Local Economic Shocks and the Market for Credit

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Abstract

WORK IN PROGRESS, NOT FOR EXTERNAL DISTRIBUTION The economic turmoil from local labor market shocks can spillover into the commercial banking system. Constricted deposit supplies and decreased asset values affect banks' credit supply decisions. Utilizing a set of continuous difference-in-differences regressions, I identify plausibly exogenous shifts in local deposit supply and asset values generated by the granting of Permanent Normal Trade Relations with China. This local deposit supply transmission generated balance sheet wide funding constraints, especially for banks operating in multiple markets. The banks most constrained by this import competition adjusted their credit supplies between products and across geographic markets. Banks reduced small business lending but increased mortgage originations. This adjustment entailed lending outside of their home markets and securitizing an increasing proportion of the loans they originated. This "flight to liquidity" was aided by the presence of an active secondary markets for mortgages and few geographic constraints for mortgage lending.

JEL Codes: D22; G21; L25.

1 Introduction

Commercial banks are exposed to risks through the customers in the markets they serve, and in recent times, there have been large disruptions in select local labor markets. Whether because of natural disasters, changes in trade policy, or shifts in the broader macro-economy, local labor market shocks typically follow a similar pattern. The firms most exposed to shocks cut wages, reduce their workforce, or even cease operations (Pierce and Schott (2016)). Commercial banks have not been immune to the adverse affects of these recent local economic shocks, as these shocks which begin at the firm level often spill over to the banks which serve these firms. Studies have shown that the banks most exposed to import competition reduce their credit supply, even to firms not directly exposed to the trade shock. Given the scale of the commercial banking system and its importance in economic development, it is essential to grasp the channels through which spillovers occur and understand how banks adjust to them.

Two problems arise when addressing the question of banks' responses to local economic shocks. The first is that many economic shocks begin, at least partly, within the financial system itself.[1] Disentangling cause, effect, and reaction becomes a futile task when the troubles originated with the banks in question. The second is that because such shocks often impact both sides of banks' balance sheets, it is difficult to determine what mechanism is driving a bank's response. Previous research often points to the role of the assets channel of transmission whereby increases in non-performing loans in reducing banks' credit supply (Izadi and Saadi (2023), Federico et al. (2023), Mayordomo and Rachedi (2022)). Few researchers have investigated how import competition affects the supply of deposits, the primary source of bank funding. Businesses and customers impacted by import competition deplete savings and reduce deposit holdings. Given the importance of deposits in bank funding, sufficiently large shifts in the supply of local deposits could force banks to reassess their credit supply strategies. Understanding how such local funding shocks shape credit supply is important, especially when considering the numerous drivers of local economic

[1] Prominent examples include the Great Depression, the Savings and Loan Crisis, and the Great Financial Crisis.

shocks and the increasing spread of modern bank lending and branch networks.

In this paper, I first present a simple model which shows that when banks have two types of loans they can originate, one liquid due to an active secondary market and the other which cannot be sold off of its balance sheet, expectations of future losses and deposit withdrawals affect the relative flows of capital dedicated to the origination of each type of loan.

Turning to data, I leverage banks' differential exposure to the passage of Permanent Normal Trade Relations (PNTR) with China in 2000 to study the transmission of plausibly exogenous local labor market shocks to the commercial banking system and the commercial banking system's response. My empirical design relies on measures of county and bank level exposure to import competition. Following Pierce and Schott (2016), I use tariff schedules and county labor force compositions from before the China Shock to create a measure of each county's exposure to increased import competition which accounts for the change in each industry's tariffs and the proportion of each county's workforce employed in each industry.[2] The measure varies by county but is constant across time. I then create a measure of each bank's exposure to import competition based on the location of its deposit accepting branches and those counties' exposures to import competition. Similar to county exposure, bank exposure varies across banks and is constant across time.

I first utilize a set of event studies and continuous difference-in-difference regressions to quantify the first stage impact of differential exposure to PNTR on banks' balance sheets and income statements. The supply side of lending decisions are often a function of banks' funding constraints and their expectations about future market conditions. To this end, I find that the local labor market disruptions generated from increased import competition led to a plausibly exogenous increase in non-performing loans and an inward shift in deposit supply, indicative of the deposits channel. This deposit shock was driven primarily by local customer supply of deposits, not through changes in banks' demand or through the opening and closing of bank branches. While there were statistically significant increases in non-

[2]Others such as Autor et al. (2013) measure exposure to import competition based on measured increases in imports in each sector. I employ this method because banks have the ability to open and close branches in response to local shocks and any measure of post-PNTR exposure based on concurrent branch networks may capture this endogenous response.

performing loans, they were not economically significant, and the most exposed banks rarely utilized provisions for loan losses.[3]

Once I establish that the labor market disruptions affected banks through the deposits channel, I examine its impact on credit supply decisions. I find that at the balance sheet level, there are reductions in small business lending but temporary increases in mortgage originations in the first three years following PNTR. When adjusting for bank-level lending trends prior to PNTR, I find that a one standard deviation increase in bank-level exposure led to a 24% reduction in small business loan origination and a 3% increase in mortgage originations.

To examine whether these changes were due to local credit demand or credit supply, I examine credit origination at the bank-by-county-by-year level. Similar to Khwaja and Mian (2008) and Izadi and Saadi (2023), I use a continuous difference-in-difference regression with bank-by-county and county-by-year fixed effects to control for local credit demand and isolate changes in each bank's local credit supply decisions caused by increased import competition. I find that bank level exposure led banks to reallocate lending at the local level from small business loans to mortgage loans, especially in markets not affected by increased import competition. I find that, when controlling for local credit demand, a one standard deviation increase in bank-level exposure led to a 15% reduction in small business loan origination and a 19% increase in mortgage originations. The size of these estimates arises from the fact that as banks were adjusting credit strategies between small business and mortgage lending, they were also adjusting along geographic lines by originating mortgages outside of markets in which they had branches.

Underlying each of these analyses is the assumption that in the absence of PNTR, local trends in deposits holding and lending behaviour would have evolved similarly to their pre-shock trajectories and in parallel across counties and banks with varying exposure levels. This "Strong Parallel Trends" assumption is necessary for identification under continuous treatment (Callaway et al. (2024)), I support this assumption by providing balance tests and event study specifications. Additionally, I show that the main results are robust to using

[3]Provisions for loan losses are an income statement item which allow banks to write off the expected losses from under performing loans. The provisions are made in advance whether or not losses actually occur.

a discrete treatment generated from the continuous exposure measures. Inference in such a discrete settings requires a weaker version of the parallel trends assumption.

My research contributes to a large literature studying the economic impact of China's reception of Permanent NTR. Many papers investigate the harm increased import competition inflicted upon industries and labor markets most exposed to these tariff changes (Autor et al. (2013), Pierce and Schott (2016), Autor et al. (2016)). Autor et al. (2021) find evidence of labor market scarring nearly twenty years after the Shock, and beyond the direct labor market consequences, other studies have found evidence that the Shock reduced the provision of local public goods (Feler and Senses (2017)), led to an increase in "deaths of despair" (Pierce and Schott (2020)), and was amplified by local housing market conditions (Xu et al. (2019)).[4] The papers most closely related to mine investigate credit market changes following the China's ascension to the World Trade Organization. Izadi and Saadi (2023) show that small business lending decreased in counties most exposed to the Chinese import competition, and Federico et al. (2023) and Mayordomo and Rachedi (2022) similarly show that increased import competition induced credit constrictions in Italy and Spain. I expand on their work by investigating the role of the deposits channel in driving these credit supply responses and by analyzing the substitution between small business and mortgage lending. I show that the deposits channel played an important role in constricting balance sheets, and while banks reduced their small business lending, they increased their mortgage lending.

My paper is also related to research studying the movement of local shocks through bank networks. As with other firms, banks' internal capital markets allow for the movement of funds between different geographic segments of each bank. Many investigations into the role banks' internal capital markets leverage exogenous credit and liquidity shocks from hurricanes (Schuwer et al. (2018)), the shale oil boom (Gilje et al. (2016)), and floods (Rehbein and Ongena (2022)) to understand their ability to transmit both positive and negative shocks across geographic markets. Natural disasters are useful for studying the transmission of economic shocks since many economic shocks originate in the financial system (Clark et al.

[4]Sasahara (2022) provides a more complete overview of the existing literature and methods used in the analysis of the China Shock and other import competition induced shocks.

(2021)).[5] In times of economic turmoil internal capital markets can allow banks to continue lending to sustain lending activities (Quincy (2023)) or they can force firms to siphon capital from peripheral operations (Biermann and Huber (2023)). I complement these papers by isolating a plausibly exogenous and persistent local economic shock originating in the real economy, and I examine adjustment along both product space and geographic market dimensions. A persistent shock such as this differs from many of the transitory shocks studied before. While many of the previously mentioned papers show networks being used to transfer liquidity to increase credit supply in affected markets, my analysis shows the opposite, as banks shift credit supply away from impacted markets and into assets that can be sold into secondary credit markets. Rather than a "flight to quality," the most exposed banks participate in a "flight to liquidity".

Finally, I contribute to the research studying the deposits channel of transmission. Many banking models recognize that although demand deposits are a cheap source of funding, their inherent volatility is a fundamental weakness (Diamond and Dybvig (1983)). This weakness ties bank level outcomes to the real economy (Diamond and Rajan (2006)). Khwaja and Mian (2008) illustrate this principal, examining unexpected liquidity shocks to Pakistani banks, and Karam et al. (2014) similarly investigate the impact of credit rating downgrades on banks' access to deposits. Each shows that when access to deposits is lost, credit supply is impacted. I expand on this literature by investigating small loss of deposits commiserate with real economic conditions. Rather than a bank run, which leads to a sudden halt in all credit supply, I show that the smaller decline in deposits leads to credit reallocation. In the face of constricted funding, banks lend more in markets with active secondary markets.

In Section 2, I provide background on the change in trade policy which created the China Shock. In Section 3, I provide an overview of the data and explain the county and bank level measures I use to quantify exposure to increased import competition. In Section 4, I show that the China Shock produced a plausibly exogenous decrease in funding for banks exposed to it, and in Section 5, I explore how these funding shocks affected local lending patterns. In Section 6, I conclude.

[5] Lazzaroni and Bergeijk (2014) provide a more extensive summary of studies examining the macroeconomic impact of natural disasters.

