The Role of Access to Community Bank Capital in Place-Based Policies

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Abstract

To assist policymakers and economic developers in measuring the effectiveness of using firm-specific incentives to attract large manufacturing investments and catalyze broader economic development, I study the role of access to community bank capital in catalyzing spillovers from large manufacturing plants to small business development. I construct a novel dataset of large manufacturing plant openings between 2010 and 2018 and estimate the impact of these openings on small business lending, creation, and expansion in the local economy, using difference-in-differences designs with multiple control groups. The results suggest that community banks drive post-opening increases in small business lending, which translates to higher growth rates in small business creation and expansion. Small businesses in complementary industries experience the largest growth, while small businesses that may compete for labor and other resources do not. Designing and calibrating a spatial equilibrium model, I find that in counties with high access to local community bank branches, as much as 25% of the growth in small business establishments is attributable to the presence of community banks.These findings will inform policymakers evaluating which places will benefit from place-based policies and financial regulators monitoring the consolidation of the banking industry.

1 Introduction

Policymakers at the local, state, and federal levels rely heavily on place-based policies to incentivize development in targeted communities. For example, the 50 U.S. states appropriated over \$82 billion for firm-specific subsidies between 2002 and 2017 (Slattery and Zidar, 2020) and federal lawmakers have provided over \$50 billion in tax credits and incentives through the CHIPS Act and the Inflation Reduction Acts since 2022. Past research has studied the impact of large manufacturing investments on local economies, focusing both on direct employment gains and indirect spillovers to firms and workers in the region, finding that million-dollar plants ("MDPs") generate modest direct employment gains and small spillover effects to the local economy.[1] While the average MDP generates spillovers to the local economy, substantial heterogeneities are found with spillover effects ranging from significantly negative to positive (Monte et al., 2018; Greenstone et al., 2010). Despite evidence that incentivizing MDPs has failed to generate substantial spillovers for many communities, few papers have investigated the underlying mechanisms that drive successful place-based policies and subsequent economic growth, which is essential to inform economic developers and policymakers on whether their locality would benefit from such policies.

This paper investigates one mechanism through which communities can capture spillover effects from place-based policies: access to financial capital from local banks. Specifically, I evaluate the role of local lending to small businesses in promoting small business creation and expansion after MDP openings. Access to financial capital is acutely important for small businesses, with over one third of small businesses applying for a loan or cash advance and almost three quarters holding outstanding debt during 2023 (Federal Reserve Banks, 2024). Small businesses are particularly sensitive to the presence of local lenders, where existing relationships with loan officers can offset the inherent challenges with signaling creditworthiness for entrepreneurs lacking audited financial statements and other hard information (Ranish et al., 2025; Nguyen, 2019). Given the importance of relationship lending for small businesses, local community banks leverage competitive advantages to compete in the small business loan market. While institutional and regulatory constraints disincentivize large banks from engaging in small business lending, community banks leverage competitive advantages from flatter loan approval processes and soft information collection to provide higher acceptance rates and higher partial approval rates for small businesses (Berger and Udell, 1995, 2006; Federal Reserve Banks, 2024).

Spillovers from large firm investments to small businesses remain understudied in the literature, with most

[1]The opening of MDPs are found to increase county-level employment by between 0% - 7.6%, generate 2-3% county-level wage growth, increase county-level manufacturing productivity by 0-9%, and increase incumbent firm productivity by 3 - 13% driven by spillovers to incumbents within the same industry as the MDP (Greenstone et al., 2010; Patrick, 2016; Patrick and Partridge, 2022; Bloom et al., 2019; Slattery and Zidar, 2020; Kim, 2020; Monte et al., 2018).

papers focusing on employment and productivity spillovers to incumbent manufacturing firms. Small business creation and expansion are primary drivers of regional growth and entrepreneurship, and the spillover effects from MDPs to small businesses are motivated by numerous channels. These channels include income effects as higher wages and salaries increase demand for trade and consumer services provided by small businesses, supply-side effects increasing the demand for local suppliers, and knowledge spillovers that lead to entrepreneurial spawning (Neumark et al., 2011; Haltiwanger et al., 2013; Gompers et al., 2005). Therefore, the formation and expansion of small businesses may contribute meaningfully to the generation of economic development and growth after MDP openings.

A possible constraint to studying the local bank mechanism and subsequent small business development after large MDP openings is the plausibly endogenous sorting of MDPs into communities with higher entrepreneurship, which may also be correlated to the presence of community banks and small businesses. Further, community banks may sort into markets by opening branches based on the same underlying characteristics as the MDPs. To address the endogeneity, I outline three identification strategies. First, I leverage the "runner-up" counterfactual approach outlined by (Greenstone et al., 2010) to construct counterfactuals for counties with MDPs using counties that were considered, but not selected, for investments. I augment this approach by including counties where firms announced and planned openings. but ultimately cancelled the investments due to exogenous factors. Second, I construct a counterfactual using a matching procedure which matches counties with MDP openings to similar counties without openings based on a variety of demographic, economic, and financial characteristics. Third, I implement a synthetic control approach following Arkhangelsky et al. (2021) to construct a synthetic control for counties with MDP openings. To further address endogeneity, I prepare an exogenous measure of predicted access to community bank credit to validate the empirical results and provide descriptive statistics on bank entry and exit patterns in counties with MDP openings that reveal minimal selection into or out of treated or control counties.

I start by examining the lender response to MDP openings, evaluating the change in small business lending activity within the county. I find that community banks increase the number of annual small business loan originations by between 16-26% over the following 5 years after an MDP opening, while non-community banks exhibit minimal changes in lending patterns. These findings support the hypothesis that community banks are more responsive to demand shocks from MDP openings and function as a conduit for small business development during periods of positive economic shocks.

After establishing the underlying mechanism, I evaluate the role of access to local community bank credit in promoting small business development after MDP openings. I subset the MDP counties based on access to community bank credit and find that counties with higher access to capital experience statistically significant increases in small business establishments and employment, while lower-access counties do not. Establishment count and employment at new small businesses exhibit minimal statistically significant increases in the invested counties, suggesting that most of the small business growth is driven by expansions, rather than startups.

The project offers three contributions to the literature. First, it builds upon recent works studying the effectiveness of place-based policy in the U.S. that incentivize investment by large manufacturers in targeted communities (Patrick and Partridge, 2022; Slattery and Zidar, 2020; Greenstone et al., 2010; Kim, 2020; Monte et al., 2018) by constructing a refreshed dataset, relying on MDP investments between 2010 – 2018. Second, after validating the results from previous papers studying employment and productivity spillovers, I evaluate a new outcome of MDP openings: small business creation and expansion, with careful consideration of the plausibly endogenous relationship between entrepreneurship and bank/plant location choices. Third, it contributes to the literature on the role of financial intermediation in supporting small business development by studying the role of community banks in promoting small business development during periods of demand shocks (Neumark et al., 2011; Neumark and Simpson, 2015; Rupasingha and Wang, 2017).

The paper has important policy implications for economic developers and financial regulators. For economic developers, the analysis highlights the role of community banks in maximizing the benefits of MDP openings, where communities with fewer community banks may need additional financial support to sponsor small business development. For financial regulators, the paper raises awareness of the impact of accelerating bank consolidation and community bank branch closures on local economies.

2 Institutional Information

2.1 Small Business, Debt Financing, and Community Banks

Small businesses rely on a variety of approaches to finance operations, including using cash reserves or owner personal funds, requesting informal loans from friends and family, applying for business or personal loans from financial institutions, or adjusting operations by raising prices or downsizing operations (Federal Reserve Banks, 2025). The source of financing is impacted by factors such as a small businesses' credit score or industry, whether the firm is responding to specific financial challenges, and the demography of the owner(s).[2] Consistent across most small businesses is the use of external financing, with over 50 percent of small businesses using either credit cards or loans on a regular basis and 71 percent of small businesses

[2]Small businesses owned by individuals identifying as Asian, employing less than 50 people, operating in the leisure and hospitality industry, and operating with medium to high credit risk were more likely to use funds from the owner or family and friends, while businesses owned by individuals of Black race or less than 35 years of age, employing less than 5 people, or operating in the finance and insurance or professional services and real estate industries were less likely to have outstanding debt. When faced with financial challenges, such as increased costs or weak sales, small businesses are more likely to lean on personal funds and cash reserves. Source: Federal Reserve Banks (2025).

having outstanding debt on their balance sheets — a statistic that has remained unchanged since 2016 (Federal Reserve Banks, 2025).

Within the competitive small business loan ("SBL") market, banks have maintained strong market share, with over 80 percent of small businesses using banks as their primary financial services provider (Federal Reserve Banks, 2025). In contrast to lending to larger firms, small business lending has long been associated with relationship banking, where a lack of audited financial statements and other "hard information" available for lenders to evaluate the creditworthiness of small businesses increases the value of "soft information" which is predominantly acquired through direct communication between applicant and loan officer (Berger and Udell, 1995; Boot and Thakor, 2000). This contributes significantly to the bank SBL market share, with almost two-thirds of small business owners citing existing relationships with a lender as the top reason for applying for SBLs at banks rather than online lenders or finance companies (Federal Reserve Banks, 2025).

Large banks face institutional and regulatory constraints, such as more layered loan review and approval processes and more rigorous regulatory examinations, that limit capacity to rely on relationship banking and soft information, which provides a competitive advantage in using soft information during the loan review process to community banks (Berger and Udell, 1995; Berger and Black, 2011).[3] This is particularly evident in the loan review process, where 89 percent of decision makers at community banks meet with the applicant at some stage of the loan review process, compared to only 39 percent for large banks, providing opportunities for direct transmission of soft information (Federal Deposit Insurance Corporation, 2024).

As such, community banks maintain significantly higher shares of SBLs in their loan portfolios and focus more heavily on larger working capital and commercial real estate loans compared to large banks, which often specialize in smaller loans or credit cards (Federal Deposit Insurance Corporation, 2018, 2024; Adams et al., 2023). Despite only representing around 12 percent of the banking industry by asset share, similar shares of small business owners applied for SBLs at community and noncommunity banks in 2016 and reported higher acceptance rates, partial approvals, and lender satisfaction rates at community banks (Jacewitz, 2022; Federal Reserve Banks, 2017). While the share of small businesses that applied to and relied primarily on community banks as a financial services provider decreased by 2025, the community bank market share for large ($> \$100,000$) SBLs remained constant (Federal Reserve Banks, 2025; Adams et al., 2023). Overall, community banks represent significant participants in the SBL market and have the flexibility and soft information gathering advantages to respond quickly to demand shocks in a local community.

[3] Even as banks adopt financial technology ("FinTech") platforms to expedite the loan application, review, and approval processes for a variety of products and shifts competitive advantages to larger lenders, the diffusion of FinTech to small business lending has remained limited, with less than 10 percent of banks using automation to receive, process, or approve SBL applications. Source: Federal Deposit Insurance Corporation (2024).

3 Data

3.1 MDP Openings

Previous authors have followed the data collection approach outlined by Greenstone et al. (2010) and leveraged the "Million Dollar Plant" features from issues of the *Site Selection* magazine to identify the MDP investments (Patrick, 2016; Monte et al., 2018; Bloom et al., 2019; Kim, 2020). *Site Selection* published the feature intermittantly from 1982 through 1993, providing information on large investments and the final site locations considered before the final investment was made. While most of the literature relies on the original MDP list curated by Greenstone et al. (2010) covering openings from 1980 - 1995, two recent papers expand the dataset to include years as recent as 2015 (Bloom et al., 2019; Rahul and Rodriguez, 2025) using *Site Selection* and *Southern Business & Development*'s intermittant reporting on "top deals", as well as structured internet searches. Further, Slattery (2025) prepares a list of proposed million dollar plants that received subsidies from 2002 - 2017. While the identification of announced large plant openings and, at least in the case of (Greenstone et al., 2010) and Rahul and Rodriguez (2025), the confirmation of completed construction and opening of the plants is valuable, without verifying that the MDP investments created the anticipated number of jobs, subsequent estimations are restricted to intent to treat (ITT), rather than treatment effect (ATT). Further, identification of MDP investments is limited to what is reported by the *Site Selection* magazine, which may be representative of the largest deals each year but not fully comprehensive of all openings. This may be particularly true for more recent years, where the magazine has not consistently reported on MDP openings. This may also introduce bias in the event that the "runner-up" locations for MDPs did receive investments from other firms that were not reported by the magazine, introducing potential bias in the counterfactuals used to estimate treatment effects.

To identify recent MDP openings, I use the proprietary Conway Projects dataset which provides the "near universe" of announced firm investments (including both new openings and expansions of existing operations). The data is prepared with close collaboration with economic developers and economic development associations across the U.S.. The advantage of using the dataset is to work with the near-universe of announced plant openings, expanding the list beyond what is reported by the *Site Selection* magazine. Given that Conway Projects only provides information on announced investments, I use a brute-force approach to confirm the number of job created by the investment. I rely on local newspaper reporting, local and state government economic development and annual reports, and corporate press releases to approximate the number of jobs created within 5 years of the completed investment. This overcomes the limitation of relying on the announced number of jobs created, which may be overstated in the announcement to attract local incentives or underreported in the case of expansions of existing operations.

To prepare the final sample of MDP investments, I filter the announcements to exclude investments that (a) were announced before 2008 or after 2018 and (b) project job creations that would represent less than a 15% increase in manufacturing jobs relative to pre-opening manufacturing labor force at the county level. The pre-opening manufacturing labor force threshold is applied to focus on places with the highest treatment intensity, thus increasing the statistical power in the analysis, and to create a more manageable data collection process for the analysis. After applying the initial screening, over 600 announcements remained. After conducting a manual review of each of the remaining announcements, I removed observations that did meet the 15% employment threshold based on the number of confirmed jobs created within 5 years of opening, with 76 observations remaining.[4] Treatment (i.e., the opening of, or expansion by, an MDP) is assigned at the county level.

Table 1 presents summary statistics for the MDPs. The average MDP in the sample generated far more than a 15% employment increase in the manufacturing sector, creating 815 jobs with an average investment of $263 million in the project. Importantly, the average project's announcement date was only 14 months before the grand opening of the plant which provided only a little over a year for entrepreneurs, loan officers, and the broader community to anticipate the economic shock associated with the plant opening.

Figure 1 presents a map of the MDPs including the county where each MDP is located and information on the year of establishment for each plant. While there is at least one MDP in each of the main regions of the U.S., the plants are concentrated in the Midwest and Southern U.S. which is consistent with where most of the local and state-level incentives were provided during this period. Due to the 15% filter applied on the number of jobs created compared to pre-opening manufacturing labor force, counties with significant existing manufacturing operations before 2010 (such as Detroit County,) are predominantly excluded.

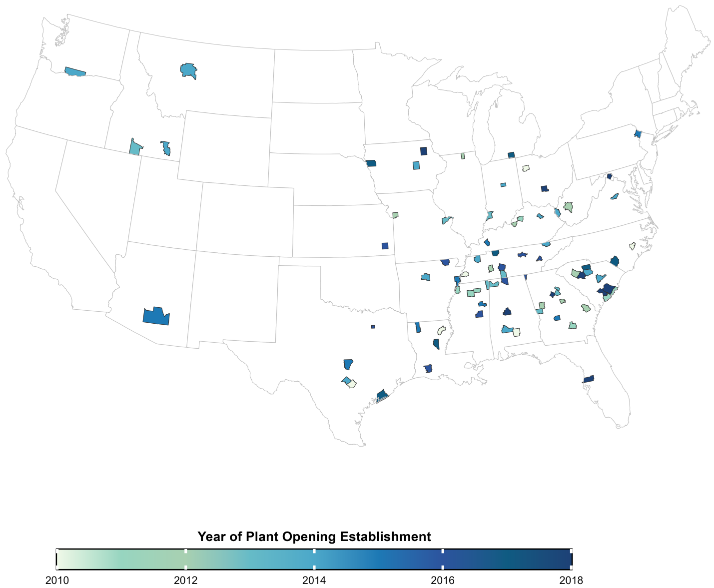
Table 1: Summary Statistics, MDP Characteristics

Variable	25th Percentile	Median	75th Percentile	N
Construction Period (in Years)	0.5	0.9	1.7	77
Employment at Plant	357.5	600.0	1000.0	77
% of County Mfg Employment	19.9	32.1	64.9	77
Cost of Project (Millions)	48.2	125.0	395.0	77

Note: 25th percentile and 75th percentile represent the lower and upper quartiles of the data; Cost of Project represents the dollar amount of the final investment in the plant reported in millions of U.S. dollars; Employment at Plant represents the sustained number of employees at the plant within 5 years of opening. The percentage of manufacturing employment is calculated using manufacturing labor force reported by the Quarterly Census of Employment and Wages.

[4] More information regarding the Conway Projects database can be found here: `https://conway.com/projects/`.

Figure 1: Location and Establishment Year of MDPs



Note: The map presents the county location of each MDP in the dataset. The color of the county corresponds to the establishment year for each plant and represents the calendar year when the plant began operations (or an expansion was completed).

3.2 Small Business Lending and Community Bank Access Measures

I collect small business lending data from the Community Reinvestment Act ("CRA"), which provides bank-county-year level data on the number and volume of loans originations to businesses with less than \$1 million in annual revenue. The statutory filing threshold set by the CRA and federal regulators was approximately \$1 billion in assets between 2005 and 2023, so SBLs originated by banks with less than \$1 billion in assets over the period of analysis will be under sampled. The data is merged with Call Report data to identify which lenders are community banks (i.e., $<$ 10 billion in total assets) and which are noncommunity banks. While both the number and dollar amount of lending can be used to measure volume of lending, the number of loans is the preferred measure given that the dollar amount can be underreported for lenders actively participating in the Small Business Association ("SBA") 7(a) program.[5]

I collect community bank access measures using data from the FDIC Summary of Deposits (SOD) survey, which provides the coordinates of all bank branches and the number of deposits held at each branch. To prepare measures of access to community banks, I calculate the number of community banks, community

[5]Previous SBA analysis highlights that lenders originating SBA 7(a) loans (which are predominantly larger banks) likely underreport loans because only the unguaranteed portions of the SBA-guaranteed loans may be reported by the lending institutions. Smaller lenders, on the other hand, are more likely to hold the entire balance of SBLs on their balance sheets, even if the loan has an SBA loan guarantee attached (U.S. Small Business Administration, Office of Advocacy, 2022). By 2024, only 36% of small banks originated SBA loans, compared to 84% of large banks (Source: FDIC 2024 Small Business Lending Survey.)

Table 2: Summary Statistics, Small Business Lending and Bank Characteristics (Median Values)

	SBLs (#)	SBLs ($, Million)	Branches (#)	Deposits ($, Million)
Panel A: All Counties				
Noncommunity Banks	210	5.9	58	4.7
Community Banks	38	4.3	133	7.9
Panel B: MDP Counties				
Noncommunity Banks	342	10.9	115	9.6
Community Banks	50	7.0	161	9.4

Note: The column values represent medians at the county-year level between 2010 - 2018. The SBL (small business loans) data is collected from the CRA and the number of banks, branches, and deposits is identified from the FDIC's Summary of Deposits data. Banks are classified as community banks if they have less than $10 billion in total assets in the year of observation. The number of banks, branches, and deposits is based on the branches that fall within 50 miles of each county centroid. Deposits and SBL volumes are in 2024 U.S. dollars, adjusted using the CPI for All Urban Customers.

bank branches, and deposits within a 100 mile radius of the county population-weighted centroid. The distance-based measures capture a reasonable distance for small businesses to access community bank credit and mitigates measurement error from using populatoin-weighted-centroid-based measures of access in place of more granular data on the location of small businesses within the county. More detailed discussion around the access measures is provided in Section 4.6.

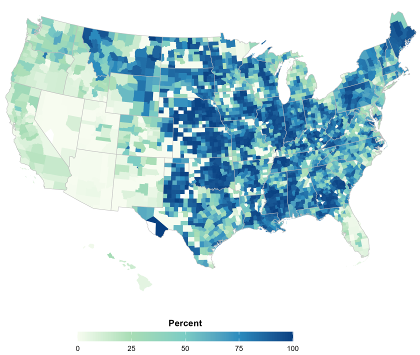
Table 2 presents summary statistics on small business lending and bank characteristics in the average and MDP opening counties. Between 2010 and 2018, non-community banks non-community banks originated more small business loans than community banks, at the median, but maintained higher branches and deposits. Comparing median U.S. counties to the median MDP counties, the MDP counties had higher small business lending activity and more community bank branches and deposits, which is consistent with the MDPs being located in counties that are less rural than the average county.

Figure 2 presents maps that visualize the percent of small business loans originated by community banks in 2010 and 2023 (panels a and b) and the percent change in the number of non-community bank branches and community bank branches between 2010 and 2023 (panels c and d). The maps highlight how many counties that were primarily served by community banks in the SBL market in 2010 experienced shifts towards non-community bank lending by 2023. This trend coincides with the loss of community bank branches throughout the east and west coasts and almost half the counties in the Midwest. During this period, non-community banks experienced fewer branch closures and even underwent branch expansions in many counties.

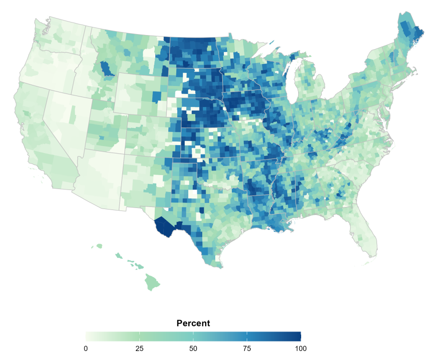
3.3 Small Business Development

I collect small business development data from the publicly available versions of the Census County Business Patterns ("CBP"), Quarterly Workforce Indicators ("QWI"), and Business Dynamic Statistics

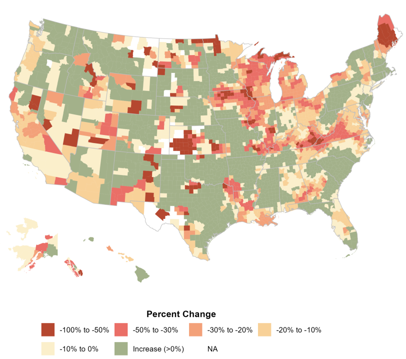
Figure 2: Maps of Small Business Lending and Access to Bank Branches



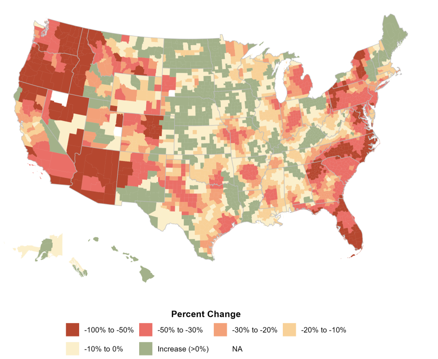
(a) Percent of Small Business Loans Originated by Community Banks (2010)



(b) Percent of Small Business Loans Originated by Community Banks (2023)



(c) Percent Change in Number of Non-Community Bank Branches



(d) Percent Change in Number of Community Bank Branches

Note: Panels (a) and (b) present the percent of small business loans originated by community banks in (2010) and (2023), respectively, at the county level. Panels (c) and (d) present the percent change in the number of non-community bank branches and community bank branches, respectively, between 2010 and 2023. The maps are prepared using data from the CRA and FDIC Summary of Deposits survey.

("BDS") datasets. CBP and QWI provide data based on the number of employees at a firm, grouping firms using size bins ranging from 1-4, 5-9, 10-19, 20-49, 50-99, and higher employment bins. BDS, on the other hand, aggregates establishments with employees ranging from 20 to 99. Therefore, to harmonize the datasets, I define small businesses as establishments with less than 20 employees when preparing small business establishment count, employees, and wages data.[6] CBP is used to collect the number of small businesses ($<$ 20 employees) in each industry at the 2-digit NAICS code level. QWI provides data on the number of employees and wages paid at small business establishments. The BDS provides data on the number of recently opened ($\leq$ 12 months of operations) small businesses and the number of employees at the new firms. Together, these are used to measure small business creation and expansion.

Table 3 presents summary statistics on small business establishments, employment, earnings, and expansions between 2005 - 2023. At the median, the average county has approximtaly 472 small business establishments with 1,396 employees, slightly lower than the median values from the MDP counties. The median county also experiences 33 new small business establishments and over 100 new small business employees each year.

Table 3: Summary Statistics: Small Business Characteristics

Variable	25th Percentile	Median	75th Percentile	N
Panel A: All Counties				
Small Business Establishments (#)	200	472	1251	29831
Small Business Employees (#)	586	1396	3854	29831
Small Business Earnings ($)	2407	2719	3105	29831
New Small Business Openings (#)	14	33	92	29831
New Small Business Employment (#)	44	115	332	29831
Panel B: MDP Opening Counties				
Small Business Establishments (#)	399	707	1422	963
Small Business Employees (#)	1138	2101	3993	963
Small Business Earnings ($)	2558	2782	3033	963
New Small Business Openings (#)	27	47	101	963
New Small Business Employment (#)	91	177	393	963

Note: The column values represent statistics at the county-year level across 2010 - 2018. Small business establishments and small business employees represents the number of establishments with less than 20 employees and the number of employees at the establishments and is collected from the County Business Patterns and Quarterly Workforce Indicators datasets, respectively. The small business earnings measure is based on average monthly earnings of small business employees collected from the Quarterly Workforce Indicators. and is presented in U.S. dollars. New small business openings and new small business employment represents the number of establishments with 19 or less employees and the number of employees at the establishments that opened within the past 12 months and is collected from the Business Dynamics Statistics dataset.

[6]These datasets do not provide data based on annual firm revenue, so while the CRA defines small businesses based on revenue, I use employment size to define small businesses when preparing the establishment count, employment, and wage variables.

3.4 Additional Data

I collect data on the productivity of the manufacturing industry, which is measured using the value of shipments from the manufacturing industry, from the U.S. Census Bureau's Economic Census (Greenstone et al., 2010; Patrick, 2016; Kim, 2020). Total employment in the county and employment in the manufacturing industry is collected from the Quarterly Census of Employment and Wages (QCEW).

4 Reduced Form Empirical Methodology

MDPs are not randomly assigned, with plant managers engaging in robust and sophisticated site selection searches to identify the ideal location for investment. Further, plant investments occur in a staggered manner, with large investments occuring consistently over time, rather than in a single year or period. Therefore, any empirical strategy must account for the non-random assignment of MDPs and the staggered nature of the treatment.

To estimate the impact of MDP investments on various economic outcomes, the primary accepted empirical strategy in the literature is a difference-in-difference ("DiD") and two-way fixed effects ("TWFE") approach, where counties with MDP openings are compared to the runner-up counties that were considered, but not selected, for the investment. While the construction of the runner-up sample was originally based on the the "Million Dollar Plants" recurring feature in the *Site Selection* magazine, recent efforts have extended the original MDP dataset, using targeted web searches and annual "Top Deals" articles from *Site Selection* to find references to recent openings and alternative locations considered before final investments were made (Bloom et al., 2019; Slattery, 2025; Rahul and Rodriguez, 2025).

While the runner-up counties provide a reasonable counterfactual for the counties with MDP openings, the approach is not without limitations. The runner-up locations often include relocation cases, where the MDP county is paired to the location of a previously existing plant that is either closed or downsized to open the new location (Patrick, 2016; Patrick and Partridge, 2022; Rahul and Rodriguez, 2025). Further, companies frequently annouce the state, rather than the specific county, of alternative locations considered for the investment, which requires additional assumptions to identify the runner-up county (Slattery, 2025). Finally, without compiling a comprehensive list of all MDP investments other than the cases evaluated by *Site Selection* and other public sources, the runner-up counties may have received investments from other firms, which would bias the estimated treatment effect.

An alternative method to construct a counterfactual is to match on pre-investment observables and geographical proximity to identify counties that are similar to MDP counties, but did not receive an investment.

This approach may outperform the runner-up approach in cases where the runner-up counties are imputed, represent relocation cases, or do not represent the true set of counties that were considered for the investment (e.g., if the plant investors were unwilling to reveal the genuine runner-up counties publicly). However, matching on observables may also be problematic if the MDP counties are selected based on unobservables that are correlated with the outcome of interest. Further, matching on geographical proximity may violate the stable unit treatment value assumption ("SUTVA") if the MDP investment in one county has spillover effects on neighboring counties, which would bias the estimated treatment effect.

The following sections outline the empirical strategy used to estimate the impact of MDP openings on small business lending and development and address how I attempt to address concerns related to estimating TWFE in a staggered treatment setting and construction of reliable counterfactuals.

4.1 Counterfactual Construction

Consistent with the literature, I construct two control groups that function as reasonable counterfactuals for the counties with MDP investments and adopt a third approach based on recent advancements in synthetic difference-in-difference ("DiD") estimation (Arkhangelsky et al., 2021).

