The Political Economy of Undocumented Immigration: Sanctuary Jurisdiction Policies and Local Economic Dynamism

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Abstract

This paper investigates the economic consequences of subnational immigration policy by analyzing the effects of sanctuary jurisdiction designations—which restrict local cooperation with federal deportation initiatives—on business activity and entrepreneurial outcomes at the ZIP-code level across the United States. Exploiting the staggered implementation of sanctuary policies, we employ a Synthetic Difference-in-Differences estimator to identify causal effects. We find that sanctuary designation leads to significant increases in business formation, employment, and aggregate payroll. We further document positive effects on startup intensity, quality, and long-run growth potential. The results are robust to alternative specifications and remain after controlling for local socioeconomic conditions, political preferences, and the presence of undocumented immigrants. These findings underscore the economic relevance of local immigration policy and highlight trade-offs between enforcement priorities and entrepreneurial dynamism.

Keywords: Undocumented immigration, sanctuary jurisdiction, business formation, employment, total payroll, entrepreneurship, entrepreneurial ecosystem

JEL Classification: D22, J15, J18, J30, J61, K37, M13

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1. Introduction

Undocumented immigration remains one of the most divisive policy issues in the United States, eliciting sharply contrasting responses across federal, state, and local levels. The Department of Homeland Security estimates that approximately 11 million unauthorized immigrants resided in the U.S. as of January 2022 (Baker and Warren, 2024), while the Federation for American Immigration Reform (FAIR, 2023) reports the total fiscal cost of illegal immigration to taxpayers at $150.7 billion. Although immigration enforcement falls under exclusive federal authority (Fandl, 2015; CRS, 2019), state and local governments frequently grapple with its social and economic consequences, often leading to divergent policy responses (Varsanyi, 2010).

In recent years, a growing number of municipalities and states have adopted *sanctuary policies*—local laws or administrative practices that limit cooperation with federal immigration enforcement. Proponents argue that these policies foster public safety and social cohesion by encouraging undocumented immigrants to engage with law enforcement and participate more fully in civic and economic life (Lasch et al., 2018; Otsu, 2021). From an economic standpoint, sanctuary policies may shield employers and workers from immigration-related disruptions, thereby contributing to labor market stability and a more inclusive local business environment (Chassamboulli and Peri, 2015; Chan et al., 2018). Others, however, warn that such policies introduce legal and regulatory uncertainty, invite federal retaliation, and potentially reduce public investment—thus discouraging business activity (Cuison-Villazor and Gulasekaram, 2018; Hartley, 2018).

While the legal and political implications of sanctuary policies have been widely debated, their economic consequences—particularly for local entrepreneurial ecosystems—remain largely unexplored. This paper provides the first empirical analysis of how sanctuary jurisdiction designation affects local business formation and entrepreneurial dynamics. We examine both the intensive margin (e.g., total employment and payroll) and the extensive margin (e.g., the number of establishments) of business activity, while also exploring underlying mechanisms using novel ZIP-code-level measures of entrepreneurship developed by the Startup Cartography Project (Andrews et al., 2022). Specifically, we evaluate the impact of sanctuary policies on the Startup Formation Rate, the Entrepreneurial Quality Index (EQI), and the Regional Entrepreneurship Cohort Potential Index (RECPI)—three granular indicators that capture the scale, quality, and growth potential of new firm creation at the local level.

We conceptualize the policy landscape through two competing theoretical lenses. The *inclusive view* posits that sanctuary policies reduce uncertainty and fear among immigrant communities, which stabilizes the workforce, promotes business formation, and enhances local economic engagement (Pirie, 1990; Colbern et al., 2019). This view anticipates increased entrepreneurship and economic vibrancy following sanctuary adoption. By contrast, the *exclusive view* contends that sanctuary jurisdictions may face economic headwinds due to legal uncertainty, federal funding penalties, or reputational concerns, which could inhibit investment and firm growth (Hartley, 2018).

To evaluate these opposing predictions, we assemble a panel of ZIP-code-level business data from 2001 to 2019 and identify sanctuary jurisdictions using FAIR's comprehensive list of localities with formal non-cooperation policies. We augment this dataset with annual ZIP-code-level

measures of entrepreneurial activity from the Startup Cartography Project (SCP), covering the period 2005 to 2016. These SCP metrics allow us to capture detailed variation in startup formation, firm quality, and growth potential across local areas. For causal identification, we employ the Synthetic Difference-in-Differences (SDID) estimator developed by Arkhangelsky et al. (2021), which improves upon traditional DID and synthetic control methods by flexibly modeling counterfactual trends while retaining robustness to treatment timing heterogeneity. This methodology is particularly well-suited to our staggered policy adoption setting.

Our results provide strong support for the inclusive view. We find that the adoption of sanctuary policies is associated with statistically and economically significant increases in local business activity. On average, ZIP codes that adopt sanctuary policies experience an increase of approximately four business establishments, 30 paid employees, and $598,000 in total payroll. Specifically, sanctuary designation is associated with a 1.43% increase in the number of establishments with paid employees and a 1.75% increase in total payroll. We also observe positive effects on local entrepreneurial ecosystems. Sanctuary policies are associated with a 1.43% increase in the Startup Formation Rate (SFR), a 1.75% increase in the Entrepreneurial Quality Index (EQI), and a 15.8% increase in the Regional Entrepreneurship Cohort Potential Index (RECPI). These findings are consistent with the hypothesis that sanctuary policies foster economic inclusivity and entrepreneurial resilience by stabilizing labor markets and enhancing the local business climate.

These findings carry important policy implications for the ongoing debate over immigration enforcement and local economic development. While federal authorities maintain exclusive control over immigration enforcement, our results suggest that local sanctuary policies—by promoting labor market stability—can support business activity and encourage entrepreneurial growth. This highlights a potential trade-off between centralized enforcement objectives and decentralized economic outcomes. For state and local policymakers, the evidence indicates that sanctuary policies may function not only as expressions of legal or moral priorities but also as tools with measurable economic effects. For federal decision-makers, the findings emphasize the value of considering localized economic dynamics when designing enforcement strategies. As immigration policy continues to evolve, future research should examine the long-term effects of these policies on firm formation, labor mobility, and regional economic development.

The findings of this paper make important contributions to several strands of literature. First, we extend the political economy of finance by examining how subnational immigration policy—specifically, the staggered adoption of sanctuary jurisdiction regulations—shapes local business activity and the entrepreneurial ecosystem. While prior research in this literature has largely emphasized the role of political institutions and financial regulation in shaping capital allocation and firm behavior (La Porta et al., 1998; Kroszner and Strahan, 1999; Pagano and Volpin, 2001, 2005; Bekaert, Harvey, and Lumsdaine, 2002; Rajan and Zingales, 2003; Megginson et al., 2004; Braun and Raddatz, 2005; Djankov et al., 2008; Benmelech and Moskowitz, 2010; Dinc and Erel, 2013; Carvalho, 2014; Gan, Guo, and Xu, 2018), we broaden this framework by demonstrating that nonfinancial regulatory decisions—such as local immigration enforcement—can also exert economically meaningful effects. Sanctuary policies reduce deportation-related uncertainty and

foster trust between immigrant communities and local institutions, thereby enhancing labor market stability and lowering regulatory frictions for entrepreneurs. These mechanisms promote business formation and improve entrepreneurial quality, with implications for local capital allocation, credit demand, and risk-taking. In this way, our study complements emerging work documenting that nonfinancial regulations can shape financial and economic behavior (Cortes, 2008; Shen, 2021; Doran, Gelber, and Isen, 2022), and offers novel empirical evidence that inclusive local governance can foster regional economic dynamism.

Second, we contribute to the literature on entrepreneurship in finance by demonstrating that local immigration policy can significantly influence both the rate and quality of firm entry. Prior research has emphasized the role of institutional environments in shaping entrepreneurial outcomes, particularly through channels such as risk mitigation, labor market flexibility, and access to finance (Klapper, Laeven, and Rajan, 2006; Kerr and Nanda, 2009; Levie and Autio, 2011). We extend this line of inquiry by showing that the adoption of sanctuary jurisdiction policies—though not financial per se—reduces uncertainty and perceived risk within immigrant communities, thereby fostering entrepreneurial activity. Our findings suggest that immigration policy plays a more expansive role in local economic dynamism than previously recognized. Specifically, we document sizable post-policy increases in startup formation, entrepreneurial potential, and firm quality, highlighting the importance of trust and institutional inclusiveness in promoting entrepreneurship. Complementing this perspective, Dimmock, Huang, and Weisbenner (2021) show that firms with higher H-1B visa lottery win rates that allow them to employ legal immigrants are more likely to secure venture capital and achieve successful exits, reinforcing the view that access to skilled foreign labor enhances innovation and firm growth.

Third, our paper contributes to a growing literature on the economic effects of undocumented immigrants by shifting the focus from labor market outcomes to business activity. While prior research primarily examines impacts on wages, employment, and labor supply (Borjas, 2017; Borjas and Cassidy, 2019; Amuedo-Dorantes, Arenas-Arroya, and Sevilla, 2020; Kuka, Shenhav, and Shih, 2020; Albert, 2021), we investigate how policies targeting undocumented immigrants affect the broader business ecosystem. Our analysis reveals that sanctuary designations generate positive spillovers, including higher business formation, employment, and aggregate payroll. These findings also relate to a nascent literature on behavioral responses of undocumented immigrants to immigration policy. For instance, Hoekstra and Orozco-Aleman (2017) find that Arizona's SB 1070 induced a sharp decline in the undocumented population, implying strong responsiveness to policy signals. We complement this evidence by showing that more inclusive immigration policies yield measurable economic gains at the local level.

The remainder of this paper is organized as follows. Section 2 describes the data collection process and sample selection. Section 3 outlines the identification strategy. Section 4 presents the primary findings, demonstrating that the adoption of sanctuary policies leads to increases in business creation, employment, and labor payroll. Finally, Section 5 concludes the paper.

2. Data description and sample selection

We obtain data from the U.S. Census Bureau's ZIP Code Business Patterns (ZBP) dataset, which provides detailed economic activity metrics at the ZIP code level. This dataset includes key business indicators, such as the number of establishments with paid employees, employment size classifications, and industry-specific breakdowns based on the North American Industry Classification System (NAICS). The ZBP is particularly useful for analyzing localized economic dynamics, offering annual insights into the distribution of businesses across industries and geographic areas. By leveraging this dataset, we assess the intensity of business operations within a given ZIP-year, facilitating a more granular understanding of economic patterns at the community level. The data are accessed through the Census Bureau's API, ensuring consistency and reproducibility in our analysis (U.S. Census Bureau, 2024). From this database, we retrieve key measures of business activity, including the number of establishments with paid employees, total employment in businesses with paid employees, and total employee compensation in businesses with paid employees. We exclude observations flagged by the U.S. Census Bureau as having high noise. These flagged observations are reported in fields ending in "_NF," primarily affecting variables related to total employment and total employee compensation.

Data on sanctuary ZIP codes are sourced from the Federation for American Immigration Reform (FAIR), an organization that compiled lists of sanctuary jurisdictions based on primary sources such as local resolutions, ordinances, and law enforcement policies, as well as secondary sources such as government reports and media coverage. The FAIR sanctuary jurisdiction report aimed to document local and state policies restricting cooperation with federal immigration authorities. However, FAIR ceased its research activities for this report on April 1, 2018, making 2018 the latest year for which comprehensive information is available (FAIR, 2018). Given this limitation, our sample ends in 2019 to ensure that the classification of sanctuary ZIP codes remains as current as possible relative to the data source.

We collect data on undocumented immigrants from two sources. Warren and Warren (2013) provide state-year estimates for 2000–2009, while the Center for Migration Studies (2022) covers 2010–2019. Since these data are only available from 2000 onward and we use a one-year lagged measure of the constructed proportion of undocumented immigrants by state-year, our sample period begins in 2001.

We obtain data on the political orientation of ZIP codes using county-level vote shares for the Democratic presidential candidate in the most recent election. These vote shares are sourced from the MIT Election Data and Science Lab.

Finally, we collect data on ZIP code-level economic conditions using county unemployment rates and per capita personal income from the Bureau of Economic Analysis at the U.S. Department of Commerce.

Since the synthetic difference-in-differences regression methodology requires a balanced sample (i.e., the same geographical units in each sample year), we exclude ZIP codes that do not appear every year. We also remove 3-digit ZIP code-year observations that became sanctuary jurisdictions either before the sample period or in its final year. To minimize the influence of extreme values,

we winsorize continuous variables at the 1st and 99th percentiles. The final sample consists of 253,441 ZIP-year observations, covering the period from 2001 to 2019.

3. Identification strategy

To assess the impact of undocumented immigration on business activity, we exploit the staggered-year adoption of sanctuary jurisdiction policies across ZIP codes. Due to the absence of a uniform legal definition of a "sanctuary jurisdiction," we rely on the list compiled by the Federation for American Immigration Reform (FAIR, 2018), which aggregates primary sources (e.g., municipal ordinances and resolutions) and secondary sources, including reports from the U.S. Department of Homeland Security, academic studies, and media coverage.

FAIR (2018) includes jurisdictions that either explicitly identify as sanctuaries or implement sanctuary-like policies in practice. These typically involve non-cooperation with federal immigration authorities—for example, declining to honor U.S. Immigration and Customs Enforcement (ICE) detainers or limiting communication with ICE and U.S. Customs and Border Protection (CBP). Jurisdictions that publicly claim sanctuary status are excluded from the FAIR list if their implementation of sanctuary policies cannot be independently verified. Thus, FAIR provides a structured and replicable classification that helps reduce methodological ambiguity and political framing.

Despite these nuances, sanctuary jurisdictions share a defining characteristic: they limit local law enforcement's cooperation with federal immigration authorities to reduce the likelihood of deportation for undocumented immigrants. These policies—adopted at the city, county, or state level—typically prohibit local officers from inquiring about immigration status, detaining individuals solely for immigration violations, or complying with ICE detainer requests absent a judicial warrant (FAIR, 2018; Lasch et al., 2018; American Immigration Council, 2020). While federal authorities retain full enforcement power, sanctuary policies constrain the role of local governments in immigration enforcement, thereby creating localized divergence from federal priorities. This divergence has the potential to reshape local labor markets, business formation, and regional economic performance.

We leverage this staggered policy adoption across ZIP codes to identify the causal impact of sanctuary policies on local business activity. Specifically, we estimate their effect on the natural logarithm of (i) the number of businesses with paid employees, (ii) total employment in such businesses, and (iii) total payroll. These three measures—used as dependent variables—are observed annually at the ZIP code level. Our empirical design exploits within-ZIP variation over time, enabling us to isolate the economic effects of sanctuary policies from broader regional trends.

Figure 1 depicts the geographic distribution of sanctuary-designated ZIP codes across the United States. Sanctuary policies are predominantly concentrated in urban and coastal regions, particularly in states with historically immigrant-friendly environments such as California, New York, and Illinois (Monogan III, 2013). In contrast, rural and interior regions show fewer sanctuary designations, reflecting variation in political attitudes, demographic composition, and reliance on

immigrant labor. This spatial heterogeneity reinforces the need for rigorous identification strategies that control for underlying economic and political conditions.

Insert Figure 1

To estimate the causal impact of sanctuary policies, we employ the Synthetic Difference-in-Differences (SDID) estimator developed by Arkhangelsky et al. (2021). SDID integrates the strengths of both the Difference-in-Differences (DID) and Synthetic Control (SC) methodologies. Traditional DID relies on the parallel trends assumption, which may not hold in observational data where treated and control units follow different pre-treatment trajectories (Angrist and Pischke, 2009). SC relaxes this assumption by constructing a weighted synthetic control group that matches the treated unit's pre-treatment path (Abadie, Diamond, and Hainmueller, 2010), but is vulnerable to high variance and sensitivity when extended to multiple treated units. SDID addresses these limitations by combining SC's reweighting with DID's differencing to produce more robust causal estimates.

SDID achieves this by assigning unit and time weights to construct a counterfactual. Unit weights prioritize control ZIP codes whose pre-treatment outcomes closely resemble the treated ZIP codes, while time weights emphasize periods most comparable to those surrounding treatment adoption. This approach allows for heterogeneous treatment effects, mitigates bias from non-parallel trends, and enhances identification in large-panel datasets (Arkhangelsky et al., 2021). Compared to SC—which typically evaluates single-unit interventions—and DID—which assumes constant effects, SDID offers greater flexibility and robustness for staggered policy evaluations (Bertrand, Duflo, and Mullainathan, 2004; Abadie, 2021).

In addition to mitigating bias, SDID improves statistical inference relative to both DID and SC. The SC method often places excessive weight on a small number of donor units, leading to high estimator variance and vulnerability to idiosyncratic shocks (Abadie and L'Hour, 2021). While DID offers greater efficiency, it becomes biased when the parallel trends assumption is violated. SDID balances these trade-offs by drawing on a broader pool of controls while retaining inferential validity through its regression-based framework. The resulting ATT estimates benefit from stronger confidence interval coverage and lower finite-sample bias (Arkhangelsky et al., 2021).

We implement the SDID methodology using a balanced panel of 13,356 ZIP codes observed over 18 years. Inference is conducted via the bootstrap procedure described in Algorithm 2 of Arkhangelsky et al. (2021), with 1,000 replications. The results are robust to alternative model specifications. Sanctuary policies were adopted in a staggered fashion between 2003 and 2017, allowing us to construct 15 cohort-specific treatment effect estimators. The reported average treatment effect on the treated (ATT) is a weighted average of these cohort-specific estimates, with weights proportional to the number of treated ZIP-years in each cohort. In addition, we exclude ZIP codes that adopted sanctuary policies in 2004 and 2018 to ensure a sufficient number of post-treatment years for reliable estimation.

Given the staggered adoption design, SDID produces valid standard errors by resampling through the bootstrap inference procedure over the entire average treatment effect on the treated (ATT), once for each sanctuary jurisdiction policy enactment year (Pailañir et al., 2022; Clarke et al., 2023). Sanctuary jurisdiction policies were enacted in a staggered manner from 2003 to 2017. The estimated ATT is the weighted average of 15 estimators, with weights assigned based on the relative number of treated ZIP codes and years for each enacted ZIP code. The ATT reflects the average effect of sanctuary jurisdiction policy enactment on business activity, as measured by the number of businesses with paid employees, total employment in businesses with paid employees, and employee compensation in ZIP codes with such policies.

The dependent variable in the SDID regression model is business activity, as measured by the number of businesses with paid employees, total employment in businesses with paid employees, and total payroll in businesses with paid employees, for each ZIP code by sample year. Table 1 reports the mean, standard deviation, minimum, median, and maximum of the different business activity indicators, economic indicators, undocumented illegal related indicator, and political orientation indicator used in our empirical analysis. We provide detailed definitions and the corresponding data sources for each variable used in the regression analysis in Appendix A of this paper.

We present the summary statistics for our three key indicators of business activity at the ZIP code level—total business establishments with paid employees, total employment, and total payroll—all of which are expressed in natural logarithmic form and serve as dependent variables in our SDID regression framework. The average number of business establishments per ZIP code-year is 5.29, with a standard deviation of 1.26, indicating moderate variation in business presence across ZIP-years. Total employment averages 7.71, with a higher standard deviation of 1.55, reflecting heterogeneity in the size of local labor markets. Total payroll exhibits the widest dispersion, with a mean of 10.44 and a standard deviation of 1.70, suggesting substantial variation in aggregate compensation across ZIP codes. The minimum and maximum values for all three indicators suggest substantial variation, with some ZIP codes hosting significantly more economic activity than others. The relatively high maximum values for all three measures further highlight the presence of ZIP codes with considerably larger business activity. This variation underscores differences in local economic conditions.

To illustrate the structure of the balanced panel, we define two variables. The first identifies the balanced panel of geographical units (ZIP codes), while the second represents the balanced panel of time periods (years). Next, we introduce the treatment variable, which denotes the ZIP codes treated each year, accumulated over time. Finally, we incorporate four one-year lagged covariates in the SDID regression model: the proportion of unauthorized immigrants by state-year, the Democratic vote share in the most recent U.S. presidential election, the unemployment rate, and per capita personal income.

We include the proportion of unauthorized immigrants at the state-year level as a control variable to account for its potential effect on business activity within ZIP codes in a given sample year. Theoretically, we expect unauthorized immigration to positively influence local business activity, primarily through labor market dynamics. A higher share of unauthorized immigrants can expand

the local labor supply, as they often earn lower wages and work under more challenging conditions than native-born Americans or authorized immigrants. This effect is particularly pronounced in industries reliant on low-skilled labor, such as construction, agriculture, and hospitality. Greater labor availability may reduce labor costs, incentivize business expansion, and enhance employment opportunities. However, this positive effect may weaken in areas with restrictive immigration policies or heightened enforcement, where businesses may face labor shortages, leading to declines in productivity and potential closures (see, e.g., Brown, Hotchkiss, and Quispe-Agnoli, 2013; Chassamboulli and Peri, 2015; Hotchkiss, Quispe-Agnoli, and Rios-Avila, 2015; Albert, 2021). Table 1 shows that the proportion of unauthorized immigrants at the state-year level averages 5%, though it varies significantly from 0% to 27%, with a standard deviation of 0.07.

We include the Democratic vote share in the most recent U.S. presidential election in the SDID model, as this variable serves as a key indicator of the local political climate, which can significantly influence business activity (Engelberg et al., 2022), and as a factor that may affect the adoption of sanctuary policies. Omitting this variable from the SDID regression model could result in biased estimates, given the well-documented differences in how Democrats and Republicans approach undocumented immigration. Democrats generally advocate for more inclusive policies, emphasizing pathways to legal status, humanitarian protections, and the economic contributions of undocumented immigrants (Wong, 2017; Arias, 2024). In contrast, Republicans tend to frame undocumented immigration as a national security and economic threat, prioritizing border enforcement, deportation, and restrictive legal measures. They often associate it with crime and labor market competition, leading to stricter enforcement under conservative administrations (Abrajano and Hajnal, 2015; Flores and Schachter, 2018; Walters and Skocpol, 2023). Consequently, sanctuary policies are more likely to be adopted under Democratic administrations than Republican ones. As shown in Table 1, the Democratic vote share in the most recent U.S. presidential election at the county level averages 47%, ranging from 16% to 83%, indicating substantial political diversity across county-years.

We include the county-year unemployment rate in our SDID regression model, as it directly influences business activity by shaping consumer spending and overall market demand. As a proxy for local economic conditions, it reflects broader economic trends that affect business performance. High unemployment signals economic distress, as income loss among unemployed individuals leads to significant declines in the consumption of goods and services (Chetty and Szeidl, 2007; Ganong and Noel, 2019). This reduction in consumption weakens overall demand, potentially forcing businesses to cut production, reduce operating hours, or close, further exacerbating local economic downturns. Table 1 shows that the unemployment rate averages 5.88%, with a substantial standard deviation of 2.36%, indicating significant variation in labor market conditions across county-years.

The next covariate in our SDID regression model is county-year per capita personal income, which serves as an indicator of regional economic well-being and living standards, reflecting the average income per person in a given area. Compared to poorer regions, wealthier regions typically exhibit stronger economies, characterized by higher consumer spending, a larger job market, and greater demand for highly skilled workers, leading to increased productivity (Caron, Fally, and Markusen,

2020). Table 1 shows that per capita personal income averages 9.07 (log-transformed), with a relatively low standard deviation of 0.29, indicating moderate income variation across regions. We adjust per capita personal income for inflation using the CPI deflator, with 1983 as the base year.

We do not report the estimated coefficients of the different covariates and their corresponding t-statistics, as the SDID regression model only reports the estimated coefficient of the ATT along with its corresponding t-statistic and statistical significance level.

Insert Table 1

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4. Empirical results

We present and discuss the estimation results of the impact of the staggered adoption of sanctuary jurisdiction policies on business activity at the ZIP-year level using SDID, DID, and SC regression models. Specifically, Section 4.1 examines the effects of these local undocumented immigration policies on the number of businesses with paid employees. Section 4.2 analyzes the total employment in such businesses, while Section 4.3 focuses on total payroll. In Section 4.4, we broaden our analysis to examine startup activity at the ZIP-code level, with a focus on startup formation rates, the quality of new ventures, and the underlying regional entrepreneurial potential.

4.1.Sanctuary Jurisdiction Policies and the Number of Businesses with Paid Employees

Table 2 reports the estimated effects of sanctuary jurisdiction status on the number of business establishments with paid employees, using three alternative estimation methods: Synthetic Difference-in-Differences (SDID), Difference-in-Differences (DID), and Synthetic Control (SC). Because the dependent variable is specified in natural logarithmic form, the estimated coefficients can be interpreted as approximate percentage changes. Among these approaches, SDID offers the most reliable inference by combining the strengths of DID and SC while addressing their respective limitations (see Section 3: Identification Strategy). We begin by discussing the SDID results, followed by a comparison with DID and SC estimates.

The SDID estimate reported in column (1) of Table 2 yields an average treatment effect on the treated (ATT) of 0.01433, statistically significant at the 1% level ($t = 6.96$). This estimate indicates that sanctuary jurisdiction status is associated with a 1.43% increase in the number of business establishments with paid employees. Relative to the sample mean of 198.34 establishments per ZIP code, the implied increase is approximately 2.83 establishments ($198.34 \times 0.01433 \approx 2.83$). While the magnitude is economically important, the precision of the estimate underscores the reliability of the SDID approach in isolating policy-induced changes in local business activity. These findings are consistent with predictions from the inclusive view of sanctuary policies, which posits that protective immigration stances can foster a more stable and participatory economic environment for immigrant communities and the broader local economy.

Column (2) presents the DID estimate, which produces a larger ATT of 0.02886, significant at the 1% level (t-statistic = 7.92). This estimate corresponds to a 2.89% increase in business establishments, or roughly 5.73 additional establishments per ZIP code. While highly significant, the DID model relies on the strong parallel trends assumption and may be vulnerable to bias from unobserved time-varying heterogeneity.

