	.039**
	(.036)	(.052)	(.027)	(.0161)	(.021)	(.020)	(.018)
TSD * Range	-.205***	-.104***	-.061***	.028**	.014	-.002	.024
	(.021)	(.024)	(.018)	(.014)	(.015)	(.022)	(.026)
Poverty rate (100s)	-.313	.437	.850***	-.696***	-.865***	-.367	.079
	(.216)	(.291)	(.215)	(.250)	(.177)	(.274)	(.177)
Unemp. rate (100s)	-1.242***	2.017***	.322	.659***	.384**	.847***	.680***
	(.254)	(.346)	(.274)	(.237)	(.184)	(.286)	(.180)
Pop. Density (100s)	-5.840	-.498	-4.322**	.504	-4.277***	1.655**	.398
	(3.788)	(2.190)	(2.202)	(1.496)	(.992)	(.709)	(1.614)
Med. HH Inc. (100ks)	1.179***	.834***	.810***	.328**	.216	.232	.464***
	(.141)	(.255)	(.179)	(.158)	(.141)	(.196)	(.102)
HPI (100s)	-.050***	.006	-.017**	.015**	-.004	-.0112*	.001
	(.007)	(.009)	(.008)	(.006)	(.006)	(.007)	(.004)
EPA - SO2 (t-1)	-.097	.0126	.022	-.002	-.017	-.061	.039
	(.078)	(.080)	(.057)	(.049)	(.059)	(.060)	(.042)
EPA - PSM (t-1)	-.055***	.062***	.080***	.019**	-.011*	.033***	-.011**
	(.011)	(.024)	(.017)	(.009)	(.006)	(.010)	(.006)
EPA - O3 (t-1)	-.100***	-.029*	.007	-.005	.006	-.031*	.029***
	(.014)	(.016)	(.014)	(.010)	(.006)	(.016)	(.007)
EPA - NO2 (t-1)	.043	-.156	.330*	-.004	-.093**	.070*	.026
	(.075)	(.102)	(.195)	(.030)	(.037)	(.041)	(.070)
EPA - Pb (t-1)	-.027	-.058	-.282	-.018	-.076	-.1454	-.103*
	(.095)	(.086)	(.176)	(.045)	(.076)	(.093)	(.058)
EPA - CO (t-1)	.075	.009	-.070	.0429*	.0394*	.0469*	-.0109
	(.049)	(.0724)	(.100)	(.025)	(.0211)	(.028)	(.020)
PAD - All GAPs (t-1)	-1.832***	-.324	2.561***	-1.361***	-.752***	-1.088	-1.029***
	(.486)	(.717)	(.505)	(.475)	(.292)	(.858)	(.340)
PAD Squared	.168	.968	-2.590***	1.741***	.955***	1.371	1.156***
	(.546)	(.844)	(.659)	(.430)	(.302)	(1.179)	(.384)
Prior Estab. Stock (10ks)	29.210***	10.070**	52.739**	.130**	.408**	.362***	.883*
	(6.614)	(4.188)	(26.004)	(.056)	(.197)	(.018)	(.495)
_cons	3.702***	2.822***	1.805***	6.85***	6.648***	6.648***	5.228***
	(.09412)	(.1599)	(.09075)	(.10038)	(.0974)	(.12439)	(.07777)
Observations	44957	42534	41210	44957	43640	44957	43551
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	.761	.868	.669	.966	.982	.971	.965

Table A58: Results of PPMLHDFE regressions on Establishment Count using the Binary Range Indicator for NAICS sectors (11–71), with State, County, and Year Fixed Effects. The table evaluates the spatial and temporal impacts of the Louisiana Black Bear's delisting, alongside controls for socioeconomic and environmental factors. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A59: Regression Results on Jobs Count – Binary Range Indicator