First, I adopt the "runner-up" strategy adopted by previous authors by identifying the counties that were considered, but ultimately not selected, by the MDPs during the site selection process (Greenstone et al., 2010; Bloom et al., 2019; Kim, 2020; Monte et al., 2018).[7] However, excluding cases where the runner-up is a county with an existing plant owned by the MDP (i.e., a relocation), is geographically close to the MDP county and threatens the SUTVA assumption, and or is imputed from a state-level runner-up announcement, I only have 11 cases with runner-ups. To supplement the runner-up counties, I identify counties where initial investments were committed or announced, but exogenous shocks (such as a sudden drop in commodity prices, concerns arising from deteriorating trade relations between U.S. and China, and unexpected permitting issues) resulted in the cancellation of the project before opening or outlay of significant investment.Appendix X provides additional information on the "cancelled" counties.[8]

Second, I utilize propensity score matching to identify three counties that are similar to the MDP counties based on pre-opening observable characteristics. [9] . The goal is to identify counterfactuals with similar pre-treatment socioeconomic trends to the counties with MDPs.[10] Details on the matching procedure are

[7]The runner-up counties are identified manually by searching site selection magazine articles, as well as press releases, and local reporting of the MDPs, and supplemented using the runner-up counties listed for corresponding MDP openings in Slattery (2025); Bloom et al. (2019).

[8]The estimated coefficients using both the runner-up and cancelled projects control groups are consistent with the results using only the runner-up counties.

[9]While using propensity score matching to estimate propensity scores and prepare inverse propensity weights is often the preferred approach in the matched-DiD literature, balance tests revealed more statistically significant imbalances using propensity score weighting rather than using distance-based matching for the 3 top control counties.

[10]Patrick (2016) provides an overview and supporting analysis to justify using matched controls over the runner-up approach.

provided in Appendix A.

Third, given the possible shortcomings of the runner-up and amtched control approaches, I implement synthetic DiD ("SDID") estimation to simulate a weighted-average counterfactual path for the treated counties based on the pre-treatment outcome trajectory (Arkhangelsky et al., 2021) which may refine or provide additional validation of the prior methodologies. A possible advantage of using SDID estimation is that it does not rely on the assumption that the MDP counties are selected based on observables, which may be violated if the MDPs are selected based on unobservables that are correlated with small business lending or growth. Further, SDID estimation does not require identifying a specific set of control counties, which may be difficult to identify given the staggered nature of MDP openings and the potential for spillover effects in neighboring counties. Further, the use of pre-treatment outcome trajectory improves the pre-treatment trend balance between the treatment and control groups which is particularly important for estimations where the parralel trends assumption may be violated by the runner-up and matched control approaches.

Table 4 presents summary statistics for the treatment (MDP counties) and control (runner-up/cancelled and matched) groups. Panel A compares pre-treatment levels and trends for socioeconomic and relevant site selection factors, highlighting that the treatment and control groups are broadly similar across a variety of characteristics. Panel B presents the 5-year percent change for the primary measures of small business lending and small business development used in the main analysis. The lack of statistically significant differences pre-opening across the treatment and control counties provides credence to the counterfactual construction and support for the common trends assumption of difference-in-difference estimation.

4.2 Estimation Strategy

The existing MDP literature relies heavily on standard DiD and TWFE models, with only (Rahul and Rodriguez, 2025) performing robustness checks using staggered DiD methods that address plausible weighting and intrinsic bad control issues. Given the staggered nature of MDP openings and the potential bias in traditional staggered two-way fixed effects models, I estimate weighted trimmed stacked DiD models. These rely on carefully constructed stacks and saturated fixed effects to ensure comparisons between units within the same calendar period without comparing already-treated units to newly-treated units (i.e., ensure clean controls) (Goodman-Bacon, 2021; Wing et al., 2024). Using a window-trimmed sample ensures that compositional imbalances across event study windows do not confound the estimated treatment effect; further, re-weighting the estimated coefficients for each event-study window ensures that the aggregated event time treatment effects are within the convex hull of the sub-experiment estimates.[11]

[11] For more information about the importance of trimming and weighting when estimating stacked DiD, see Wing et al. (2024).

Table 4: Balance Table for MDP Opening Counties and Control Groups

Variable	Opening (1)	Runner-up/Canc. (2)	Matched (3)	Joint p-value (1)-(2)	Joint p-value (1)-(3)
Panel A: Pre-Treatment Baseline Covariates					
Unemployment (%)	8.99	9.01	9.19	0.015**	0.920
Unemployment (PP Δ)	1.76	1.66	1.61	0.028**	0.986
Population (log)	3.93	4.17	3.62	0.171	0.865
Population (% Δ)	2.95	2.56	2.18	0.571	0.958
Minority (%)	26.27	37.63	23.03	< 0.001***	0.262
Minority (PP Δ)	0.96	0.79	0.80	0.769	0.795
Income per Capita (Ks)	33087.31	34369.58	32150.89	0.615	0.415
Income per Capita (% Δ)	11.65	10.87	11.75	0.836	0.971
Mfg Labor Share (%)	0.04	0.05	0.04	0.811	0.965
Mfg Labor Share (PP Δ)	-0.01	-0.01	-0.01	0.518	0.755
Subsidy Amount ($Ms)	785.75	876.40	785.32	0.202	1.000
Distance to Nearest Metro (Miles)	7.19	8.28	6.87	0.046**	0.811
Interstate Ramps (#)	16.43	29.44	11.43	0.078*	0.905
Panel B: Pre-Treatment Outcome Trends					
Small Business Loans (% Δ)	-24.72	-22.67	-23.73	0.796	0.986
Small Businesses (1-19 employees) (% Δ)	-1.98	-2.73	-2.61	0.418	0.774
Small Business Employment (% Δ)	-2.57	-1.90	-2.51	< 0.001***	0.454
Small Business Earnings (% Δ)	9.37	6.99	7.57	0.626	0.437
Small Business Openings (% Δ)	-10.61	-13.03	-14.96	0.020**	0.164
New Small Business Job Creations (% Δ)	-9.46	-11.26	-11.64	0.366	0.401
Unit-Cohort Sample Size	129	288	224		
Effective Sample Size	76.0		224.0		

Note: Columns 3 and 4 represents the p value associated with a joint Wald test comparing the difference between the mean value for the treated units and the control units, where Column 3 uses the runner-up/cancelled counties as the control and Column 4 uses propensity-matched controls. All values are based on year before the plant opening, which ranges from years between 2009 to 2017. The pooled mean values across the 9 timing groups, or sub-experiments, are calculated by weighting each group's mean by the number of treated units in the group. The Wald test is testing the hypothesis that the treated and control mean difference is jointly 0 across all 9 timing groups. "PP" and "% change" represent the 5-year percentage point change and percent change over the 5 years prior to the plant opening, respectively, for each variable. Unemployment rate, population, and minority demographic data is collected from the ACS Census data. Income per capita is collected from the Bureau of Economic Analysis. The manufacturing labor share is calculated from the Quarterly Census of Employment and Wages dataset. Distance to nearest metro is calculated based on TIGER shape files provided by the U.S. Census. Number of interstate ramps is calculated based on shapefiles provided by the Bureau of Transportation Statistics Freight Analysis Framework. The sources for the outcome variables presented in Panel B are provided in Section 2.2.2 and 2.2.3. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

The model is estimated using the following equation:

$$Y_{cae} = \alpha_0 + \alpha_1 D_{ca} + \sum_{\substack{h=-\kappa_{pre} \\ h \neq -1}}^{\kappa_{post}} \lambda_h \mathbb{1}[e = h] + \sum_{\substack{h=-\kappa_{pre} \\ h \neq -1}}^{\kappa_{post}} \delta_h (D_{ca} \times \mathbb{1}[e = h]) + \epsilon_{cae} \tag{1}$$

where Y_{cae} is the number of SBL originations in county c in sub-experiment a in event time e (in Section 3.4) and the number of small business establishments, employment, wages, new small business establishments, and new small business employment (in Section 3.5); D_{ca} is an indicator for whether county c is treated in sub-experiment a (i.e., has an MDP opening); κ_{pre} and κ_{post} are the number of pre and post periods, respectively, where a 5 year pre and post period is adopted in the analysis; $\mathbb{1}[e = h]$ is equal to 1 when the event time period is h periods from the MDP opening in sub-experiment a; δ_h is the treatment effect in each event time period h; and ϵ_{cae} is the error term. By including the saturated fixed effects for each event time period and building a stack for each sub-experiment, the model relies on comparisons between treated and control counties within each event time period, which mitigates bias from comparing treated units to control units in different event time periods with different compositions of treated and control units.

4.3 Results

4.4 Revisiting the MDP Literature

First, I revisit the MDP literature using my updated MDP dataset, three counterfactual approaches, and modern DiD estimators and compare the estimated coefficients to the results from previous studies. Specifically, I implement the DiD empirical specification from Greenstone et al. (2010) at the county level:

$$Y_{ct} = \delta \mathbb{1}(Winner)_c + \kappa \mathbb{1}(\tau \geq 0)_t + \omega \left[\mathbb{1}(Winner)_c \times \mathbb{1}(\tau \geq 0)_t\right] + \alpha_c + \lambda_t + \epsilon_{ct} \tag{2}$$

where Y_{ct} is either county-level productivity (value of shipments) in the manufacturing industry (log), total employment, or employment within the manufacturing industry in county c, year t; $\mathbb{1}(Winner)_c$ is an indicator equal to one if county c is a county with an MDP; τ is the time relative to the MDP opening year t (e.g., equal to 0 in the year of the opening, 1 in the year after the opening, etc.); α_c are county fixed effects; and λ_t are time fixed effects. The coefficient of interest is ω, which captures the average treatment effect on the treated (ATT) of MDP openings on county-level outcomes.

Model 2 is estimated for county-level manufacturing productivity, employment, and manufacturing employment using the runner-up and cancelled-projects counties, as well as the matched counties, as controls.

The estimated coefficients are presented in Table 5 and compared to the results from previous studies, as well as the estimated coefficients using model 1 and using SDID estimation. Columns (1) and (2) find that the opening of MDPs increases manufacturing productivity by between 12%-16%, while columns (3) - (6) suggest that county-wide total employment and manufacturing employment increases by 5% and 24%, respectively, after opening. These results are within the range of estimates reported by previous studies (Greenstone et al., 2010; Bloom et al., 2019; Kim, 2020; Patrick, 2016; Slattery and Zidar, 2020). With the refreshed dataset validating main findings from the MDP literature, I proceed in applying the dataset to study small business lending and the role of access to credit in mediating spillover effects from MDP openings to small business establishments.

Table 5: Regression Results for Productivity and Employment Changes After MDP Openings

	Value of Shipments			Employment			Mfg. Employment			Earnings		
Panel A: TWFE												
Post ATT	0.14**	0.12**	–	0.04**	0.04***	–	0.21***	0.27***	–	−0.00	−0.01	–
	(0.06)	(0.05)		(0.02)	(0.02)		(0.04)	(0.04)		(0.01)	(0.01)	
Observations	469	964	–	2,656	5,937	–	2,656	5,937	–	2,654	5,932	–
Panel B: Staggered DiD												
Post ATT	–	–	–	0.05***	0.05***	0.05***	0.26***	0.27***	0.26***	−0.00	−0.00	−0.01
				(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)
Observations	–	–	–	4,597	21,803	343,687	4,597	21,803	343,687	4,596	21,793	343,687
Control Group	Runner-up	Matching	–	Runner-up	Matched	SynthDiD	Runner-up	Matched	SynthDiD	Runner-up	Matched	SynthDiD

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.* Standard errors are clustered at the county level. The value of shipments of manufacturing establishments is sourced from the U.S. Census Bureau's Economic Census. Total employment and manufacturing employment is sourced from the Quarterly Census of Employment and Wages dataset. Wages are measured as average monthly earnings of employees in the county and are collected from the Quarterly Workforce Indicators. Panel A presents the estimated coefficients using two way fixed effects estimation, while Panel B presents the estimated coefficients using either the weighted trimmed stacked DiD estimator or SDID. In Panel B, when using the stacked DiD estimator, the ATT estimates are calculated by averaging the event time treatment effects over the 5 years after the MDP opening using a simple linear combination of coefficients.

4.5 Small Business Lending After MDP Openings

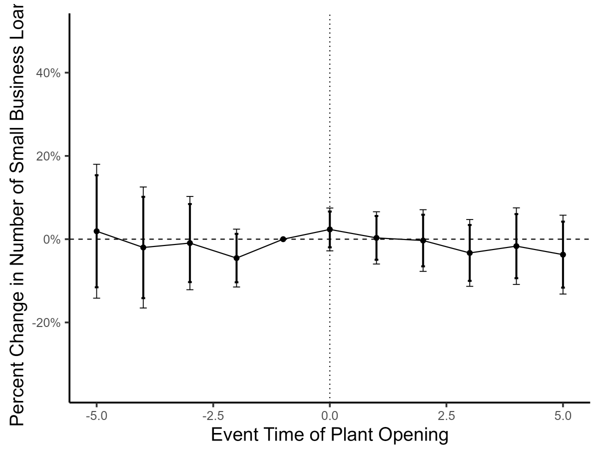
4.5.1 Main Analysis

I investigate the mechanism through which access to community banks is hypothesized to increase spillovers from MDPs to small businesses: small business lending. Equation 1 is estimated using the number of SBLs originated (logged) by (a) all banks, (b) noncommunity banks, and (c) community banks. The hypothesis is that while there may be increases in small business lending after MDP openings by both large and small banks, the flexibility and reliance on relationship banking offered by community banks will drive most of the increases in small business lending. Figure E9 presents the event study estimated using the weighted trimmed stacked DiD model focusing on the number of SBLs originated by noncommunity banks (panel a) and by community banks (b) using the runner-up strategy, and Table 13 provides estimated ATT treatment effects for each of the three outcome variables using each of the three control groups/estimation strategies. The results provide strong evidence that community banks significantly increase small business lending after the MDP opening, with the number of SBLs originated by community banks increasing by 21% annually during the five years after the opening, on average. Larger banks do not exhibit similar increases. Statistically significant and positive ATT estimates are also estimated using the matched controls and the SDID estimator, with average increases in SBL originations by community banks between 14% and 16%, respectively. Only the SDID estimator showing statistically significant and positive increases in SBL originations by large banks, and the estimated coefficient is much smaller than the estimate for community banks. The findings support the mechanism of community banks financing post-opening small business development through small business lending.

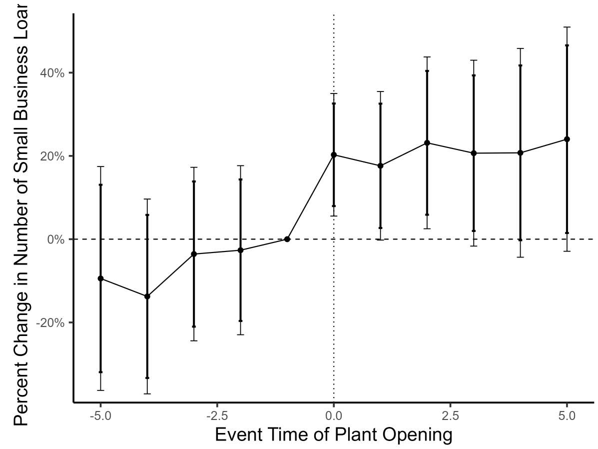
4.5.2 Discussion

After a MDP opening, there is a significant increase in small business lending driven primarily by community banks. This finding is consistent with the hypothesis that the flatter loan review hierarchy and reliance on relationship lending by smaller banks creates flexibility to respond to increased demand for small business loans following a demand shock to the local economy. While an explicit analysis of the demand for small business loans cannot be studied because the CRA does not provide information on SBL applications, the implicit evidence suggests that as the MDP pays wages to new employees and increases supply-side demand for support services from upstream and downstream sectors, entrepreneurs expand operations or start new ventures in response. The increase in demand for small business loans is met by increased originations by community banks, which use existing relationships with entrepreneurs, knowledge of local market conditions,

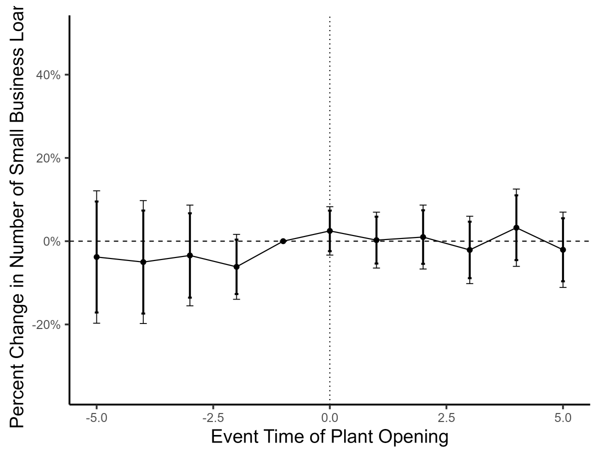
Figure 3: Event Study Plots for # of SBL Originations (log) After MDP Opening



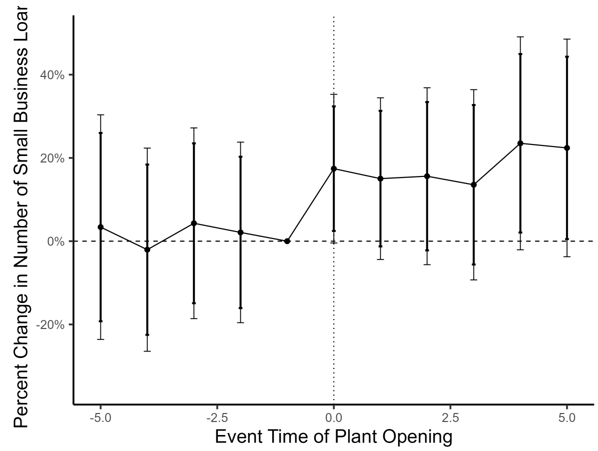
(a) Runner-Up: Noncommunity Bank



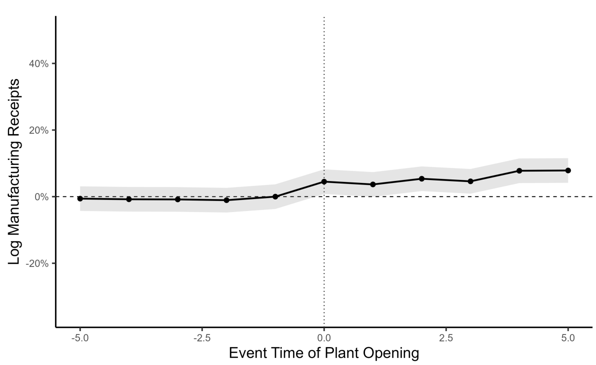
(b) Runner-Up: Community Bank



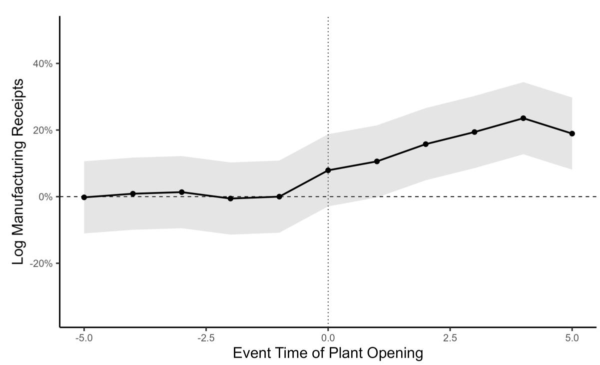
(c) Matched: Noncommunity Bank



(d) Matched: Community Bank



(e) SDID: Noncommunity Bank



(f) SDID: Community Bank

Note: Panel (a) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged noncommunity bank SBLs originated. Panel (b) presents the estimates using the runner-up/cancelled county control group with number of logged community bank SBLs originated. Panel (c) presents the estimates using the matched county control group with number of logged noncommunity bank SBLs originated. Panel (d) presents the estimates using the matched county control group with number of logged community bank SBLs originated. Panel (e) presents the estimates using the SDID with number of logged noncommunity bank SBLs originated. Panel (f) presents the estimates using the SDID with number of logged community bank SBLs originated. The 95% confidence interval are represented by the thin bands, and the 90% confidence intervals are represented by the thicker bands. Standard errors are clustered at the county level. The event study estimations for panels a, b, c, and d were performed using the weighted trimmed stacked DiD approach, while panels e and f present the SDID results. Since the SDID estimator does not separately estimate each event time coefficient, the standard errors from the ATT estimate are used to construct the confidence intervals for the event study plot. The presentation of the event study plot is not intended to present estimated coefficients for each event time period, but rather to provide a visual representation of the ATT estimate and the associated confidence intervals.

Table 6: Estimated Coefficients for # of SBL Originations (log) After MDP Opening

	(1) Runner-up	(2) Matched	(3) Synth DiD
Panel A: All Banks			
Post Opening ATT	0.02	0.03	0.07***
	(0.03)	(0.03)	(0.02)
Observations	4,587	3,272	354,362
Panel B: Community Banks			
Post Opening ATT	0.21**	0.18*	0.16***
	(0.09)	(0.09)	(0.06)
Observations	4,500	3,194	251,767
Panel C: Large Banks			
Post Opening ATT	-0.01	0.00	0.06***
	(0.03)	(0.03)	(0.02)
Observations	4,587	3,272	353,687

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening, with event time -1 as the reference group; Panel A estimates the event study using all banks; Panel B estimates the event study using only community banks; Panel C estimates the event study using only noncommunity banks. Standard errors are clustered at the county level. The number of observations for the matching estimations are based on effective sample size after weighting.

and direct touchpoints between SBL applicants and lender decision makers to underwrite and originate more small business loans. At the median, the 16 - 26 percent increase in annual small business lending represents an additional 9-15 SBLs originated by community banks each year after the MDP opening. Given that the CRA dataset underreports loans by smaller community banks, the magnitude of the increase is likely underestimated. To understand how community banks fund the increase in small business lending, Appendix G analyzes the role that deposit growth and spatial reallocation of loan portfolios play with evidence that reallocation from non-MDP counties to MDP counties contributes to the observed increase. Next, I investigate whether this increase in financing translates into additional small business creation and expansion in MDP counties.

4.6 Small Business Openings and Expansions After MDP Openings

4.6.1 Main Analysis

I study the impact of access to community bank capital on small business development after MDP openings. Driven by the increase in small business lending by community banks after MDP openings, I investigate whether counties with higher access to community banks experience higher magnitudes of spillovers to small businesses. Given the aggregated nature of the CRA data, I am unable to observe whether the entrepreneurs and small firms that receive financing from community banks open or expand at differential rates to those in communities with fewer community banks. Thus, I need to prepare a measure of access to community bank capital and identify counties with higher access. To prepare this measure, I calculate the total number of community bank branches in 2009 within 100 miles of the population-weighted county centroid and define the high-access counties as the top tercile of branches and the low-access counties as the bottom tercile of branches.[12]

Table 7 presents the estimated coefficients for the event studies using the number of small business establishments (logged) as the outcome variable. The results provide evidence that counties with high access to community bank capital experience an increase in small business establishments after MDP openings, with MDPs in high-access counties increasing the number of small business establishments by approximately 2 percent over the following five years. While the coefficient is statistically significant using the matched control group and SDID, it is not statistically significant using the runner-up/cancelled control group. Counties with low access to community banks do not experience a similar increase, with each of the three estimation methods showing no significant effects. This finding supports the hypothesis that community banks are a critical channel through which MDPs generate positive spillovers to small businesses and is robust to alternative measures of access.

To evaluate whether the increase in small business establishments is coupled with increases in employment and wages, I replicate the analysis using the number of employees at small businesses and monthly earnings by small business employees as the outcome variables. The results, presented in Panel A Table 8, reveal similar patterns to those in Table 7, with both employment and earnings increasing by 2 percent after opening. For the earnings measure, all three counterfactual groups return statistically significant and positive coefficients.

To uncover whether the observed small business development is driven by new business creation or expansion of existing businesses, I use the number of small businesses that began operations within the previous 12 months as the outcome variable. Reported in Panel B of Table 8, these results suggest that the increase in small business establishments in high-access counties is driven by expansion of existing businesses, with no estimation finding statistically significant and positive effects for new small businesses.

[12] Total branches is the preferred measure of community bank intensity because the branch presence is particularly important for small business lending by community banks, given the localized business model of small business lending. I use branches in 2009 because it is the year before the first MDP opening in the sample, and post-opening deposits may be endogenous to the MDP. As presented in Section E.2, the results are robust to alternative measures of community bank market (e.g., 25 or 50 miles from the county centroid) and community bank intensity (e.g., using number of deposits rather than branches or top quartile rather than tercile. The number of deposits is a reasonable alternative measure of access because community banks primarily fund their lending through deposits, and lenders with higher deposits will have more capacity to originate SBLs.)

Table 7: Estimated Coefficients for Small Business Growth After MDP Opening

	(1) Runner-up/Canc.	(2) Matched	(3) Synth DiD
Panel A: All Counties			
Post ATT	-0.00	0.01	0.01**
	(0.01)	(0.01)	(0.01)
Observations	4,587	3,267	344,448
Panel B: High Access Treated Counties			
Post ATT	0.02*	0.03**	0.02*
	(0.01)	(0.01)	(0.01)
Observations	3,707	2,717	355,990
Panel C: Low Access Treated Counties			
Post ATT	-0.01	0.00	0.01
	(0.01)	(0.01)	(0.01)
Observations	3,212	2,431	356,351

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening, with event time -1 as the reference group; Panel A estimates the event study using the number of small business establishments (logged) for all treated counties; Panel B estimates the event study using only the high-access treated counties; Panel C estimates the event study using the low-access treated counties. The number of small business establishments is measured as the count of establishments with less than 20 employees. Standard errors are clustered at the county level.

Table 8: Estimated Coefficients for High Access Counties After MDP Opening

	Establishment Count		Employment		Earnings	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Small Businesses						
Post ATT	0.02*	0.03**	0.03*	0.03**	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	3,707	2,717	3,707	2,715	3,707	2,715
Panel B: New Small Businesses						
Post ATT	0.00	0.03	0.03	0.08	–	–
	(0.03)	(0.04)	(0.05)	(0.05)	–	–
Observations	3,701	2,703	3,701	2,703	–	–
Control	Runner-up	Matched	Runner-up	Matched	Runner-up	Matched

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using high-access treated counties for outcome variables measuring small business establishments, employment, and earnings at all firms with less than 20 employees; Panel B estimates the event study using high-access treated counties for outcome variables measuring small business establishments and employment all firms with less than 20 employees that began operations within the previous 12 months. Data on the earnings of employees at small businesses that began operations within the previous 12 months is not available from publicly available sources. Standard errors are clustered at the county level.

4.6.2 Heterogeneity by Industry

The literature highlights that the spillover effects from MDPs are primarily captured by economically proximate industries, and economic theory suggests that as the MDPs demand labor and other inputs, the industries that compete against MDPs for labor and other resources may face rising wages and input costs. Further, the income effects of the MDP openings may increase demand for service industries as in-migration and rising wages increase demand for a variety of services. To determine whether these supply-side and income effects impact spillovers to small businesses, I replicate the previous analysis using the number of small businesses in three industry groups as the outcome variable: (a) supporting industries that are economically proximate to the MDPs and likely to experience positive spillovers from the MDP openings, (b) industries that compete for the labor and other resources used by the MDPs and may experience negative spillovers from the MDs, and (c) service industries that may experience positive spillovers from the income effects of the MDP investments.

The results, presented in Figure F16, illustrate how small businesses in supporting industries that reside in counties with high community bank access and experience the most substantial positive spillovers from MDPs. Small businesses in competing industries exhibit no statistically significant changes in counties with high access to community banks, while competing small businesses in counties with low access to community banks experience a negative spillover from the MDPs. While the estimated ATT for service industry small business growth is positive, the parallel trends assumption is violated under both the runner-up and matched control groups, so the positive estimates should be interpreted with caution. Together, the results support the hypothesis that supporting or economically proximate small businesses capture most of the positive spillovers, while small businesses that compete against the MDPs for labor and resources experience null changes when there is high access to community bank capital, or negative spillovers when there are lower levels of access to community banks. These findings provide additional evidence that access to community bank is an important conduit through which small businesses capture spillover effects and remain resilient when faced with new competition for inputs.

Table 9: Estimated Coefficients for Small Business Growth by Industry After MDP Opening

	Supporting Industries	Competing Industries	Service Industries
	(1)	(2)	(3)
Panel A: All Counties			
Post ATT	0.04***	-0.01	0.02***
	(0.01)	(0.02)	(0.01)
Observations	344,448	355,990	356,351
Panel B: High Access Treated Counties			
Post ATT	0.06***	0.03	0.05***
	(0.02)	(0.03)	(0.01)
Observations	344,448	355,990	356,351
Panel C: Low Access Treated Counties			
Post ATT	0.04*	-0.02	0.02*
	(0.02)	(0.03)	(0.01)
Observations	344,448	355,990	356,351
	SDID	SDID	SDID

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening, with event time -1 as the reference group; Panel A estimates the event study using all treated counties; Panel B estimates the event study using only the high-access treated counties; Panel C estimates the event study using the low-access treated counties. The supporting industries include NAICS codes 23 (construction), 42 (wholesale trade), 48-49 (transportation and warehousing), 54 (professional, scientific, and technical services), and 56 (administrative and support and waste management and remediation services). The industries competing for labor and other resources include NAICS codes 11 (agriculture, forestry, fishing, and hunting and primarily comprised of forestry and logging small businesses), 21 (mining, quarrying, and oil and gas extraction), and 31-33 (manufacturing). The service industries include NAICS codes 44-45 (retail trade), 53 (real estate, rental, and leasing), 62 (health care and social assistance), 72 (accommodation and food services), 81 (other services). Standard errors are clustered at the county level.

