# Deposit shocks, constrained banks and credit supply: Evidence from U.S. lottery winners

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**Preliminary. Comments Welcome**

**Abstract**

This paper estimates the causal effect of exogenous shocks in the supply of deposits on credit supply. The identification strategy exploits a novel natural experiment: U.S. jackpot lottery winners from Powerball and Mega Millions to determine shocks in the supply of deposits. I find that the banks in the treatment group (i.e., those affected by the jackpot winner shock) experienced a large increase in deposits, total lending and small business loan origination. I control for local credit demand by identifying banks that received the winners' shock and by studying their loan origination at different locations (e.g., CBSAs) where they have operations. Relative to bank-attributes, and consistent with frictions originating from adverse selection, the set of small- and medium-sized banks and those with the most illiquid balance sheet significantly increased loan origination after the winner's shock. Finally, the results show that the bank's charter choice matters for credit supply, which suggest that the regulatory mix in the U.S. can have real effects.

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# 1 Introduction

Do shocks in the supply of deposits affect loan origination? The slow recovery of the economy from the 2008-09 financial crisis despite extensive policy intervention, combined with the decline in bank lending, received considerable attention from policymakers (e.g., Bernanke (2008)), and emphasizes the need to investigate the impact of shocks to providers of capital.[1]

This paper explores how banks respond to deposit shocks, and what kinds of bank attributes may enhance the impact of deposits flows. Since banks can play a crucial role in the functioning of the economy because small-sized businesses do not have ready alternatives to banks for their financing needs (Bernanke (1983)), quantifying the extent to which bank lending reacts to exogenous shocks to deposits is a first-order question since numerous firms in the U.S. borrow exclusively from banks. Furthermore, understanding which banks are most affected can lead to more targeted and effective implementation of policy interventions.[2] Since the literature suggests that many banks rely heavily on deposit financing, and local deposit supply impacts local lending, the ideal experiment in this case would randomly assign deposits across banks in different locations.[3]

A close variation of such an experiment is to look at U.S. jackpot lottery winners from Powerball and Mega Millions. Both are jointly shared jackpot games offered in 43 states as of June 2013 (see Figure 1). This paper's research design relies on the fact that having a jackpot winner in a specific local area and time is randomly assigned, conditional on the sales of lottery tickets. Since each lottery ticket has the same chance of winning, the probability of selling a winning ticket is a linear function of the lottery sales. An interesting feature of the setting is that the amount won is also random, conditional on sales.[4] This allows one to test whether there is a positive causal effect of the amount received, less income tax withholdings, on the outcome variable (e.g.,

[1]Besides the credit supply channel as an explanation for slow pace of recovery, there are other explanations that include: reduced aggregate demand (e.g., Mian and Sufi (2012)), uncertainty (e.g., Bloom et. al. (2012)), and structural factors (Charles et al. (2012)).

[2]If firms have costless access external capital markets, then their functioning should be insensitive to the shocks experienced by their capital providers. However, frictions, i.e., adverse selection and moral hazard, can lead to financially-constrained firms.

[3]If banks operate in the Miller-Modigliani frictionless world, bank lending would not be constrained by the availability of deposits. Banks would simply issue debt, or equity, to offset a loss of deposits. However, Stein (1998) shows that if banks face adverse selection problems, then shocks that compromise the ability to raise deposits will lead to declines in lending since banks will face difficulty replacing deposits with other forms of financing (e.g., commercial paper).

[4]The mean jackpot prize, after tax withholdings and in 2014 dollars, is around $45.6 million.

deposits and small business lending). The quasi-experimental design allows one to use a difference-in-difference strategy to estimate the treatment effect at the local-level. The setting also provides falsification tests (e.g., prizes that were unclaimed or winners that reside in states different from where the winning tickets were sold) that support the identification condition: in the absence of the winner's shock the average change in the outcome variable for the treatment group does not differ relative to the control group.

Furthermore, using branch office deposits data from the Summary of Deposits and the estimated amount received by each jackpot winner, it is possible to determine the branch, and thus the bank that received the prize. This last characteristic of the quasi-experimental design allows one to study the precise effect of the shock at the bank level, since I have estimates of the dates in which the winner received (and deposited) their prize. This also allows for estimation of small business loan origination of banks in the treatment group, relative to other banks in the control group, controlling for any observable and unobservable time-varying effects at the CBSA level (e.g., demand-side effects affecting the lending behavior of all banks within a given CBSA-year).[5]

This paper proceeds as follows. First, I estimate the causal effect of the jackpot winners' shock at the local-level (i.e., CBSA) on deposits and small business lending. I next estimate the winners' shock effect at the bank-level (both at the intensive and extensive margin). Subsequently, I examine the heterogeneity in the response to the exposure of treatment with respect to bank-attributes. Specially, the paper looks at whether a bank's choice between state and national charter matters for credit supply, since banking regulators can implement rules inconsistently.[6] The paper also examines the possible mechanism by which the regulatory mix can affect credit-supply.[7]

There are four primary findings. First, the jackpot winners' shock leads to a significant increase in deposits (a 4.05% yearly change) and an increase in small business lending at the CBSA level (4.28%). The shock's effect on small business lending is greater in those CBSAs with high levels of local bank concentration (6.79%), and the point estimate of the elasticity of total small business lending with respect to deposits is 0.49 at the CBSA

[5]In this case, the regressions are identified through variation between the treatment group and control group within a given CBSA in a given year.

[6]Banks in the U.S. face a dual supervisory system, under which they are chartered and supervised by federal and state-level entities. Banks can choose between a state and national charter. With a state charter, they are able to choose whether or not to be members of the Federal Reserve System.

[7]Possible mechanisms are that federal regulators provide a kind of certification that lessens the bank's adverse-selection problems, and/or that the state regulators are more lenient which could increase the adverse-selection problems for the set of state chartered banks.

level, using the winners' shock as instrument.[8] This magnitude is underestimated by a factor of 1.6 when is not properly accounted for by using the two-stage least square model (2SLS).

Second, banks in the treatment group experience a significant increase in deposits and total lending (a 1.98% and 2.38% average quarterly change after a one-standard-deviation increase); and the shock induces an increase in small business lending at the bank-level (5.02% after a one-standard-deviation change), controlling for demand conditions in the local markets. In addition, the effect of the winners' shock on lending for the set of non-large banks is not persistent. Third, there is no evidence that the treated banks experience a relative worsening in their loan portfolio in terms of nonperforming loans and decrease of interest revenues, and also the winner's shock does not have a significant effect at the extensive margin. Finally, the findings suggest that the bank's regulator choice can affect lending behavior and the results support the state regulators leniency and the federal regulators certification mechanisms.[9]

These findings are robust when I consider different specifications of the treatment variable, from using the placebo tests provided by the setting (e.g., unclaimed prizes), to the possibility of pre-existing trends in the data, to using alternative geographical units of analysis, to using different control groups, to controlling for demand-side effects in a given CBSA-year, among others.

The findings suggest that a set of banks were financially constrained (i.e., small- and medium-sized banks and those with the most illiquid balance sheet) before experiencing the jackpot winners' shock. This is consistent with frictions originating from adverse selection.[10] In addition, the bank's choice between state or federal charter can affect lending as well, possibly through laxer behavior from state regulators and certification from federal regulators (such as the OCC).