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33	NAICS 53	NAICS 71
Range Ind	-.107	-.178	-.163*	-.011	.012	.057	.594**
	(.070)	(.153)	(.092)	(.034)	(.046)	(.037)	(.269)
TSD * Range	-.121***	-.172**	-.053	.027**	-.020	.007	-.047
	(.038)	(.071)	(.051)	(.014)	(.021)	(.018)	(.035)
Poverty rate (100s)	.530	-.928	.923	-1.660***	-.996***	-.995***	.244
	(.839)	(1.093)	(.876)	(.277)	(.250)	(.288)	(.640)
Unemp. rate (100s)	-.876	.510	1.669*	.750***	.126	1.018***	.931
	(.624)	(1.166)	(.972)	(.274)	(.270)	(.363)	(.650)
Pop. Density (100s)	-.944	21.652	1.484	.500	-3.444***	2.787***	-1.429
	(8.485)	(15.023)	(3.064)	(1.439)	(1.266)	(.787)	(1.229)
Med. HH Inc. (100ks)	1.431***	-.112	.620	.664***	.551***	.421**	.351**
	(.318)	(.810)	(.410)	(.166)	(.172)	(.183)	(.175)
HPI (100s)	-.0395***	.045	.028	.007	-.012*	.003	.0131
	(.012)	(.042)	(.022)	(.007)	(.007)	(.005)	(.015)
EPA - SO2 (t-1)	.101	.245	.058	.059	.029	.048	-.017
	(.148)	(.247)	(.330)	(.056)	(.045)	(.051)	(.060)
EPA - PSM (t-1)	-.049*	-.001	.068*	.008	.021**	.036**	-.006
	(.027)	(.044)	(.040)	(.009)	(.010)	(.018)	(.017)
EPA - O3 (t-1)	-.071***	.121	.125**	-.012	.024**	-.037*	.040**
	(.026)	(.080)	(.050)	(.010)	(.010)	(.022)	(.016)
EPA - NO2 (t-1)	-.477***	.052	-.076	-.013	-.101***	-.134***	
	(.127)	(.669)	(.303)	(.038)	(.030)	(.035)	
EPA - Pb (t-1)	-.342	.2478	.496*	.084	-.075	-.057	-.311***
	(.265)	(.235)	(.256)	(.055)	(.058)	(.060)	(.118)
EPA - CO (t-1)	.225***	.325*	.247*	.032	.067**	.055*	-.216**
	(.084)	(.187)	(.137)	(.025)	(.034)	(.029)	(.102)
PAD - All GAPs (t-1)	.680	-2.449	3.400*	-.568	-1.350**	-.412	1.269
	(1.207)	(1.937)	(2.027)	(.497)	(.655)	(.624)	(1.505)
PAD Squared	-1.727	1.161	-4.037**	.146	1.227	.322	-1.881
	(1.296)	(1.944)	(1.983)	(.406)	(.754)	(.617)	(1.557)
Prior Estab. Stock (10ks)	13.160**	27.356***	-20.507	.077	.280*	.165***	1.526*
	(5.529)	(4.905)	(26.664)	(.052)	(.163)	(.016)	(.899)
_cons	5.660***	6.338***	5.575***	8.996***	9.880***	8.614***	7.910***
	(.3108)	(.424)	(.316)	(.125)	(.109)	(.129)	(.315)
Observations	47546	45079	43698	47546	46223	47546	39433
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	.876	.931	.885	.973	.980	.979	.972

Table A59: Results of PPMLHDFE regressions on Job Count using the Binary Range Indicator for NAICS sectors (11–71), with State, County, and Year Fixed Effects. Interaction terms with Time Since Delisting (TSD) highlight the temporal dynamics of delisting effects. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A60: Regression Results on Sales Volume – Binary Range Indicator

