# Household Stock Market Participation, Local Banks, and Local Economy Development *

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**ABSTRACT**

Using the Madoff Ponzi Scheme as a natural quasi-experiment, we provide evidence of a negative correlation between financing flows in the national stock market and local credit market for small businesses. We find that, after an exogenous increase in bank deposits due to the Madoff Ponzi Scheme, counties where the victims reside have an increase in credit supply to small businesses. Moreover, our analysis further that small-bank-dominated counties exhibit a greater increase in small business credit supply following the Ponzi scheme. Our results suggest that increased credit supply to small businesses leads to improved economic outcomes, including higher levels of entrepreneurial activities, more newly created establishments, and more jobs. These findings underscore the role of local banks in absorbing capital withdrawn from the stock market by households and reallocating it to the local economy, and how households' capital reallocation affects local business development.


*All errors are our own.

# I. Introduction

In perfect financial markets, the local credit supply is expected to have no impact on the local economy and households' capital reallocations from the nationwide stock market to the local credit market is also expected to have no real effects. However, small businesses are hard to obtain funding from the capital market and rely heavily on local credit supply. Due to limited access to the deep internal capital market, deposits from local households make up a large percentage of the local credit supply. Therefore, a shift of households' wealth from the stock market to local bank deposits could impact the local small business credit market and generate real effects. Despite separate studies on investors' capital allocation and banks' deposit-taking and lending activities, little empirical evidence exists to show the relationship between financing flows from the national stock market to the local credit market. In this paper, we fill a void in the literature by examining the role of banks in absorbing households' capital withdrawn from the equity market and allocating it to the local small business credit market, and its implication on local economic development.

To examine the role of banks, we study the real economic outcome in counties exposed to different levels of capital market scandal. This empirical strategy's intuition is that the exposure to the households' stock market non-participation due to market scandals differs in different regions. High uncertainty induced by capital market scandals leads retail investors to withdraw funds from the stock market and save deposits at the branches in the local area. This portfolio reallocation of investors' money from the capital market to the local bank deposits can be considered as a positive credit supply shock. The deposit influx of retail investors affects local banks' lending activities. Small firms or startups benefit from the increasing amount of small business loans. Therefore, counties exposed to a high level of capital market scandal shall see an increase in small business loans and a change in local business patterns.

In this paper, we focus on one well-known market scandal, the Madoff Ponzi Scheme, which was uncovered in 2008. There are two benefits of using this setting. First, victims of the Madoff Ponzi Scheme are geographically concentrated. Regions with different exposures allow using difference-in-difference settings to compare the level of economic effects. Second, the size of Madoff events is enormous. The court-ordered restitution was $17 billion. Gurun, Stoffman, and Yonker (2018) find that Madoff Ponzi Scheme triggered a $363 billion outflow from the stock market. The large inflow of local deposits guarantees significant effects on the local economy.

Our proxy for the market scandal can also be viewed as a quasi-natural experiment to local credit supply. Following the oil shale boom (Gilje, 2019) and Chinese students' enrollment in the U.S. universities (Yang, 2022), we use the Madoff Ponzi Scheme, which is unrelated to county-specific characteristics, to identify an exogenous increase in the local bank deposit. This setting is particularly clean and has the following advantages: First, an essential concern in their papers is the non-credit-based interpretations. A positive credit supply shock is usually associated with positive consumer demand shocks and wealth shocks. As a result, small business loans and the business pattern are affected not only by the bank's credit supply side but also the consumer demand side. Such concern does not exist in our paper. The Madoff Ponzi Scheme was a negative shock to households' wealth and probably decreased consumer demand. The supply side story is reasonable if a local economy experiences a bad time but still has a good business pattern, such as a higher startup formation rate and job creation. In other words, the estimation of the Madoff exposure impact will only be underestimated instead of overestimated in our paper.

Second, an essential assumption for local credit supply to have real impacts on the economy is the limitation of bank internal capital markets. Gilje (2019) distinguishes the lending markets dominated by small and big banks, arguing that small banks do not benefit from the deep internal capital markets. The Madoff Ponzi scheme, uncovered in December 2008, coincided with the 2008 financial crisis. During this nationwide crisis, it is hard for banks to raise money from internal capital markets due to the lack of liquidity. Therefore, the condition for real impacts naturally exists for the Madoff Ponzi Scheme.

Using a sample with 3,203 U.S. counties over the period 2006–2011 and the difference-in-differences regressions, we find a positive and significant association between the Ponzi Scheme exposure and bank deposits as well as small business lending. Specifically, having at least one Madoff victim is associated with a 3.3% increase in local bank deposits, which implies approximately $80 million increase in the bank deposits. Increasing one victim in the affected area is associated with 1.6% increase in local bank deposits. Correspondingly, having at least one Madoff victim is associated with a 3.8% increase in small business loans, which implies approximately $3 million increase in the small business loans. Increasing one victim in the affected area is associated with 1.5% increase in the small business loans. Besides, for small business loans, the previous effects are more prominent in small-bank-dominated areas. This result is align with Gilje (2019), as small banks heavily rely on local funding.

In terms of the real effects, we find that increasing one victim in the affected area is associated with a 2.8% increase in new business registration and does not have an impact on entrepreneurial quality. Furthermore, increasing one victim in the affected area increases firm establishment by 0.5%, especially small firms with employee sizes less than 20. Finally, increasing one victim in the affected area increases start-up firms' job creation by 0.2%. In all, an influx of local deposit increases small business loan and have real effects on small firms or start-up firms.

We conclude that the investors' reallocation from the national capital market to the local credit market plays a significant role in enhancing local small business development. This real effect exists when local banks have limited access to internal capital markets, which is embedded naturally in our empirical design. Banks' response to the deposit influx of retail investors by increasing small business loans is the key channel for our results.

To the best of our knowledge, this paper is one of the first to identify the real effects of households' portfolio reallocation on the real economy. We highlight the substation effects between the local small business investment through bank and the nationwide big firm investment through the capital market. Prior papers study the local lending and households' portfolio reallocation separately. For example, Gurun et al. (2018) show that, following the Madoff Ponzi Scheme as a trust shock, residents who lived in the exposed area withdrew assets from the investment advisor. They focus on the impact of trust on the financial intermediation industry and trust shock transmission through the social network. Using shale discoveries as a shock to the local credit supply, Gilje (2019) find that local deposits are positively associated with local lending, and this positive effect is more pronounced for areas dominated by small banks. Yang (2022) examines how banks' lending activities change facing increased deposit that contains private information. In our paper, we find the funding outflow by households from the national capital market is negatively correlated with the funding inflow of the local credit market. Local banks have a positive effect on local economy development via two channels: (1) they absorb the households' capital withdrawn from the stock market; and (2) they allocate the deposits from the local households to the small businesses in the local economy. Overall, we identify a real effect of the households' capital re-allocation on local economy.

The rest of the paper is organized as follows. We provide an overview of the literature and develop the hypothesis in section II. Section III discusses the sample formation. We present the main results in Section IV. Section VI concludes the paper.