4.6.3 Evaluating Endogeneity of Community Bank Access

One possible limitation of the analysis is the plausible endogeneity of community bank presence, where community banks may choose to locate in counties with better small business growth prospects, leading to correlations between community bank access and local conditions that also shape post-opening growth. Given the persistence of bank presence in the U.S., using a simple lag of community bank presence or access may not sufficiently resolve any endogeneity.[13] To address this endogeneity, I calculate a predicted community bank access measure using two exogenous instrument-type variables. First, I use the number of banks located in a county pre-Great Depression (1928), relying on the persistence of branch presence and the resetting of county-level characteristics during the Great Depression and subsequent 90 years. Second, I use the number of years since bank branching deregulation in each state, relying on the staggered deregulatory efforts by U.S. states between pre-1970s through 1997, where states that delayed deregulating branching have higher densities of community banks (Kroszner and Strahan, 2014; Calem et al., 1994). Each of these exogenous variables are used to predict the community bank access measure based on the number of branches with 100 miles of the population-weighted centroid of each county, as defined in Section 3.5.1. Table C1 presents the estimated coefficients and F-stat for the predicted community bank access measure.

To separately identify the effect of MDP openings on counties with higher access to community bank credit vs. counties with lower access, I subset the treated units into "low access" and "high access" counties based on the predicted number of community bank branches within 100 miles of the population-weighted centroid of each county. I define high-access counties as the top tercile of predicted community bank presence in 2009, where preliminary robustness tests validate that the results are robust to alternative thresholds (e.g., top quartile). Using the predicted community bank access measure, I reestimate the event study specification from Section 3.5.2 and present the results in Tables C3 and C4. The results are generally consistent with the main analysis, providing additional support for the hypothesis that access to community bank credit is an important channel through which MDPs generate positive spillovers to small businesses.

4.7 Robustness Checks

I conduct a variety of robustness checks to validate the results and mitigate concerns over various confounding factors. First, the sample of banks included in the small business lending analysis is expanded to include banks that did not report CRA data in all 11 years of a given sub-experiment. While this introduces measurement error by including banks that likely originated loans but did not report through the CRA for all years, it also expands the set of community banks to include smaller lenders that were closer to the CRA

[13] 74% of the bank branches active during 2009 were opened before or during 2000, and the correlation between the number of branches within U.S. counties in 2000 and 2009 is 0.99, per author calculations.

filing threshold. An initial investigation of the data confirms that approximately 72% of the community banks within each sub-experiment report CRA data in all 11 years (see Figure F1), which means that 28% of the community banks are excluded from the main analysis. The estimations performed in Section 3.4 are replicated using the expanded sample of banks, and the results (presented in Table F1) are consistent with the main analysis, suggesting that the results are not driven by the selection of banks that report CRA data in all years.

Second, I investigate whether community banks select into (out of) counties with (without) MDP openings. If productive community banks select into MDP opening counties (by opening a branch) after observing the entrepreneurial and productive characteristics of the counties, or select out of a control county (by closing a branch), then the results from Section 3.4 and 3.5 may be driven by selection bias rather than the true effect of MDP openings and exogenous community bank presence. Excluding banks from the analysis that do not report CRA data in all years of a given sub-experiment in the main analysis mitigates the possible selection bias of banks selectively opening or closing branches. To further investigate the possible confounder, I compare the distribution of community bank branch establishment year for surviving branches and the closing year for closed branches across the treatment and control groups and find no significant differences, mitigating concerns that banks are disproportionately selecting into MDP opening counties or out of control counties (see Appendix C).

Third, I replicate the analysis using alternative employment thresholds used to select the sample of MDP openings, including 10% and 20% increases to the pre-opening manufacturing labor force at the county level. The estimated coefficients are presented in Table F2 and F17 and highlight that while increasing the intensity threshold to 20% does not significantly change the results, expanding the sample to include MDPs that represent only 10% of pre-opening manufacturing labor force leads to reduced statistical significance for the small business loan origination analysis. This suggests that the intensity of the MDP employment to the local labor force may be a key factor in driving the spillover effects to small businesses, however the results for the small business development analysis were generally consistent with the main analysis.

Fourth, I replicate the analysis of small business development after MDP openings using an alternative definition of community bank access – the number of community bank branches within 100 miles of the county centroid. The results are consistent with the main analysis.

5 Quantitative Spatial Equilibrium Model

The spatial equilibrium model (SEM) is built upon the framework of Monte et al. (2018), which incorporates migration and commuting decisions of households into the U.S. setting and simulates MDP openings as shocks to the productivity of businesses within the county. To expand the framework to study the impact of MDPs on small business, I incorporate business heterogeneity following the models outlined by Rothenberg et al. (2025) and Zárate (2022). Finally, to explicitly model the role of small business lending by community and non-community banks, I adapt the endogenous bank lending model outlined by Aguirregabiria et al. (2025) to the SBL setting. The economy consists of a set of locations (counties) n, $i \in N$, where workers reside in n and work in i. Each county has two types of businesses, indexed by $z \in \{s, l\}$, where s denotes small businesses and l denotes all other (non-small) businesses.

Each county also has a representative household that supplies labor (L) and consumes (C) the output of the businesses. The economy has a fixed supply of labor $\bar{L}$, which faces costly trade and migration across counties following the standard gravity trade cost function. In addition to using labor as an input, small businesses receive financing from community banks and non-community banks to reduce the cost of entry/operation. Banks receive interest payments and face competition for loans in each market.

5.1 Model Overview

5.1.1 Worker Utility, Consumption, and Commuting

Workers choose a county in which to live (n), a county in which to work (i), and a type of business for which to work (z). The mass of workers choosing to reside in n and work in i, z is represented as $L_{n,i,z}$. The workers face commuting frictions between i and n and have heterogenous preferences for locations. The utility of a worker is based on the idiocyncratic preference b_{ni}, consumption of final goods C_{nz}, and consumption of residential housing H_{nz}. The utility function of worker ν follows Cobb-Douglas functional form:

$$U_{niz}(\nu) = \frac{b_{ni}(\nu)}{\kappa_{ni}} \left(\frac{C_{nz}(\nu)}{\alpha}\right)^{\alpha} \left(\frac{H_{nz}(\nu)}{1-\alpha}\right)^{1-\alpha} \tag{3}$$

where κ_{ni} is the iceberg commuting cost between n and i; b_{ni} is the idiosyncratic preference shock for location i, n; C_{nz} is the consumption of final goods by worker ν residing in n and working in sector z; H_{nz} is the consumption of housing by worker ν residing in n and working in sector z; and α is the share of consumption in final goods. The utility function is an expanded version of the utility function in Monte et al.'s (2018) to include sector-specific preferences.

The idiosyncratic shocks are drawn from an independent and identically distributed Fréchet distribution ($G_{niz}(b) = \exp(-B_{niz}b^{-\epsilon})$) with scale parameter B_{ni}, measuring the average amenity of living in n and commuting to i, and shape parameter ϵ, which captures the dispersion of preferences for working and living in different locations. Given that all workers L_{niz} earn the same wages and consume the same bundle of goods, b_{ni} ensures that workers are heterogenous in their preferences for residence and working locations.

Following the properties of the Fréchet distribution, the probability that a worker chooses to live in n and work in county i for sector z is equal to the utility of that choice relative to the utility of all other choices. The indirect utility function, measuring the maximum satisfaction a worker can achieve given their wages and prices of final goods, is specified as:

$$V_{niz} = \frac{b_{ni}w_{iz}}{\kappa_{ni}P_n^{\alpha}Q_n^{1-\alpha}} \tag{4}$$

where w_{iz} is the wage in location i for sector z, P_n is the price index of final goods in location n, and Q_n is the price index of housing in location n (Monte et al., 2018). Given the distribution of the idiosyncratic preference, the indirect utility of workers in n, i, z also follows the Fréchet distribution. Specifically, V follows $G_{niz}(V) = \exp(-\Psi_{niz}V^{\epsilon})$, where $\Psi_{niz} = B_{ni}(\kappa_{ni}P_n^{\alpha}Q_n^{1-\alpha})^{-\epsilon}w_{iz}^{\epsilon}$ based on the Fréchet distribution of b_{ni}. The probability that a worker chooses to live in n and work in i, z is therefore given by:

$$\lambda_{niz} = \frac{B_{niz}\left(\kappa_{ni}P_n^{\alpha}Q_n^{1-\alpha}\right)^{-\epsilon}w_{iz}^{\epsilon}}{\sum_{n'\in N}\sum_{i'\in N}\sum_{z'\in\{s,l\}}B_{n'i'z'}\left(\kappa_{n'i'}P_{n'}^{\alpha}Q_{n'}^{1-\alpha}\right)^{-\epsilon}w_{i'z'}^{\epsilon}} \tag{5}$$

Conditional on the idiosyncratic preference shock, workers choose to reside in locations that offer higher average amentities (B_{ni}) with lower price levels for consumption and housing, work in locations and in sectors with higher wages, and choose commuting flows with lower commuting costs. Conditional on a worker residing in n, the probability of working in i, z is represented as $\lambda_{niz|n}$. The labor market clearing condition requires that the total labor supply in each location and sector equals the total workers commuting to that location and sector:

$$L_{iz} = \sum_{n\in N}\lambda_{niz|n}R_n \tag{6}$$

where R_n is the total supply of workers residing in location n.

The average income of workers residing in n and working in sector z is thus given by:

$$\bar{v}_{nz} = \sum_{i \in N} \lambda_{niz|n} w_{iz} \tag{7}$$

Workers have a nested Constant Elasticity of Substitution (CES) preference over the varieties of goods produced in each sector and each location, where consumers have a love of variety as in Dixit and Stiglitz (1977). The total quantity of consumer expenditure by workers residing in county n is given by:

$$C_n = \left[\sum_{z \in \{s,l\}} C_{nz}^{\frac{\xi-1}{\xi}} \right]^{\frac{\xi}{\xi-1}}, C_{nz} = \left[\sum_{i \in N} \int_0^{M_{iz}} c_{niz}(g)^{\frac{\rho_z-1}{\rho_z}} dg \right]^{\frac{\rho_z}{\rho_z-1}} \tag{8}$$

where $c_{niz}(g)$ is the consumption of variety g produced in location i and sector z by workers residing in location n.

5.1.2 Production

Each business produces a differentiated variety (g) of a final good using labor as an input. Businesses operate under monopolistic competition and increasing returns to scale, as in Krugman et al. (1980) and Dixit and Stiglitz (1977). Consistent with Monte et al. (2018), the total amount of labor required to produce $x_{iz}(g)$ units of output is expressed as: $l_{iz}(g) = F_{iz} + x_{iz}(g)/A_{iz}$, where businesses incur fixed cost F_{iz}, and variable costs are scaled by A_{iz}, the productivity of businesses in location i and sector z. Equilibrium prices follow the standard markup over marginal cost, where $p_{niz}(g) = \frac{\sigma}{\sigma-1} \frac{d_{niz} w_{iz}}{A_{iz}}$, σ is the elasticity of substitution between varieties, and d_{niz} is the iceberg trade cost between locations i and n. Under the zero profits assumption, equilibrium output is given by $x_{iz}(g) = A_{iz} F_{iz}(\sigma - 1)$. Since the total measure of produced varieties (M_{iz}) is proportional to the measure of employed workers (L_{iz}), the number of businesses in each location and sector is given by:

$$M_{iz} = \frac{L_{iz}}{\sigma F_{iz}} \tag{9}$$

5.1.3 Goods Trade

Consumption occurs within the county where a worker resides (n), where goods are purchased either within-county or from other counties, subject to trade costs. The price index P_n in location n, and sector-specific price index P_{nz} follow a CES functional form:

$$P_n = \left(\sum_z P_{nz}^{1-\xi} \right)^{\frac{1}{1-\xi}} \tag{10}$$

$$P_{nz} = \left[\sum_{i \in N} \int_0^{M_{iz}} p_{niz}(g)^{1-\sigma_z} dg \right]^{\frac{1}{1-\sigma_z}} = \left[\sum_{i \in N} M_{iz} p_{niz}^{1-\sigma_z} \right]^{\frac{1}{1-\sigma_z}} \tag{11}$$

where $p_{niz}(g)$ is the price of variety g and P_{nz} is the Dixit-Stiglitz equilibrium price index. The CES preferences over varieties of goods and the resulting price index lead to the following gravity equation for bilateral trade flows:

$$\pi_{niz} = \frac{\frac{L_{iz}}{F_{iz}} \left(\frac{d_{niz} w_{iz}}{A_{iz}} \right)^{1-\sigma_z}}{\sum_{k \in N} \frac{L_{kz}}{F_{kz}} \left(\frac{d_{nk} w_{kz}}{A_{kz}} \right)^{1-\sigma_z}} \tag{12}$$

where π_{niz} is the share of expenditure on goods from location i and sector z by consumers in location n.

Given the demand function for each variety, the share of location n's expenditure on goods produced in location i, sector z (E_{niz}) is given by:

$$E_{niz} = \left(\frac{P_{nz}^{1-\xi}}{\sum_{z' \in Z} P_{nz'}^{1-\xi}} \right) \left(\frac{M_{iz} p_{niz}^{1-\sigma}}{\sum_{i' \in N} M_{i'z} p_{ni'z}^{1-\sigma}} \right) \tag{13}$$

Intuitively, expenditure in each sector is decreasing in the price level from location n and the price of goods in county n from county i, and increasing in the number of varieties produced in county i.

Given consumers' love of variety, higher employment in county-sector (i, z) increases the measure of varieties produced in i (equation 9). This raises the share of destination (n)'s sector (z) expenditure allocated to varieties produced in (i, z) (equation 12) and lowers the destination-sector price index P_{nz} (equation 10), generating home-market agglomeration forces in the model.

5.1.4 Banks and Small Business Lending

Banks ($j^{\mathcal{Z}}$), indexed by $j^{\mathcal{Z}} \in J^{\mathcal{Z}}$, provide financing to small businesses through small business loans. Motivated by Aguirregabiria et al. (2025), the banks operate in $M^{\mathcal{B}}$ geographical markets, which are defined as the area within 50 miles of each county centroid.[14] Banks are either community banks ($j^{\mathcal{C}}$) or non-community banks ($j^{\mathcal{NC}}$), where $\mathcal{Z} \in \{\mathcal{C}, \mathcal{NC}\}$. The profit function for bank $j^{\mathcal{Z}}$ is equal to interest earnings on small business loans minus the costs of managing the portfolio:

[14]Similar to the analysis performed in Section 4.6, there is a mismatch between the county-level data, such as the data provided by the BEA, CRA, BLS, etc., and the more granular branch-level data provided by the SOD. Therefore, a distance-based measure is used for bank markets, where a bank is considered as lending within market if there is a branch within 50 miles of the population-weighted county centroid where the small business is established, as listed in the CRA data. .

$$\Pi_j^{\mathcal{Z}} = \sum_{m^{\mathcal{B}} \in M^{\mathcal{B}}} p^{\mathcal{L}}_{j^{\mathcal{Z}} m^{\mathcal{B}}} q^{\mathcal{L}}_{j^{\mathcal{Z}} m^{\mathcal{B}}} - C(q^{\mathcal{L}}_{j^{\mathcal{Z}} m^{\mathcal{B}}}) \tag{14}$$

where $p^{\mathcal{L}}_{j^{\mathcal{Z}} m^{\mathcal{B}}}$ is the price of small business loans in market $m^{\mathcal{B}}$ for bank $j^{\mathcal{Z}}$, $q^{\mathcal{L}}_{j^{\mathcal{Z}} m^{\mathcal{B}}}$ is the quantity of small business loans provided by bank $j^{\mathcal{Z}}$ in market $m^{\mathcal{B}}$, and $C(q^{\mathcal{L}}_{j^{\mathcal{Z}} m^{\mathcal{B}}})$ is the cost function of managing the loan portfolio. The cost function includes the expected cost of loan default or prepayment. Each bank's variable cost $\tilde{C}_{j^{\mathcal{Z}} m^{\mathcal{B}}}$ of providing small business loans is a function of observables $\mathbf{x}^{\mathcal{L}}_{j^{\mathcal{Z}} m^{\mathcal{B}}}$ and unobservables $\omega^{\mathcal{L},\mathcal{Z}}_{j^{\mathcal{Z}} m^{\mathcal{B}}}$: $\tilde{C}(q^{\mathcal{L}}_{j^{\mathcal{Z}} m^{\mathcal{B}}}) = (\mathbf{x}^{\mathcal{L}}_{j^{\mathcal{Z}} m^{\mathcal{B}}} \gamma^{\mathcal{L},\mathcal{Z}} + \omega^{\mathcal{L},\mathcal{Z}}_{j^{\mathcal{Z}} m^{\mathcal{B}}}) q^{\mathcal{L}}_{j^{\mathcal{Z}} m^{\mathcal{B}}}$, where $\gamma^{\mathcal{L},\mathcal{Z}}$ is a vector of scaling coefficients. The vector of observables includes the number of branches in the market ($n^{\mathcal{B}}_{j^{\mathcal{Z}} m^{\mathcal{B}}}$), the bank's number of deposits in market $m^{\mathcal{B}}$ ($q^{\mathcal{D}}_{j^{\mathcal{Z}} m^{\mathcal{B}}}$), the bank's total deposits across all branches in its network ($\sum_{m^{\mathcal{B}} \in M^{\mathcal{B}}} q^{\mathcal{D}}_{j^{\mathcal{Z}} m^{\mathcal{B}}}$), and the productivity of the businesses in market $m^{\mathcal{B}}$ ($A_{m^{\mathcal{B}}}$):

$$\mathbf{x}^{\mathcal{L}'}_{j^{\mathcal{Z}} m^{\mathcal{B}}} \gamma^{\mathcal{L},\mathcal{Z}} = \gamma^{\mathcal{L},\mathcal{Z}}_n h_1(n_{jm^{\mathcal{B}}}) + \gamma^{\mathcal{L},\mathcal{Z}}_d q^{\mathcal{D}}_{j^{\mathcal{Z}} m^{\mathcal{B}}} + \gamma^{\mathcal{L},\mathcal{Z}}_D \sum_{m^{\mathcal{B}} \in M^{\mathcal{B}}} q_{j^{\mathcal{Z}} m^{\mathcal{B}}} + \gamma^{\mathcal{L},\mathcal{Z}}_A A_{m^{\mathcal{B}}} + \gamma^{\mathcal{L},\mathcal{Z}}_{nA} h_2(n_{j^{\mathcal{Z}} m^{\mathcal{B}}}, A_{m^{\mathcal{B}}}) \tag{15}$$

The functions h_1 and h_2 allow for non-linear effects of the number of branches and the interaction between the number of branches and business productivity, where more branches reduces the monitoring cost of loans and represents economies of scale and scope between branches in the same market, and small business productivity represents a coarse measure of creditworthiness of the borrower. The terms $\gamma^{\mathcal{L},\mathcal{Z}}_d$ and $\gamma^{\mathcal{L},\mathcal{Z}}_K$ capture the extent to which local deposits and total deposits, respectively, reduce the cost of providing small business loans.

Businesses M_{iz} demand small business loans from banks to reduce the cost of entering and operating in the county i. Specifically, the number of SBLs received by firms ($q^{\mathcal{L}}_{iz}$) reduces fixed costs for small businesses, such that the effective fixed cost for small businesses in location i is given by $F_{iz} = \bar{F}_{iz} \left(q^{\mathcal{L}}_{iz}\right)^{\mu}$, where $\bar{F}_{iz}$ is the average fixed cost for small businesses in location i, sector z and μ is the elasticity of fixed costs with respect to loan quantity. While business profit is intuitively reduced by interest and principal payments, data constraints lead to the modeling of latent net business surplus, in the spirit of Aguirregabiria et al. (2025), as described in Section 5.2.3.

To simplify the model, bank lending is not constrained by network-level deposits or access to interbank wholesale market as in Aguirregabiria et al. (2025). An investigation into the impact of MDP investments on deposit growth finds minimal county-level deposit growth after MDP openings, and Aguirregabiria et al. (2025) provides additional evidence that local deposit growth does not necessarily translate into increased lending locally, which is the main focus of this analysis (see Appendix **??** for further discussion). Therefore, lending bank-level lending is constrained by observed baseline bank-level lending with incremenetal increases driven by market expansions, as summarized in Section 5.2.3.

In the spirit of the social surplus concept outlined by Aguirregabiria et al. (2025), the market for small business lending is represented as a borrower-bank match surplus. Each bank $j^{\mathcal{Z}}$ offers a loan relationship that differs in price ($p^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}}$), relationship cost, monitoring cost, application cost, branch access, and unobserved match quality. Rather than separately identifying the small business lending demand function for small businesses and cost function for community and non-community banks, the net surplus of small business lending is defined as:

$$NLS^{\mathcal{L}}_{j^{\mathcal{Z}}is} = \mathbf{x}^{\mathcal{L}'}_{j^{\mathcal{Z}}m^{\mathcal{B}}}\beta^{\mathcal{L},\mathcal{Z}} - p^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}} + \zeta^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}} + \epsilon^{\mathcal{L}}_{j^{\mathcal{Z}}is} \tag{16}$$

where business value of credit ($\mathbf{x}^{\mathcal{L}'}_{j^{\mathcal{Z}}m^{\mathcal{B}}}\beta^{\mathcal{L},\mathcal{Z}}$) approximates the reduction in fixed costs from small business loans and is a function of the same observables as the cost function. $\zeta^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}}$ is a vector of observables to the business but not the researcher, and $\epsilon^{\mathcal{L}}_{j^{\mathcal{Z}}is}$ are match-specific unobservables that follow the type one extreme value distribution. Specifically, businesses benefit from higher access to bank branches, the economies of scale captured by higher deposits held locally, and the total deposits captures concern around the probability of a bank's default or a bank run, where consumer concern is decreasing in a bank's total deposits. Each of these factors are expected to impact the net lending surplis differently for community banks and non-community banks, which operate with unique competitive advantages (e.g., relationship lending advantages by community banks may increase the marginal net surplus value of maintaining a local branch for community banks more than non-community banks). Defining market share ($s^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}}$) of bank $j^{\mathcal{Z}}$ in market $m^{\mathcal{B}}$ as the fraction of small business loans in market $m^{\mathcal{B}}$, the logit assumption on $\epsilon^{\mathcal{L}}_{j^{\mathcal{Z}}is}$ leads to the following:

$$s^{\mathcal{L},\mathcal{Z}}_{j^{\mathcal{Z}}m^{\mathcal{B}}} = \frac{\mathbb{1}_{\{m^{\mathcal{B}} \in M^{\mathcal{B}}_{j^{\mathcal{Z}}}\}} \exp\{\mathbf{x}^{\mathcal{L},\mathcal{Z}'}_{j^{\mathcal{Z}}m^{\mathcal{B}}}\beta^{\mathcal{L},\mathcal{Z}} - p^{\mathcal{L},\mathcal{Z}}_{j^{\mathcal{Z}}m^{\mathcal{B}}} + \zeta^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}}\}}{1 + \sum_{j^{\mathcal{Z}'} \in J^{\mathcal{Z}}} \mathbb{1}_{\{m^{\mathcal{B}} \in M^{\mathcal{B}}_{j^{\mathcal{Z}'}}\}} \exp\{\mathbf{x}^{\mathcal{L}'}_{j^{\mathcal{Z}'}m^{\mathcal{B}}}\beta^{\mathcal{L},\mathcal{Z}} - p^{\mathcal{L}}_{j^{\mathcal{Z}'}m^{\mathcal{B}}} + \zeta^{\mathcal{L}}_{j^{\mathcal{Z}'}m^{\mathcal{B}}}\}} \tag{17}$$

Given the competitive nature of the small business lending market, each bank chooses a vector of interest rates to maximize profit. Following a Nash-Betrand style competition, the pricing pricing equations follow:

$$p^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}} - c^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}} = \frac{1}{1 - s^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}}} \tag{18}$$

where $c^{\mathcal{L}}_{j\mathcal{Z}m^{\mathcal{B}}}$ is the marginal cost of providing small business loans. If $s^{\mathcal{L}}_{om^{\mathcal{B}}}$ is the market share of the outside option in market $m^{\mathcal{B}}$, then the logit model implies that $\ln(s^{\mathcal{L},\mathcal{Z}}_{j^{\mathcal{Z}}m^{\mathcal{B}}})$ - $\ln(s^{\mathcal{L}}_{om^{\mathcal{B}}}) = \mathbf{x}^{\mathcal{L}'}_{j^{\mathcal{Z}}m^{\mathcal{B}}}\beta^{\mathcal{L},\mathcal{Z}} - p^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}} + \zeta^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}}$. Substituting in the pricing equation, the market share of bank $j^{\mathcal{Z}}$ in market $m^{\mathcal{B}}$ can be expressed as a function of the cost shifters and unobservables:

$$ln(s^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}}) - ln(s^{\mathcal{L}}_{om^{\mathcal{B}}}) + \frac{1}{1 - s^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}}} = (\omega^{\mathcal{L},\mathcal{Z}}_{n})h_1(n_{j^{\mathcal{Z}}m^{\mathcal{B}}}) + (\omega^{\mathcal{L},\mathcal{Z}}_{d})q^{\mathcal{D}}_{j^{\mathcal{Z}}m^{\mathcal{B}}} + (\omega^{\mathcal{L},\mathcal{Z}}_{D}) \sum_{m^{\mathcal{B}} \in M^{\mathcal{B}}} q_{j^{\mathcal{Z}}m^{\mathcal{B}}} + (\omega^{\mathcal{L},\mathcal{Z}}_{A})A_{m^{\mathcal{B}}} \tag{19}$$

$$+ (\omega^{\mathcal{L},,\mathcal{Z}}_{nA})h_2(n_{jm^{\mathcal{B}}}, A_{m^{\mathcal{B}}}) \tag{20}$$

5.1.5 General Equilibrium

The model's equilibrium is characterized by seven endogenous variables $\{w_{iz}, P_{nz}, L_{iz}, R_{iz}, \bar{v}_{iz}, Q_{iz}, q^{\mathcal{L}}_{iz}\}$ and scalar $\bar{U}$. The equilibrium values of these variables solves the goods market equilibrium, the labor market clearing, land market clearing, and the small business lending market clearing conditions.

An overview of the model is presented in Figure H1.

5.2 Calibration

The model is calibrated to the year 2009, which is the year before the first MDP opening in the sample. The primary data sources for calibration include the Bureau of Economic Analysis, U.S. Census, CRA, and existing literature for standard parameters.

5.2.1 Commuting

Following the approach outlined in Monte et al. (2018), commuting flows are calibrated from the American Community Survey (ACS) 5-year estimates for county-to-county commuting patterns. To exclude the influence of telework and business travels, the ACS flows are restricted to workers who commute less than 120 kilometers, following Monte et al. (2018). To re-impute the flows that are greater than 120 kilometers, I use the model's commuting gravity equation to predict baseline commuting flows. The gravity equation is:

$$\log(Flow_{ni}) = \eta_n + \eta_i - \phi \log(dist_{ni}) + \epsilon_{ni} \tag{21}$$

, where $Flow_{ni}$ is the number of workers commuting from county n to county i, η_n and η_i are county fixed effects, $dist_{ni}$ is the distance between counties n and i, and ϵ_{ni} is the error term. I estimate the parameter $\phi = -1.94$ using the gravity equation for commuting flows. I estimate the Fréchet shape parameter ϵ using the identified ϕ and instrument wage using the productivities recovered from the model, as in Monte et al. (2018). Using Two-Stage-Least-Squares, I estimate the Fréchet shape parameter ϵ to be 3.85.[15]

[15] Since the commuting flows are estimated using the ACS 5-year estimates which do not provide flows by employer size, the parameters cannot be estimated separately for small and large businesses.