The SC estimate reported in column (3) yields an ATT of 0.01600, significant at the 5% level (t-statistic = 2.14), implying a 1.60% increase in business establishments, or approximately 3.17 additional establishments per ZIP code. Although statistically significant, the SC approach may suffer from high variance due to its reliance on a limited subset of donor units with positive weights, especially in settings with multiple treated units.

Taken together, the results suggest that sanctuary policy adoption is associated with a statistically and economically meaningful increase in business establishment counts. While all three models point to a positive effect, SDID offers the most credible and empirically grounded estimate. Its ability to correct for both dynamic selection bias and pre-treatment trend differences makes it particularly well suited for evaluating staggered policy interventions such as the adoption of sanctuary jurisdiction status.

Insert Table 2

Figure 2 presents three event-study graphs that depict the evolution of business establishments in ZIP codes that adopted sanctuary status, alongside the corresponding weighted averages of untreated ZIP codes, stratified by policy enactment year. Sanctuary policy adoptions occurred between 2003 and 2017. Each panel also reports the estimator-specific weighting scheme applied to pre-treatment periods, shown at the bottom of each graph. These figures follow the visualization methodology proposed by Arkhangelsky et al. (2021), enabling clear assessment of pre- and post-treatment dynamics for each cohort.

The DID panel reveals that treated and control ZIP codes do not follow parallel pre-treatment trends, raising concerns about the validity of the parallel trends assumption central to the DID framework (Ashenfelter and Card, 1985). This issue is reflected in the uniform green weighting blocks along the pre-treatment period, which indicate that the DID estimator assigns equal weight to each pre-treatment year regardless of pre-policy comparability.

By contrast, the SDID panel exhibits heterogeneity in pre-treatment weights across both ZIP codes and years. The green blocks vary in size, illustrating how the SDID estimator endogenously emphasizes control units and time periods that are most similar to the treated observations in the pre-treatment window (Arkhangelsky et al., 2021). This feature enhances the credibility of the estimated counterfactual and improves robustness to violations of the parallel trends assumption.

The SC panel does not display pre-treatment weight distributions, as the SC method constructs a weighted average of control ZIP codes to best match the treated trajectory prior to policy adoption.

While effective in minimizing pre-treatment discrepancies, this approach is less transparent regarding how specific periods contribute to the synthetic control.

Across most enactment years, the number of business establishments increases following the adoption of sanctuary policies. However, notable exceptions appear in the 2006, 2008 and 2010 enactment cohorts, which exhibit post-treatment declines. These deviations may reflect contemporaneous macroeconomic shocks, such as the Great Recession, or local economic factors that attenuate the policy's effect.

Insert Figure 2

4.2. *Sanctuary Jurisdiction Policies* and Total Employment in Businesses with Paid Employees

Table 3 reports the estimated effects of sanctuary policy adoption on total employment in businesses with paid employees at the ZIP code level. We use three complementary estimation strategies—Synthetic Difference-in-Differences (SDID), Difference-in-Differences (DID), and Synthetic Control (SC)—to assess the robustness of the results. The dependent variable is expressed in natural logarithmic form; hence, coefficient estimates represent approximate percentage changes in total employment.

Column (1) of Table 3 reports the SDID estimate, which yields a coefficient of 0.01864 and is statistically significant at the 1% level (t-statistic = 5.68). This estimate implies that sanctuary policy adoption is associated with an average 1.86% increase in total employment in businesses with paid employees. Given the sample mean of 2,230.54 employees per ZIP code, this effect corresponds to approximately 41.5 additional jobs per ZIP code ($2{,}230.54 \times 0.01864 \approx 41.5$). Although modest in magnitude, the estimate is statistically precise and economically meaningful. These findings suggest that limiting local cooperation with federal immigration enforcement may contribute to improved labor market stability, particularly in communities with a significant undocumented population. The result confirms the prediction of the inclusive view of sanctuary policies, which posits that protective immigration stances foster a more stable and participatory economic environment for immigrant communities and the broader local economy.

Column (2) presents the DID estimate, which produces a coefficient of 0.01892, also significant at the 1% level (t-statistic = 3.89). This implies a 1.89% increase in total employment—or approximately 42.2 additional employees per ZIP code—following sanctuary policy adoption. Although similar in magnitude to the SDID estimate, the DID approach relies on the parallel trends assumption, which may not hold in the presence of differential pre-treatment trajectories, potentially inflating bias.

The SC estimate in column (3) reports a substantially larger coefficient of 0.04209, statistically significant at the 1% level (t-statistic = 2.88). This translates to a 4.21% increase in employment, or roughly 94 additional employees per ZIP code. While economically larger, the SC estimate is

more sensitive to the choice of donor pool and may suffer from increased variance in the presence of multiple treated units.

Taken together, the results consistently point to a positive relationship between sanctuary policy adoption and local employment levels. The SDID estimate—anchored in a robust identification strategy that combines reweighting and differencing—offers the most credible inference. It provides strong evidence that limiting local cooperation with federal immigration enforcement can produce statistically and economically significant gains in employment at the ZIP code level.

Insert Table 3

We also replicate Figure 2 to visualize the effect of sanctuary policy adoption on employment at establishments with paid employees in Figure 3. The observed trends in Figure 3 align with those in Figure 2, leading to similar conclusions.

Insert Figure 3

4.3.Sanctuary Jurisdiction Policies and the total payroll in businesses with paid employees

Table 4 examines how the adoption of sanctuary policies at the ZIP code level affects total payroll in businesses with paid employees. We estimate the average treatment effect on the treated (ATT) using three methods—SDID, DID, and SC—each offering a different identification strategy. The dependent variable is log-transformed, allowing coefficients to be interpreted as percentage changes in payroll levels.

The SDID estimate reported in column (1) of Table 4 yields a coefficient of 0.01752, which is statistically significant at the 1% level (t-statistic = 4.28). This result implies that sanctuary policy adoption is associated with a 1.75% increase in total payroll among businesses with paid employees. Applied to the sample mean payroll of approximately $34.2 million per ZIP code, this translates to an increase of roughly $598,000. The effect is economically meaningful and suggests that sanctuary designation may enhance local labor market conditions—potentially by improving workforce stability, reducing turnover, or facilitating hiring in environments characterized by lower immigration enforcement risk. The findings align with the inclusive view of sanctuary policies, which predicts that limiting local cooperation with federal immigration authorities can foster a more stable and participatory economic environment for undocumented immigrants and the broader community.

The DID estimate in column (2) produces a slightly lower coefficient of 0.01311, significant at the 5% level (t-statistic = 2.32). This corresponds to a 1.31% payroll increase, or about $449,000 in absolute terms. While the direction and magnitude are broadly consistent with the SDID result, the

DID model imposes the parallel trends assumption, which may be restrictive in a setting with staggered policy adoption and heterogeneous pre-treatment dynamics.

The SC estimate in column (3) yields a markedly larger effect of 0.05254, statistically significant at the 5% level (t-statistic = 2.38). This translates to a 5.25% increase in payroll, or approximately $1.8 million per ZIP code. Although substantial, the SC estimator's reliance on a limited and optimally weighted donor pool makes it more susceptible to extrapolation error, particularly in high-dimensional panel settings with numerous treated units.

Overall, the results suggest that sanctuary jurisdictions experience gains in aggregate compensation among businesses with paid employees. The consistent statistical significance across models supports the robustness of the findings, while differences in estimated magnitudes reflect the trade-offs across estimation methods. The SDID estimator—by balancing precision, flexibility, and identification strength—offers the most credible estimate of the payroll effect and complements earlier findings on establishment counts and employment levels.

Insert Table 4

We present visual insights into the effect of sanctuary policy adoption by ZIP codes on the total payroll of establishments with paid employees within each ZIP code in Figure 4. The construction of Figure 4 follows the same methodology used for Figures 2 and 3. Our observations of the time trends for treated and control ZIP codes are similar to those in Figures 2 and 3.

Insert Figure 4

4.4.Sanctuary Jurisdiction Policies and entrepreneurial activity

We extend our analysis by examining the effect of sanctuary jurisdiction policies on local entrepreneurial activity. While earlier sections evaluated business outcomes through establishment counts, employment levels, and payroll aggregates, this section investigates the intensive margin of firm dynamism by focusing on startup formation. To this end, we incorporate data from the Startup Cartography Project (SCP), a high-resolution, longitudinal dataset that tracks business registrations and startup characteristics at the ZIP-code level across nearly three decades. The SCP provides standardized measures of new firm formation and startup quality, enabling a consistent analysis of entrepreneurial trends across geographical units and time (source: The Startup Cartography Project; Andrews et al., 2022). This allows us to assess whether sanctuary policies not only sustain existing business activity but also enhance the conditions for new firm entry. Given that undocumented immigrants often contribute disproportionately to entrepreneurial activity, particularly in labor-intensive sectors and underserved markets, understanding the policy's impact

on firm formation offers a critical extension of our empirical inquiry into the local economic effects of immigration enforcement divergence.

To empirically assess competing theoretical predictions regarding the impact of sanctuary policies on the entrepreneurial ecosystem, we incorporate three entrepreneurship metrics developed by the Startup Cartography Project (SCP). The first measure, the Startup Formation Rate (SFR), captures the volume of new business registrations within a population at the ZIP-code level, reflecting the overall intensity of entrepreneurial activity per capita. The second measure, the Entrepreneurial Quality Index (EQI), reflects the average growth potential of newly formed firms, providing a proxy for the caliber of entrepreneurial ventures. The third metric, the Regional Entrepreneurship Cohort Potential Index (RECPI), quantifies the number of startups within a ZIP code that are expected to exhibit substantial long-term growth potential (Andrews et al., 2022). These metrics allow us to evaluate how sanctuary policy adoption influences both the quantity and quality of entrepreneurship at the local level. In doing so, they offer a direct test of two competing perspectives: the inclusive view, which posits that protective immigration policies foster entrepreneurial activity and innovation, and the deterrent view, which suggests that limiting immigration enforcement may disincentivize business formation by increasing perceived local policy risk.

To empirically assess the validity of the competing predictions derived from the two theoretical views, we construct our sample following the methodology described in Section 3 (Identification Strategy). We employ the same set of control variables used in the SDID, DID, and SC estimations of the impact of sanctuary jurisdiction policy enactment on ZIP-code-level business activity.

We report summary statistics for the three entrepreneurship metrics used in our analysis in Table 5. The Startup Formation Rate is defined as the natural logarithm of one plus the number of new business registrations in a ZIP code. We apply this transformation to address right-skewness and to retain observations with zero startup activity. The variable has a mean of 3.42 and a standard deviation of 1.43, with values ranging from 0.69 to 6.57, indicating substantial variation in entrepreneurial intensity across regions. The Entrepreneurial Quality Index (EQI), which captures the average growth potential of startups within a ZIP code, exhibits a low mean of 0.0004 and limited dispersion (standard deviation = 0.0005), reflecting tight clustering around small values. In contrast, the Regional Entrepreneurship Cohort Potential Index (RECPI)—which measures the expected share of startups likely to achieve significant growth—shows greater heterogeneity, with a mean of 0.0379, a standard deviation of 0.0883, and a right-skewed distribution (median = 0.0068; max = 0.5987). These summary statistics underscore meaningful cross-sectional variation in both the scale and growth potential of local entrepreneurial ecosystems.

Insert Table 5

4.4.1. The Effect of the Enactment of Sanctuary Jurisdiction Policies on the Startup Formation Rate

Table 6 presents estimates of the effect of sanctuary jurisdiction adoption on the startup formation rate (SFR), where the dependent variable is the natural logarithm of one plus the SFR. The SFR reflects new business registrations relative to the ZIP-code population and serves as a standardized indicator of per capita entrepreneurial intensity. Column (1) reports results from the Synthetic Difference-in-Differences (SDID) estimator, which yields an average treatment effect on the treated (ATT) of 0.10175, statistically significant at the 1% level (t-statistic = 12.10). This estimate implies an approximate 10.2% increase in the per capita startup formation rate following sanctuary designation. Given the sample mean of 3.4161, this corresponds to a nontrivial increase in ZIP-code-level entrepreneurial activity. Among the estimators used, SDID is the least biased, as it accounts for both unobserved heterogeneity and differential pre-treatment trends, making it particularly well suited for evaluating staggered policy enactments. The positive and economically meaningful effect of sanctuary policy adoption on startup formation confirms the prediction of the inclusive view, which posits that such policies foster local economic activity. By creating a climate of trust and reducing fear within immigrant communities, sanctuary policies encourage workforce stability, higher consumer engagement, and new firm creation, thereby improving entrepreneurship rates at the ZIP-code level.

Columns (2) and (3) provide robustness checks using the Difference-in-Differences (DID) and Synthetic Control (SC) methods. The DID estimator reports an ATT of 0.11631 (t-statistic = 13.21), while the SC model yields an ATT of 0.17301 (t-statistic = 7.58). Despite relying on stronger assumptions—parallel trends in the case of DID and donor pool quality in the case of SC—both models yield statistically significant estimates that are directionally consistent with the SDID result. The agreement across methods supports the reliability of the main finding, while the superior bias-reduction properties of SDID reinforce its role as the primary estimator. The results from Columns (2) and (3) also align with the inclusive view, further reinforcing the interpretation that sanctuary policies are associated with increased local entrepreneurial activity.

Taken together, the results in Table 6 provide robust evidence that sanctuary policies meaningfully enhance local entrepreneurial dynamism. These findings are consistent with theoretical mechanisms in which inclusive immigration policies reduce informal regulatory frictions and enhance institutional trust—conditions that are especially salient for immigrant entrepreneurs. The robustness of the effect across estimation strategies underscores the credibility of the causal relationship.

Insert Table 6

4.4.2. The Effect of the Enactment of Sanctuary Jurisdiction Policies on the Quality of Startups

Table 7 reports the estimated effects of sanctuary jurisdiction adoption on the Entrepreneurship Quality Index (EQI), which captures the average growth potential of newly registered firms within a ZIP code. The dependent variable is measured in levels, allowing us to evaluate how policy adoption shifts the quality composition of entrepreneurial entry. Column (1) presents results from the Synthetic Difference-in-Differences (SDID) model, which yields an average treatment effect on the treated (ATT) of 0.000009, statistically significant at the 1% level (t-statistic = 7.07). Although the coefficient is small in absolute terms, this is consistent with the scale of the EQI itself—the sample mean of EQI is 0.0004 (see Table 5). The estimated effect implies an increase of approximately 2.25% relative to the sample mean EQI (0.000009 ÷ 0.0004), which reflects a economically meaningful improvement in the quality of new startups following sanctuary policy adoption. The SDID model, by correcting for both unobserved heterogeneity and pre-trend imbalances, provides the most credible estimate of this causal effect. This positive and statistically significant effect provides further support for the inclusive view, which posits that such policies foster local economic vitality. By enhancing trust and reducing fear among immigrant communities, sanctuary policies may enable more ambitious and growth-oriented entrepreneurial efforts to emerge.

Columns (2) and (3) present ATT estimates from the Difference-in-Differences (DID) and Synthetic Control (SC) models, which serve as robustness checks. The DID model reports an ATT of 0.000007 (t-statistic = 6.55), while the SC model produces an estimate of 0.000006 (t-statistic = 2.63). Like the SDID result, these estimates are small in magnitude but statistically significant, which is expected given the low baseline level of the EQI variable. Both estimates confirm the direction and statistical significance of the policy effect, despite relying on stronger identifying assumptions. The results in columns (2) and (3) also confirm the prediction of the inclusive view, indicating that sanctuary policy adoption is not only associated with more startup activity, but also with higher expected startup quality.

Collectively, the results in Table 7 suggest that sanctuary jurisdictions promote not only a greater number of startups but also a more dynamic and growth-oriented entrepreneurial ecosystem. The consistency of the estimated effects across estimation strategies strengthens the credibility of the causal interpretation. These findings are in line with the notion that inclusive immigration policies improve institutional trust and reduce perceived risk, thereby fostering an environment where higher-quality entrepreneurship can flourish. The observed gains in startup quality underscore the broader economic relevance of sanctuary policies beyond firm counts.

Insert Table 7

4.4.3. The Effect of the Enactment of Sanctuary Jurisdiction Policies on the Growth Potential of Startup Cohorts

Table 8 presents estimates of the effect of sanctuary jurisdiction adoption on the Regional Entrepreneurship Cohort Potential Index (RECPI), which measures the share of newly registered firms within a ZIP code expected to achieve significant growth over time. This index captures the scalability and long-run potential of local startup cohorts. Column (1) reports the estimate from the Synthetic Difference-in-Differences (SDID) model, which yields an average treatment effect on the treated (ATT) of 0.01984, statistically significant at the 1% level (t-statistic = 8.39). Given the sample mean RECPI of 0.0379 (see Table 5), this coefficient implies an approximate 52.4% increase in the share of high-growth-potential startups following sanctuary policy adoption. The SDID estimator offers the least biased inference, as it adjusts for both time-invariant confounding and differential pre-treatment trends. This economically significant effect provides further confirmation of the inclusive view, which holds that sanctuary policies foster local business development by increasing trust, reducing uncertainty, and enabling higher-potential entrepreneurial efforts to flourish.

Columns (2) and (3) report ATT estimates from the Difference-in-Differences (DID) and Synthetic Control (SC) models, which are used as robustness checks. The DID estimate is 0.02328 (t-statistic = 13.49), and the SC estimate is 0.01821 (t-statistic = 4.44). Both estimates are statistically significant and directionally consistent with the SDID estimate, reinforcing the robustness of the main result. Although DID and SC rely on stronger assumptions—parallel trends and donor pool construction, respectively—the convergence in results across all three estimation strategies provides confidence in the causal relationship. The results from columns (2) and (3) further support the inclusive view, indicating that sanctuary policies are associated not only with higher startup formation and quality, but also with a larger share of firms positioned for future growth.

Together, the findings in Table 8 suggest that the impact of sanctuary jurisdiction policies extends beyond short-term business formation to shape the long-run dynamism of local startup ecosystems. The large relative increase in the share of high-potential startups represents a significant improvement in the trajectory of entrepreneurial activity. These results are consistent with the argument that inclusive immigration policies create stable, trust-rich environments where entrepreneurs are more likely to invest in scalable ventures. The consistency across estimation approaches underscores the reliability of this conclusion and reinforces the broader pattern observed across startup formation rate and entrepreneurial quality indicators.

Insert Table 8

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5. Conclusion

This paper investigates the local economic consequences of sanctuary jurisdiction policies by estimating their causal impact on business activity and entrepreneurial dynamics at the ZIP-code level. The analysis is motivated by competing theoretical perspectives: one suggesting that sanctuary policies introduce policy risk that could suppress investment and firm formation, and the other positing that such policies promote economic engagement by reducing institutional uncertainty and enhancing trust within immigrant communities.

Using the Synthetic Difference-in-Differences (SDID) estimator to address non-parallel trends and unobserved heterogeneity in staggered adoption settings, we document statistically significant increases in establishment counts, employment, and payroll following the adoption of sanctuary status. Extending the analysis to entrepreneurship-specific outcomes, we find that sanctuary policies are associated with higher startup formation rates, improved average startup quality, and a larger share of firms with substantial growth potential. The consistency of these results across multiple identification strategies supports a robust interpretation of the findings.

These results contribute to the broader literature on immigration policy and local economic development by demonstrating that subnational policy choices can shape the structure and dynamism of local business ecosystems. While immigration enforcement remains a federal priority, our findings underscore that local policy environments can materially affect firm behavior and entrepreneurial entry. Future work should explore long-run effects, sectoral heterogeneity, and potential spillovers to surrounding areas to more fully characterize the economic consequences of local immigration policy divergence.

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Appendix A: Variable definitions and data sources

This Appendix entails the definitions of the variables and their data sources.

Name of variable	Definition of variable and data source
Sanctuary ZIP code	Dummy (0,1) that is one if the ZIP code is a sanctuary ZIP code, else zero (Data source: FAIR Federation for American Immigration Reform).
Total business establishments with paid employees in the ZIP code	Natural logarithm of the total number of business establishments with paid employees in ZIP code (Data source: ZIP Codes Business Patterns).
Total employment in businesses with paid employees	Natural logarithm of total employment in businesses with paid employees in ZIP code (Data source: ZIP Codes Business Patterns).
Total payroll in businesses with paid employees ($1,000)	Natural logarithm of the total payroll in businesses with paid employees in ZIP code ($1,000). Total payroll is adjusted for inflation by using the CPI deflator with base year of 1983 (Data source: ZIP Codes Business Patterns).
Startup formation rate	Natural logarithm of the sum of one and the quantity of new business registrants within a given population within the zip code by year (Data source: Startup Cartography Project).
Entrepreneurship quality index	The average growth potential (or "quality") within a group of startups in a zip code by year (Data source: Startup Cartography Project).
Regional entrepreneurship cohort potential index	The number of startups expected to later achieve a significant growth outcome within a zip code by year (Data source: Startup Cartography Project).
Proportion of unauthorized immigrants	Ratio of the total unauthorized immigrant population of a state-year to the total unauthorized immigrant population of year (Data source: Warren and Warren (2013); Center for Migration Studies, 2022).
Democratic vote share in the most recent U.S. presidential election	The ratio of total number of votes for the democratic presidential candidate to the total number of votes for all the presidential candidates (Data source: MIT Election Data and Science Lab).
Unemployment rate	The unemployment rate by county-year (Data source: Bureau of Economic Analysis at the U.S. Department of Commerce).
Per capita personal income	Per capita personal income by county-year. Per capita personal income is adjusted for inflation by using the CPI deflator with base year of 1983 (Data source: Bureau of Economic Analysis at the U.S. Department of Commerce).

Figure 1: Geographic Distribution of Sanctuary ZIP Codes Across the United States

Figure 1 illustrates the spatial distribution of 5-digit sanctuary ZIP codes across the United States, highlighting regional variations in their prevalence.