This study is related to strands of literature in banking and corporate finance. There is

[8] I defend the validity of the winners' shock as instrument for deposits in Section 4.2.1.

[9] We should be concern that selection bias would affect the estimates of the regulatory mix tests since banks do not choose randomly between a state and national charter. However, Agarwal et al. (2014) find that the nature of unobservable factors that drive the bank sorting decision into and from the state charter might be time-invariant. Thus, bank fixed effects is a sufficient correction to account for charter shopping.

[10] Additionally to the findings relative to nonperforming loans and decrease of interest revenues, the extensive margin results of no significant effect of the winner's shock on the loan acceptance rates can be interpreted as support for the costly external finance model since the probability of granting loans was not affected, then the banks were extending credit on average to clients who presumably had prior relationship with.

literature on the bank lending channel that emphasizes the role of financially-constrained banks in amplifying the real effects of aggregate shocks (e.g., Bernanke and Blinder (1992), Kashyap, Stein and Wilcox (1993), Kashyap and Stein (1995, 2000), Houston (1996)). The paper is related to a literature on the economics of regulation in banking (e.g., Kroszner and Strahan (1999), Berger and Hannan (1998), Barth, Caprio, and Levine (2004)) especially to Agrawal, Lucca, Seru, and Trebbi (2014), who exploit exogenous rotations between federal and state supervisors of state-chartered banks to show that the regulatory outcomes are inconsistent across supervisors. It is also related to the literature on relationship banking. This literature suggests that relationships generate value since banks obtain soft information about borrowers to help in the credit decision (e.g., Berger and Udell (1995), Petersen and Rajan (2002), Berger et al. (2005), Agarwal and Hauswald (2010)). More recent literature looked at the significance of local capital supply on local outcomes (e.g., number of firms), or focused on establishing the causal link between shocks to the liability side of banks' balance sheet and lending to firms (e.g., Becker (2007), Khwaja and Mian (2008), Paravisini (2008), Gilje (2012), Schnabl (2012), Jimenez et al. (2012), Gilje et al. (2013)). However, most of these recent papers are studies outside of the U.S. For the studies in the U.S., most of previous papers do not isolate supply shocks from local demand conditions, or they do not deal with selection bias in the estimation (e.g., the treated banks self-selected into treatment by opening branches in those areas that received a shock).

This paper contributes to the literature on lending channel and regulation in banking in several ways: it utilizes a novel natural experiment that allows a closer approximation to the ideal laboratory setting, the study is nationally representative of the U.S., it allows isolation of supply shocks from local demand conditions; it is the first in the literature that looks at whether the dual supervisory system in the U.S. can affect credit-supply; in particular, it studies the effect of a bank's choice between state or federal charter on lending behavior, and lastly the paper looks at how small business lending responds to deposit shocks, since small firms are more likely to be affected by bank lending decisions (e.g., Petersen and Rajan (1994, 1995)). Finally, the paper contributes to the broader literature regarding the effect of financial constraints on corporate financial policies (e.g., Fazzari et al. (1988), Whited (1992), Kaplan and Zingales (1997), Alti (2003)).

This article is organized as follows. Section 2 provides some background on U.S. lotteries. Section 3 provides details on the data sources. Section 4 explains the research design and presents the findings. Finally, section 5 concludes the paper.

# 2 Institutional background on U.S. lotteries

In the U.S. there is no national lottery. The introduction of government-sponsored lotteries started in Puerto Rico in 1934 and New Hampshire in 1964. Currently, lotteries are established in 44 states, the District of Columbia, and Puerto Rico. Powerball and Mega Millions are two U.S. joint shared jackpot games offered in 44 and 43 states, respectively. The six remaining non-participating states do not run state lotteries by law.[11] Figure 1 shows the U.S. states that offered both Mega Millions and Powerball as June 2013.

Powerball is a shared jackpot game. It is coordinated by the Multi-State Lottery Association (MUSL), a non-profit organization formed by an agreement with various U.S. state lotteries. Powerball's current minimum advertised jackpot is $40 million (annuity). There is no maximum jackpot for the Powerball, it increases when there is no top-prize winner (jackpot). The game uses five white balls out of a drum with 59 balls and one red ball out of a drum with 35 red balls from which winning numbers are chosen. The jackpot is won by matching all five white balls in any order and the red "Powerball". The odds of winning the jackpot are 1 in 175,223,510.[12]

Mega Millions, which is sold in 43 states, has a minimum jackpot of $15 million. Mega Millions uses five different numbers from 1 to 75 (white balls) and one number from 1 to 15 ("Mega Ball") to select its winning numbers. The player can win the jackpot by matching all six winning numbers in a drawing. The current odds of winning the jackpot are 1 in 258,890,850.[13]

The jackpot winner can choose between the annuity or cash option. The annuity option is paid in 30 graduated installments over 29 years or a lump sum payment which is the approximate present value of the installments. If a player chooses the cash option, then the lottery will pay the entire cash amount to the winner less income tax withholding

[11] On October 13, 2009, the Powerball and the Mega Millions consortium signed an agreement to allow U.S. lotteries to sell both games, no longer requiring exclusivity. The expansion occurred on January 31, 2010, as 10 Mega Millions members began selling Powerball tickets for their first drawing on February 3. Simultaneously, 23 Powerball members began offering Mega Millions tickets for their first drawing on February 2. Subsequently, during 2010, Arizona, Colorado, Maine, Montana, Nebraska, Oregon and South Dakota started offering Mega Millions. Finally, Louisiana joined Mega Millions in 2011. Alabama, Alaska, Hawaii, Mississippi, Nevada and Utah do not have state lotteries.

[12] Currently, each ticket costs $2, or $3 with the Power Play option. Prior to January 15, 2012, the game cost $1 each, or $2 with the Power Play option. Power Play is a special feature that allows a winner to increase the original prize amount other than the jackpot.

[13] Each ticket costs $1 per play.

amounts required by federal and state laws.[14] The winner has between 90 days to one year to claim the prize depending on the state lottery. After that period, the prize becomes unclaimed.

To claim the jackpot, the player must go to the lottery headquarters to verify that the ticket is actually a winning ticket. Usually for jackpot winners, there is a 15 day wait period before a prize can be paid.[15] This wait period allows for all the states to balance and bring their funds to pay the prize. However, the wait period depends on the state lottery. For example, California requires 6 to 8 weeks after they submit the claim. From conversations with representatives of more than half of the U.S. state lotteries, I have data on their respective wait period.[16] After submitting a valid claim, the lottery pays the winner. If the winner chooses the lump sum payment, she receives the prize minus withheld taxes. The way lotteries pay the winners varies from state. According from talks with representatives, around more than half the lotteries offer wire transfer to receive their winning. In addition, some also offer to pay by check which in most states is mail to the winner. The lotteries representatives' prior is that the winners deposit the winning in their respective city and in their existing bank accounts.[17] Finally, the place where the winners buy their tickets is usually close to where they live, or in some cases where the winner works, according to lottery representatives.[18] However, you do not have to be a state resident to play the state lottery; you can be visiting the state and still play. Fortunately, the data of the winner's state of residence is usually available in the press releases from the lotteries.

All states lotteries, except five, have laws that require to release the winner's name, city of residence, the name and location of the retailer who sold the winning ticket, game, date, and amount won upon request.[19] There are instances in which there are

[14]If the winner has a debt owed to the state, the winner will receive the prize minus income tax withholding and the amount owed to the state.

