THE UNIVERSITY OF CHICAGO

SPILLOVER OF LOCAL ECONOMIC SHOCKS THROUGH MULTI-MARKET BANKS: EVIDENCE FROM TRADE LIBERALIZATION

A DISSERTATION SUBMITTED TO
THE FACULTY OF THE UNIVERSITY OF CHICAGO
BOOTH SCHOOL OF BUSINESS
IN CANDIDACY FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

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CHICAGO, ILLINOIS
JUNE 2021

This dissertation is lovingly dedicated to my mother, Jasbinder Kaur Bhue. Her support, constant encouragement, and unconditional love have sustained me throughout my life.

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ACKNOWLEDGMENTS

I am grateful to Amir Sufi, Eric Zwick, Raghuram G. Rajan, Joao Granja, Emanuele Colonnelli, and other participants in the Finance Research Seminar at the University of Chicago Booth School of Business for their valuable comments. I acknowledge financial support from the Fama-Miller Center for Research in Finance for data purchase. I am responsible for all remaining errors.

I am grateful for funding provided through the Liew Fama-Miller Fellowship and Fama-Miller Research Grant.

I greatly appreciate the discussions and interactions I had with my fellow students throughout my time in graduate school and while working on my dissertation. In particular, I benefited tremendously from numerous discussions with Greg Buchak, Paymon Khorrami, Peter Chen, Carter Davis, Mihir Gandhi, Nam (Vera) Chau, Ehsan Azarmsa, Jian (Jane) Li, James Traina, Eliot Abrams, and Klakow Akepanidtaworn.

I want to thank my family for all of their support. I especially want to thank my mother, Jasbinder, and my husband, Kevin, for their constant patience, love, and encouragement. Lastly, I am grateful to my dog *Leo* for improving my quality of life and keeping me sane during the COVID-19 pandemic.

ABSTRACT

This paper proposes a new mechanism - *the Deposit Channel* - by which local economic shocks propagate to other regions through multi-market banks. Using China import competition as a local economic shock, I find a significant decline in deposit growth in affected counties. Banks with a significant presence in affected counties - exposed banks - show a reduction in the growth rates of deposits, assets, and loans as well as an increase in their cost of deposit funding. Exposed banks decrease their portfolio loan origination rates by 5%, decrease the share of hard-to-securitize mortgages, and increase their loan-denial rates, even in unaffected counties. They bid up the deposit rates in affected counties while keeping them unchanged in unaffected ones. By contrast, asset-side transmission using the share of loans in affected counties as an exposure measure does not have any significant impact on bank-level outcomes.

Keywords: China Trade Shock, Bank Deposits, Shock Transmission, Multimarket Bank Networks.

CHAPTER 1

INTRODUCTION

How are banks affected by local economic shocks? How do they smooth the effect of such shocks? What are the different mechanisms by which such local economic shocks can transmit to other unaffected regions through the bank branch network? What are the implications for central banks and public policy to mitigate the spread and amplification of such shocks via the banking network? The answers to these important questions may improve our understanding of how banks play a crucial role in integrating different regional economies. Although some theoretical papers study the role of network architecture in the transmission of shocks (for a review, see Cabrales et al. (2015)), they either assume an abstract link between the firms or they have limited nature of micro-foundations of such links, such as those that arise from mutual ownership of the claims to the returns of the underlying projects (asset-side overlap). Surprisingly, little empirical work studies the role of bank deposits and branch networks in the regional transmission of local economic shocks. This paper aims to fill this gap in the literature by proposing and testing a new channel of local shock transmission - *the Deposit Channel* - thereby also highlighting the crucial role of deposit-taking activity by banks even in the era of growing capital markets and direct funding sources such as interbank lending markets.

I use the empirical setting of the China trade shock as a local economic shock to study how it affects multi-market banks. Specifically, what are the mechanisms of shock transmission through the bank branch network and banks' actions to smoothen its effect? The China trade shock has been used extensively to study trade competition's effect on local labor markets (Autor et al. (2013)). Pierce and Schott (2016) examined the effect of increased competition from China to a sharp decline in US manufacturing employment and income.

Nevertheless, surprisingly, little evidence on the effect of trade shocks on the financial system exists. Trade shocks could affect the financial system through their impact on either the assets or the liabilities of the local financial institutions. For instance, unemployment and the resulting income loss could deplete the bank branch deposits in the affected regions. Alternatively, the poor economic condition could affect the value of loans on the bank's balance sheet, thus, affecting the asset side of the bank. This distress on one side of the bank balance sheet has implications for bank behavior on the other side. I provide empirical support for the deposit channel of shock transmission and compare it with the asset-side channel in the context of the Chinese import shock affecting the US banking system.

An important feature of the branch deposit market is that it relies on local consumer income and consumption shocks. This reliance makes it an ideal outcome variable for studying the effects of local economic shocks, such as those originating from Chinese import competition.

China's rapid economic growth during the last few decades can be attributed to the massive increase in its exports to the rest of the world. In particular, China has positioned itself as a major manufacturing hub. China's share of US imports from low-income countries increased by 89 % from 2000 to 2007. This acceleration of Chinese imports to the US increased after China joined the World Trade Organization (WTO) in 2001, which served as an inflection point in the growth trajectory. Autor et al. (2013) (ADH, henceforth) find that rising imports cause higher unemployment, lower labor-force participation, and reduced wages in local labor markets that house import-competing manufacturing industries.[1] I argue such massive local unemployment is bound to affect residents' savings in the form of bank deposits, which they use to smooth consumption.

I use ADH's data and empirical methodology to test the impact of Chinese imports on local deposits. I find bank deposits grow 7.5% less as one moves from a county at the 25th percentile of import-shock exposure to one at 75th percentile in a cross-sectional distribution. This result is based on the 2SLS estimation methodology that uses Chinese import growth in other high-income markets to instrument for the growth of Chinese imports to the US, thus tackling endogeneity issues due to potential demand shocks for Chinese goods in the US.

To study how the China shock affects banks, I define measures of bank-level exposure through the deposit markets. I use the share of branches in affected counties (similar to the measure in Gilje et al. (2016)) which is equal to the share of bank branches located in China-shock-exposed counties. I use this bank-level measure of exposure to the China shock to study several bank outcomes, including balance-sheet variables and deposit rates. The deposit channel of regional economic-shock transmission predicts that bank deposits decline and deposit rates increase after a local economic shock due to consumption smoothing. As depositors withdraw deposits, the banks are expected to

1. In their specification, import competition explains one-quarter of the contemporaneous aggregate decline in US manufacturing employment.

react by increasing their average deposit rates to stem the deposits' outflow. Consistent with this prediction, I find bank deposits grow 5.6% more slowly. The average deposit rate increases by 4% for exposed banks compared to unaffected banks after the onset of the Chinese import shock.

Deposit rates are one of the primary levers banks use to smooth economic shock transmission through the banking network. Using branch-level data, I find that exposed banks increase the deposit rates for different products in affected counties; however, the rates do not change significantly for unaffected counties, which shows how banks optimally choose to minimize the costs associated with local shocks. I also find a significant decline in the growth rate of assets and loans for exposed banks, which shows banks were constrained by the deposit outflow and reduced their balance sheet growth. This reduction in lending provides evidence of financial frictions that prevent banks from completely substituting the decline in deposits by direct funding from capital markets.

To further study the transmission of the China shock on lending outcomes of exposed banks, I use two different but complementary databases that provide information on loan originations at the local level along with other loan and borrower characteristics: the CRA's Small Business Lending (SBL) and Home Mortgage Disclosure Act (HMDA) databases. The information on borrower location is essential to separate the supply-side effect of the deposit channel from the reduction in loan demand due to poor economic conditions directly owing to the China shock. Moreover, the datasets allow me to use Khwaja and Mian (2008)'s loan-level estimator to control for borrower demand.

An empirical challenge arises from separating regional spillovers through banks' internal networks from common shocks to all regions in which banks lend. I account for this possibility by including regional, precisely, county x year–fixed effects in all specifications. Thus, I compare loans made by banks in the same county-year that are exposed to the same regional shock but that belong to different banks and hence to different bank networks. To control for bank-specific, time-invariant factors affecting lending outcomes, I include bank fixed effects in all specifications.

Using Small Business Lending data, I find a 4% (6%) drop occurs in the small-business-loan origination rate for exposed banks in unaffected (affected) counties after the China shock. A bank at the 75th percentile of exposure to the China shock originates loans at a rate that is 6% slower than a bank at the 25th percentile exposure in unaffected counties. This result is robust to bank and county x year fixed effects to control for changing county-level characteristics that influence small loan originations.

The reduction in the loan-origination rate is also present in large multi-market banks in addition to community banks, highlighting the severity of financial constraints. I also find a reduction in lending by exposed banks to counties where the industry employment structure differs significantly from the affected counties, which confirms that supply-side constraints and not loan-demand factors (industry shocks) drive my results. I find exposed banks increase their risk-taking activities as measured by ex-post default rates, thus increasing the banking network's fragility and potentially attracting the attention of regulators.

Similarly, using HMDA data, I find exposed banks significantly reduce the mortgage origination rate in all counties, including unaffected counties. A bank at the 75th percentile of exposure to the China shock originates mortgages at a rate that is 6% slower than a bank at the 25th percentile exposure in unaffected counties. This result is robust to bank and county x year fixed effects to control for changing county-level characteristics that influence mortgage originations.

One implication of the decline in the deposit growth rate is that it constrains banks' ability to originate on-balance-sheet loans. Therefore, a sharper test for studying the impact of the China shock via the deposit channel on lending outcomes focuses on portfolio loans. The share of hard-to-securitize loans, such as jumbo loans, which are not securitized by GSEs and hence are more likely to be portfolio loans, decrease, and the denial rate of loan applications increase for exposed banks. This result is present in both affected and unaffected counties, highlighting the supply-side lending constraints exposed banks face due to poor deposit growth.

Finally, I also develop a measure of asset-side exposure of banks to the China shock to study its impact on bank outcomes and compare the two shock transmission channels. Using the small business lending database, I create a bank-asset-exposure measure based on the share of the number and amount of loans originated in affected counties. I test the first stage by regressing the ex-post loan-default share on this measure and find a significant positive correlation. That is, asset-side exposed banks perform poorly on their loan outcomes. However, banks with a higher share of loans in affected counties do not seem to differ from other banks in terms of the growth of their deposits, average deposit rates, assets, and loans. In other words, despite a higher probability of default rate and potential riskiness of their asset portfolio, exposed banks experience no depositor run. This finding implies the transmission link from the asset side of the China shock to US banks is weaker than the deposit channel.

This paper contributes to several strands of literature. First, it contributes to the research on the transmission of shocks throughout the economy. This literature has focused on input-output networks (e.g., Acemoglu et al. (2012), Acemoglu et al. (2016), Barrot and Sauvagnat (2016)), financial networks (e.g., Acemoglu et al. (2015), Cabrales et al. (2015)), firms' internal network (Giroud and Mueller (2019)), and social networks (Bailey et al. (2016)). By contrast, little is known about whether and how banks' branch networks facilitate the propagation of local economic shocks and how these networks affect lending outcomes. An important benefit of using FDIC Summary of Deposits (SoD) data is that we can completely characterize the entire branch network structure: the SoD includes the location and deposits of all depository institutions in the US.

Second, this paper contributes to the literature on international trade and finance. Whereas earlier studies focus primarily on the role of financial markets in promoting trade (Manova (2013), Svaleryd and Vlachos (2005)), this paper asks the opposite question: What is the impact of international trade on the domestic financial system? I provide empirical support for a dominant channel - a decline in deposit growth - through which regional economic shocks, such as the China trade shock, can transmit through the banking system. My paper complements the findings in Federico et al. (2019), who study the China shock in the context of Italian banks. Although both papers find the reduced lending capacity of the exposed banks, they differ in the mechanism driving this effect. Federico et al. find a reduction in core capital caused by an increase in non-performing loans for the exposed banks in Italy. Therefore, Federico et al. investigate and find support for the asset-side channel in Italian banks. However, in the US, I test both channels of shock transmission but find stronger evidence supporting the deposit-side channel; that is, exposed banks face a reduction in core deposits due to the impact of the China shock on the local economies. Also, note Federico et al. use the loan concentration across manufacturing industries to measure banks' exposure to the China shock. In contrast, this paper follows Autor et al. (2013) and uses geographic variation in the impact of the China shock on the US regional economies. Therefore, this paper can be extended to infer the impact of a more generalized regional economic-shock transmission on the banking network.