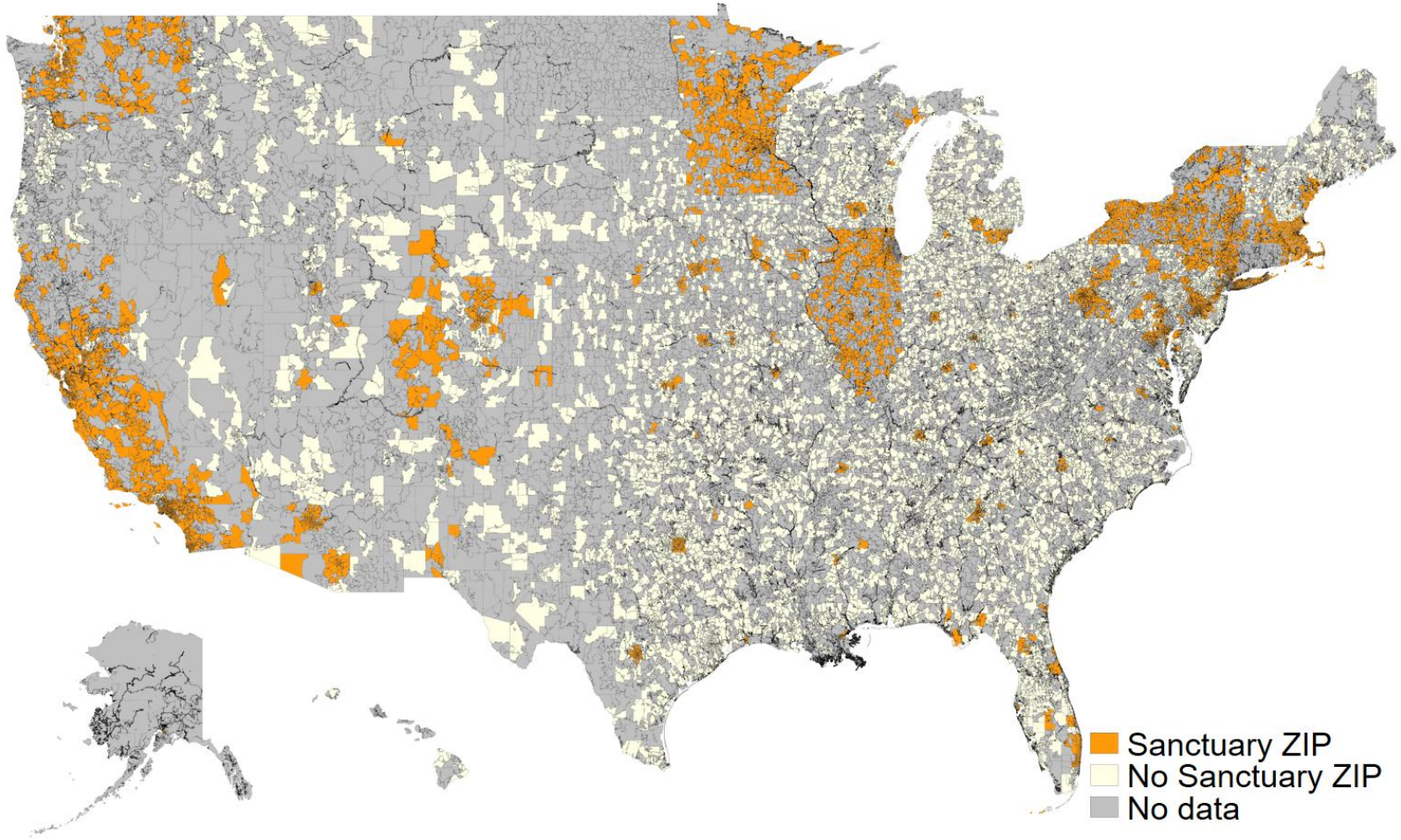
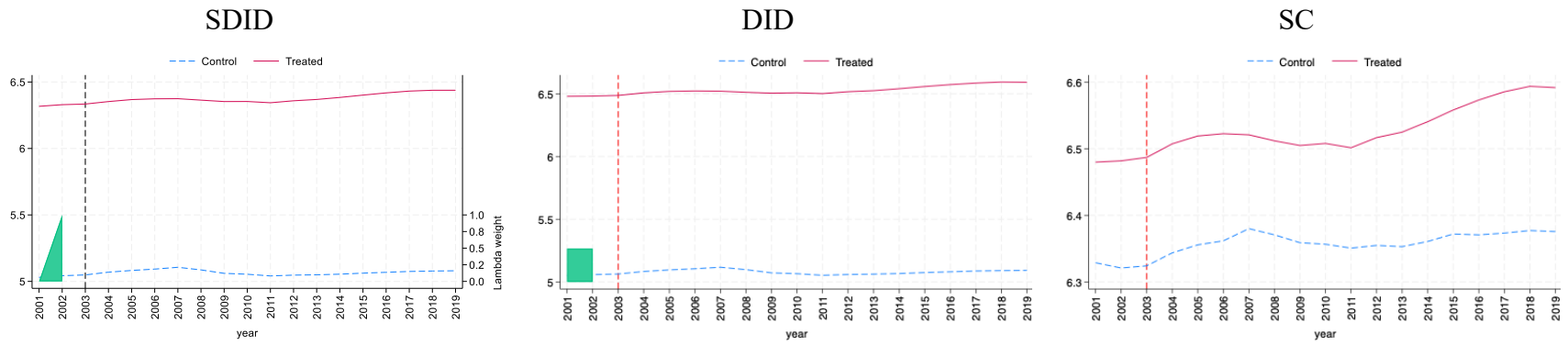


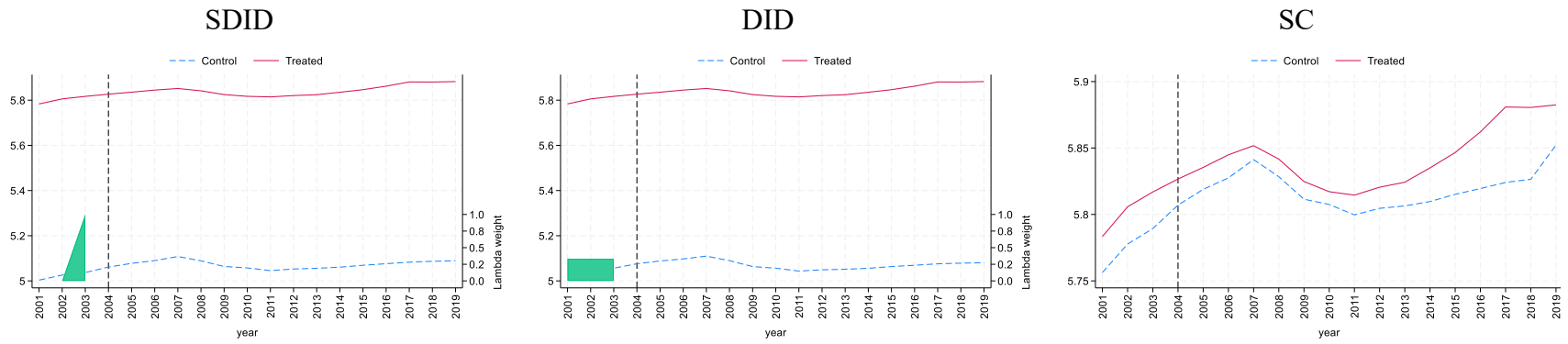
Figure 2: Graphical Analysis of Sanctuary ZIP Code Impact on Business Establishments with Paid Employees

This figure presents visual representations of the impact of a ZIP code's designation as a sanctuary ZIP code on the total number of business establishments with paid employees, categorized by estimation methodology and sanctuary ZIP code enactment year. Each panel corresponds to a different enactment year and contains three graphs, each representing one of the three estimation methodologies: SDID, DID, and SC. The graphs are based on the estimated models from Table 2.

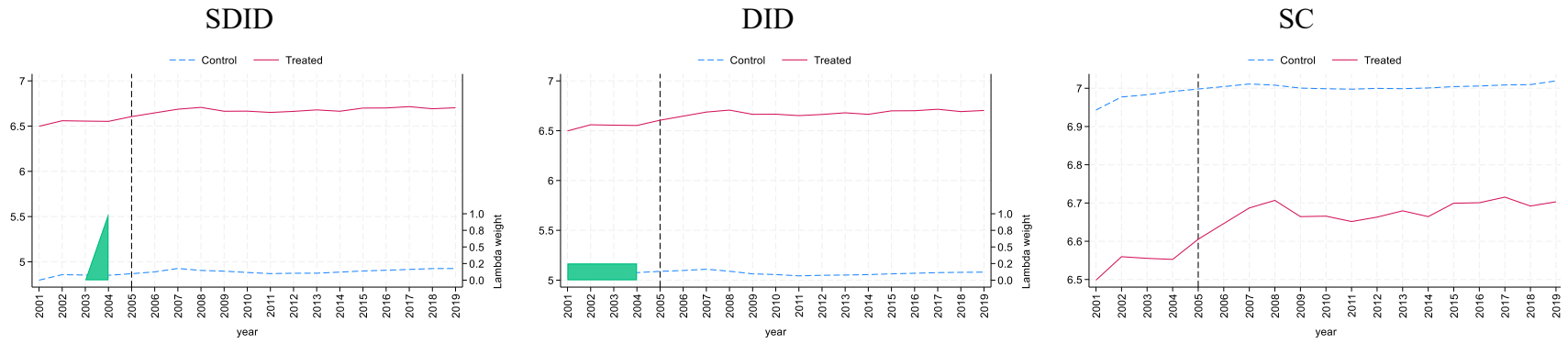
Panel A: Enactment year 2003



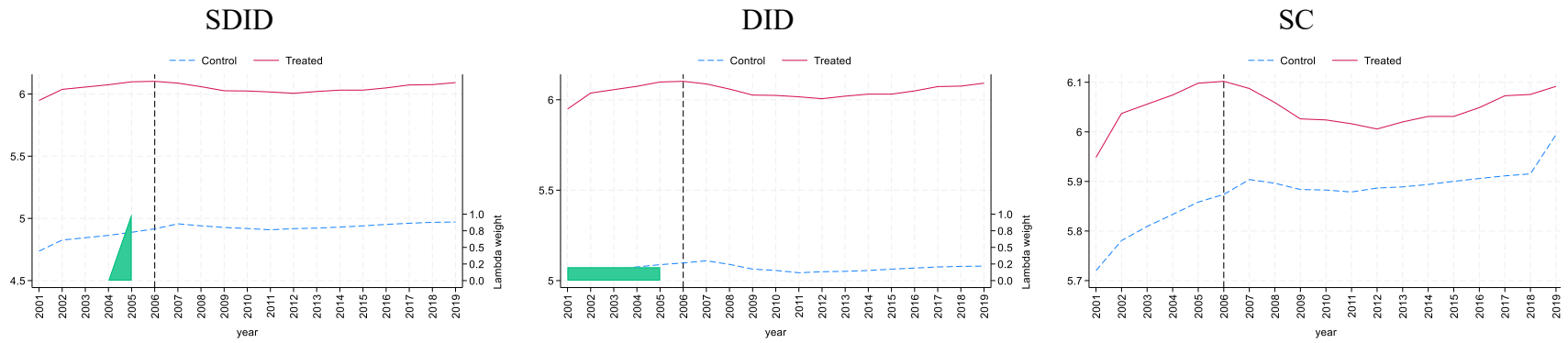
Panel B: Enactment year 2004



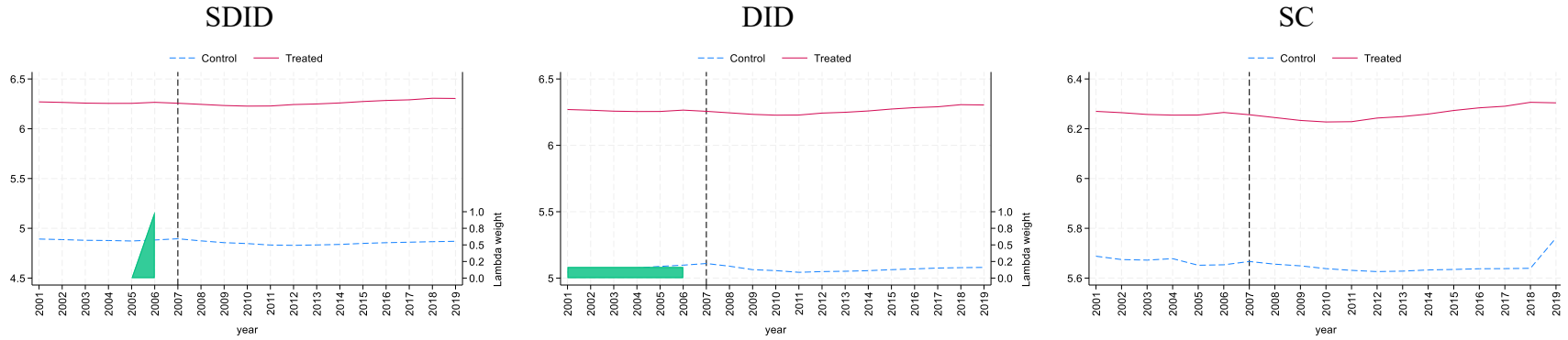
Panel C: Enactment year 2005



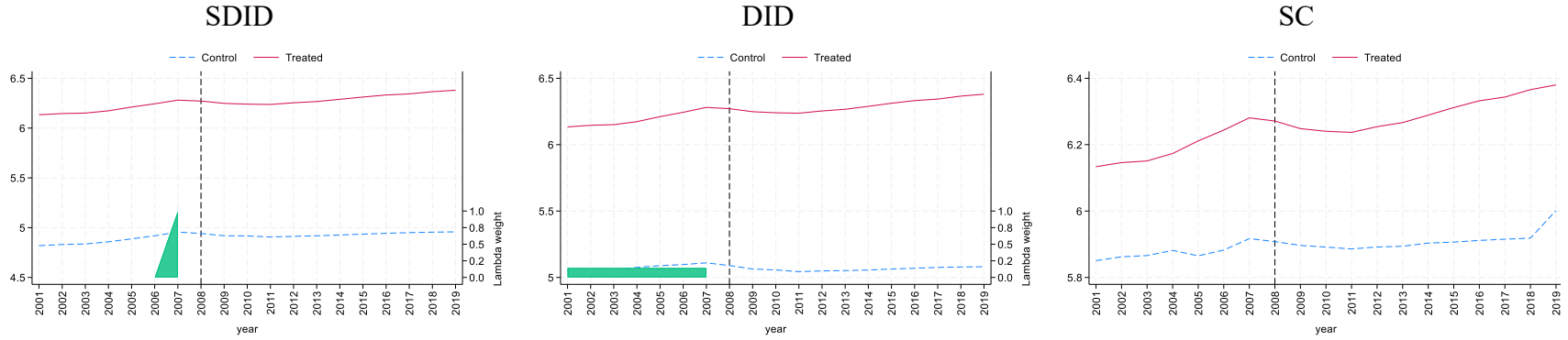
Panel D: Enactment year 2006



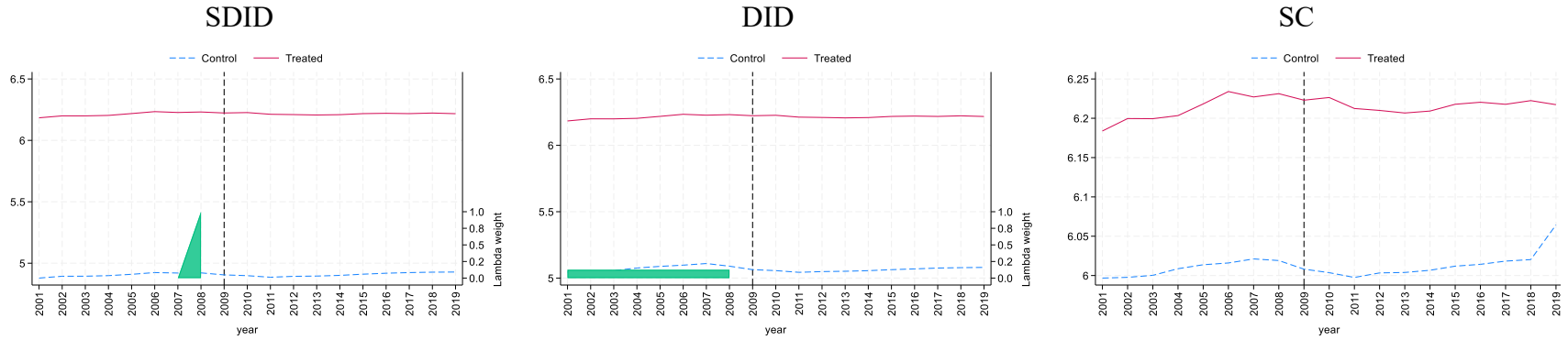
Panel E: Enactment year 2007



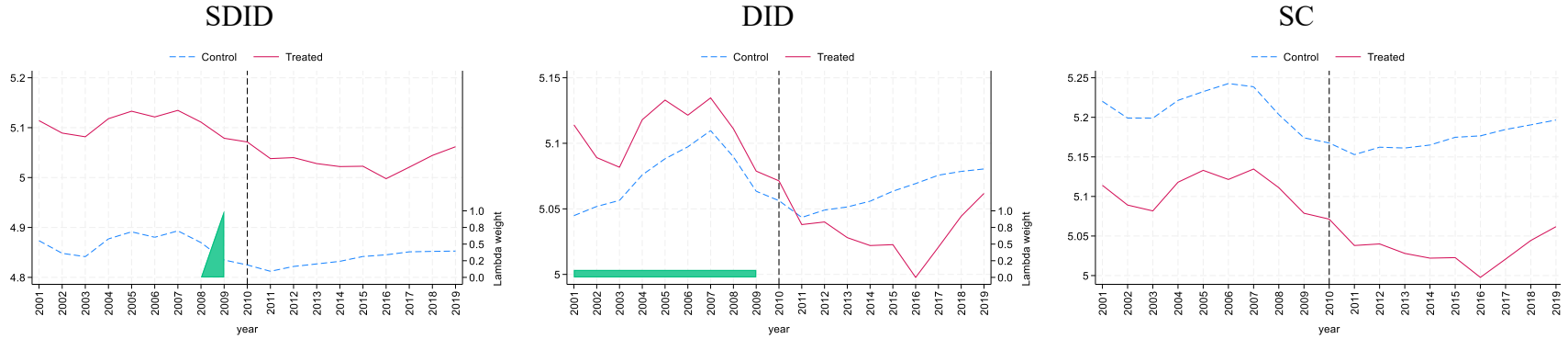
Panel F: Enactment year 2008



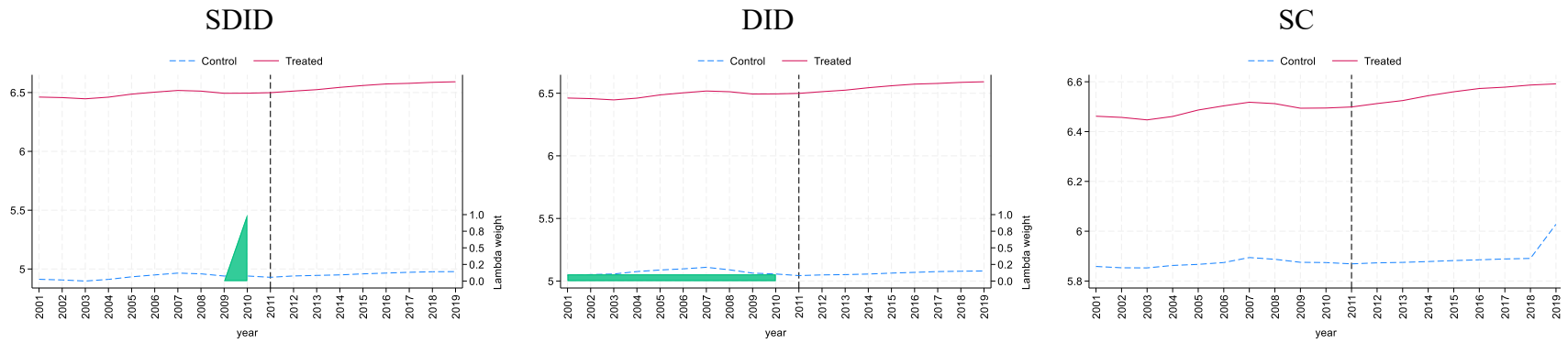
Panel G: Enactment year 2009



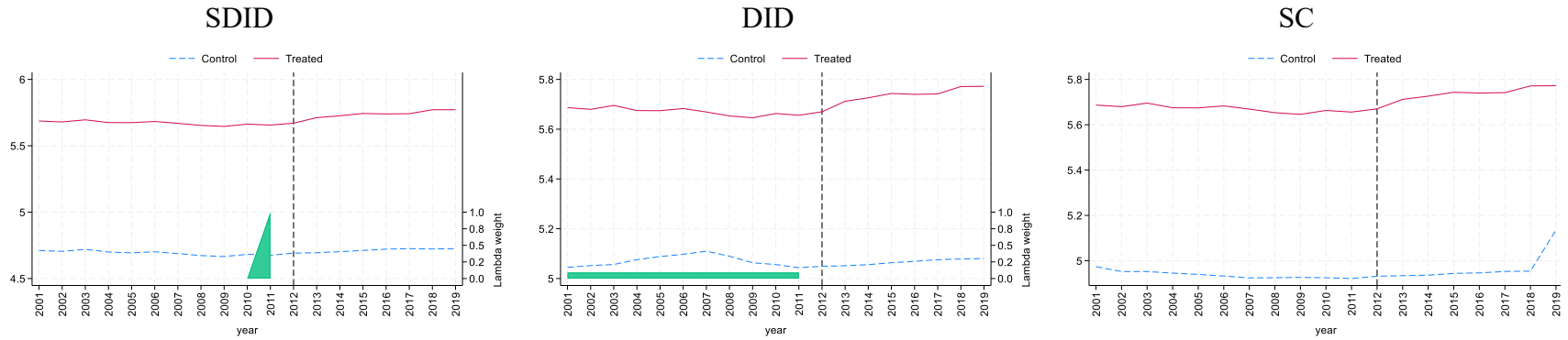
Panel H: Enactment year 2010



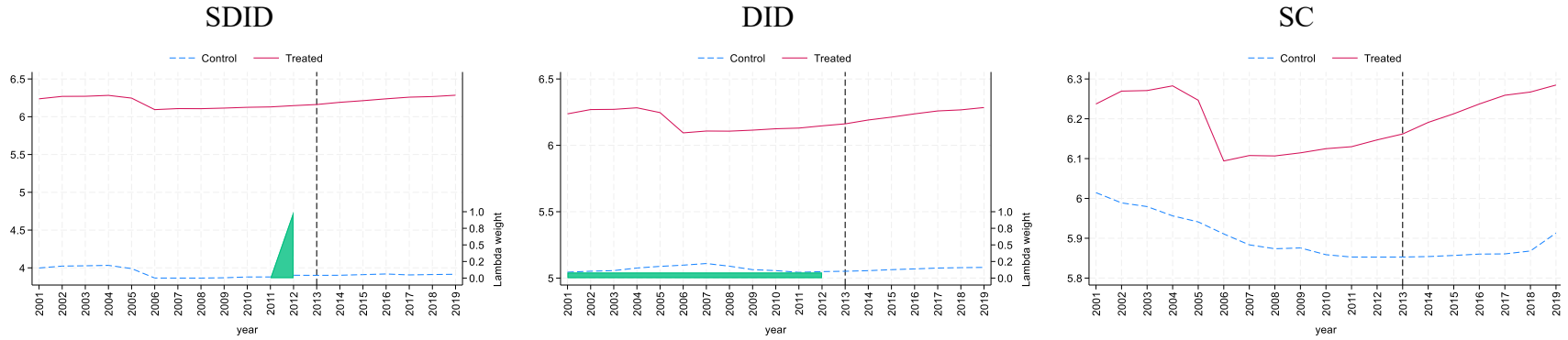
Panel I: Enactment year 2011



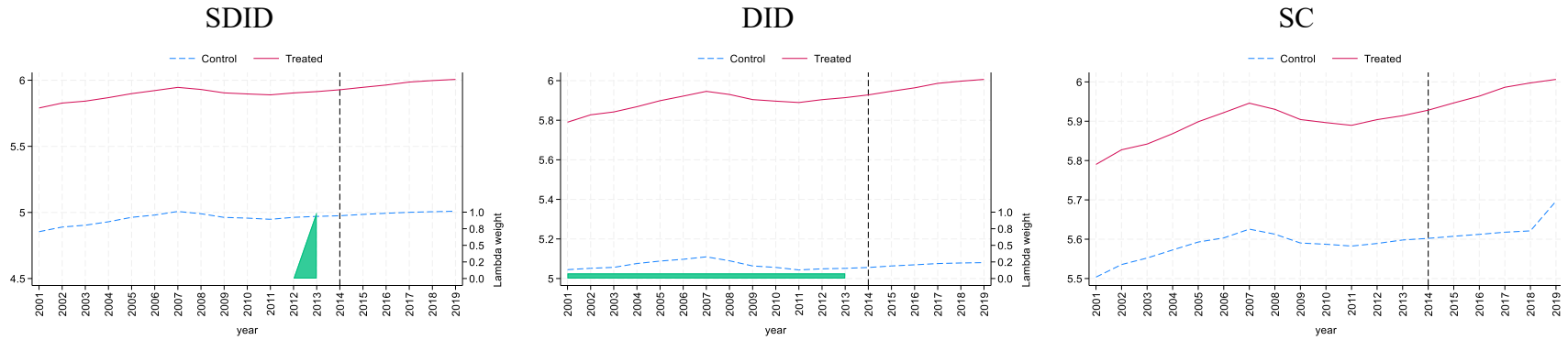
Panel J: Enactment year 2012



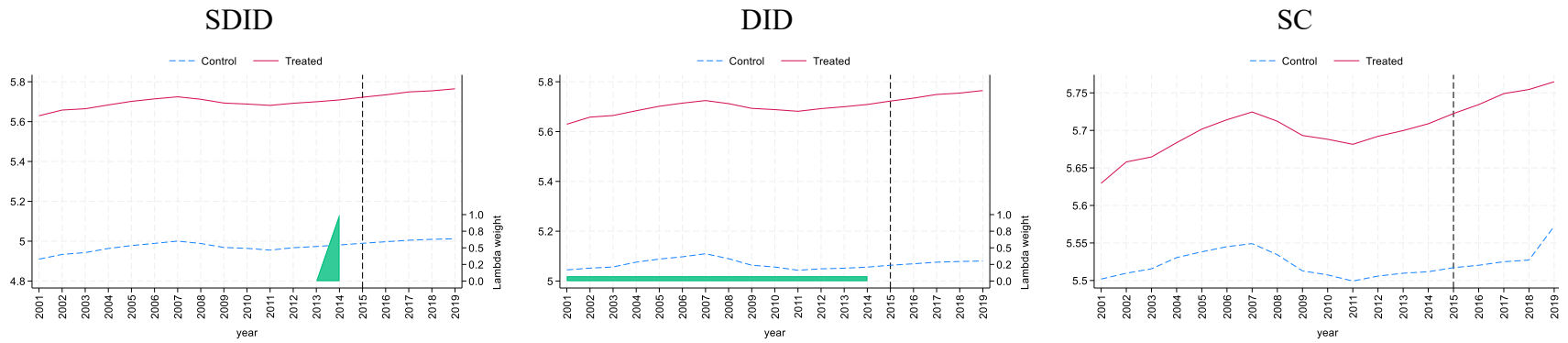
Panel K: Enactment year 2013



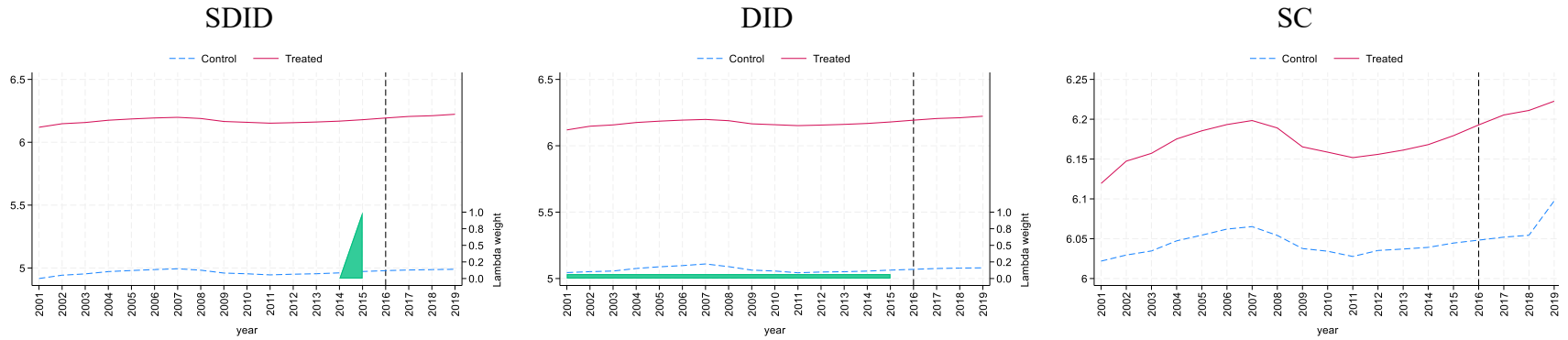
Panel L: Enactment year 2014



Panel M: Enactment year 2015



Panel N: Enactment year 2016

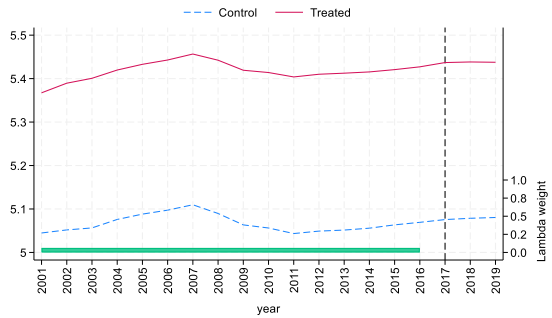


Panel O: Enactment year 2017

SDID



DID



SC

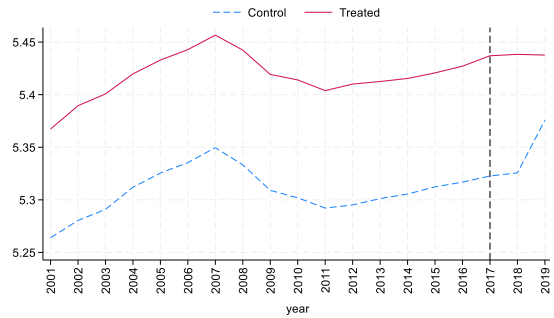
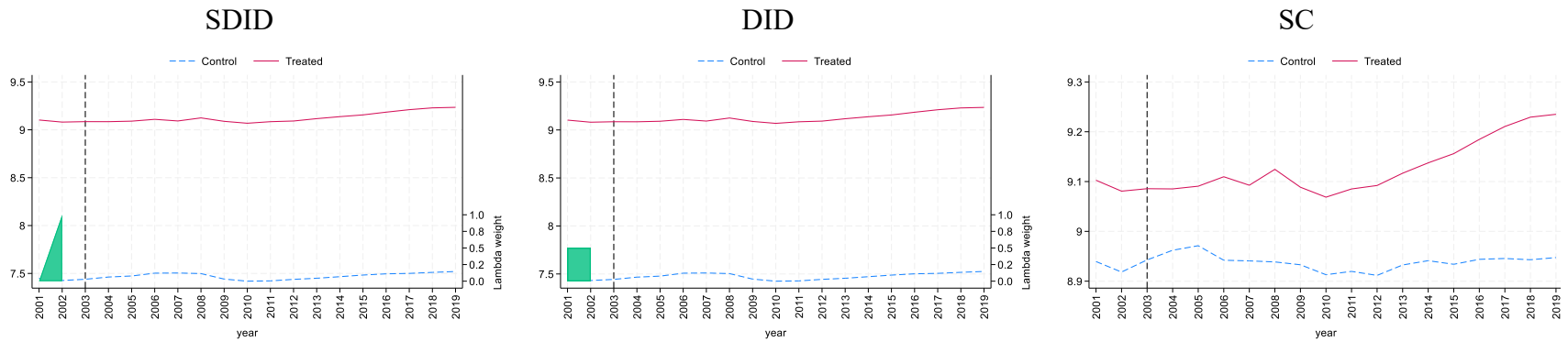