Variable	**NAICS 11**	**NAICS 21**	**NAICS 22**	**NAICS 23**	**NAICS 31-33**	**NAICS 53**	**NAICS 71**
Range Ind	-.211*	-.0935	-.339*	.0302	.774**	.058	.319**
	(.120)	(.171)	(.202)	(.047)	(.363)	(.042)	(.159)
TSD * Range	-.195***	-.118	-.031	-.002	.040	-.021	.037
	(.067)	(.111)	(.057)	(.023)	(.073)	(.021)	(.096)
Poverty rate (100s)	2.646***	-1.403	1.401	-.496	-1.042	.945**	2.854**
	(.716)	(1.143)	(.911)	(.327)	(.645)	(.462)	(1.151)
Unemp. rate (100s)	-3.612***	3.949**	1.130	-.442	3.374***	.293	-.743
	(1.211)	(1.967)	(.995)	(.676)	(1.159)	(.949)	(.949)
Pop. Density (100s)	-8.336	39.369	6.162*	4.457*	-8.089**	8.913***	-1.916
	(12.324)	(39.028)	(3.504)	(2.379)	(3.683)	(1.437)	(2.076)
Med. HH Inc. (100ks)	1.352***	-.793	.164	.812***	-.322	.827***	-.084
	(.498)	(1.262)	(.467)	(.188)	(.464)	(.288)	(.316)
HPI (100s)	-.057**	.122*	.043*	.027***	.076***	.040***	.061**
	(.024)	(.063)	(.024)	(.009)	(.016)	(.011)	(.024)
EPA - SO2 (t-1)	.454**	.069	-.243	.144*	.383*	.218*	.1209
	(.228)	(.327)	(.209)	(.080)	(.198)	(.122)	(.145)
EPA - PSM (t-1)	-.024	.087	.088**	-.028*	-.0405**	.035	.039
	(.045)	(.067)	(.040)	(.015)	(.020)	(.047)	(.041)
EPA - O3 (t-1)	-.131**	.407***	.094	-.029	-.0585	-.085*	.001
	(.065)	(.149)	(.065)	(.026)	(.045)	(.050)	(.035)
EPA - NO2 (t-1)	-.773	.748	.115	.205***		.115	-.119
	(.689)	(.480)	(.511)	(.036)		(.077)	(.165)
EPA - Pb (t-1)	-.926***	-.273	.034	-.308	-.583**	-.238	-.660*
	(.234)	(.548)	(.448)	(.260)	(.287)	(.297)	(.356)
EPA - CO (t-1)	.0494	.737**	.233	.074	.146	.078	-.128
	(.199)	(.371)	(.220)	(.076)	(.123)	(.074)	(.168)
PAD - All GAPs (t-1)	1.103	-7.691***	7.923***	-1.712*	-2.821*	.676	1.545
	(1.570)	(2.403)	(2.008)	(.896)	(1.489)	(.858)	(1.693)
PAD Squared	-3.534*	7.835***	-7.130***	1.359	1.04	.340	-1.281
	(1.883)	(2.509)	(2.024)	(.875)	(1.819)	(1.055)	(1.917)
Prior Estab Stock (10ks)	9.831	34.728***	2.014	.222**	.467***	.083**	2.039***
	(7.507)	(10.159)	(40.183)	(.106)	(.146)	(.042)	(.686)
_cons	11.093***	12.108***	11.098***	14.157***	15.751***	12.682***	12.025***
	(.373)	(.764)	(.341)	(.161)	(.291)	(.162)	(.392)
Observations	47546	45034	43701	47546	39494	47532	46132
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	.790	.915	.819	.941	.906	.951	.933

Table A60: Results of PPMLHDFE regressions on Sales Volume using the Binary Range Indicator for NAICS sectors (11–71), with State, County, and Year Fixed Effects. Controls for air quality attainment, PAD designations, and economic conditions are included. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A61: Regression Results on Establishment Count – Continuous Range Indicator

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33	NAICS 53	NAICS 71
% Range	-.00104***	-.00029	-.00039	.00078***	-.00011	.00028**	.00023**
	(.00035)	(.00046)	(.00025)	(.00009)	(.00021)	(.00014)	(.0001)
TSD * Range	-.00171***	-.00099**	-.00045**	.00027**	.00012	-.00007	.00012
	(.00021)	(.00021)	(.00018)	(.00012)	(.00011)	(.00016)	(.00019)
Poverty rate (100s)	-.304	.441	.857***	-.699***	-.866***	-.369	.076
	(.217)	(.291)	(.215)	(.250)	(.176)	(.273)	(.178)
Unemp. rate (100s)	-1.245***	2.014***	.315	.663***	.382**	.846***	.681***
	(.254)	(.346)	(.274)	(.237)	(.183)	(.286)	(.180)
Pop. Density (100s)	-5.887	-.538	-4.329**	.521	-4.279***	1.656**	.400
	(3.804)	(2.181)	(2.203)	(1.499)	(.992)	(.709)	(1.616)
Med. HH Inc. (100ks)	1.186***	.828***	.812***	.329**	.216	.231	.463***
	(.141)	(.256)	(.179)	(.158)	(.141)	(.196)	(.102)
HPI (100s)	-.050***	.006	-.017**	.016**	-.004	-.011*	.001
	(.007)	(.009)	(.008)	(.006)	(.006)	(.007)	(.004)
EPA - SO2 (t-1)	-.096	.013	.022	-.002	-.017	-.061	.038
	(.078)	(.080)	(.057)	(.049)	(.059)	(.060)	(.042)
EPA - PSM (t-1)	-.055***	.062***	.080***	.019**	-.011*	.033***	-.011**
	(.011)	(.024)	(.017)	(.009)	(.006)	(.010)	(.006)
EPA - O3 (t-1)	-.100***	-.029*	.006	-.005	.006	-.031*	.029***
	(.014)	(.016)	(.014)	(.010)	(.006)	(.016)	(.007)
EPA - NO2 (t-1)	.042	-.155	.330*	-.003	-.092**	.071*	.027
	(.074)	(.102)	(.195)	(.030)	(.037)	(.041)	(.069)
EPA - Pb (t-1)	-.028	-.062	-.283	-.0183	-.076	-.146	-.103*
	(.095)	(.084)	(.176)	(.045)	(.076)	(.093)	(.058)
EPA - CO (t-1)	.074	.009	-.070	.043*	.040*	.047*	-.0107
	(.049)	(.072)	(.100)	(.025)	(.021)	(.028)	(.021)
PAD - All GAPs (t-1)	-1.835***	-.313	2.566***	-1.361***	-.753***	-1.089	-1.031***
	(.486)	(.717)	(.505)	(.475)	(.292)	(.859)	(.340)
PAD Squared	.172	.959	-2.593***	1.743***	.955***	1.371	1.156***
	(.547)	(.844)	(.659)	(.430)	(.302)	(1.179)	(.384)
Prior Estab. Stock (10ks)	29.227***	10.086**	52.786**	.131**	.408**	.362***	.883*
	(6.619)	(4.175)	(26.001)	(.056)	(.197)	(.018)	(.495)
_cons	3.695***	2.825***	1.801***	6.852***	6.648***	6.650***	5.230***
	(.094)	(.160)	(.091)	(.100)	(.097)	(.125)	(.078)
Observations	44957	42534	41210	44957	43640	44957	43551
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	.761	.868	.669	.965	.983	.971	.965