[15]The date when the winner claims the prize can be extracted from the dates of the press releases.

[16]In some cases if the winner claims the prize after two weeks, she can receive the jackpot in her bank account the following day. In those states from which I did not receive an answer, I contacted all the state lotteries, I assume a 15 day wait period depending on the date the winner claimed the prize and the date of the game (all which can be found in the press releases).

[17]For example, one state lottery states the following on their Winner's Handbook relative to what to do with their winnings: "Your current bank or credit union is a good place to start".

[18]For instance, the Poweball website states (http://www.powerball.com) the following: "The vast majority of winning tickets are purchased by someone who is close to the lottery terminal where it was purchased".

[19]Delaware, Kansas, Maryland, and Ohio allow the winner to remain anonymous (i.e., not required to release the name). However, these states do reveal the name and location of the retailer who sold

multiple winners in different states, in those cases the different winners share the prize equally. These features of the U.S. lotteries allows me to compile a data set from different sources, including hand-collected data, of all jackpot winners for the period 2002-2013 for Mega Millions and for the period 2003-2013 for Powerball.[20] The data set includes if the prize was claimed, whether the winner choose the cash option or the annuity option, date of the game, date when the prize was claim, approximate date in which the winner receive the prize, name and city of residence, zip code of the retailer, federal and state tax rates, among other things.

Table 1 shows summary statistics relative to the jackpot winner Mega Millions (MM) and Powerball (PB) over the period 2002-2013 for MM and 2003-2013 for PB (up to June 2013).[21] There are 284 jackpot winners almost evenly split between Mega Millions (139) and Powerball (145).[22] These winners are located across 41 states, over 43 that offered the games; PB has jackpot winners in 38 states and MM has winners in 16. In addition, the winners are spread across 142 CBSAs.[23]

Figure 2 is a map of the U.S. with counties' shading reflecting which county there was a jackpot winner over the 2002-2013 period. Of the 284 jackpot winners, 263 (92.6%) choose the cash option and the rest choose the annuity option or are unclaimed prizes, 21 (7.4%). Most of the winners, 255 (89.8%), buy the winning ticket in their state of residence. The mean jackpot prize, after tax withholdings and in 1999 dollars, is $32.9 million.[24] The mean prize is almost identical between the two games, $33.2 million for MM and $32.7 million in the case of PB (Appendix Table 1). Finally, the winners, in the full years of the sample 2003-2012, are also evenly spread out over the time period with 26.7 jackpot winners per year between both games (Appendix Table 1).

the winning ticket; game, date, and the prize receive.

[20]The reason for the starting date in the case of Mega Millions is that in May 2002 the current game name and format (game matrix and prize amounts) were introduced. In the case of Powerball, 2003 is the earliest year in which I could gather all the data for jackpot winners.

[21]The reason the data set compiled ends in June 2013 is because the Summary of Deposits from the Federal Deposit Insurance Corporation (FDIC) ends in June 2013.

[22]There were 286 jackpot winners over this period. However, for one winner I do not have the amount received, and in the other case I do not have the location of the retailer. Thus, I am left with 284 jackpot winners.

[23]Core Based Statistical Areas (CBSAs) consist of the county or counties associated with at least one core urbanized area of at least 10,000 population. Metropolitan Statistical Areas are CBSAs associated with at least one urbanized area that has a population of at least 50,000. Micropolitan Statistical Areas are CBSAs associated with at least one urban cluster that has a population of at least 10,000 but less than 50,000.

[24]This is around $45.6 million in today's prices (2014).

# 3 Data Sources

The U.S. lotteries jackpot winners' data set was hand collected and comes from different public sources, complemented with data from discussions with U.S. lotteries representatives.[25] To first study the causal effect of the jackpot winners, as a shock in the supply of deposits, I estimate the effects on the deposits at the CBSA level. The data comes from the Summary of Deposits (SOD) which is the annual survey of branch office deposits for all FDIC-insured institutions. SOD provides the Branch office deposits as of June 30 of every year.[26] To estimate the deposits at CBSA level, I sum up all the branch deposits in each CBSA/year. I use the data from 1999 to 2013.

The lending data comes from the Community Reinvestment Act (CRA) disclosure and aggregate reports from the Federal Financial Institutions Examination Council (FFIEC). The CRA requires banks above a certain asset threshold to report small business lending each year and by Census tract. The asset threshold was $1.186 billion in 2013 and is adjusted with CPI.[27] CRA disclosure report provides data by bank, county, CBSA and year; and the aggregate report offers total lending data. The small lending data that are made publicly available are two: i) the total dollar amount of small business loan origination, defined as loans under $1 million, and ii) the dollar amount of small business loan origination to businesses with $1 million in annual gross revenue or less. I use the data from 1999 to 2012.

To complement the CRA data, I use the Report of Condition and Income, Call Report. There are two advantages of this data set, i) it includes data on all banks regulated by the Federal Reserve System, Federal Deposit Insurance Corporation, and the Comptroller of the Currency; and ii) the data is available at the quarterly frequency. However, the Call Report is only available nationally at the bank-level. I use the data from 1999 to 2013. More details about this data set are available in the Appendix. Finally, in some estimating equations, I also include CBSA characteristic controls derived from Census data.

[25] I contacted the 43 U.S. state lotteries that offer both Powerball and Mega Millions, and other industry representatives (e.g., North American Association of State & Provincial Lotteries (NASPL)). I received answers from 23 state lotteries.

[26] The setting allows estimating the date in which the winner received (and deposited) her prize. Unfortunately, the SOD data is only available at the year level. However, the Call Report, financial data set at the bank level, is available at the quarterly frequency.

[27] Previous to 2005, the asset threshold was $250 million.

# 4 Research Design and Results

## 4.1 Local-level Analysis: Deposits

This paper's research design is based on the observation that having a jackpot winner in a specific local area and time is a completely random shock, conditional on the sales on lottery tickets. From the previous section, and based on state lotteries representatives' prior, I test the hypothesis that lottery winners deposit on average their prize in their respective CBSA. This hypothesis is tested directly in the first stage of estimation using the SOD data.[28] Specially, I estimate the following specification:

$$log(deposits)_{it} = \alpha_i + \alpha_t + \beta\, 1(winner)_{it} + \gamma' X_{it-1} + \varepsilon_{it} \tag{1}$$

where $i$ indexes CBSA, $t$ indexes year, and *deposit* denotes deposits. $1(winner)$ is an indicator function equal to one in those CBSA/year with Jackpot winners, that chooses the cash option and resides in the state where the ticket winning was sold, andzero otherwise, $\alpha_i$ and$\alpha_t$ are CBSA are year fixed effects, and $X$ is a vector of CBSA's demographic characteristics.[29] Since each lottery ticket has the same chance of winning, the probability of selling a winning ticket is a linear function of the lottery sales. However, I do not have data of lottery sales at CBSA level. To proxy for CBSA's sales I use the lag of the CBSA characteristics.[30] Thus, conditional on the proxies for sales each CBSA has the same chance of selling a winning lottery number, $E[\varepsilon_{it}/1(winner)_{it} = 1\,, X_{it-1}] = E[\varepsilon_{it}/1(winner)_{it} = 0\,, X_{it-1}]$, and the parameters of (1) are unbiased and consistently estimated. The parameter of interest is $\beta$, and the variation used for identification is the average change in deposits for CBSAs with jackpot winner at year $t$ with respect to the average change in deposits for CBSAs without winners at time $t$. The control groups are CBSAs from the 43 states with state lotteries (i.e., possible treated group). Thus, this is a difference-in-difference estimator. In the different specifications in the paper, the point estimates reflect the shock's effect

[28] The local-level results shown in the paper are at the CBSA level, but the results are qualitatively similar at the county level.