2 Background

2.1 Permanent Normal Trade Relations To understand how changes in trade policy affect local labor markets, it is important to first provide an overview of US trade policy before and after PNTR. The US's Harmonized Trade Schedule maintains two tariff schedules for imports– Column One and Column Two.[6] The two schedules outline the tariff rates assessed on different categories of imported goods from a given country, and countries assessed under Column One rates are colloquially referred to as having Normal Trade Relations (NTR). NTR is beneficial for firms exporting into the US, as all tariffs in the Column One are less than or equal to the Column Two rates. With the passage of the Trade Act of 1974, countries that had been taxed at Column One rates would permanently hold that tariff schedule.[7] Prior to 1974, communist countries, including China, had been excluded from NTR status, and accordingly, their imports had been taxed at Column Two rates.

Section 402 of the Trade Act allowed the President of the US to issue annual waivers which would allow imports from a given Column Two country to be assessed at NTR rates, and in 1980, President Carter granted China one such annual waiver.[8] Opening trade with China was seen as a way to achieve two goals: pushing the Chinese economic model towards a market economy and maintaining political and security stability in Asia (Alexandroff (1998)). President Carter and succeeding US presidents continued to grant China these annual waivers. The opening of trade and political relations had a large influence on the economic connection between the two countries, and from 1985 and 1995, bilateral trade between the US and China increased from \$7.7 billion USD to over \$57.3 billion USD[9].

Nonetheless, uncertainty regarding the continued renewal of these waivers persisted, as Congress frequently threatened to revoke the President's authority to issue NTR waivers.

[6] Prior to 1998, permanent NTR was referred to as Most Favored Nation status. As of September 2023, Cuba, North Korea, Russia and Belarus are the only countries with Column Two status.

[7] https://www.govinfo.gov/content/pkg/COMPS-10384/pdf/COMPS-10384.pdf

[8] https://www.cartercenter.org/news/features/p/china/40-anniversary-china-relations.html

[9] Bilateral trade is defined as the sum of imports from and exports to China. Trade data from US Census Bureau, Trade in Goods with China.

Uncertainty surrounding the extension of the waivers provided a protective shield for many domestic firms producing at a relative disadvantage to their Chinese counterparts, as firms considering offshoring needed to carefully weigh the cost savings of moving production to China with the risks that tariff waivers might not be renewed ((Pierce and Schott (2016))).

Over time, World Trade Organization (WTO) member countries additionally raised concerns about the United States' annual waiver process, questioning its consistency with the rules of the WTO. By withholding permanent NTR status from China, the United States effectively prevented China from joining the WTO. This issue prompted the introduction H.R. 4444 on May 15, 2000, a bill that would grant China permanent NTR status upon its accession to the WTO. The bill's promoters believed that the offshoring of labor-intensive production processes, importation of low-cost goods, and expansion of export markets for American farmers would stimulate economic growth in both the US and China and encourage further human rights reforms in China.

The bill faced opposition from numerous unions and labor groups which argued that the permanent reduction of tariffs on Chinese goods would hurt domestic firms and workers. Despite the resistance, the bill successfully passed through Congress and the Senate in Mid 2000, and on October 10, 2000, President Clinton signed the bill into law. Following China's accession to the World Trade Organization on December 11, 2001, tariff rates on Chinese imports were officially and permanently set at Column One rates.

The China Shock, as it has come to be known, did not involve an abrupt reduction of tariffs; rather, it resolved the uncertainty that tariffs on some imports could have significantly increased had Congress blocked China's temporary NTR waiver. The resolution of this uncertainty ushered in a period of rapid offshoring and decline in specific industries exposed to these tariff schedules.

2.2 Commercial Banks and Secondary Lending Markets

The late 1990s and early 2000s were a time of transition in the financial world. Changing regulations, new technologies and shifting competitive landscapes affected markets for the assets and liabilities central to commercial banks' traditional business models.

Customer deposits have traditionally played a central role in bank funding. Commercial banks rely on a combination of demand deposits, time deposits, borrowed funds, and bank capital to fund their asset portfolios. Due to their low cost and limited sensitivity to interest rate fluctuations, demand deposits have been an essential part of these liabilities. For reference, in 2000, demand deposits comprised nearly 82 percent of bank liabilities.

Over the last 40 years, new financial instruments and changes in technology have introduced competition to the traditional funding model. Money Market Funds, designed to offer liquid and secure accounts with modest returns, have increasingly siphoned retail deposits away from commercial banks with the promise of higher returns than savings account with the same flexibility of easy withdrawals. Despite originating in the 1970s, these funds experienced substantial growth in the 1990s, growing from approximately $350 billion in 1990, to over $900 billion by the end of 2000.[10] By directly competing for bank deposits, Money Market Funds have applied pressure to banks' traditional funding models.

Regulatory changes similarly reshaped commercial banking markets. The Riegle–Neal Interstate Banking and Branching Efficiency Act of 1994 (IBBEA) established a standardized national framework permitting banks to operate branches beyond their home state. While some states had previously allowed reciprocal interstate branching, such agreements were not widespread, leading to limited interstate branch networks. Following the IBBEA's passage, there was rapid interstate expansion through both de-novo branching and mergers and acquisitions. According to Rice and Johnson (2008), between 1992 and 2000, the number of out-of-state branches surged from 62 to nearly 20,000. With the ability to expand their branch networks, banks could theoretically safeguard their balance sheets against local shocks by diversifying operations across multiple interstate markets.

Simultaneously, advancements in internet technologies, such as Fannie Mae's Desktop Underwriter software, began to reduce financial frictions in the origination of credit. The software allowed banks to verify their ability to sell mortgage loans to Fannie Mae before originating them. Fannie Mae and Freddie mac increasingly injected liquidity into the mortgage market, growing their combined portfolios of mortgage loans from nearly $175 Billion in 1995 to over $450 in 2005[11]. Such injections of liquidity fundamentally reshaped the business

[10]Source: Federal Reserve Economic Data (FRED).

[11]Source: Federal Reserve Economic Data (FRED).

model of originating mortgages. Banks and other non-bank financial intermediaries could originate loans and immediately sell them off of their balance sheets.

During this era, mortgage brokers gained prominence, playing a crucial role in connecting potential borrowers with banks eager to extend loans. This arrangement allowed banks to connect with borrowers located on the opposite side of the country[12].

In summary, the confluence of enhanced technological accessibility, evolving regulatory environments, and heightened competition within the financial sector created a compelling backdrop for examining the banking system.

3 Data and Defining Exposure Measures

3.1 Data To examine local banking responses to increased import competition, I link datasets covering the operations of commercial banks with local markets' exposure to import competition. The FDIC's Quarterly Call Reports offer a comprehensive view of FDIC-insured commercial banks' balance sheets, spanning from 1994 to the present. These reports provide valuable insights into various balance sheet and income statement items including assets, deposits, non-performing loans, income, losses, and more. A full list of balance sheet items and their codes are found in the Appendix Table 9.

To understand the geographic dispersion of bank operations, I utilize the FDIC's Summary of Deposits (SOD). The SOD is an annual survey collected in June of each year, beginning in 1994, documenting all FDIC-insured bank branches and their associated deposits. To link the SOD with lending data, I aggregate each bank's deposits to the county-by-year level. Additionally, I classify banks as either single- or multi-market entities based on the geographical spread of their branches across county markets. The primary focus of this paper is on banks operating in multiple markets, so single market banks are dropped from the

[12] A home buyer would go to a broker, the broker would then "shop" the mortgage around multiple banks, finding the one that would lend the money at the best terms. Banks could then either hold the mortgages on balance sheet or offload them to Freddie Mac. Freddie Mac began using automated underwriting system which streamlined much of this process. See Wall Street Journal "Why Big Lenders Are So Afraid Of Fannie Mae and Freddie Mac"

sample.

I collect data on each bank's small business and mortgage loan originations from the the Home Mortgage Disclosure Act (HMDA) disclosure files and the Community Reinvestment Act (CRA).[13] Data from the HMDA files provides details on the size of each originated mortgage, the county of origination, the bank originating the loan, and whether or not the loan is held on the originating bank's balance sheet or sold within a year. I aggregate the amount of mortgages held on balance sheet and the amount sold to the bank-by-county-by-year level. I denote the mortgages that are sold within a year as being scrutinized.

The CRA reports number and size of small business loans under $1 million that each bank originates in each county each year.[14] I integrate this data with local lending and deposits information.

I employ annual county-level data obtained from the Bureau of Labor Statistics (BLS) to account for local demographic and labor market characteristics. These data include average income income, population, college attainment levels, and employment rates, and I use averages of each variable from the years 1996 to 1999, before permanent NTR, as time invariant controls in the county level analyses. For bank level analyses, I utilize the 1996 to 1999 averages of each bank's assets, non-performing loans divided by assets, and equity divided by assets as time invariant controls. Summary statistics of bank level data are shown in Table 10.

3.2 County Exposure to Import Competition

Many of the industries most exposed to increased import competition following PNTR were located in clustered geographic regions. I adopt the approach outlined by Pierce and Schott (2020) to measure each county's exposure to increased import competition. This method involves analyzing the composition of each county's labor market in 1999, the year before the shock, and calculating the difference between Column One and Column Two tariff rates for industries operating

[13]Reporting of small business loan and mortgage loan is required by all banks, thrifts, and credit unions that are above a certain asset threshold, determined each year. The thresholds are set such that the regulatory burden does not overly strain small institutions.

[14]Greenstone et al. (2020) note that CRA data is fairly representative of all small business lending, as in 2007 it covered 86% of all small business loans under $1 million.

within that county.[15] These differences are computed using the 1999 tariff rates provided by Feenstra et al. (2002) for each industry group, and $CountyExposure$ is the weighted sum of these tariff gaps, where the weights are the labor market shares in that county. The resulting measure is the extent to which a given county's labor market was exposed to increased import competition at the time PNTR was adopted. County Exposure is computed as follows:

$$CountyExp_c = \sum_{i \in I} \frac{L_{i,c}}{L_i}(ColumnTwoRate_i - NTRrate_i) \tag{1}$$

Figure 1 illustrates the geographic distribution of CountyExposure, revealing significant exposure to increased import competition in some, but not all, counties. Important for my empirical strategy, there is significant intra-state variation in exposure, with the exception of several western states.

3.3 Bank Exposure to Import Competition

Banks can be exposed to local economic shocks through both sides of their balance sheets. For this study, however, I focus on exposure through their deposit collecting branches. Banks collect from local markets for several reasons. For one, deposit creation relies heavily on the presence of physical bank branches. Honka et al. (2017), for example, shows that a primary driver in depositors' bank choice is the distance to the nearest branch. Additionally, there are regulatory, time, and cost related frictions which signify an investment in operating in a particular markets. Credit origination, on the other hand, is less geographically focused, as many of the processes necessary to originate and service loans can be completed from afar. That is not to say that location is not important, as there may be informational advantages related to originating credit in the same markets where a bank has branches, but these frictions are less restrictive with credit than with deposits.