Table A61: Results of PPMLHDFE regressions on Establishment Count using the Continuous Range Indicator for NAICS sectors (11–71), with State, County, and Year Fixed Effects. The percentage of county land within the range allows for a nuanced spatial analysis of delisting impacts. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A62: Regression Results on Jobs Count – Continuous Range Indicator

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31-33	NAICS 53	NAICS 71
% Range	-.0007	-.0022*	-.0016**	-.0000	-.0001	.0001	.0037*
	(.0007)	(.00115)	(.00071)	(.00027)	(.00048)	(.00028)	(.0020)
TSD * Range	-.0010**	-.00135**	-.0008**	.00013	-.00014	-.00007	-.0003
	(.00045)	(.00063)	(.0004)	(.00015)	(.00022)	(.00014)	(.00033)
Poverty rate (100s)	.545	-.917	.904	-1.666***	-.994**	-1.006***	.246
	(.838)	(1.094)	(.874)	(.277)	(.250)	(.289)	(.641)
Unemp. rate (100s)	-.880	.515	1.683*	.759***	.121	1.021***	.919
	(.625)	(1.170)	(.970)	(.273)	(.270)	(.363)	(.649)
Pop. Density (100s)	-.987	21.005	1.423	.498	-3.449***	2.783***	-1.430
	(8.486)	(14.801)	(3.026)	(1.440)	(1.264)	(.788)	(1.230)
Med. HH Inc. (100ks)	1.445***	-.146	.603	.660***	.552***	.417**	.356**
	(.317)	(.802)	(.410)	(.166)	(.172)	(.183)	(.175)
HPI (100s)	-.039***	.047	.029	.007	-.012*	.003	.013
	(.012)	(.042)	(.022)	(.007)	(.007)	(.005)	(.015)
EPA - SO2 (t-1)	.102	.248	.057	.0585	.029	.048	-.016
	(.148)	(.247)	(.330)	(.056)	(.045)	(.051)	(.060)
EPA - PSM (t-1)	-.049*	-.002	.068*	.008	.021**	.036**	-.006
	(.027)	(.044)	(.040)	(.009)	(.010)	(.018)	(.017)
EPA - O3 (t-1)	-.072***	.121	.125**	-.0122	.024**	-.037*	.040**
	(.026)	(.079)	(.050)	(.010)	(.010)	(.022)	(.016)
EPA - NO2 (t-1)	-.477***	.066	-.075	-.013	-.100***	-.132***	
	(.127)	(.665)	(.303)	(.038)	(.03)	(.035)	
EPA - Pb (t-1)	-.340	.255	.497*	.083	-.074	-.058	-.310***
	(.265)	(.236)	(.256)	(.055)	(.058)	(.060)	(.118)
EPA - CO (t-1)	.225***	.327*	.247*	.032	.067**	.055*	-.216**
	(.084)	(.187)	(.137)	(.025)	(.034)	(.029)	(.102)
PAD - All GAPs (t-1)	.678	-2.407	3.395*	-.570	-1.350**	-.417	1.276
	(1.207)	(1.932)	(2.027)	(.497)	(.656)	(.624)	(1.506)
PAD Squared	-1.720	1.090	-4.043**	.145	1.227	.323	-1.883
	(1.296)	(1.947)	(1.984)	(.406)	(.754)	(.617)	(1.557)
Prior Est Stock (10ks)	13.183**	27.419***	-20.655	.077	.280*	.1646***	1.525*
	(5.533)	(4.908)	(26.632)	(.052)	(.163)	(.016)	(.898)
_cons	5.648***	6.350***	5.585***	8.998***	9.881***	8.622***	7.916***
	(.309)	(.419)	(.316)	(.125)	(.109)	(.129)	(.316)
Observations	47546	45079	43698	47546	46223	47546	39433
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	.876	.931	.885	.973	.980	.979	.972