The findings in this paper are related to Byun and Lee (2019), who study the effects of China's shock on regional economies through small and local community banks. Although both papers find slower deposit growth and reduced lending to local agents by local banks, the two papers differ significantly in their empirical methodology and objectives. First, Byun and Lee (2019) focus exclusively on the community banks and their impact on the local lending due to the China shock. In contrast, this paper investigates the cross-region transmission of the China shock to all regions, particularly unaffected counties, using the sample of all banks. In this manner, the scope of the study is more general and has broader policy implications. Second, this paper proposes and compares two distinct regional economic shock transmission channels to the banking networks - the deposit and asset side - and finds stronger support for the deposit channel. By contrast, Byun and Lee (2019) do not separate the two channels. Third, this paper closely examines the different margins of adjustments banks employ to smooth the effect of such shocks: their ability to modify rates on different deposit products depending on the location, exposure intensity, and the market power in deposit markets; the nature and type of loans originated based on the borrower and industry characteristics; and the risk-taking behavior of banks. Fourth, this paper uses better identification techniques and new datasets that include borrower identity, location, and other characteristics, which help control demand-side effects and separately identify the supply-side effect on lending due to the China shock. Byun and Lee (2019), on the other hand, cannot separate the reduced loan demand directly due to the China shock from their estimates of decline in local lending for community banks using Call Report data.

Third, the paper contributes to the growing literature studying the transmission of liquidity shocks to the banking system (Gilje et al. (2016); Cortés and Strahan (2017); Bustos et al. (2020)). Cortés and Strahan (2017) use natural disasters as an exogenous credit-demand shock and find multi-market banks reallocate capital to affected areas by decreasing credit in unaffected markets and raising more deposits by increasing deposit rates. In this paper, banks bid up their deposit rates to stem the outflow of deposits from the branches located in areas affected by China Shock. Gilje et al. (2016) use the positive liquidity shock induced by oil and natural gas shale discoveries and find exposed banks utilize positive deposit flows to originate more hard-to-securitize mortgages in nonboom counties. I complement the findings in these papers by using a negative liquidity shock due to a trade shock to examine how banks adjust to regional economic shocks. In contrast to Gilje et al. (2016), I find exposed banks decrease the size of their balance sheets by reducing lending not only in affected regions but also in unaffected areas. Therefore, the findings in this paper are consistent with the previous literature.

Lastly, the paper adds to the growing literature on the effects of the China shock on the US local economies. ADH and Pierce and Schott (2016) provide empirical evidence for the negative impact on the US labor markets due to the increased import competition from China. Many papers utilize the empirical design of these papers to study the impact of the China shock on local economies. For example, local economies subject to significant exposures to the China shock are shown to have an increase in the share of votes cast for Democrats (Che et al. (2016)), an increase in high school graduation rates (Greenland and Lopresti (2016)), higher mortality rates (Pierce and Schott (2020)), and a decline in population growth (Greenland et al. (2019)) to name a few.

The rest of the paper is organized as follows: section 2 presents the datasets used for this study and discusses identification challenges and the empirical methodology used to tackle them. Section 3 discusses the main empirical findings in the paper, and through a series of sequential tests, develops support for the deposit channel. Section 4 discusses the asset channel as the major alternative explanation of my findings and compares its results with the deposit channel. Finally, section 5 concludes.

CHAPTER 2

DATA AND EMPIRICAL METHODOLOGY

I rely on the work of ADH to construct the measure of the intensity of the China trade shock across the US. The regional heterogeneity of the Chinese import competition and the local nature of the labor and deposit markets makes the empirical study of the effect of the China shock on local financial markets more credible. Specifically, I use ADH's regression specification at the county level to study the effect of import competition on the deposits.

2.1 Data

ADH uses a variety of databases to construct their main sample. For instance, the UN Comrade dataset on US trade at the six-digit Harmonized System (HS) product level from different countries, the 1990 Census data to construct commuting zones, County Business Patterns data for county x industry-level employment data, and Census Integrated Public Use Micro Samples and the American Community Survey (ACS) for population, employment, and wage structure by education, age, and gender.[1] I use the processed data file available to download from David Dorn's data page.[2]

The SoD from FDIC has information about the branch-level deposits at an annual frequency. This file also contains important information about the location (latitude-longitude, zip, county, state) of the branch, bank, and bank headquarters, as well as

1. For detailed data explanation, readers can refer to ADH's data section and online appendix.

2. Available at https://www.ddorn.net/data.htm. Accessed on Feb 2, 2020.

the key identifiers to link this dataset to other bank datasets such as Call Reports. Call Reports provide important financial-statement information at the bank-quarter level. I use the data from 1994 to 2007 at an annual frequency to match the overall sample frequency.

To study the effect on lending outcomes for the affected banks, we need information about their loan originations at the regional level. This aspect is key to separate demand from the supply-side effects of bank loans. I use two important datasets that convey the characteristics of the loans originated as well as the location of the borrower. First, I use Home Mortgage Disclosure Act (HMDA) public-use database for the years 1994-2007. The HMDA requires many financial institutions to maintain, report, and publicly disclose loan-level information about mortgages. This dataset contains information about the loan and borrower characteristics, the lender identity, the subsequent outcome of the loan application (approved or rejected), and whether the lender sold the loans to the GSE in the same year.

Another key dataset used is the small business lending data from the Community and Reinvestment Act (CRA) small business loans database provided by the Federal Financial Institutions Examination Council (FFIEC) according to Regulations 12 parts 25, 228, 345, and 195 of the aforementioned Act. This dataset includes information on the total number and amount of loans originated by lenders at the county-year level.[3]

Whereas the CRA dataset is a comprehensive dataset on small-business lending at the county level, it does not contain the performance of SBL loans made by the banks.

3. The reporting threshold for financial institutions was increased from a minimum asset size of $250 million before 2005 to $1 billion.

Therefore, I use the SBA loan-level dataset of government-guaranteed loans, which have loan-level information and performance outcomes, including charge-offs (defaults). This dataset contains a rich set of information such as the identities and addresses of borrowers and lenders, loan amounts, interest rates, and maturities of all government-guaranteed loans.

I create a number of merged datasets at the county-year, bank-year, branch-year, and county-bank-year levels to conduct the empirical analysis at various project stages. For instance, I first study the effect of the China trade shock on county-level deposit outcomes. Then, I create bank-level exposure metrics and study the effect of the China shock on bank-level balance sheet outcomes. At this stage, I also examine the banks' margins of adjustment to the trade shock at the branch-level in terms of deposit rates and volume for both affected and not-affected counties. Thereafter, I study the impact of the China shock through exposed banks on lending outcomes at the bank-county-year level.

Table 7.1 shows the descriptive statistics of the different datasets for the analysis. Panel A shows the statistics at the county-year level for the log changes in deposits and the Chinese import competition-intensity measure for the two periods, before and after 2001, the year China joined the WTO. Panel B presents the summary statistics for key variables using the Call Report data at the bank-year level. Panel C lists the bank exposure measures based on the location of bank branches in exposed counties. Although the median number of banks were not exposed to the China Shock, significant variation exists in the exposure measure to the upper end of the distribution. The 75th-percentile bank has around 80% exposure to the China shock.

Panels D and E show descriptive statistics for the SBL and HMDA loan database, respectively, at the bank-county-year level. The key statistics measure the changes in the logarithm of loan/mortgage originations, the fraction of exposed banks and counties, and the fraction of community banks present in the sample. Both SBL and HMDA datasets include a significant fraction of exposed banks at around 36%-42%. Both datasets also include a significant number of community banks with assets less than $2 billion. Around 40% of the observations in my sample belong to the large multi-market banks, which helps us study the transmission of the China shock to unexposed counties.

2.2 Empirical Methodology

I adapt ADH's specification to the deposit markets at the county level because it is well suited to identify the effect of regional forces. The reason is that both labor and deposit markets are local in nature, owing to the different costs associated with search and migration.[4] The regional measure of the Chinese import competition intensity as defined by ADH is the change in Chinese import exposure per worker in a region, where imports are apportioned to the region according to its share of national industry employment:

$$\Delta IPW_{uit} = \sum_{j} \frac{L_{ijt}}{L_{ujt}} \frac{\Delta M_{ucjt}}{L_{it}} \tag{2.1}$$

4. Manning and Petrongolo (2017) estimates that labor markets are local in nature because the attractiveness of jobs to applicants sharply decays with distance. Also, workers are discouraged from searching in areas with strong competition from other job-seekers. Likewise, branches play an important part in deposit-taking and other financial services making these markets local.

In this expression, imports are apportioned to the region according to its share of national industry employment. L_{it} is the start of period employment (year t) in region i, and ΔM_{ucjt} is the observed change in US imports from China in industry j between the start and end of the period. The variation in ΔIPW across local labor markets is due to the differences in the local industry employment structure at the beginning of time period t. Figure 6.1 plots the spatial distribution of the Chinese import intensity measure at the county-level. The plot shows significant spatial heterogeneity, which helps identify the effect of the China trade shock on the banking markets using a standard difference-in-differences estimation strategy. Figure 6.2 plots the average deposit growth rate for the exposed and less exposed counties over the years, where *exposed counties* are defined as those with an above-median China shock intensity measure based on its cross-sectional distribution. The deposit growth rate for more exposed counties drops after 2001 relative to less exposed counties. Before 2001, the two groups' deposit growth rates run in tandem, thus validating the parallel-trends requirement for a difference-in-differences strategy. The following section reviews the endogeneity issues that make the OLS estimates of causal effect biased and discusses the instrumental-variable (IV) estimation used to resolve that concern.

2.2.1 Endogeneity issues and IV estimation

Endogeneity issues stem from the inability to separate the US demand for the import of Chinese goods from the supply-side effect of the growth of Chinese exports around the world. During this time period, the rapid growth of Chinese imports is primarily attributed to the rising productivity of Chinese manufacturers and China's accession to the WTO, which resulted in lower trade barriers.

ADH use the contemporaneous composition and growth of Chinese imports in eight other developed countries as an IV for the growth of Chinese imports in the US to identify the supply-driven component of Chinese imports. Specifically, they use the non-US exposure variable ΔIPW_{uit} that is constructed using data on contemporaneous industry-level growth of Chinese exports to other high-income markets:

$$\Delta IPW_{oit} = \sum_{j} \frac{L_{ijt-1}}{L_{ujt-1}} \frac{\Delta M_{ocjt}}{L_{it-1}} \tag{2.2}$$

The above expression is similar to equation 2.1, and ΔM_{ocjt} refers to the realized imports from China to other high-income markets. The use of lagged employment variables helps mitigate the simultaneity bias because contemporaneous employment by region may be affected by anticipated China trade. ADH discuss the threat to identification issues in detail for interested readers.

CHAPTER 3

RESULTS

I provide strong empirical evidence for the deposit-side channel of the transmission of trade shocks to the banking network. This support comes from a series of sequential tests: the regions more affected by the China shock see a decline in bank deposits, and the banks that have a significant presence (in terms of branch locations) in these regions - exposed banks - decrease their overall lending, including to the unexposed regions. The results also highlight the different margins of adjustment banks take to smooth such shocks.

3.1 Impact on Deposits

As the China shock leads to higher unemployment rates and wage decline in the affected regions, the workers are forced to tap into their savings to smooth consumption. Employees searching for new job opportunities might also migrate out of such affected regions (Greenland et al. (2019)). These local economic changes are bound to reduce the amount of deposits held at the bank as the depositors continue to withdraw their savings. Figure 6.3 panels (a) and (b) display the spatial distribution of changes in Chinese import intensity (ΔIPW) and bank deposits (ΔD) at the county-level, respectively, for 2001-2007. Comparing both panels, one can see a significant negative spatial correlation between the two variables. Counties in dark blue in panel (a) are light blue in panel (b), and vice versa. Panel (c) of Figure 6.3 shows the negative correlation between deciles of changes in import intensity and average deposits in those deciles. The circles are proportional to the population's size, and the slope of the line is -2.17 and significant at the 95% confidence interval.

I explore the robustness and interpretation of this result in subsequent tables. To test the effect of the China shock on county-level deposit markets, I run the following IV regression (2SLS estimates):

$$\Delta D_{it} = \gamma_t + \beta_1 \Delta IPW_{uit} + X_{it}\beta_2 + \epsilon_{it} \tag{3.1}$$

The specification includes first differences for the two periods, 1994 to 2000 and 2000 to 2007, and separate duration dummies for each time period (in γ_t). ΔD_{it} refers to the differences in the log of deposits between the two time periods. The change in import exposure ΔIPW_{uit} is instrumented by the variable ΔIPW_{oit}. Standard errors are clustered at the state level to account for spatial correlations across counties.