## II. Literature Review

Our paper is closely related to the growing literature on the role of the local access to finance and determinants of economic growth. Prior work has identified a number of financing forms to explain the local economic growth. Ashcraft (2005) and Butler, Fauver, and Spyridopoulos (2019) show that agricultural firms operating in counties with high levels of bank deposits are associated with a larger shift in the corn productivity in response to the ethanol-induced high demand for the corn. Samila and Sorenson (2011) find that Metropolitan Statistical Areas (MSAs) with venture capital financing are associated with a higher formation of new firms, employment, and aggregate income. On the other side, shocks to the credit supply affect the real economy. Earlier literature studies how the shock to the bank affects its depositors or borrowers (Ashcraft, 2005; Chava and Purnanandam, 2011) or the income growth (Jayaratne and Morgan, 2000) and how the bank crisis affected the real estate markets (Peek and Rosengren, 2000). Recently, literature has focused on the shock to credit supply on local small businesses. In Gilje (2019), the shale boom increases local credit supply and has significant real effects on the lending markets. This effect is more prevalent in markets with more small-bank market share. Industries that rely on external financing have more establishments. In Greenstone, Mas, and Nguyen (2020), counties with negative predicted lending shocks experienced declines in small business loan originations. However, they found that the change in small business loans has an economically insignificant impact on employment growth and establishment growth rates. In this paper, we consider the investors' portfolio reallocation from the risky capital market to the local credit market as the source of the local credit supply. Therefore, this behavior of households could have a significant impact on local small business development.

Second, our paper contributes to the existing literature on banks' deposit-taking and lending activities. The funding sources of the small business loans are inclusive. On the one hand, banks' internal capital markets are an important source for funding bank loans. Houston, James, and Marcus (1997) find that loan growth at subsidiary banks is more sensitive to the holding company's cash flow than its own. Campello (2002) and Gilje, Loutskina, and Strahan (2016) examine the advantage of internal financing for big banks. Small banks have more limitations on internal finance and rely on external finance channels such as deposits (Gilje, 2019). Therefore, banks with small or large sizes behave differently in lending when facing shocks. Bord, Ivashina, and Taliaferro (2021) show that facing the 2007 real estate price collapse, small banks with a large credit supply decreased their credit to small firms. On the other side, regional and local banks are less affected.

On the other hand, loans to small businesses are based heavily on soft information, which can be obtained by deposit-taking behavior. Loan officers have access to soft information (Petersen and Rajan, 2002; Degryse and Ongena, 2005; Agarwal and Hauswald, 2010). In Levine, Lin, Peng, and Xie (2020), the new airline routes decrease the communication cost within banks. Since small business loan requires more soft information, the enhanced efficiency in communication boosts the credit supply in small business loan. In (Yang, 2022), an increase in local bank deposit inflow conveys private information. Bank obtained the information and increased the small business loans. Also, Adams, Brevoort, and Driscoll (2021) shows that the lending distance in the past twenty years doesn't change for individual banks. This suggests that small businesses continue to depend on local banks. An increase in local credit supply will probably affect local banks and increase small business loans. In our paper, given the 2008 financial crisis, banks' internal capital market has less liquidity. Banks rely heavily on the local deposit market. Therefore, banks tend to increase small business loans as the local deposit contains information about lending. This is the key channel for our main results.

Third, our paper also relates to investors' reallocation behavior after experiencing shocks in capital markets. Prior literature shows that investors withdraw investment or decrease stock market participation after market scandals or a decline in trust (Kostovetsky, 2015; Giannetti and Wang, 2016). According to Gurun et al. (2018), Madoff Ponzi Scheme destroyed the residents of communities' trust in the national capital market. Consequently, Madoff Ponzi Scheme triggered a $363 billion outflow from the stock market. At least 27% of the funds flow to the local deposits. Our paper focus on the real effects of portfolio reallocation behavior.

Lastly, Our paper also contributes to a growing literature highlighting the effects of lifetime macroeconomic experiences on economic behavior. Notably, Malmendier and Nagel (2011) show that lifetime experiences of stock market returns and inflation affect households' decisions to hold stocks and other financial assets. Giannetti and Wang (2016) show the negative effect of corporate scandals on households' demand for equity. We highlight the role of bank deposits as the channel through which households reallocate their capital from the equity market to the local economy following the capital market scandals.

# III. Sample Formation and Overview

## *A. Sample formation*

**Madoff Ponzi Scheme data** We follow Gurun et al. (2018) and collect Madoff Ponzi Scheme victims data from the court documents released by the U.S. federal bankruptcy court in February 2009 [1].The list contains 13,722 consumers of the Bernard L. Madoff Investment Securities (BMIS). BMIS was established by Bernard Madoff and perpetrated fraud until it was uncovered in December 2008. We identify one unique victim to be the one with a unique name and address combination. International investors are excluded from the original data set. After cleaning the data, we have 10,970 victims, which is similar to the 10,276 victims in Gurun et al. (2018). The Madoff Ponzi Scheme targeted at wealthy people. Many victims are concentrated in the certain areas. As shown in figure 1, victims are mainly from the East coast and Southwest coast of the country.

**CRA small business loans and bank branch data.** We collect annual data on small business lending from the CRA data set provided by the Federal Financial Institutions Examination Council (FFIEC). All banking institutions that are regulated by the Office of the Comptroller of the Currency (OCC), the Federal Reserve System, or the Federal Deposit Insurance Corporation (FDIC) and that meet asset size thresholds established annually by the FFIEC must report information on small business loans. The CRA classifies small business loans as commercial or industrial loans (or loans secured by nonfarm, nonresidential real estate) with an original loan amount that is less than or equal to $1 million. Under the CRA, each filing institution reports small business loans at the county level, so that we have small business lending at the bank-county-year level. Specifically, the CRA contains information on the aggregate number and dollar value of small business loans that a bank makes in a county. The CRA reports these loans in size categories. In our study, we

[1] Available at http://www.scribd.com/doc/11705845/Bernie-Madoff-s-Clients-The-List.

distinguish between small business loans of $100,000 or less and those with original loan amounts that are greater than $100,000 and less than or equal to $1 million. For each county in each year, we compute loan amount, which equals the log of one plus the total dollar amount (in thousands) of small business loans originated by all banks in each county. Our initial sample comprises the universe of county-year data recorded in the CRA data set over the period from 2006 through 2011. Our sample starts in 2006 following Gurun et al. (2018).

**The Summary of Deposits data.** The Summary of Deposits (SOD) provides branch-level data on deposits and the geographic locations of the headquarters and branches of all FDIC-insured depository institutions on an annual basis. Since firms, especially small firms, tend to borrow from geographically close bank branches, we assume that a bank's CRA small business loans in a county are linked to the bank's branch(es) in that county (Petersen and Rajan, 2002; Berger, Miller, Petersen, Rajan, and Stein, 2005; Agarwal and Hauswald, 2010; Berger, Bouwman, and Kim, 2017; Nguyen, 2019).

**Entrepreneurial entry and quality data** Guzman and Stern (2015, 2020) combine the comprehensive business registration data with predictive analytics to compute estimates of entrepreneurial "quality" over time—which measures the predicted probability that a new business launched in a location and time period will have a high growth outcome—computed at the county-quarter level. For our purpose of analysis, we aggregate it to the county-year level by taking the average.

**Firm establishment data** We obtain firm establishment data from the County Business Patterns survey, which is conducted by the US Census Bureau.[1]

**Job creation data** Job creation data first comes from the U.S. Census Quarterly Workforce Indicators (QWI) dataset. We obtained the total employment in each county for a given year. Firms are categorized by different ages – startups (0-1 year-olds), 2-3 year-olds, 4-5 year-olds, and firms 6 years old or older. Then, we follow the definition in Adelino, Ma, and Robinson (2017) and calculate the net job creation and then scale with the total employment as of 2010.