Table A62: Results of PPMLHDFE regressions on Job Count using the Continuous Range Indicator for NAICS sectors (11–71), with State, County, and Year Fixed Effects. This table explores how the extent of habitat overlap influences temporal and sectoral outcomes. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A63: Regression Results on Sales Volume – Continuous Range Indicator

Variable	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 3133	NAICS 53	NAICS 71
% Range	-.00166	-.0017	-.00394**	.00009	.00571**	.00023	.00234**
	(.00123)	(.00137)	(.002)	(.0004)	(.00261)	(.00035)	(.00107)
TSD * Range	-.00116	-.00095	-.00085*	-.00009	.0005	-.00016	.00059
	(.00075)	(.00109)	(.00049)	(.00023)	(.00067)	(.0002)	(.00077)
Pov. rate (100s)	2.682***	-1.401	1.383	-.501	-1.044	.944**	2.867**
	(.714)	(1.143)	(.906)	(.327)	(.644)	(.462)	(1.152)
Unemp rate (100s)	-3.626***	3.966**	1.147	-.440	3.352***	.287	-.772
	(1.211)	(1.975)	(.994)	(.676)	(1.156)	(.950)	(.949)
Pop. Den. (100s)	-8.398	38.486	6.008*	4.454*	-8.081**	8.913***	-1.913
	(12.336)	(39.095)	(3.451)	(2.380)	(3.680)	(1.437)	(2.072)
Med HH Ic (100k)	1.378***	-.831	.136	.810***	-.321	.827***	-.057
	(.497)	(1.257)	(.462)	(.188)	(.462)	(.288)	(.316)
HPI (100s)	-.056**	.125**	.044*	.027***	.076***	.040***	.060**
	(.024)	(.063)	(.024)	(.010)	(.016)	(.011)	(.024)
EPA - SO2 (t-1)	.453**	.067	-.245	.144*	.383*	.218*	.121
	(.228)	(.326)	(.210)	(.080)	(.198)	(.122)	(.145)
EPA - PSM (t-1)	-.024	.086	.088**	-.028*	-.041**	.034	.038
	(.045)	(.068)	(.040)	(.015)	(.020)	(.047)	(.041)
EPA - O3 (t-1)	-.132**	.407***	.095	-.028	-.059	-.085*	.001
	(.065)	(.148)	(.065)	(.026)	(.045)	(.050)	(.035)
EPA - NO2 (t-1)	-.773	.766	.120	.206***		.116	-.118
	(.690)	(.479)	(.512)	(.036)		(.077)	(.165)
EPA - Pb (t-1)	-.923***	-.267	.036	-.309	-.583**	-.238	-.660*
	(.234)	(.548)	(.448)	(.260)	(.287)	(.297)	(.355)
EPA - CO (t-1)	.049	.739**	.234	.074	.145	.079	-.128
	(.199)	(.372)	(.220)	(.076)	(.123)	(.074)	(.168)
Broad PADs (t-1)	1.103	-7.653***	7.910***	-1.713*	-2.836*	.676	1.555
	(1.569)	(2.398)	(2.003)	(.896)	(1.491)	(.859)	(1.699)
PAD Squared	-3.528*	7.766***	-7.146***	1.359	1.055	.340	-1.281
	(1.882)	(2.514)	(2.020)	(.875)	(1.820)	(1.056)	(1.923)
Prior Estab (10ks)	9.863	34.824***	1.695	.222**	.466***	.083**	2.047***
	(7.514)	(10.141)	(40.108)	(.106)	(.146)	(.041)	(.686)
_cons	11.070***	12.128***	11.116***	14.161***	15.771***	12.68395***	12.01247***
	(.372)	(.764)	(.336)	(.161)	(.286)	(.16205)	(.39275)
Observations	47546	45034	43701	47546	39494	47532	46132
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	.790	.916	.820	.941	.907	.951	.933