[29] I include the following (lag) CBSA controls: race composition (% white), sex composition (% male), age composition (% over age 45), and income per capita. In addition, since some CBSA are in multiples states, I also include state fixed effects (FE). However, the results are almost identical without state FE.

[30] The point estimates after just controlling for the lag of population do not vary when other (lag) demographics controls are introduced.

only on the year that it occurred. Finally, I report the standard errors clustered at the CBSA level, to account for serial correlation, and robust to heteroskedasticity.

An interesting feature of the setting is that also the amount won is randomly assigned, conditional on lottery sales.[31] This allows one to test whether there is a positive causal effect on the possible amount received and the outcome variable. Thus, I create different variables to estimate the intensity of treatment (i.e., prize won effect).[32] I use $log(1 + prize)$ as the treatment variable, where prize is the amount won after withheld federal and state taxes in 1999 dollars. Also, I create the following variable: $prize_{it}/deposits_{it-1}$ where $prize_{it}$ is the amount won in CBSA $i$ and year $t$, and $deposits_{t-1}$ are the deposits in CBSA $i$ and year$t - 1$ (year before treatment). Finally, I also create the following indicators variables: $1(Prize\, in\, top\, quartile)$ which is equal to one if there was a winner and the amount received is in the top quartile of the prize distribution and zero otherwise, and $1(Prize\, below\, top quartile)$ is equal to one if there was a winner and the amount is not in the top quartile of the distribution and zero otherwise.

The quasi-experimental setting allows for different falsification tests. Thus, I create an indicator variable (Non-cash Winner) equal to 1 if there is a jackpot winner but the prize was unclaimed or the winner choose the annuity option, and zero otherwise. Also, I generate a dummy variable equal to one (Winner out-of-state) if the winner lives in a state different where the winning tickets was sold and zero otherwise. Finally, I create an indicator variable that combines the variables non-cash winners and out-of-state winners (Non-cash and winner out-of-state).

### 4.1.1 Results

The bottom panel of Table 1 shows the show summary statistics on CBSA characteristics and deposit growth depending whether the CBSA had a jackpot winner or not. The third column reports the p-values on t-test for difference. Not surprisingly, CBSA with winners have higher population (p-value is 0.00). There are also significant differences in the other demographics characteristics. Consequently, the regression specifications include this set of CBSA characteristics. Most importantly, there is no statistical dif-

[31]In those cases in which there are multiple winners in the same CBSA/year, I add up the prizes received.

[32]Similar to the winner dummy, all the treatment variables are not zero only in those cases in which the winner chooses the cash options and resides in the state in which the winning ticket was sold.

ference in deposit growth between both groups (p-value is 0.952) from 1994 to 2001 which support the fact that the jackpot winner's shock is random assign.

Table 2 Panel A reports the parameters of interest from the regression specification (1). Also, recall that (lag) CBSAs demographics controls are included, and that the control group are CBSAs from the 43 states with state lotteries. Column (1) shows the point estimates imply that those CBSA with jackpot winners experience an increase on average of 3.13% in deposits in the (calendar) year of the shock. Columns (2) and (3), and Appendix Table 3 column 1, report the estimates for the different treatment variables. For example, column (2) reports the average increase in deposits is 4.05% from the winners' shock.[33] Column (4) shows that those CBSAs that have a jackpot winner in the top quartile of the prize distribution experience an increase of 8.75% in deposits, while the other CBSAs with winners not in the top quartile experience a change of 1.13%.[34] To see to what extent the reduced form estimates are sensitive to the inclusion of time-varying observable factors. Appendix Table 2 reports the point estimates after controlling only for (lag) CBSA population. The estimates are very similar to Table 2 in which all (lag) demographics controls are introduced.

*Robustness Check*

To test the identification condition, Table 2 Panel C column 1 reports the point estimate of the indicator variable that combines the variables non-cash winners and out-of-state winners (Non-cash and winner out-of-state). There is no significant change in deposit (0.80%) in those cases in which the prizes were unclaimed, the winner was from a different state and the winners choose the annuity option. Appendix Table 3 columns (2)-(3) shows the separately the estimates of Non-cash Winner and Winner out-of-state dummy variables. Column 2 shows that in those cases in which the prize was unclaimed or the winner choose the annuity option (Non-cash Winner), there is no significant change in deposits (-0.62%). Column (6) reports a similar estimate of change in deposits (-0.88%) for those cases in which the winner's state of residence is different from where the winning tickets were sold (Winner out-of-state). These findings support the identification condition that in the absence of the winner's shock, the average changes in deposits for the treatment group do not differ with the control group.

[33] $exp\,[0.00382 * ln(1 + 32,964.8)] - 1$. From Table 1, we have that the average jackpot winner received $ 32.9 million.

[34] In untabulated results, the point estimates weighted by the CBSA's 2001 log(population) are similar.

To further examine the identification condition, columns (2) in Table 2 Panel C presents the specification (1) augmented with leads. I add dummy variables for 1, 2, and 3 years before the shock, and the winner indicator (year 0). The coefficients on the winner leads are all insignificant at conventional test levels; and in the year of the shock, deposits increase on average 3.27%. Thus, there is no evidence of pre-existing trends in the data.

In Appendix Table 3 columns (1) and (2) reports the point estimates of the different treatment variables when I split the sample in into two subsamples based on the (lag) population size: bellow 500,000 and above 500,000. As expected, for all the treatment variables the winners' shock does not have a significant effect on deposits for CBSAs with population above 500,000.[35] For example, column (1) in Appendix Table 3 reports that for those CBSAs with population higher than 500,000 the winners' shock does not affect the deposits (-0.0066).

Finally, Table 2 Panel C columns (3) and (4) report the results using different control groups as a robustness check. In column (3) I restrict the sample to states with jackpot winners, the sample consists of states with at least one jackpot winner. The point estimate for the average change in deposits (3.29%) is similar to column (1) in Panel A. Finally, column (4) reports the estimates excluding from the sample those states with more than 8 jackpot winners, the average change in deposits is 3.92% in the year there is a jackpot winner. Thus, the results are not driven by the CBSAs in those states with relative more winners.[36]

Overall, these estimates provide evidence of a positive causal effect of the jackpot winner's shock on deposits, and support the hypothesis that lottery winners on average deposit their winnings in their respective CBSAs.

## 4.2 Local-level analysis: small business lending

Having established a strong relationship between the jackpot winner's shock and deposits, I turn to examining the effect of these shocks on small business loan origination. To examine the effects of jackpot winners on bank lending at the CBSA level, using CRA Aggregate data, I estimate the same specification as (1) but the outcome variable

[35]The results are similar for different population cut-offs (e.g., above or bellow 200,000 ).