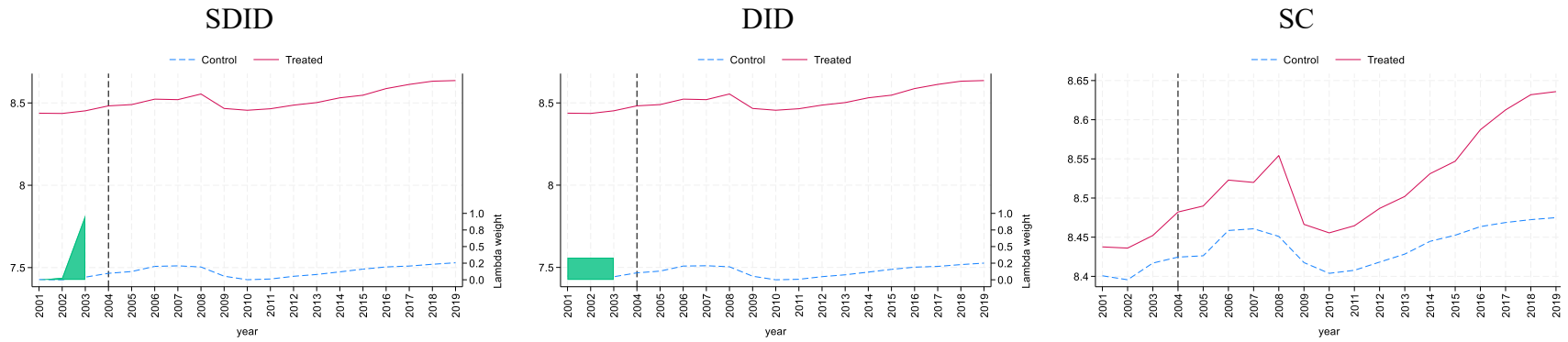
Figure 7: Graphical Analysis of Sanctuary ZIP Code Impact on Total Employment in Businesses with Paid Employees

This figure presents visual representations of the impact of a ZIP code's designation as a sanctuary ZIP code on the total employment in businesses with paid employees, categorized by estimation methodology and sanctuary ZIP code enactment year. Each panel corresponds to a different enactment year and contains three graphs, each representing one of the three estimation methodologies: SDID, DID, and SC. The graphs are based on the estimated models from Table 3.