Table A63: Results of PPMLHDFE regressions on Job Count using the Continuous Range Indicator for NAICS sectors (11–71), with State, County, and Year Fixed Effects. This table explores how the extent of habitat overlap influences temporal and sectoral outcomes. Standard errors are in parentheses and are clustered at the county level. Statistically significant impacts are denoted by asterisks. These asterisks denote statistical significance at the following levels: ***p < 0.01, **p < 0.05, *p < 0.1.

CONCLUSION

This dissertation provides a comprehensive exploration of the intersections between environmental policies and economic dynamics, highlighting the nuanced ways in which conservation and economic objectives interact across sectors and geographies. Key findings from the three chapters underscore the importance of tailoring policy interventions to the specific economic and environmental contexts:

Chapter 1 demonstrated that PADs, while effective in preserving biodiversity, have heterogeneous impacts on LIS depending on the level of conservation stringency and existing PAD coverage. Policies should account for these non-linear effects to mitigate economic disruptions while enhancing ecological benefits.

Chapter 2 revealed that wildfires, though destructive, create opportunities for recovery-focused sectors. Sector-specific support and resilience-building measures are vital for enhancing adaptive capacities in wildfire-prone regions.

Chapter 3 showed that delisting species like the Louisiana Black Bear post-recovery has both positive and negative economic implications. Long-term monitoring and targeted interventions are necessary to balance economic growth with sustainable conservation outcomes.

By employing advanced econometric models and leveraging rich datasets, this dissertation advances the understanding of conservation's economic trade-offs and opportunities. Future research should focus on integrating climate adaptation, economic resilience, and conservation objectives to foster sustainable development. Policymakers must prioritize adaptive strategies that align with regional needs, ensuring that economic growth complements environmental stewardship.

VITA

Prubesh Lutchmunsing Balgobin was born and raised on the beautiful island of Mauritius, a multicultural nation whose rich biodiversity has profoundly shaped his worldview. Prubesh is fluent in Creole, French, and English, reflecting his global outlook and adaptability. His academic and professional journey spans multiple continents and disciplines, embodying his dedication to addressing complex global challenges.

Prubesh began his academic journey at the University of Cape Town in South Africa, where he earned a Bachelor of Science in Mathematics. There, he developed a robust foundation in analytical and quantitative reasoning, skills that would underpin his multidisciplinary pursuits. Building on this foundation, he completed dual Master's degrees in Professional Accounting and International Finance at Deakin University in Australia, where he gained deep expertise in financial analysis, decision-making frameworks, and the intricacies of global financial markets. Furthering his passion for applied economics and policy, Prubesh earned a Master of Arts in Economics from the University of Tennessee, Knoxville. During his time at UT, he specialized in empirical research and econometrics, advancing his understanding of the intersection between economics, sustainability, and public policy. His academic journey culminates in this dissertation, which explores the economic impacts of environmental policies, showcasing his ability to integrate mathematical precision, financial acumen, and economic insight to address real-world issues.

Prubesh's professional career spans nearly a decade in the Commodity and Futures Market, where he developed unparalleled expertise in global trade dynamics, risk management, and market behavior. His practical experience complements his academic achievements, enabling him to bridge theory and practice effectively. At the University of Tennessee, he served as both an Instructor and a Graduate Research Assistant, mentoring students and conducting data-driven research on pressing economic and environmental challenges.

Beyond his academic and professional endeavors, Prubesh is deeply committed to giving back to his community and the planet. He actively engages in charity work for stray animals, recognizing the vital role non-human species play in maintaining ecosystems. His vision extends far beyond personal success. Prubesh aspires to become a Finance Tycoon focused on sustainable development projects that enhance the welfare of families and corporations across all income brackets. He envisions fostering a circular economy while advocating for the recognition and remuneration of non-human contributors to planetary sustainability.

Prubesh Lutchmunsing Balgobin’s multidisciplinary expertise, global experience, and passion for sustainability uniquely position him to drive transformative change at the nexus of finance, economics, and environmental stewardship. His journey exemplifies a commitment to excellence, innovation, and creating a better future for all.