[36]Those states with more than 8 jackpot winners for the period from 2002 to 2013 are CA, GA, IN, MI, NJ, NY, OH and PA.

is the log of small business loan origination in CBSA $i$ and year $t$.[37] The identifying assumption in this case is that the treatment variable (jackpot winner) is a supply shock, rather than reflecting demand conditions, in the areas where the banks have operations (i.e., the liquidity shocks do not affect credit demand in the area). This assumption is plausible, at least in short periods, since I am estimating the winner's effect at the CBSA level in the calendar year of the shock.[38][39] Recall that the estimates in the paper report the shock's effect only on the year that it occurred. The tests in the robustness check section will examine the identifying assumption.

Since the interest of the paper is in the bank lending channel, the origination of small business loans is of great importance especially since these loans are harder to securitize. In addition, the relationship banking literature acknowledges that banks have an important role in mitigating frictions, i.e., asymmetric information, especially for small firms. Thus, small firms are relative more bank-dependent businesses. For example, previous papers have found evidence that banks obtain soft information on firms to help the credit decision (e.g., Agarwal and Hauswald (2010)).

### 4.2.1 Results

Table 2 Panel A columns (4)-(10) report the estimates of equation (1) in which the outcome variables is either small business loan originations with \$1 million or less in revenue, and total small business loan originations (loans under \$1 million). Columns (2) to (2) show the point estimates for the different treatment variables. All the estimates confirm the positive casual effect of the jackpot winners shock on small business loan origination. Column (4) in Table 2A reports a significant economic increase (4.31%) in loans to businesses with revenues lower than \$1 million for those treated CBSA, a similar result (3.71%) is shown in column (8) for total small business loan originations. Column (9) reports the average increase in small business lending is 4.28% from the treatment shock. Appendix Table 3 column (7) in Table 4 reports that CBSAs with winners in the top quartile experience a 4.52% increase in total small business loan,

[37] Unfortunately, the SOD data set does not have lending data.

[38] Unless, the jackpot winner spends a substantial part of their wealth in the same year to have an effect on the local demand conditions of the entire CBSA.

[39] Anecdotal evidence shows that Andrew Jackson "Jack" Whittaker, Jr, who won the Powerball Jackpot in 2002, is the most renowned case of financial troubles for a jackpot winner. After winning the lottery, he had several personal tragedies and legal issues throughout the years. However, even in this extreme case, there is no evidence the winner spent most of his fortune the same year of winning.

and the other CBSAs with winners not in the top quartile experience a 3.40% growth.

We should expect the jackpot winner shock to have a greater influence on small business lending in those CBSA in which smaller banks are the dominant players. The reason is that smaller banks are relative more constraint since their marginal source of funds is deposits. To obtain a proxy variable for which CBSAs small banks prevailed, using the SOD data, I construct a measure of the ratio of the number of branches in each CBSA/year for which the banks have assets lower or equal to $2 billion (in 1999 dollars) relative to the total of branches in each CBSA. Then, I create quintiles from the yearly distribution of the ratio of branches. Finally, I create an indicator variable (Small bank) that takes the value of one if the CBSA is in the 5th quintile of the yearly distribution and and zero otherwise. The variable of interest in this case is the interaction between the winner indicator and the small bank dummy. Table 2 Panel B columns (1) and (3) show the estimates of the interaction, CBSA with a winner shock and in which the small banks predominated, are economical and highly significant. For example, the loans to businesses with revenues lower than $1 million increase in 13.1% (Table 2C Column 1) in those CBSA with a jackpot winner and with small banks as the dominant players. Appendix Table 5 shows that the results are robust to using a different threshold for asset ($1 billion). Appendix Table 6 reports the point estimates of the interaction variables three years before the shock for both asset thresholds, to exclude the possibility of pre-trends. The point estimates are all negative and insignificant.

*Robustness Check*

To examine the identification condition, Tables 2 Panel C column (5) and (9), and Appendix Table 3 columns (5)-(6) and (8)-(9), report the different placebos tests that the quasi-experimental setting provides. All the estimates of the Non-cash Winner, Winner out-of-state, and Non-cash and winner out-of-state variables are insignificant. These findings support the identification condition that in the absence of treatment, the average changes in small business lending do not differ between the treatment and control group.

Tables 2 Panel C column (6) and (10) report the estimates of lead variable for 1 to 3 years before the shock and the winner indicator (year 0). In both cases the coefficients of the lead, or pre-treatment, variables are insignificant which suggests that there are no pre-existing trends in the data; while the estimates of the winner variable (year 0) are large in economic terms and highly significant. Columns (3) and (4) of Table 2 Panel C show that the findings are economic significant for different control groups (treated states and those states with less than 8 winners). Finally, Appendix Table 4 columns (3) to (6) report the estimates of the different treatment when I split the sample according to the size of the population. Similar to the case of deposits, the results are as expected (i.e., no significant changes in those CBSAs with population above 500,000).

To test the identifying assumption that the winner's shock is a supply shock, since states collect taxes from the winners the results could be driven by an increase in demand due to an increase in public state spending. Fortunately, not all states have individual income taxes. Thus, to test for the identifying assumption, I generate a dummy variable equal to 1 for those states with individual income taxes (state taxes). Under the identifying assumption, there should not be a difference in the causal effect of the winners shock on those states that collect taxes relative to those state that do not. The variable of interest in this test is the interaction between the winner indicator and the state taxes dummy. Table 2 Panel B columns (2) and (4) show that the interaction term in both cases is negative and not significant. These results rule out the hypothesis that the increase in loan origination is due to an increase in demand from state spending coming the taxes collected on winners.

To further examine the identifying assumption. Since, I have data on the address of the retailer that sold the winning ticket. Thus, I can assume, as mentioned from the talks with lotteries representatives, that the winners reside on average on the retailer's county. Given that some CBSA are compose on several counties. Thus, I can include CBSA-year fixed effects to control for any observable and unobservable time-varying effect at the CBSA level (such as local demand conditions). The set of fixed effects implies that the regressions are identified through variation between treatment group (counties with a lottery winner) and control group (counties without winners) within a given CBSA in a given year. Under the identifying assumption, there should be a significant difference in deposits between the counties with a jackpot winner relative to counties with no winner within a given CBSA in a given year, but there should not be a difference between small business lending growth between with counties (i.e., in the credit supply hypothesis we should expect an increase in the entire CBSA). The hypothesis is that the local bank that receives the winner's shock increases lending across the entire CBSA, and not only near the winner's location (i.e., winner's county). The specification is the following:

$$log(small\,lending)_{ijt} = \alpha_{jt} + \beta\, prize_{it}/deposits_{it-1} + \gamma' X_{it-1} + \varepsilon_{ijt}$$

where the outcome variable is small business lending in county $i$ in CBSA $j$ in year $t$, $\alpha_{jt}$ is a vector of CBSA-by-year fixed effects, $X$ is a vector of county demographic characteristics similar to (1), and $prize_{it}/deposits_{it-1}$; where $prize_{it}$ is prize received by the winner in county $i$ in year $t$, and $deposits_{t-1}$ are the deposits in county $i$ in the year prior to treatment $(t-1)$. The standard errors are clustered at the county level to account for serial correlation.

Appendix Table 7 report the point estimates.[40] Column (1) shows that on average those counties with winners increase their deposits in 2.12% (after one-standard deviation increase) relative to those counties without winners within a given CBSA in a given year. Column (2) shows the coefficients of the pre-treatment variables (3 year before the shock); the estimate is negative and insignificant which rejects the hypothesis of pre-trend in the data. Most importantly, columns (3) and (5) show that on average, within a given CBSA in a given year, the small business growth for those counties with winners is not significantly different with respect to counties with winners. These findings support the identifying assumption that the winner's shock is a supply shock.