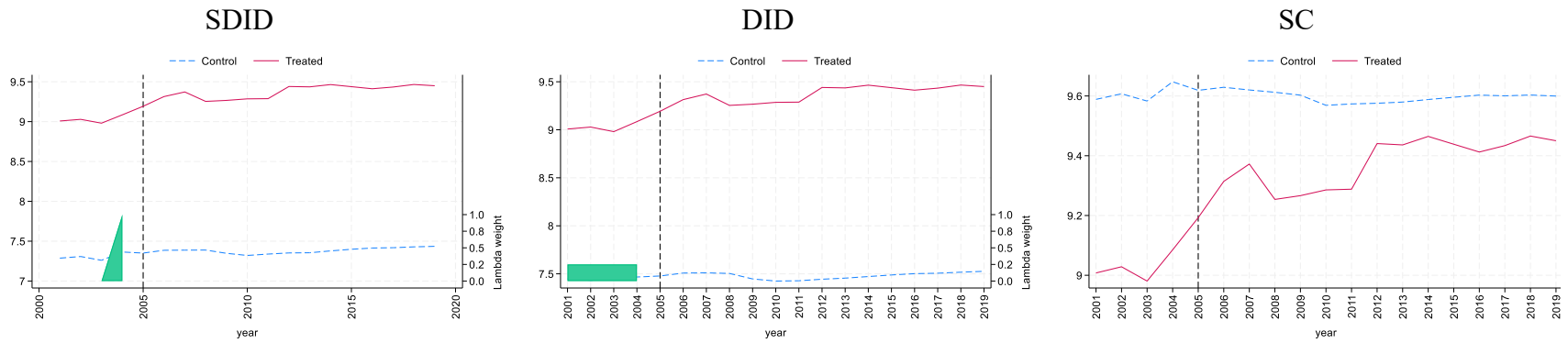
Panel A: Enactment year 2003



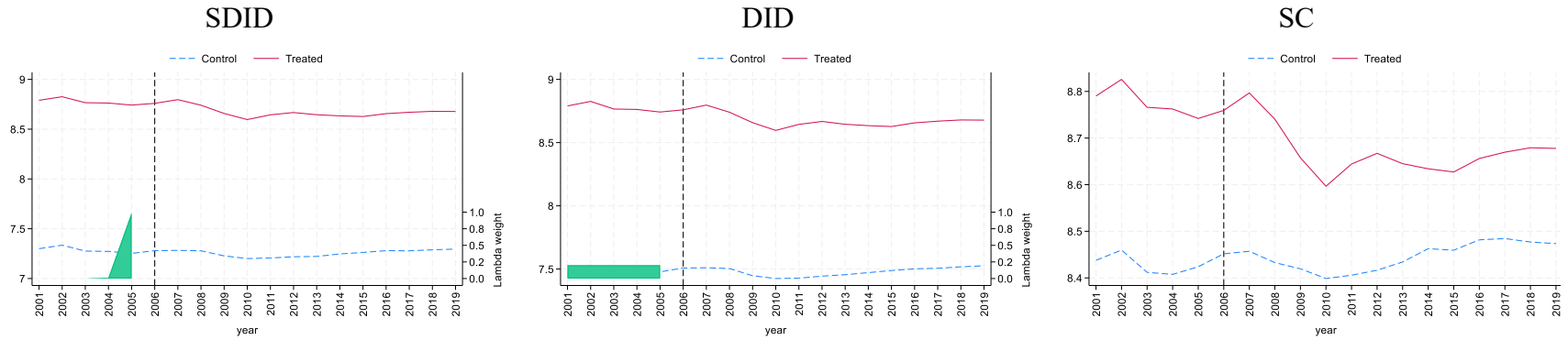
Panel B: Enactment year 2004



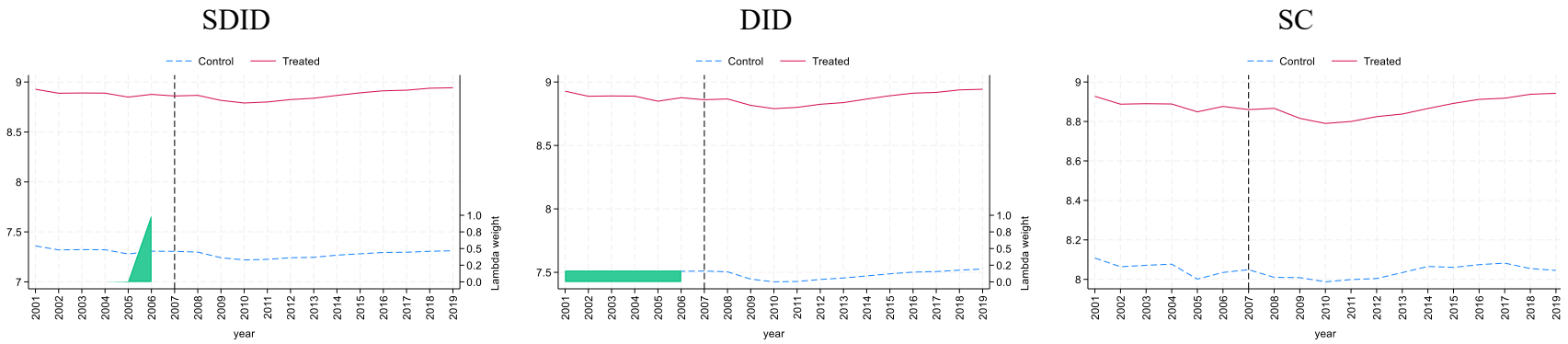
Panel C: Enactment year 2005



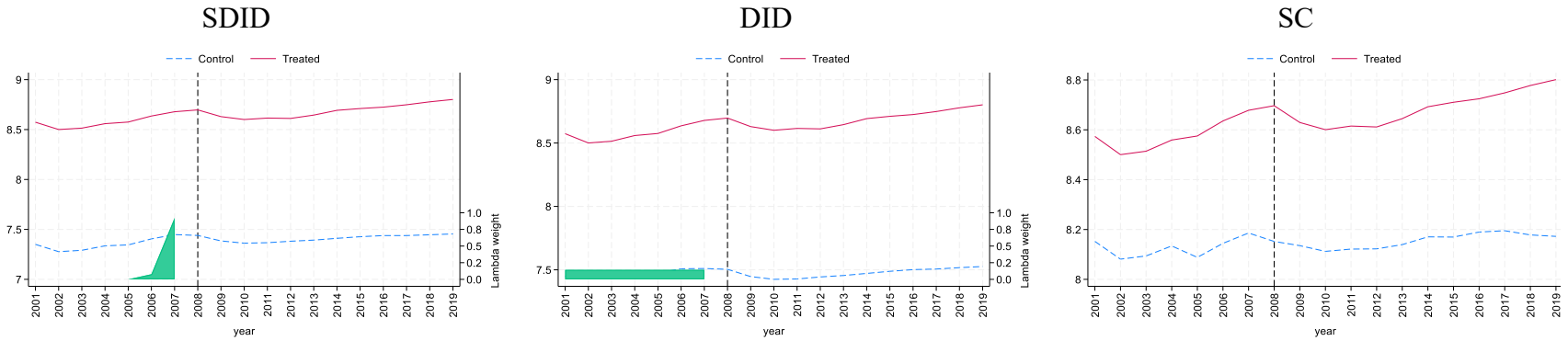
Panel D: Enactment year 2006



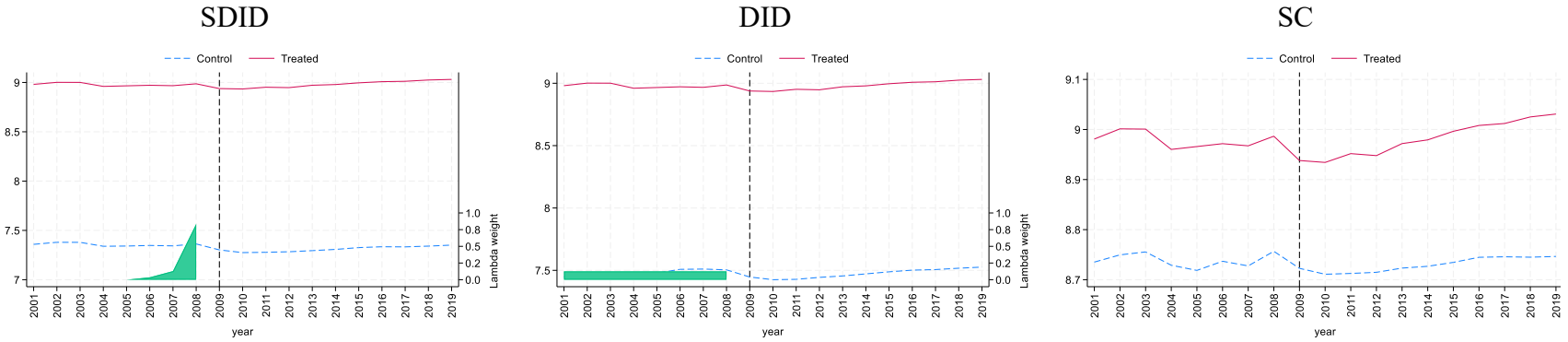
Panel E: Enactment year 2007



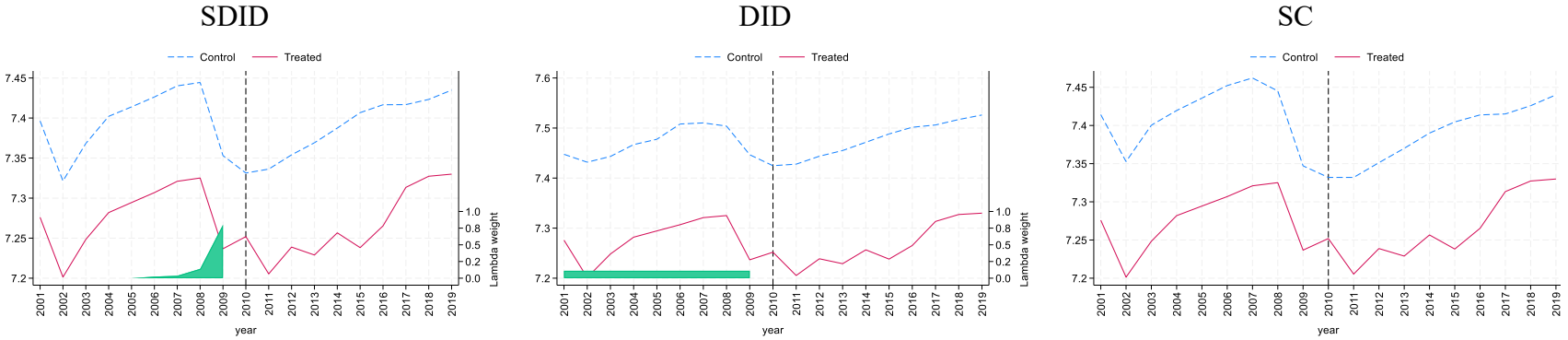
Panel F: Enactment year 2008



Panel G: Enactment year 2009

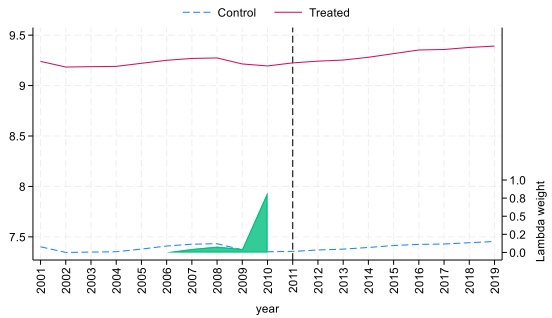


Panel H: Enactment year 2010

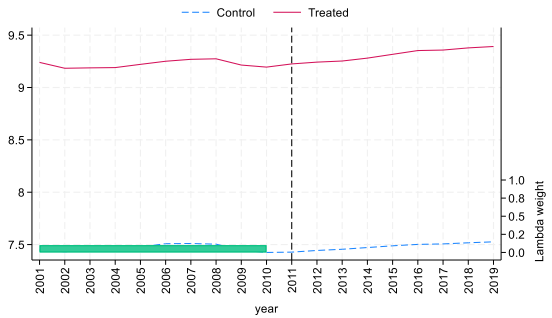


Panel I: Enactment year 2011

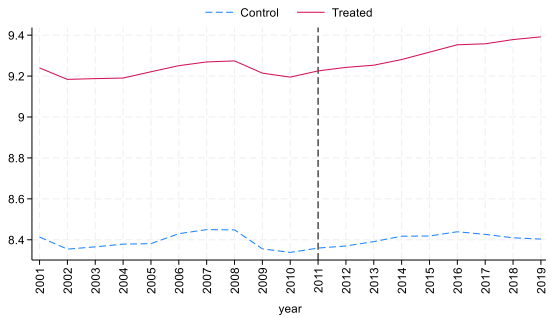
SDID



DID

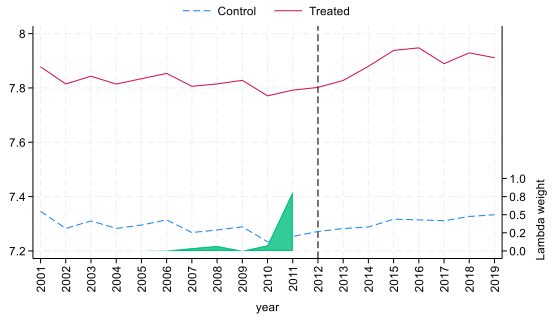


SC

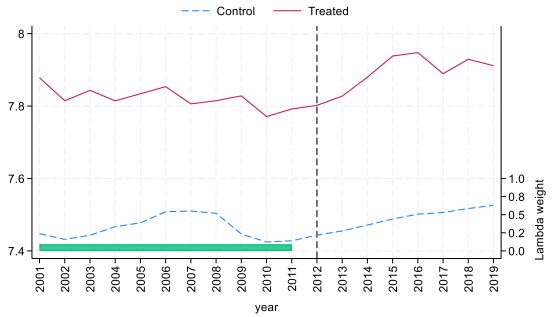


Panel J: Enactment year 2012

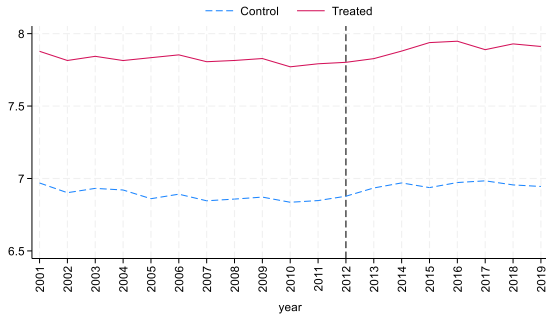
SDID



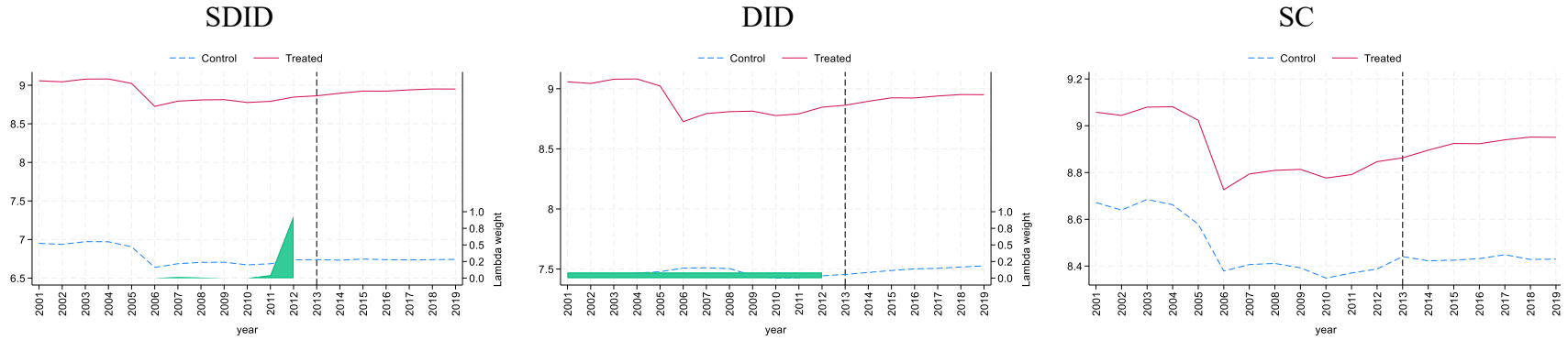
DID



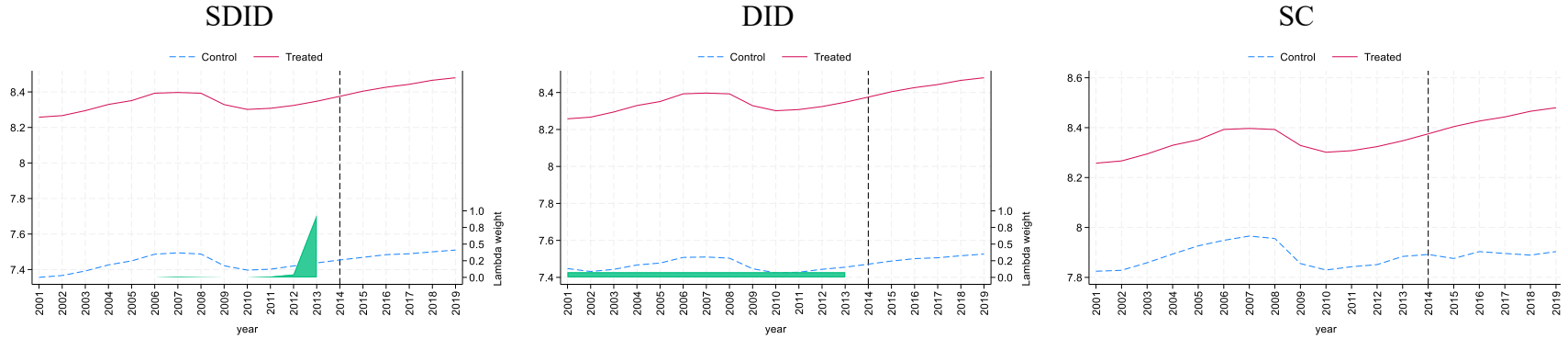
SC



Panel K: Enactment year 2013

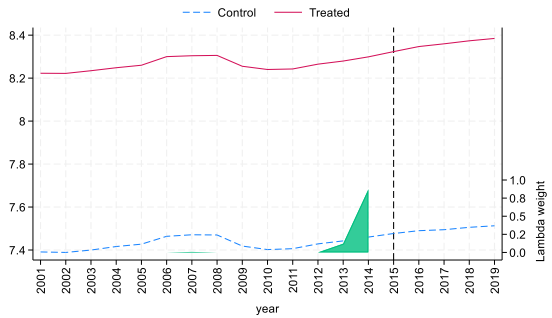


Panel L: Enactment year 2014

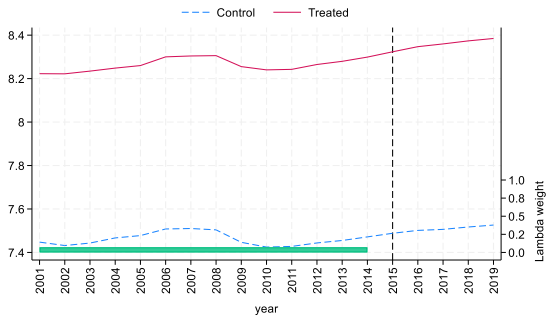


Panel M: Enactment year 2015

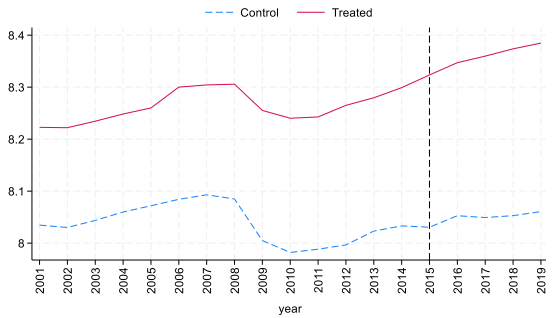
SDID



DID

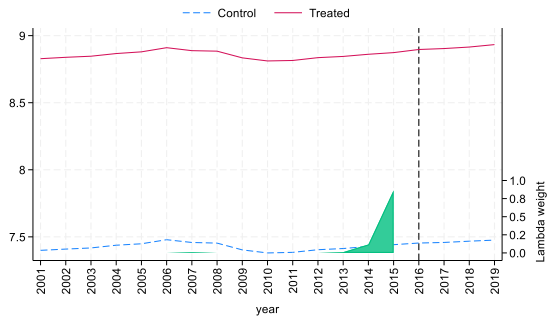


SC

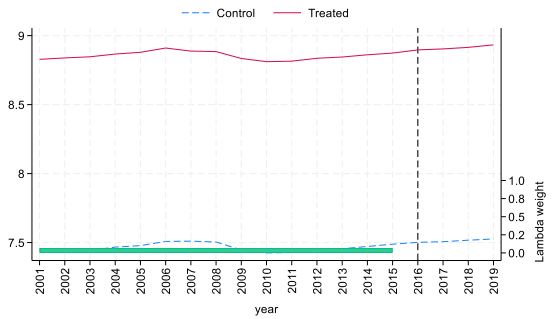


Panel N: Enactment year 2016

SDID



DID

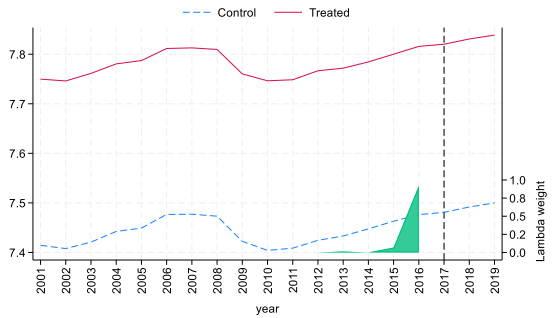


SC

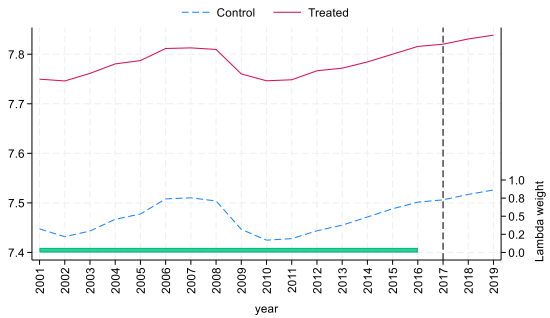


Panel O: Enactment year 2017

SDID



DID



SC

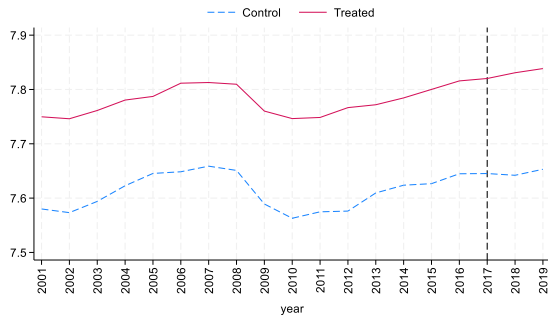
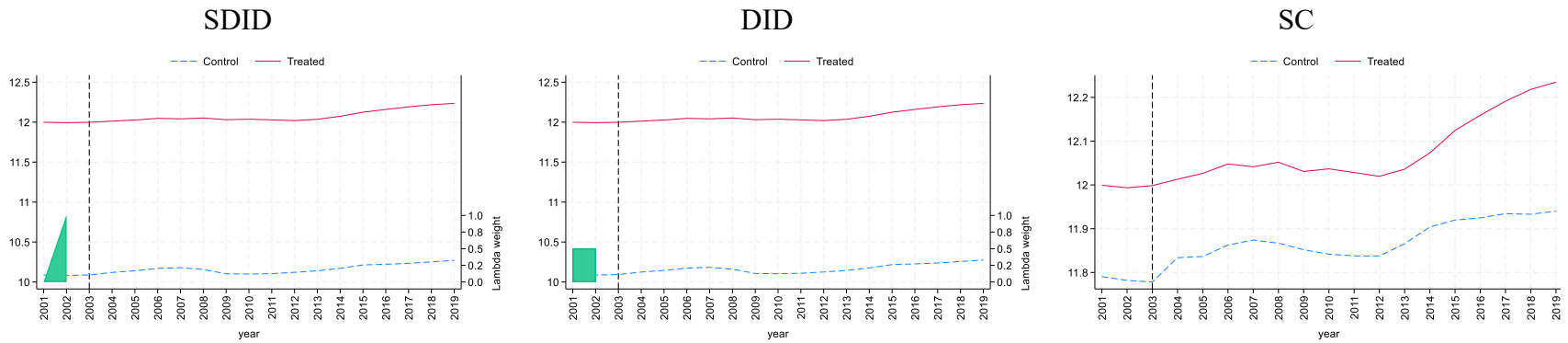


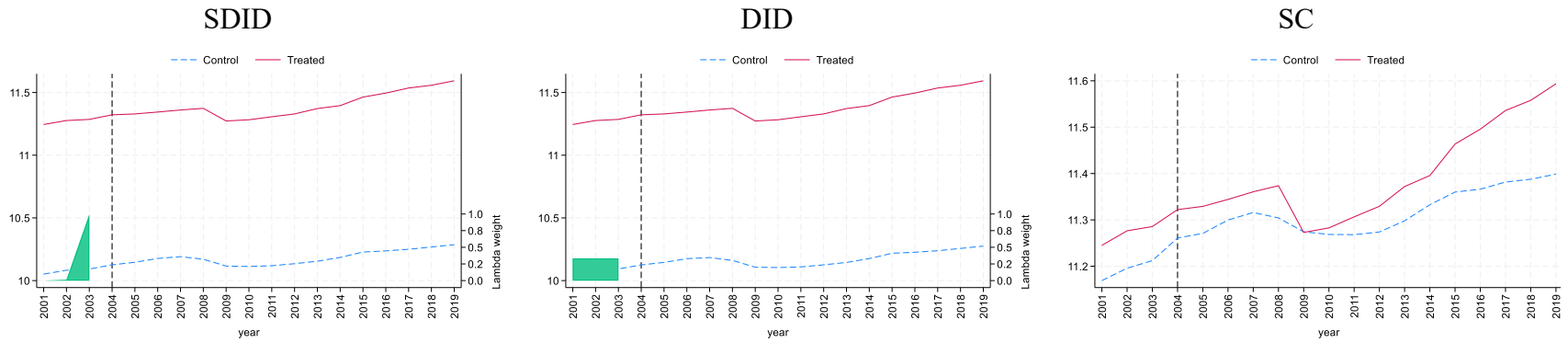
Figure 8: Graphical Analysis of Sanctuary ZIP Code Impact on Total Payroll in Businesses with Paid Employees

This figure presents visual representations of the impact of a ZIP code's designation as a sanctuary ZIP code on the total payroll in businesses with paid employees, categorized by estimation methodology and sanctuary ZIP code enactment year. Each panel corresponds to a different enactment year and contains three graphs, each representing one of the three estimation methodologies: SDID, DID, and SC. The graphs are based on the estimated models from Table 4.