[1]See Gilje (2019) for an example using this data to explore the real effects of a local supply shock.

Table 1 lists the steps taken to form our sample comprising 19,191 county-year observations representing 3,203 unique counties.

### *B. Sample overview*

Table 2 provides the summary statistics for our sample. All continuous variables are winsorized at the $1^{st}$ and $99^{th}$ percentiles, and the dollar values are in 2008 dollars.

We show that the sample mean/median deposits is 2,275 (363) million, with the mean/median small business loans at 77 (11) million. Our key variable of interest is natural logarithm of the number of Madoff victims in a county, *Madoff Exposure*. The mean/median is 0.169 (0). About 1% of county-year observations in our sample have at least one Ponzi Scheme victim and the average number of victims in each county is 3. The summary statistics for most other control variables are consistent with those in prior work (Gurun et al., 2018; Yang, 2022).

Panel B of Table 2 provides the Pearson correlation matrix. We show that there is a positive association between *Madoff exposure*/*Madoff exposure dummy* and local bank deposits, and a positive association between the log of one plus total number of victims (*Madoff exposure*) and four different measures of county-level small business loans. Examination of the correlation matrix suggests that multicollinearity is unlikely an issue. Given that omitted variable bias in univariate correlations can mask the true relations between the variables, we next employ multiple regressions to examine the factors associated with local small business loans.

## IV. Main Results

### *A. Madoff fraud and local bank deposit*

Our empirical tests are based on the hypothesis that areas with higher exposure will experience greater effects of the trust shock and larger changes in aggregate investment behavior (Gurun et al. 2018). To validate this hypothesis, we employ the following difference-in-differences regression specification:

$$\begin{aligned}\log(\text{Deposits})_{i,j,t} =& \alpha + \beta_1 \text{Post}_{i,t} \times \text{Madoff exposure dummy}_i/\text{Madoff exposure}_i \\ &+ \beta_2 \times \text{County characteristics}_{i,t} + \text{County FE} \\ &+ \text{Year FE/State–Year FE} \end{aligned} \tag{1}$$

All explanatory variables are at the county level and lagged by one year. $Log(Bank\ deposit)_{i,j,t}$ is the natural logarithm of the total amount of bank deposits in county $i$, state $j$, and year $t$. The key variable of interest is *Post* × *Madoff exposure dummy*$_i$ that equals one if county $i$ has at least one Madoff victim. To control for differences between counties that may be correlated with Madoff exposure, we also control for a number of county-level demographic variables interacted with the post period indicator, including median age, median income, population, and the natural log of the county's beginning bank deposit. The control variables are largely follow Gurun et al. (2018) and Barrios, Hochberg, and Yi (2020). We include county fixed effects (FEs) to control for time-invariant observables that might drive both Madoff exposure and bank deposits. We include year fixed effects to control for time trends in the local bank deposits.

Table III Panel A presents the regression results. Columns (1), (2), and (3) of Panel A present the regression results using the *Madoff exposure dummy*. We show that there is a positive and significant association between *Post* × *Madoff exposure dummy*$_i$ and counties' bank deposits. In terms of economic significance, having at least one Madoff victim is associated with a 3.356% ($e^{0.033}-1$)increase in local bank deposits, which is equivalent to $80 million ($2,275 million *3.356%) increase in the bank deposits. To show that our results are robust and broad, columns (4), (5), and (6) of Panel A present the regression results using the continuous version *Madoff exposure*.

We next examine whether the *Madoff exposure* is associated with the counties' small business loans. To test our main hypothesis, we use the following difference-in-differences regression:

$$\begin{aligned}\log(\text{SBL})_{i,j,t} =& \alpha + \beta_1 \text{Post}_{i,t} \times \text{Madoff exposure dummy}_i/\text{Madoff exposure}_i \\ &+ \beta_2 \times \text{County characteristics}_{i,t} + \text{County FE} \\ &+ \text{Year FE/State–Year FE} \end{aligned} \tag{2}$$

where the dependent variable is the natural log of the total amount of the small business loans in county $i$, state $j$, and year $t$. The control variables and fixed effects of Equation (2) are the same as those of Equation (1) Table III Panel B presents the regression results. Columns (1) and (2) of Panel B present the regression results using the *Madoff exposure dummy*. We show that there is a positive and significant association between $Post_{i,t} \times$ *Madoff exposure dummy*$_i$ and counties' small business loans. In terms of economic significance, having at least one Madoff victim is associated with a 3.873% ($e^{0.038} - 1$)increase in small business loans, which is equivalent to about $3 million ($76 million *3.873%) increase in the small business loans. To show that our results are robust and broad, columns (4), (5), and (6) of Panel A present the regression results using the continuous *Madoff exposure*.

Above all, after households decrease their holdings in the stock market in a county, around 3.75% ($3 million/$80 million) of the capital flows from the stock market to the local economy through the bank deposits channel.

### *B. The parallel trends*

Our baseline identification relies on a difference-in-differences design with granular fixed effects that absorb the state-year level confounders. However, there could be remaining identification concerns. This section discusses these concerns and how we address them.

The validity of difference-in-differences tests depends on the parallel trends assumption: Absent the Madoff Ponzi Scheme, treated counties' bank deposits and small business loans would have evolved in the same way as those of control counties. To provide evidence for this assumption, we re-estimate the baseline specification in Equation (1) by replacing the indicator *Post* with the indicators *2 year before*, *1 year before*, *1 year after*, *2 year after*, and *3 year after*. These five indicators flag the years relative to the year of the Madoff Ponzi Scheme. For example, *2 year before* indicates year 2006 and *1 year after* indicates year 2009. Other indicator variables are defined similarly. The coefficients on *2 year before* and *1 year before* are especially important because their significance and magnitude indicate whether there is any difference in the bank deposits and small business loans prior to the Madoff Ponzi Scheme. Figure 2 and Table IV present the results.

We find that the treated group and the control group share a similar trend in the bank deposits and small business loans prior to the Madoff Ponzi Scheme, thus supporting the parallel trends assumption necessary for the difference-in-differences test. Moreover, the absence of significant lead effects indicates that the Madoff Ponzi Scheme is unlikely to be anticipated by the treated counties. Importantly, the effect of households' stock market non-participation on bank deposits and small business loans occurs after the Madoff Ponzi Scheme, suggesting a causal effect.

### *C. Decomposing the small business loans*

As shown in Table V, the capital withdrawn by households from the stock market following the Madoff Ponzi Scheme leads to a sharp increase in small business lending in the middle loan-size category (i.e., greater than \$100,000 and less than \$250,000). We do not observe such effects for smaller or larger loans. As shown in Columns 3–4, $Post_{i,t} \times Madoff\ exposure\ dummy_i$ enters positively and significantly at the 1% level in the regressions. In contrast, when examining the smaller or larger loan-size category in Columns 1–2 and 5–6, $Post_{i,t} \times Madoff\ exposure\ dummy_i$ enters insignificantly and with an economically small coefficient estimate. Since loan size is positively related to the size of the borrowing firm, and lending to smaller firms requires greater reliance on soft information, these different findings across the loan-size categories offer support for the view that the increase in bank deposits due to households' decreased equity holdings facilitates the small business lending in the mid-size firms, which require less soft information compared with small firms and more financing sources compare with large firms.