5.2.2 Goods Trade

Following the approach outlined in Monte et al. (2018), trading flows are calibrated from the Commodity Flow Survey (CFS) for origin-destination trade patterns between 131 CFS regions. The CFS regions are mapped to counties, with trade values allocated to counties based on residential income (calculated as $\bar{v}_i R_i$). Using the trade flows, county-level trade deficits are imputed which supports the recovery of unobserved productivities for small and non-small businesses at the county level by solving the equality between county and sector-level income and expenditure:

$$w_{iz} L_{iz} = \sum_{n \in N} \frac{\frac{L_{iz}}{F_{iz}} (d_{ni} w_{iz} / A_{iz})^{1-\sigma}}{\sum_{i' \in N} \frac{L_{i'z}}{F_{i'z}} (d_{ni'} w_{i'z} / A_{i'z})^{1-\sigma}} [\bar{v}_{nz} R_n + D_n] = 0 \tag{22}$$

where I use baseline values from collected data for w_{iz}, L_{iz}, d_{ni}, and recovered values for $\bar{v}_{nz}$, R_{iz}, and D_n. Given that the CFS data does not provide trade flows for small business and big business separately, I assume that the flows are representative of non-small business. To calibrate the flows for small business, which are more likely to operate in local markets, I propose using moment matching to align the model's predicted trade flows with moments sourced from the Federal Reserve's Small Business Credit Survey (SBCS). Specifically, approximately 21% of small businesses identify the market for key customers as 0 miles (businesses's headquarters), 58% idenify key customers within 0-50 miles (locally), 27% within 51-500 miles (regionally), and another 23% as outside 500 miles (nationally). Given these statistics, I calibrate the small business productivity to align with trade flows that match approximately 60% within either 50 miles of the county centroid or within the county boundaries, 30% within 500 miles, and 10% outside 500 miles.[16]

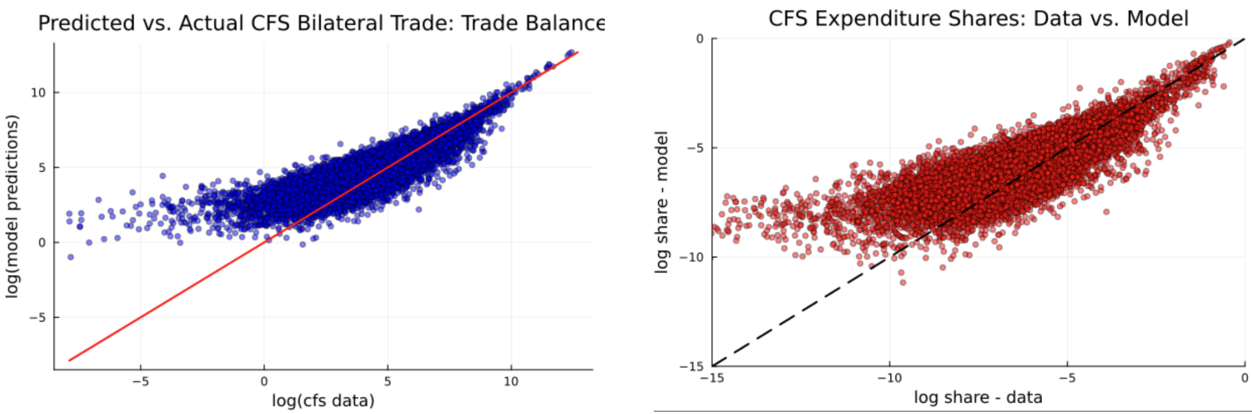
The expenditure shares on tradable goods from small and large businsses were calculated based on equation (12). Using the trade gravity model and CFS data, I estimate the composite parameter $\psi_l(\sigma - 1)$ for non-small business to be -1.12. Given the selected value for σ of 4, the implied value for ψ_l is 0.37. For the small business sector, the moment matching returns a value of 0.8 for ψ_s. The higher value for ψ_s is consistent with the expectation that small businesses are more likely to operate in local markets, and therefore have a higher elasticity of trade costs to distance than the non-small business sector.

Figure 4 compares the large business trade balances and expenditure shares for each CFS region to those predicted by the model and confirms that the model predicts trade flows for the large business sector well, with only slight over-predictions for sparse regions. Figure 5 presents the cumulative distribution plot for the percent of small business trade flows within 0-50 (or within county), 50-500, and 500+ of business

[16] Using the data appendix from the 2024 SBCS of Employer Firms, I use the responses for the survey question "Distance from hq business delivers products / renders services to key customers". Participating small businesses were encouraged to select all responses that applied, so the percentages do not sum to 100%.

headquarters. For each distance threshold, the distribution is centered within 5 percentage points of the targeted moments (see Section 5.2.3 for more details).

Figure 4: Comparison of Observed Trade Patterns and Large Business Model Predictions



Note: The figures present the logged values of CFS region-to-region trade shares (panel A) and expenditure shares (panel B). The dashed line is 45 degrees to represent the region where predicted values are equal to the observed values. The predicted values are for goods produced by large businesses, which are assumed to follow the patterns reflected in the CFS data.

5.2.3 Small Business Lending

Given the setup outlined in Section 5.1.4, there are two channels through which MDP investments will influence small business lending. First, the MDP introduces a productivity shock to the small business sector which shifts the share of SBL originations through equation 23. Second, the productivity shock may lead to population growth in the MDP county through general equilibrium effects which increases the market size in the county, further increasing SBL originations. The following sections outline the calibration approach for each.

Direct Effect of Productivity Shock on Small Business Lending

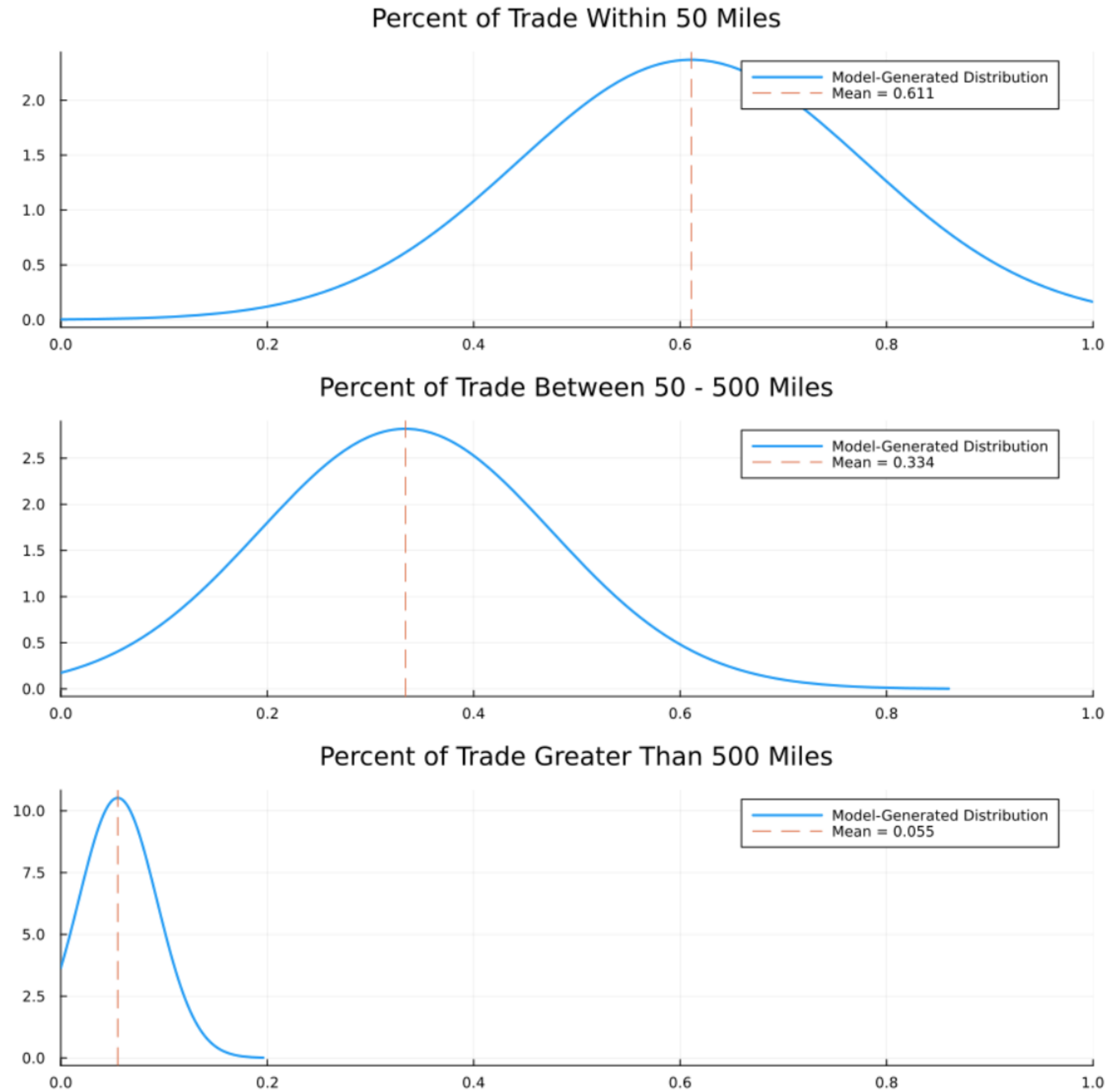
Following the approach outlined in Aguirregabiria et al. (2025), small business lending flow is calibrated using the reduced form equation:

$$y^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}t} = \mathbf{z}'_{m^{\mathcal{B}}t}\theta_0^{\mathcal{L},\mathcal{Z}} + \sum_{n=1}^{n_{max}} \theta_n^{\mathcal{L},\mathcal{Z}} \mathbb{1}_{\{n_{j^{\mathcal{Z}}m^{\mathcal{B}}t} \geq n\}} + \theta_A^{\mathcal{L},\mathcal{Z}} ln(A_{m^{\mathcal{B}}t}) + \theta_d^{\mathcal{L},\mathcal{Z}} q^{\mathcal{D}}_{j^{\mathcal{Z}}m^{\mathcal{B}}t} + \theta_D^{\mathcal{L},\mathcal{Z}} \sum_{m^{\mathcal{B}} \in M^{\mathcal{B}}} q_{j^{\mathcal{Z}}m^{\mathcal{B}}t} \tag{23}$$

$$+ \theta_{nA}^{\mathcal{L},\mathcal{Z}} \sum_{n=1}^{n_{max}} \theta_n^{\mathcal{L},\mathcal{Z}} \mathbb{1}_{\{n_{j^{\mathcal{Z}}m^{\mathcal{B}}t} \geq n\}} \times ln(A_{m^{\mathcal{B}}t}) + \eta^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}t}$$

where $y^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}t} = ln(\frac{s^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}t}}{s^{\mathcal{L}}_{0m^{\mathcal{B}}t}}) + 1/(1 - s^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}t})$ and represents bank $j^{\mathcal{Z}}$'s market-competition-adjusted market share in $m^{\mathcal{B}}$, $\mathbb{1}_{\{n_{j^{\mathcal{Z}}m^{\mathcal{B}}t} \geq n\}}$ is equal to 1 if $j^{\mathcal{Z}}$ has at least n branches in $m^{\mathcal{B}}$ in year t, and $\mathbf{z}'_{m^{\mathcal{B}}t}$ is the vector

Figure 5: Comparison of Observed Trade Patterns and Small Business Model Predictions



Note: The figures present the cumulative distribution function of the percent of trade flows for goods produced by small businesses that are within 50 miles, 50-500 miles, and 500+ miles of the business headquarters. The targeted moments for these three thresholds is 60%, 30%, and 10% based on author calulcations of data provided by the Federal Reserve Smmall Business Credit Survey.

of observed market characteristics in market $m^{\mathcal{B}}$ in year t, including population, income per capita, and the total large bank share to control for more competitive and larger markets.

To directly study the role of local community bank branches in fueling post-MDP small business growth, I use both the number of branches and the productivity of small businesses, and the interaction of these factors to explain the bank lending share in each market. The dummy variables for branches allow nonlinear effects of operating 1, 2, 3, 4, 5, 6, or greater than 6 branches in $m^{\mathcal{B}}$. The interactions with small business productivities allow banks to lend more to productive small businesses.

A challenge with estimating the structural equation 23 is that small business productivity is unobservable and therefore challenging to measure. To prepare a measure of small business productivity across time, I use the calibrated spatial equilibrium model for each year between 2010 and 2023 to recover small business productivities and prepare a panel of county-level small business productivities. By using time-varying productivities, I can include county-level fixed effects to control for time-invariant differences in demand for SBLs and other unobserved factors that influence the spatial distribution of bank lending patterns, reducing confounding effects of unobservables ($\omega^{\mathcal{L},\mathcal{Z}}_{j^{\mathcal{Z}}m^{\mathcal{B}}}$).

To estimate equation 23, I use the Heckman-inspired two-step control function approach similar to Aguirregabiria et al. (2025). Since banks choose where to establish branches, the number of branches may be endogenous to the market share of SBLs. In addition to relying on strong fixed effects, Aguirregabiria et al. (2025) estimate a switching regression model with separate regimes for bank-market pairs with and without a branch, and use the propensity scores estimated by the control function as an additional control in equation 23. While I draw on the two-stage control function approach, I estimate a joint model that includes both branch-market pairs that operate and do not operate branches in the market. By estimating the joint model, rather than estimating them separately, I can directly estimate the effect of operating one branch on the market share of SBLs compared to not operating any branches. Estimating the joint model is more feasible in my setting compared to Aguirregabiria et al. (2025) given that I am not simultaneously estimating the share of deposits. The estimation is performed both for community banks ($\mathcal{Z} = \mathcal{C}$) and non-community banks ($\mathcal{Z} = \mathcal{NC}$) separately, as the two types of banks have different lending strategies and competitive advantages.

The results from the estimation are presented in Table 10. The estimated coefficients highlight the importance of both branch access and productivity of small businesses in the SBL origination process. The lending response to the number of branches is monotonic and increasing for the first 3 branches for community banks and 5 for non-community banks, afterwhich the marginal benefit of operating an additional branch within the market is decreasing. While non-community banks with 0 branches in the market have smaller market shares in counties with more productive small businesses – potentially because they struggle to

Table 10: Estimation of Direct Structural Equation for Small Business Lending Share

	50 Miles	
	Community Bank	Non-Community Bank
Panel A: Estimated cumulative productivity coefficients		
Productivity	-0.064	-0.534^{***}
	(0.057)	(0.053)
Productivity $\times \geq 1$ Branch	0.471^{***}	0.569^{***}
	(0.054)	(0.057)
Productivity $\times \geq 2$ Branches	0.231^{***}	0.437^{***}
	(0.074)	(0.055)
Productivity $\times \geq 3$ Branches	0.240^{***}	0.057
	(0.083)	(0.060)
Productivity $\times \geq 4$ Branches	-0.132	0.211^{***}
	(0.085)	(0.061)
Productivity $\times \geq 5$ Branches	-0.196^{**}	0.111^{*}
	(0.098)	(0.063)
Productivity $\times \geq 6$ Branches	-0.373^{***}	-0.705^{***}
	(0.081)	(0.059)
Panel B: Implied total productivity effects by branch bin		
0 Branches	-0.064	-0.534^{***}
	(0.057)	(0.053)
1 Branch	0.407^{***}	0.035
	(0.068)	(0.076)
2 Branches	0.638^{***}	0.472^{***}
	(0.082)	(0.071)
3 Branches	0.879^{***}	0.530^{***}
	(0.080)	(0.068)
4 Branches	0.747^{***}	0.741^{***}
	(0.085)	(0.067)
5 Branches	0.550^{***}	0.851^{***}
	(0.090)	(0.074)
≥ 6 Branches	0.177^{***}	0.146^{***}
	(0.053)	(0.051)
Fixed-effects and controls		
Year FE	Yes	Yes
Bank FE	Yes	Yes
County FE	Yes	Yes
Branch control function	Yes	Yes
County controls	Yes	Yes
Fit statistics		
Observations	719,761	719,761
R^2	0.68889	0.68889
Within R^2	0.22367	0.22367

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the outcome variable is $y^{\mathcal{L}}_{jm^{\mathcal{B}}t} = ln(s^{\mathcal{L}}_{jm^{\mathcal{B}}}) - ln(s^{\mathcal{L}}_{0m^{\mathcal{B}}}) + 1/(1 - s^{\mathcal{L}}_{jm^{\mathcal{B}}})$, which approximates the market share of small business loans for bank j in market $m^{\mathcal{B}}$ in year t; control variables include population, income per capita, and the total large bank share in the market, as well as the third-order polynomial of the estimated propensity scores from the two-stage control function; the branch dummy variables are defined cumulatively, where each bank that has at least 1 branch in market $m^{\mathcal{B}}$ in year t is assigned a value of 1 for the $1Branch$ variable; the cumulative productivity effects are calculated as the sum of the relevant branch dummy variables and interactions, depending on the number of branches in market $m^{\mathcal{B}}$ in t. The productivity variable is the inverted productivity for the small business sector in each year. The productivity is normalized to have a mean of 1 each year, and the time fixed effect controls for the year-to-year changes in average productivity across the panel.

compete with banks with a stronger local presence – the interaction terms reveal marginally increasing returns to branch access for the first few branches. Specifically, community banks with at least 1 branch in $m^{\mathcal{B}}$ have 47% higher market shares than banks with 0 branches, while non-community banks have 57% higher market shares. While the marginal return of additional branches becomes negative after 3 branches and 5 branches for community banks and non-community banks, respectively, the cumulative effects are positive. The cumulative effects of branch access on lending to productive small businesses are presented in Panel B and show that community banks with 6 or more branches retain 18% higher market share compared to community banks with no branches and similar but smaller effects for non-community banks. Comparing the community bank and non-community bank results, the results suggest that community banks are more responsive to small business productivity than non-community banks in markets with branch access, with cumulative effects that are higher in for each branch bin other than the "5 branches" bin, which is consistent with the hypothesis that community banks have a competitive advantage in relationship lending when maintaining a physical presence locally.

Indirect Effect of Productivity Shock on Small Business Lending: Market Size and General Equilibrium Effects

While the structural estimation from equation 23 identifies how productivity levels and branch access influences the share of SBLs by community banks and non-community banks, the indirect response by these institutions to the general equilibrium effects are better captured by the quasi-experimental design adopted in Sections 4.5 and 4.6. Specifically, calibrating directly to the observed changes in SBL by community banks and non-community banks in MDP counties allows a structural estimation that captures the full general equilibrium response to the productivity shock, while the structural estimation from equation 23 only identifies the direct effect of branch access and small business productivity levels on SBL share.

To prepare the market share variable, I follow Aguirregabiria et al. (2025) and define the market-size variable ($H^{\mathcal{L}}_{m^{\mathcal{B}}t}$) as proportional to the total population in county $m^{\mathcal{B}}$ in year t. Specifically, $H^{\mathcal{L}}_{m^{\mathcal{B}}t} = \lambda^{\mathcal{L}} Population_{m^{\mathcal{B}}t}$, where $\lambda^{\mathcal{L}}$ is a constant scaling parameter. The parameter is selected such that the market share variable satisfies the constraint $\sum_j s^{\mathcal{L}}_{jm^{\mathcal{B}}t} = Q^{\mathcal{L}}_{m^{\mathcal{B}}t}/H^{\mathcal{L}}_{m^{\mathcal{B}}t} \leq 1$ for all markets; that is, $\lambda^{\mathcal{L}} = \max_{m^{\mathcal{B}},t} \frac{Q^{\mathcal{L}}_{m^{\mathcal{B}}t}}{Population_{m^{\mathcal{B}}t}}$. The advantage of defining markets based on population is that the market can be endogenously solved in the model when shock-induced migration changes the population in counties. Therefore, as population in a county increases, the demand for small business loans increases as well. The inclusion of year and county fixed effects reduces the impact of any measurement errors in the market-size variable.

To allocate the additional small business loan demand from the expanded market size to banks, the new demand is first bifurcated into loans fulfilled by banks in the model (inside share) and loans fulfilled by outside options (outside share) using the sum of $s^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}}$ estimated based on the productivity shock and estimated coefficients from Table 10. To calibrate the allocation of the inside share of new loan demand, I use the weighted stacked difference-in-difference approach and estimate the bank-level response to the MDP openings based on the number of branches in the market and bank type (i.e., community bank or non-community bank) following the general framework outlined in Aguirregabiria et al. (2025). Specifically, I estimate the following equation:

$$y_{j^{\mathcal{Z}}cae} = \sum_{\mathcal{Z}\in\{\mathcal{C},\mathcal{NC}\}} \left[\theta_0^{\mathcal{L},\mathcal{Z}}\mathbb{1}_{\{n_{jc}=0\}} + \theta_1^{\mathcal{L},\mathcal{Z}}\mathbb{1}_{\{n_{jc}\geq 1\}} + \theta_2^{\mathcal{L},\mathcal{Z}}\mathbb{1}_{\{n_{jc}\geq 2\}}\right] \times \mathbb{1}_{\{\mathcal{Z}_|=\mathcal{Z}'\}} \times D_{ca} \times \mathbb{1}[e\geq 0] + \gamma D_{ca} + \sum_{\substack{h=-\kappa_{pre}\\ h\neq -1}}^{\kappa_{post}} \lambda_h \mathbb{1}[e=h] + \alpha_j + \epsilon_{caej} \tag{24}$$

where $y_{j^{\mathcal{Z}}cae}$ is bank $j^{\mathcal{Z}}$'s market share of small business loans in county c in subexperiment a for event time e, $\theta_n^{\mathcal{L},Z'}$ is the parameter representing the average 5-year change in market share post-MDP opening ($D_{ca} \times \mathbb{1}[e \geq 0]$) based on whether there are 1 or 2+ branches within 50 miles of the county centroid both for community banks and non-community banks, $\alpha_{\mathcal{C}}$ and $\alpha_{\mathcal{NC}}$ represent the post-opening response to the MDP by community banks and non-community banks in treated counties, respectively; α_1 is a fixed effect for treated counties, λ_h are event time fixed effects, α_j are bank-level fixed effects, and ϵ_{caej} is the error term. $\theta_0^{\mathcal{L},\mathcal{Z}}$, $\theta_1^{\mathcal{L},\mathcal{Z}}$, and $\theta_2^{\mathcal{L},\mathcal{Z}}$ are the parameters of interest that capture the average 5-year change in market share post-MDP opening for community and non-community banks with 0, 1, and 2+ branches within 50 miles of the county centroid, respectively. The estimation is performed jointly for community banks and non-community banks to capture the differential response to the MDP openings based on bank type. Using the product of the cumulative effects of branch access and the bank-specific loan share ($s^{\mathcal{L}}_{j^{\mathcal{Z}}m^{\mathcal{B}}}$) estimated from equation 23, the estimated coefficients from equation 24 are used to allocate the additional small business loan demand to banks based on their branch access and bank type.

The results from the estimation are presented in Table 11. Based on the runner-up and cancelled control group, community banks with no local branches lose market share equal to 48% in the 5 years after the MDP opening, on average. Community banks with at least 1 branch lose slightly less market share, equal to around 34%, while community banks with two or more local branches gain market share equal to approximately 66%, on average. Non-commmunity banks, on the other hand, lose 38% after the MDP opening if they have no local branches, 72% for those with at least 1 branch, and approximately 21% for those with two or more branches, on average.[17] While these these coefficients confirm that community banks with 2 or more local

[17] While the nonmonotonic response is unexpected, a review of the distribution of branches by banks in the sample reveals that very few banks only have one branch in a MDP or control county. Most banks either have 0 or at least 2 branches within the counties which may contribute to low precision or statistical power for estimating the ≥ 1 Branch dummy variable.

Table 11: Estimation of Indirect Structural Equation for Small Business Lending Share

	Runner-up / Cancelled Controls 50 Miles	Matched Controls 50 Miles
Panel A: Community Banks – Cumulative Effects		
0 Branches	-0.480^{**}	-0.858^{***}
	(0.193)	(0.176)
$\geq$ 1 Branch	-0.337^{*}	-0.720^{***}
	(0.193)	(0.191)
$\geq$ 2 Branches	0.662^{***}	0.411^{***}
	(0.132)	(0.103)
Fit statistics		
Observations	84,241	53,233
R^2	0.54863	0.42790
Panel B: Noncommunity Banks – Cumulative Effects		
0 Branches	-0.384^{***}	-0.196^{***}
	(0.089)	(0.061)
$\geq$ 1 Branch	-0.718^{***}	-0.572^{***}
	(0.244)	(0.218)
$\geq$ 2 Branches	0.207^{**}	0.401^{***}
	(0.096)	(0.071)
Fit statistics		
Observations	84,241	53,233
R^2	0.54863	0.42790
Fixed-effects		
Event-time FE	Yes	Yes
Treated-cohort FE	Yes	Yes
Bank FE	Yes	Yes

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the outcome variable is $y_{j\mathcal{Z}_{cae}} = ln(s_{j\mathcal{Z}_{cae}}) - ln(s_{0cae}) + 1/(1 - s_{j\mathcal{Z}_{cae}})$, which approximates the market share of small business loans for bank j in county c in event time e, sub experiment a; the branch dummy variables are defined cumulatively, where each bank that has at least 1 branch in county c in event time e is assigned a value of 1 for the $1Branch$ variable; the cumulative productivity effects are calculated as the sum of the relevant branch dummy variables and interactions, depending on the number of branches the bank has in county c in event time e.

branches capture most of the expanded market after the productivity shock, the estimation results when using the matched control group reveal more comparable gains by community banks a non-community banks with 2 or more local branches.

A summary of the calibration parameters is presented in Table 12.

Table 12: Summary of Calibration Parameters

Parameter	Baseline Value	Source
Armington Elasticity of Substitution (σ)	4	Broda and Weinstein (2006), Giri et al. (2021)
Sector Elasticity of Substitution Between Goods (ξ)	1.24	Edmond et al. (2015)
Consumer Expenditure Share on Tradable Goods (α)	0.67	Consumer Expenditure Surveys, 2021-2024
Elasticity of Commuting Costs to Distance (ϕ)	1.94	Estimated from commuting gravity equation
Elasticity of Not-Small Sector Trade Costs to Distance (ψ_l)	0.37	Estimated from trade gravity equation
Elasticity of Small Sector Trade Costs to Distance (ψ_s)	0.8	Calibrated using Method of Moments during Productivity Inversion
Elasticity of Fixed Cost Reduction to Debt (μ)	0.11	Estimated from reduced form analysis and model inversion
Fréchet Distribution Scale Parameter (B_{ni})	3108x3108	Model inversion
Fréchet Distribution Shape Parameter (ϵ)	3.85	Estimated from commuting gravity equation

Note: The table presents the summary of the calibration parameters for the model. The parameters are calibrated using data from the year 2009, which is the year before the first MDP opening in the sample. The data sources for calibration include the Bureau of Economic Analysis, U.S. Census, CRA, and existing literature for standard parameters.

The parameter that links the small business loans to the fixed costs of small businesses is μ. While μ cannot be directly observed without detailed microdata on the volume, pricing, and terms of small business lending and borrower financials, it can be approximated using the reduced form estimates and strutural model estimates from this paper. Expressing the relationship between fixed costs for a firm and small business loans in terms of percent changes ($\hat{F}_s$, $\hat{q^{\mathcal{L}}}$), $\hat{F}_s$ is proportional to the change in $\hat{q^{\mathcal{L}}}$ raised to the power of μ. Differentiating with respect to small business employment, μ can be expressed as:

$$\mu = -\frac{\partial \hat{F}_s}{\partial \hat{L}_s} / \frac{\partial \hat{q^{\mathcal{L}}}}{\partial \hat{L}_s} \tag{25}$$

. Relying on the reduced form estimates from Section 4.5 and 4.6, $\frac{\partial \hat{q^{\mathcal{L}}}}{\partial \hat{L}_s}$ is approximately $\frac{0.16}{0.02} = 8$. To recover $\frac{\partial \hat{F}_s}{\partial \hat{L}_s}$, I use the model to simulate the effect of a 5% decrease in small business fixed costs (holding small business loans constant) and estimate a central value across all $\frac{\partial \hat{F}_s}{\partial \hat{L}_s} = \frac{\log(0.95)}{\log(1.0598)} = -0.8829$. Therefore, μ is approximately $-0.8829/8 = 0.11$. This suggests that a 1% increase in small business loans leads to an 11% decrease in fixed costs for small businesses.

5.3 Counterfactual Analysis

The model is used to analyze small business lending and small business growth after MDP openings. To introduce the MDP shock into the model, the productivity for small and large businesses is increased by 3%, lower than the 5% used by Monte et al. (2018), to represent the agglomeration effects from the MDP. Rather than use a coarse measure of access to community bank lending based on the number of branches, I use the market share of SBLs by community banks in 2010 as the measure of access. While the number of branches is an intuitive and simple measure of access, not all branches may be equally active in the SBL market, and consistent with the hypotheses of Section 4.6, communities that are served by community banks are more likely to have more responsive supplies of small business credit. Therefore, the high-access counties are defined as those in the top tercile of community bank SBL market shares in 2010 based on the 50-mile radius, and the low-access counties are defined as those in the bottom tercile. In general, the results are more muted using the total number of community bank branches to measure access.

First, I use the calibrated model to validate the predicted effects of MDP openings on small business lending and small business establishments, employment, and wages. Figure 6 compares the ATT estimated from Sections 4.5 and 4.6 to the average ATT output from the model after shocking productivity in each county by 5%. The estimated coefficients of small business lending by commercial banks and wage growth in high-access MDP counties are generally consistent with the model predictions. However, the model predictions are much higher for small business establishment and employment growth compared to the reduced form estimates.