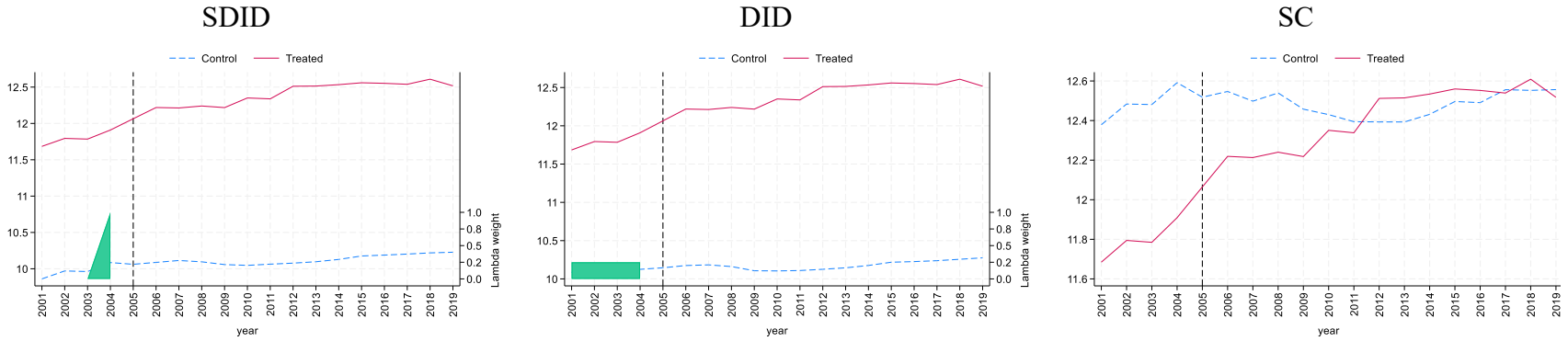
Panel A: Enactment year 2003



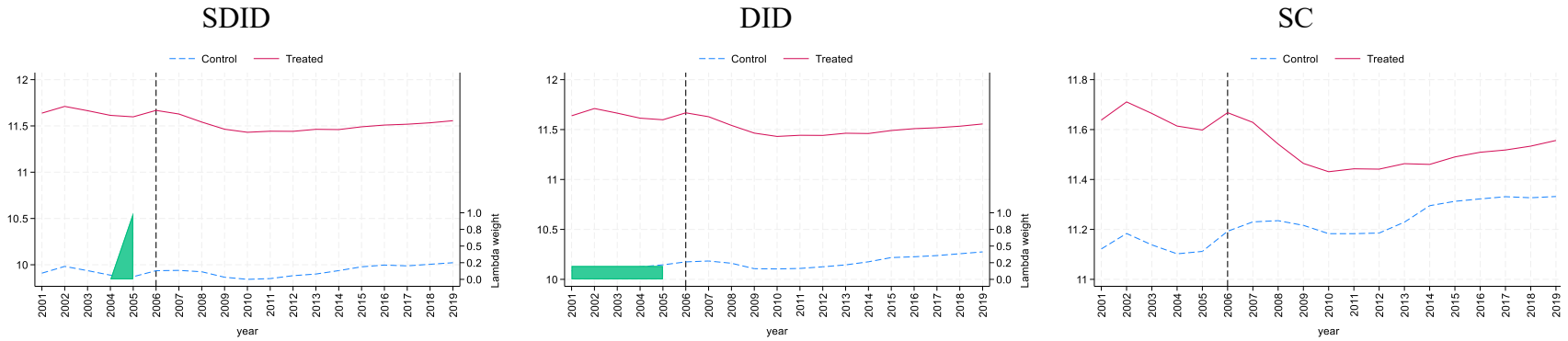
Panel B: Enactment year 2004



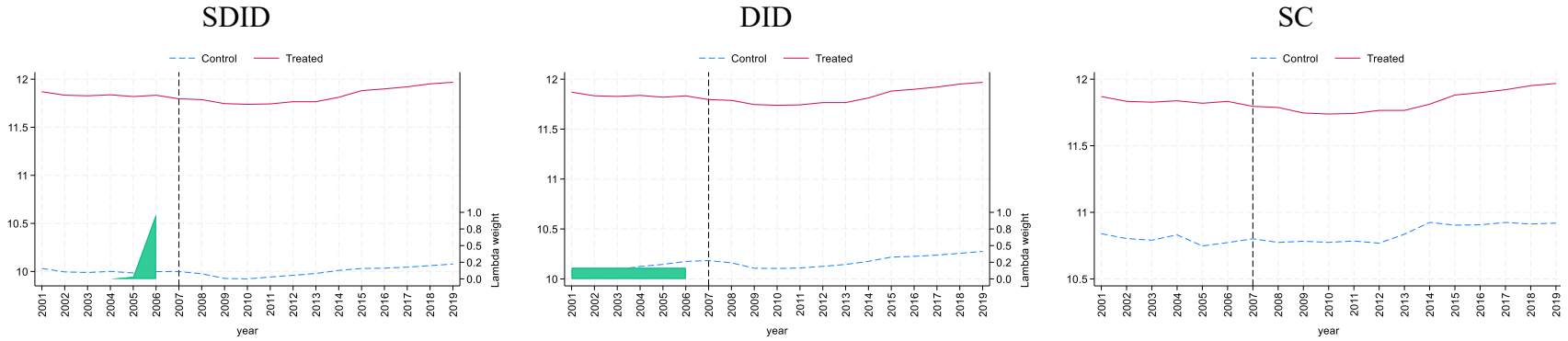
Panel C: Enactment year 2005



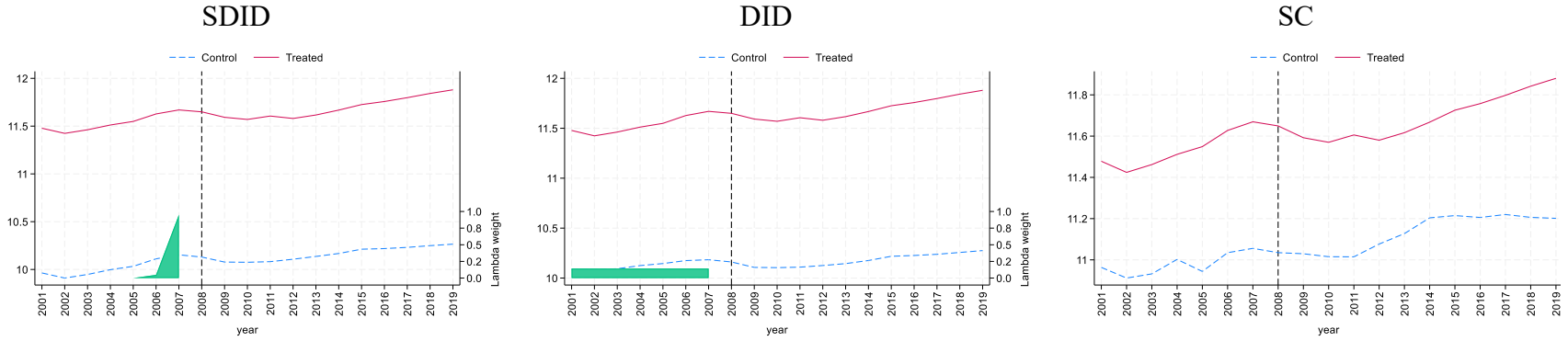
Panel D: Enactment year 2006



Panel E: Enactment year 2007

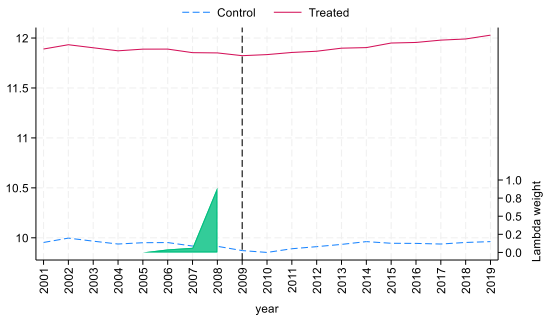


Panel F: Enactment year 2008

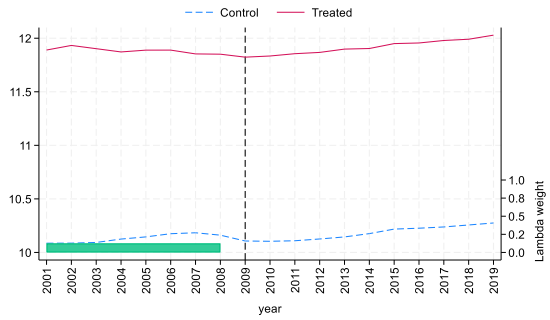


Panel G: Enactment year 2009

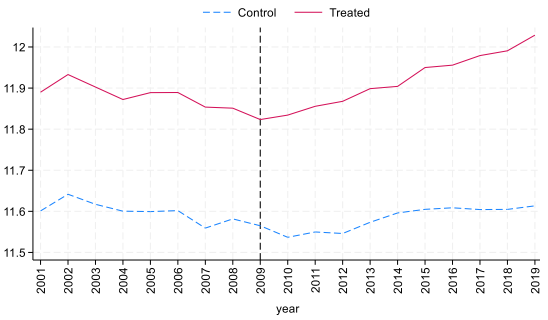
SDID



DID



SC

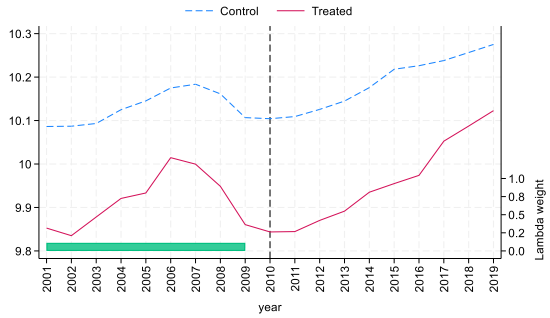


Panel H: Enactment year 2010

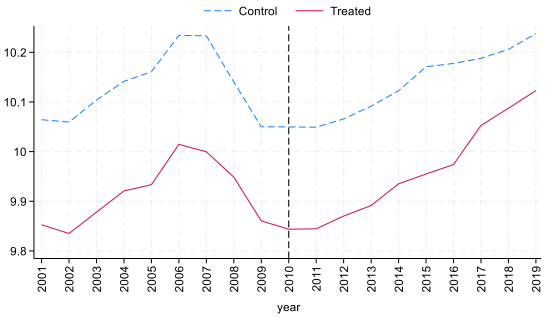
SDID



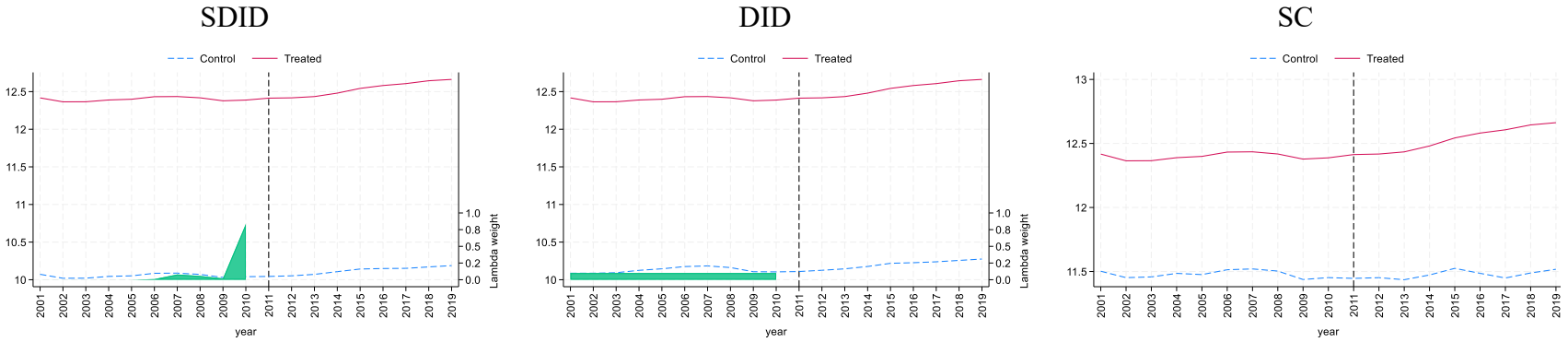
DID



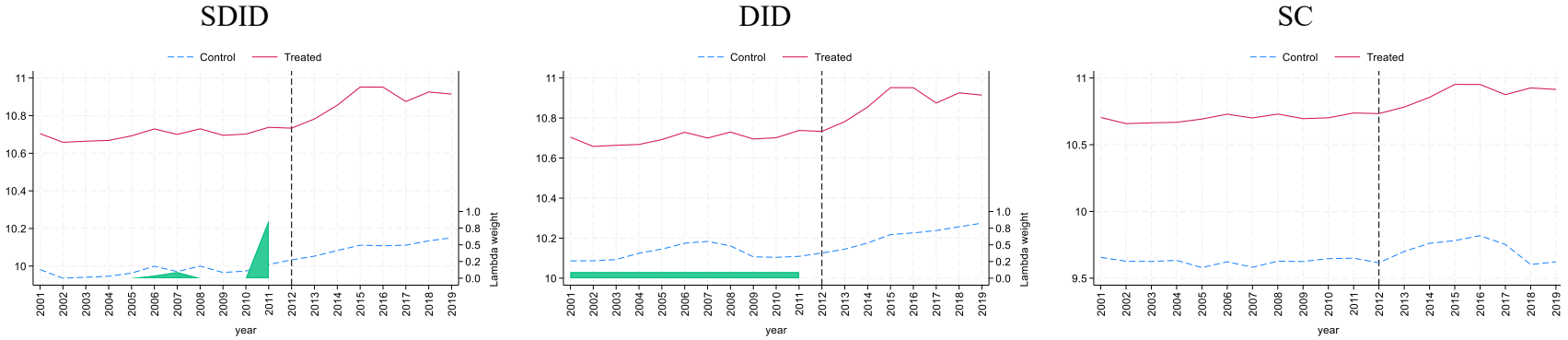
SC



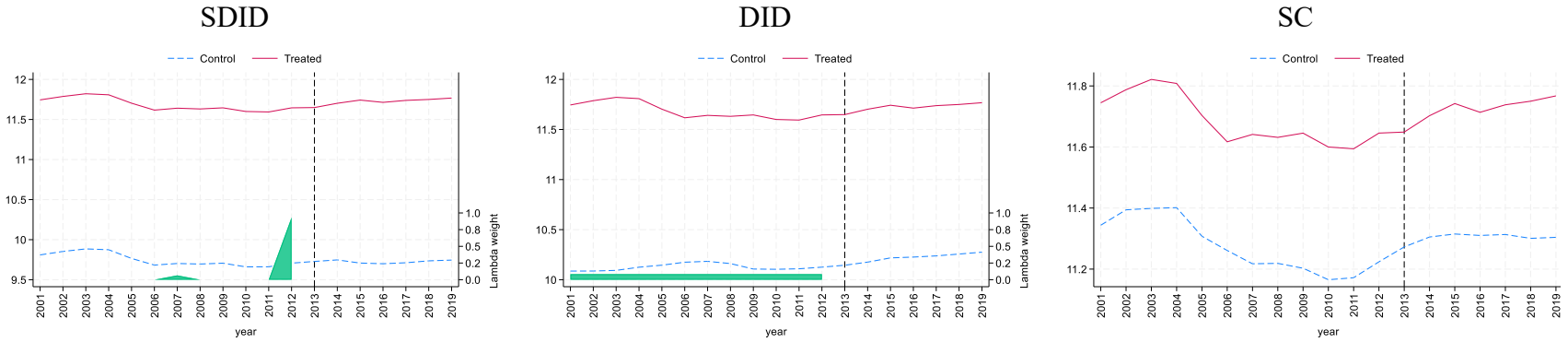
Panel I: Enactment year 2011



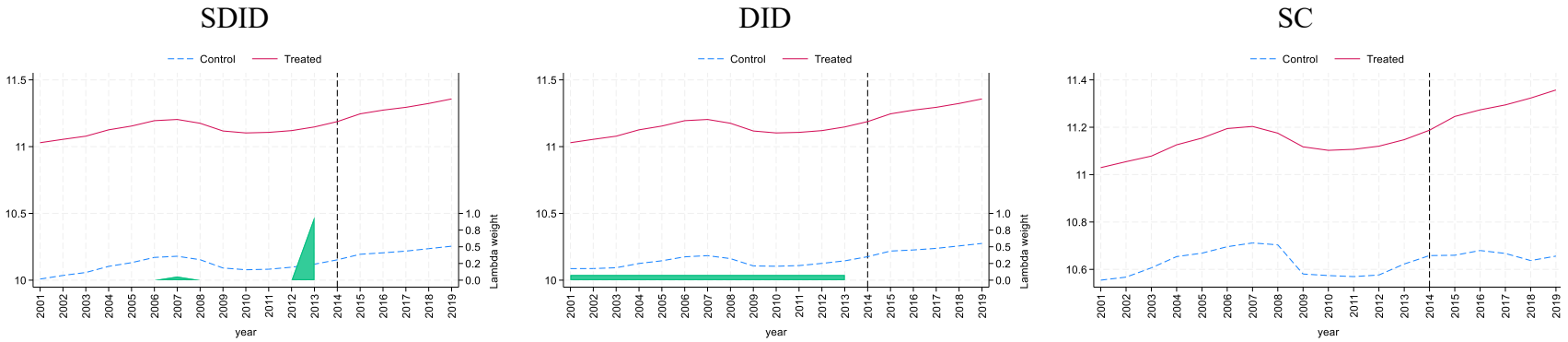
Panel J: Enactment year 2012



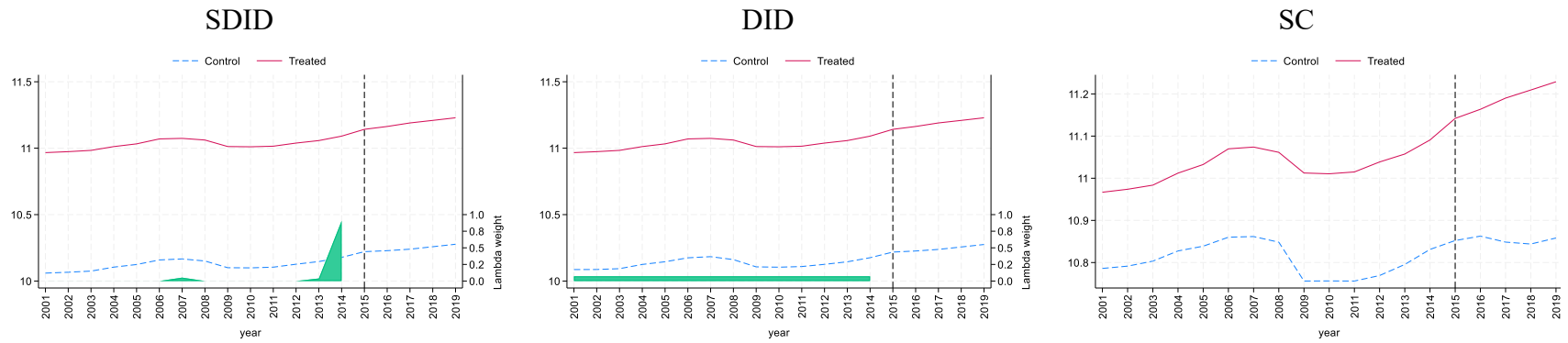
Panel K: Enactment year 2013



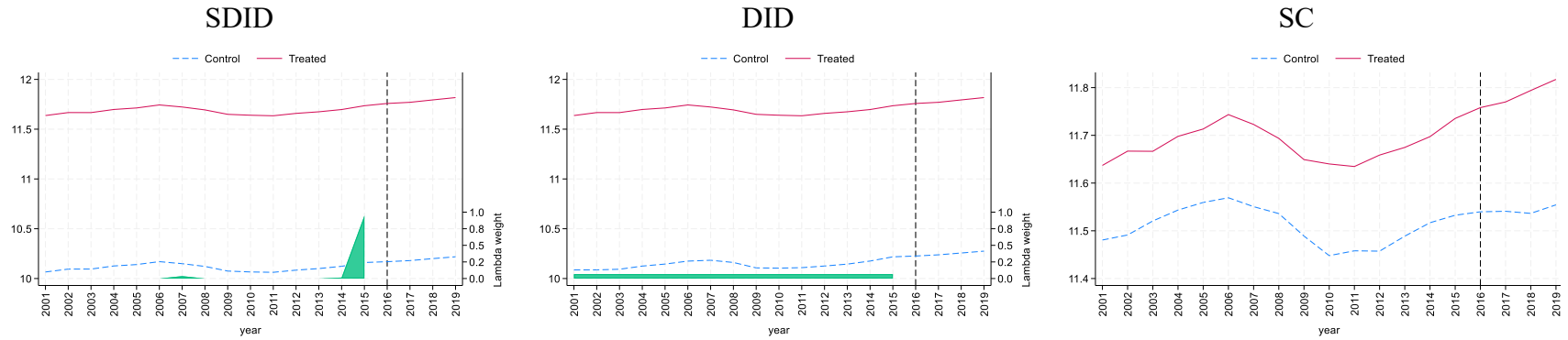
Panel L: Enactment year 2014



Panel M: Enactment year 2015



Panel N: Enactment year 2016



Panel O: Enactment year 2017

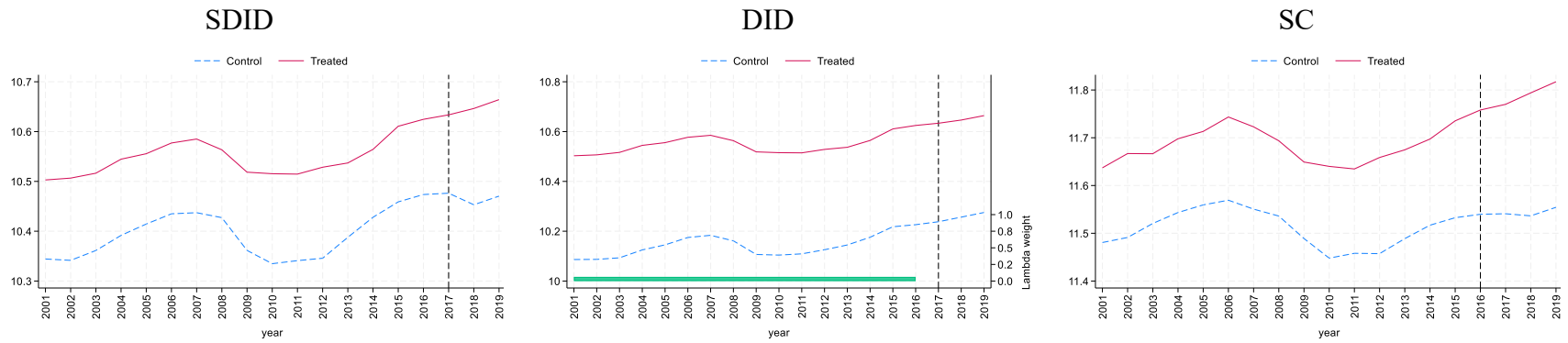
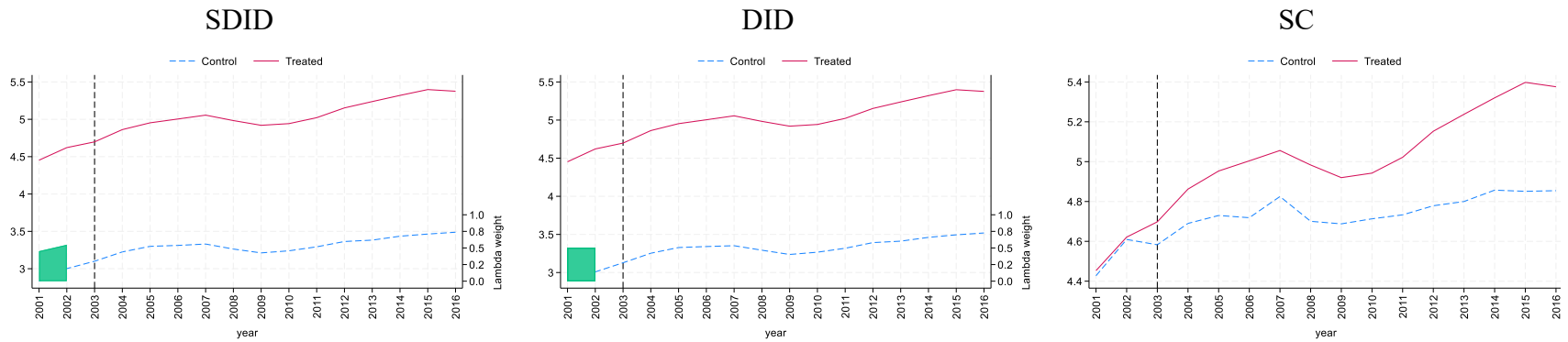


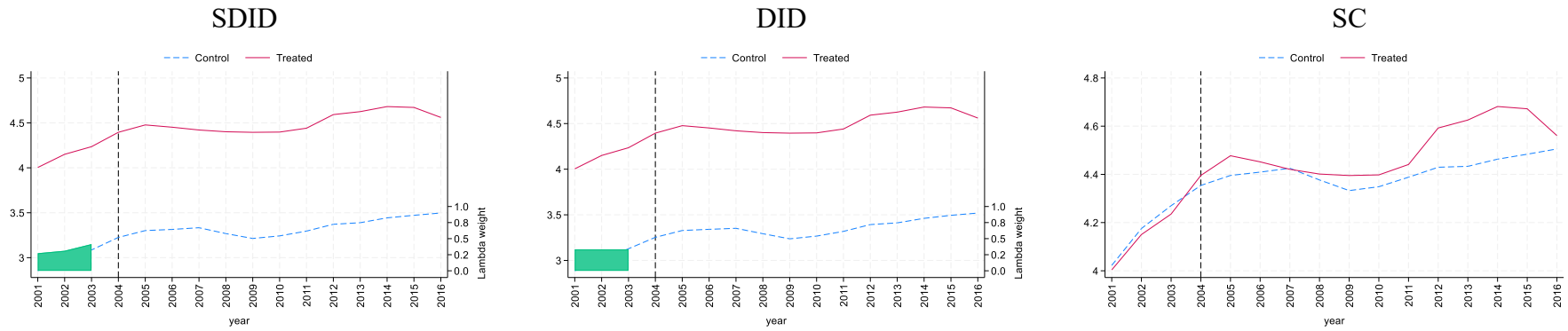
Figure 4: Graphical Analysis of Sanctuary ZIP Code Impact on Startup Formation Rate

This figure presents visual representations of the impact of a ZIP code's designation as a sanctuary ZIP code on the startup formation rate, categorized by estimation methodology and sanctuary ZIP code enactment year. Each panel corresponds to a different enactment year and contains three graphs, each representing one of the three estimation methodologies: SDID, DID, and SC. The graphs are based on the estimated models from Table 6.

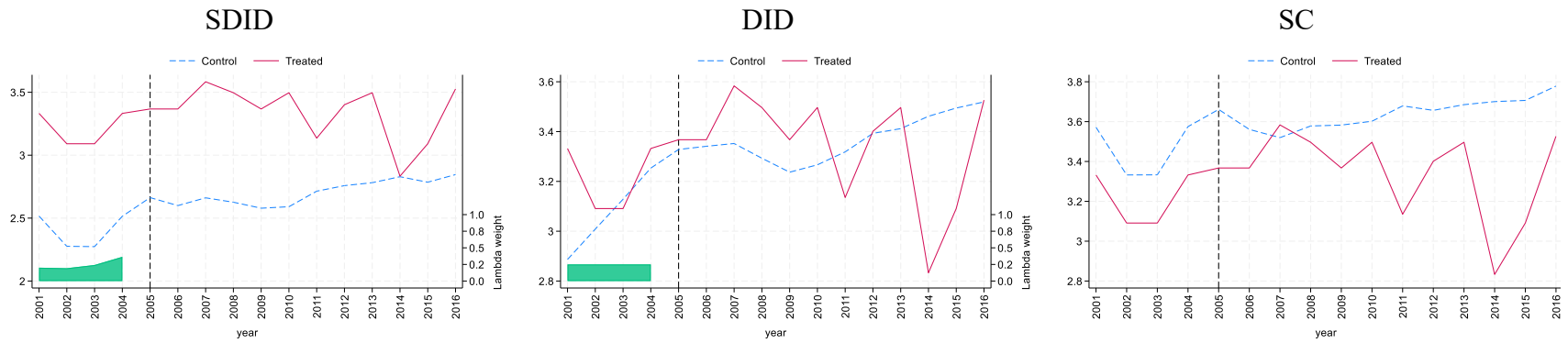
Panel A: Enactment year 2003



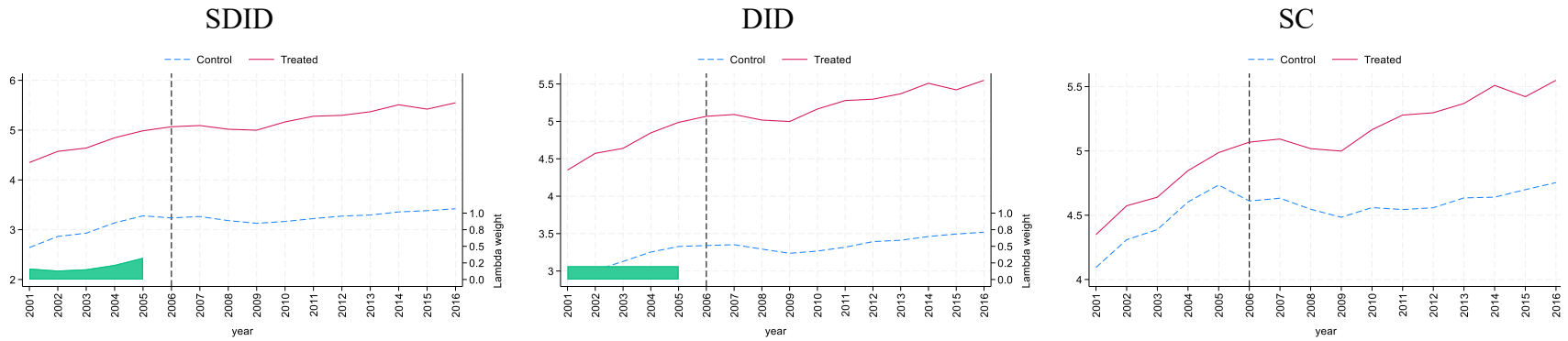
Panel B: Enactment year 2004



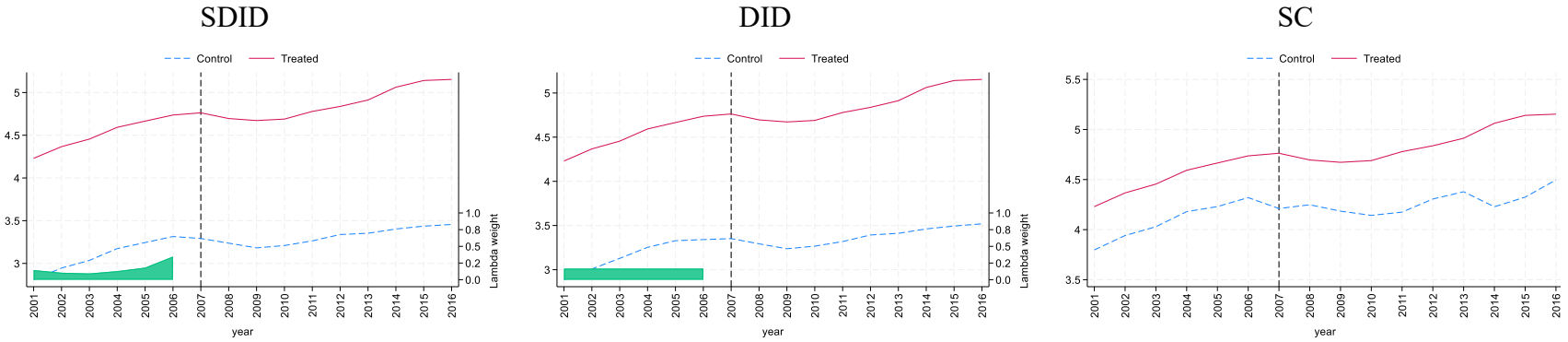
Panel C: Enactment year 2005



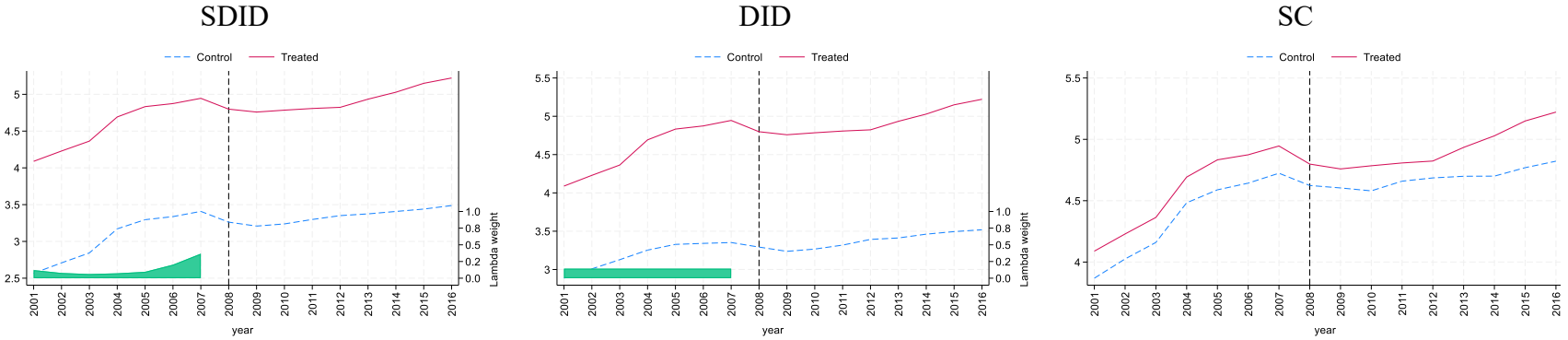
Panel D: Enactment year 2006



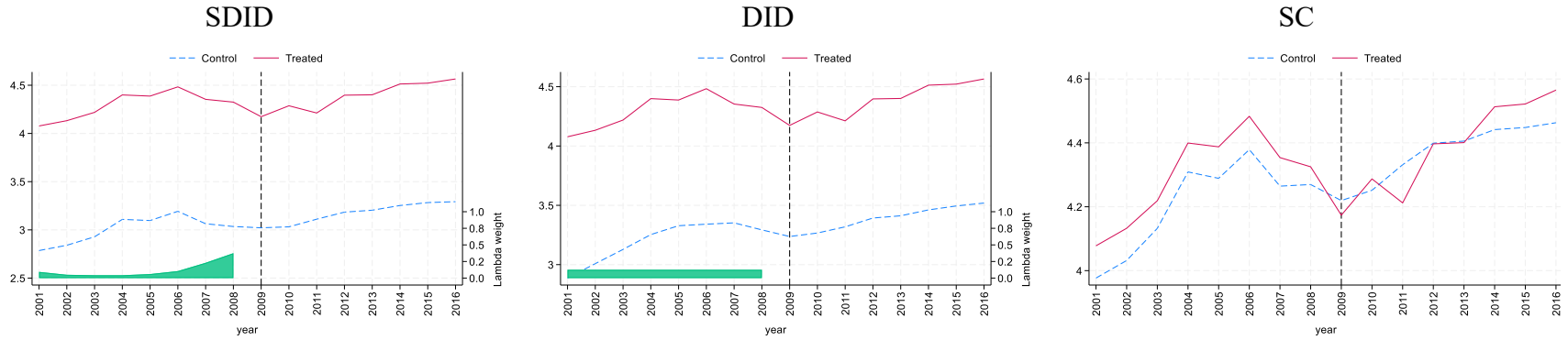
Panel E: Enactment year 2007



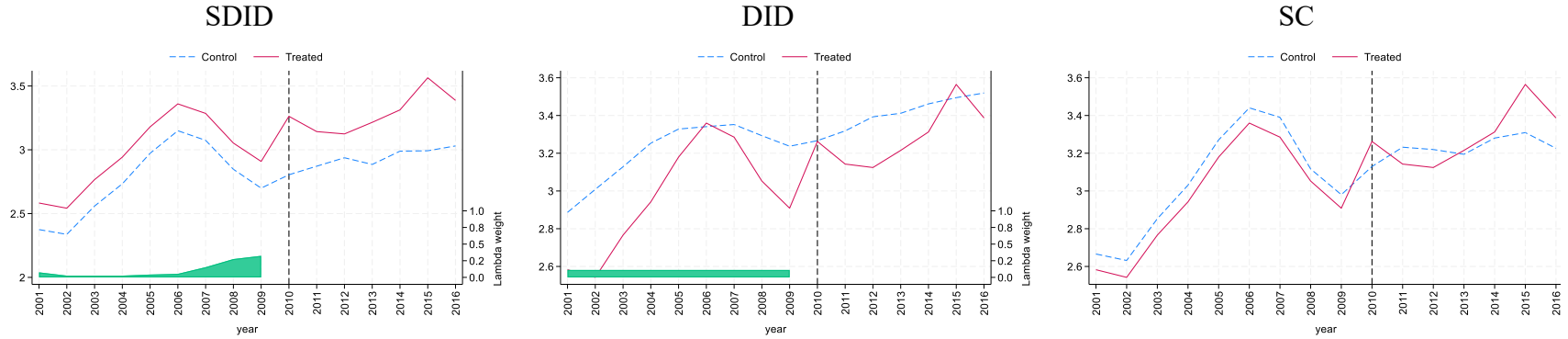
Panel F: Enactment year 2008



Panel G: Enactment year 2009

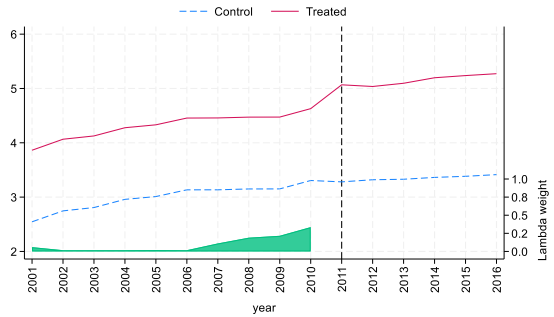


Panel H: Enactment year 2010

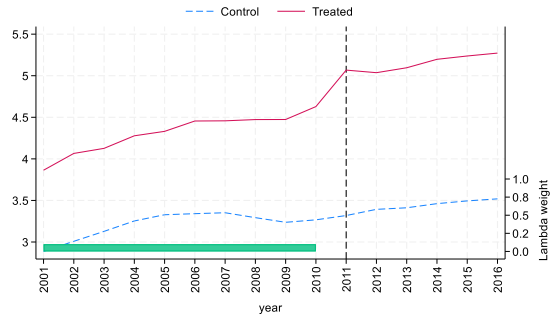


Panel I: Enactment year 2011

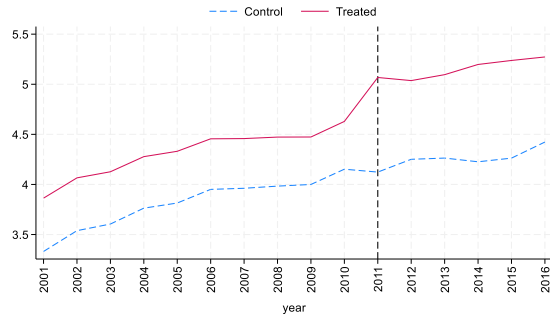
SDID



DID

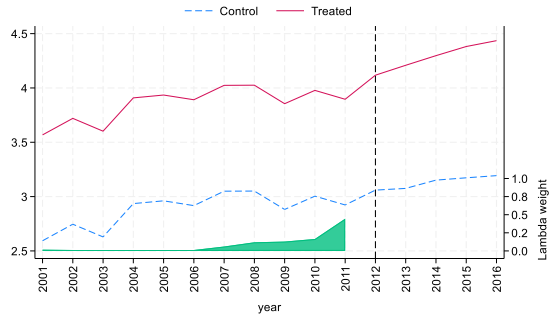


SC

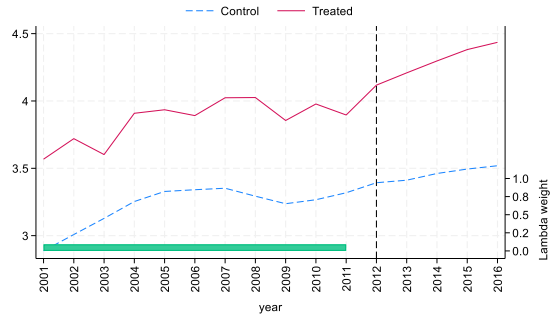


Panel J: Enactment year 2012

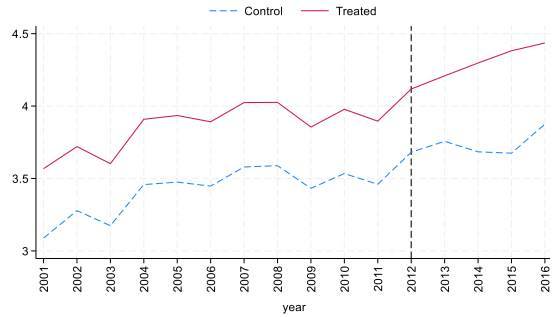
SDID



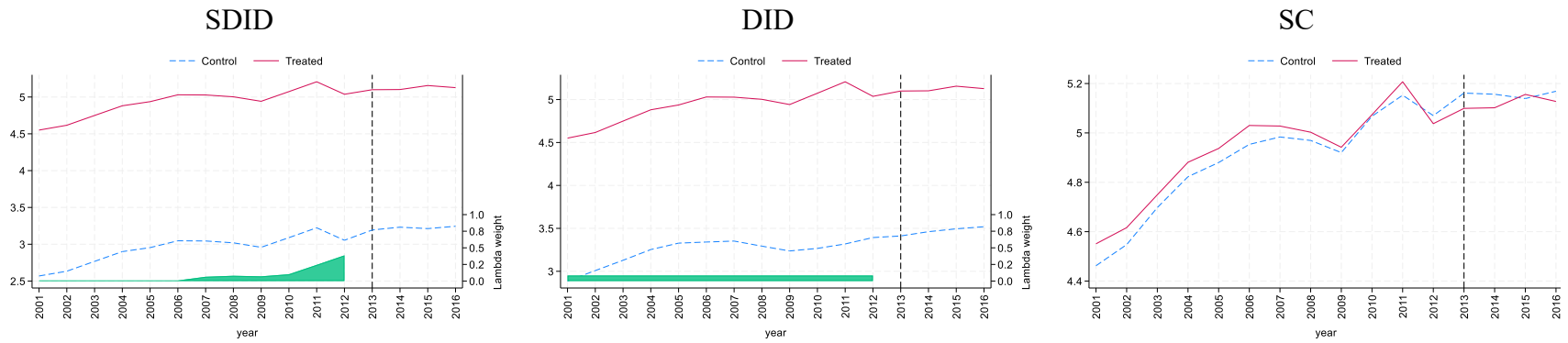
DID



SC



Panel K: Enactment year 2013



Panel L: Enactment year 2014

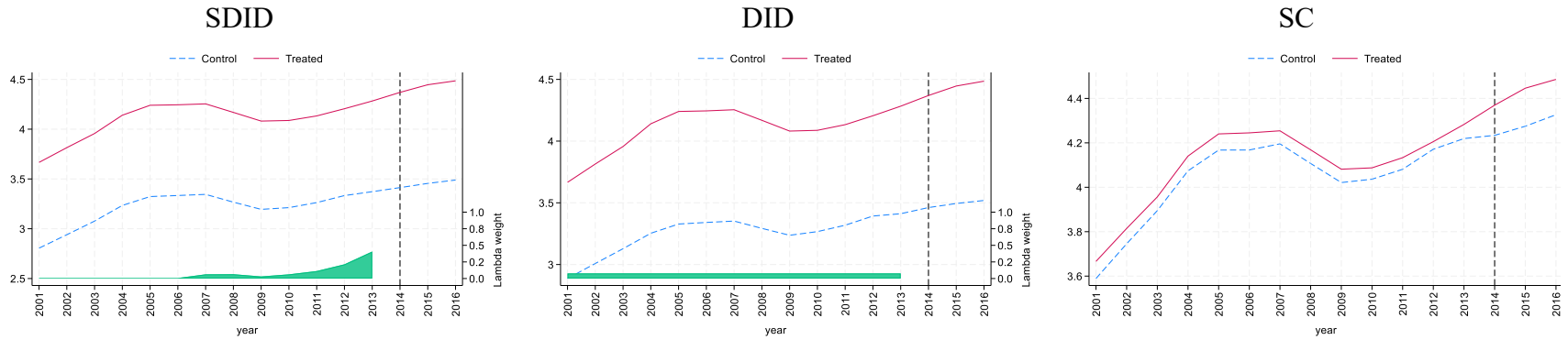
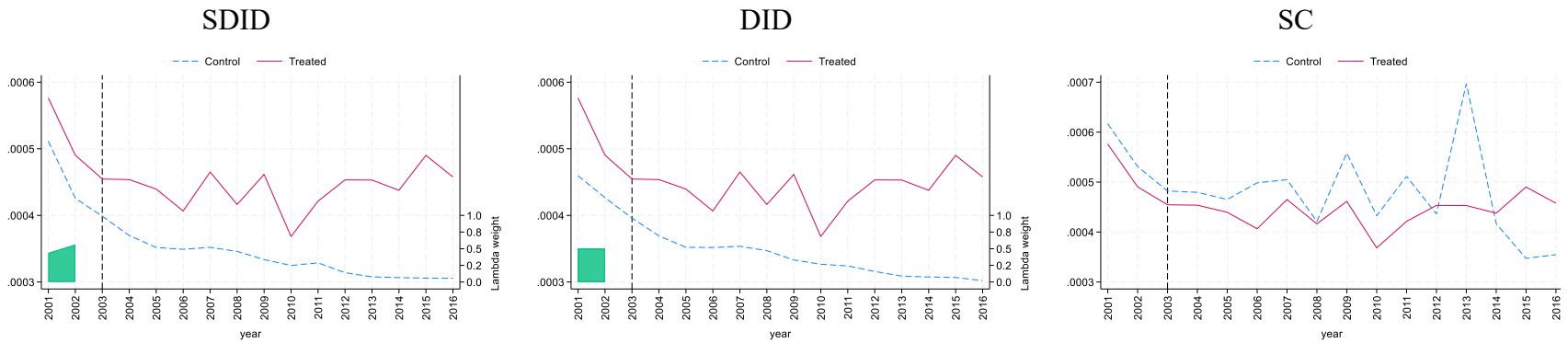