### *D. Effects of bank size and Madoff exposure on credit supply*

To explore how the local bank size affects banks' credit supply behavior, we conduct a difference-in-difference-in-difference approach. Our hypothesis is that small banks, compared to large banks, are closer to the local market and heavily rely on local deposits. With the Madoff Ponzi scheme, small banks are experiencing a positive credit supply shock. To manage the risk, they will increase small business loan supply to the local market. We conduct the following regression:

$$
\begin{aligned}
\log(\text{SBL})_{i,j,t} =& \beta_1 \text{Post}_{i,t} \times \text{Madoff exposure dummy}_i \times \text{Small bank dominated}_i \\
&+ \beta_2 \text{Post}_{i,t} \times \text{Small bank dominated}_i + \beta_3 \text{Post}_{i,t} \times \text{Madoff exposure dummy}_i \\
&+ \beta_4 \text{Madoff exposure dummy}_i \times \text{Small bank dominated}_i \\
&+ \beta_5 \text{Post}_{i,t} + \times \beta_6 \text{Madoff exposure dummy}_i + \times \beta_7 \text{Small bank dominated}_i \\
&+ \beta_8 \times \text{County characteristics}_{i,t} + \text{State-Year FE} \\
&/(+\text{Year FE} + \text{State FE}) + \alpha
\end{aligned} \tag{2}
$$

Small bank dominated$_i$ is a dummy variable and equals one if the small banks' market share is above the median in 2008 in this county. Small bank is defined to be a bank with total assets smaller than 2 billion.

Table VI presents the results. Counties affected by Madoff Ponzi scheme and dominated by small banks are able to provide more small business loans to the local market.

## V. Local economy outcome

### *A. Entrepreneurial activities*

In this subsection, we explore two questions: (1) Does newly increased small business loans lend to newly registered business?; and (2) Does the new small business loans have compositional effects on the type of business launched?

To explore the first question, we use the number of new business registrations in a county in a given year as the outcome variable. Table VII Panel A presents the results. Counties with at least one Madoff victim experienced 3.4% higher new business registration compared to unaffected counties. An increase of one victim in the exposed counties will increase the new business registration growth rate by 2.8%.

To explore the second question, we use the Entrepreneurial Quality Index (EQI), which measures the predicted probability that a new business launched in a location and time period will have a high growth outcome. In Table VII Panel B, we estimate our models using EQI as the outcome variable. As can be seen from the models in the table, we observe no significant change in EQI in the treated cities post the Madoff Ponzi Scheme, suggesting that the composition of types of entrepreneurs in a city is not significantly altered by the newly available capital withdrew by the households from the stock market.

### *B. Decomposing establishments and the job creation*

The third outcome we explore is that given local banks allocate more credit for the small businesses, counties with high Madoff Ponzi Scheme exposure might have more newly created establishments and more newly created jobs by new firms.

To capture the newly created establishments, we get firm establishment data from the County Business Patterns survey by the U.S. Census Bureau. We employ an aggregate measure and nine sub-category measures based on the number of employees in an establishment.

Table VIII presents the regression results. The dependent variable is the natural log of firm establishments in a given county. For the sub-categories, we use the number of establishments with the size of employees ranging from 1 to 4, from 5 to 9, from 10 to 19, from 20 to 49, from 50-99, from 100 to 249, from 250 to 499, from 500 to 999, and more than 1,000.

Across the ten different measures of the number of firm establishments, we find the significant results in columns (1)–(4). The findings show that, on average, counties with a high exposure to the Madoff scheme only create more small establishments. The results are consistent with our findings in Table VII Panel A.

To capture job creation, we get data from the U.S. Census Quarterly Workforce Indicators (QWI) dataset. We use an aggregate measure and nine sub-category measures based on the number of employees in an establishment.

Table VIII presents the regression results. The dependent variable is the natural log of total employment in a given county. For the sub-categories, we use the log of employment from firms with ages ranging from 0 to 1, from 2 to 3, from 4 to 5, and higher than 6.

Across the five different measures of job creation, we find significant results in columns (1)–(2). The findings show that, on average, counties with high exposure to the Madoff scheme only create more jobs for start-ups. The results are also consistent with our findings in table VII Panel A and TableVIII.

In summary, we conclude that there are three potential outcomes: counties with more fund outflow from the capital markets by households tend to have more small business loans, a higher level of entrepreneurial activities, more newly created establishments, and more newly created jobs.

## VI. Conclusions

In perfect financial markets, households' capital allocations between the nationwide stock market and local credit market have no real effects on the local economy. However, there is evidence suggesting that small firms tend to borrow from geographically close bank branches. Relatedly, local banks have a comparative advantage in lending to small businesses, thus providing more credit to the local small businesses (Levine et al., 2020). We hypothesize that the presence of local banks have implication for the capital allocation between the national capital market and the local economy.

Using a sample of 19,191 county-year observations over 2006–2011 and a difference-in-differences identification, we show that there is a positive and significant association between the decrease in the households' equity holdings caused by the Madoff Ponzi Scheme and the small business lending by local banks. Additional analyses using the dynamic effects and the parallel trend test suggest that the effect of the households' stock market non-participation and the local small business lending is likely to be the cause. Besides, the increase in small business loans is more prominent in small-bank-dominated areas.

We further show that the counties where households transfer the capital from the stock market to the local banks are more associated with more new business registrations with the same composition of types of entrepreneurs. Small firms and start-up firms benefit from the increased local credit supply.

We conclude that better access to local banks increases the capital flow from the stock market to the local economy, leading to improvement in the local small businesses and entrepreneurial entry. Our findings provide evidence of a negatively correlated financing flow in the national stock market and the local credit market.

# Appendix

All continuous variables are winsorized at the 1 st and 99 th percentiles. All values are reported in 2008 constant dollars.

| Variable | Definition |
|---|---|
| Number of Madoff victims | The number of Madoff Ponzi scheme victims in a given county. |
| Madoff exposure | The natural log of the number of Madoff Ponzi scheme victims in a given county. |
| Madoff exposure dummy | An indicator variable that takes the value of one if there is at least one Madoff Ponzi Scheme victim in a given county. |
| Deposits | The total amount (in thousands) of deposits held by all banks in a given county. |
| Log(Deposits) | The natural log of the total amount of deposits held by all banks in a given county. |
| Total SBL | The total amount (in thousands) of small business loans originated by all banks in a given county. |
| Log(Total SBL) | The natural log of the total amount of small business loans originated by all banks in a given county. |
| SBL <$100K | The total amount (in thousands) of small business loans with an original loan amount of less than $100,000 originated by all banks in a given county. |
| Log(SBL <$100K) | The natural log of the total amount of small business loans with an original loan amount of less than $100,000 originated by all banks in a given county. |
| SBL [$100K, $250K) | The total amount (in thousands) of small business loans with an original loan amount greater than or equal to $100,000 and less than $250,000 originated by all banks in a given county. |
| Log(SBL [$100K, $250K)) | The natural log of the total amount of small business loans with an original loan amount greater than or equal to $100,000 and less than $250,000 originated by all banks in a given county. |
| SBL [$250K, $1million) | The total amount (in thousands) of small business loans with an original loan amount greater than or equal to $250,000 and less than $1 million originated by all banks in a given county. |
| Log(SBL [$250K, $1 million)) | The natural log of the total amount of small business loans with an original loan amount greater than or equal to $250,000 and less than $ 1 million originated by all banks in a given county. |
| Median age | The average age in a given state. |
| Beginning deposits | The beginning deposits (measured in 2005) by all branches in a given county. |
| Log(Beginning deposits) | The natural log of the beginning deposits (measured in 2005) by all branches in a given county. |
| Median income | The average median income in a given state. |
| Log(Median income) | The natural log of the average state-level median income |
| Total population | The total population in a given county. |