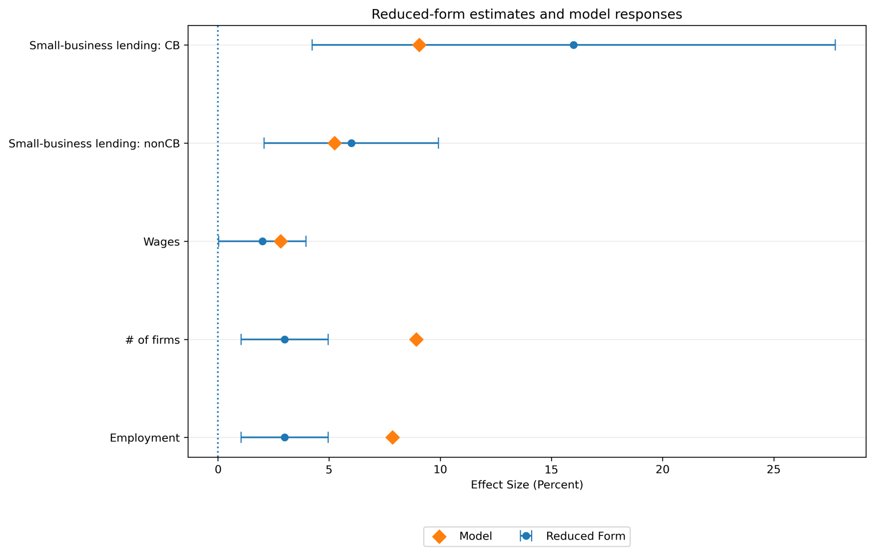
Second, I use the model to analyze the role of local community banks in supporting small business during without external shocks. Specifically, I run the calibrated model with no productivity shock excluding all community banks that have a branch within the county.

Table 13: Counterfactual Results: Closure of Local Community Banks

Outcome	No Local CBs (%)
SBL: CBs	-76.53
SBL: NonCBs	-1.25
SBL: Total	-18.53
Small Business Firms	-7.96
Small Business Employment	-4.52
Small Business Wages	-1.41
Total Welfare	-0.22

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*;

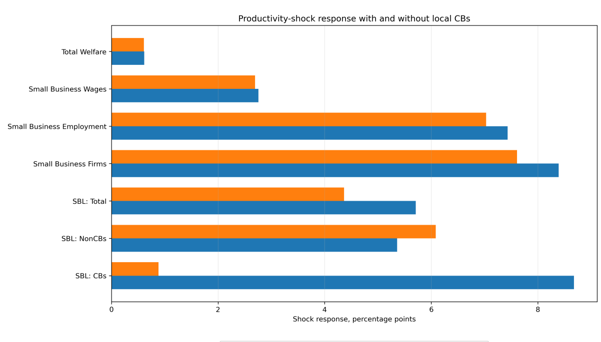
Figure 6: Comparison of Reduced Form ATT and Model Predictions



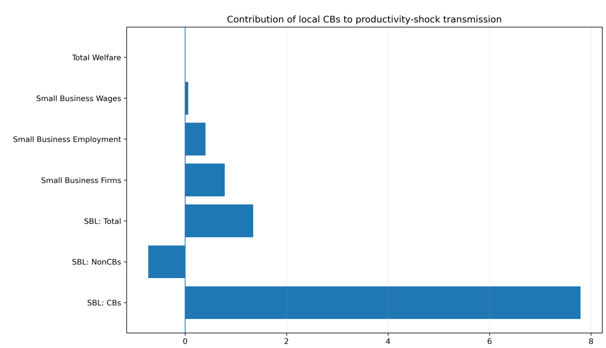
Note: The figure presents the estimated ATT from Sections 4.5 and 4.6 in blue and the average model prediction after iteratively shocking productivity in each county. Standard errors from the reduced form estimates are represented by the blue error bars. The model predictions are based on a shock to productivity of 3%.

Finally, I use the model to analyze how community banks impact the productivity shock by comparing the change in key economic variables in a no-community bank scenario to a full community bank scenario after a 3% productivity shock. The results are summarized in the table below.

Figure 7: Average Impact of Community Banks on Generating Spillovers from Productivity Shocks



(a) Comparing Change in Full Model vs. No Local Community Bank Model



(b) Difference Between Change in Full Model vs. No Local Community Bank Model

5.3.1 Discussion

As hypothesized, the increase in small business lending by community banks translates into increased small business development after MDP openings, with counties that have higher access to community banks experiencing 2-3 percent increases in small business establishments, employment, and earnings in the 5 years after the opening. Interpreted based on the median number of pre-opening small business establishments, the additional 7-12 SBLs originated by community banks each year after the MDP opening leads to an increase of approximately 24 small business establishments, 104 small business employees, and $57 of monthly income for small business employees. A comparison of the magnitudes suggests that the number of small business loans are likely underestimated given the underreporting of small banks in the CRA dataset. The industry-level analysis provides additional insights into the economic mechanisms through which MDPs generate small business growth. In both the high-access and low-access counties, small businesses in the service industry experience statistically significant growth, suggesting that the income effects of the MDP increase demand for restaurants, health care, and other service industries in the county. For small businesses in supporting industries, only those businesses in the high-access counties experience statistically significant increases, highlighting the importance of community bank small business financing to invest in the capacity to provide inputs or logistical support to the MDP production process. Finally, while small businesses in competing industries experience substantial contractions in counties with lower access to community bank capital, there is a null response in counties with higher access to community banks. Together, these results provide evidence that while community banks can spur small business growth in supporting industries, they also can provide resiliency for small businesses in competing industries by providing financial capital to offset rising wages and input costs.

6 Conclusion

This paper investigates the role of access to banking capital in promoting spillovers from MDPs to small businesses. Using a novel dataset of large MDPs and publicly available measures of small business lending and small business development, I causally establish that community banks significantly increase SBL originations after MDP openings. Through this mechanism, counties with MDPs that have higher levels of community bank capital experience statistically and economically significant increases in small business establishments, employment, and earnings, particularly in industries that support the large plant. As bank consolidation and branch closures reduce access to community banks across the U.S., these findings provide key insights for economic developers and financial regulators on the importance of access to community bank capital in promoting local economic development and small business growth. For policymakers or economic developers interested in using firm-specific incentives to attract large investments and spur local economic development, evaluating local lending conditions and supplementing credit shortages with targeted programs to support entrepreneurs and expanding small businesses may be critical to maximizing the spillover effects of large investments. For financial regulators monitoring the effects of bank acquisitions and mergers, understanding the role that community banks play in spurring small business growth during periods of positive demand shocks may support future the design of future regulations and governance.

Future research can continue to investigate the mechanisms that spur spillovers from MDPs and contribute to the ongoing debate over whether location-focused or individual-focused policies are most effective at promoting economic development.

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A Matching

A.1 Introduction

As noted by Patrick (2016), constructing counterfactuals for the MDP openings using matching can outperform the runner-up approach when plant managers and executives are not incentivized to reveal the true rankings of the MDP finalists during the site selection process. Therefore, matching on pre-opening observable characteristics may provide a more accurate counterfactual for the MDP openings. While Patrick (2016) uses geograpphical proximity during the matching process, I expand the set of potential matches to include all counties within the MDP opening Census Division. By including a broader set of potential matches, I can identify similar counties to the MDP openings without restricting the sample to geographically neighboring counties, which may introduce bias from spillover effects within commuting markets that violates the stable unit treatment value assumption ("SUTVA") of causal inference (Monte et al., 2018).

A.2 Matching Procedure

The matching estimation is conducted using the nearest neighbor approach, restricted to within-Census-district matches.[18] The approach estimates propensity scores using a logistic regression model where the observable characteristics of the counties are 5 year trend variables to capture the pre-opening trends in the counties. The characteristics included in the model are the percent change (or percentage point change) in population, unemployment rate, income per capita, manufacturing employment, distance to the nearest MSA, and the number of interstate ramps. The first four characteristics are included to capture salient economic trends in the counties that may be evaluated during the site selection search process. Distance to the nearest MSA and number of interstate ramps, which are measured as levels and not trends, are included to capture the transportation and logistic networks in the counties which are particularly important factors evaluated during site selection processes. Given that the sample of MDP openings studied includes only openings that increased pre-opening manufacturing employment by at least 15%, the matching procedure is restricted to counties that had less than 10,000 manufacturing employees to exclude large industrial markets that would not be have been included in the analysis had it received a MDP investment creating at least 1,500 jobs.

[18] The matching procedure is implemented using the `MatchIt` package in `R`.

A.2.1 Matching Diagnostics

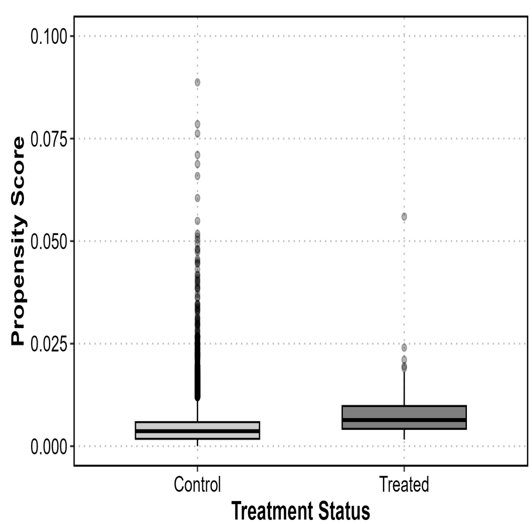
Table A1 presents the balance of covariates before and after performing matching procedure, highlighting the improved balance after matching. In addition to improved covariate balance, the matching procedure also has considerable common support, where overlap in estimated propensity scores between the control and treated units is observed across the full range of propensity scores. Figure **??** presents the propensity score overlap plot for the pooled sample of matches, where the distribution of propensity scores for the treated and control units are plotted as boxplots. The plot reveals that there is considerable overlap in propensity scores between the treated and control units.

Table A1: Balance Table for MDP Opening Counties and Matched Counties

Variables	No Openings	Opening	NormDiff	p.value
Unemployment (PP change)	0.59	0.86	0.18	0.16
Population (% change)	2.68	4.54	0.34	0.02
Minority (PP change)	0.93	0.98	0.04	0.77
Income per Capita (% change)	14.10	14.22	0.02	0.87
Mfg Labor Share (PP change)	-0.01	-0.01	-0.29	0.04
Distance to Nearest Metro (Miles)	8.28	7.93	-0.03	0.80
Number of Interstate Ramps	12.51	17.09	0.20	0.13
Sample Size	296	78		374

Note: ND represents the normalized difference between the MDP opening counties and each of the control groups. The balance table is prepared using 2009 values since the first MDP opening in the dataset was in 2010. Each of the percent and percentage point change calculation is performed using the 5-year change from 2004 to 2009. The total sample size for the control group is less than three times the number of treated units because some treated untis are matched to the same control unit, where the duplicated control unit is dropped from the balance table.

Figure A1: Propensity Score Overlap for Pooled Sample of Matches



Notes: The figure presents the pooled estimated propensity scores for the control and treated counties. The inner quartile range and medians are presented as boxplots, while the whiskers represent the range of propensity scores within 1.5 times the interquartile range. Observations with estimated propensity scores outside this range are plotted as dots.

B Defining SBL Market for Banks

B.1 Introduction

Defining a bank's geographical market is highly dependent on numerous factors, including the financial product being evaluated, the bank's size and specialization, and level of competition within the market. While financial technology and automation of credit evaluations enabled banks to expand lending beyond local markets centralized around physical branches, small business lending remains highly concentrated around branch networks. Banks overwhelming define SBL market based on the location of their branches, [19], and community banks focus on small business customers within 40 miles, on average.

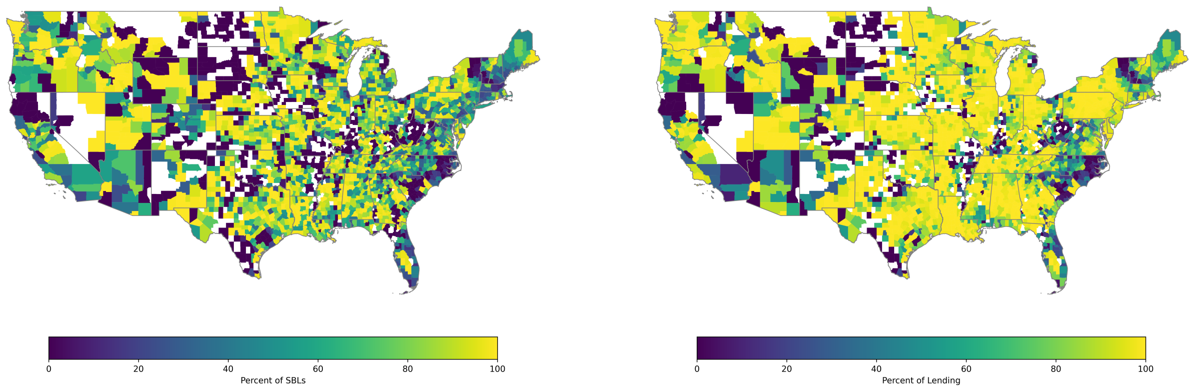
To prepare measures access to community bank SBL, I rely on the branch-dependent definition of lending markets and evaluate the historical correlation between different distances from bank branches and SBLs originated and reported in the CRA dataset. While the CRA data does not list the geographical coordinates of the SBL borrower or collateral, it provides the county identifier for the borrower, which allows me to investigate the average distance from the county (population-weighted) centroid to the closest branch of the originating community bank.

Figure B1 presents the percent of SBLs originated by community banks within each county in the U.S. between 2005 - 2023 that have a branch by the lending institution either within county or a neighboring county (panel a) or within 100 miles (panel b). The distance threshold of 100 is used because while a community bank's market may be closer to 40 miles, on average, the location of the borrower is assumed to be the county (population-weighted) centroid. Therefore, a higher distance threshold is used to address inherent measurement error from this assumption. The maps reveal that the percent of SBLs originated by community banks that are within 100 miles of a branch is higher in almost every county compared to the percent within county or a neighboring county, providing support for preparing the bank access measure using distance rather than county designations. The graphical evidence is further supported by national averages: 90% of SBLs were originated with 100 miles of a lender's branch between 2005 - 2023, while only 43% were originated within the county or neighboring county of a lender's branch.

Evaluating the distribution of the percent of SBLs originated within market across counties confirms that fewer counties have lower percent of SBLs originated within market and more counties have higher percentagtes using the distance-based approach rather than the county jurisdiction-based approach. Figure B2 plots the cumulative distribution function of the percent of SBLs originated within market based on

[19] 80 percent of banks defined the market based on the location of their branches in 2024. Source: Small Business Lending Survey 2024 - Section 5 - Markets and Competition, accessed at https://www.fdic.gov/publications/small-business-lending-survey-2024-section-5-markets-and-competition.

Figure B1: Percent of SBL Originations by Community Banks within Local Market (2005-2023)



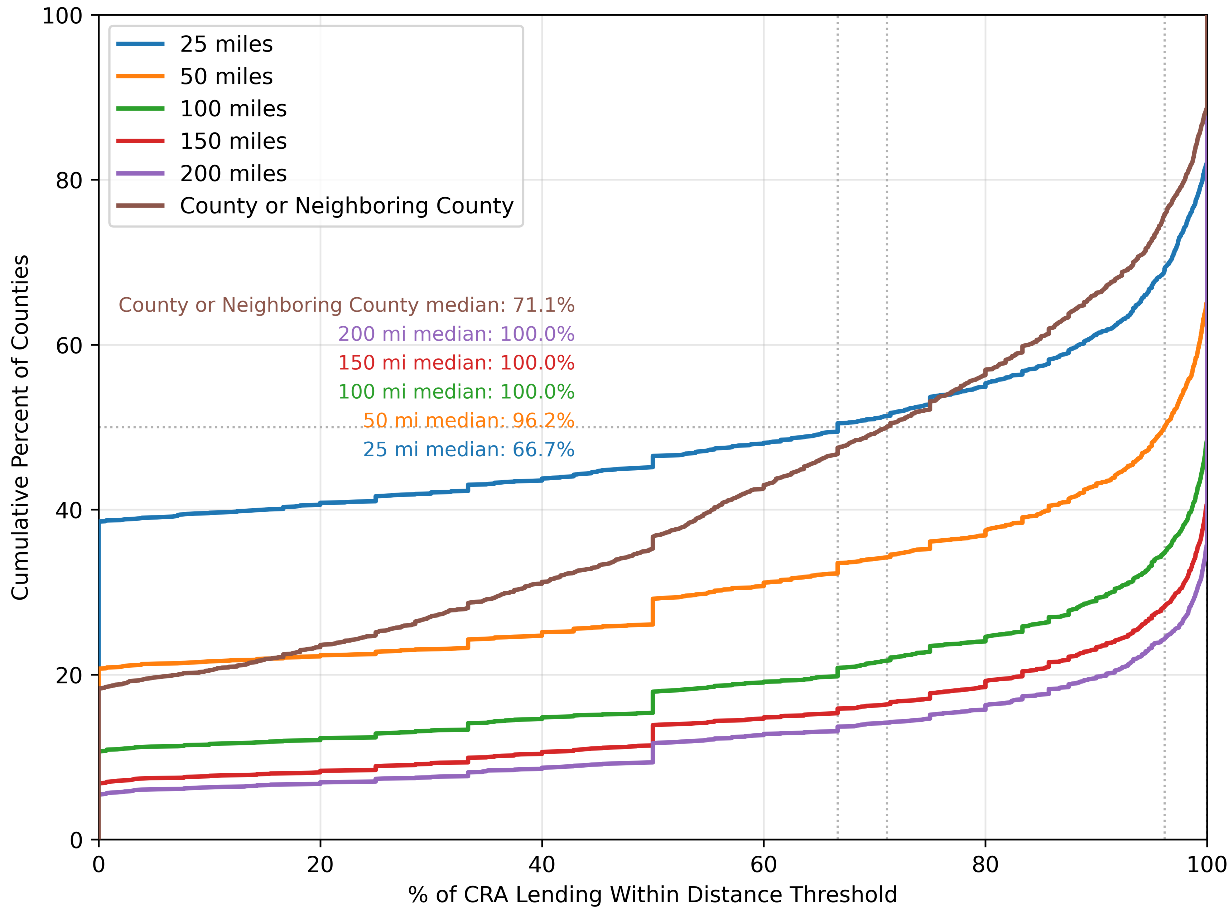
(a) Within County or Neighboring County of Branch

(b) Within 100 Miles of Branch

Note: Panel (a) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged noncommunity bank SBLs originated. Panel (b) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged community bank SBLs originated. The 95% confidence interval are represented by the thin bands, and the 90% confidence intervals are represented by the thicker bands. Standard errors are clustered at the county level. The event study estimations were performed using the weighted trimmed stacked DiD approach.

the county/neighboring county definition, as well as different distance thresholds for the distance-based definition. The plot shows that only 10% of counties have 0% of SBLs that do not have a lender branch within 100 miles, while around 30% of counties have 0% of SBLs originated by lenders with branches either within county or within a neighboring county. At the median, 100% of SBLs are within 100 miles of a lender branch, while only 71.1% of SBLs are within the same or neighboring county of a lender's branch. While a higher distance threshold will naturally lead to higher percentages of SBLs originated within market, the plot reveals that even at a distance threshold of 50 miles, the percent of SBLs originated within market is higher for more counties compared to the county/neigboring county definition. The marginal increase in percent within market is much smaller comparing the 100 to 150 and 200 mile thresholds, providing additional support for using the 100 mile threshold to define the SBL market for community banks.

Figure B2: Cumulative Distribution Function of Small Business Lending by County-Based and Distance-Based Measures (2005-2023)



Note: The CDF plot presents the cumulative distribution function of the percent of SBLs originated within market based on the county/neighboring county definition, as well as different distance thresholds for the distance-based definition.

C Predicted Bank Access Measures

Table C1: Estimated Coefficients for Predicted Community Bank Access (Branches)

	Community Bank Access (Branches (log) Within 50mi) (1)
Total Banks (1928)	0.0268***
	(0.0069)
Years Since Deregulation	−0.0152***
	(0.0029)
Observations	58,813
R^2	0.1143
Year Fixed Effects	Yes
Wald F-Statistic	18.40

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.* The access to community bank outcome is measured as the number of logged branches within 50 miles of the county population-weighted centroid each year from 2005 through 2023. Standard errors are clustered at the county level.

Figure C1: Estimated Coefficients for Small Business Growth Based on Predicted Community Bank Access (Branches) Counties After Plant Openings

	(1) Runner-up/Canc.	(2) Matched	(3) Synth DiD
Panel A: All Counties			
Pretrends	-0.00	-0.00	–
	(0.01)	(0.01)	–
Post ATT	-0.00	0.01	0.01^{**}
	(0.01)	(0.01)	(0.01)
Observations	4,587	3,267	344,448
Panel B: High Deposit Counties			
Pretrends	-0.02^{*}	-0.01^{*}	–
	(0.01)	(0.01)	–
Post ATT	0.02	0.02^{*}	0.03^{***}
	(0.01)	(0.01)	(0.01)
Observations	3,696	2,717	355,990
Panel C: Low Deposit Counties			
Pretrends	0.02^{**}	0.02^{**}	–
	(0.01)	(0.01)	–
Post ATT	-0.02	-0.01	0.01
	(0.01)	(0.01)	(0.01)
Observations	3,586	2,706	356,351

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using all treated counties; Panel B estimates the event study using only the high-access treated counties; Panel C estimates the event study using the low-access treated counties. Standard errors are clustered at the county level.

Figure C2: Estimated Coefficients for Small Business Outcomes Based on Predicted High Community Bank Access (Branches) Counties After Plant Openings

	Establishment Count			Employment			Earnings		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: All Small Businesses									
Post ATT	0.02	0.02*	0.02**	0.03	0.03*	0.02*	-0.00	-0.01	0.02*
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	3,696	2,717	–	3,694	2,713	–	3,694	2,713	–
Panel B: New Small Businesses									
Post ATT	-0.01	0.04	–	0.02	0.09	–	–	–	–
	(0.04)	(0.04)	–	(0.06)	(0.07)	–	–	–	–
Observations	3,690	2,703	–	3,690	2,703	–	–	–	–
Control	Runner-up	Matched	Synth DiD	Runner-up	Matched	Synth DiD	Runner-up	Matched	Synth DiD

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using high-access treated counties for outcome variables measuring small business establishments, employment, and earnings at all firms with less than 20 employees; Panel B estimates the event study using high-access treated counties for outcome variables measuring small business establishments and employment all firms with less than 20 employees that began operations within the previous 12 months. Data on the earnings of employees at small businesses that began operations within the previous 12 months is not available from publicly available sources. Standard errors are clustered at the county level.

Table C2: Estimated Coefficients for Predicted Community Bank Access (Deposits)

	Community Bank Access (Deposits (log) Within 50mi) (1)
Total Banks (1928)	0.0384***
	(0.0091)
Years Since Deregulation	−0.0060*
	(0.0033)
Observations	58,708
R^2	0.1232
Year Fixed Effects	Yes
Wald F-Statistic	12.66

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.* The access to community bank outcome is measured as the number of logged deposits within 50 miles of the county population-weighted centroid each year from 2005 through 2023. Standard errors are clustered at the county level.

Figure C3: Estimated Coefficients for Small Business Growth Based on Predicted Community Bank Access (Deposits) Counties After Plant Openings

	(1) Runner-up/Canc.	(2) Matched	(3) Synth DiD
Panel A: All Counties			
Pretrends	-0.00	-0.00	–
	(0.01)	(0.01)	–
Post ATT	-0.00	0.01	–
	(0.01)	(0.01)	–
Observations	4,587	3,267	–
Panel B: High Deposit Counties			
Pretrends	-0.01	-0.01	–
	(0.01)	(0.01)	–
Post ATT	0.01	0.02	0.02**
	(0.01)	(0.01)	(0.01)
Observations	3,685	2,717	–
Panel C: Low Deposit Counties			
Pretrends	0.02**	0.02*	–
	(0.01)	(0.01)	–
Post ATT	−0.02*	-0.01	–
	(0.01)	(0.01)	–
Observations	3,608	2,706	–

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using all treated counties; Panel B estimates the event study using only the high-access treated counties; Panel C estimates the event study using the low-access treated counties. Standard errors are clustered at the county level.

Figure C4: Estimated Coefficients for Small Business Outcomes Based on Predicted High Community Bank Access (Deposits) Counties After Plant Openings

	Establishment Count			Employment			Earnings		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: All Small Businesses									
Post ATT	0.02	0.02*	0.02**	0.03	0.03*	0.02*	-0.00	-0.01	0.02*
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	3,696	2,717	–	3,694	2,713	–	3,694	2,713	–
Panel B: New Small Businesses									
Post ATT	-0.01	0.04	–	0.02	0.09	–	–	–	–
	(0.04)	(0.04)	–	(0.06)	(0.07)	–	–	–	–
Observations	3,690	2,703	–	3,690	2,703	–	–	–	–
Control	Runner-up	Matched	Synth DiD	Runner-up	Matched	Synth DiD	Runner-up	Matched	Synth DiD

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using high-access treated counties for outcome variables measuring small business establishments, employment, and earnings at all firms with less than 20 employees; Panel B estimates the event study using high-access treated counties for outcome variables measuring small business establishments and employment all firms with less than 20 employees that began operations within the previous 12 months. Data on the earnings of employees at small businesses that began operations within the previous 12 months is not available from publicly available sources. Standard errors are clustered at the county level.

D Community Bank Branch Entry and Exit

The location of community bank branches are not randomly assigned; they were strategically placed by banks to service their customers and maximize profits. Therefore, the entry and exit of community banks into communities through the opening and closing of branches may be endogenous to the local economic conditions that attract MDPs. The site selection process historically relies on factors that are broadly unrelated to community bank presence, with the top factors evaluated during the process being transportation infrastructure, ease of permitting and regulatory procedures, skilled workforce, supply and price of industrial land, utility infrastructure, and state and local tax incentives.[20] However, the presence of community banks may contribute to the broader economic climate and entrepreneurship of a community which may influence these factors. While it is difficult to gauge whether productive community banks are selecting into or out of communities which attract MDPs, I evaluate the trends in community bank branch openings and closings in the treatment and control groups to determine whether there are disproportionately more branches opening in the treated counties or more closures in the control counties.

First, I plot the distribution of branch establishment years for community bank branches active in the MDP opening counties, the runner-up/cancelled counties, and the matched control counties as of 2023. The cumulative distribution function of branch establishment years for branches active in 2023 is plotted in Figure D1. The plot reveals minimal variation in the year of branch establishment between the groups, particularly during the period of analysis between 2005 and 2023. By 2005, 68.6% of branches active in the MDP opening counties in 2023 were already established, and almost 81% were active as of 2010. To assign a statistical significance to the visual evidence, I perform two-sample Kolmogorov-Smirnov tests comparing the distribution of branch establishment years for branches active in 2023 between the MDP opening counties and the runner-up/cancelled counties, as well as between the MDP opening counties and the matched control counties. The results of the tests are presented in Table D1, which fail to reject the null hypothesis that the distributions are the same at the 5% significance level.

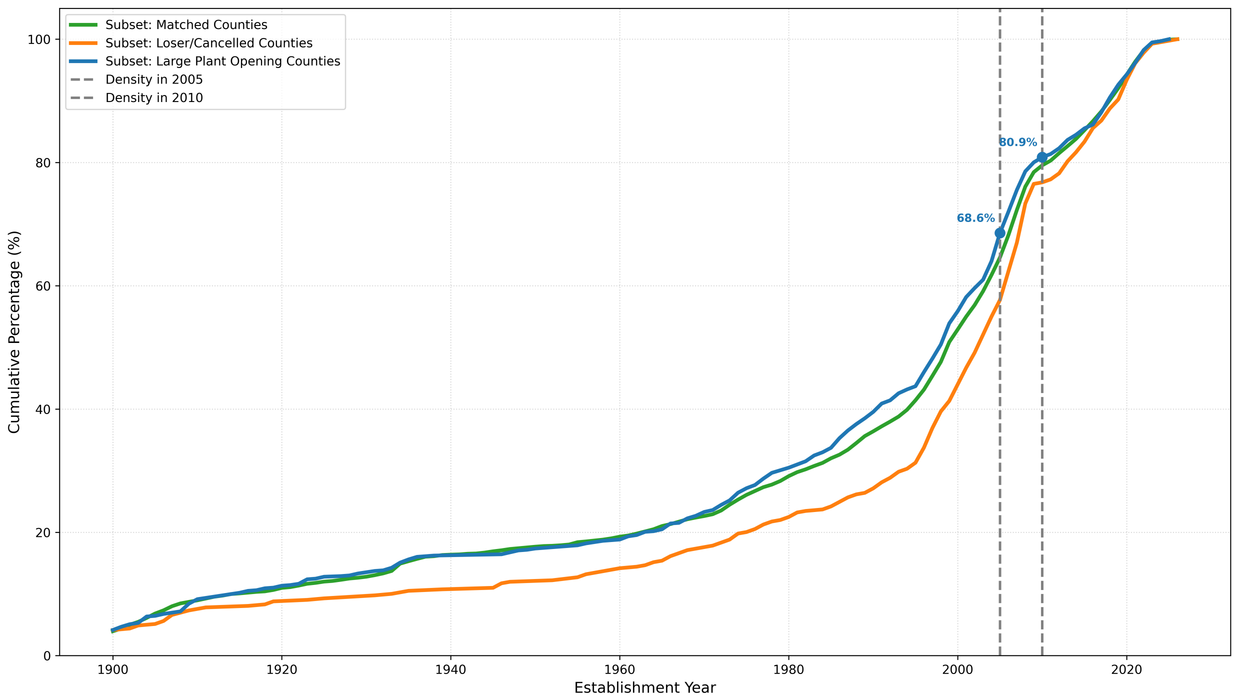
Table D1: Two-Sample Kolmogorov-Smirnov Test Results for Community Bank Branch Establishment Year (as of 2023)

Comparison Group	KS Statistic	p-value
Large Plant Opening County vs. Runner-up/Canc. County	0.0654	0.9702
Large Plant Opening County vs. Matched Control County	0.0635	0.9510

Note: This table reports the results of the Two-Sample Kolmogorov-Smirnov (KS) test comparing the distribution of branch opening year across time. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[20] Source: The november 2014 issue of the Site Selection magazine, page 84.