In light of these considerations, I adopt the methodology proposed by Kundu et al. (2021) to measure each bank's exposure to increased import competition. The measure is the deposit weighted average of $CountyExp$, where the deposit weights reflect the relative

[15] Of the nearly 10,000 HS8 code items in the 1999 data, nearly 8 percent had NTR gaps of zero. Summary Statistics: Mean NTR Gap = 0.32, sd = 0.23, max = 4.84, min = 0. Example difference between NTR and Column 2 rates: HS code 91069085 (watches) 0.08 vs. 2.52. HS code 22082020 (Pisco and Singani alcohol) 0 vs. 2.13. HS code 28049000 (tellurum and boron) 0 vs. 0.

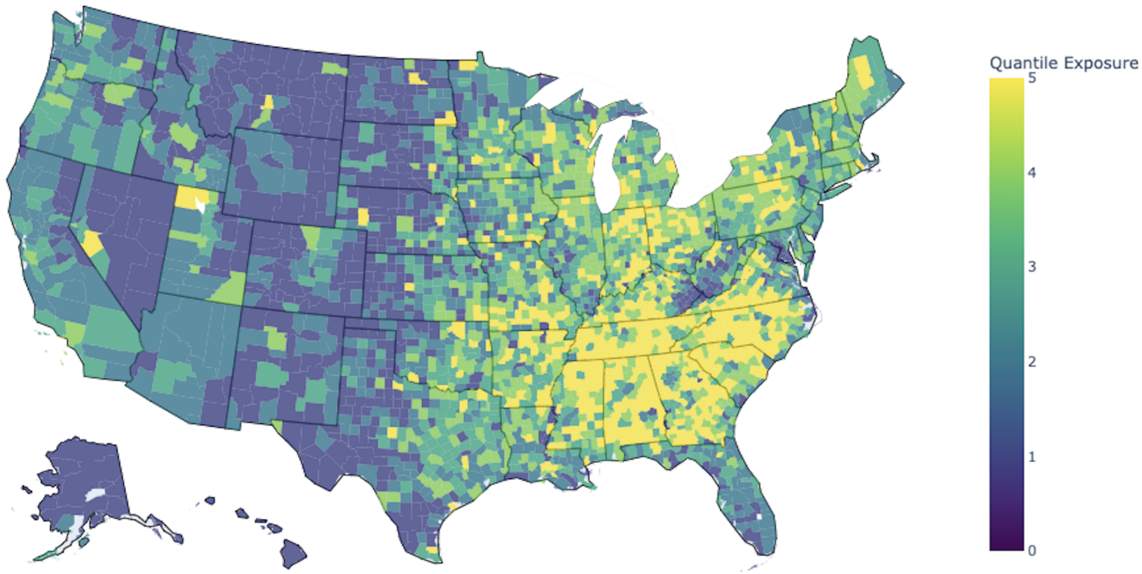


Figure 1: Map of County Exposure

Note: The map shows the quantiles of each county's CountyExposure measure. The measure incorporates the difference between NTR and Column Two tariffs for each industry and the industrial composition of each county's labor market.

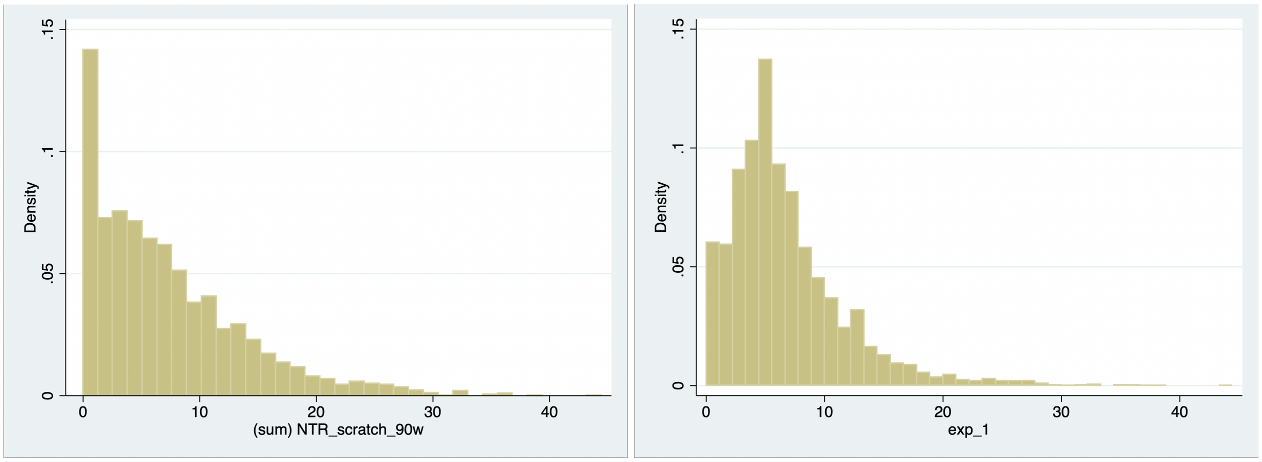
share of each bank's deposits that are raised in a given county. Bank exposure measures the extent to which a given bank's deposit base is exposed to increased import competition, and it is calculated as follows:

$$BankExp_i = \sum_{c \in C} \frac{d_{i,c}}{d_i} CountyExp_c \tag{2}$$

where $d_{i,c}$ are bank i's deposits in county c; d_i is the sum of bank i's deposits across all counties it operates in; and $CountyExp_c$ is county c's exposure to the China Shock.

The cross-sectional distributions of $CountyExposure$ and $BankExp$ are shown in Figure 2. The mean and median of $CountyExposure$ are 7.23 and 5.68, respectively, and the measure ranges from a minimum of zero in the least exposed county to a maximum of 44.44 in the most exposed. The mean and median of $BankExp$ are 6.76 and 5.60, and as with $CountyExposure$, the least exposed bank had zero exposure, while the most exposed bank measured 44.44. For the main analyses, I normalize both measures such that the means are equal to zero and standard deviations are equal to one.

Figure 2: Distribution of County and Bank Exposure to Import Competition



(a) County Exposure

(b) Bank Exposure

Note: Distributions of bank and county level exposure to increased import competition.

4 Empirical Strategy

The following analyses link the economic shock accompanying increased import competition to banks' credit supply decisions. To achieve this, I begin with a simple model of banks, which guides the analysis. I then outline the empirical strategy and present a first stage analysis which links banks' exposure to increased import competition with balance sheet effects capable of affecting credit supply decisions.

4.1 Model of Bank Behavior

To understand how a local economic shock may affect banks, consider a simple optimization problem. Similar to firms, banks maximize the present discounted value of future profit, subject to regulatory requirements. Banks choose origination and loan sales levels maximize to maximize the present discounted value of future profits subject to regulatory requirements and their initial stocks of assets and liabilities:

$$V(M_t, L_t) = \mathbb{E}[\sum_{s=0}^{T} \beta^s(\pi_s - \Omega \times \mathbb{1}(CR_s < \theta_{CR}) - \psi \times \mathbb{1}(LR_s < \theta_{LR})] \tag{3}$$

The first regulatory requirement deals with capital adequacy levels. Banks must maintain a deposit to bank capital ratio less than θ_{CR}. Additional units of regulatory capital can be acquired at cost ω. The second regulatory requirement pertains to banks maintaining sufficient reserve levels, as the ratio of deposits to reserves must remain less than θ_{LR}. If the ratio falls below required amounts, banks can borrow additional units of reserves at cost Ψ.

Each period's operating profit is a function of the revenue generated from servicing mortgage, M, and small business loans, L, and from interest earned on reserve balances, R. Some fraction of each bank's mortgage loans, s_m, can additionally be sold into the secondary market at some exogenous price, p_s. The bank must pay interest, r_d, on deposits held at the bank.

$$\pi_t = r_m(1 - s_m)M_t + p_s s_m M_t + r_L L_t + r_r R_t - r_d D_t - C(O_{m,t}, O_{L,t}) \tag{4}$$

While revenue is generated loans and reserves, the stock of each asset changes over time. Mortgage loans default at the rate d_m and decrease by p_s, the fraction sold into secondary markets each period, and small business loans default at the rate d_L. Banks' mortgage and business loan portfolios evolve as follows

$$M_{t+1} = (1 - d_m - s_m)M_t + O_{m,t} \tag{5}$$

$$L_{t+1} = (1 - d_L)L_t + O_{L,t} \tag{6}$$

Where $O_{m,t}$ and $O_{L,t}$ are the amounts of new mortgage and small business loans originated by a bank in a given period. Funding levels constrict the rate of new originations:

$$O_{M,t} + O_{L,t} + R_t \leq D_t + E_t - M_t - L_t \tag{7}$$

For simplicity, assume that prior to each period, each bank chooses an optimal deposit level D_t. The interest paid on these deposits, r_d is then a function of the bank's supply and customers' demand. An exogenous shift in customer demand will affect the price at which any given amount of deposits can be gathered.

The bank chooses s_m, O_M, O_L, D_t subject to funding constraints and regulatory requirements, with expectations of future realizations of d_m, d_L, r_r, r_m, and r_L. Optimal s_m balances the revenue generated from selling mortgages with the discounted cost of decreasing the stock of mortgages in the future, while optimal O_m and O_L balance the present cost of originating this credit with the future returns from increases in the stock of each asset. Whereas the future returns from small business loans are realized solely as the revenue generated from servicing the loans, the returns from mortgage loan originations are multifaceted. In periods with low default rates and non-binding regulatory constraints, the primary benefit of mortgage loans is their interest revenue, but if there are large shifts in default rates, returns in other assets, or regulatory constraints become binding, these assets can be sold and transformed into reserves. In essence, mortgage loans become a buffer against economic turmoil.

4.2 Identification Strategy

To identify the impact of this shock on bank behavior, I compare outcomes between banks with different levels of exposure to PNTR before and after the adoption of PNTR. The first stage of this analysis examines the direct impact of exposure to PNTR on outcomes which drive banks' credit supply decisions.