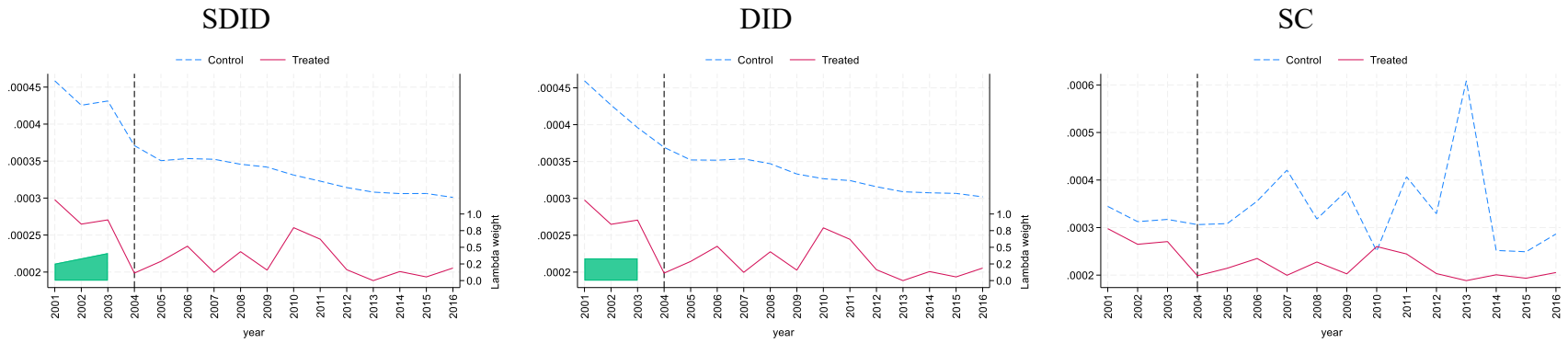
Figure 5: Graphical Analysis of Sanctuary ZIP Code Impact on Entrepreneurship Quality Index

This figure presents visual representations of the impact of a ZIP code's designation as a sanctuary ZIP code on the entrepreneurship quality index, categorized by estimation methodology and sanctuary ZIP code enactment year. Each panel corresponds to a different enactment year and contains three graphs, each representing one of the three estimation methodologies: SDID, DID, and SC. The graphs are based on the estimated models from Table 7.

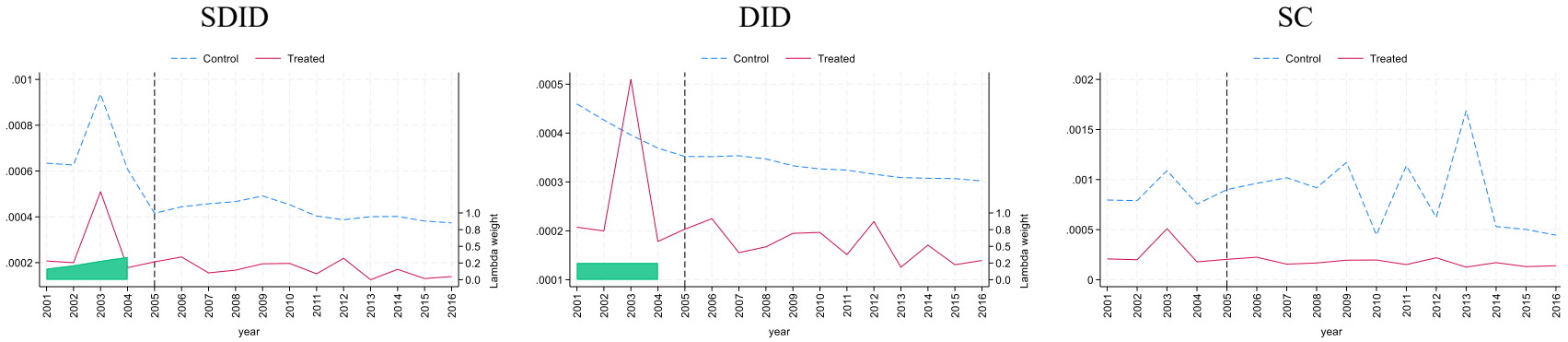
Panel A: Enactment year 2003



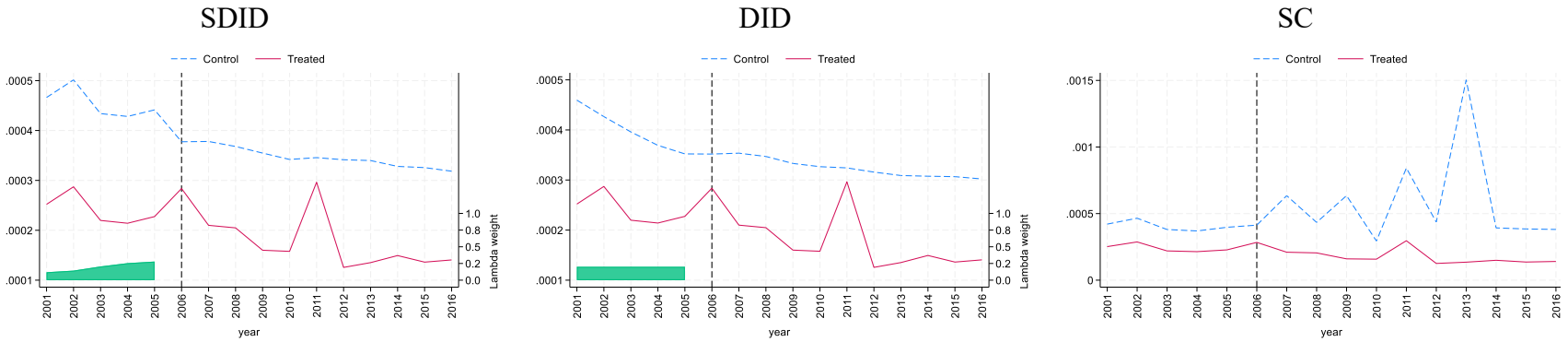
Panel B: Enactment year 2004



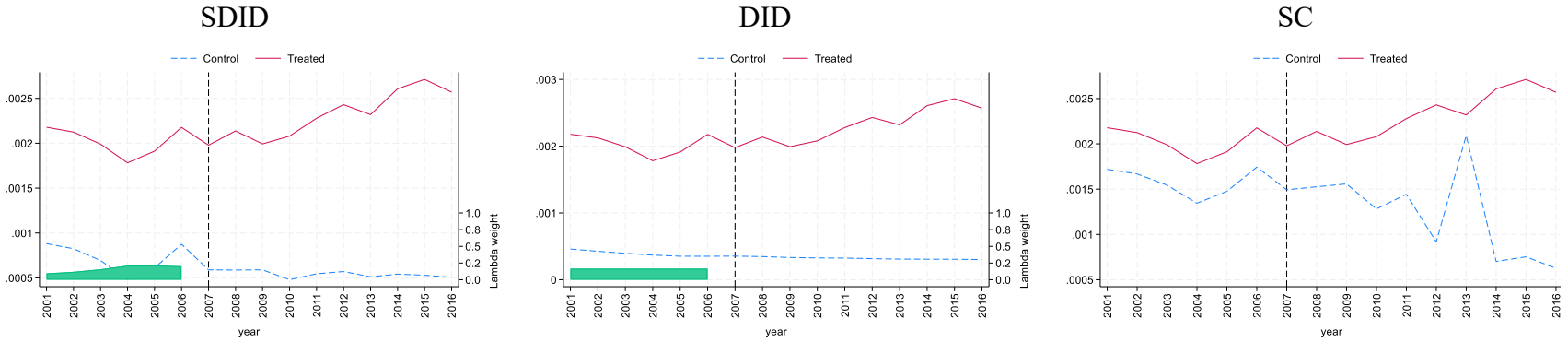
Panel C: Enactment year 2005



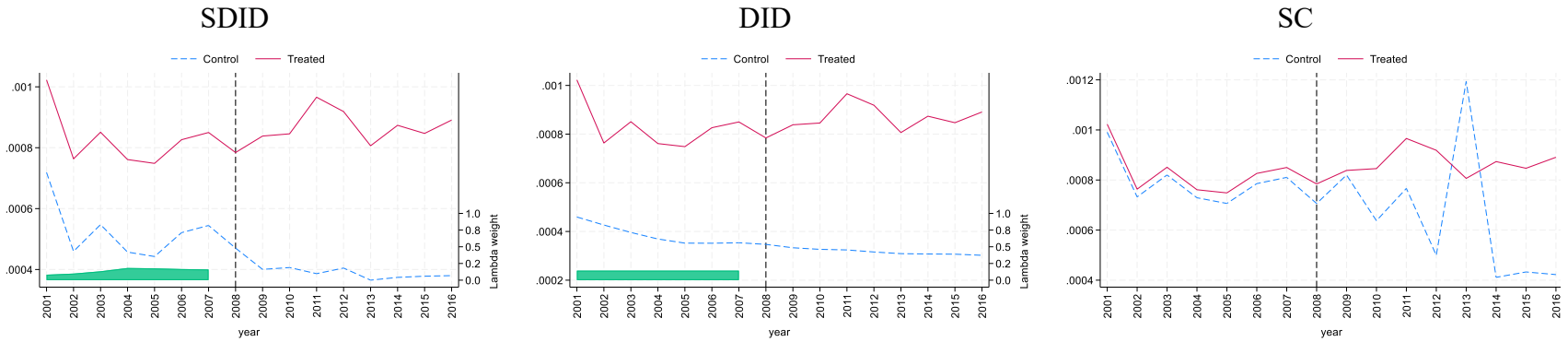
Panel D: Enactment year 2006



Panel E: Enactment year 2007

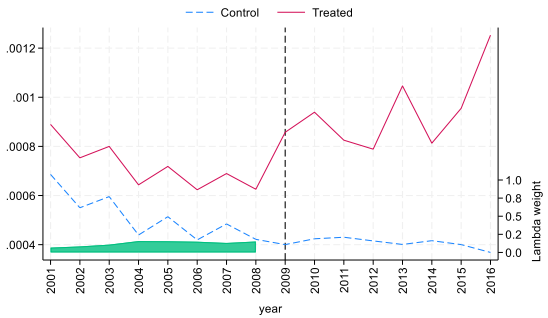


Panel F: Enactment year 2008

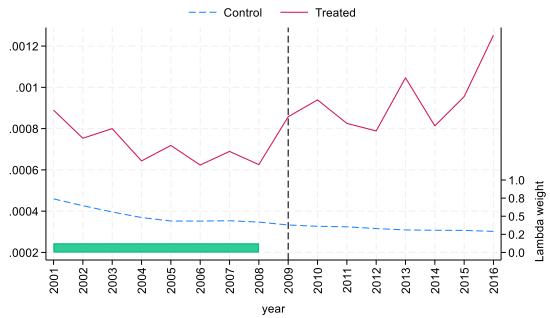


Panel G: Enactment year 2009

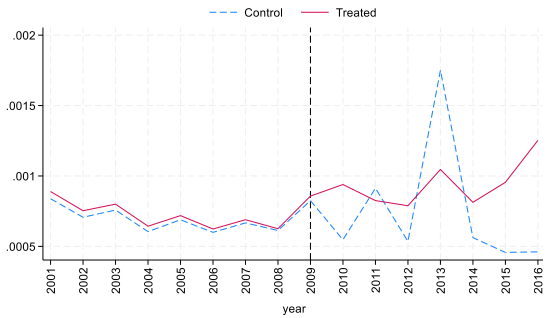
SDID



DID

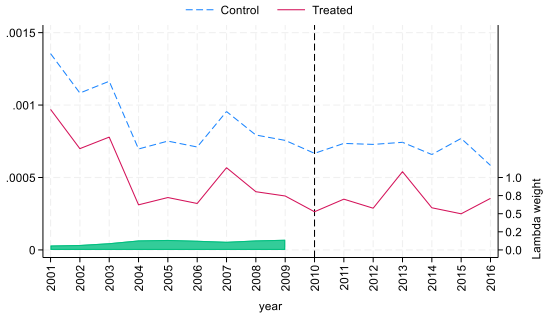


SC

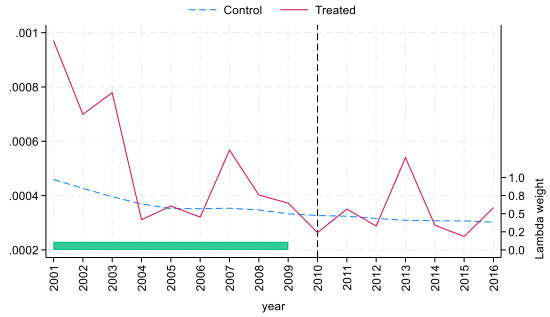


Panel H: Enactment year 2010

SDID



DID

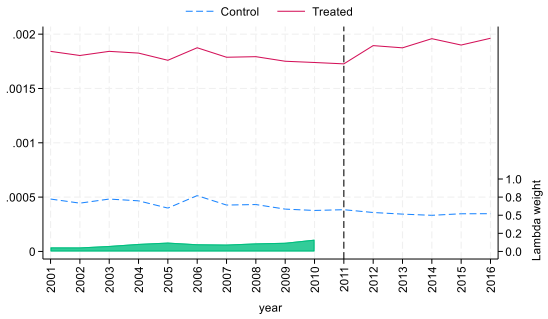


SC

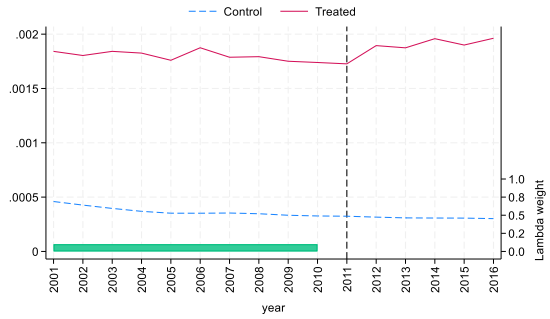


Panel I: Enactment year 2011

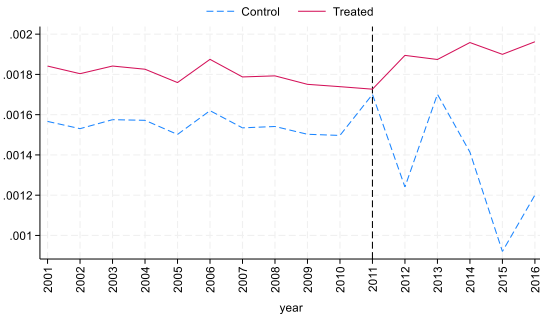
SDID



DID

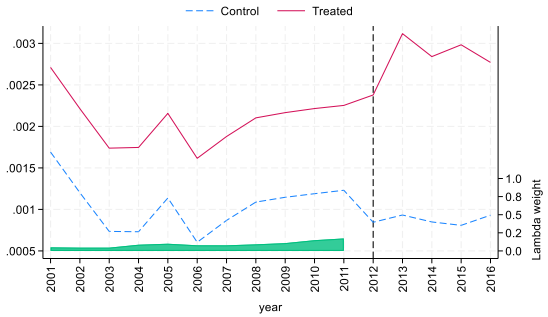


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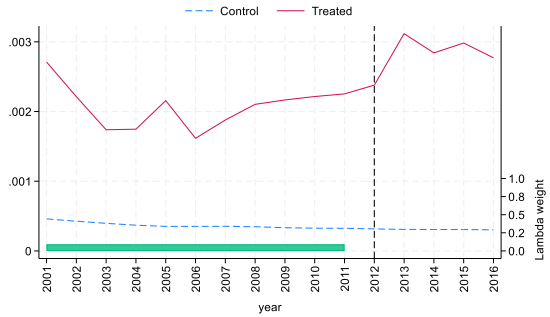


Panel J: Enactment year 2012

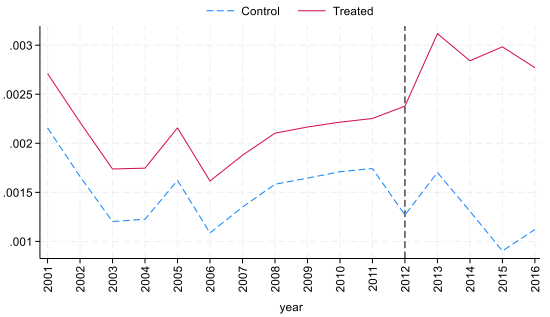
SDID



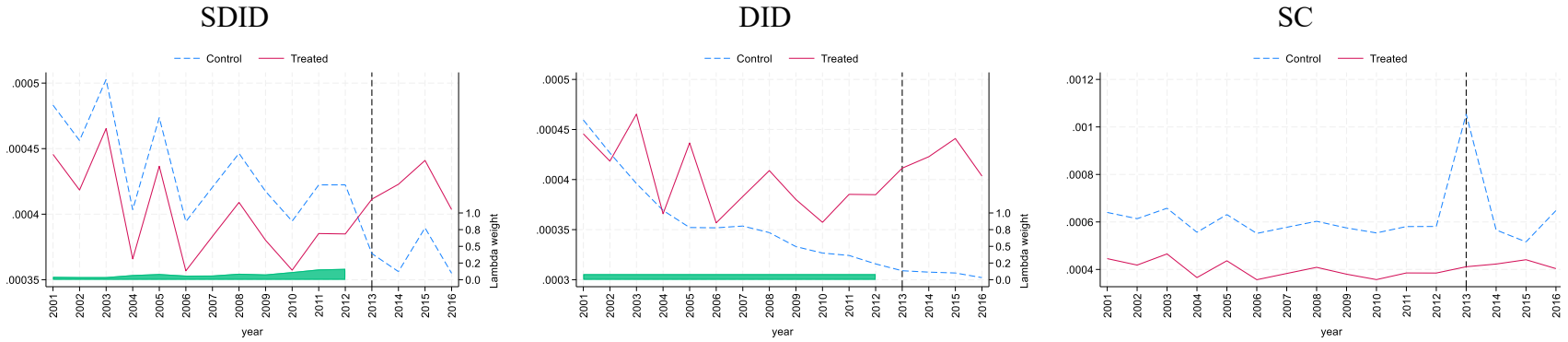
DID



SC



Panel K: Enactment year 2013



Panel L: Enactment year 2014

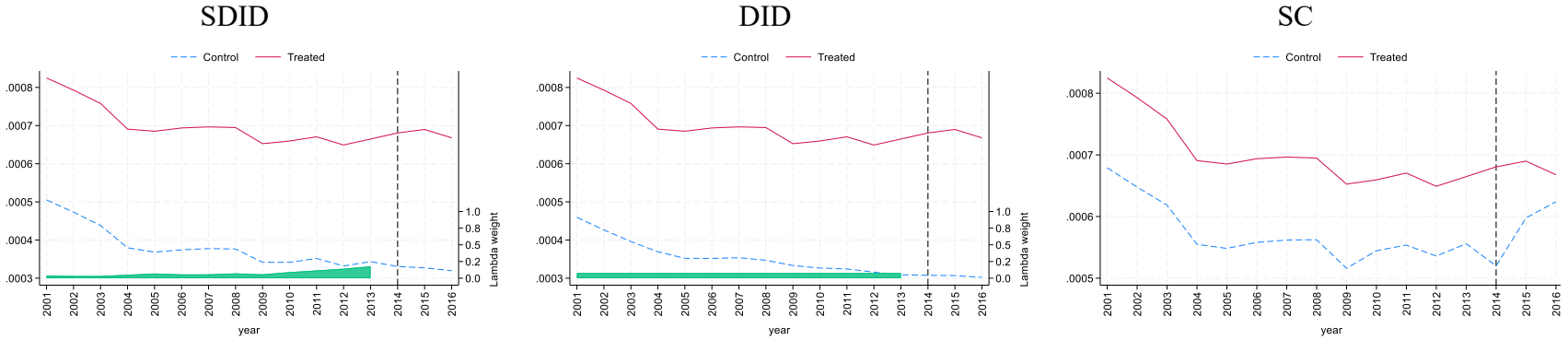
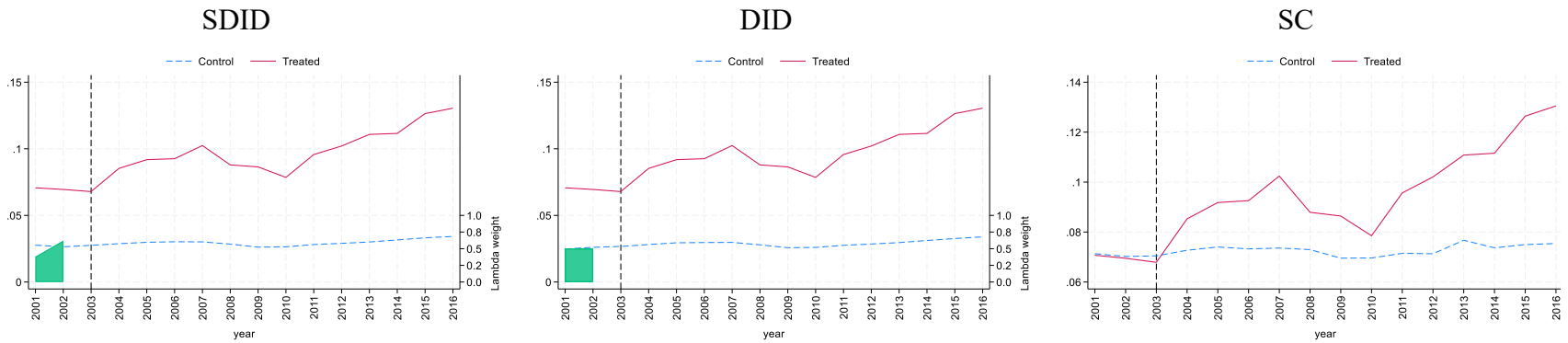


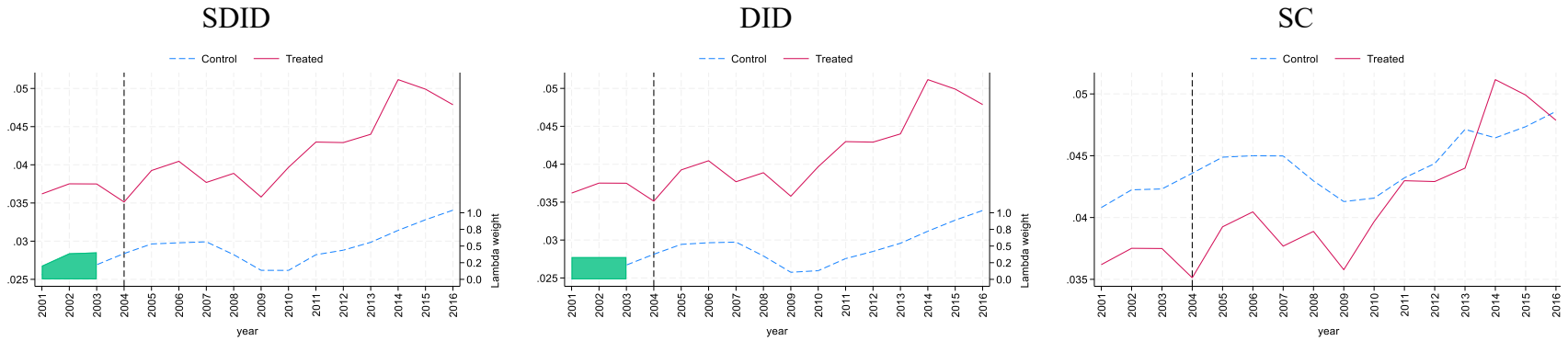
Figure 6: Graphical Analysis of Sanctuary ZIP Code Impact on Regional Entrepreneurship Cohort Potential Index

This figure presents visual representations of the impact of a ZIP code's designation as a sanctuary ZIP code on the regional entrepreneurship cohort potential index, categorized by estimation methodology and sanctuary ZIP code enactment year. Each panel corresponds to a different enactment year and contains three graphs, each representing one of the three estimation methodologies: SDID, DID, and SC. The graphs are based on the estimated models from Table 8.