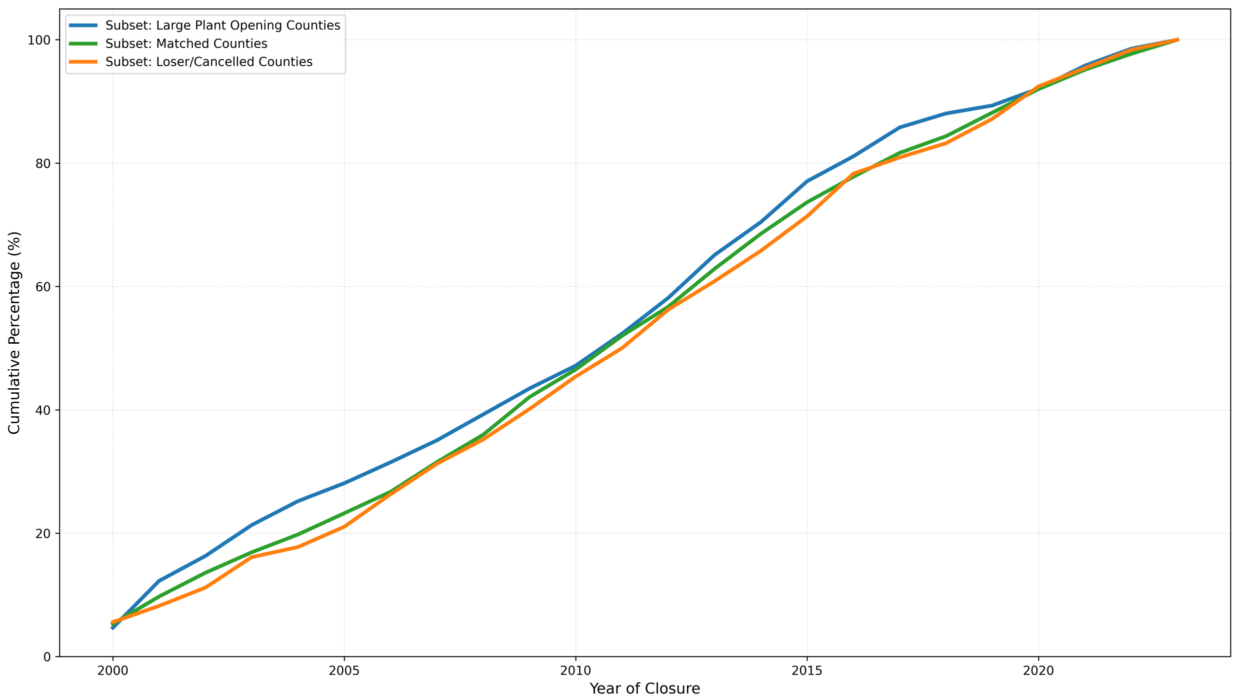
Figure D1: Cumulative Distribution Function of Community Bank Branch Establishment Year for Branches Active in 2023 by Treatment and Control Group



Note: The CDF plot presents the cumulative distribution function of the year of establishment for community bank branches open as of 2023. The CDF is presented separately for the MDP opening counties, as well as the runner-up/cancelled counties and the matched counties. The cumulative number of active branches that were operating by 2005 and 2010 for the MDP opening counties are listed as reference points.

Second, I plot the distribution of branch closure year for community bank branches that closed between 2000 and 2023 in the MDP opening counties, the runner-up/cancelled counties, and the matched control counties. The cumulative distribution function is plotted in Figure D2 and reveals minimal variation in the year of branch closure between the groups. The two-sample Kolmogorov-Smirnov tests comparing the distribution of branch closure years for branches in the MDP opening counties and the runner-up/cancelled counties, as well as between the MDP opening counties and the matched control counties, are presented in Table D2, which fail to reject the null hypothesis that the distributions are the same at the 5% significance level.

Figure D2: Cumulative Distribution Function of Community Bank Branch Closure Year for Branches by Treatment and Control Group



Note: The CDF plot presents the cumulative distribution function of the year of closure for community bank branches closed between 2000 and 2023. The CDF is presented separately for the MDP opening counties, as well as the runner-up/cancelled counties and the matched counties.

Table D2: Two-Sample Kolmogorov-Smirnov Test Results for Community Bank Branch Closure Year (2000 - 2023)

Comparison Group	KS Statistic	p-value
Large Plant Opening County vs. Runner-up/Canc. County	0.1250	0.9942
Large Plant Opening County vs. Matched Control County	0.0833	1.0000

Note: This table reports the results of the Two-Sample Kolmogorov-Smirnov (KS) test comparing the distribution of branch closures across time. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

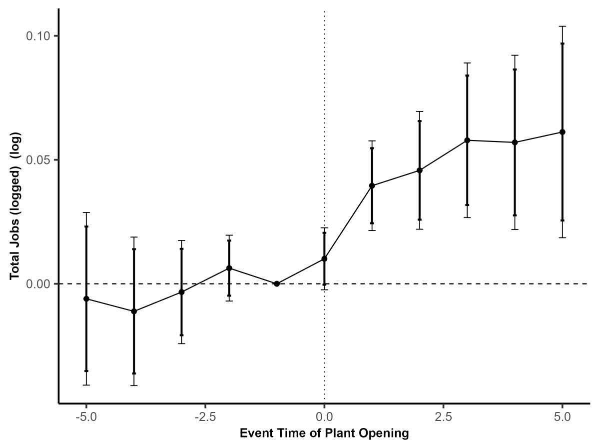
Together, the evidence of branch entry and exit trends suggests that there is minimal selecting into counties based on treatment status by community banks.

E Event Study Plots

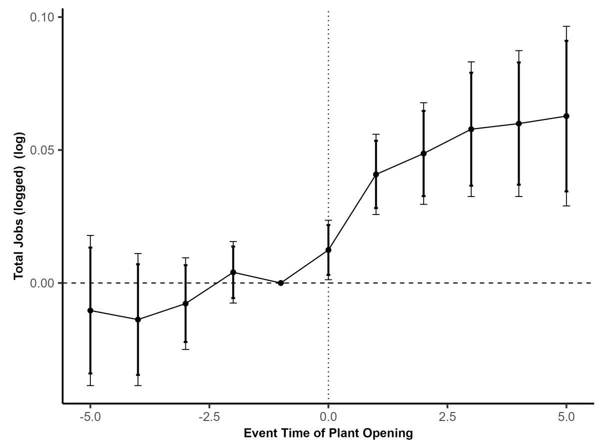
E.1 Total Jobs

E.2 Manufacturing Jobs

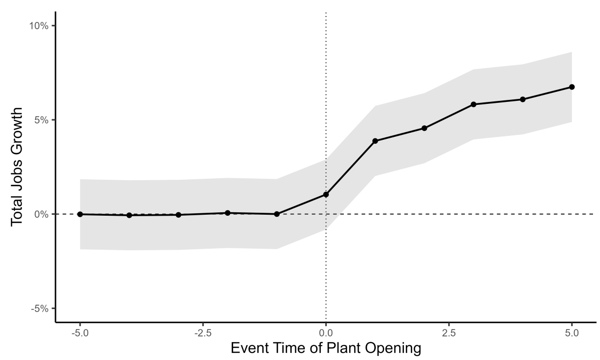
Figure E1: Event Study Plots for # of Jobs (log) After MDP Opening



(a) Runner-Up



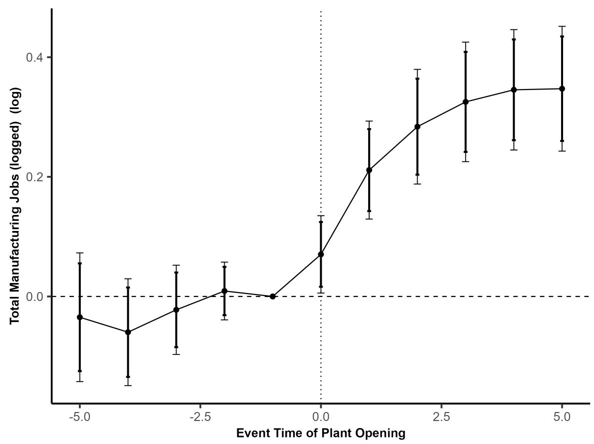
(b) Matched



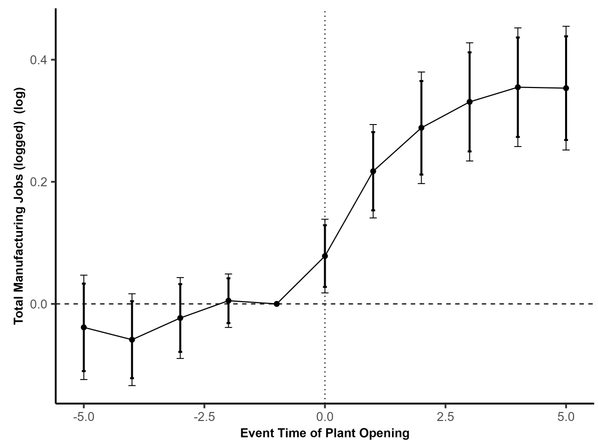
(c) SDID

Note: Panel (a) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged noncommunity bank SBLs originated. Panel (b) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged community bank SBLs originated. Panel (c) presents the event study plot estimated using the matched county control group with number of logged noncommunity bank SBLs originated. Panel (d) presents the event study plot estimated using the matched county control group with number of logged community bank SBLs originated. Panel (e) presents the event study plot estimated using the synthetic DiD with number of logged noncommunity bank SBLs originated. Panel (f) presents the event study plot estimated using the synthetic DiD with number of logged community bank SBLs originated. The 95% confidence interval are represented by the thin bands, and the 90% confidence intervals are represented by the thicker bands. Standard errors are clustered at the county level. The event study estimations for panels a, b, c, and d were performed using the weighted trimmed stacked DiD approach, while panels e and f present the synthetic DiD results. Since the synthetic DiD estimator does not separately estimate each event time coefficient, the standard errors from the ATT estimate are used to construct the confidence intervals for the event study plot. The presentation of the event study plot is not intended to present estimated coefficients for each event time period, but rather to provide a visual representation of the ATT estimate and the associated confidence intervals.

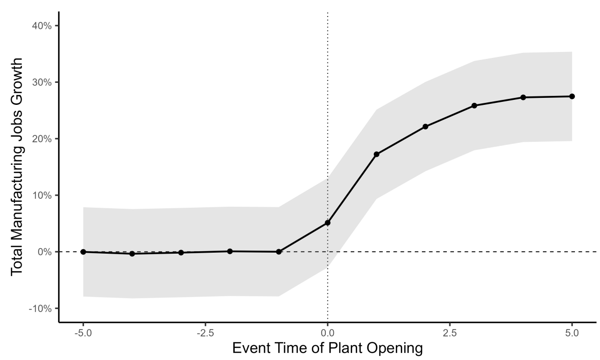
Figure E2: Event Study Plots for # of Manufacturing Jobs (log) After MDP Opening



(a) Runner-Up



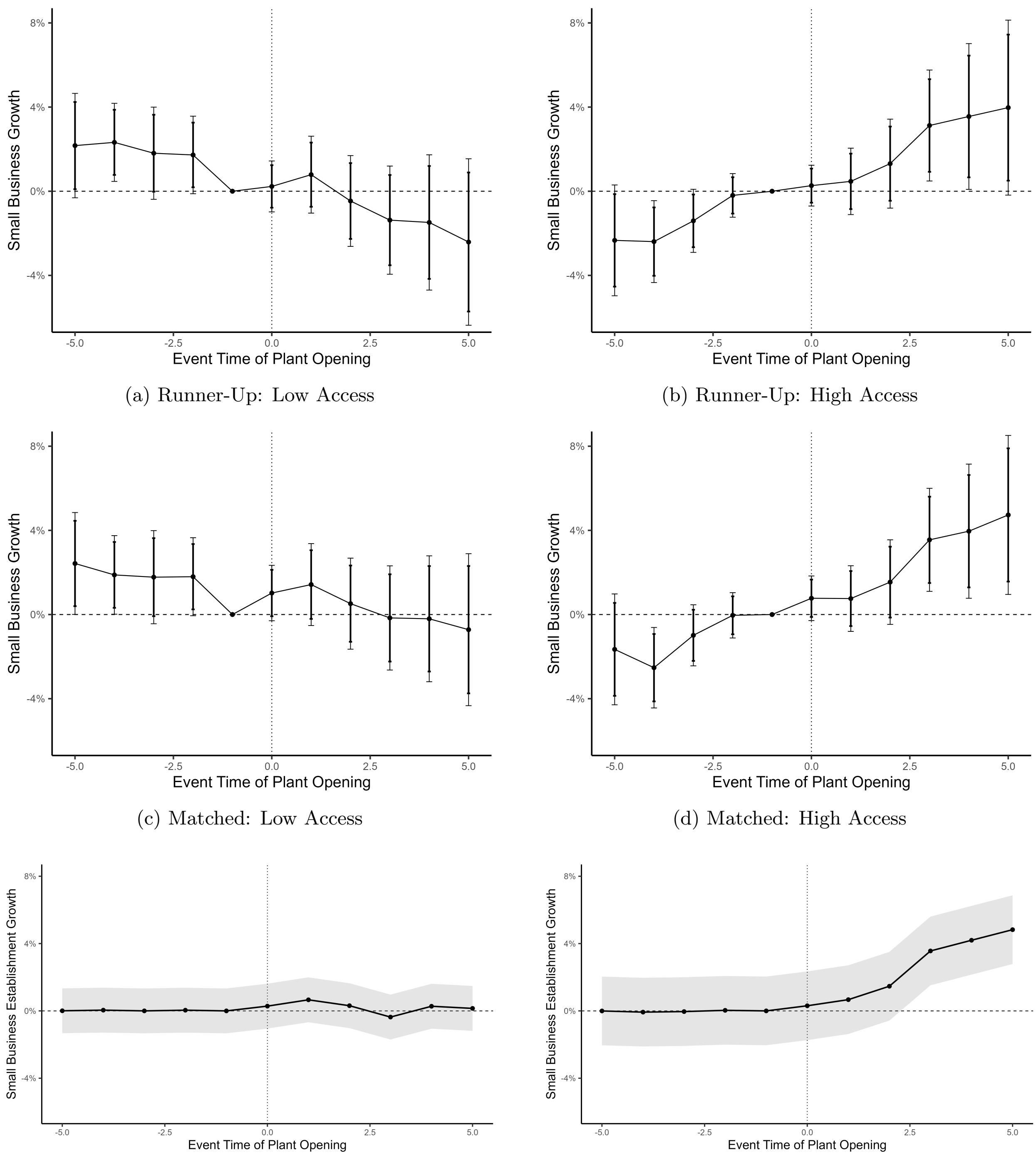
(b) Matched



(c) SDID

Note: Panel (a) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged noncommunity bank SBLs originated. Panel (b) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged community bank SBLs originated. Panel (c) presents the event study plot estimated using the matched county control group with number of logged noncommunity bank SBLs originated. Panel (d) presents the event study plot estimated using the matched county control group with number of logged community bank SBLs originated. Panel (e) presents the event study plot estimated using the synthetic DiD with number of logged noncommunity bank SBLs originated. Panel (f) presents the event study plot estimated using the synthetic DiD with number of logged community bank SBLs originated. The 95% confidence interval are represented by the thin bands, and the 90% confidence intervals are represented by the thicker bands. Standard errors are clustered at the county level. The event study estimations for panels a, b, c, and d were performed using the weighted trimmed stacked DiD approach, while panels e and f present the synthetic DiD results. Since the synthetic DiD estimator does not separately estimate each event time coefficient, the standard errors from the ATT estimate are used to construct the confidence intervals for the event study plot. The presentation of the event study plot is not intended to present estimated coefficients for each event time period, but rather to provide a visual representation of the ATT estimate and the associated confidence intervals.

Figure E3: Event Study Plots for # of Small Business Establishments (log) After MDP Opening



(a) Runner-Up: Low Access

(b) Runner-Up: High Access

(c) Matched: Low Access

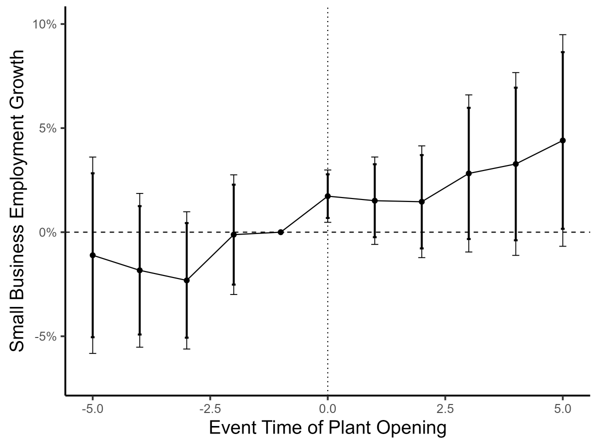
(d) Matched: High Access

(e) SDID: Low Access

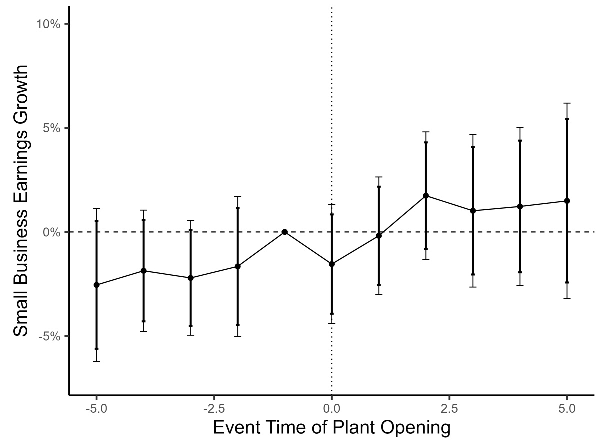
(f) SDID: High Access

Note: Panel (a) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged noncommunity bank SBLs originated. Panel (b) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged community bank SBLs originated. Panel (c) presents the event study plot estimated using the matched county control group with number of logged noncommunity bank SBLs originated. Panel (d) presents the event study plot estimated using the matched county control group with number of logged community bank SBLs originated. Panel (e) presents the event study plot estimated using the synthetic DiD with number of logged noncommunity bank SBLs originated. Panel (f) presents the event study plot estimated using the synthetic DiD with number of logged community bank SBLs originated. The 95% confidence interval are represented by the thin bands, and the 90% confidence intervals are represented by the thicker bands. Standard errors are clustered at the county level. The event study estimations for panels a, b, c, and d were performed using the weighted trimmed stacked DiD approach, while panels e and f present the synthetic DiD results. Since the synthetic DiD estimator does not separately estimate each event time coefficient, the standard errors from the ATT estimate are used to construct the confidence intervals for the event study plot. The presentation of the event study plot is not intended to present estimated coefficients for each event time period, but rather to provide a visual representation of the ATT estimate and the associated confidence intervals.

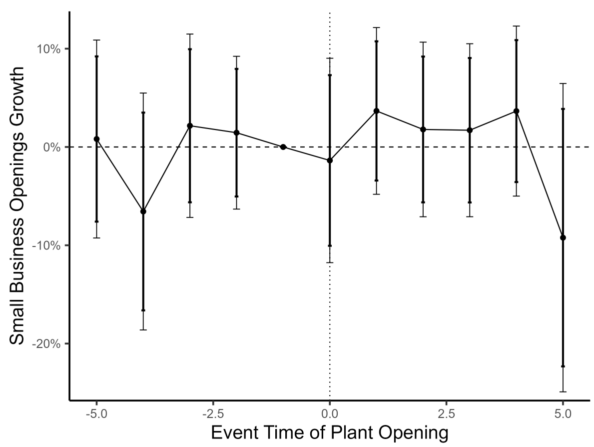
Figure E4: Event Study Plots for High Access Counties After MDP Opening (Runner-Up Approach)



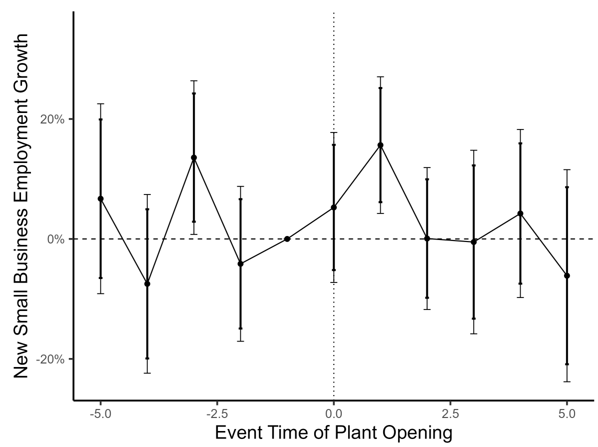
(a) Small Business Employment



(b) Small Business Earnings



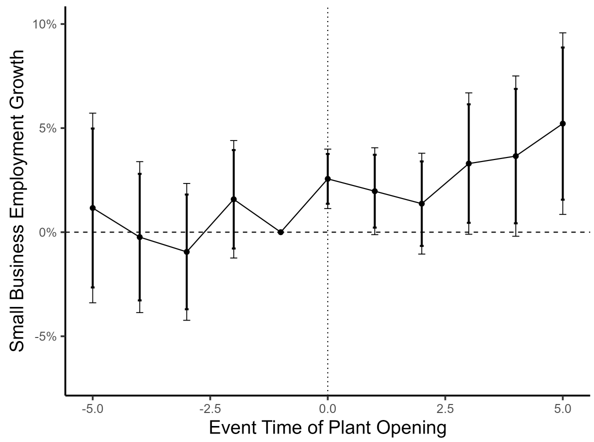
(c) Small Business Openings



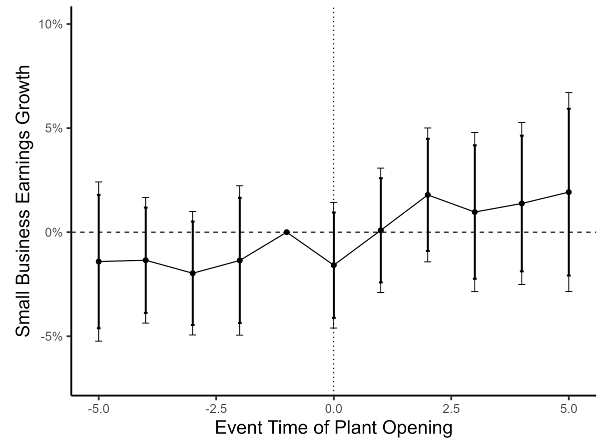
(d) Employees at New Small Businesses

Note: Panel (a) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged noncommunity bank SBLs originated. Panel (b) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged community bank SBLs originated. Panel (c) presents the event study plot estimated using the matched county control group with number of logged noncommunity bank SBLs originated. Panel (d) presents the event study plot estimated using the matched county control group with number of logged community bank SBLs originated. Panel (e) presents the event study plot estimated using the synthetic DiD with number of logged noncommunity bank SBLs originated. Panel (f) presents the event study plot estimated using the synthetic DiD with number of logged community bank SBLs originated. The 95% confidence interval are represented by the thin bands, and the 90% confidence intervals are represented by the thicker bands. Standard errors are clustered at the county level. The event study estimations for panels a, b, c, and d were performed using the weighted trimmed stacked DiD approach, while panels e and f present the synthetic DiD results. Since the synthetic DiD estimator does not separately estimate each event time coefficient, the standard errors from the ATT estimate are used to construct the confidence intervals for the event study plot. The presentation of the event study plot is not intended to present estimated coefficients for each event time period, but rather to provide a visual representation of the ATT estimate and the associated confidence intervals.

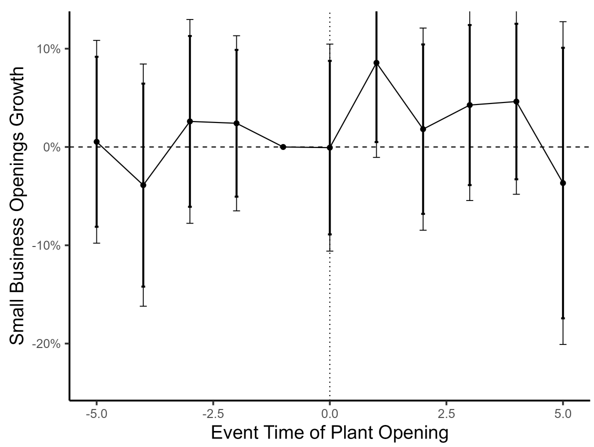
Figure E5: Event Study Plots for High Access Counties After MDP Opening (Matching Approach)



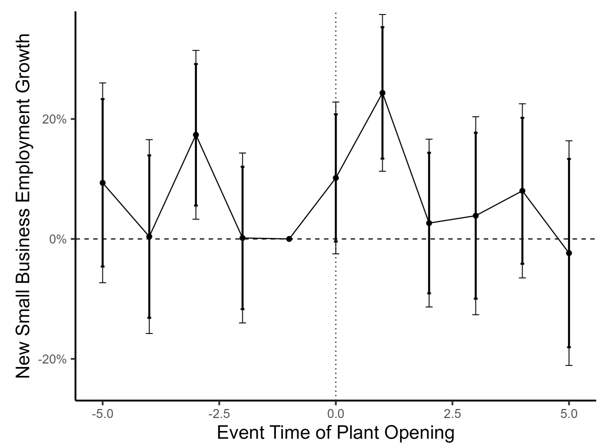
(a) Small Business Employment



(b) Small Business Earnings



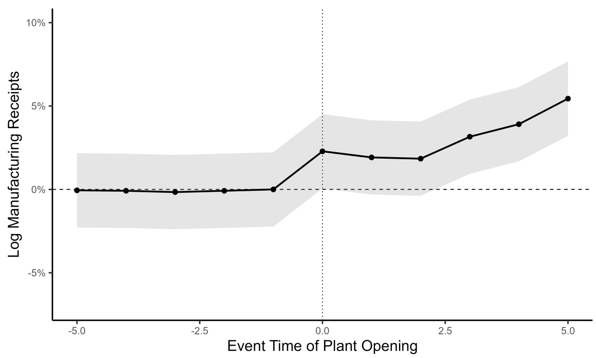
(c) Small Business Openings



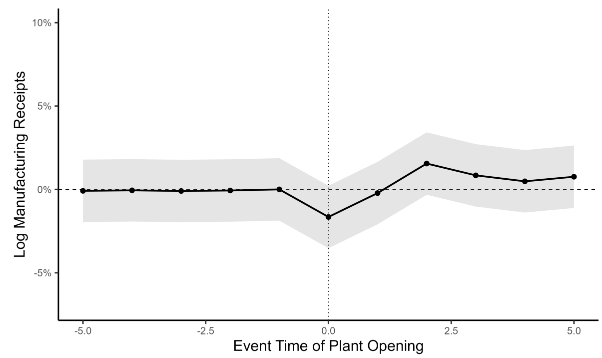
(d) Employees at New Small Businesses

Note: Panel (a) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged noncommunity bank SBLs originated. Panel (b) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged community bank SBLs originated. Panel (c) presents the event study plot estimated using the matched county control group with number of logged noncommunity bank SBLs originated. Panel (d) presents the event study plot estimated using the matched county control group with number of logged community bank SBLs originated. Panel (e) presents the event study plot estimated using the synthetic DiD with number of logged noncommunity bank SBLs originated. Panel (f) presents the event study plot estimated using the synthetic DiD with number of logged community bank SBLs originated. The 95% confidence interval are represented by the thin bands, and the 90% confidence intervals are represented by the thicker bands. Standard errors are clustered at the county level. The event study estimations for panels a, b, c, and d were performed using the weighted trimmed stacked DiD approach, while panels e and f present the synthetic DiD results. Since the synthetic DiD estimator does not separately estimate each event time coefficient, the standard errors from the ATT estimate are used to construct the confidence intervals for the event study plot. The presentation of the event study plot is not intended to present estimated coefficients for each event time period, but rather to provide a visual representation of the ATT estimate and the associated confidence intervals.