As a final test on the identifying assumption, local demand may increase from the winner's shock because firm's net worth (i.e., firm's collateral) may be increasing due to possibly changing housing prices. To rule out this hypothesis, I interact the different treatment variables with an indicator of whether the MSA is above the median relative to Saiz (2010) housing elasticity measure.[41] Under the identifying assumption, there should not be a difference in the effect of the winners shock on those MSA above the median and below the median elasticity. Appendix Table 8 reports the estimates of the interaction of the different treatment variables and the indicator of whether the MSA is above the median of Saiz (2010) housing elasticity measure. The point estimates of the interaction are all insignificant at conventional test levels which support the identifying

[40] I find similar results for the different treatment variables.

[41] Saiz (2010) housing supply elasticity measure includes a geographic and regulatory component that is meant to capture the relative ease with which the housing stock in an area can adjust to a positive shift in the demand for housing. Areas where is it relatively easy to build tend to see more construction, and smaller house price increases, when demand for housing increases, whereas low elasticity areas tend to see higher prices and lower levels of new construction. Finally, Saiz (2010) measure only includes data about the MSA.

assumption.

In general, the results in Table 2 show a positive causal effect of the jackpot winner shock on small business lending. Additionally, these findings also indicate that the local supply of deposits matter for small business loan origination in the U.S., even after the developments in the financial sector: state banking deregulation (Kroszner and Strahan (1999); Johnson and Rice (2008)), increase in securitization (Loutskina and Strahan (2009), and the developed on nonpersonal means of information transmission (Petersen and Rajan (2002)).

Local-level *Elasticity of Total Small Business Lending*

To further show the overall effect of the jackpot winner shocks on local lending is required assumptions about the appropriate general equilibrium effects. With this caveat in mind, I estimate a two-stage least square model (2SLS) where total small business loan origination is the dependent variable, and the independent variable is the contemporaneous deposits at the CBSA level.[42] The empirical specification is (1) which includes the CBSA and year fixed-effects, and the set of (lag) CBSA characteristic controls. Finally, the instrument is log(1+prize). The models are estimated on data from 1999 through 2012, since this is that last period available from the CRA aggregate.

Table 3 reports the estimates. Column (1) shows that the first stage F-statistic is 13.41, above the conventional threshold of 10 for weak instruments (e.g., Stock et al. (2002)). The argument for the exclusion restriction is that there is only an increase in small business lending through the winner's shock only when there is growth in deposits as shown in columns (1), (5) and (9) of Table 2C (and Appendix Table 3 columns (2)-(3), (5)-(6) and (8)-(9) ). Thus, the instrument (log(1+prize)) only affects small business lending through its effect on deposits. Table 3 columns (2) and (3) report the OLS and reduced form regressions. Since this is one-instrument estimation, then 2SLS equals indirect least squares (i.e., ratio of reduced form to first stage coefficients on the instrument). Therefore, as Column (4) shows the 2SLS estimate is 0.49 (=0.0036/0.0074) which is the elasticity of total small business lending with respect to deposits. The magnitude of the elasticity of total small business lending with respect to deposits is underestimated by a factor of 1.6 when is not properly accounted for using the 2SLS model. Finally, from Table 1 we have that the average jackpot winner received $ 32.9 million (in 1999 dollars) and from the estimates in Columns (1) and (4) in Table 3, then

[42]The deposits at the CBSA level are only for those banks that meet the CRA asset size threshold to be subject to data reporting requirements.

the average total small business lending increase 3.78% on average.[43] This estimate is large in economic terms and highly significant.

### 4.3 Bank-level analysis

Since the SOD provides deposit data for each branch and I estimate the amount received by each jackpot winner, then on principle I can identify the possible branch, and thus the bank, that received the prize. The assumptions of the matching algorithm are the following: the winner deposits in her respective CBSA, and in those branches that are closest in driving distance to where she bought the ticket. The deposit findings in Table 2 support the first assumption, and the second assumption is plausible from discussions with state lottery representatives. More details about the algorithm are available in the Appendix.

The identifying assumption is that the winner's shock is exogenous to the bank, conditional on bank characteristics. Since it is exogenous that the bank have a branch in the winner's CBSA and a (possible) prior relationship with those eventual winners (e.g., the winner had an existing account in the first place with the bank). The identifying assumption is supported by the fact that banks do not open branches trying to systematic predicts jackpot lottery winners.[44]

In the bank-level analysis, using data from the Call Report, the empirical specification is the following:

$$log(outcome)_{it} = \alpha_i + \alpha_t + \beta\, prize_{it}/deposits_{it-1} + \gamma' X_{it-1} + \varepsilon_{it} \tag{2}$$

where the dependent variables are deposit (or loans) for bank $i$ at quarter $t$. The preferred specification for the treatment variable to account for the intensity of treatment, given the heterogeneity in size in the banking industry, is $prize_{it}/deposits_{it-1}$; where $prize_{it}$ is prize received by the bank $i$ in quarter $t$, and $deposits_{t-1}$ are the deposits in bank $i$ at the quarter prior to treatment $(t-1)$. Finally, $\alpha_i$ and$\alpha_t$ are bank and quarter fixed effects, and $X$ is a vector of bank characteristics in quarter $t-1$. An

[43] $[exp\,[0.0074 * ln(1 + 32,964.8)] - 1] * 0.49$.

[44] The point estimates using the identified banks that received the winners' shock, from the matching algorithm, will have attenuation bias. Thus, in this case the estimates will underestimate the effect of treatment, making it more difficult to find results and can be considered a lower bound of the true causal effect.

interesting feature of the Call Report is that the data is quarterly, and thus it allows one to use the data on the estimated date in which the winner received (and deposited) her prize. Specification (2) is also a difference-in-difference estimator. I report the standard errors clustered at the bank level to account for serial correlation and robust to heteroskedasticity.

The CRA disclosure data allows studying the small business lending of banks in the treatment group, to that of other banks in the control group, in the different CBSAs in which they originated loans. Thus, the empirical specification is the following:

$$log(small\,lending)_{ijt} = \alpha_{jt} + \beta\, prize_{it}/deposits_{it-1} + \gamma' X_{it-1} + \rho\, \psi_{ijt-1} + \varepsilon_{ijt} \qquad (3)$$

where the outcome variable is small business lending for bank $i$ in CBSA $j$ in year $t$, $\alpha_{jt}$ is a vector of CBSA-by-year fixed effects, $X$ is a vector of bank characteristics similar to (2), and $\psi$ is the number of branches for bank $i$ in CBSA $j$ and year $t-1$. $prize_{it}/deposits_{it-1}$; where $prize_{it}$ is prize received by the bank $i$ in year $t$, and $deposits_{t-1}$ are the deposits in bank $i$ in the year prior to treatment $(t-1)$.[45] I control for the number of branches each bank has in every CBSA, since the higher the number of branches the bank has the higher the probability of being treated (i.e., received the deposit from the jackpot winner). Thus, conditional on the number of branches, and other bank characteristics, the treatment variable is exogenous. The standard errors are clustered at the bank level to account for serial correlation. Finally, the battery of fixed effects implies that the regressions are identified through variation between treatment group and control group banks within a given CBSA in a given year. The fixed effects control for any observable and unobservable time-varying effect at the CBSA level, including demand-side effects affecting the lending behavior of all banks within a given CBSA-year.