3.1.1 County-level: 2SLS Estimation

Table 7.2 displays the IV regression estimates for the effect of the China shock on deposit growth at the county-level. This table presents the same regression specifications as in Table 3 of ADH to facilitate comparison. Specifically, this table adds a set of demographic and labor-force measures to test the robustness and potentially eliminate confounding factors.[1] The point estimates in Table 7.2 imply the bank deposits of a county

1. Column 2 adds geographic dummies for the nine Census divisions that absorb region-specific trends in the deposit growth rates. Column 3 also controls for the start-of-period share of a county's

at the 75th percentile of import exposure declined by about 4.3-7.5 percent points more than in a county at the 25th percentile between 2000 and 2007. This difference represents a significant reduction in deposits as the median county's deposits grow at 31% from 2000 to 2007.

3.2 Bank-level Exposure Measures

In the previous subsection, I uncovered how the China shock affects bank deposits at the county-level. The affected counties exhibit a significant decline in deposit growth relative to unaffected counties. A natural subsequent question is: How this regional shock affects banks. To answer this question, I need measures of bank-level exposure through the deposit markets.

I use the SoD from the FDIC to get the information on the number of branches and amount of deposits held by each bank in each county-year. The measure of exposure at the bank-level is defined as the share of branches in affected counties (similar to the measure in Gilje et al. (2016)), which is equal to the fraction of branches owned by each bank that are located in a China-shock-exposed county.[2] This measure ranges from 0 (for banks with no branches in affected counties, or banks with branches in affected counties during the years before 2001) to one (for banks with all of their branches in

population with a college education, the share of the population that is foreign-born, and the share of working-age women employed. Column 5 adds two variables that capture a county's occupations' susceptibility to substitution by technology or task offshoring, and column 5 adds all the controls to the first-difference model.

2. A China-shock-exposed county is defined as a county with the China shock import intensity measure above the median of its distribution.

affected counties after the onset of the Chinese shock). This variable equals zero for all bank-years before 2001, the year of the onset of China import growth. After 2001, the variable increases within the bank over time as more branches open or close in boom counties.

For example, JP Morgan Chase has several branches across the US, dispersed in affected and unaffected counties. Figure 6.4 panel (a) shows the location of branches of JP Morgan Chase across the US as of 2005. Depending on the share of branches in affected counties, the fraction exposure of JP Morgan Chase is 0.484. Panel (b) of the same figure shows the zoomed-in version of JP Morgan branches in Illinois. Another example is of state banks in Illinois, shown in panel (c). Ranked in the increasing order of exposure, the locations of the branches of three banks are displayed in red (South Point Bank), green (Prairie State Bank), and yellow (Main Street Bank & Trust) with the corresponding values of fraction exposure equal to 0.143, 0.4, and 0.94, respectively. In other words, the greater the share of branches in affected counties (dark blue), the higher the exposure measure.

Another way to define this measure is to use the share of branch deposits as the measure of exposure to the China shock. This measure captures the size effect of large branches in affected areas, whereas the previous measure treats each branch equally. One downside of using this measure is that it is affected by the China Shock itself - because the affected areas see a decline in deposits. This bank-level measure changes with time, with no change in economic exposure to the branch locations. In this paper, I use the share of the number of branches as the primary exposure measure at the bank-year level. However, all specifications are run using the share of deposits measure, and the results are shown in the Appendix for robustness.

3.3 Bank-level results

I first establish that the banks exposed to the China shock see a reduction in their deposits due to deposit outflow by depositors - the deposit channel. I run the following regression specification to examine the impact on bank balance sheets:

$$y_{it} = \alpha_i + \gamma_t + \beta_1 BankExposure_{it} + X_{it}\beta_2 + \epsilon_{it} \tag{3.2}$$

Here, the unit of analysis varies by bank i and year t. The main coefficient of interest is β_1, the coefficient of the bank-exposure measure. I include lags of bank characteristics as control variables (X_{it}), as well as the bank (α_i) and year (γ_t) fixed effects. Bank controls include size (ln(assets)), return on assets (Interest income/Assets), the ratio of portfolio loans (C&I Loans/Assets), and the deposit ratio (Deposits/Assets). Standard errors are clustered by bank.

The deposit channel of regional economic-shock transmission dictates that bank deposits decline and deposit rates increase after the shock. As depositors withdraw deposits, the banks are expected to react by increasing their average deposit rates (measured by interest expense on deposits/ deposits) to stem the outflow of deposits. Deposit rates are one of the primary levers banks use to smooth the transmission of economic shocks through the banking network (see Cortés and Strahan (2017)).

Table 7.3 panel (a) show the results of the China shock on banks' balance-sheet outcomes (see specification in equation 3.2). Columns 1 and 2 shows the results for the growth in deposits both with and without lagged controls. The coefficient on bank exposure is positive and significant at the 95% confidence interval. As one moves from the 25th percentile to the 75th percentile bank in exposure to the China trade shock, the growth in deposits decreases by 0.8*0.55 = 0.44%; that is, we see a roughly 0.5% growth-rate difference. Similarly, the uninsured deposits decline by 1.03% for exposed banks.

Column 4 shows a significant increase in the cost of deposits for affected banks. An interquartile change in bank exposure to the China shock increases the deposit rates by 0.8*4.34 = 3.5%. Similarly, columns 5-8 show the growth rate of assets, and loans including real estate and C&I loans, decline after the exposure to the China shock. These results show the decline in deposits has a significant impact on the lending side of the balance sheet, thus providing evidence supporting the importance of deposits in bank financing.

Panel (b) of the table shows the exact specification using the share of deposits in exposed counties as an independent variable. Comparing columns in panels (a) and (b), one can see the coefficients on the two bank exposure measures are similar in magnitude and statistical significance, adding robustness to my bank exposure measures. Similarly, panel (c) presents the results for a standard difference-in-differences specification. The treatment variable is a dummy variable that equals one if the bank exposure measure of the bank is greater than the median of its distribution. This specification helps avoid the concern that a few outlier banks are not driving my previous results based on continuous bank exposure measures. This specification also helps to test whether any pre-trends may confound my results. The results show coefficients of similar magnitude and statistical significance as in panel (a).

Finally, I test the assumption of no pre-trend in these variables that are required to validate the use of a difference-in-differences specification. I run the following specification:

$$y_{it} = \alpha_i + \gamma_t + \beta_1 Treat_{it} \times year_t + X_{it}\beta_2 + \epsilon_{it}. \tag{3.3}$$

The above specification is very similar to equation 3.2 except bank exposure is replaced by the interaction term $Treat_{it}xyear_t$. Figure 6.5 plots the coefficients on the interaction term for the key outcome variables in Table 7.4. None of the coefficients are statistically significant in the pre-shock period - before 2000, which confirms that both affected and unaffected banks had similar pre-trends before the China shock and that the coefficients in Table 7.4 reflect the *causal* effect of the China shock on bank outcomes.

3.3.1 Impact on Deposit Rates

The Ratewatch database provides detailed product-level weekly deposit rates information for all depository institutions at the branch - level. Exposed banks tend to increase their average interest expense on deposits to stem the deposit outflow, as shown in column 3 of Table 7.3. However, rates are not determined at the bank - level; rather, they are set at the local branch - level.[3] Studying how multi-market banks adjust their deposit

3. Ratewatch provides information on the master branch that sets the deposits rates for all branches under its purview.

rates at the regional level, depending on the degree of exposure to the China shock. Do exposed banks increase their deposit rates across all branches in a systematic manner? Or does a heterogeneous effect arise depending on the degree of shock exposure? Are banks able to compensate for some of the increase in deposit costs in affected counties by decreasing rates in unaffected counties? These crucial questions can be tested using my research setting:

$$y_{ijt} = \alpha_i + \gamma_{jt} + \beta_1 BankExposure_{it} + \epsilon_{ijt}. \tag{3.4}$$

Here, i refers to the bank, j refers to the county, and the analysis is at the branch-month-year level. The dependent variable y_{ijt} represents the changes in deposit rates of different products for exposed banks. The specification includes bank-branch fixed effects (α_i) to account for time-invariant branch-specific factors affecting deposit-rate changes and county x month-year fixed effects (γ_{jt}) to control for county-specific time-varying factors such as liquidity demand and supply shocks, the concentration of the deposit markets, and so on. The standard errors in this specification are clustered at the bank branch level.

Table 7.4 panel (a) show the results for different deposit products - both long-term - certificates of deposits (CDs) and short-term - money-market fund and savings account. Each product has three associated columns - All, Less Affected, and More Affected counties. The entire sample of different deposit products shows positive and statistically significant coefficients. Therefore, this means that exposed banks, in general, increase their average deposit rates after the China shock. This result is expected because it is in line with the bank-level deposit rates result in column (3) of Table 7.4.

The more interesting results are for the sample of counties split by the degree of exposure to the China shock. 'Less Affected' counties show no changes in deposit rates for exposed and unaffected bank branches, which implies 'More Affected' counties drive the increase in deposit rates for the total sample of bank branches.[4]

Since deposit markets are segmented in geographic areas, a decrease in depositors' demand will lead banks to increase the deposit rates to clear the local markets. The above result is partly intuitive because banks are expected to stem the outflow of deposits from more affected counties to dampen the effect of the China shock on its network. However, the banks can partly compensate for the increase in the costs of deposits by decreasing rates in unaffected counties. I do not find any such counter-measures employed by banks, perhaps because deposit rates are also determined by other factors, such as local market competition, which may prevent banks from decreasing their deposit rates.

One concern might be that the results of deposit rates can be driven by confounding factors such as the deposit markets' concentration. Specifically for banks with high values of the bank exposure measure, the results could be driven by a correlation between the China shock regional distribution and the deposit market concentration. For exam-

4. Although I discuss in detail the alternative mechanism of the asset-side transmission channel in section 4, these results also provide empirical support against the asset-side channel of regional shock transmission. Any adverse effect emanating from the asset-side of the balance sheet affects the volume and costs of deposits at the bank-level, not at the branch-level. Therefore, if the asset-side channel dominates, one should see a uniform increase in deposit rates for more and less affected regions, contrary to the results in Table 7.4.

ple, suppose the regions more affected by the China shock also happen to be the areas with a higher (or lower) value of deposit concentration as measured by the Herfindahl-Hirschman Index (HHI). For banks with significant branches in exposed areas, deposit market concentration is a confounding factor that helps explain the results of deposit rates (Drechsler et al. (2017)). I run the following specification:

$$y_{ijt} = \alpha_i + \gamma_{jt} + \beta_1 BankExposure_{it} \times HighConc_{jt} + \beta_2 BankExposure_{it} + \epsilon_{it}. \tag{3.5}$$

Here, High Conc. is a dummy variable that equals 1 for counties with above-median HHI across all county-years. The specification helps to test if exposed banks operating in high- versus low - deposit-concentrated areas differ. Panel (b) presents the results for the different deposit products. The coefficient is positive for the exposed banks in general; however, it is negative on the interaction term for all products, which implies that for high-concentration counties, the increase in deposit rates is positive ($\beta_1 + \beta_2$) but lower in magnitude than (β_2). This finding is expected because market power gives banks the ability to pay lower deposit rates relative to branches located in high-competition counties. Thus, competition in deposit markets exacerbates the effects of regional economic shocks.

3.4 Effect on Lending

The deposit channel affects the banks' lending by constraining the size of the balance sheet. In other words, if deposit growth is decreased, so is the capital available for lending. Table 7.3 column 5 shows a decline in lending growth for exposed banks at the balance sheet level. However, this decline in lending can result from a decline in loan demand due to poor economic conditions in shock-affected areas. Therefore, we cannot separate the decline in bank lending due to credit-supply constraints (deposit channel) from the decline in loan demand solely based on this result.

To overcome this obstacle and better control for loan demand-side factors, one needs lending information at the regional level by each bank. Two key databases that provide information on borrower location and other loan characteristics include the CRA small business loans and the HMDA loan application register databases. The main outcome variable is the growth in mortgage/loan originations at the county-year level by each bank. Specifically, I estimate a three-dimensional panel regression of the growth in mortgage originations in counties on each bank's Chinese import exposure:

$$LoanGrowth_{ijt} = \alpha_i + \gamma_{jt} + \beta_1 BankExposure_{it} + X_{it}\beta_2 + \epsilon_{ijt} \tag{3.6}$$

α_i and γ_{jt} are the lender and county x year fixed effects for bank i, county j, and year t. County x year fixed effects control factors such as house prices, housing demand, income growth, and so on, affecting the mortgage/loan markets (similar in spirit to Khwaja and Mian (2008) loan-level estimator specification). Standard errors are clustered at the bank and county x year level. Alternatively, to test for any pre-trend differences and avoid outliers driving the result, I also run the specification.

$$LoanGrowth_{ijt} = \alpha_i + \gamma_{jt} + \beta_1 HighExposure_i \times Post_t + X_{it}\beta_2 + \epsilon_{ijt}$$

$HighExposure_i$ is a dummy variable equals to 1 if the bank exposure is above the median of its cross-sectional distribution. Post is a dummy equals to 1 after 2001.