| | |
|---|---|
| Log(Total population) | The log of the total population in a given county. |
| New Business Registration | The number of new business registrations in a given county. |
| Log(1+New Business Registration) | The natural log of one plus the number of new business registrations in a given county. |
| Entrepreneurial quality index | The average of all firms' quality in a given county. Firm's quality is defined to be the conditional probability of the growth outcome within a specified population of start-ups. We follow the same definition in Guzman and Stern (2020). |
| Total number of firm establishments in county | The number of establishments in a county in a given year. Data is obtained from the County Business Patterns survey by the Census Bureau (CBP). |
| Log(1+Total number of firm establishments in county) | The natural log of one plus the number of establishments in a county. |
| Number of establishments: 1-4 employee size | The number of establishments, with the size of employees ranging from 1 to 4, in a given county. |
| Log(1+ Number of establishments: 1-4 employee size) | The natural log of one plus the number of establishments, with the size of employees ranging from 1 to 4, in a given county. |
| Number of establishments: 5-9 employee size | The number of establishments, with the size of employees ranging from 5 to 9, in a given county. |
| Log(1+ Number of establishments: 5-9 employee size) | The natural log of one plus the number of establishments, with the size of employees ranging from 5 to 9, in a given county. |
| Number of establishments: 10-19 employee size | The number of establishments, with the size of employees ranging from 10 to 19, in a given county. |
| Log(1+ Number of establishments: 10-19 employee size) | The natural log of one plus the number of establishments, with the size of employees ranging from 10 to 19, in a given county. |
| Number of establishments: 20-49 employee size | The number of establishments, with the size of employees ranging from 20 to 49, in a given county. |
| Log(1+ Number of establishments: 20-49 employee size) | The natural log of one plus the number of establishments, with the size of employees ranging from 20 to 49, in a given county. |
| Number of establishments: 50-99 employee size | The number of establishments, with the size of employees ranging from 50 to 99, in a given county. |
| Log(1+ Number of establishments: 50-99 employee size) | The natural log of one plus the number of establishments, with the size of employees ranging from 50 to 99, in a given county. |
| Number of establishments: 100-249 employee size | The number of establishments, with the size of employees ranging from 100 to 249, in a given county. |
| Log(1+ Number of establishments: 100-249 employee size) | The natural log of one plus the number of establishments, with the size of employees ranging from 100 to 249, in a given county. |
| Number of establishments: 250-499 employee size | The number of establishments, with the size of employees ranging from 250 to 499, in a given county. |

| | |
|---|---|
| Log(1+ Number of establishments: 250-499 employee size) | The natural log of one plus the number of establishments, with the size of employees ranging from 250 to 499, in a given county. |
| Number of establishments: 500-999 employee size | The number of establishments, with the size of employees ranging from 500 to 999, in a given county. |
| Log(1+ Number of establishments: 500-999 employee size) | The natural log of one plus the number of establishments, with the size of employees ranging from 500 to 999, in a given county. |
| Number of establishments: 1000 or more employee size | The number of establishments, with the size of employees equal to or higher than 1000, in a given county. |
| Log(1+ Number of establishments: 1000 or more employee size) | The natural log of one plus the number of establishments, with the size of employees equal to or higher than 1000,in a given county. |
| Total job creation | Total job creation in a given county.<br>First, total employment data is collected from<br>the U.S. Census Quarterly Workforce Indicators (QWI) dataset.<br>Then, net job creation is calculated by minus the total job creation two years ago.<br>Finally, total job creation is defined by net job creation scaled with total employment in 2010.<br>Similar definition can be found in Adelino et al. (2017). |
| Job creation: firm age 0-1 year | Job creation for firms with age 0-1 year in a county in a given year.<br>First, total employment data is collected from QWI dataset.<br>Then, net job creation is equal to the total employment data<br>for firms with age 0-1 year for a given year.<br>Finally, job creation is defined by net job creation scaled with total employment in 2010.<br>Similar definition can be found in Adelino et al. (2017). |
| Job creation: firm age 2-3 years | Job creation for firms with age 2-3 years in a county in a given year.<br>First, total employment data is collected from QWI dataset.<br>Then, net job creation is equal to the total employment data<br>for firms with age 2-3 for the given year<br>minus the to the total employment data for firms with age 0-1 two years ago.<br>Finally, job creation is defined by net job creation scaled with total employment in 2010.<br>Similar definition can be found in Adelino et al. (2017). |

| | |
|---|---|
| Job creation: firm age 4-5 years | Job creation for firms with age 4-5 years in a county in a given year.<br>First, total employment data is collected from QWI dataset.<br>Then, net job creation is equal to the total employment data<br>for firms with age 4-5 for the given year<br>minus the to the total employment data for firms with age 2-3 two years ago.<br>Finally, job creation is defined by net job creation scaled with total employment in 2010.<br>Similar definition can be found in Adelino et al. (2017). |
| Job creation: firm age 6 or more years | Job creation for firms with age 6 or more years in a county in a given year.<br>First, total employment data is collected from QWI dataset.<br>Then, net job creation is equal to the total employment data<br>for firms with age larger than 5 for the given year<br>minus the to the total employment data for firms with age larger than 3 two years ago.<br>Finally, job creation is defined by net job creation scaled with total employment in 2010.<br>Similar definition can be found in Adelino et al. (2017). |

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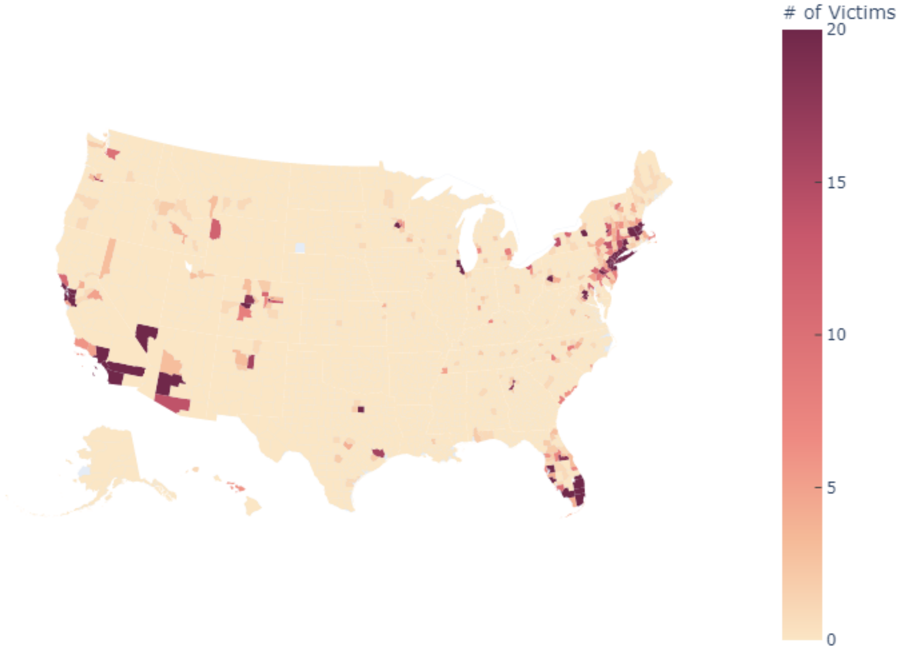
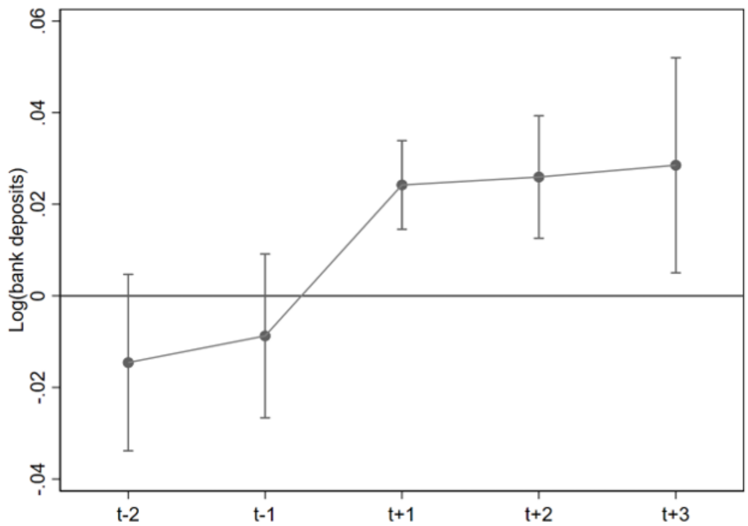
**Figure 1.** Distribution of Madoff exposure