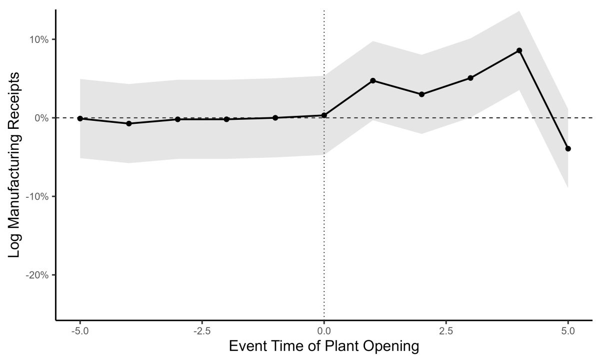
Figure E6: Event Study Plots for High Access Counties After MDP Opening (SDID Approach)



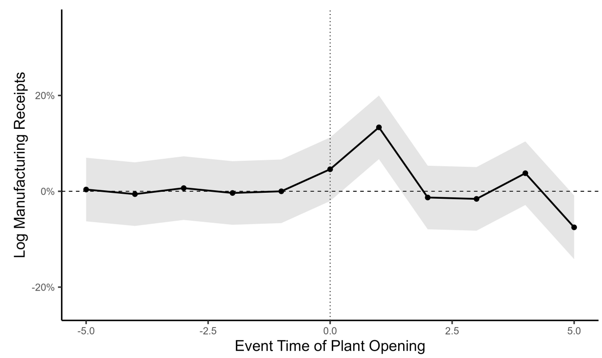
(a) Small Business Employment



(b) Small Business Earnings



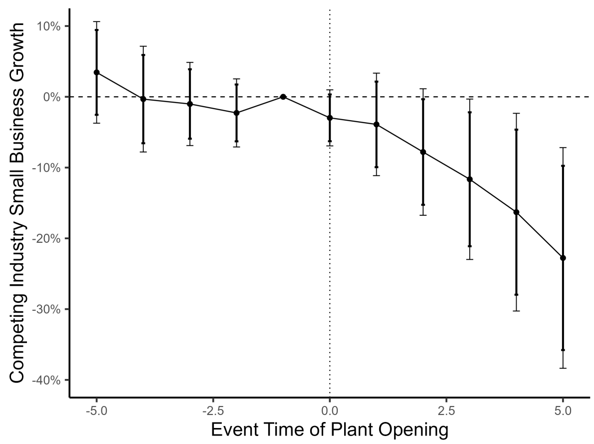
(c) Small Business Openings



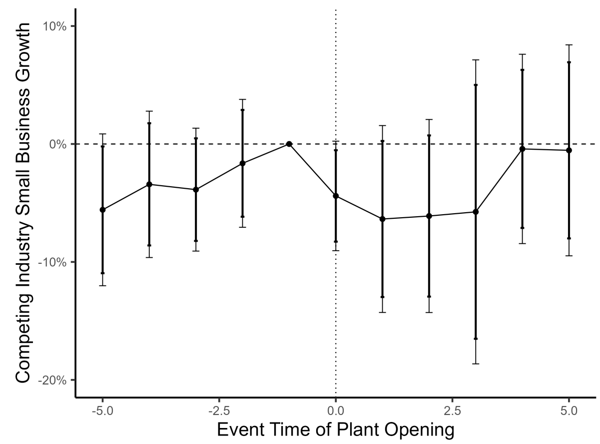
(d) Employees at New Small Businesses

Note: Panel (a) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged noncommunity bank SBLs originated. Panel (b) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged community bank SBLs originated. Panel (c) presents the event study plot estimated using the matched county control group with number of logged noncommunity bank SBLs originated. Panel (d) presents the event study plot estimated using the matched county control group with number of logged community bank SBLs originated. Panel (e) presents the event study plot estimated using the synthetic DiD with number of logged noncommunity bank SBLs originated. Panel (f) presents the event study plot estimated using the synthetic DiD with number of logged community bank SBLs originated. The 95% confidence interval are represented by the thin bands, and the 90% confidence intervals are represented by the thicker bands. Standard errors are clustered at the county level. The event study estimations for panels a, b, c, and d were performed using the weighted trimmed stacked DiD approach, while panels e and f present the synthetic DiD results. Since the synthetic DiD estimator does not separately estimate each event time coefficient, the standard errors from the ATT estimate are used to construct the confidence intervals for the event study plot. The presentation of the event study plot is not intended to present estimated coefficients for each event time period, but rather to provide a visual representation of the ATT estimate and the associated confidence intervals.

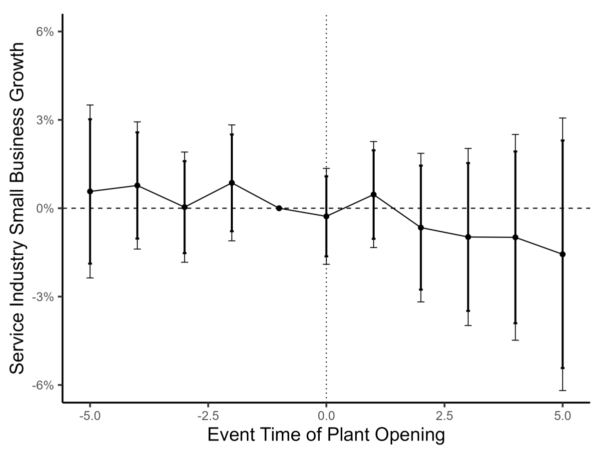
Figure E7: Event Study Plots for Small Business Growth by Industry After MDP Opening (Runner-Up Approach)



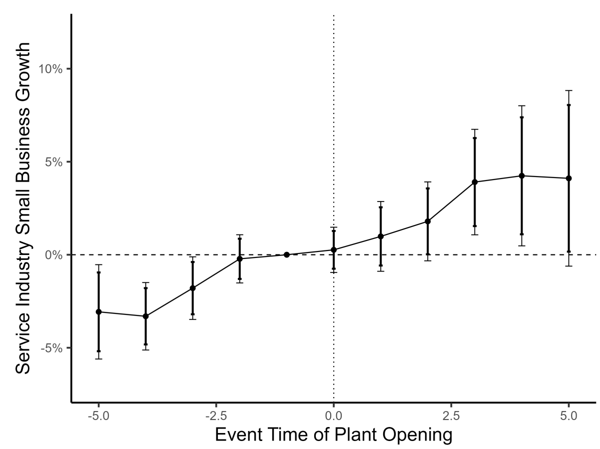
(a) Low Access: Competing Industries



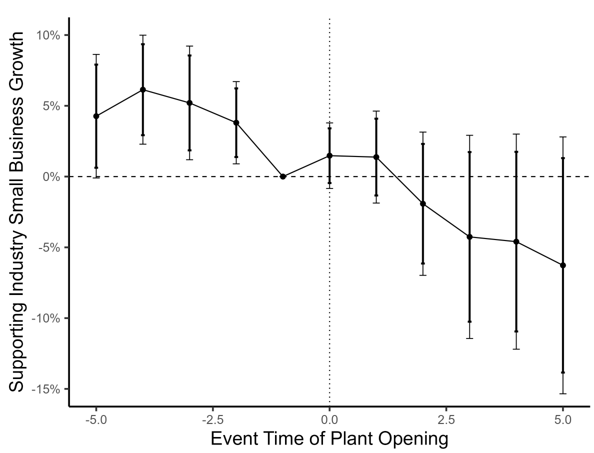
(b) High Access: Competing Industries



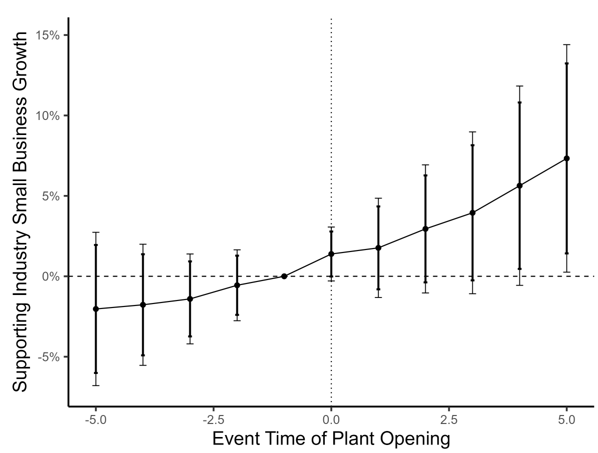
(c) Low Access: Service Industries



(d) High Access: Service Industries



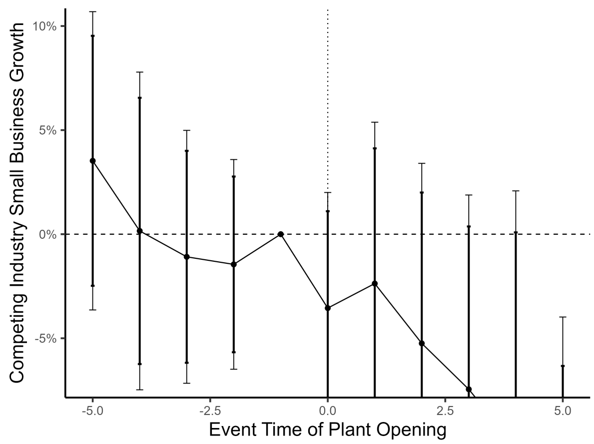
(e) Low Access: Support Industries



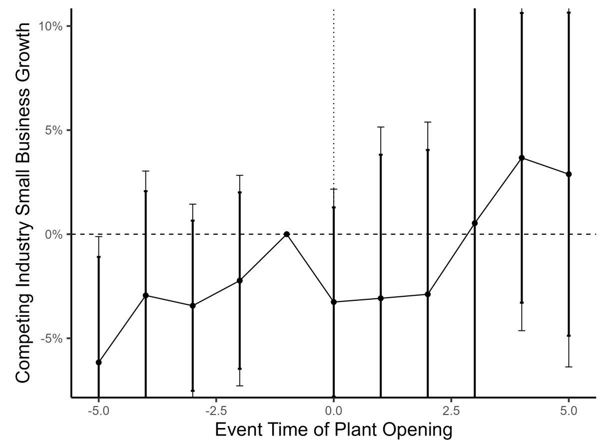
(f) High Access: Support Industries

Note: Panel (a) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged noncommunity bank SBLs originated. Panel (b) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged community bank SBLs originated. Panel (c) presents the event study plot estimated using the matched county control group with number of logged noncommunity bank SBLs originated. Panel (d) presents the event study plot estimated using the matched county control group with number of logged community bank SBLs originated. Panel (e) presents the event study plot estimated using the synthetic DiD with number of logged noncommunity bank SBLs originated. Panel (f) presents the event study plot estimated using the synthetic DiD with number of logged community bank SBLs originated. The 95% confidence interval are represented by the thin bands, and the 90% confidence intervals are represented by the thicker bands. Standard errors are clustered at the county level. The event study estimations for panels a, b, c, and d were performed using the weighted trimmed stacked DiD approach, while panels e and f present the synthetic DiD results. Since

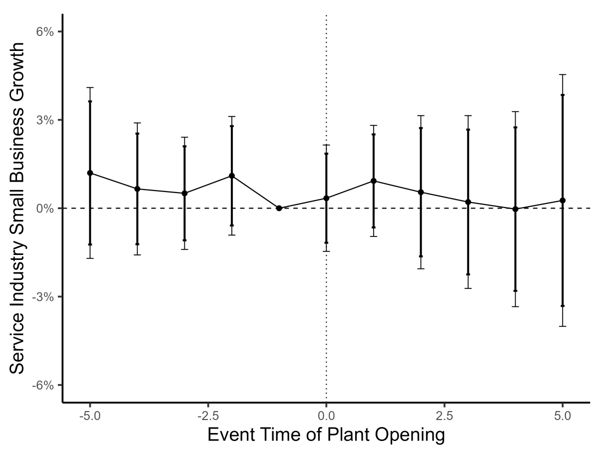
Figure E8: Event Study Plots for Small Business Growth by Industry After MDP Opening (Matching Approach)



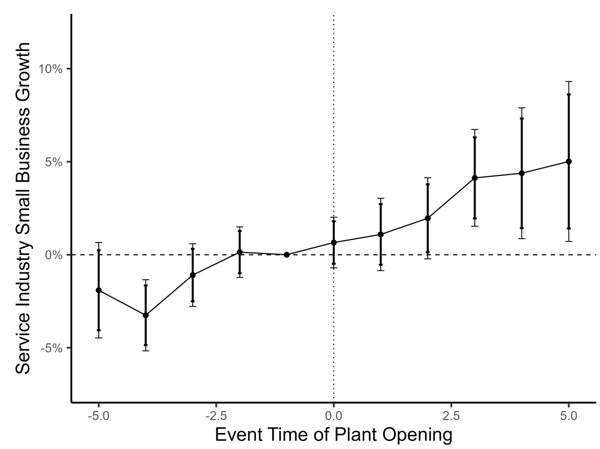
(a) Low Access: Competing Industries



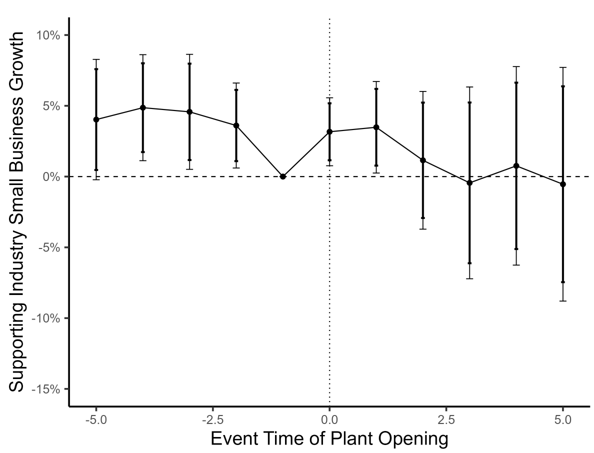
(b) High Access: Competing Industries



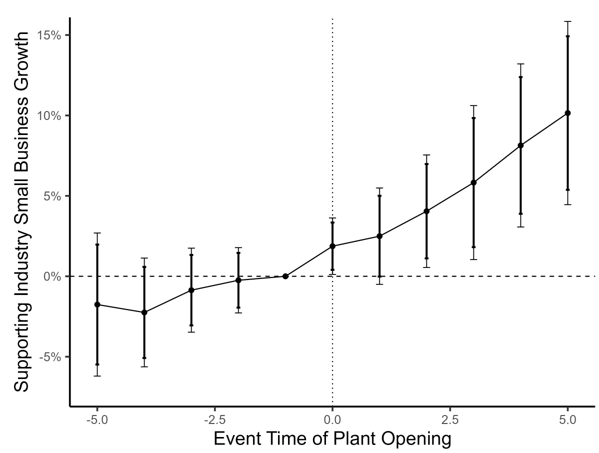
(c) Low Access: Service Industries



(d) High Access: Service Industries



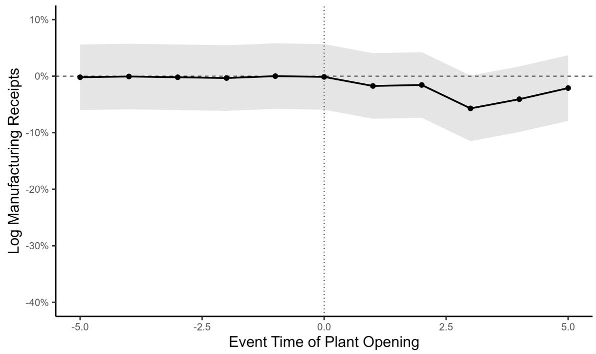
(e) Low Access: Support Industries



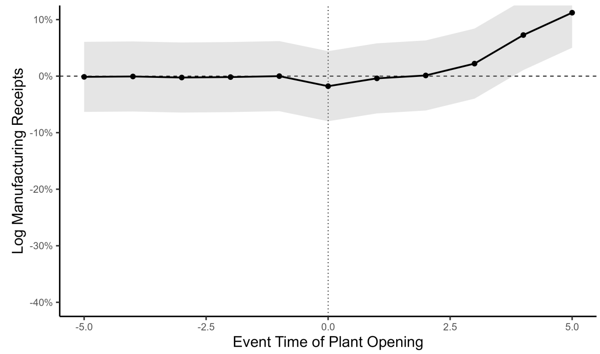
(f) High Access: Support Industries

Note: Panel (a) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged noncommunity bank SBLs originated. Panel (b) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged community bank SBLs originated. Panel (c) presents the event study plot estimated using the matched county control group with number of logged noncommunity bank SBLs originated. Panel (d) presents the event study plot estimated using the matched county control group with number of logged community bank SBLs originated. Panel (e) presents the event study plot estimated using the synthetic DiD with number of logged noncommunity bank SBLs originated. Panel (f) presents the event study plot estimated using the synthetic DiD with number of logged community bank SBLs originated. The 95% confidence interval are represented by the thin bands, and the 90% confidence intervals are represented by the thicker bands. Standard errors are clustered at the county level. The event study estimations for panels a, b, c, and d were performed using the weighted trimmed stacked DiD approach, while panels e and f present the synthetic DiD results. Since

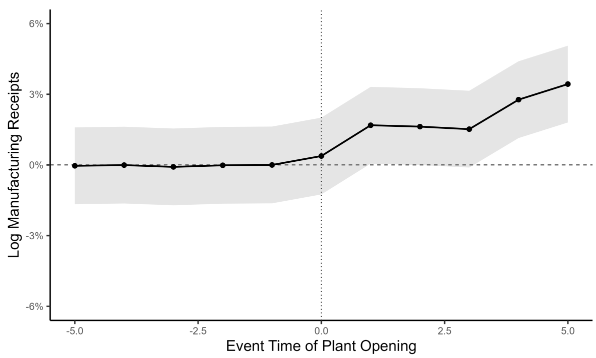
Figure E9: Event Study Plots for Small Business Growth by Industry After MDP Opening (SDID Approach)



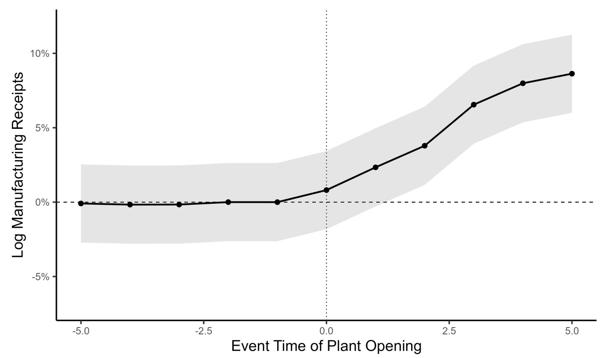
(a) Low Access: Competing Industries



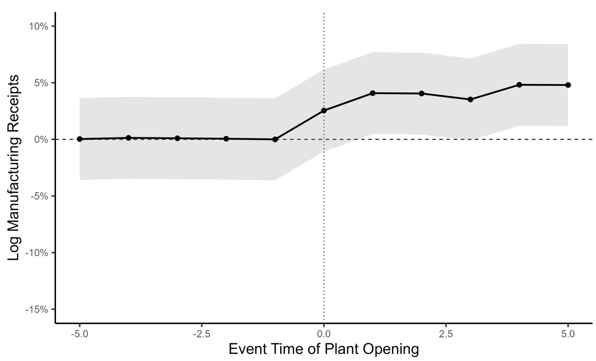
(b) High Access: Competing Industries



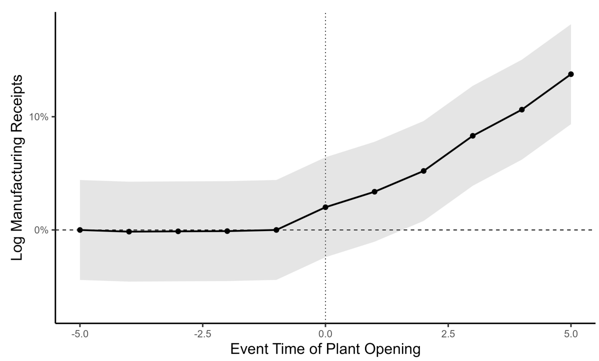
(c) Low Access: Service Industries



(d) High Access: Service Industries



(e) Low Access: Support Industries



(f) High Access: Support Industries

Note: Panel (a) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged noncommunity bank SBLs originated. Panel (b) presents the event study plot estimated using the runner-up/cancelled county control group with number of logged community bank SBLs originated. Panel (c) presents the event study plot estimated using the matched county control group with number of logged noncommunity bank SBLs originated. Panel (d) presents the event study plot estimated using the matched county control group with number of logged community bank SBLs originated. Panel (e) presents the event study plot estimated using the synthetic DiD with number of logged noncommunity bank SBLs originated. Panel (f) presents the event study plot estimated using the synthetic DiD with number of logged community bank SBLs originated. The 95% confidence interval are represented by the thin bands, and the 90% confidence intervals are represented by the thicker bands. Standard errors are clustered at the county level. The event study estimations for panels a, b, c, and d were performed using the weighted trimmed stacked DiD approach, while panels e and f present the synthetic DiD results. Since the synthetic DiD estimator does not separately estimate each event time coefficient, the standard errors from the ATT estimate are used to construct the confidence intervals for the event study plot. The presentation of the event study plot is not intended to present estimated coefficients for each event time period, but rather to provide a visual representation of the ATT estimate and the associated confidence intervals.

F Robustness Checks

Figure F1: Distribution of Reporting Periods by Banks across the Sub-Experiments (Out of 11 Possible Reporting Years)

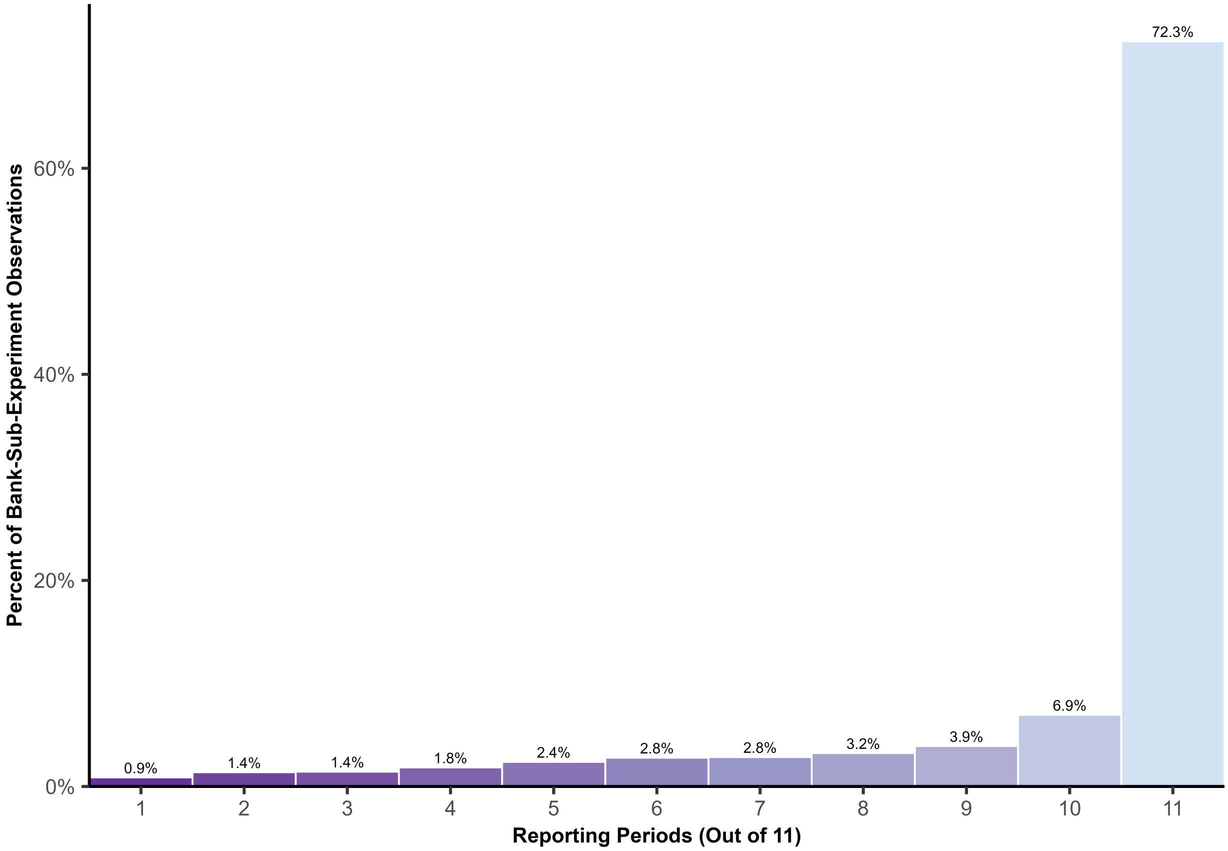


Figure F2: Noncommunity Bank SBL Originations (log)

Note: The figure presents the percent of community banks across the nine sub-experiments that reported data in each event time period, ranging from 1 to 11 years, with 11 being the total number of event time periods in each sub-experiment. The distribution is presented at the bank-sub-experiment level, rather than the bank level, because some banks operating in counties functioning as a control reported data through the CRA for all years within a specific sub-experiment (e.g., from 2005 - 2015 for the 2010 treatment cohort) but not all years in a different sub-experiment(e.g., dropped below the filing threshold in 2016 and therefore did not file in all years for any of the other treatming cohorts).

Table F1: Estimated Coefficients for Small Business Lending After MDP Openings for All Banks (Including Banks that did not Report CRA Data in All Years)

	(1) Runner-up	(2) Matched	(3) Synth DiD
Panel A: All Banks			
Pretrends (Agg.)	-0.02	-0.03	–
	(0.05)	(0.04)	–
Post Opening ATT	0.04	0.06*	0.07***
	(0.04)	(0.03)	(0.02)
Observations	4,598	30,635	354,362
Panel B: Community Banks			
Pretrends (Agg.)	0.00	0.04	–
	(0.11)	(0.09)	–
Post Opening ATT	0.19*	0.17**	0.16***
	(0.09)	(0.07)	(0.06)
Observations	4,568	29,407	251,767
Panel C: Large Banks			
Pretrends (Agg.)	-0.01	-0.04	–
	(0.05)	(0.04)	–
Post Opening ATT	-0.01	0.02	0.06***
	(0.03)	(0.03)	(0.02)
Observations	4,598	30,635	353,687

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using all banks; Panel B estimates the event study using only community banks; Panel C estimates the event study using using only noncommunity banks. Standard errors are clustered at the county level. The sample of banks included in the analysis is expanded to include institutions that did not report CRA data in all years of a given sub-experiment.

Table F2: Estimated Coefficients for Small Business Lending After MDP Openings with Alternative MDP Thresholds

	10% Threshold		20% Threshold	
	Runner-up	Matched	Runner-up	Matched
	(1)	(2)	(3)	(4)
Panel A: All Banks				
Pretrends (Agg.)	-0.04	-0.04	-0.02	-0.03
	(0.04)	(0.03)	(0.06)	(0.05)
Post Opening ATT	-0.01	0.01	0.05	0.06*
	(0.03)	(0.02)	(0.04)	(0.03)
Observations	5,082	31,119	4,301	30,349
Panel B: Community Banks				
Pretrends (Agg.)	-0.13	-0.04	-0.04	0.04
	(0.08)	(0.07)	(0.12)	(0.11)
Post Opening ATT	0.14*	0.07	0.24**	0.17**
	(0.08)	(0.06)	(0.10)	(0.08)
Observations	4,985	29,395	4,215	28,636
Panel C: Large Banks				
Pretrends (Agg.)	-0.00	-0.03	-0.02	-0.04
	(0.05)	(0.04)	(0.06)	(0.06)
Post Opening ATT	-0.02	0.00	0.01	0.04
	(0.03)	(0.02)	(0.04)	(0.03)
Observations	5,082	31,119	4,301	30,349
Number of MDPs	107	107	58	58

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using all banks; Panel B estimates the event study using only community banks; Panel C estimates the event study using using only noncommunity banks. Standard errors are clustered at the county level. The sample of MDP openings are either expanded (10%) or contracted (20%) from the baseline (15%) to test whether the results are robust to different definitions of MDPs.

Table F3: Estimated Coefficients for Small Business Establishments After MDP Openings with Alternative MDP Thresholds

	10% Threshold		20% Threshold	
	Runner-up	Matched	Runner-up	Matched
	(1)	(2)	(3)	(4)
Panel A: All Counties				
Pretrends	0.00	-0.00	-0.00	-0.00
	(0.01)	(0.00)	(0.01)	(0.01)
Post ATT	-0.00	0.01	-0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	5,071	31,306	4,301	30,536
Panel B: High Access Treated Counties				
Pretrends	-0.00	-0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Post ATT	0.01	0.02***	0.02	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	3,839	30,074	3,135	26,455
Panel C: Low Access Treated Counties				
Pretrends	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Post ATT	-0.01	0.00	-0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	3,674	29,909	3,465	29,700

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using all counties; Panel B estimates the event study using only the MDP counties with high-access to community banks based on deposits; Panel C estimates the event study using only the MDP counties with low-access to community banks based on deposits. Standard errors are clustered at the county level. The sample of MDP openings are either expanded (10%) or contracted (20%) from the baseline (15%) to test whether the results are robust to different definitions of MDPs.