3.4.1 Small Business Lending Results

Although mortgage originations represent a significant share of bank lending activity, they can be sold off-balance-sheet either by agency or private securitization. Therefore, I use the small business lending data from the CRA small business loans database provided by the FFIEC. The major advantage of this database over HMDA is that small business lending loans are portfolio loans and, hence, are more likely to be affected by capacity constraints induced by the deposit channel. Figure 6.6 panel (a) shows the average SBL loan-origination growth for exposed and less exposed banks. One can see a visual decline in exposed banks' growth rate (solid line) relative to less exposed banks (dashed line) after 2000.

Table 7.5 present the results for SBL loan originations using specifications in equations 3.6, and 3.7. As per column 1, exposed banks exhibit a 1.4% decline in loan origination relative to less exposed banks. In column 2, which uses specification 3.6, the coefficient on bank exposure is negative and statistically significant. As one moves from the 25th-percentile to the 75th-percentile bank in exposure to the China trade shock, the growth in SBL loan originations decreases by 0.8*6 = 4.8%; that is, we see a roughly 5% growth-rate difference.

Column 3 presents the results for the less affected counties. Here, again, a negative and statistically significant coefficient indicates the decline in lending is due to the deposit channel of shock transmission because loan demand does not seem to be affected directly by the China shock. Not surprisingly, column 4 shows a decline in lending for affected counties, and the difference between the less and more affected counties is statistically significant here. The positive sign makes sense because one should expect affected counties to suffer from lower loan demand in addition to loan-supply shocks.[5]

Panel (b) of Figure 6.6 tests the difference in SBL loan growth rates between exposed and less exposed banks before the China shock period. The figure shows that none of the coefficients before 2000 are statistically significant.

One concern in the literature is that community banks are more likely to depend on deposits for their funding. Because community banks are small in size and are usually limited in their geography scope (usually, they are single-market banks that take deposits and lend in the same region), the results may be driven by them instead of large multi-market banks. Table 7.6 panel (a) tests for the differences between community and large exposed banks in their loan origination. We can see that both large and community-exposed banks decrease their loan-origination growth after the China shock. As expected, the effect on large exposed banks is less severe (column 3 inter-

5. The bottom line is that affected counties also see a decline in SBL lending by exposed banks because $\beta_1 + \beta_2 < 0$.

action coefficient) than community banks, perhaps because large banks have greater access to interbank funding at reduced costs than community banks.

Some of the less affected counties by the China shock may be simultaneously experiencing lower loan demand due to similarity in their industry employment structure. Likely, my primary China shock exposure measure at the county - level depends on the existing manufacturing industry employment structure. However, establishing that the reduction in lending outcomes is also present in counties whose industry employment mix is very different from affected counties would provide additional evidence supporting the deposit channel because the confounding effect of loan demand would not be an issue.

A way to measure the similarity between the multidimensional industry employment structure between two counties is to calculate their corresponding industry-employment vectors' cross-product. A low cosine value implies less industry overlap between the two counties. Hence, to the extent to which loan demand depends on the industry, this approach provides a way to isolate confounding loan demand from our estimation.

Panel (b) of Table 7.6 present the results. Low cosine is a dummy for lower than the median distribution of counties correlation structure with affected counties. We can see that even for counties with significantly different industry structures than affected counties, exposed banks decrease their loan-origination rates. The difference in origination rates between low- and high-correlation counties (with respect to affected counties) is statistically insignificant. Finally, in column 3, we test if the lending outcome depends on banks' market power in the deposit market as captured by bank-level

HHI dummy (bank HHI is calculated as deposit-weighted county HHI for all counties in which the bank has branches.). We can see no difference in terms of bank deposit market power in lending outcomes. In other words, regional economic shocks, such as the China shock's impact on banks through the deposit channel, does not vary with the deposit market power of the bank, even though deposit market concentration has an impact on deposit rates setting (see Table 7.4).

3.4.2 HMDA Results

Although GSEs and private securitization can easily securitize most mortgages originated by banks, some mortgages are difficult to securitize and remain on the balance sheet as portfolio loans. I complement my analysis using the HMDA dataset to study the effect of deposit shock on the mortgage industry. I use the same regression specification as in equation 3.6 but focus on outcomes in less affected counties to study the spillover effect of China Shock.

Table 7.7 present the results of the impact of the China shock on different mortgage outcomes via the deposit channel. Column 1 shows the results for the growth in mortgage originations in less affected counties. Column 1 shows results for the specification that uses $BankExposure_{it}$ as the main regressor and shows a statistically significant decline in mortgage originations' growth. In terms of magnitude, as one moves from the 25th-percentile to the 75th-percentile bank in exposure to the China trade shock, the growth in mortgage originations decreases by 0.8*7.43 = 5.9%; that is, we see a roughly 6% growth-rate difference.

Figure 6.7 panels (a) and (b) show the dynamic effects of log and the growth of mortgage originations, respectively, for exposed banks. The absence of any significant coefficient before 2001 shows that exposed and less exposed banks do not have any statistically significant differences in mortgage originations' growth rates. This finding validates the assumption of difference-in-differences estimation in column 1. The growth rate of exposed banks declines significantly after 2001 and remains lower than less-exposed banks for the remainder of the study.

Most mortgage loans are taken off the balance sheet by a securitization process and sold to Government Sponsored Enterprises (GSEs) such as Fannie Mae and Freddie Mac. However, only conforming mortgage loans (dollar limit on the loan size) are sold to these agencies. Typically, loans beyond a size threshold are called jumbo loans, which are most likely held on the balance sheet as portfolio loans. Therefore, the deposit channel should not affect the conforming loan market because they are quickly sold to the GSEs and do not constrain the origination of new loans. One should expect the share of jumbo-loan originations to decline for exposed banks due to funding constraints. Table 7.7 column 2 presents the results for the ratio of jumbo loans to total mortgage originations. Column 2 shows a statistically significant decline of about 3% in the share of jumbo loans for exposed banks.

Lending capacity constraints are also likely to increase the loan-denial rate for all loan applications. Table 7.7 column 3 shows the results for the denial rate of mortgage applications. Exposed banks are 13% more likely to deny mortgage applications than less exposed banks. These different mortgage outcomes in less affected counties provide strong empirical support for the strength of the deposit channel of regional economic-shock transmission.

3.5 Risk-Taking Behavior by Banks

Thus far, I have established that regional economic shocks may severely affect banks through the deposit channel. Exposed banks experience a decline in their deposit growth rates and see a significant decline in their portfolio lending. They also seem to be taking active actions such as increasing their deposit rates to smooth the impact of such shocks. This action is bound to impact the bank's net interest income because they reduce the interest income-generating assets and increase their interest expense on deposits. To smooth the effects of such shocks on the banks' profits, banks may increase the interest income by originating more risky loans.

Banks' increased risk-taking can also be directly influenced by the regional nature of the China import shock. For instance, consider a bank with high exposure to the China shock. Therefore, the China shock affects a significant fraction of this bank's branches. Suppose this bank used to lend to small businesses much closer to its branches, due to the advantage of gathering soft information about them. In that case, the China shock might directly affect the bank's lending due to lower loan demand induced by poor economic conditions. Thus, this bank is forced to originate new loans farther away from its branches, where the loan demand might be regular. This increase in lending distance decreases the banks' ability to collect reliable soft information by making the process more expensive (Petersen and Rajan (2002)). This reduction in due diligence is likely to increase the risk of new loan originations.

To see the effect on banks' risk-taking, I use the SBA 7a loan database, a subset of the CRA small business loans that the government guarantees and have a richer set of the borrower, loan characteristics, and performance information. I calculate the lending distance between the borrower and the lending bank's nearest branch and call it the lending distance. Figure 6.8 panel (a) plots the average lending distance between exposed and less exposed banks. We can see from the raw data that the exposed banks' average lending distance increases after 2000.

To formally test this hypothesis, I run the regression in equations 3.6 and 3.7 using lending distance and different measures of loan charge-offs (defaults) as dependent variables. The results are presented in Table 7.8. We can see that for exposed banks, the lending distance (column 1), probability of default (column 2), the log charged-off amount (column 3), and the growth of the charged-off amount go up significantly after the China shock. An exposed bank increases the lending distance by 3.3% in the post-shock period, has a 1% increased probability of default, and has a 20% increase in the charge-off amount. Panels (b), (c), and (d) test for pre-trend differences in these outcome variables and do not find any statistically significant difference.

Therefore, affected banks actively increase their risk-taking behavior after experiencing economic shock via the deposit channel. In addition to the deposit rates, banks use this mechanism to smooth the effect of the China shock.

CHAPTER 4

ALTERNATIVE EXPLANATIONS

After providing support for the deposit channel of the China shock transmission, this section deals with the alternative channels that may explain the observed results. One prominent alternative explanation is the asset-side channel. Consider a bank that lends primarily to the China-shock-affected counties. The loans such banks make are likely to have a higher probability of loss due to the China shock-exposed counties' poor economic conditions. Loan losses will make such banks riskier, and the depositors of such banks will demand a risk premium to hold deposits with them. This premium will lead to an increase in the deposit rates of such banks and a decline in deposits - a slow depositor run on risky banks.

The above channel explains all of the findings in this paper; however, its action is in reverse from asset to the deposit side. Therefore, testing whether this channel plausibly explains the transmission of trade shocks instead of the deposits channel is essential. An ideal experiment for testing this channel is to have complete information on the lending side of the bank balance sheet and the loan performance at the regional level. Unlike the deposit market, comprehensive information on the lending side is not possible for many reasons. Most of the loans are packaged into tranches and sold as asset-backed securities, making them off the balance sheet. Also, no regulatory requirement exists for banks to disclose such data, except for a few specific types of loans, such as CRA loans. In summary, ruling out this channel's presence is extremely difficult because of incomplete information on the asset side of the banks.

However, the reasons above also indicate the asset-side channel may not dominate the deposit channel because of the different diversification and securitization activities, as well as the presence of FDIC insured deposits that do not react to the asset-side risk factors. Nonetheless, I use the small business lending dataset and jumbo mortgages from the HMDA dataset as a source of portfolio loans to test the effect of the China shock on banks' lending outcomes and study its propagation to the deposit side.

To test the deposit channel, I create a bank-level exposure measure based on the branch-level deposit information. Similarly, I require a bank-level exposure measure based on the loans given in affected counties. I create two bank-asset-exposure measures based on the share of the number, and the amount of small business loans and jumbo mortgages originated in affected counties. I call these measures "Bank Asset Exposure" and "Bank Asset Exposure amt", respectively.

An obvious first test is to see if the banks sorted according to this asset-side China shock exposure are riskier than less exposed banks. For a subset of such loans - SBA 7a loans, which have information on loan performance, I test if exposed banks are more likely to experience default. Table 7.9 panel (a) shows that exposed banks have a higher share of charged-off loans by number and amount for both measures of asset exposure. This finding confirms the crucial first-stage result that banks with greater portfolio loan exposure to the China-shock-affected counties have a higher share of defaulted loans and are riskier than less exposed banks.

Second, I use these measures to see the impact of balance-sheet outcomes at the bank-level (counterpart to Table 7.3). The specification includes bank and year fixed effects, and standard errors are clustered at the bank-level. None of the seven outcomes are significant at a 95% level. Therefore, banks with high exposure to China shock counties in terms of SBL loans are no different from less exposed banks.[1]

I use both the asset-side exposure and bank deposit exposure simultaneously to study their effect on deposits at the branch level. Panel (c) presents the results of this outcome. For the first three columns, we use the entire sample of counties and find that asset-side exposed banks see an increase in their deposit growth rates contrary to the expectation. In contrast, consistent with the deposit channel, exposed banks show a statistically significant decline in deposits. Column 3 uses both measures in the exact specification and shows banks with high asset exposure to the China shock have a higher deposit growth rate than unexposed banks. Also, banks with higher exposure to the China shock on the deposit side decrease their deposit growth.

Columns 4,5 and 6 show the results for less affected counties using both exposure measures. As before, all asset-side coefficients are positive, which challenges the significance of the asset side-channel. Interestingly, deposit growth also increases for exposed banks in less affected counties, which can happen, because we have no reason to believe that deposit growth should decline in unaffected areas.

Finally, table 7.10 present the results of the regression of small business loan origination rates on the asset-side exposure and bank deposit exposure measure. Columns

1. Note in this regression that this result is based solely on the sorting done by SBL loan exposure. The true measure of exposure might be different from this measure. However, due to the reasons mentioned above, calculating the true asset exposure measure is impossible.

1,2,7, and 8 present the results for the entire sample. Columns 3,4, and 5,6 present results for the less affected and more affected counties, respectively. All coefficients on the asset side exposure are either statistically insignificant or positive and significant at 90% confidence. These results are not in line with the prediction of the asset-side channel effect on lending outcomes. In contrast, the coefficients on bank deposit exposure measure are negative and significant in sync with the effect of the deposit channel of shock transmission. These results confirm that the asset side channel is not the dominant channel of shock transmission to lending outcomes.