I estimate the coefficients in the following event study specification:

$$y_{b,t} = \sum_{\tau=1996}^{\tau=2006} \beta_\tau \mathbb{1}\{\tau = t\} \times BankExp_b + \sum_{\tau=1996}^{\tau=2006} \gamma_\tau \times X_b + \delta_b + \delta_t + \epsilon_{bt} \tag{8}$$

where y_{bt} is the dependent variable of interest at bank b in year t, $BankExp_b$ is bank b's exposure to increased import competition, and X_{bt} is a vector of time invariant bank level controls interacted with a post-dummy. The bank level controls are 1996 to 1999 averages of assets, non-performing loan ratio, and equity ratios[16]. Each regression includes time fixed effects which control for quarter specific shocks which affected every bank and bank fixed effects which control for time invariant bank-level factors which drive banks' individual credit and funding decisions. The coefficients of interest are the β_τs which represent the difference in outcomes in year τ for the average bank, relative to 1999, due to a 1 standard deviation increase in $BankExp$. Event studies present a visual representation of the dynamic response of outcomes over time, and they are useful in assessing the validity of identification assumptions. In addition, I estimate the coefficients in the following difference-in-difference equation to summarize the effect of exposure across the full period:

$$y_{bt} = \beta(\mathbb{1}\{t \geq 2000\} \times BankExp_b) + \gamma(\mathbb{1}\{t \geq 2000\} \times X_{bt}) + \delta_b + \delta_t + \epsilon_{bt} \tag{9}$$

Where y_{bt} is the coefficient of interest and $\mathbb{1}\{t \geq 2000\}$ is an indicator variable equal to 1 if year t is greater than 2000 and 0 otherwise. The same time-invariant bank controls are

[16] These variables are a measures of each bank's size, the quality of their asset portfolio, and their leverage.

used as before, and the regressions include bank and time fixed effects. The "Strong Parallel Trends" assumption is necessary for the identification of a the average treatment effect. The assumption states that regardless of their exposure level, all banks would have experienced similar outcomes had they received a specific exposure level.[17]

The identification assumption is supported first by the fact that bank exposure is found using the expanse of bank networks in the year prior to the shock, and the process of passing PNTR was primarily political, outside the scope of bank influence.[18] The extent of banks' branch networks was established prior to the announcement of PNTR, and thus PNTR would not have shaped their branch networks. This is not to say that banks operating in regions with high manufacturing shares were not different from other banks, as there are advantages to specializing in lending to the customers in a given area. For identification, though, we need that the banks serving high exposed areas did not select into these markets because of differences in bank quality which might affect potential outcomes. Though an imperfect test of this assumption, I examine whether pre-PNTR measures of bank quality were balanced across exposure levels by regressing a selection of time invariant bank characteristics on bank exposure.[19] Results of these regressions are shown in Table 1.

4.3 Local Labor Markets

I begin by establishing that the passage of NTR resulted in local labor market disturbances capable of influencing local deposit-holding behaviors and asset values. Previous research has demonstrated that the industries most exposed to increased import competition witnessed substantial reductions in labor demand, and many of these industries were geographically clustered (CITE). Limited out migration magnified the local repercussions of the job losses in the most exposed industries[20]. In the counties

[17] **THIS IMPOSES STRONG ASSUMPTIONS. TO Examine reductions in these, I nonparametrically estimate the Average Causal Response function. Additionally, in the appendix, I show that results are robust to using a discrete treatment measure, which reduces the strength of the necessary parallel trends assumptions.**

[18] Note on Corporate Lobbying by other labor groups.

[19] Specific measures include the log of assets, deposits, borrowed funds, non-performing loans, net income, interest expense, provisions for credit and loan losses, salaries, and the number of branches and number of counties in which the bank maintained branches.

[20] Autor et al. (2021) find only modest rates of out-migration from the affected counties.

Table 1: Balance of Pre-Shock Covariates

	Variable = Pre-Shock Average of				
	Assets	Deposits	Borrowed Funds	Non-Perf Loans	Net Income
est	-0.013*	-0.010	-0.000***	-0.025***	-0.000***
se	(0.008)	(0.007)	(0.000)	(0.006)	(0.000)
n	3519	3519	3519	3381	3519
r2	0.001	0.001	0.002	0.005	0.002
	Variable = Pre-Shock Average of				
	Interest Expense	Provisions	Salaries	Branches	Dep. Markets
est	0.002	0.004	-0.026***		-0.003
se	(0.007)	(0.005)	(0.008)		(0.001)
n	3519	3514	3519		3366
r2	0.000	0.000	0.003		0.001

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Results from the regression of BankExp on pre-shock averages of each variable. Coefficients for balance sheet items are estimated using OLS with robust standard errors. Coefficents for Branches and Deposit Markets are estimated using Poisson regression.

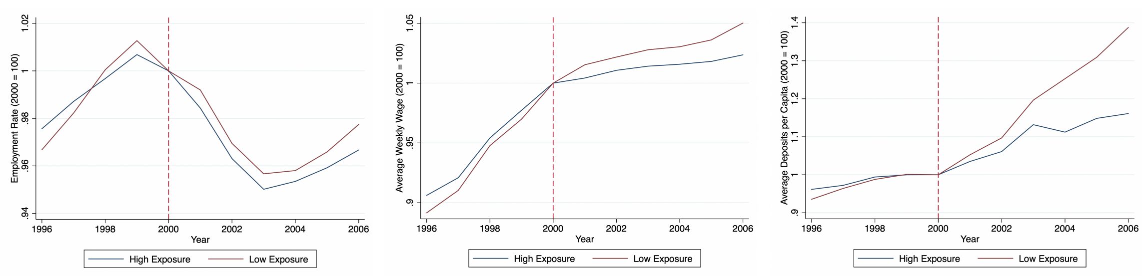
most exposed to import competition, opting out of the labor force was the primary means of adjustment to the reductions in labor demand (CITE). These exits coupled with increased mechanization of labor processes to increase unemployment rates and reduce wages in the industries and counties most exposed to increased import competition.

Comparing average wage and employment growth across different levels of exposure reveals the impact of import competition on local labor markets. I separate counties into high and low exposure based on whether their $CountyExposure$ measure was above or below the median and find the population weighted average growth employment levels and wages across time. The time trends are depicted in Figures 3 (A) and (B), and following the year 2000, a clear divergence in each series emerges. Employment rates and average wages in high exposure counties fell below those in low exposure counties. This matches the 2 to 3.5%

reduction in per capita unemployment and mean log wages found by Autor et al. (2013).

Even with worker adjustment programs and other safety nets, such labor market change people and business' savings and deposit holding behavior. At the individual level, the loss of employment this may lead to a reduction of new savings and increased draw down of the existing stock of savings. A noticeable divergence between deposits in high and low exposure counties begins after the China Shock, shown Panel (C) of Figure 3, as the quantity of deposits in high-exposure counties declines relative to the less exposed counties. A full analysis of county markets, shown in Appendix AX, supports this evidence.

Figure 3: County Variables by Exposure to Import Competition



(a) Employment Rate (b) Average Wage (c) Deposits

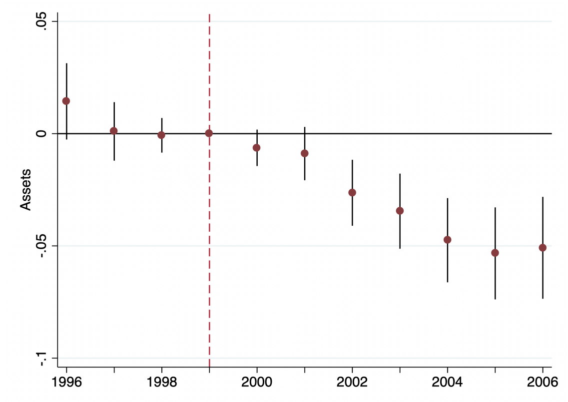
Note: The figure presents the average employment rate, weekly wage, and deposits per capita at the county level, normalized so that the value in the year 2000 is equal to 1. Counties are divided into high and low based on the value of their exposure relative to the median.

4.4 First Stage Response I now connect exposure to import competition with outcomes that may affect individual banks' credit supply decisions with XXX analyses of these connections: event study estimates (equation xxx), difference-in-difference regressions (equation xxx), and non-parametric estimates of the effect size.

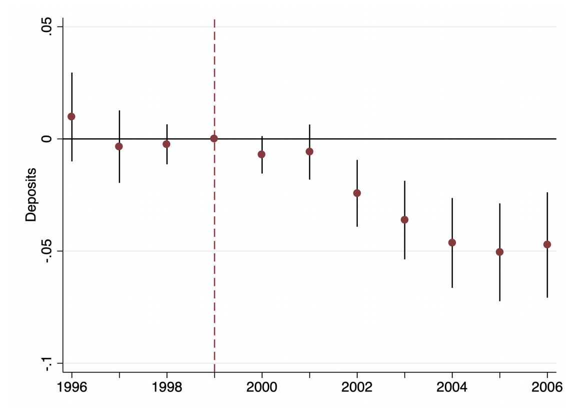
I analyze two parts of bank operations– balance sheet items (stocks) and income statement items (flows). Balance sheet items include the log of assets, deposits, and non-performing loans. Income statement items include the log of net income, provisions for credit losses, and provisions for loan losses. Figure 4 presents the event studies, and results of the regression analysis are displayed in Table 2. The event studies show that .... and the regression analyses further support this, showing that a 1 standard deviation... led to a ....

in xxxx.

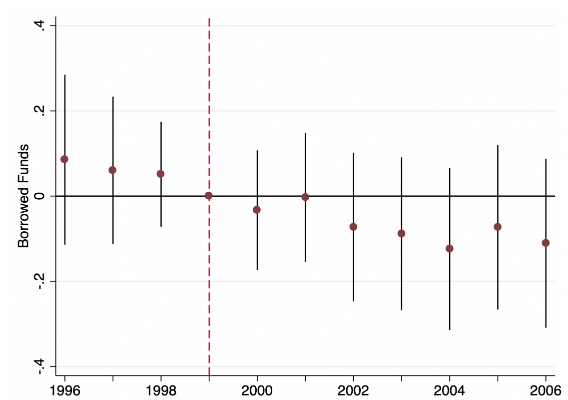
Figure 4: Bank Level Event Studies: Stocks



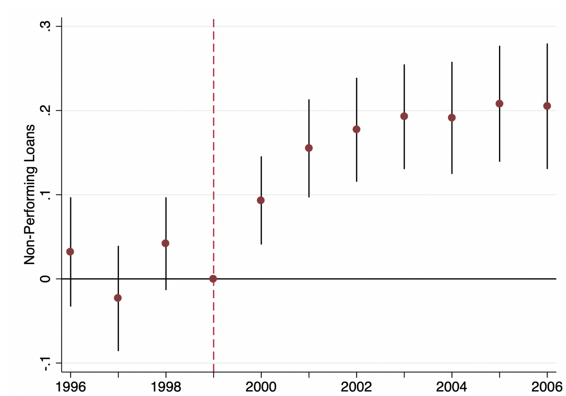
(a) Assets



(b) All Deposits



(c) Borrowed Funds



(d) Non-Performing Loans

Note: The figure presents event study estimates of the effect of exposure to import competition on bank level outcomes. Estimates show the impact of a one standard deviation increase in bank exposure on each balance sheet item. Data come from FDIC's Quarterly Call Report. Regressions include bank and year fixed effects and time-invariant bank characteristics interacted with year-indicator variables. Standard errors are clustered at the bank level.