Table F4: Estimated Coefficients for Small Business Establishments After MDP Openings with Deposit-Based CB Access

	(1) Runner-up/Canc.	(2) Matched	(3) Synth DiD
Panel A: All Counties			
Pretrends	-0.00	-0.00	–
	(0.01)	(0.01)	–
Post ATT	-0.00	0.01*	0.01**
	(0.01)	(0.01)	(0.01)
Observations	4,587	30,822	344,448
Panel B: High Access Treated Counties			
Pretrends	-0.01	-0.01	–
	(0.01)	(0.01)	–
Post ATT	0.02	0.03***	0.03***
	(0.01)	(0.01)	(0.01)
Observations	3,685	29,920	355,990
Panel C: Low Access Treated Counties			
Pretrends	0.01	0.01	–
	(0.01)	(0.01)	–
Post ATT	-0.00	0.01	0.00
	(0.01)	(0.01)	(0.01)
Observations	3,542	29,777	356,351

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using all counties; Panel B estimates the event study using only the MDP counties with high-access to community banks based on deposits; Panel C estimates the event study using only the MDP counties with low-access to community banks based on deposits. Standard errors are clustered at the county level. The sample of MDP openings are either expanded (10%) or contracted (20%) from the baseline (15%) to test whether the results are robust to different definitions of MDPs.

Table F5: Estimated Coefficients for Small Business Growth After MDP Openings with 50 Mile Threshold, Branch-Based CB Access

	(1) Runner-up/Canc.	(2) Matched
Panel A: All Counties		
Pretrends	-0.00	-0.00
	(0.01)	(0.01)
Post ATT	-0.00	0.01^{*}
	(0.01)	(0.01)
Observations	4,587	30,822
Panel B: High Access Treated Counties		
Pretrends	-0.02^{*}	-0.02^{**}
	(0.01)	(0.01)
Post ATT	0.02^{*}	0.03^{***}
	(0.01)	(0.01)
Observations	3,707	29,942
Panel C: Low Access Treated Counties		
Pretrends	0.02^{**}	0.02^{**}
	(0.01)	(0.01)
Post ATT	-0.01	0.00
	(0.01)	(0.01)
Observations	3,212	26,532

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using the number of small business establishments (logged) for all treated counties; Panel B estimates the event study using only the high-access treated counties; Panel C estimates the event study using the low-access treated counties. The number of small business establishments is measured as the count of establishments with less than 20 employees. Standard errors are clustered at the county level. The high access treated counties are defined as counties with the number of community bank branches within 50 miles of the county centroid in 2009 that fall within the top tercile, and low access is defined as counties within the bottom tercile.

Table F6: Estimated Coefficients for High Access Counties After MDP Opening with 50 Mile Threshold, Branch-Based CB Access

	Establishment Count		Employment		Earnings	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Small Businesses						
Post ATT	0.02*	0.03***	0.03*	0.03**	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	3,707	29,942	3,707	29,906	3,707	29,906
Panel B: New Small Businesses						
Post ATT	0.00	0.03	0.03	0.04		
	(0.03)	(0.03)	(0.05)	(0.04)		
Observations	3,701	29,513	3,701	29,513		
Control	Runner-up	Matched	Runner-up	Matched	Runner-up	Matched

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using high-access treated counties for outcome variables measuring small business establishments, employment, and earnings at all firms with less than 20 employees; Panel B estimates the event study using high-access treated counties for outcome variables measuring small business establishments and employment all firms with less than 20 employees that began operations within the previous 12 months. Data on the earnings of employees at small businesses that began operations within the previous 12 months is not available from publicly available sources. Standard errors are clustered at the county level. The high access treated counties are defined as counties with the number of community bank branches within 50 miles of the county centroid in 2009 that fall within the top tercile.

Table F7: Estimated Coefficients for Small Business Growth by Industry After MDP Opening with 50 Mile Threshold, Branch-Based CB Access

	Supporting Industries		Competing Industries		Service Ind
	(1)	(2)	(3)	(4)	(5)
Panel A: All Counties					
Pretrends	0.01	0.00	-0.02	-0.01	-0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Post ATT	0.00	0.03**	−0.08**	−0.09***	-0.00
	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)
Observations	4,587	30,779	4,559	30,022	4,587
Panel B: High Access Treated Counties					
Pretrends	-0.01	-0.02	-0.04	-0.02	−0.02**
	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)
Post ATT	0.04*	0.06***	-0.04	-0.04	0.03**
	(0.02)	(0.02)	(0.04)	(0.03)	(0.01)
Observations	3,707	29,899	3,679	29,142	3,707
Panel C: Low Access Treated Counties					
Pretrends	0.05***	0.04***	-0.00	0.01	0.01
	(0.02)	(0.01)	(0.03)	(0.03)	(0.01)
Post ATT	-0.02	0.01	−0.11**	−0.12***	-0.01
	(0.03)	(0.02)	(0.04)	(0.04)	(0.01)
Observations	3,212	26,499	3,190	25,935	3,212
Control	Runner-up/Canc.	Matched	Runner-up/Canc.	Matched	Runner-up/Canc

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using all treated counties; Panel B estimates the event study using only the high-access treated counties; Panel C estimates the event study using the low-access treated counties. The supporting industries include NAICS codes 23 (construction), 42 (wholesale trade), 48-49 (transportation and warehousing), 54 (professional, scientific, and technical services), and 56 (administrative and support and waste management and remediation services). The industries competing for labor and other resources include NAICS codes 11 (agriculture, forestry, fishing, and hunting and primarily comprised of forestry and logging small businesses), 21 (mining, quarrying, and oil and gas extraction), and 31-33 (manufacturing). The service industries include NAICS codes 44-45 (retail trade), 53 (real estate, rental, and leasing), 62 (health care and social assistance), 72 (accommodation and food services), 81 (other services). Standard errors are clustered at the county level.

Table F8: Estimated Coefficients for Small Business Growth After MDP Openings with 25 Mile Threshold, Branch-Based CB Access

	(1) Runner-up/Canc.	(2) Matched
Panel A: All Counties		
Pretrends	-0.00	-0.00
	(0.01)	(0.01)
Post ATT	-0.00	0.01*
	(0.01)	(0.01)
Observations	4,587	30,822
Panel B: High Access Treated Counties		
Pretrends	-0.01	-0.01
	(0.01)	(0.01)
Post ATT	0.03***	0.05***
	(0.01)	(0.01)
Observations	3,751	29,986
Panel C: Low Access Treated Counties		
Pretrends	0.01	0.01
	(0.01)	(0.01)
Post ATT	-0.02	-0.01
	(0.01)	(0.01)
Observations	3,586	29,821

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using the number of small business establishments (logged) for all treated counties; Panel B estimates the event study using only the high-access treated counties; Panel C estimates the event study using the low-access treated counties. The number of small business establishments is measured as the count of establishments with less than 20 employees. Standard errors are clustered at the county level. The high access treated counties are defined as counties with the number of community bank branches within 25 miles of the county centroid in 2009 that fall within the top tercile, and low access is defined as counties within the bottom tercile.

Table F9: Estimated Coefficients for High Access Counties After MDP Opening with 25 Mile Threshold, Branch-Based CB Access

	Establishment Count		Employment		Earnings	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Small Businesses						
Post ATT	0.03***	0.05***	0.03*	0.03**	-0.03	-0.02
	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)	(0.03)
Observations	3,751	29,986	3,751	29,950	3,751	29,950
Panel B: New Small Businesses						
Post ATT	0.04	0.07**	0.01	0.03		
	(0.03)	(0.03)	(0.05)	(0.05)		
Observations	3,745	29,557	3,745	29,557		
Control	Runner-up	Matched	Runner-up	Matched	Runner-up	Matched

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using high-access treated counties for outcome variables measuring small business establishments, employment, and earnings at all firms with less than 20 employees; Panel B estimates the event study using high-access treated counties for outcome variables measuring small business establishments and employment all firms with less than 20 employees that began operations within the previous 12 months. Data on the earnings of employees at small businesses that began operations within the previous 12 months is not available from publicly available sources. Standard errors are clustered at the county level. The high access treated counties are defined as counties with the number of community bank branches within 25 miles of the county centroid in 2009 that fall within the top tercile.

Table F10: Estimated Coefficients for Small Business Growth by Industry After MDP Opening with 25 Mile Threshold, Branch-Based CB Access

	Supporting Industries		Competing Industries		Service Ind
	(1)	(2)	(3)	(4)	(5)
Panel A: All Counties					
Pretrends	0.01	0.00	-0.02	-0.01	-0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Post ATT	0.00	0.03**	−0.08**	−0.09***	-0.00
	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)
Observations	4,587	30,779	4,559	30,022	4,587
Panel B: High Access Treated Counties					
Pretrends	-0.01	-0.02	-0.02	-0.01	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Post ATT	0.05**	0.08***	-0.05	-0.06	0.04**
	(0.02)	(0.02)	(0.04)	(0.04)	(0.01)
Observations	3,751	29,943	3,723	29,186	3,751
Panel C: Low Access Treated Counties					
Pretrends	0.03	0.02	0.02	0.02	0.00
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)
Post ATT	-0.04	-0.01	−0.08*	−0.10***	-0.02
	(0.03)	(0.02)	(0.05)	(0.04)	(0.01)
Observations	3,586	29,778	3,558	29,021	3,586
Control	Runner-up/Canc.	Matched	Runner-up/Canc.	Matched	Runner-up/Canc

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using all treated counties; Panel B estimates the event study using only the high-access treated counties; Panel C estimates the event study using the low-access treated counties. The supporting industries include NAICS codes 23 (construction), 42 (wholesale trade), 48-49 (transportation and warehousing), 54 (professional, scientific, and technical services), and 56 (administrative and support and waste management and remediation services). The industries competing for labor and other resources include NAICS codes 11 (agriculture, forestry, fishing, and hunting and primarily comprised of forestry and logging small businesses), 21 (mining, quarrying, and oil and gas extraction), and 31-33 (manufacturing). The service industries include NAICS codes 44-45 (retail trade), 53 (real estate, rental, and leasing), 62 (health care and social assistance), 72 (accommodation and food services), 81 (other services). Standard errors are clustered at the county level.

Table F11: Estimated Coefficients for Small Business Growth After MDP Openings with 50 mile Threshold, Deposit-Based CB Access

	(1) Runner-up/Canc.	(2) Matched
Panel A: All Counties		
Pretrends	-0.00	-0.00
	(0.01)	(0.01)
Post ATT	-0.00	0.01*
	(0.01)	(0.01)
Observations	4,587	30,822
Panel B: High Access Treated Counties		
Pretrends	-0.01	−0.01*
	(0.01)	(0.01)
Post ATT	0.02	0.03***
	(0.01)	(0.01)
Observations	3,740	29,975
Panel C: Low Access Treated Counties		
Pretrends	0.01*	0.01*
	(0.01)	(0.01)
Post ATT	-0.01	-0.00
	(0.01)	(0.01)
Observations	3,201	26,521

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using the number of small business establishments (logged) for all treated counties; Panel B estimates the event study using only the high-access treated counties; Panel C estimates the event study using the low-access treated counties. The number of small business establishments is measured as the count of establishments with less than 20 employees. Standard errors are clustered at the county level. The high access treated counties are defined as counties with community bank deposits held by branches within 50 miles of the county centroid in 2009 that fall within the top tercile, and low access is defined as counties within the bottom tercile.

Table F12: Estimated Coefficients for High Access Counties After MDP Opening with 50 Mile Threshold, Deposit-Based CB Access

	Establishment Count		Employment		Earnings	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Small Businesses						
Post ATT	0.02	0.03***	0.03**	0.03***	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	3,740	29,975	3,740	29,939	3,740	29,939
Panel B: New Small Businesses						
Post ATT	-0.00	0.03	0.06	0.07		
	(0.04)	(0.03)	(0.06)	(0.06)		
Observations	3,734	29,546	3,734	29,546		
Control	Runner-up	Matched	Runner-up	Matched	Runner-up	Matched

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using high-access treated counties for outcome variables measuring small business establishments, employment, and earnings at all firms with less than 20 employees; Panel B estimates the event study using high-access treated counties for outcome variables measuring small business establishments and employment all firms with less than 20 employees that began operations within the previous 12 months. Data on the earnings of employees at small businesses that began operations within the previous 12 months is not available from publicly available sources. Standard errors are clustered at the county level. The high access treated counties are defined as counties with community bank deposits held by branches within 50 miles of the county centroid in 2009 that fall within the top tercile.

Table F13: Estimated Coefficients for Small Business Growth by Industry After MDP Opening with 50 Mile Threshold, Deposit-Based CB Access

	Supporting Industries		Competing Industries		Service Ind
	(1)	(2)	(3)	(4)	(5)
Panel A: All Counties					
Pretrends	0.01	0.00	-0.02	-0.01	-0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Post ATT	0.00	0.03^{**}	-0.08^{**}	-0.09^{***}	-0.00
	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)
Observations	4,587	30,779	4,559	30,022	4,587
Panel B: High Access Treated Counties					
Pretrends	-0.01	-0.01	-0.02	-0.01	-0.02^{**}
	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)
Post ATT	0.04^{*}	0.07^{***}	-0.04	-0.05	0.03^{*}
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)
Observations	3,740	29,932	3,712	29,175	3,740
Panel C: Low Access Treated Counties					
Pretrends	0.04^{**}	0.03^{**}	-0.01	-0.00	0.00
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Post ATT	-0.03	-0.01	-0.12^{**}	-0.13^{***}	-0.01
	(0.02)	(0.02)	(0.05)	(0.04)	(0.01)
Observations	3,201	26,488	3,179	25,924	3,201
Control	Runner-up/Canc.	Matched	Runner-up/Canc.	Matched	Runner-up/Canc

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using all treated counties; Panel B estimates the event study using only the high-access treated counties; Panel C estimates the event study using the low-access treated counties. The supporting industries include NAICS codes 23 (construction), 42 (wholesale trade), 48-49 (transportation and warehousing), 54 (professional, scientific, and technical services), and 56 (administrative and support and waste management and remediation services). The industries competing for labor and other resources include NAICS codes 11 (agriculture, forestry, fishing, and hunting and primarily comprised of forestry and logging small businesses), 21 (mining, quarrying, and oil and gas extraction), and 31-33 (manufacturing). The service industries include NAICS codes 44-45 (retail trade), 53 (real estate, rental, and leasing), 62 (health care and social assistance), 72 (accommodation and food services), 81 (other services). Standard errors are clustered at the county level.

Table F14: Estimated Coefficients for Small Business Growth After MDP Openings with 25 Mile Threshold, Deposit-Based CB Access

	(1) Runner-up/Canc.	(2) Matched
Panel A: All Counties		
Pretrends	-0.00	-0.00
	(0.01)	(0.01)
Post ATT	-0.00	0.01*
	(0.01)	(0.01)
Observations	4,587	30,822
Panel B: High Access Treated Counties		
Pretrends	-0.01	-0.01
	(0.01)	(0.01)
Post ATT	0.03**	0.04***
	(0.01)	(0.01)
Observations	3,740	29,975
Panel C: Low Access Treated Counties		
Pretrends	0.02*	0.01
	(0.01)	(0.01)
Post ATT	-0.01	0.00
	(0.01)	(0.01)
Observations	3,630	29,865

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using the number of small business establishments (logged) for all treated counties; Panel B estimates the event study using only the high-access treated counties; Panel C estimates the event study using the low-access treated counties. The number of small business establishments is measured as the count of establishments with less than 20 employees. Standard errors are clustered at the county level. The high access treated counties are defined as counties with community bank deposits held by branches within 25 miles of the county centroid in 2009 that fall within the top tercile, and low access is defined as counties within the bottom tercile.

Table F15: Estimated Coefficients for High Access Counties After MDP Opening with 25 Mile Threshold, Deposit-Based CB Access

	Establishment Count		Employment		Earnings	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Small Businesses						
Post ATT	0.03**	0.04***	0.03*	0.03**	-0.02	-0.02
	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)	(0.03)
Observations	3,740	29,975	3,740	29,939	3,740	29,939
Panel B: New Small Businesses						
Post ATT	0.03	0.07**	0.03	0.05		
	(0.03)	(0.03)	(0.05)	(0.05)		
Observations	3,734	29,546	3,734	29,546		
Control	Runner-up	Matched	Runner-up	Matched	Runner-up	Matched

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using high-access treated counties for outcome variables measuring small business establishments, employment, and earnings at all firms with less than 20 employees; Panel B estimates the event study using high-access treated counties for outcome variables measuring small business establishments and employment all firms with less than 20 employees that began operations within the previous 12 months. Data on the earnings of employees at small businesses that began operations within the previous 12 months is not available from publicly available sources. Standard errors are clustered at the county level. The high access treated counties are defined as counties with community bank deposits held by branches within 25 miles of the county centroid in 2009 that fall within the top tercile.

Table F16: Estimated Coefficients for Small Business Growth by Industry After MDP Opening

	Supporting Industries		Competing Industries		Service Industries	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Counties						
Pretrends	0.01	0.01	-0.02	-0.02	-0.01	-0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Post ATT	0.00	0.03**	−0.08**	-0.04	-0.00	0.01
	(0.02)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)
Observations	4,587	3,266	4,559	3,248	4,587	3,267
Panel B: High Access Treated Counties						
Pretrends	-0.01	-0.01	-0.04	-0.04	−0.02**	−0.02*
	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)
Post ATT	0.04*	0.05***	-0.04	-0.00	0.03**	0.03**
	(0.02)	(0.02)	(0.04)	(0.04)	(0.01)	(0.01)
Observations	3,707	2,716	3,679	2,698	3,707	2,717
Panel C: Low Access Treated Counties						
Pretrends	0.05***	0.04***	-0.00	0.00	0.01	0.01
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)
Post ATT	-0.02	0.01	−0.11**	−0.08**	-0.01	0.00
	(0.03)	(0.02)	(0.04)	(0.04)	(0.01)	(0.01)
Observations	3,212	2,430	3,190	2,412	3,212	2,431
Control	Runner-up/Canc.	Matched	Runner-up/Canc.	Matched	Runner-up/Canc.	Matched

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using all treated counties; Panel B estimates the event study using only the high-access treated counties; Panel C estimates the event study using the low-access treated counties. The supporting industries include NAICS codes 23 (construction), 42 (wholesale trade), 48-49 (transportation and warehousing), 54 (professional, scientific, and technical services), and 56 (administrative and support and waste management and remediation services). The industries competing for labor and other resources include NAICS codes 11 (agriculture, forestry, fishing, and hunting and primarily comprised of forestry and logging small businesses), 21 (mining, quarrying, and oil and gas extraction), and 31-33 (manufacturing). The service industries include NAICS codes 44-45 (retail trade), 53 (real estate, rental, and leasing), 62 (health care and social assistance), 72 (accommodation and food services), 81 (other services). Standard errors are clustered at the county level.

Table F17: Estimated Coefficients for Small Business Growth by Industry After MDP Opening with 25 Mile Threshold, Deposit-Based CB Access

	Supporting Industries		Competing Industries		Service Ind
	(1)	(2)	(3)	(4)	(5)
Panel A: All Counties					
Pretrends	0.01	0.00	-0.02	-0.01	-0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Post ATT	0.00	0.03^{**}	-0.08^{**}	-0.09^{***}	-0.00
	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)
Observations	4,587	30,779	4,559	30,022	4,587
Panel B: High Access Treated Counties					
Pretrends	-0.01	-0.02	-0.02	-0.00	-0.02^{*}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Post ATT	0.05^{**}	0.07^{***}	-0.03	-0.04	0.03^{**}
	(0.02)	(0.02)	(0.04)	(0.04)	(0.01)
Observations	3,740	29,932	3,712	29,175	3,740
Panel C: Low Access Treated Counties					
Pretrends	0.03^{*}	0.03	0.00	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Post ATT	-0.03	0.00	-0.06	-0.08^{**}	-0.01
	(0.03)	(0.02)	(0.05)	(0.04)	(0.01)
Observations	3,630	29,822	3,602	29,065	3,630
Control	Runner-up/Canc.	Matched	Runner-up/Canc.	Matched	Runner-up/Canc

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using all treated counties; Panel B estimates the event study using only the high-access treated counties; Panel C estimates the event study using the low-access treated counties. The supporting industries include NAICS codes 23 (construction), 42 (wholesale trade), 48-49 (transportation and warehousing), 54 (professional, scientific, and technical services), and 56 (administrative and support and waste management and remediation services). The industries competing for labor and other resources include NAICS codes 11 (agriculture, forestry, fishing, and hunting and primarily comprised of forestry and logging small businesses), 21 (mining, quarrying, and oil and gas extraction), and 31-33 (manufacturing). The service industries include NAICS codes 44-45 (retail trade), 53 (real estate, rental, and leasing), 62 (health care and social assistance), 72 (accommodation and food services), 81 (other services). Standard errors are clustered at the county level.

G Mechanism: Funding Small Business Lending Growth After MDP Opening

To investigate mechanism through which community banks increase small business lending in MDP counties, I evaluate two potential channels: (1) an increase in local deposits that provide additional funding for SBL originations, and (2) a shift of SBL originations from non-MDP counties to MDP counties.

G.1 Deposit Growth After MDPs

To analyze the role of post-MDP deposit growth in driving the observed increase in small business lending by community banks, I estimate equation 2 using the number of (logged) deposits in community banks that are 25, 50 and 100 miles within the population-weighted county centroid as the dependent variable. Deposits are an important source of liquidity and funding mechanism for community banks; however, the flow of deposits throughout a bank's branch network can reduce reliance on locally held deposits when originating loans. Therefore, the increase in small business lending after MDP openings may be financed by deposits from outside the local market, through interbank wholesale funding, by reallocating credit from nearby counties to the MDP county, or by shifting the loan portfolio composition towards SBLs. Evaluating the relationship between MDP openings and locally held deposits can provide initial evidence on the mechanism through which community banks fund their increase in SBLs originations in MDP counties.

Table G1 presents the estimated ATT treatment effects for each of the three distance thresholds using the runner-up/cancelled county (panel A) and matched county (panel B) control groups/estimation strategies. The analysis returns no statistically significant changes in deposits within 5 years after the MDP investment across any of the distance thresholds or control groups. Therefore, the increase in small business lending by community banks after MDP openings is unlikely to be driven primarily by an influx of deposits to local branches.

G.2 Reallocation of SBL Originations

To analyze the role of SBL reallocations from non-MDP counties to MDP counties to fund the observed increase in small business lending by community banks, I estimate equation 2 using the percent of originations by banks operating in MDP counties that are originated in each county. Estimating the share of loans originated in MDP counties, rather than the magnitude of lending, provides initial insights into whether SBL lending is being reallocated to MDP counties, even if the absolute levels of lending are not increasing.

Table G2 presents the estimated ATT treatment effects for community bank, non-community bank,

Table G1: Estimated Coefficients for # of Locally-Held Deposits (log) After MDP Opening

	(1) 25 Miles	(2) 50 Miles	(3) 100 Miles
Panel A: Runner-up/Cancelled			
Pretrends	-0.02	-0.03	0.01
	(0.03)	(0.02)	(0.02)
Post ATT	0.02	0.00	-0.01
	(0.03)	(0.02)	(0.02)
Observations	4,596	4,598	4,598
Panel B: Matched			
Pretrends	-0.01	0.00	0.01
	(0.01)	(0.01)	(0.01)
Post ATT	0.00	0.01	-0.00
	(0.03)	(0.01)	(0.01)
Observations	30,369	30,635	30,635

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using the runner-up/cancelled county control group, and Panel B estimates the event study using the matched county control group. The outcome variables are the number of deposits (logged) in community banks with branches within 25 miles (Column 1), 50 miles (Column 2), and 100 miles (Column 3) of the population-weighted county centroid. When estimated using non-community banks, the results are not statistically significant.

and all banks using the runner-up/cancelled county (Column 1) and matched county (Column 2) control groups/estimation strategies. The analysis returns a statistically significant and positive increase in the percent of originations made in MDP counties by community banks using the runner-up/cancelled county control group and a large, positive estimated coefficient using the matched counties, however the coefficient is not statistically significant. Given that the estimated coefficient is very similar to the estimated growth in the number of small business loans originated, this suggests that much of the increase in small business lending by community banks in MDP counties is driven by reallocation of lending from other counties.

Table G2: Estimated Coefficients for % of SBLs Originated by Community Banks (log) After MDP Opening

	(1) Runner-up	(2) Matched
Panel A: All Banks		
Pretrends (Agg.)	-0.03	-0.04
	(0.05)	(0.04)
Post Opening ATT	0.02	0.03
	(0.07)	(0.06)
Observations	4,598	30,635
Panel B: Community Banks		
Pretrends (Agg.)	-0.07	0.02
	(0.10)	(0.09)
Post Opening ATT	0.21**	0.14
	(0.10)	(0.09)
Observations	4,511	28,921
Panel C: Large Banks		
Pretrends (Agg.)	-0.01	-0.04
	(0.04)	(0.04)
Post Opening ATT	-0.01	0.02
	(0.06)	(0.05)
Observations	4,598	30,635

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using all banks in the MDP and counterfactual counties, Panel B estimates the event study using only community banks, and Panel C estimates the event study using only non-community banks. The outcome variables are the percent of total SBL originations that are originated in each county by banks (logged). Column (1) estimates using the runner-up/cancelled county control group, and Column (2) estimates using the matched counties.

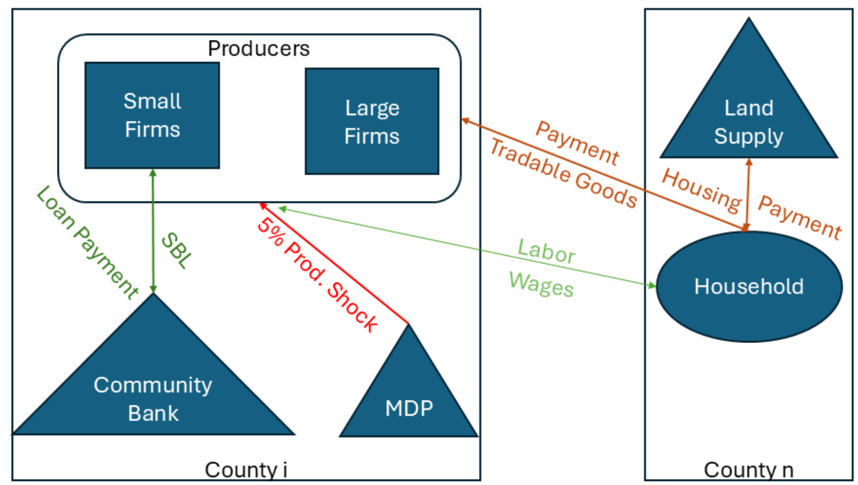
Table G3: Estimated Coefficients for % of SBLs Originated by Community Banks (log) After MDP Opening

	Community Banks		Large Banks	
	(1) Runner-up	(2) Matched	(3) Runner-up	(4) Matched
C&I Loans to Small Businesses				
Pretrends (Agg.)	-0.00	-0.00^{**}	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Post Opening ATT	-0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	8019	45131	3179	7755
CRE Loans to Small Businesses				
Pretrends (Agg.)	0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Post Opening ATT	0.01^{*}	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	8019	45131	3179	7755
C&I Loans to Non-Small Businesses				
Pretrends (Agg.)	0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Post Opening ATT	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	8019	45131	3179	7755
CRE Loans to Non-Small Businesses				
Pretrends (Agg.)	0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Post Opening ATT	-0.00	-0.00	0.01^{*}	0.01^{**}
	(0.00)	(0.00)	(0.01)	(0.00)
Observations	8019	45131	3179	7755
Residential Real Estate Loans				
Pretrends (Agg.)	-0.01	-0.01^{**}	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Post Opening ATT	-0.00	0.00	0.01	0.00
	(0.00)	(0.00)	(0.01)	(0.00)
Observations	8019	45131	3179	7755
Agricultural Loans				
Pretrends (Agg.)	-0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Post Opening ATT	-0.00	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	8019	45131	3179	7755
Construction Loans				
Pretrends (Agg.)	0.00	0.01^{*}	0.01	0.01
	(0.01)	(0.00)	(0.01)	(0.01)
Post Opening ATT	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.01)	(0.01)
Observations	8019	45131	3179	7755

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*; the pretrends (agg.) estimated coefficients are the average of the event study coefficients for the 5 years before the MDP opening, with event time -1 as the reference group; the post opening ATT estimated coefficients are the average of the event study coefficients for the 5 years after the MDP opening; Panel A estimates the event study using all banks in the MDP and counterfactual counties, Panel B estimates the event study using only community banks, and Panel C estimates the event study using only non-community banks. The outcome variables are the percent of total SBL originations that are originated in each county by banks (logged). Column (1) estimates using the runner-up/cancelled county control group, and Column (2) estimates using the matched counties.

H Model Diagram

Figure H1: Diagram of Spatial Equilibrium Model



Small Business Lending: Community bank branches and small business productivity determine SBL share in each county
Consumption/Trade: Household consumes small and large firm products based on sectoral prices, average income, trade costs, and elasticity of substitution between goods and sectors. Land supply if fixed.
Production: Production is increased by SBLs through decreases in effective fixed costs.
Commuting: Household commuting decisions are based on commuting costs, tradable goods and land prices, and wages
Million Dollar Plant: MDP opening increases productivity at in-county small and large firms.