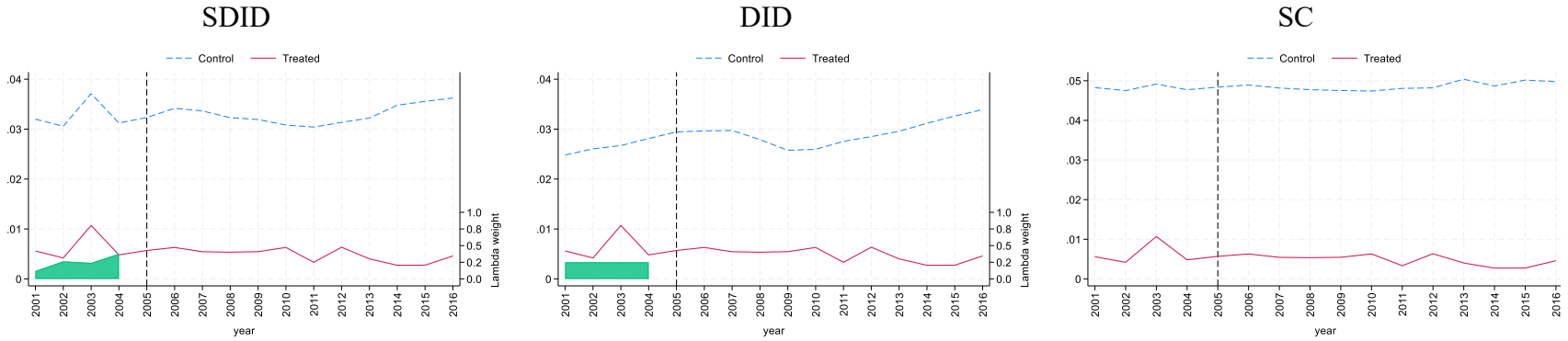
Panel A: Enactment year 2003



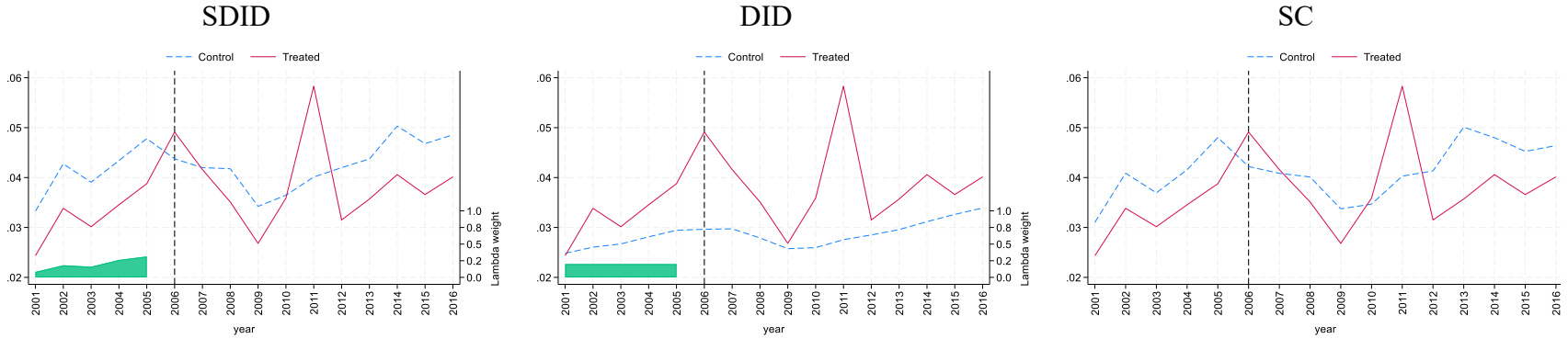
Panel B: Enactment year 2004



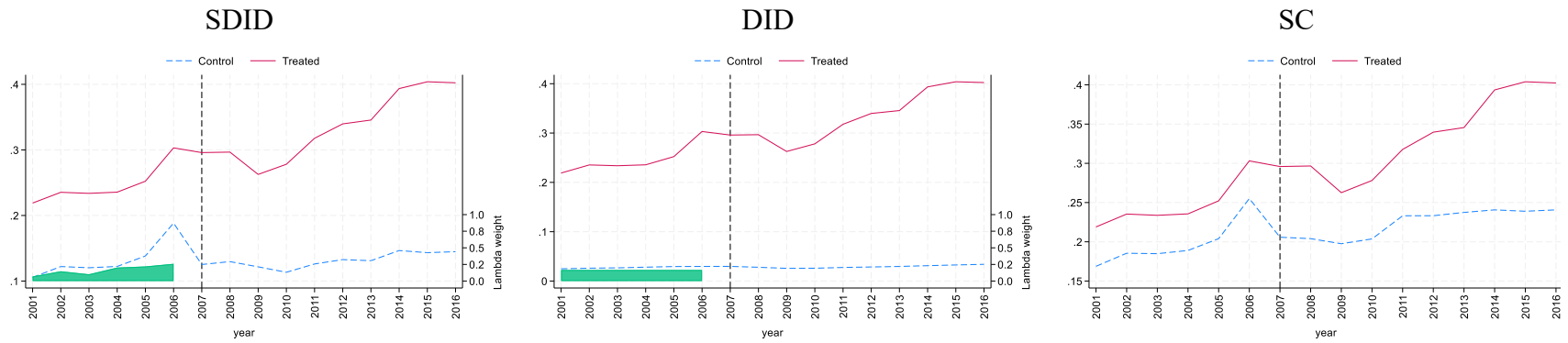
Panel C: Enactment year 2005



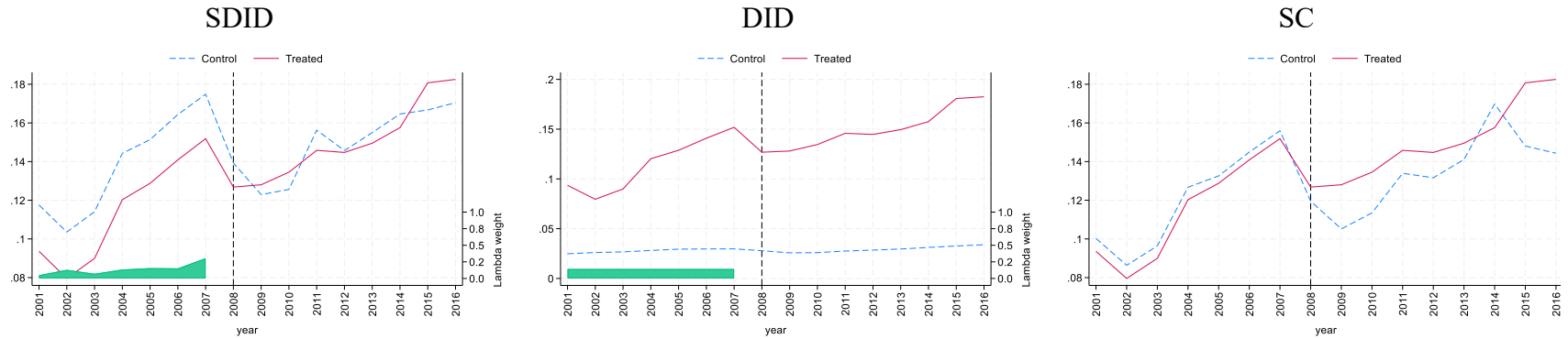
Panel D: Enactment year 2006



Panel E: Enactment year 2007

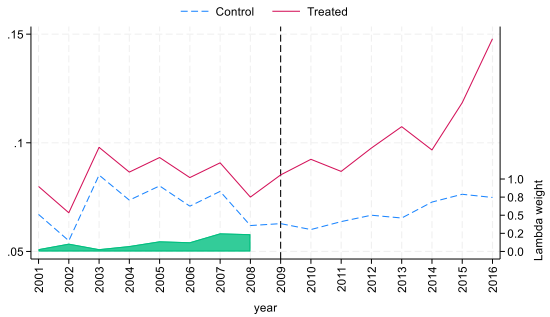


Panel F: Enactment year 2008

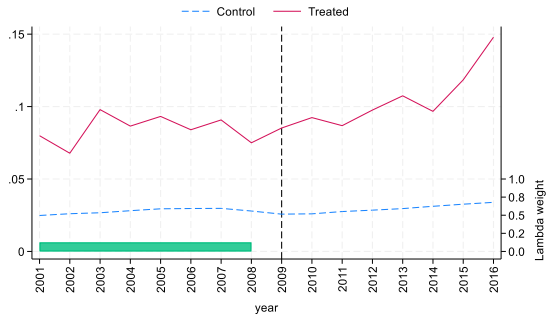


Panel G: Enactment year 2009

SDID



DID

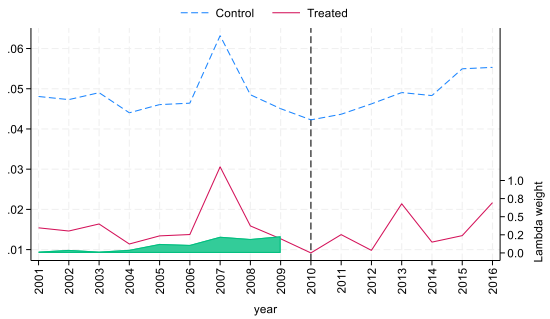


SC

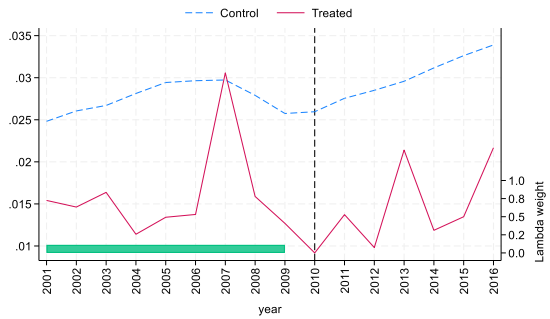


Panel H: Enactment year 2010

SDID



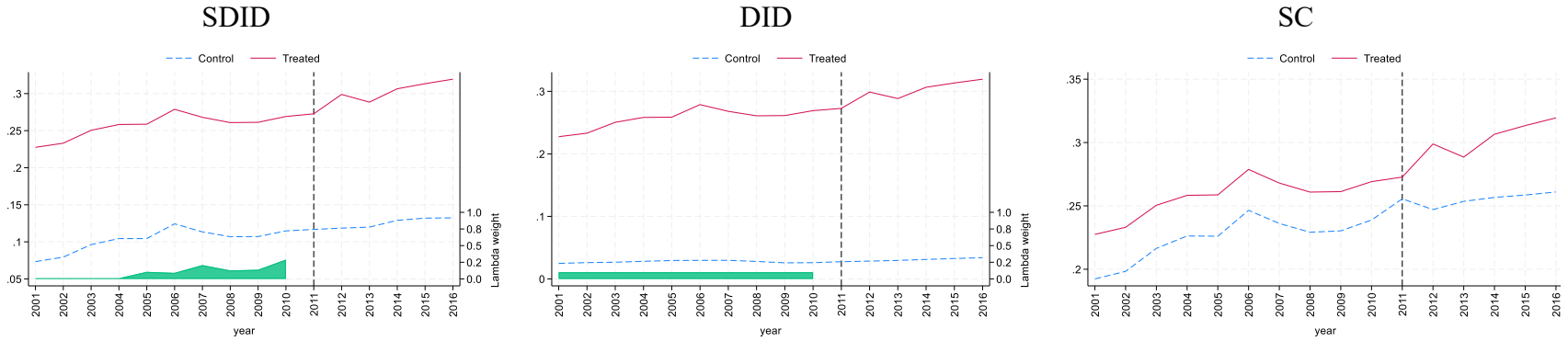
DID



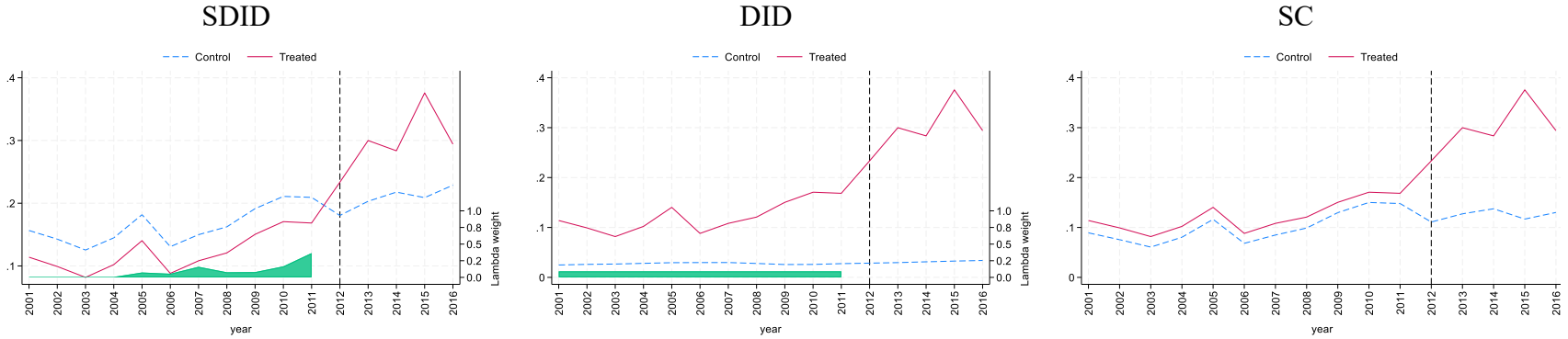
SC



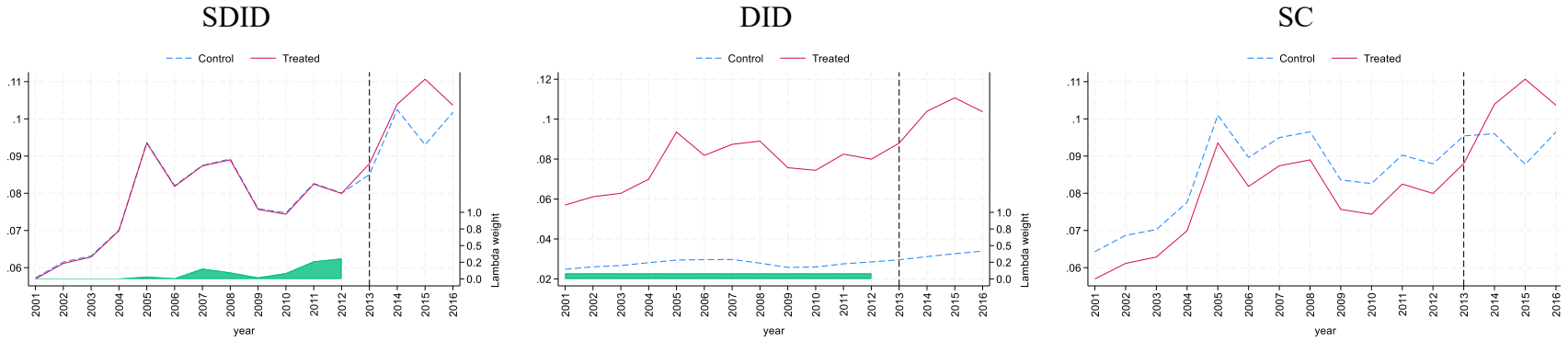
Panel I: Enactment year 2011



Panel J: Enactment year 2012



Panel K: Enactment year 2013



Panel L: Enactment year 2014

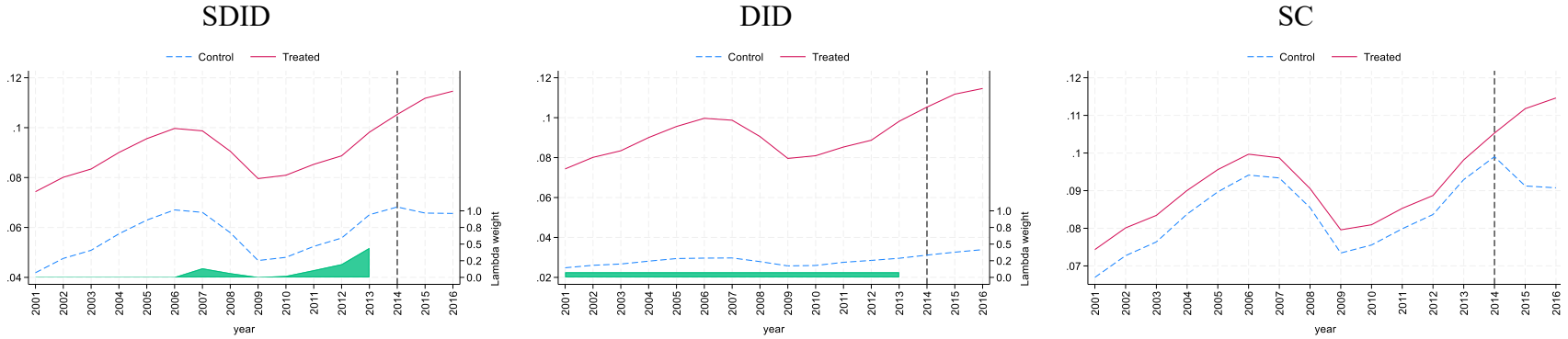


Table 1: Summary Statistics of the Full Sample

This table presents the summary statistics for the full sample. Variable definitions are provided in Appendix A.

Variable	Nobs	Mean	Stdev.	Min	Median	Max
Total business establishments with paid employees	253,441	5.29	1.26	2.56	5.38	7.63
Total employment in businesses with paid employees	253,441	7.71	1.55	4.38	7.83	10.64
Total payroll in businesses with paid employees ($1,000)	253,441	10.44	1.70	6.81	10.53	13.93
Proportion of unauthorized immigrants	253,441	0.05	0.07	0.00	0.02	0.27
Per capita personal income	253,441	9.07	0.29	8.48	9.05	9.89
Unemployment rate	253,441	5.88	2.36	2.30	5.30	12.80
Democratic vote share in the most recent U.S. presidential election	253,441	0.47	0.14	0.16	0.47	0.83

Table 2: Economic Impact of Sanctuary Status on Total Business Establishments with Paid Employees

This Table presents SDID regression results on the effects of ZIP codes becoming sanctuary zones on total business establishments with paid employees by regression estimation methodology. We present the results by using the SDID regression model in column (1). We present the results by using the DID regression model in column (2). We present the results by using the SC regression model in column (3). We present the estimated coefficient and the corresponding t-test statistic of the ATT of becoming sanctuary zip code. The t-test statistic is constructed based on standard errors that are estimated by using 1,000 bootstrap replications. The three estimation models include control variables, year fixed effects, and ZIP code fixed effects. For brevity, we do not report the estimated coefficients and corresponding t-test statistics for these variables. We define the variables in Appendix A of this paper. We use asterisks to denote statistical significance at 1% (***), 5% (**), or 10% (*) level, respectively.

Dependent variable:		Total Business Establishments with Paid Employees		
Estimation model:		SDD	DID	SC
		(1)	(2)	(3)
ATT of becoming sanctuary ZIP code	Coefficient	0.01433***	0.02886***	0.01600**
	t-stat	(6.96)	(7.92)	(2.14)
Control variables		Yes	Yes	Yes
Year FE		Yes	Yes	Yes
ZIP code FE		Yes	Yes	Yes
Number of observations		253,441	253,441	253,441

Table 3: Economic Impact of Sanctuary Status on Total Employment in Businesses with Paid Employees

This table presents SDID regression results on the effects of ZIP codes becoming sanctuary zones on total employment in businesses with paid employees, based on different regression estimation methodologies. Column (1) reports results using the SDID regression model, column (2) presents results from the DID regression model, and column (3) provides results from the SC regression model. We present the estimated coefficient and the corresponding t-test statistic of the ATT of becoming sanctuary zip code. The t-test statistic is constructed using standard errors estimated from 1,000 bootstrap replications. All three estimation models include control variables, year fixed effects, and ZIP code fixed effects. For brevity, we do not report the estimated coefficients or t-test statistics for these variables. Variable definitions are provided in Appendix A. Asterisks denote statistical significance at the 1% (******), 5% (**), and 10% (**) levels.

Dependent variable:		Total Employment in Businesses with Paid Employees		
Estimation model:		SDD	DID	SC
		(1)	(2)	(3)
ATT of becoming sanctuary ZIP code	Coefficient	0.01864***	0.01892***	0.04209***
	t-stat	(5.68)	(3.89)	(2.88)
Control variables		Yes	Yes	Yes
Year FE		Yes	Yes	Yes
ZIP code FE		Yes	Yes	Yes
Number of observations		253,441	253,441	253,441

Table 4: Economic Impact of Sanctuary Status on Total Payroll in Businesses with Paid Employees

This table presents SDID regression results on the effects of ZIP codes attaining sanctuary status on total payroll in businesses with paid employees, based on different regression estimation methodologies. Column (1) reports results from the SDID regression model, column (2) presents results from the DID regression model, and column (3) provides results from the SC regression model. We present the estimated coefficient and the corresponding t-test statistic of the ATT of becoming sanctuary zip code. The t-test statistic is computed using standard errors derived from 1,000 bootstrap replications. All three estimation models incorporate control variables, year fixed effects, and ZIP code fixed effects. For brevity, we do not report the estimated coefficients or t-test statistics for these controls. Variable definitions are provided in Appendix A. Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Dependent variable:		Total payroll in businesses with paid employees		
Estimation model:		SDD	DID	SC
		(1)	(2)	(3)
ATT of becoming sanctuary ZIP code	Coefficient	0.01752***	0.01311**	0.05254**
	t-stat	(4.28)	(2.32)	(2.38)
Control variables		Yes	Ye	Yes
Year FE		Yes	Yes	Yes
ZIP code FE		Yes	Yes	Yes
Number of observations		253,441	253,441	253,441

Table 5: Summary Statistics of the subsample of attributes of entrepreneurship

This table presents the summary statistics for the full sample. Variable definitions are provided in Appendix A.

Variable	Nobs	Mean	Stdev.	Min	Median	Max
Startup formation rate	225,856	3.4161	1.4317	0.6931	3.2958	6.5695
Entrepreneurship quality index	225,856	0.0004	0.0005	0.0001	0.0002	0.0037
Regional entrepreneurship cohort potential index	225,856	0.0379	0.0883	0.0001	0.0068	0.5987

Table 6: Economic Impact of Sanctuary Status on Startup Formation Rate

This table presents SDID regression results on the effects of ZIP codes attaining sanctuary status on startup formation rate, based on different regression estimation methodologies. Column (1) reports results from the SDID regression model, column (2) presents results from the DID regression model, and column (3) provides results from the SC regression model. We present the estimated coefficient and the corresponding t-test statistic of the ATT of becoming sanctuary zip code. The t-test statistic is computed using standard errors derived from 1,000 bootstrap replications. All three estimation models incorporate control variables, year fixed effects, and ZIP code fixed effects. For brevity, we do not report the estimated coefficients or t-test statistics for these controls. Variable definitions are provided in Appendix A. Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Dependent variable:		Startup formation rate		
Estimation model:		SDD	DID	SC
		(1)	(2)	(3)
ATT of becoming sanctuary ZIP code	Coefficient	0.10175***	0.11631***	0.17301***
	t-stat	(12.10)	(13.21)	(7.58)
Control variables		Yes	Yes	Yes
Year FE		Yes	Yes	Yes
ZIP code FE		Yes	Yes	Yes
Number of observations		225,856	225,856	225,856

Table 7: Economic Impact of Sanctuary Status on Entrepreneurship Quality Index

This table presents SDID regression results on the effects of ZIP codes attaining sanctuary status on entrepreneurship quality index, based on different regression estimation methodologies. Column (1) reports results from the SDID regression model, column (2) presents results from the DID regression model, and column (3) provides results from the SC regression model. We present the estimated coefficient and the corresponding t-test statistic of the ATT of becoming sanctuary zip code. The t-test statistic is computed using standard errors derived from 1,000 bootstrap replications. All three estimation models incorporate control variables, year fixed effects, and ZIP code fixed effects. For brevity, we do not report the estimated coefficients or t-test statistics for these controls. Variable definitions are provided in Appendix A. Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Dependent variable:		Entrepreneurship quality index		
Estimation model:		SDD	DID	SC
		(1)	(2)	(3)
ATT of becoming sanctuary ZIP code	Coefficient	0.00009***	0.00007***	0.00006***
	t-stat	(7.07)	(6.55)	(2.63)
Control variables		Yes	Yes	Yes
Year FE		Yes	Yes	Yes
ZIP code FE		Yes	Yes	Yes
Number of observations		225,856	225,856	225,856

Table 8: Economic Impact of Sanctuary Status on Regional Entrepreneurship Cohort Potential Index

This table presents SDID regression results on the effects of ZIP codes attaining sanctuary status on regional entrepreneurship cohard potential index, based on different regression estimation methodologies. Column (1) reports results from the SDID regression model, column (2) presents results from the DID regression model, and column (3) provides results from the SC regression model. We present the estimated coefficient and the corresponding t-test statistic of the ATT of becoming sanctuary zip code. The t-test statistic is computed using standard errors derived from 1,000 bootstrap replications. All three estimation models incorporate control variables, year fixed effects, and ZIP code fixed effects. For brevity, we do not report the estimated coefficients or t-test statistics for these controls. Variable definitions are provided in Appendix A. Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Dependent variable:		Regional entrepreneurship cohard potential index		
Estimation model:		SDD	DID	SC
		(1)	(2)	(3)
ATT of becoming sanctuary ZIP code	Coefficient	0.01984***	0.02328***	0.01821***
	t-stat	(8.39)	(13.30)	(4.44)
Control variables		Yes	Yes	Yes
Year FE		Yes	Yes	Yes
ZIP code FE		Yes	Yes	Yes
Number of observations		225,856	225,856	225,856