To further verify that these first stage impacts arose from the exogenous impact of exposure rather than endogenous adjustments in banks' branch structures, I analyze the number of branches that each bank operated and the number of county markets in which each bank had a branch. I estimate the coefficients in a Poisson model similar to that in Equation XXX. Event studies are shown in the bottom panels of Figure 5 and regression results are

Table 2: First Stage Effects of Exposure to Import Competition

	Assets	Deposits	Borrowed Funds	Non.Perf Assets	Income
Post x BankExp	-0.036***	-0.032**	-0.106	0.150***	-0.075***
	(0.009)	(0.010)	(0.077)	(0.023)	(0.012)
... x npr	-0.023**	-0.026**	-0.078	-0.355***	0.007
	(0.008)	(0.008)	(0.049)	(0.066)	(0.011)
... x asset	0.028***	0.020**	-0.128***	-0.048***	0.016*
	(0.005)	(0.006)	(0.030)	(0.013)	(0.007)
... x eqr	1.390***	2.560***	2.675**	-0.903	-0.936**
	(0.232)	(0.598)	(0.995)	(0.652)	(0.363)
N	158389	158388	158389	153168	150886
R^2	0.970	0.956	0.775	0.769	0.891
Mean	12.304	12.083	6.583	6.889	6.354

	Interest Exp.	Loss Provisions	Salaries	branches	dep mkts
Post x BankExp	-0.017	-0.003	-0.016		
	(0.012)	(0.038)	(0.009)		
... x npr	-0.036**	-0.285***	-0.029**		
	(0.011)	(0.056)	(0.009)		
... x asset	0.020**	-0.046*	0.024***		
	(0.007)	(0.022)	(0.006)		
... x eqr	4.174***	0.806	1.696***		
	(0.504)	(0.484)	(0.294)		
N	158389	153724	158389		
R^2	0.948	0.644	0.964		
Mean	7.963	5.498	7.531		

Standard errors in parentheses

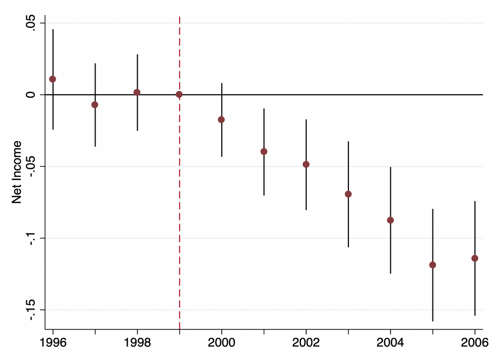
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Continuous difference-in-differences regression with time and bank fixed effects. Dependent variables include the log of assets, total deposits, core deposits, and brokered deposits. Covariates include *BankExp*, and the 1997 to 1999 averages of each bank's assets, non-performing loan ratio and, equity ratio. Covariates are interacted with an indicator *Post* which is equal to 1 for observations after the year 2000.

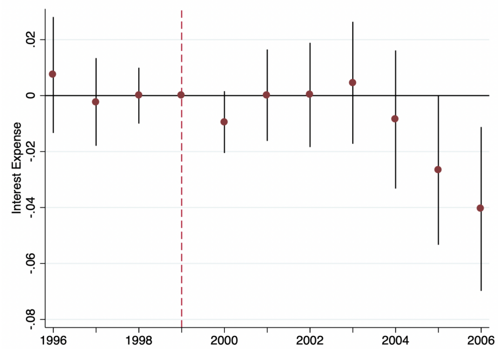
shown in Table XXX. The results show that....

I also find that these deposits shifts were driven by local supply, rather than bank demand, by utilizing bank-by-county-by-year records of deposits to compare deposits within the same

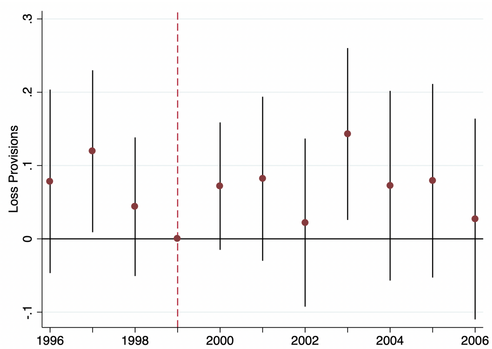
Figure 5: First Stage Bank Level Event Studies: Flows



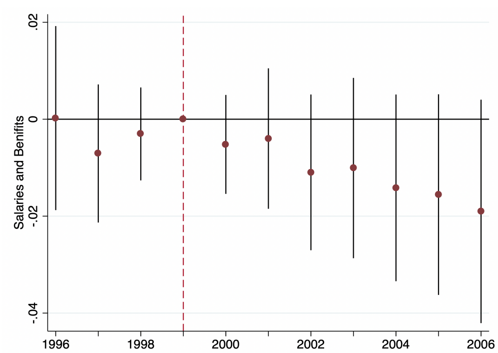
(a) Net Income



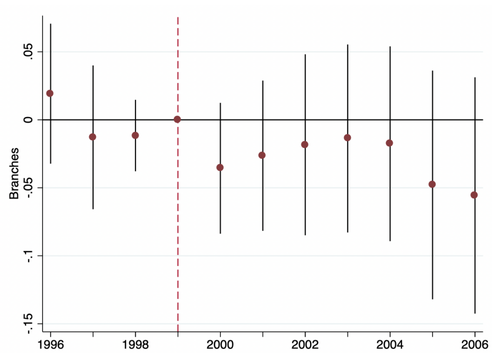
(b) Interest Expense



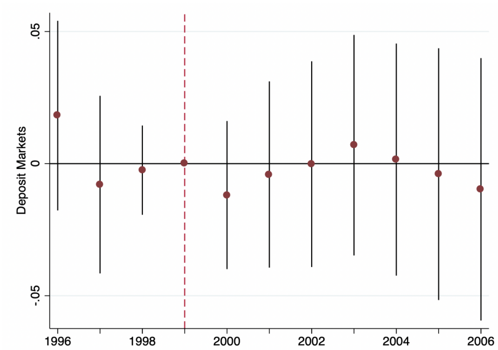
(c) Provision for Credit and Loan Losses



(d) Salaries and Benefits



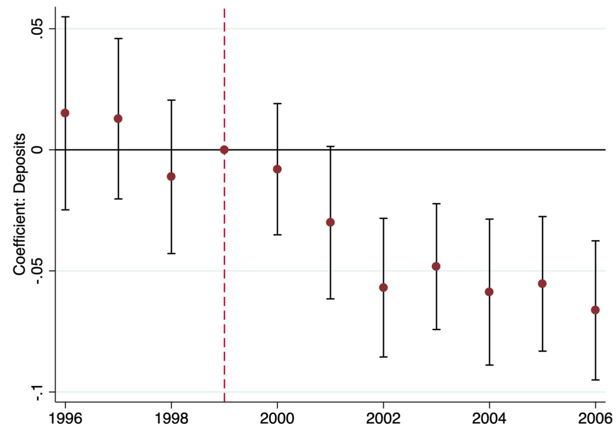
(e) Branches



(f) Deposit Markets

Note: The figure presents event study estimates of the effect of exposure to import competition on bank level outcomes. Regressions include bank and year fixed effects and time-invariant bank characteristics interacted with year-indicator variables. Branch and Deposit Market regressions utilize Poisson Pseudo-Maximum Likelihood estimation. Standard errors are clustered at the bank level. Interest expense is the sum of deposit interest expense (EDEP) and other interest expense (EOTHINT).

Figure 6: Effect of Import Competition on Deposit Supply



Note: The figure presents the event study estimates of the effect of exposure to import competition on local demand for deposits. Regressions include bank-state-year and bank-county fixed effects. Standard errors are clustered at the bank-year level.

bank and within the same state, but across counties with varying levels of exposure to increased import competition.[21] I estimate the following equation:

$$y_{bct} = \beta(Post_t \times CountyExp_c) + \gamma(Post_t \times X_{bc}) + \delta_{b,s,t} + \delta_{b,c} + \epsilon_{b,c,t} \tag{10}$$

where $y_{b,c,t}$ is the log of bank b's deposits in county c in year t and X_{bc} is a vector of bank and county controls interacted with the *post* indicator. The bank-by-county fixed effects, $\delta_{b,c}$ control for potential non-random placement of bank branches and all time-invariant factors that may affect deposit activity for a bank in a given county, and bank-by-state-by-year fixed effects, $\delta_{b,s,t}$ control for any shock that hits bank deposits in bank b in year t across all markets in state s, including deposit prices. This fixed effect structure isolates inter-county changes in deposits that can be attributed to local deposit supply. The event study is shown in Figure 6.

Collectively, the evidence suggests that exposure to increased import competition led to a significant first stage response, as non-performing loans increased and deposit supply decreased.

[21] Evidence indicates that banks do not set deposit prices at the individual branch level, rather, they implement uniform pricing strategies across states or regions that incorporate multiple states (Radecki (1998), Edelstein and Morgan (2006), Granja and Paixao (2021), Begenau and Stafford (2022)).

These results underscore the importance of local deposit shocks, as they can influence the overall funding of banks. Thus, the deposits channel serves as a vital link between bank funding and local economic shocks.

5 Main Results

Thus far, first stage results have indicated that increased import competition had a negative impact on the most exposed banks, and exposure acted primarily through reducing local deposit supply, which impacts bank funding. It is crucial to understand banks respond to such shocks. Funding constraints can have a multifaceted effect on bank lending, including the amount they lend, the markets in which they choose to lend, and the borrowers to which they extend credit.