### 4.3.1 Results

Table 4 reports the results of the matching algorithm. From 2002 through June 30th 2013 there were 191 non-group winners, which choose the cash option and reside in the

[45] The banks in the treatment group are the ones identified in the matching algorithm.

state where the winning ticket was sold, and the algorithm matched 134 winners.[46] Of the winners matched, 71 were single matched. The mean driving distance in minutes from the retail location that sold the winning ticket and the branch is 16.23 minutes. In addition, Table 4 shows that the branches in the treatment group had lower deposit growth from 1994 to 2001 (p-value is 0.00). Finally, Table 4 reports the bank-level attributes whether the banks was treated or not. There are differences in size, profitability and equity/assets ratio between both groups. Consequently, I include these characteristics as control in (2) and (3).

*Deposits and Total Lending*

Similar to the local-level section, the analysis starts with the estimates of the winners' shock effect on deposits. Panel A of Table 5 reports the parameters of interest from (2). Column (1) reports that a one standard deviation increase in the the intensity of treatment variable (*prize/deposits*) leads to an increase of 1.30% in the deposits (=0.0814*0.1598) in the quarter of the shock (0 m, 3 m). Column (2) reports the effect of treatment in the year of treatment (0 m, 12 m) (1.98% average quarterly change after an one standard deviation increase). Column (3) reports the result with the lead variable of *prize/deposits* that captures the effect on deposits before the winners' shock (-12m, 0m) and Table 5 Panel C reports the estimate of (2) augmented with lead variables, in both cases the results are insignificant. These findings suggest that there are no pre-existing trends in the data.

Since in the treatment group there is heterogeneity in asset sizes and I do not expect the winners' shock to have any significant effect on the large banks. Panel B shows the point estimates if I split the sample into two subsamples based on the (lag) bank's asset size those in the bottom 99% of the asset size distribution and those in the top 1%.[47] As can be seen from Panel B of Table 5 columns (2) and (3), the effect of the shock is concentrated among those banks in the 99% of the asset distribution. In addition, the estimates of (2) augmented with lead variables show no evidence of pre-existing trends. Overall, the estimates provide evidence that the jackpot winners' shock have

[46] The reason to focus on non-group prizes is that in some instances the prize is not divided equally between the members of the group (e.g., pool of workers that buy tickets together), and in some cases the data about how the groups share their price is not available in the press releases. Therefore, to reduce the possibility of mistakes I focus on non-group winners.

[47] In untabulated results, the findings are similar for other size distribution cut-offs (90% and 95% of the asset distribution).

an economic and significant increase on deposits of the treatment group. In addition, the results show that the largest set of banks is not affected, as expected, by winners' shock.

Additionally, the results in Table 5 (e.g., columns (1)-(3) of Panel B) show that the individual matching algorithm reasonable matched those banks that received the jackpot winning since the point estimates reflect the effect on the exact quarter that I estimated the winner claimed and deposited her prize, and there are no pre-treatment quarterly trends in the results (recall that the SOD data used to match the treated banks is yearly data).

Panel A of Table 5 columns (4)-(6) reports the estimate of (2) in which the outcome variable is total loans. Since the winners' shock effects can range within the year of treatment, I estimate the effect for the year of treatment. Column (4) and (5) report the estimate in the quarter of the shock (0m, 3m) and in the year of treatment (0m, 12m). In the first case, lending increases on average by 2.46% in the same quarter of the shock (=0.154*0.1598) and a 2.38% average quarterly change, after a one standard deviation increase, using the treatment variable for the year of the shock. Columns (6) and Table 5C column (4) show that the pre-treatment coefficients are insignificant, rejecting the hypothesis of pre-existing trends.

Panel B of Table 5 report the estimates for two subsamples based on the (lag) asset size. Column (6) shows that there is no effect for the larger banks in the treatment group. Column (4) and (5) report the point estimates for each quarter after treatment or lag variables ((0m, 3m), (3m, 6m), (6m, 9m) and (9m, 12m)) and lead variables. Interesting, columns (4) and (5) show that there is a credit supply effect only in the first three quarters of treatment and in the fourth quarter the shock's effect disappears. Finally, Column (4)-(6) exclude the hypothesis of pre-trends in the data.[48]

Appendix Table 10 reports the point estimates in which the dependent variable is total small business loans. Column (1) shows the coefficient of the treatment variable *prize/deposits* in the year of treatment (0m, 12m). Relative to the estimates for total loans, the average effect is larger for total small business loans (3.87% quarterly change on average after a one standard deviation increase). A possible explanation for this result is that these type of loans are harder to securitize, thus if the bank has marginal lending opportunities that are profitable, the shock induces a higher increase in this

[48]Appendix Table 9 shows that the winner's shock does not have an effect on bank's securities investment.

loan category. Finally, Column (2) shows that the results are not driven by pre-trends in the data.

In summary, the results in this section show a positive causal effect of the jackpot winners' shock on deposits and lending at the bank level. In addition, as expected, there is no treatment effect on the larger banks. The shock's positive effect on lending for the non-larger banks is only in the first three quarters, and also as expected the estimated effect is larger on small business lending.

*Small Business Lending and Local Demand Conditions: Intensive and Extensive Margin*

In order to further test that the findings are not driven by demand-side effects. I estimate the causal effect of the winners' shock on small business lending at the bank-level in the different CBSAs in which the banks originated loans, which allows one to control for any unobservable time-varying effect at the CBSA level.[49] Table 6 reports the parameters of interest from the regression specification (3). Column (1) and (3) show the coefficients of $prize/deposits$ to account for the intensity of treatment. A one standard deviation increases on average small business loan originations to businesses with revenues lower than $1 million by 5.89% (=.00946*6.223) in the year of the shock, and total small business loan originations by 5.02% (=.00946*5.304). Columns (2) and (4) report the coefficients of the pre-treatment variables; in both cases the results are insignificant which rejects the hypothesis of pre-trend in the data.

To study the extensive margin, I estimate a linear probability model (LPM) as (3) in which the outcome variable is a loan indicator equal to 1 if the loan was granted and zero otherwise. I estimate the specifications using OLS despite the binary type of the dependent variable. The object is that since (3) has a large number of fixed effects and using a non-linear model (e.g., probit) results in an incidental parameters problem. The control variables and the set of fixed effects are the same as before. I also include borrower control characteristics. Table 6 column (5) reports the estimate. The winners' shock does not affect the probability of lending. Since the winner's shock induces an increase in lending to small business but not an increase in probability of lending, an interpretation of the findings is that on average the increase in lending is to the current clients and not new clients.

[49] The estimates are qualitatively similar at the county level. In addition, I have also estimated models that include bank fixed effects. This alternative approach produced similar results.