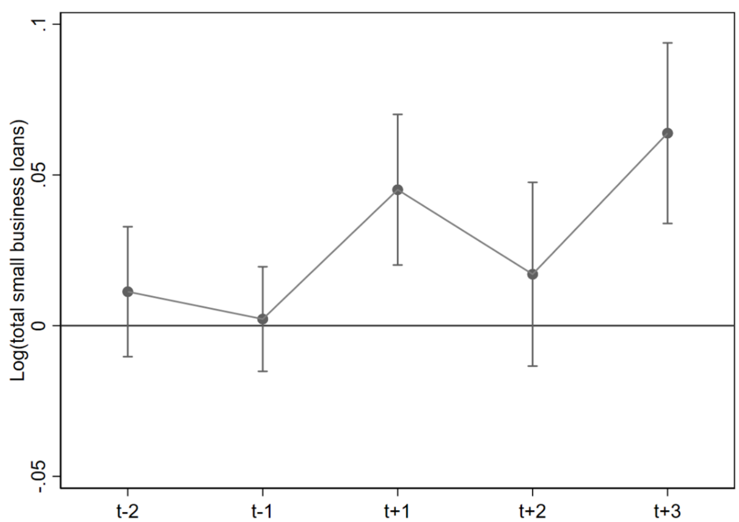



This figure shows that number of victims of the Madoff Ponzi Scheme by county. We count victims as the number of unique names on the list of victims supplied to the court. Here is the link to the list:

**Figure 2.** Dynamic effects: Decrease in households' stock market participation, bank deposits, and small business loans




Panel A: Madoff exposure and bank deposits




Panel B: Madoff exposure and small business loans

Panel A shows the dynamic effect of the decrease in households' stock market participation due to the Madoff Ponzi Scheme on the bank deposits in a given county around the year of the Madoff Ponzi Scheme. Panel B shows the dynamic effect of the decrease in households' stock market participation on the amount of small business loans in a given county around the year of the Madoff Ponzi Scheme.

## Table I Sample formation

This table reports the impact of various data matching steps and data filters on our sample formation. Our sample starts from Federal Deposit Insurance Corporation (FDIC) Summary of Deposits database over the period 2006–2011.

| | # county-year obs. | # county-year obs. removed | # unique counties |
|---|---|---|---|
| All county-year observations in FDIC Summary of Deposits database over the period 2006-2011 | 19,191 | | 3,203 |
| Merged with small business loans data from Community Reinvestment Act | 19,191 | 0 | 3,203 |
| **Final sample** | **19,191** | | **3,203** |

## Table II Summary statistics

This table presents a sample overview. The sample consists of 19,191 county-year observations (representing 3,203 counties) with data on Madoff exposure, bank deposits, and small business loans over the period 2006–2011. Panel A provides the summary statistics. Panel B presents the correlations for variables employed in the baseline regression. Definitions of the variables are provided in the Appendix. Superscripts ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Summary statistics for Madoff exposure and county characteristics

| | N | Mean | p25 | Median | p75 | SD |
|---|---|---|---|---|---|---|
| Deposits | 19,191 | 2,275,073.200 | 155,316.000 | 362,507.000 | 905,955.000 | 13,369,855.000 |
| Log(Deposits) | 19,191 | 12.926 | 11.953 | 12.801 | 13.717 | 1.499 |
| Total SBL | 19,191 | 76,871.485 | 3,446.000 | 11,522.000 | 43,765.000 | 293,273.910 |
| Log(Total SBL) | 19,191 | 9.432 | 8.145 | 9.352 | 10.687 | 1.883 |
| SBL <$100K | 19,191 | 29,623.248 | 1,699.000 | 4,878.000 | 15,671.000 | 137,290.100 |
| Log(SBL <$100K) | 19,191 | 8.601 | 7.438 | 8.493 | 9.660 | 1.689 |
| SBL [$100K, $250K) | 19,191 | 11,465.710 | 473.000 | 1,938.000 | 7,751.000 | 36,134.716 |
| Log(SBL [$100K, $250K)) | 19,191 | 7.124 | 6.161 | 7.570 | 8.956 | 2.890 |
| SBL [$250K, $1million) | 19,191 | 35,782.527 | 1,000.000 | 4,575.000 | 19,820.000 | 128,072.930 |
| Log(SBL [$250K, $1million)) | 19,191 | 7.775 | 6.909 | 8.429 | 0.894 | 3.399 |
| Number of Madoff victims | 19,191 | 3.403 | 0.000 | 0.000 | 0.000 | 50.552 |
| Madoff exposure | 19,191 | 0.169 | 0.000 | 0.000 | 0.000 | 0.613 |
| Madoff exposure dummy | 19,191 | 0.097 | 0.000 | 0.000 | 0.000 | 0.296 |
| Median age | 18,050 | 37.434 | 35.300 | 37.500 | 39.800 | 3.790 |
| Beginning deposits | 19,191 | 12.775 | 11.799 | 12.652 | 13.559 | 1.556 |
| Log(Beginning deposits) | 19,191 | 2.618 | 2.549 | 2.614 | 2.678 | 0.107 |
| Median income | 18,050 | 35,223.280 | 29,607.000 | 33,710.000 | 39,179.000 | 8,732.043 |
| Log(Median income) | 18,050 | 10.442 | 10.296 | 10.426 | 10.576 | 0.226 |
| Total population | 18,050 | 89,830.233 | 11,448.000 | 24,843.000 | 61,382.000 | 296,649.700 |
| Log(Total population) | 18,050 | 10.239 | 9.346 | 10.120 | 11.025 | 1.356 |
| Log(1+New Business Registration) | 18,333 | 3.989 | 2.708 | 3.822 | 5.109 | 1.901 |
| EQI | 18,333 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 |
| Log(1 + Number of firm establishments) | | | | | | |
| Total | 18,682 | 8.272 | 7.258 | 8.128 | 9.117 | 1.468 |
| 1-4 employee size | 18,682 | 7.697 | 6.713 | 7.545 | 8.498 | 1.421 |
| 5-9 employee size | 18,682 | 6.664 | 5.666 | 6.564 | 7.542 | 1.482 |
| 10-19 employee size | 18,682 | 6.151 | 5.130 | 6.043 | 7.096 | 1.587 |
| 20-49 employee size | 18,682 | 5.547 | 4.443 | 5.460 | 6.621 | 1.750 |
| 50-99 employee size | 18,682 | 4.310 | 3.219 | 4.205 | 5.407 | 1.849 |
| 100-249 employee size | 18,682 | 3.638 | 2.565 | 3.611 | 4.796 | 1.931 |
| 250-499 employee size | 18,682 | 2.358 | 0.000 | 2.565 | 3.611 | 1.856 |
| 500-999 employee size | 18,682 | 1.464 | 0.000 | 0.000 | 2.565 | 1.654 |
| 1,000 or more employee size | 18,682 | 0.946 | 0.000 | 0.000 | 1.946 | 1.467 |
| Job creation | | | | | | |
| Total | 17,813 | 1.040 | 1.000 | 1.017 | 1.073 | 0.105 |
| Firm age 0-1 years | 17,813 | 0.047 | 0.029 | 0.040 | 0.056 | 0.053 |
| Firm age 2-3 years | 17,813 | -0.002 | -0.009 | -0.002 | 0.004 | 0.028 |
| Firm age 4-5 years | 17,813 | -0.006 | -0.010 | -0.004 | 0.000 | 0.019 |
| Firm age 6+ years | 17,813 | -0.052 | -0.093 | -0.044 | -0.005 | 0.099 |