In summary, based on the above results, the data do not support evidence for an asset-side transmission channel, at least using the limited definition of small business loans and jumbo mortgages as an exposure measure. On the other hand, the deposit channel is much stronger and produces consistent results as per the hypothesis and mechanisms.

CHAPTER 5

CONCLUSION

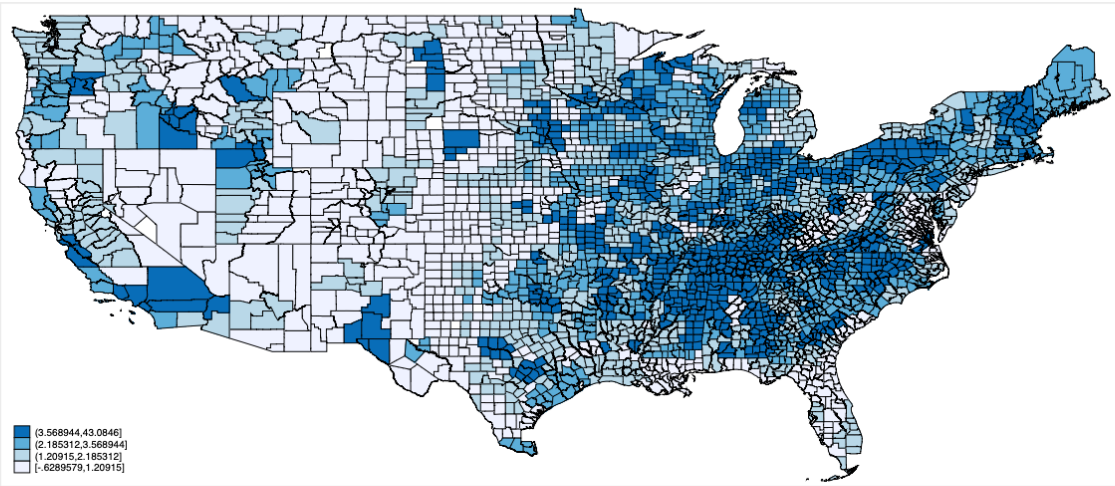
This paper proposes a new mechanism - *the deposit channel* - by which local economic shocks propagate to other regions through multi-market banks. I exploit the heterogeneity in China shock exposure as an experiment to test how local economic shocks transmit through the bank branch network. I find a significant decline in deposit growth in affected counties where county exposure is measured by ADH's Chinese import intensity per worker. Banks with a significant presence in affected counties - exposed banks - show a reduction in their deposits, assets, and loan growth rates, as well as an increase in their cost of deposit funding. These exposed banks increase the rates on different deposit products in affected counties while keeping them unchanged in unaffected ones. These actions help lessen the impact of the economic shock on bank outcomes.

Exposed banks decrease their portfolio loan-origination rates by 5%, decrease the share of hard-to-securitize mortgages, and increase their loan-denial rates, even in unaffected counties. This decline in credit origination is present not only in community banks but also in large banks, which suggests access to national or global capital markets is not sufficient to substitute for the decline in deposit growth fully. By contrast, asset-side transmission using the share of loans in affected counties as the exposure measure does not have any significant impact on bank-level outcomes. Therefore, the deposit channel of local economic-shock transmission is a powerful mechanism through which distress spreads to unaffected regions.

CHAPTER 6

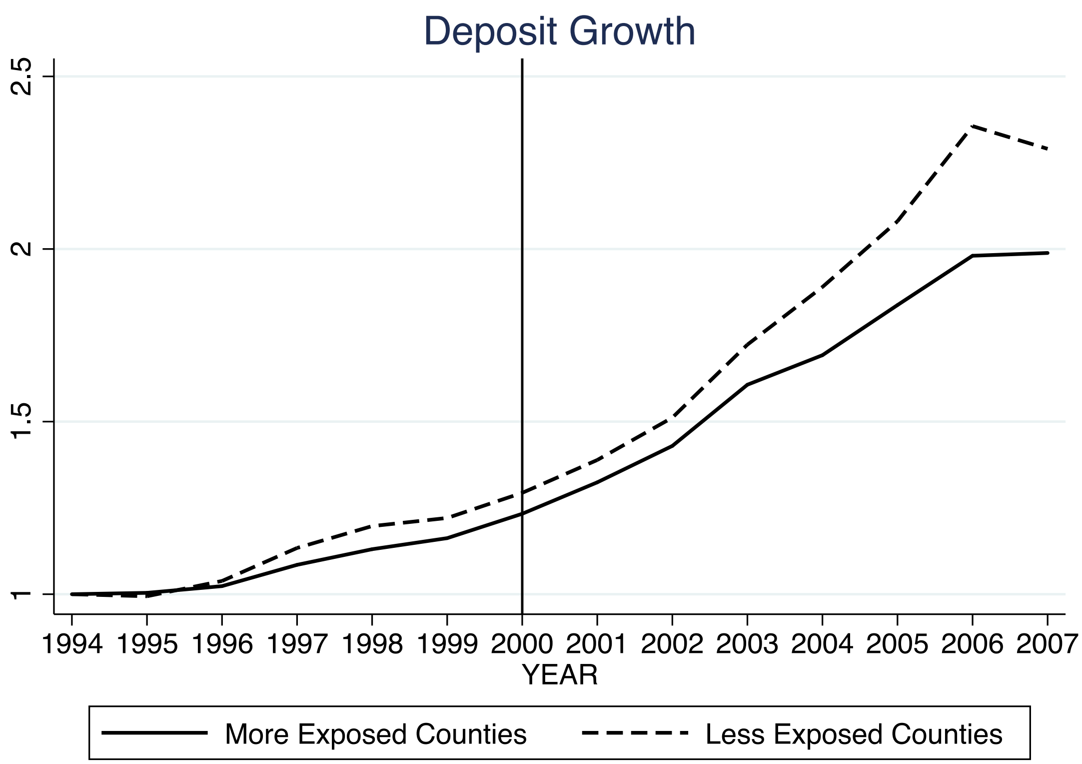
FIGURES

Figure 6.1: Regional Heterogeneity of China Trade Shock



This figure plots the variation in the Chinese import competition intensity measure from ADH at the county-level. The darker the color of the county, the more severe the exposure to the China shock.

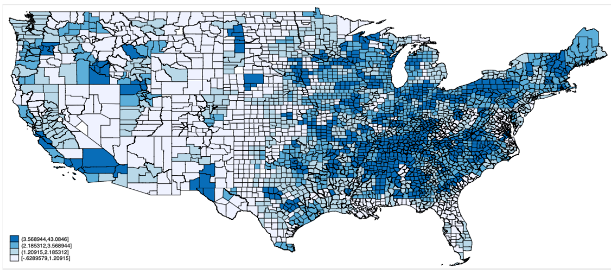
Figure 6.2: Deposit Growth: By Exposed and Less Exposed counties



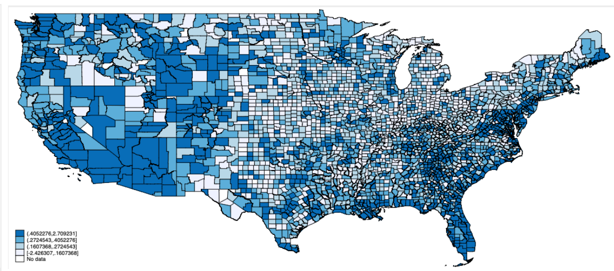
This figure plots the average deposit growth rates for more exposed (solid) and less exposed (dashed) counties. More (Less) exposed counties are the ones with import intensity measures above (below) the median of its distribution.

Figure 6.3: Significant Negative Spatial Correlation: 2001-2007

(a) Δ Imports from China



(b) Δ Deposits



Left panel shows the county-level import intensity measure for the period 2000-2007. The right panel plots the changes in deposits at the county-level. This figure shows the negative spatial correlation between the two variables.

Panel (c): County-Level Correlation

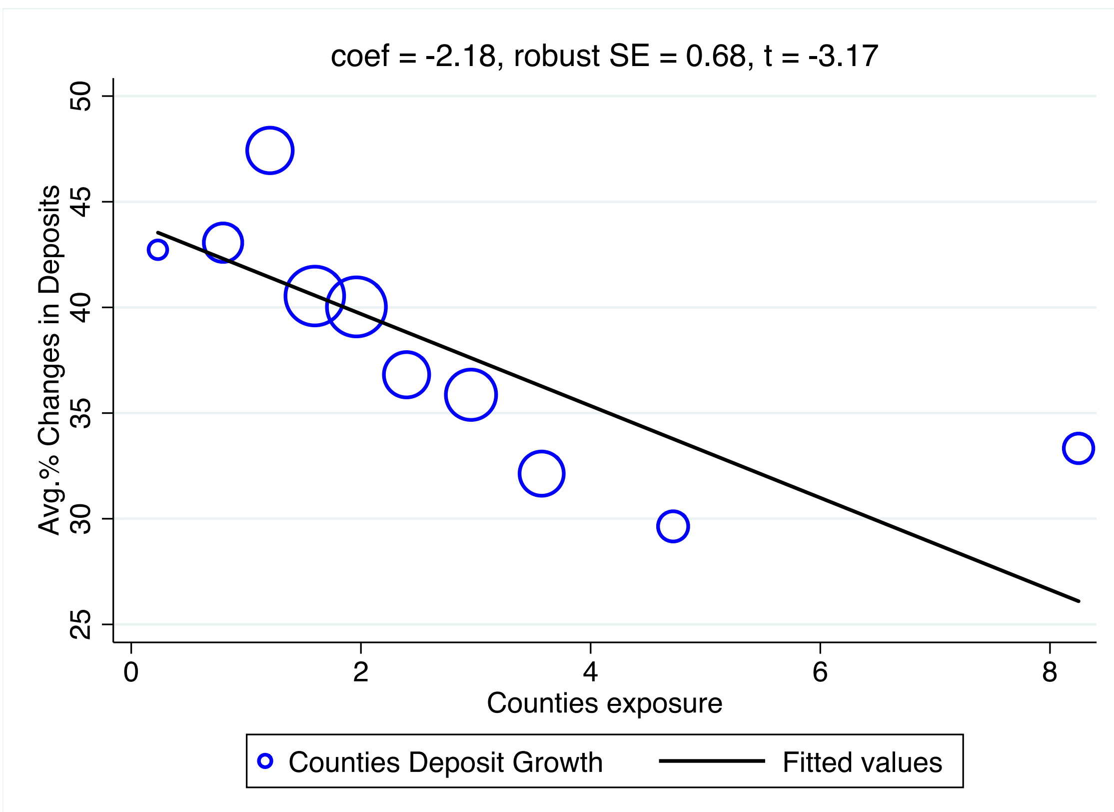
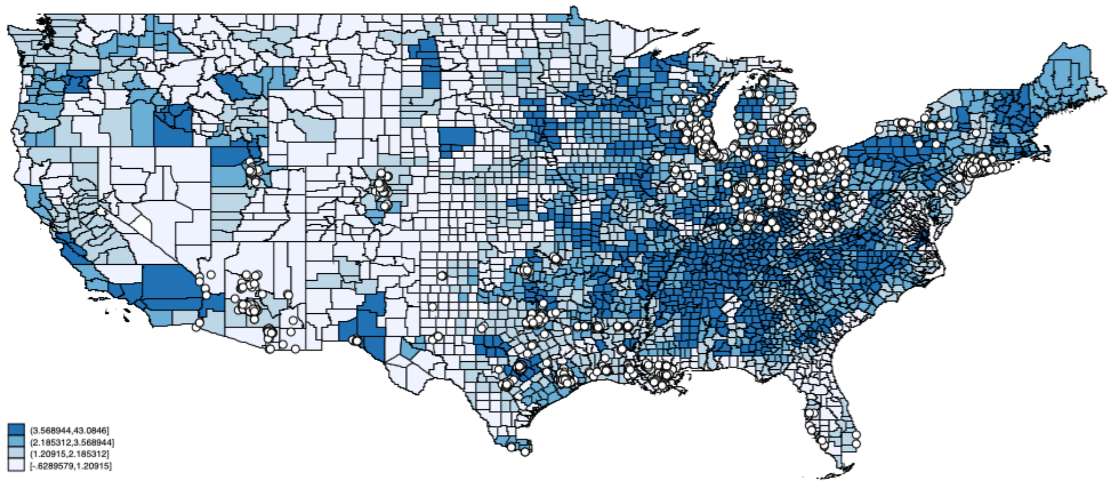


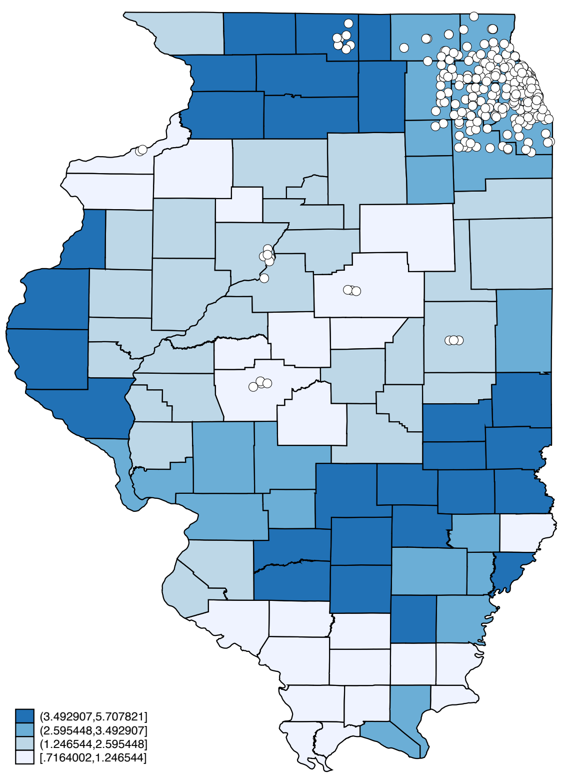
Figure plots a scatter plot and linear regression line of the deciles of average changes in deposits for every decile of changes in the import intensity measure.