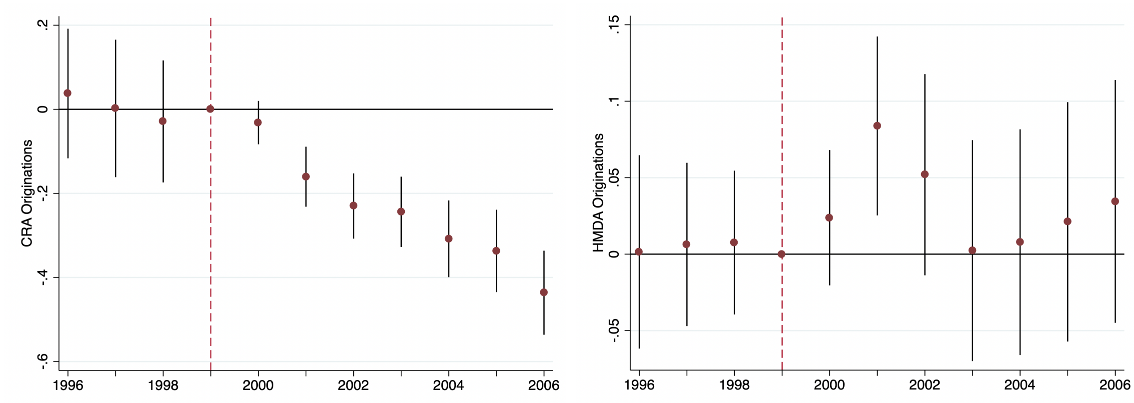
Key to this analysis is the differentiation between small business lending and mortgage lending. These two lending types differ significantly, with small business loans being information-intensive and often reliant on relational capital, while mortgage loans tend to be more standardized, as they involve collateral that is easier to value and borrower creditworthiness that can be readily assessed. Furthermore, a liquid secondary market exists for mortgages, whereas no such market exists for small business loans.[22]

5.1 Bank Level Lending Responses Banks can adjust their loan portfolios along several margins. Returning to the model presented in Section 4.1, the stock of mortgages and small business loans can be replenished through the purchase or origination of new loans. If the bank does not replenish the stock, it will naturally decrease as loans mature or as borrowers default. Additionally, the stock may decrease if the bank sells a particular asset in a secondary market. The decision to originate new loans is a function of the expected returns on these loans, expected default risks, and funding conditions. Banks make adjustments to their origination strategies in response to updated and realized expectations.

[22] In 1990, there were nearly $1 billion in outstanding Agency, GSE, and PLS issued Mortgage Backed Securities. By 2000, this had increased to nearly $3 billion. Source: Office of Federal Housing Enterprise Oversight's MORTGAGE MARKET NOTE 08-3.

To examine these adjustments, I estimate event studies similar to (EQUATION) and DiD specifications using the flow of new small business loans and mortgage loans. Given the presence of pre-trends, I also present detrended Difference-in-Difference coefficients which adjust for these pretrends[23]. The detrended DiD coefficients can be interpreted as the change in a given outcome relative to its existing linear trend due to a 1 standard deviation increase in a bank's exposure to increased import competition.

Figure 7: Bank Level Event Studies, Credit Origination



(a) CRA Detrended

(b) HMDA Detrended

Note: The figure presents event study estimates of the effect of exposure to import competition on bank level outcomes. Estimates show the impact of a one standard deviation increase in bank exposure on each balance sheet item. Data come from FDIC's Quarterly Call Report. Regressions include bank and year fixed effects and time-invariant bank characteristics interacted with year-indicator variables. Standard errors are clustered at the bank level

Detrended event studies are shown in Figure 7, raw event studies are shown in Table 13, and results of the regression are shown in Table 3.

5.2 Local Credit Supply Response

To verify that relative shifts in the origination of credit reflect bank supply orthogonal local demand, I analyze credit originations

[23] The process of detrending the coefficients begins by estimating the model using data from prior to the shock. In this pre-shock calibration, a bank exposure is interacted with a linear time trend. This linear time trend is then projected forward and differenced from the full data set. The regression coefficients are then estimated using differenced dataset. The process is outlined in Appendix XXX from XXX and is implemented by CITE TUCKER

Table 3: Impact of Exposure on Credit Origination

	Regular DiD		Detrended DiD	
	amt cra	amt hmda	amt cra	amt hmda
Post x BankExp	-0.003	-0.003	-0.240***	0.030
	(0.005)	(0.003)	(0.049)	(0.028)
... x asset	-0.006	-0.006***	-0.004	-0.008
	(0.004)	(0.002)	(0.037)	(0.017)
... x npr	0.281	0.375	2.806	2.423
	(0.741)	(0.243)	(5.287)	(2.098)
... x eqr	-0.163	-0.043	-1.722	-0.492
	(0.159)	(0.058)	(1.333)	(0.510)
N	9128	27742	9128	27742
R^2			1.000	0.996

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

at the bank-by-county level. I use each bank's originations in a given county each year to estimate the coefficients in the following event study design, similar to Xu (2022):

$$y_{bct} = \sum_{\tau=1996}^{\tau=2006} \beta_\tau \mathbb{1}\{\tau = t\} \times BankExp_b + \sum_{\tau=1996}^{\tau=2006} \gamma_\tau \times X_b + \delta_{b,c} + \delta_{t,c} + \epsilon_{b,c,t} \tag{11}$$

where y_{bct} is the log of originations by bank b in county c in year t. The specification is similar to EQUATION XXX, but now include bank-by-county fixed effects, $\delta_{b,c}$, to control for .... and county-by-year fixed effects, $\delta_{t,c}$, to control for shocks to local credit demand. The specification isolates changes in credit origination between banks within county. Table 4 presents the results. The first panel considers observations from all counties, while the second panel is limited to observations from counties with county exposure less than the median exposure level, and the third panel is limited to observations from counties with exposure greater than the median level.

Table 4: Effect of Bank Exposure on Local Credit Supply

All Counties	(1)	(2)	(3)	(4)
	num_cra	amt_cra	num_hmda	amt_hmda
Post x BankExp	-0.119***	-0.153***	0.036***	0.190***
	(0.003)	(0.011)	(0.002)	(0.008)
N	197109	196750	240460	240460
R^2		0.858		0.828

High Exposure Counties	(1)	(2)	(3)	(4)
	num_cra	amt_cra	num_hmda	amt_hmda
Post x BankExp	-0.109***	-0.106***	0.020***	0.130***
	(0.004)	(0.016)	(0.003)	(0.011)
N	78559	78451	96386	96386
R^2		0.851		0.834

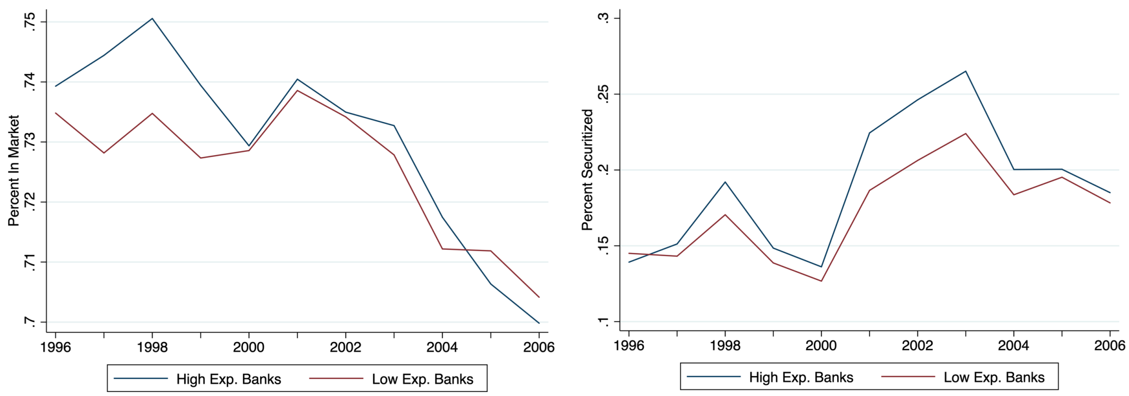
Low Exposure Counties	(1)	(2)	(3)	(4)
	num_cra	amt_cra	num_hmda	amt_hmda
Post x BankEx	-0.129***	-0.196***	0.047***	0.237***
	(0.004)	(0.016)	(0.003)	(0.011)
N	118550	118299	144074	144074
R^2		0.861		0.824

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

5.3 Reallocation and Securitization Beyond adjusting originations between product groups, banks can adjust along the geographic dimension. While banks may have informational advantages for lending to borrowers in the markets they serve, fluctuations in credit demand may force them to look beyond beyond the markets in which they have branches. Additionally, banks can sell loans that they originate, in this way insulating their income from future changes in loan quality. Panels A and B in Figure 8 show the trends in in-market lending and securitization across high and low exposure banks.

Figure 8: Relocation and Securitization of HMDA Loans



(a) Percent HMDA In-Market

(b) Percent HMDA Sold

Note: The figure presents the percent of mortgage loans originated in markets in which banks had branches and the percent of mortgage loans that were sold by banks above and below the median exposure level.

5.4 Robustness I first show that results are robust to the use of a discrete treatment measure. For these analyses, banks with $BankExp_b$ greater than the median are considered treated, and those with exposure below the median are considered untreated. Within the same difference-in-differences setup, identification needs a weaker form of the parallel trends assumption. Now .... Event studies and regression results from the discrete are shown in APPENDIX.

I then show that

6 Summary and Concluding Remarks

In this paper, I show that the local labor market shock generated by the granting of Permanent Normal Trade Relations with China in 2000 had implications beyond decreased employment and wages. Banks rely on cheap funding from customer deposits in local markets, and when those local markets experience economic shocks, deposit supply is constrained. I show that banks saw statistically significant declines in deposit supply in markets exposed to the China Shock, and these local deposit declines aggregated up to the balance sheet level.

These funding constraints had far-reaching implications for how and where banks extended credit. While the impact of exposure to import competition was relatively modest when viewed at the level of banks' balance sheets, the banks achieved this limited pass-through of funding shocks by strategically shifting their lending focus. Specifically, they reallocated their lending from small business loans to mortgage loans in markets that were less exposed to increased import competition. The ability to offload mortgage loans to secondary markets played a crucial role in this reallocation process, as it allowed banks to fill funding gaps by moving mortgages off their balance sheets, thus freeing up lending capital. With any analysis like this, caution must be taken when assigning causality. Violations of the identification assumption can limit the ability for a causal interpretation of reduced form parameters. I support identification in many of my analyses by showing parallel pretrends and event study plots.

The results of this study provide valuable insights into our understanding of how local exogenous shocks impact the financial system. While previous research has often emphasized the role of non-performing loans in influencing credit supply, it's crucial to recognize that funding constraints play an equally significant role too. The deposits channel reveals that local exogenous shocks can result in tightened bank funding. When banks face funding limitations, they adapt by altering both the nature and geographic distribution of the credit they provide. Instead of reallocating to safer assets, they tend to pivot towards more liquid assets that can be easily sold off their balance sheets. However, as demonstrated by the events of the Great Financial Crisis just eight years after the China Shock, a flight to the most liquid assets may not promote stability in the greater financial system.

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8 Appendix: County Responses

In this appendix, I analyze county level responses to increased import competition using a difference-in-differences regression design. I investigate three sets of county level outcomes: labor market responses, bank responses, and lending responses. Labor market responses include the average wage, the unemployment rate, manufacturing share. The bank responses include the log of deposits, the number of branches. The lending responses include the number and amount of small business loan originations and mortgage originations.