Panel B: The correlation matrix

| | Log(Deposits) | Log(Total SBL) | Log(SBL <$100K) | Log(SBL [$100K, $250K)) | Log(SBL [$250K, $1million)) | Madoff exposure | Madoff exposure dummy | Median age | Log(Beginning deposits) | Log(Median income) | Log(Total population) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Log(Deposits) | 1 | | | | | | | | | | |
| Log(Total SBL) | 0.882*** | 1 | | | | | | | | | |
| Log(SBL <$100K) | 0.880*** | 0.979*** | 1 | | | | | | | | |
| Log(SBL [$100K, $250K)) | 0.731*** | 0.879*** | 0.836*** | 1 | | | | | | | |
| Log(SBL [$250K, $1million)) | 0.735*** | 0.884*** | 0.812*** | 0.799*** | 1 | | | | | | |
| Madoff exposure | 0.540*** | 0.462*** | 0.493*** | 0.335*** | 0.325*** | 1 | | | | | |
| Madoff exposure dummy | 0.522*** | 0.472*** | 0.499*** | 0.352*** | 0.340*** | 0.842*** | 1 | | | | |
| Median age | -0.317*** | -0.341*** | -0.326*** | -0.307*** | -0.314*** | -0.058*** | -0.056*** | 1 | | | |
| Log(Beginning deposits) | 0.991*** | 0.885*** | 0.884*** | 0.742*** | 0.748*** | 0.506*** | 0.497*** | -0.313*** | 1 | | |
| Log(Median income) | 0.559*** | 0.599*** | 0.601*** | 0.490*** | 0.500*** | 0.396*** | 0.399*** | -0.150*** | 0.548*** | 1 | |
| Log(Total population) | 0.946*** | 0.917*** | 0.912*** | 0.784*** | 0.778*** | 0.513*** | 0.509*** | -0.412*** | 0.947*** | 0.531*** | 1 |

## Table III Madoff exposure, local bank deposits and local small business loans

This table presents the baseline regression estimates of the relation between the natural log of the number of Madoff Ponzi scheme victims (*Madoff exposure*) in a given county and county-level bank deposits and small business loans from difference-in-differences regressions. The sample consists of 19,191 county-year observations (representing 3,203 unique counties) with data on the local bank deposits and small business loans over the period 2006–2011. Panel A examines the relation between *Madoff exposure* and counties' bank deposits. This panel conducts the robusness checks on the main findings in Table 6 of (Gurun et al., 2018). Panel B examines the relation between *Madoff exposure* and counties' small business loans. Definitions of the variables are probided in the Appendix. Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the county level. ***, ** * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Madoff exposure and bank deposits

| | Log(Deposits) | | | | | |
|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
| Post × | | | | | | |
| Madoff exposure dummy | 0.015** | 0.033*** | 0.033*** | | | |
| | (0.007) | (0.009) | (0.009) | | | |
| Madoff exposure | | | | 0.007** | 0.016*** | 0.016*** |
| | | | | (0.003) | (0.004) | (0.004) |
| Controls | NO | YES | YES | NO | YES | YES |
| County FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | Absorbed | YES | YES | Absorbed |
| State-year FE | NO | NO | YES | NO | NO | YES |
| Adjusted R-squared | 0.996 | 0.996 | 0.997 | 0.996 | 0.996 | 0.997 |
| No. of observations | 19,189 | 18,050 | 18,050 | 19,189 | 18,050 | 18,050 |

Panel B: Madoff exposure and small business loans

| | Log(Total SBL) | | | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| Post × Madoff exposure dummy | 0.030** | 0.038*** | | |
| | (0.012) | (0.012) | | |
| Post × Madoff exposure | | | 0.007 | 0.015*** |
| | | | (0.005) | (0.006) |
| County FE | YES | YES | YES | YES |
| Year FE | YES | Absorbed | YES | Absorbed |
| State-year FE | NO | YES | NO | YES |
| Adjusted R-squared | 0.975 | 0.977 | 0.975 | 0.977 |
| No. of Observations | 19,189 | 19,171 | 19,189 | 19,171 |

## Table IV Testing for parallel trends

This table examines the parallel trends between the treated group and the control group. The regression specification is the same as that in Table III, except that we replace the indicator *Post* with the indicators *2 year before*, *1 year before*, *1 year after*, *2 year after*, and *3 year after*. These five indicators flag the years relative to the year of the Madoff Ponzi Scheme. Definitions of the variables are provided in the Appendix. Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the county level. ***, ** * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Madoff Exposure Indicator

| VARIABLES | Log(Deposits)<br>(1) | Log(Total SBL)<br>(2) |
|---|---|---|
| Madoff exposure dummy × 2 year before | -0.015 | 0.008 |
| | (0.010) | (0.011) |
| Madoff exposure dummy × 1 year before | -0.009 | 0.001 |
| | (0.009) | (0.009) |
| Madoff exposure dummy × 1 year after | 0.024*** | 0.043*** |
| | (0.005) | (0.013) |
| Madoff exposure dummy × 2 year after | 0.026*** | 0.018 |
| | (0.007) | (0.015) |
| Madoff exposure dummy × 3 year after | 0.029** | 0.062*** |
| | (0.012) | (0.015) |
| County FE | YES | YES |
| Year FE | YES | YES |
| Adjusted R-squared | 0.997 | 0.977 |
| No. of observations | 18,050 | 19,171 |