Figure 6.4: Bank Exposure measure example

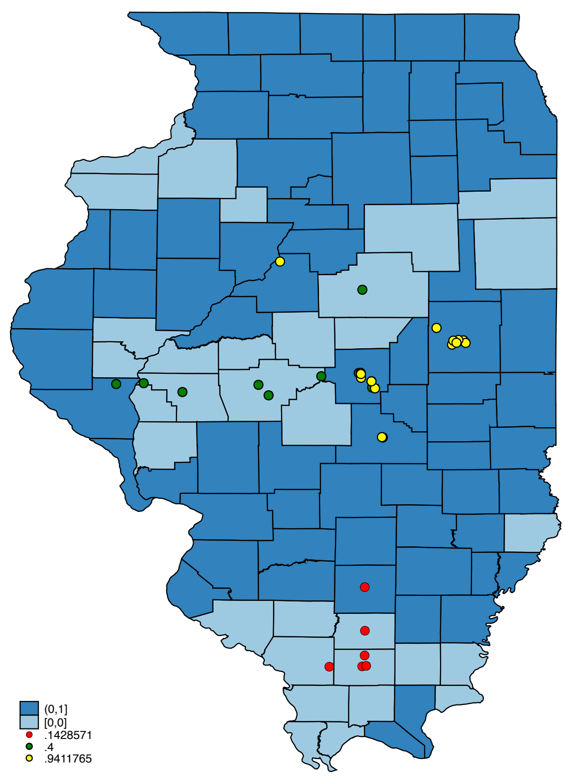
(a) JP Morgan Chase: FracExp 0.484



(b) JP Morgan Chase: FracExp 0.484 IL

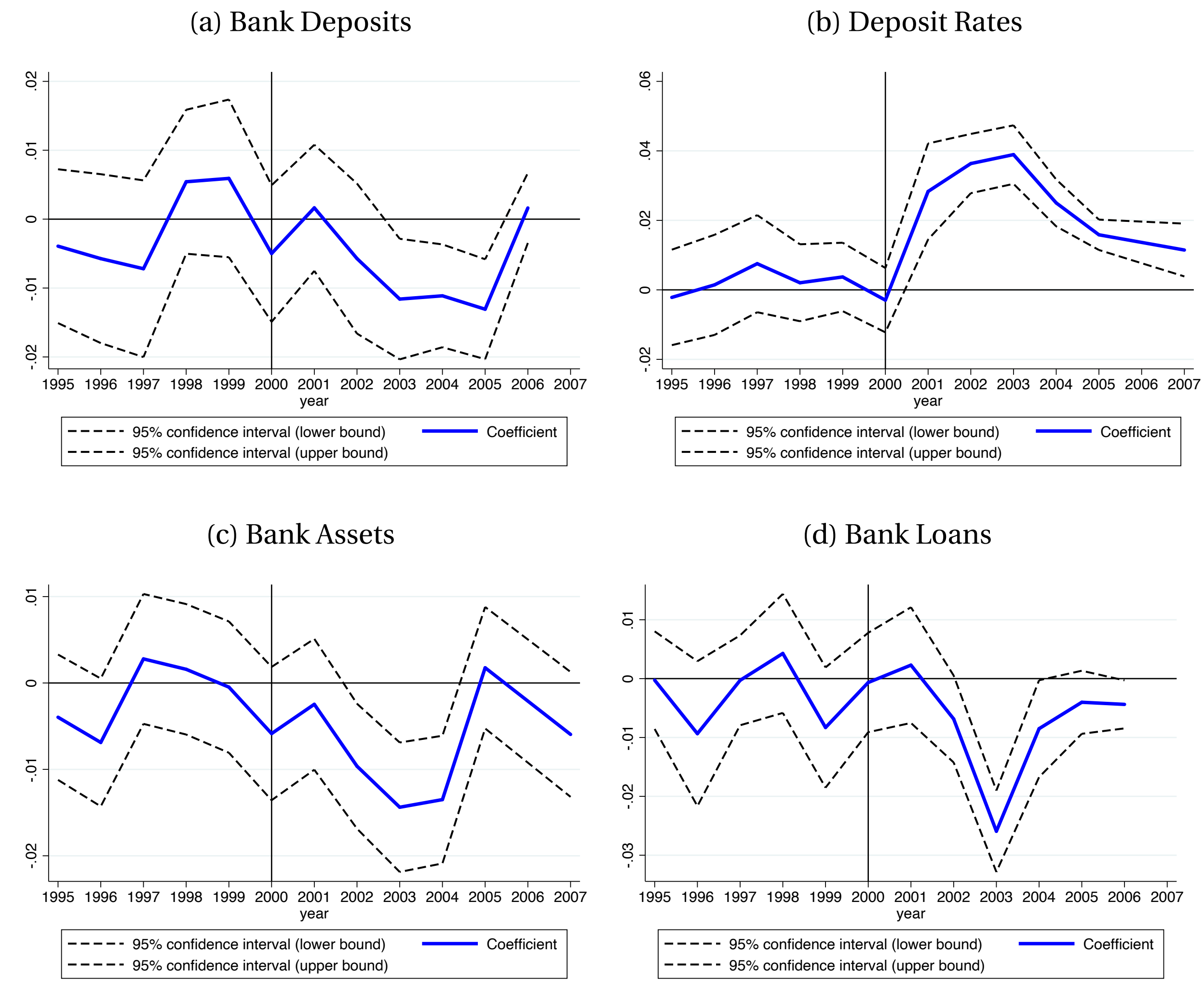


(c) IL State Banks



Panel (a) plots the branch locations of JP Morgan Chase bank over the spatial distribution of the Chinese import intensity measure at the county-level. Panel (b) plots the Illinois state branch locations of JP Morgan Chase bank over the spatial distribution of the Chinese import intensity measure at the county-level. Panel (c) plots the branch locations of three Illinois state banks (with different bank exposure measures) over the spatial distribution of the Chinese import intensity measure at the county-level.

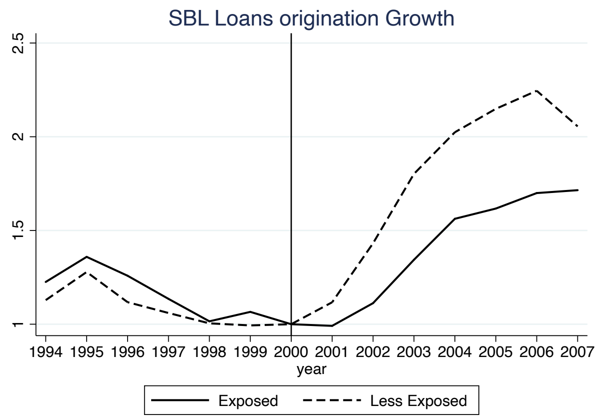
Figure 6.5: Bank-level Dynamic Effects



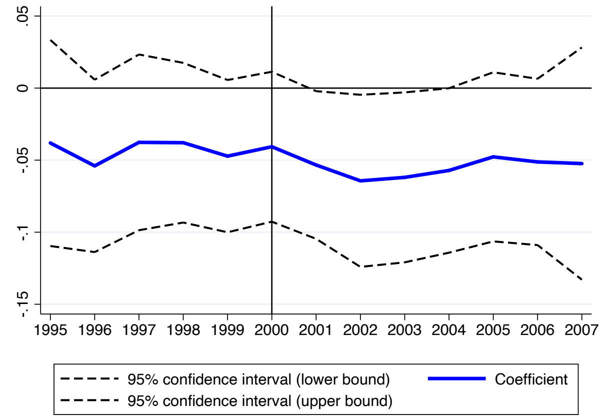
This figure plots the coefficients (along with 95% confidence bands) on the interaction term for the bank and year-level regresssion $y_{it} = \alpha_i + \gamma_t + \beta_1 Treat_{it} x year_t + X_{it}\beta_2 + \epsilon_{it}$. The dependent variables in panels (a), (b), (c), and (d) are the changes in deposits, deposit rates, assets, and loans, respectively.

Figure 6.6: Small Business Loan origination rates

(a) Origination Growth



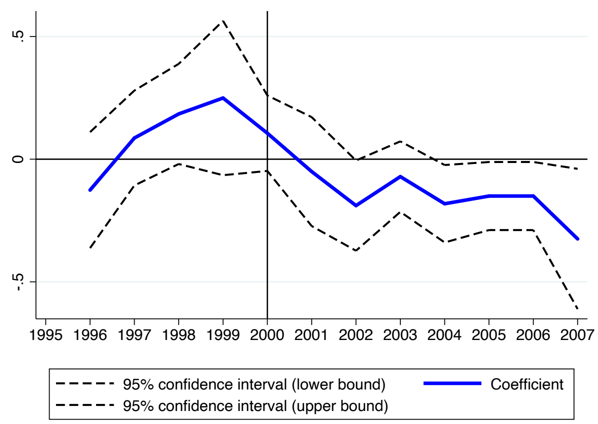
(b) Dynamic Regressions



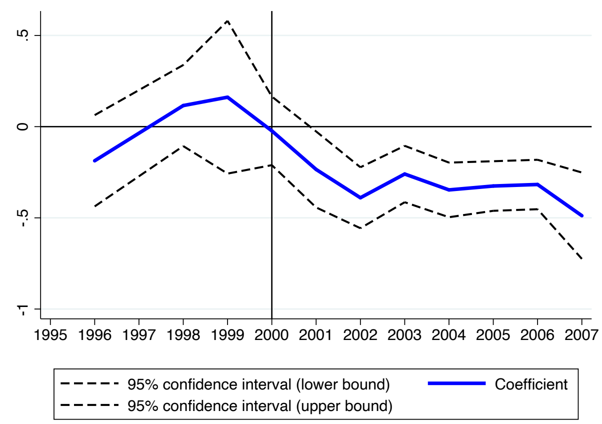
Panel (a) plots the average SBL loan origination rate for more exposed and less exposed banks. Panel (b) plots the coefficients (along with 95% confidence bands) on the interaction term for the bank and county-year level regression $y_{ijt} = \alpha_i + \gamma_{jt} + \beta_1 Treat_{it} xyear_t + X_{it}\beta_2 + \epsilon_{ijt}$ using the SBL data. The dependent variables loan-origination growth.