First, I divide counties into those above and below the median exposure level and plot the population weighted average of the outcome variables. Figure 3 plots the employment rate, average weekly wage, and deposits, showing that high exposure counties saw lower employment rates, lower weekly wages, and fewer deposits. Figure **??** shows the amount of small business and mortgage loan originations and the number of bank branches. The plots show that, at least temporarily, high exposure counties saw fewer loan originations. High exposure counties did, however, have more bank branches than low exposure counties, perhaps suggesting that branch consolidations that accompany bank acquisitions did not affect high exposure counties.

I then estimate the coefficients in the following equations:

$$Outcome_{c,t} = \beta(Post_t \times CountExp_c) + \gamma Post_t \times X_c + \delta_c + \delta_t + \epsilon_{c,t} \tag{12}$$

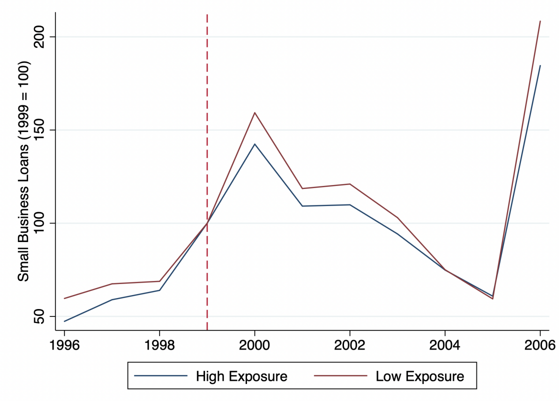
where X_c is a vector of time invariant county controls, δ_c are county fixed effects, and δ_t are time fixed effects. Event studies are shown in Figure 10 and Table 5 presents the coefficient estimates.

Table 5: County Level Lending Responses

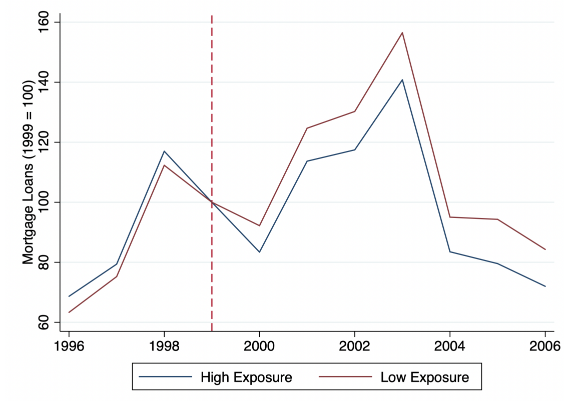
	Num CRA	Amt CRA	Num HMDA	Amt HMDA	Sold HMDA	Deposits	Branches
Post x CountyExp	-0.025**	-0.028	-0.081***	-0.143***	-0.211***	-0.047***	-0.012**
	(0.011)	(0.018)	(0.017)	(0.026)	(0.038)	(0.016)	(0.006)
... x Avg. Pay	-0.408***	-0.463***	-0.303***	-0.469***	-0.273*	0.374***	0.121***
	(0.038)	(0.062)	(0.066)	(0.099)	(0.146)	(0.083)	(0.032)
... x Manuf. Share	0.156**	0.150	-0.189	-0.330*	-0.164	0.383***	0.089*
	(0.076)	(0.126)	(0.123)	(0.190)	(0.269)	(0.127)	(0.047)
... x Educ.	-0.019***	0.078***	-0.074***	-0.158***	-0.209***	-0.043***	-0.028***
	(0.005)	(0.008)	(0.008)	(0.012)	(0.018)	(0.014)	(0.007)
N	28639	28639	28639	28639	28639	28620	28620
R^2	0.946	0.897	0.899	0.874	0.815	0.645	0.743

Note: Continuous difference-in-differences regression with time and county fixed effects. Dependent variables include the log of the number and amount of small business and mortgage loans originated, the amount of mortgage loans securitized, number of bank branches, and deposits in each county. Covariates include *CountyExp*, and the 1997 to 1999 averages of each county's average pay, manufacturing share, and percent of population with college degree. Covariates are interacted with an indicator *Post* which is equal to 1 for observations after the year 2000.

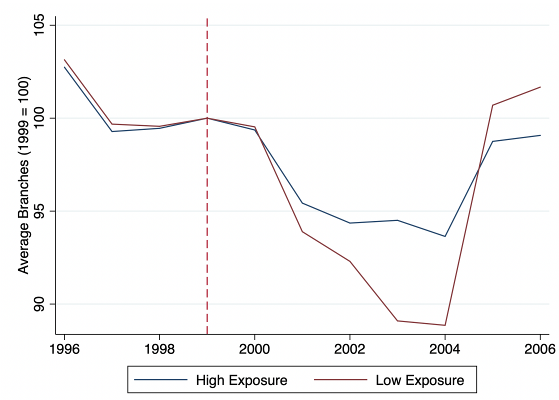
Figure 9: Trends in High and Low Exposure Counties



(a) Small Business Loans



(b) Mortgage Loans



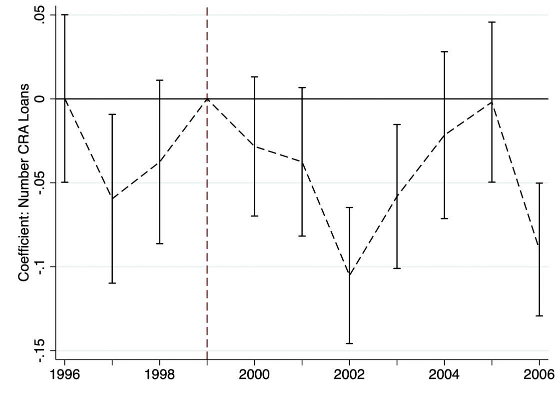
(c) Bank Branches

Note: The figure presents the average employment rate, weekly wage, and deposits per capita at the county level, normalized so that the value in the year 2000 is equal to 1. Counties are divided into high and low based on the value of their exposure relative to the median.

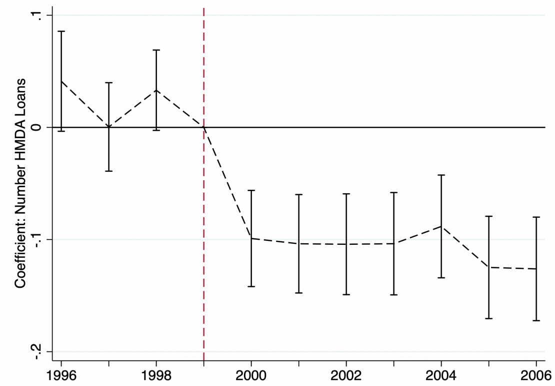
9 Appendix: Robustness Checks

To check the robustness of my analyses, I begin by discretizing the exposure measures and re-running the regressions. For county exposure, I create the a discrete treatment variable which is equal to 1 for counties whose exposure is greater than the median, which is -0.02, and zero otherwise. Similarly, I create a new bank level treatment variable that is equal to 1 if the bank exposure is greater than the median, which is -0.22, and 0 otherwise. By using a discrete treatment measure, a weaker form of the identification assumption is necessary for

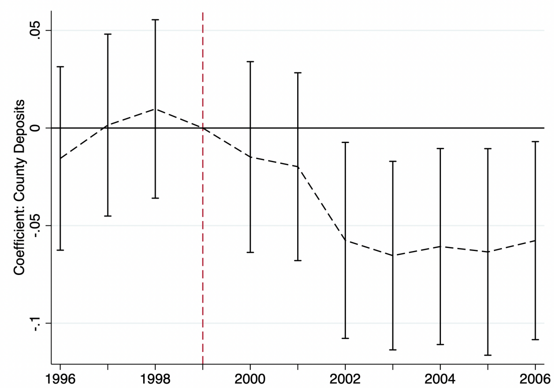
Figure 10: County Lending Responses to China Shock



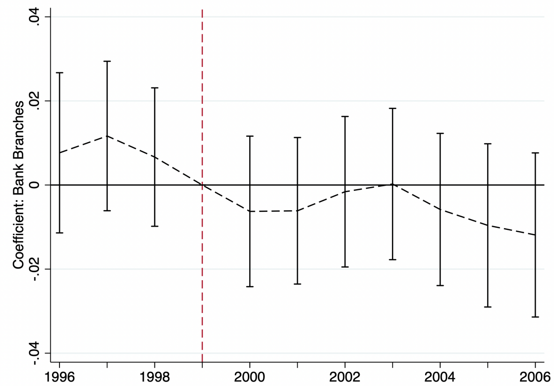
(a) Small Business Loans



(b) Mortgage Loans



(c) Deposits



(d) Bank Branches

Note: Dependent variables include the logarithm of the number of Small Business Loans and Mortgage Loans originated by all FDIC insured banks in a given county in a year. The event study plots the coefficient for each county's exposure measure interacted with a year dummy.

a causal interpretation of the results. The identification assumption for discrete treatment is that differences in outcomes of high and low exposure banks would continue along the existing differential trend if both were exposed to small shocks.

In addition to this robustness check, I utilize a Double Machine Learning (DML). Specifically, I use Microsoft ALICE's PartialDML python package. Estimation works as follows.

Consider the partially linear model :

$$y = \beta_0 \times T + g(X) + \epsilon$$
$$T = m(X) + v$$

I begin by removing any fixed effects using the demeaning method (See "Analysis of Panel Data," 3rd edition, page 62). The algorithm then splits the data into a test and a training set. Using machine learning methods in the training data-set, T is regressed on X to find $\hat{m}()$ and y is regressed on X to find $\hat{g}()$. Specifically, the algorithm uses a RandomForest regression to estimate these first stage models. The coefficient of interest, β_0 is then the OLS coefficient of the regression of $(y - \hat{g}(X))$ on $T - \hat{m}(X)$ using the test data. The logic is similar to the Frisch-Waugh-Lovell theorem, but in this case, the partial effects of covariates are removed using non-parametric methods, and the data is split into test and training sets in order to reduce bias. For a more complete overview, see Athey et al. (2019).

The main analyses are repeated using each of the above robustness checks. Results are presented below.