Panel B: Madoff Exposure Continuous Measure

| VARIABLES | Log(Deposits)<br>(1) | Log(Total SBL)<br>(2) |
|---|---|---|
| Madoff exposure × 2 year before | 0.000 | 0.000 |
| | (0.000) | (0.000) |
| Madoff exposure × 1 year before | 0.000 | 0.000 |
| | (0.000) | (0.000) |
| Madoff exposure × 1 year after | 0.016*** | 0.015*** |
| | (0.003) | (0.006) |
| Madoff exposure × 2 year after | 0.016*** | 0.003 |
| | (0.004) | (0.007) |
| Madoff exposure × 3 year after | 0.019** | 0.028*** |
| | (0.005) | (0.007) |
| County FE | YES | YES |
| Year FE | YES | YES |
| Adjusted R-squared | 0.997 | 0.977 |
| No. of observations | 18,050 | 19,171 |

## Table V Madoff exposure and local small business loans decomposition

This table examines the Madoff scheme exposure and counties' small business loans decomposition from difference-in-differences regressions. The regression specification is the same as that in Table III Panel B, except that we split the *Log(Total SBL)* into small business loans with loan amount at origination smaller than $100,000 (*Log(SBL<$100K*), between $100,000 and $250,000(*Log(SBL[$100K, $250K)*), and between $250,000 and $1000,000(*Log(SBL[$250K, $1million)*) Definitions of the variables are probided in the Appendix. Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the county level. ***, ** * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

| | Log(SBL<$100K) | | Log(SBL [$100K, $250K)) | | Log(SBL [$250K, $1million)) | |
|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
| Post × Madoff exposure dummy | 0.013 | | 0.070** | | 0.015 | |
| | (0.013) | | (0.031) | | (0.041) | |
| Post × Madoff exposure | | 0.005 | | 0.032** | | 0.008 |
| | | (0.005) | | (0.012) | | (0.015) |
| County FE | YES | YES | YES | YES | YES | YES |
| Year FE | Absorbed | Absorbed | Absorbed | Absorbed | Absorbed | Absorbed |
| State-year FE | YES | YES | YES | YES | YES | YES |
| Adjusted R-squared | 0.987 | 0.987 | 0.830 | 0.830 | 0.803 | 0.803 |
| No. of Observations | 19,171 | 19,171 | 19,171 | 19,171 | 19,171 | 19,171 |

## Table VI Effects of bank size and Madoff exposure on credit supply

This table reports results for a regression form of difference-in-difference-in-differences, where the coefficient of interest is the triple interaction term. We examine how the bank size affects credit supply behavior in Madoff affected area. The dependent variables are the same as that in Table III. We multiply a new dummy variable, small bank dominated, to the independent variable, which is the same as Gilje (2019). Definitions of the variables are provided in the Appendix. Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the county level. ***, ** * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

| VARIABLES | Log(Total SBL) (1) | Log(Total SBL) (2) |
|---|---|---|
| Madoff exposure dummy | 2.126*** | 1.985*** |
| | (0.085) | (0.090) |
| Small bank dominated | -1.588*** | -1.538*** |
| | (0.056) | (0.062) |
| Post × Madoff exposure dummy | -2.262*** | -2.229*** |
| | (0.095) | (0.104) |
| Post × Small bank dominated | 1.065*** | 1.104*** |
| | (0.052) | (0.061) |
| Madoff exposure dummy × Small bank dominated | -0.359 | -0.298 |
| | (0.243) | (0.252) |
| Post × Madoff exposure dummy × Small bank dominated | 0.761*** | 0.740*** |
| | (0.202) | (0.202) |
| Controls | YES | YES |
| State FE | YES | NO |
| Year FE | YES | NO |
| State-Year FE | NO | YES |
| Adjusted R-squared | 0.704 | 0.723 |
| Observations | 18,047 | 18,047 |

## Table VII Madoff exposure and entrepreneurial activities

This table examines the Madoff scheme exposure and counties' entrepreneurial activities from difference-in-differences regressions. The dependent variable in Panel A is the natural log of new business registrations. The dependent variable in Panel B is the average entrepreneurial quality index defined in Guzman and Stern (2020). Definitions of the variables are provided in the Appendix. Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the county level. ***, ** * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Madoff exposure and entrepreneurial entry

| | Log(1+New Business Registration) | |
|---|---|---|
| VARIABLES | (1) | (2) |
| Post × | | |
| Madoff exposure dummy | 0.034*** | |
| | (0.013) | |
| Madoff exposure | | 0.028*** |
| | | (0.006) |
| Controls | YES | YES |
| County FE | YES | YES |
| Year FE | Absorbed | Absorbed |
| State-year FE | YES | YES |
| Adjusted R-squared | 0.983 | 0.983 |
| No. of Observations | 17,749 | 17,749 |

Panel B: Madoff exposure and entrepreneurial quality

| | Entrepreneurial quality index | |
|---|---|---|
| VARIABLES | (1) | (2) |
| Post × | | |
| Madoff exposure dummy | 0.000026 | |
| | (0.000035) | |
| Madoff exposure | | 0.000003 |
| | | (0.000016) |
| Controls | YES | YES |
| County FE | YES | YES |
| Year FE | Absorbed | Absorbed |
| State-year FE | YES | YES |
| Adjusted R-squared | 0.244 | 0.244 |
| No. of Observations | 17,749 | 17,749 |

## Table VIII Madoff exposure and firm establishments

This table examines the Madoff scheme exposure and firm's establishment from difference-in-differences regressions. The dependent variables are the natural log of firm establishments in a given county. Definitions of the variables are provided in the Appendix. Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the county level. ***, ** * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

| | Ln(1+#Establishment): Split sample by the employee size | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Total | 1–4 employees | 5–9 employees | 10–19 employees | 20 - 49 employees | 50 - 99 employees | 100-249 employees | 250-499 employees | 500-999 employees | 1,000 or more employees |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Post × Madoff exposure | 0.005*** | 0.007*** | 0.004** | 0.007*** | 0.005 | -0.001 | -0.003 | -0.010 | -0.017 | -0.001 |
| | (0.001) | (0.001) | (0.002) | (0.002) | (0.003) | (0.005) | (0.005) | (0.009) | (0.013) | (0.010) |
| County FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | Absorbed | Absorbed | Absorbed | Absorbed | Absorbed | Absorbed | Absorbed | Absorbed | Absorbed | Absorbed |
| State-year FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Adjusted R-squared | 0.999 | 0.999 | 0.996 | 0.994 | 0.986 | 0.965 | 0.965 | 0.946 | 0.922 | 0.952 |
| Observations | 18,676 | 18,676 | 18,676 | 18,676 | 18,676 | 18,676 | 18,676 | 18,676 | 18,676 | 18,676 |

## Table IX Madoff exposure and the job creation

This table examines the Madoff scheme exposure and job creation from difference-in-differences regressions. The dependent variable is the job creation defined in Adelino et al. (2017). Definitions of the variables are provided in the Appendix. Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the county level. ***, ** * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

| | Job creation rate: Split sample by the firm age | | | | |
|---|---|---|---|---|---|
| | Total | 0–1 years | 2–3 years | 4–5 years | 6 or more years |
| VARIABLES | (1) | (2) | (3) | (4) | (5) |
| Post × Madoff exposure | 0.001 | 0.002*** | 0.000 | 0.000 | -0.007*** |
| | (0.002) | (0.000) | (0.000) | (0.000) | (0.001) |
| County FE | YES | YES | YES | YES | YES |
| Year FE | Absorbed | Absorbed | Absorbed | Absorbed | Absorbed |
| State-year FE | YES | YES | YES | YES | YES |
| Adjusted R-squared | 0.521 | 0.479 | 0.149 | 0.155 | 0.346 |
| Observations | 17,782 | 17,782 | 17,782 | 17,782 | 17,782 |