Figure 6.7: HMDA Dynamic Regressions

(a) Ln(Orig)

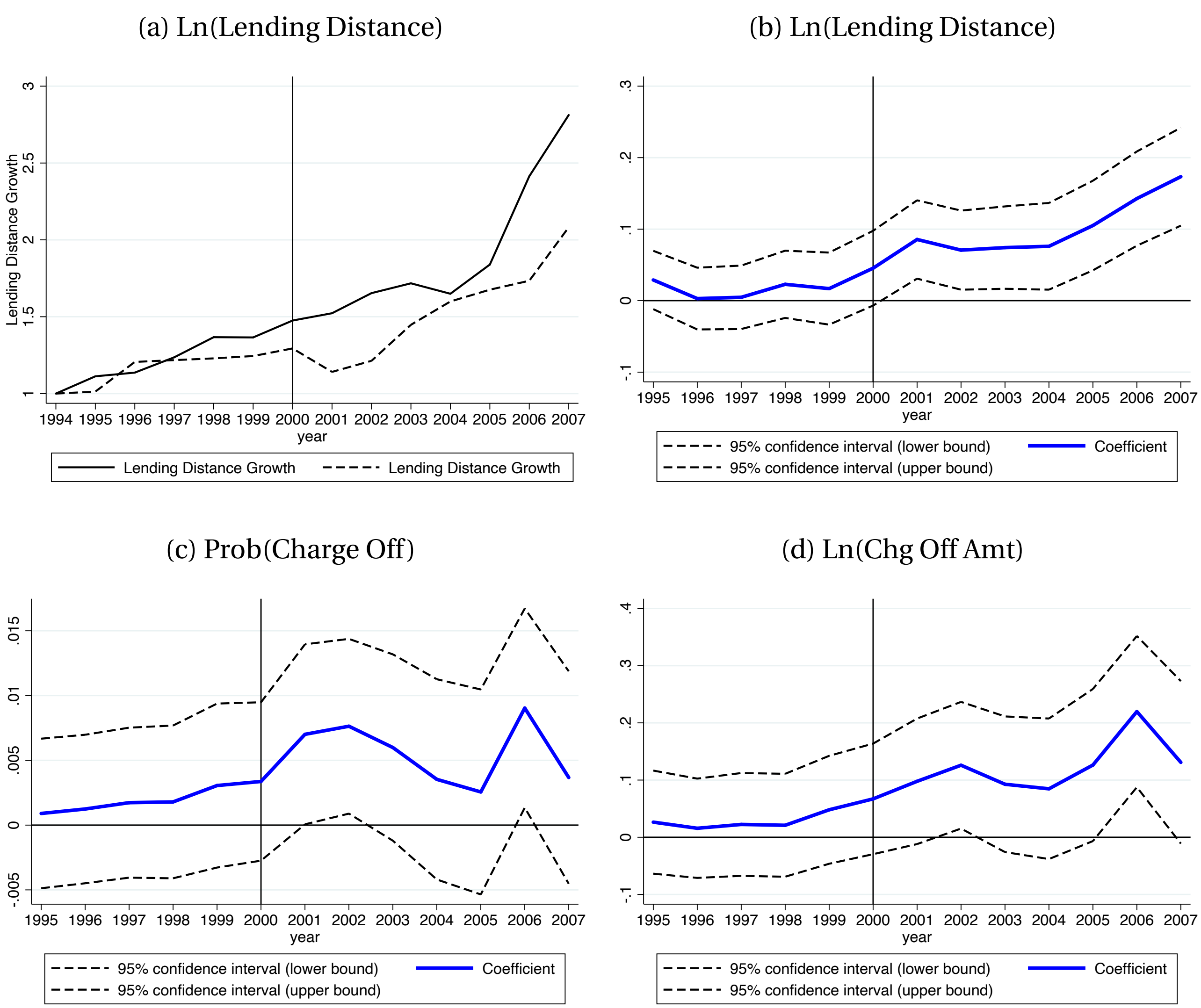


(b) Orig Growth



This figure plots the coefficients (along with 95% confidence bands) on the interaction term for the bank and county-year-level regresssion $y_{ijt} = \alpha_i + \gamma_{jt} + \beta_1 Treat_{it} xyear_t + X_{it}\beta_2 + \epsilon_{ijt}$ using HMDA data. The dependent variables in panels (a), and (b) are the log of mortgage-originations, and mortgage-origination growth, respectively.

Figure 6.8: Bank risk measures: Dynamic Effects



Panel (a) plots the average SBA loan (log) lending distance for more exposed and less exposed banks. Panels (b)-(d) plots the coefficients (along with 95% confidence bands) on the interaction term for the bank-county-year level regresssion $y_{ijt} = \alpha_i + \gamma_{jt} + \beta_1 Treat_{it} xyear_t + X_{it}\beta_2 + \epsilon_{ijt}$ using SBA data. The dependent variables in panels (b), (c), and (b) are the log of lending distance, probability of loan getting charged-off, and log of charged-off amount, respectively.

CHAPTER 7

TABLES

Table 7.1: Descriptive Statistics

Panel A: County - Year Level

Time Period (1994-1999)	count	mean	sd	p1	p25	p50	p75	p99
Δ Deposits	3082	0.195	0.165	-0.184	0.095	0.178	0.272	0.812
Δ US Import China	3092	1.248	1.574	0.004	0.402	0.814	1.480	7.028
Δ Oth Dev Import	3092	1.062	0.996	0.000	0.440	0.767	1.392	4.447
Observations	3092							

Time Period (2000-2007)	count	mean	sd	p1	p25	p50	p75	p99
Δ Deposits	3083	0.299	0.208	-0.204	0.161	0.272	0.405	0.932
Δ US Import China	3092	2.816	2.755	0.015	1.209	2.185	3.569	13.338
Δ Oth Dev Import	3092	2.690	2.268	0.000	1.202	2.389	3.541	10.352
Observations	3092							

Panel B: Bank - Year Level (Amount in $ Millions)

	count	mean	sd	p1	p25	p50	p75	p99
Assets	106,533	546	8,756	8.23	40.3	80.9	176	6,380
Deposits	106,533	321	3,378	5.6	34.1	68	146	4,207
Loans	106,533	338	5,064	2.56	22.1	48.1	112	4,081
RE Loans	106,533	165	2,077	0	10.8	28.6	73.7	1,866
C&I Loans	106,533	75.8	1,375	0	2.49	6.59	17.5	767
Net Int. Income	106,531	4.95	74.3	.066	.397	.799	1.75	61.5
Qly Avg MBS	47,697	58.7	1,073	0	.014	2.44	11.6	596
Dep Rate %	106,462	.834	.312	.171	.622	.851	1.03	2.01
Observations	106,533							

Descriptive Statistics (continued)

Panel C: Bank Exposure Measure

	count	mean	sd	p1	p25	p50	p75	p99
Bank Exposure	22,687	0.296	0.424	0.000	0.000	0.000	0.800	1.000
Bank Exposure depwt	22,618	0.297	0.434	0.000	0.000	0.000	0.885	1.000
Observations	22,687							

Panel D: SBL data

	count	mean	sd	p1	p25	p50	p75	p99
Ln Orig	809,184	.813	.398	.693	.693	.693	.693	2.77
$\Delta Orig\{t-1,t\}$	758,610	-.00134	.265	-1.1	0	0	0	1.01
Exposed bank dummy	809,184	.42	.494	0	0	0	1	1
Less Exp Counties	809,184	.479	.5	0	0	0	1	1
Community bank dummy	809,184	.611	.488	0	0	1	1	1
Observations	809,184							
No. of Banks	4105							
No. of Counties	3216							

Panel E: HMDA data

	count	mean	sd	p1	p25	p50	p75	p99
Ln Orig	1,972,384	.418	1.08	0	0	0	0	5.27
$\Delta Orig\{t-1,t\}$	1,849,110	-.0176	.572	-2.71	0	0	0	2.15
Exposed bank dummy	1,972,384	.356	.479	0	0	0	1	1
Less Exp Counties	1,972,384	.477	.499	0	0	0	1	1
Community bank dummy	1,972,384	.585	.493	0	0	1	1	1
Observations	1,972,384							
No. of Banks	5115							
No. of Counties	3110							

This table plots summary statistics for different merged datasets used in this paper. Panel (a) shows cross-county-level changes in import intensity and deposits for the two separate time periods. Panel (b) shows key bank-level variables using Call Report data. Panel (c) shows the cross-sectional distribution of bank exposure measures. Panels (d) and (e) display summary statistics at the bank-county-year level for SBL and HMDA merged datasets, respectively.

Table 7.2: Imports from China and Change in Bank Deposits in counties, 1994–2007: 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)
			Δ Deposits		
Δ Import China	-0.0333***	-0.0273***	-0.0187***	-0.0192***	-0.0186***
	(0.010)	(0.007)	(0.005)	(0.005)	(0.005)
I$\{2000-2007\}$	0.2129***	0.2016***	0.1511***	0.2046***	0.2084***
	(0.025)	(0.022)	(0.030)	(0.023)	(0.034)
% College Educated -1			0.0026**		-0.0005
			(0.001)		(0.001)
% Foreign Born -1			0.0050***		0.0006
			(0.001)		(0.001)
% Women Employment -1			0.0012		-0.0046**
			(0.002)		(0.002)
% Emp in routine occupation -1				0.0013	0.0009
				(0.005)	(0.005)
% Offshorability Index -1				0.1204***	0.1434***
				(0.028)	(0.024)
Census division dummies	✗	✗	✓	✓	✓
Observations	6165	6165	6165	6165	6165
R^2	0.129	0.196	0.251	0.263	0.272
Adjusted R^2	0.128	0.195	0.249	0.261	0.270
F					
Standard errors clustered at state-level					

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents regression results for the instrumental-variable regression of changes in deposits on changes in Chinese import intensity as in ADH. All regressions include a constant and a dummy for the 2000–2007 period. Routine occupations are defined such that they account for 1/3 of US employment in 1980. The offshorability index variable is standardized to mean of 0 and standard deviation of 10 in 1980. Robust standard errors in parentheses are clustered on state. Models are weighted by the start of the period county share of the national population.

Table 7.3: Effect of China Trade Shock on Bank Balance Sheets

Panel (a): Using Share of Branches as Bank Exposure

	(1) Δ Deposits	(2) Δ Deposits	(3) Δ Uninsured Dep	(4) Ln(Dep Rate)	(5) Δ Assets	(6) Δ Loans	(7) Δ CI Loans	(8) Δ RE Loans
Bank Exposure	-0.0057***	-0.0055**	-0.0103**	0.0434***	-0.0041**	-0.0063**	-0.0124**	-0.0098***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.002)	(0.003)	(0.006)	(0.003)
Ln(Assets)		-0.0618***	-0.2002***	0.1771***			-0.0966***	-0.0537***
		(0.004)	(0.008)	(0.005)			(0.009)	(0.006)
Int Inc./Assets		-0.0263	-0.5332	2.9602**	-0.1576	-1.0147***	-1.0151***	-1.3070***
		(0.189)	(0.583)	(1.160)	(0.105)	(0.133)	(0.179)	(0.322)
CI Loans/Assets		0.2258***	0.1940***	0.0389	0.2666***	-0.0830***	-2.0773***	0.4390***
		(0.022)	(0.041)	(0.030)	(0.016)	(0.028)	(0.063)	(0.034)
Deposits/Assets					-0.0676***	-0.0429	-0.1650***	-0.0404
					(0.019)	(0.033)	(0.059)	(0.038)
Observations	117526	97103	88809	97947	94658	44667	44646	44662
R^2	0.290	0.312	0.156	0.868	0.316	0.285	0.229	0.254
Adjusted R^2	0.214	0.238	0.059	0.854	0.241	0.168	0.102	0.131
Bank & Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Standard errors clustered at bank-level								

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel (b): Using Share of Deposits as Bank Exposure

	(1) Δ Deposits	(2) Δ Deposits	(3) Δ Uninsured Dep	(4) Ln(Dep Rate)	(5) Δ Assets	(6) Δ Loans	(7) Δ CI Loans	(8) Δ RE Loans
Bank Exposure DepShare	-0.0055***	-0.0057**	-0.0095**	0.0422***	-0.0039**	-0.0061**	-0.0126**	-0.0094***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.002)	(0.003)	(0.006)	(0.003)

Panel (c): Using Diff-in-Diff Design

	(1) Δ Deposits	(2) Δ Deposits	(3) Δ Uninsured Dep	(4) Ln(Dep Rate)	(5) Δ Assets	(6) Δ Loans	(7) Δ CI Loans	(8) Δ RE Loans
High Exposure=1 X Post=1	-0.0055***	-0.0056**	-0.0101**	0.0407***	-0.0040**	-0.0055**	-0.0123**	-0.0090***
	(0.002)	(0.002)	(0.005)	(0.004)	(0.002)	(0.003)	(0.006)	(0.003)

This table presents results for the regression of bank balance-sheet growth rates on bank exposure measures. Panel (a) uses the share of the number of branches in exposed counties as the bank exposure measure. Panel (b) uses the share of the amount of deposits in exposed counties as the bank exposure measure. In Panel (c), treat dummy is equal to 1 if bank exposure is above its cross-sectional median.