Table 6: Local Deposits Discrete Treatment

	Full Sample		Established Markets	
	dep	dep	dep	dep
Continuous Treatment				
Post x CountyExp	-0.045***	-0.042***	-0.019**	-0.017*
	(0.01)	(0.01)	(0.01)	(0.01)
N	193,995	189,943	97,715	95,584
R^2	0.95	0.96	0.97	0.98
Discrete Treatment				
Post x Treated	-0.041***	-0.031***	-0.038***	-0.037***
	(0.010)	(0.010)	(0.010)	(0.010)
N	193,995	189,943	97,715	95,584
R^2	0.95	0.96	0.97	0.98
DML Continuous Treatment				
Post x CountyExp	-0.042***	-0.022	-0.041***	-0.041***
	(0.011)	(0.015)	(0.011)	(0.014)
DML Discrete Treatment				
Post x Treated	-0.32**	-0.04***	-0.037***	-0.011
	(0.013)	(0.012)	(0.012)	(0.016)
Bank-by-County FE	yes	yes	yes	yes
Bank-by-Year FE	yes		yes	
Bank-by-Year-by-State FE		yes		yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 7: Bank Deposits, Discrete Treatment

	Dependent Var.				
	ldep	Core Dep	Broke Dep.	Branches	Markets
Continuous Treatment					
Post x BankExp	-0.023***	-0.022**	-0.035***	-0.004	0.011*
	(0.009)	(0.009)	(0.013)	(0.007)	(0.006)
N	154,465	154,465	154,465	153,226	153,226
R^2	0.97	0.97	0.95	0.96	0.93
Discrete Treatment					
Post x Treated	-0.033**	-0.030**	-0.041**	-0.001	0.004
	(0.014)	(0.014)	(0.020)	(0.011)	(0.010)
N	154,465	154,465	154,465	153,226	153,226
R^2	0.97	0.97	0.95	0.96	0.93
DML Continuous Treatment					
Post x BankExp	-0.028***	-0.031***	-0.041***	-0.005**	0.01***
	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)
DML Discrete Treatment					
Post x Treated	-0.04***	-0.039***	-0.049***	-0.001	0.003
	(0.004)	(0.004)	(0.006)	(0.003)	(0.002)

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 8: Impact of Import Competition on Local Credit Supply (Bank-by-County Level)

	Small Business Loans		Mortgage Loans		
	Number	Amount	Number	Amount	Securitized
Continuous Treatment					
Post x BankExp	-0.036***	-0.042	0.050***	0.135***	0.330***
	(0.014)	(0.031)	(0.006)	(0.009)	(0.016)
Post x BankExp x CountyExp	0.009	0.009	-0.013***	-0.044***	-0.061***
	(0.012)	(0.026)	(0.005)	(0.008)	(0.014)
R^2	0.90	0.79	0.87	0.83	0.73
Discrete Treatment					
Post x BankTreated	-0.105***	-0.083*	0.117***	0.192***	0.547***
	(0.021)	(0.048)	(0.010)	(0.015)	(0.028)
Post x BankTreated x CountyTreated	0.004	-0.023	-0.038**	-0.058**	-0.019
	(0.043)	(0.090)	(0.016)	(0.024)	(0.044)
R^2	0.90	0.79	0.87	0.83	0.73
DML Continuous Treatment					
Post x BankExp	-0.002	0.045***	-0.016	-0.028	-0.14***
	(0.008)	(0.017)	(0.015)	(0.021)	(0.035)
Post x BankExp x CountyExp	0.109***	0.17***	0.072***	0.062***	-0.097***
	(0.008)	(0.015)	(0.013)	(0.016)	(0.027)
DML Discrete Treatment					
Post x BankTreated	-0.093***	-0.046*			
	(0.013)	(0.027)			
Post x BankTreated x CountyTreated	0.347***	0.522***			
	(0.021)	(0.042)			

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Note: The table presents the results of the continuous difference-in-difference regression using bank-by-county-by-year observations. Each regression includes bank-by-county and county-by-year fixed effects. Dependent variables include the log of small business lending, home mortgage originations, and home mortgage originated then sold within a year.

Table 9: FDIC Items

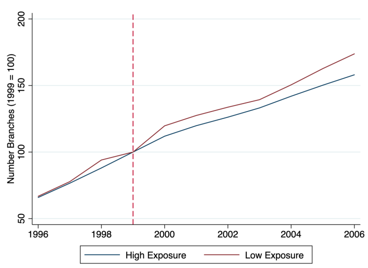
Item	Code	Description

Table 10: Summary Statistics: Bank Level Data

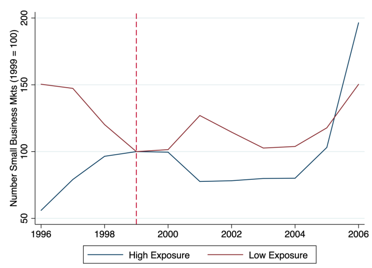
Item	Code	Description

10 Appendix: Additional Figures and Tables

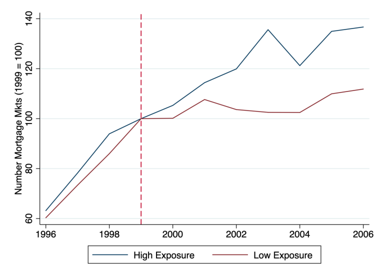
Figure 11: Trends in High and Low Exposure Banks



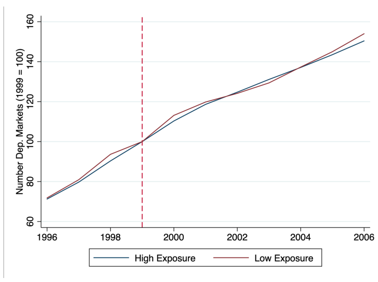
(a) Number Branches



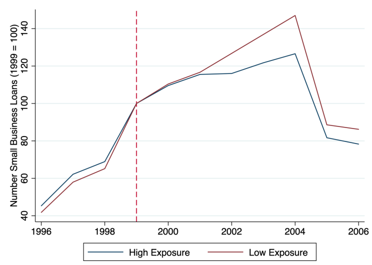
(b) Number CRA Markets



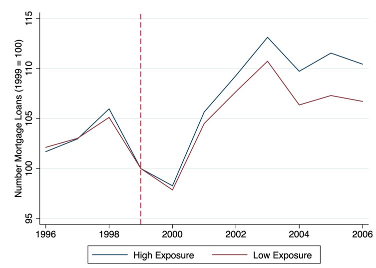
(c) Number Mortgage Markets



(d) Number Deposit Markets



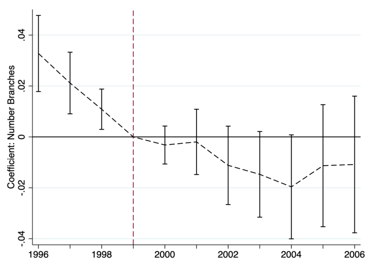
(e) Number CRA Loans



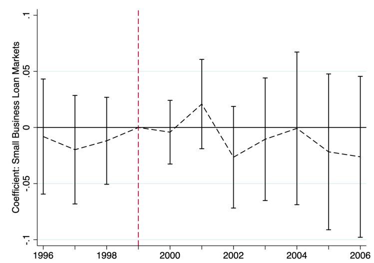
(f) Number Mortgage Loans

Note:

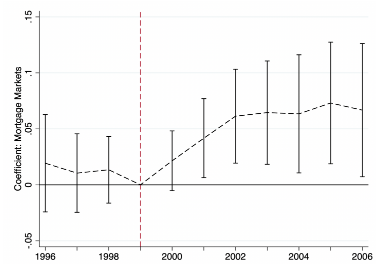
Figure 12: Bank Responses to Increased Import Competition



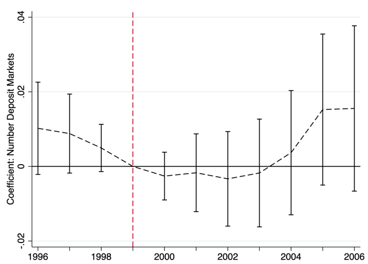
(a) Number Branches



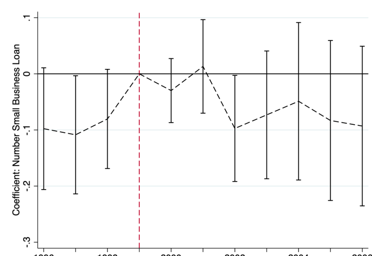
(b) Number CRA Markets



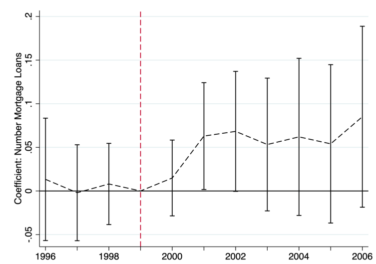
(c) Number Mortgage Markets



(d) Number Deposit Markets



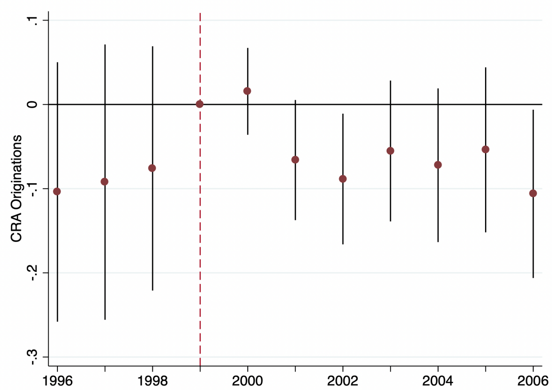
(e) Number CRA Loans



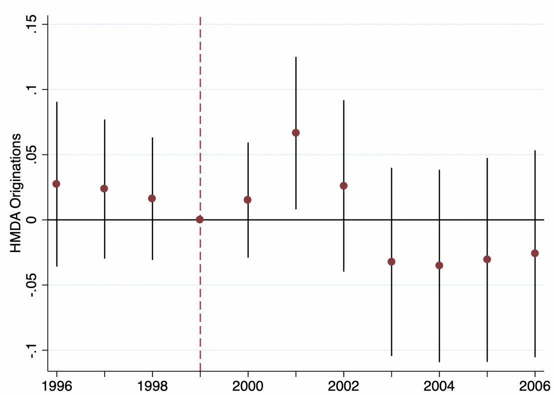
(f) Number Mortgage Loans

Note: The figure presents the event studies of the reaction of ..... to exposure to the China Shock. Regressions are continuous difference-in-difference regressions with bank and year fixed effects. Standard errors are clustered at the bank level, and the coefficient for year 1999 is standardized to zero.

Figure 13: RAW Bank Level Event Studies, Credit Origination



(a) CRA Raw



(b) HMDA Raw

Note: The figure presents event study estimates of the effect of exposure to import competition on bank level outcomes. Estimates show the impact of a one standard deviation increase in bank exposure on each balance sheet item. Data come from FDIC's Quarterly Call Report. Regressions include bank and year fixed effects and time-invariant bank characteristics interacted with year-indicator variables. Standard errors are clustered at the bank level