Table 7.4: Impact on Branch-level Deposit Rates

Panel (a): Different Deposit Products

	(1) All	(2) Less Affected	(3) More Affected	(4) All	(5) Less Affected	(6) More Affected
		d_06MCD10K			d_12MCD10K	
Bank Exposure	0.0032***	0.0017	0.0080***	0.0031***	0.0009	0.0068***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Observations	726518	345520	380998	726697	345423	381274
R^2	0.368	0.367	0.371	0.376	0.378	0.376
Adjusted R^2	0.358	0.356	0.360	0.366	0.367	0.365
Branch & County x Year FE	✓	✓	✓	✓	✓	✓

	(1) All	(2) Less Affected	(3) More Affected	(4) All	(5) Less Affected	(6) More Affected
		d_36MCD10K			d_60MCD10K	
Bank Exposure	0.0031***	0.0012	0.0038**	0.0033***	0.0021	0.0039**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Observations	621991	287103	334888	521652	239571	282081
R^2	0.315	0.317	0.314	0.263	0.265	0.263
Adjusted R^2	0.302	0.304	0.302	0.249	0.250	0.249
Branch & County x Year FE	✓	✓	✓	✓	✓	✓

	(1) All	(2) Less Affected	(3) More Affected	(4) All	(5) Less Affected	(6) More Affected
		d_MM2.5K			d_SAV2.5K	
Bank Exposure	0.0010*	0.0027	-0.0009	0.0013***	0.0044***	-0.0019
	(0.001)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)
Observations	673906	319491	354415	638859	303738	335116
R^2	0.196	0.198	0.194	0.190	0.194	0.188
Adjusted R^2	0.182	0.184	0.180	0.175	0.179	0.172
Branch & County x Year FE	✓	✓	✓	✓	✓	✓

Std Errors clustered at Bank and County x Year Level.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Impact on Branch-level Deposit Rates (continued)

Panel (b): Deposit Rates by Market Power

	(1)	(2)	(3)	(4)	(5)	(6)
	d_06MCD10K	d_12MCD10K	d_36MCD10K	d_60MCD10K	d_MM2.5K	d_SAV2.5K
Bank Exposure x High Conc.	-0.0022**	-0.0030***	-0.0033***	-0.0044***	0.0007	-0.0023***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bank Exposure	0.0037***	0.0038***	0.0038***	0.0043***	0.0008	0.0018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
High Conc.	0.0003	0.0003	-0.0009	-0.0013	-0.0006	0.0009
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	726483	726662	621956	521652	673871	638824
R^2	0.368	0.376	0.315	0.263	0.196	0.190
Adjusted R^2	0.358	0.366	0.302	0.249	0.182	0.175
Branch & County x Year FE	✓	✓	✓	✓	✓	✓

Standard errors in parentheses
Include Branch and County x Year Fixed Effects.
Std Errors clustered at Branch Level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents results for the regression of branch-level deposit rates on the bank exposure measures. Panel (a) uses the share of the number of branches in exposed counties as bank exposure measure. Results are presented separately for all, less affected, and more affected counties. Panel (b) presents the results accounting for the concentration of deposit markets. High conc. is a dummy equal to 1 for a county if its HHI is above its cross-sectional distribution. All regressions include branch and county x year fixed effects. Standard errors are clustered at the Branch Level.

Table 7.5: SBL Loan originations

	(1)	(2)	(3)	(4)	(5)
		Growth of SBL Loan Originations			
			Less Affected	More Affected	
High Exposure=1 X I{$year \geq 2001$}=1	-0.0145**				
	(0.006)				
Bank Exposure		-0.0621***	-0.0461***	-0.0725***	-0.0687***
		(0.013)	(0.016)	(0.012)	(0.011)
Bank Exposure X Less Exp Counties					0.0194***
					(0.006)
Less Exp Counties					-1.4093
					(813839.892)
Observations	340547	294704	149040	145624	294704
R^2	0.143	0.197	0.218	0.177	0.197
Adjusted R^2	0.022	0.071	0.094	0.042	0.071
Bank & County x Year FE	✓	✓	✓	✓	✓

Standard errors in parentheses
Include bank and county x year fixed effects.
Std Errors clustered at bank and county x year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents results for the regression of county-level SBL loan originations by each bank on bank exposure measures. Treat dummy is equal to 1 if bank exposure is above its cross-sectional median. Results are presented separately for all, less affected, and more affected counties. All regressions include bank and county x year fixed effects. Standard errors are clustered at the bank and county x year level.

Table 7.6: SBL Loan originations: By Bank size and Industry

Panel (a): Growth of SBL Loan Originations by size of banks

	Growth in Loan Originations		
	Large	Community	
Bank Exposure X Community Bank			-0.0308***
			(0.009)
Bank Exposure	-0.0371***	-0.0763***	-0.0438***
	(0.012)	(0.012)	(0.013)
Community Bank			0.0046
			(0.005)
Observations	85624	238390	335276
Adjusted R^2	0.001	0.020	0.023
Bank & County x Year FE	✓	✓	✓

Standard errors in parentheses
Std Errors clustered at bank and county x year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel (b): Growth of SBA Loan Originations by Industry Similarity

	Growth in Loan Originations			
	Low Similarity	High Similarity		
Frac. Exposed	-0.0733***	-0.0615***	-0.0626***	-0.0647***
	(0.014)	(0.015)	(0.010)	(0.012)
Frac. Exp x Low Cosine			-0.0040	
			(0.005)	
Frac. Exp x HHI				-0.0032
				(0.008)
Observations	93988	158523	252716	281795
R^2	0.234	0.144	0.169	0.203
Adjusted R^2	0.078	0.038	0.052	0.074
Bank & County x Year FE	✓	✓	✓	✓

Standard errors in parentheses
Std Errors clustered at bank and county x year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel (a) presents results for SBL loan-origination rate by large and community banks. Panel (b) presents results by industry similarity and bank HHI. Low cosine is a dummy for lower than the median distribution of counties correlation structure with affected counties. The similarity (correlation) between the multidimensional industry employment structure between two counties is calculated by the cross product of their corresponding industry-employment vectors. All regressions include bank and county x year fixed effects. Standard errors are clustered at the bank and county x year level.

Table 7.7: HMDA Mortgage Originations

	(1)	(2)	(3)
		Less Affected	
	Growth in Mortgages	Jumbo Loan Ratio	Denial Rate
Bank Exposure	-0.0743**	-0.0269**	0.1275***
	(0.030)	(0.011)	(0.044)
Observations	375508	277866	389440
R^2	0.133	0.302	0.261
Adjusted R^2	0.088	0.250	0.222
Bank & County x Year FE	✓	✓	✓

Standard errors in parentheses

Include Bank and County x Year Fixed Effects.

Std Errors clustered at Bank and County x Year Level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents results for the regression of county-level mortgage originations, jumbo loan share, and mortgage application-denial rates by each bank on bank exposure measures. Treat dummy is equal to 1 if bank exposure is above its cross-sectional median. Results are presented for less affected counties. All regressions include bank and county x year fixed effects. Standard errors are clustered at the bank and county x year level.

Table 7.8: SBA Loan Performance Outcomes

	(1) Ln(Distance)	(2) Charge Off	(3) Ln(Chg Off Amt)	(4) Δ Chg off Amt
Bank Exposure	0.0328**	0.0107***	0.1949***	0.1175***
	(0.016)	(0.002)	(0.032)	(0.020)
Observations	127189	127189	127189	113987
R^2	0.633	0.197	0.427	0.013
Adjusted R^2	0.593	0.110	0.365	-0.099
Bank & County x Year FE	✓	✓	✓	✓

	(1) Ln(Distance)	(2) Charge Off	(3) Ln(Chg Off Amt)	(4) Δ Chg off Amt
High Exposure=1 X Post=1	0.0350**	0.0106***	0.1950***	0.1127***
	(0.016)	(0.002)	(0.032)	(0.020)
Observations	127189	127189	127189	113987
R^2	0.633	0.197	0.427	0.013
Adjusted R^2	0.593	0.110	0.365	-0.099
Bank & County x Year FE	✓	✓	✓	✓

Standard errors in parentheses

Std Errors clustered at bank and county x year level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents results for the regression of county-level SBA loan performance metrics by each bank on bank exposure measures. Dependent variables in columns 1-4 are the log of lending distance, probability of default (charged-off), the log of charged-off amount, and growth in charged-off amount, respectively. Treat dummy is equal to one if bank exposure is above its cross-sectional median. All regressions include bank and county x year fixed effects. Standard errors are clustered at the bank and county x year level.

Table 7.9: Asset Channel of Shock Transmission

Panel (a): Asset Exposure Measure and Charge-Offs

	(1) Frac Chg Off	(2) Frac Chg Off Amt	(3) Frac Chg Off	(4) Frac Chg Off Amt
Bank Asset Exposure	0.0190**	0.0120**		
	(0.009)	(0.006)		
Bank Asset Exposure amt			0.0179**	0.0114**
			(0.009)	(0.006)
Observations	19334	19334	19334	19334
R^2	0.243	0.237	0.243	0.237
Adjusted R^2	0.113	0.106	0.113	0.106
Bank & County x Year FE	✓	✓	✓	✓

Panel (b): Impact of Asset Channel on Bank Balance sheet

	(1) Δ Deposits	(2) Δ Uninsured Dep	(3) Δ Dep Rate	(4) Δ Assets	(5) Δ Loans	(6) Δ CI Loans	(7) Δ RE Loans
Bank Asset Exposure	-0.0030	-0.0183	-0.0149	-0.0004	-0.0022	-0.0256*	-0.0120
	(0.007)	(0.015)	(0.014)	(0.006)	(0.007)	(0.014)	(0.008)
Ln(Assets)	-0.0621***	-0.3076***	-0.0497**			-0.1865***	-0.1628***
	(0.007)	(0.013)	(0.017)			(0.011)	(0.007)
Int Inc./Assets	0.1503***	0.1619	-0.5698	-0.0089	-0.3826**	-0.6075**	-0.4225
	(0.038)	(0.292)	(0.383)	(0.017)	(0.172)	(0.271)	(0.306)
CI Loans/Assets	0.1739***	0.1280**	-0.0342	0.2650***	-0.2121***	-3.2115***	0.5718***
	(0.034)	(0.065)	(0.060)	(0.026)	(0.033)	(0.074)	(0.042)
Deposits/Assets				-0.1592***	-0.1859***	-0.2600***	-0.2764***
				(0.026)	(0.031)	(0.051)	(0.032)
Observations	62699	59532	60223	60819	60595	59998	60187
R^2	0.392	0.205	0.498	0.378	0.363	0.292	0.359
Adjusted R^2	0.283	0.059	0.406	0.265	0.248	0.164	0.243
Bank & Year FE	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Asset Channel of Shock Transmission (continued)

Panel (c): Testing Asset Channel's Impact on Deposit Growth

	(1) **Full Sample** Dep Growth	(2) **Full Sample** Dep Growth	(3) **Full Sample** Dep Growth	(4) **Less Affected** Dep Growth	(5) **Less Affected** Dep Growth	(6) **Less Affected** Dep Growth
Bank Dep Exposure		-0.0075***	-0.0152***		0.0617***	0.0982***
		(0.001)	(0.003)		(0.007)	(0.011)
Bank Asset Exposure amt	0.0137***		0.0139***	0.0393***		0.0310***
	(0.005)		(0.005)	(0.007)		(0.010)
Dep Growth[t-1]	-0.0732***	-0.0370***	-0.0689***	-0.0652***	-0.0395***	-0.0697***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
Observations	572514	541788	406211	281202	259094	192385
R^2	0.340	0.269	0.294	0.348	0.331	0.362
Adjusted R^2	0.143	0.126	0.122	0.154	0.141	0.149
Branch & County x Year FE	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

Include Bank and County x Year Fixed Effects.

Std Errors clustered at bank and county x year level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel (a) presents results for the regression of fraction of charged-off loans by number and amount on bank asset exposure measures. Panel (b) shows the result of the regression. Panel (c) reports branch-level deposit regressions including both bank deposit exposure and bank asset exposure as independent variables. Panels (a) and (c) include bank and county x year fixed effects, and their standard errors are clustered at the bank and county x year level. Panels (b) includes bank and year fixed effects, and their standard errors are clustered at the bank level.

Table 7.10: Asset Channel of Shock Transmission: Lending Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta Orig\{t-1,t\}$							
	All		Less Affected		More Affected		All	
Asset Exposure wt	0.0316	0.1510*	0.0694*	0.2629*	-0.0038	0.1799**	-0.0003	0.1807*
	(0.023)	(0.085)	(0.040)	(0.146)	(0.029)	(0.083)	(0.021)	(0.095)
Dep Exposure		-0.1308**		-0.2294*		-0.2229**		-0.1925**
		(0.063)		(0.127)		(0.087)		(0.082)
Asset Exposure X Less Exp Counties							0.0530**	-0.0705
							(0.027)	(0.067)
Dep Exposure X Less Exp Counties								0.1178*
								(0.067)
Observations	120511	62302	60084	36917	60327	30549	120511	62302
R^2	0.317	0.428	0.349	0.163	0.293	0.406	0.317	0.428
Adjusted R^2	0.127	0.178	0.164	0.085	0.084	0.129	0.127	0.178
Branch & County x Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports branch-level small business lending regressions including both bank deposit exposure and bank asset exposure as independent variables. The specification includes bank and county x year fixed effects, and their standard errors are clustered at the bank and county x year level.

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