Thus, these results confirm that the jackpot winners' shock has a large economic and significant effect on lending in the treated banks across the different CBSAs in which they have locations, and that the results are not driven by demands conditions in the local markets.[50]

Finally, it is of interest estimating the elasticity of total small business lending with respect to deposits at bank-level. I estimate a 2SLS model in which the outcome variable is total small business lending for bank i in CBSA j in year t and the regressor of interest is total deposits for bank i in CBSA J in year t (from the SOD). The problem for inference in this case is that OLS estimates may be biased if deposits are correlated with the unobservable determinants of small business lending. For example, variation in deposits is potentially correlated with demand for credit (e.g., Jayaratne (2000), Paravisini (2008)). I identify the causal impact of deposits on small business lending using the intensity of treatment variable (*prize/deposits*) as instrument.

The necessary condition to interpret the 2SLS estimate as the causal impact of deposits on small business lending is that the winners' shock only impacts lending through the deposits. Thus, the exclusion restriction could be violated if the winners' shock impacts small business lending through channels (e.g., local demand) other than deposits.[51] However, I argue that this exclusion assumption is reasonable in this setting. Recall that the fixed effects (i.e., CBSA-by-year) in this case control for any unobservable time-varying effect at the local-level, including demand-side effects. Table 7A reports the first stage, reduced form, OLS and 2SLS estimates. Column (1) shows that the first stage F-statistic is 10.6. Column (4) reports the 2SLS point estimate of 0.934 (=5.036/5.394) for the elasticity of small business lending with respect to deposits.

There is an important caveat to the IV analysis of Table 7A, following Imbens and Angrist (1994), I interpret the 2SLS estimate as the local average treatment effect (LATE) of deposits on small business lending for the sub-population of compliers whose deposits are altered due to the winners' shock. However, it is possible that the effect of deposits is different for banks that are not the marginal recipient. To address this issue, I study the characteristics of the complier group I estimate the first stage, using Call report data, for different bank groups according to their attributes.Table 7B reports the estimates. Column 1 reports the distribution of the population of commercial banks by the

[50]In untabulated results, the estimates of the treatment variable (*prize/deposits*) when I split the sample to the CBSAs with a jackpot winner, and those without one, are economic and highly significant in both cases. In addition, there is no evidence of pre-trends in the data in both subsamples.

[51]In addition to the testable assumption that winner's shock is associated with bank's deposits.

regulatory capital measure tier 1 risk-based capital ratio and balance sheet liquidity. Column 2 reports the distribution of compliers by tier1-liquidity groups, calculated as the ratio of the first stage for that subgroup to the overall first stage, multiplied by the proportion of the population in the group (i.e., the proportion of the treated who are compliers). There are almost no compliers in the bottom of the tier 1 distribution and interestingly, for the banks not in bottom of the tier 1 distribution; the compliers are almost evenly split between those below and above the median in terms of balance sheet liquidity. Column 3 displays the relative likelihood of a bank belonging to a particular group, in the complier group compared to the population at large. We see that those banks not in the bottom of the tier 1 distribution are almost equally represented among the compliers compared to the population at large.

*Costly External Financing or Agency Problems?*

The findings show that the jackpot winner's shocks positively increases loan origination for the set of smaller banks. However, what is the precise mechanism that drives the results? There are two hypotheses that can explain the findings: underinvestment and free cash flow. The costly external financing, or underinvestment, hypothesis states that banks which are financially constrained, due to adverse-selection problems, can have profitable marginal investment opportunities that are not exploited (Myers and Majluf (1984); Stein (1998)), while the agency problems, or free cash flow, hypothesis asserts that financial frictions can constraint empire-building managers from overinvesting which could negatively impact the bank's credit risk (Jensen (1986, 1993); Stulz (1990); Hart and Moore (1995)).[52] Using Call Report data, I estimate whether there is an increase in the nonperforming loans to total loans, and a decrease of interest revenues to total loans within the year, two, three and four years of treatment. The empirical specification is (2) where the outcome variables are nonperforming loans to total loans, and interest revenues to total loans.

Table 8 reports the estimates. Columns (1) to (4) report the point estimates in the case of nonperforming loans, and for columns (5) to (8) for interest revenues. For both variables there are no a significant effects in the year of treatment, and within two, three and four years of the shock. There could concerts related to the power of the tests. However, recall that the sample period includes the great recession in which the

[52] Stutz (1990) and Hart and Moore (1995) models predict ex-post overinvestment in those states in which the available funds relative to investment opportunities are higher than expected.

default rates increased significantly, and, most importantly, the test uses the same data set in which I was able to reject the null hypothesis of no effect on deposits and loans (e.g., Table 5).

In addition, the extensive margin findings in Table 6 can be interpreted as support for the costly external finance model since the probability of granting loans was not affected, then the banks were extending credit on average to clients which presumably they have prior relationship (and have developed soft information about them).These results can be interpreted as support for the underinvestment hypothesis related to costly-external finance models, and thus that frictions prevent small banks from taking advantage of profitable lending opportunities. As consequence, these results are not consistent with the Modigliani–Miller proposition for banks.

## 4.4 Bank-attributes and credit supply

Having established a positive causal effect of the winner's shock on bank's credit supply, controlling for local demand conditions, I turn to examining the heterogeneity in the response to the exposure of treatment. Following Stein (1998) cross-sectional predictions related to the extent of information asymmetry problems that banks face.[53] Using bank size as proxy to the extent of information asymmetry that banks face when they want to raise financing; therefore, presumably small banks face relative higher problem of adverse selection, and thus rely more on deposits (e.g., greater asymmetric information about the value of the loan portfolio). I split the sample according to the (lag) bank's asset size, the results in Table 5B columns (5)-(6) and Table 9A columns (1)-(4) show that the set of non-large banks (those in the 99% of the asset distribution) are the ones that on average increase lending after the winner's shock. The findings are consistent with Stein (1998) since the small banks are the only ones that significantly respond to the winner's shock.[54] In addition, the findings that show no effect of the winner's shock on the set of large banks are consistent with Kashyap and Stein (1995, 2000) and Campello (2002) that indicate that large banks can offset Fed policies. The reason is that large banks can undo Fed policies on the margin due to relative greater access to

[53]The monetary authority can influence lending, through open market operations, by tightening the access to information-insensitive external funds such as deposits. However, because of information frictions there is heterogeneity in the way banks are affected in their ability to fund loans (Stein (1998)).

[54]In untabulated results, the findings are similar for other size distribution cut-offs (90% and 95% of the asset distribution). In addition, the results of Table 9A are similar using CRA disclosure data.

non-deposits financing.

Following the previous findings of no significant treatment effect on deposits (Table 5B columns (2)-(3)) and lending for the set of large banks (Table 5B columns (5)-(6) and Table 9A columns (1)-(4)). The subsequent tests will focus on the set on non-large banks. Next, I test on whether the lending behavior depends on how liquid (or illiquid) is the LHS of the bank's balance sheet. To this end, I split the sample in those banks above and bellow the median in the ratio of cash and securities relative to assets. Table 9A columns (5)-(8) report the point estimates. The results show that the shock's effect on total loans according to how illiquid the balance sheets are similar to both groups of banks. However, for small business lending the shock's effect is greater for those banks with the relative illiquid balance sheet. This last finding is consistent also with Stein (1998) since the most illiquid banks could face greater adverse selection problem since their balance sheet could be more difficult to valuate. In addition, the banks with the most illiquid balance sheet cannot so easy sell their illiquid asset to fund illiquid loans.

Subsequently, for the set of non-large banks, I study the causal effect of shocks to the bank's liability side on credit supply depending on the bank's capital. In the presence of banks' capital regulation, the binding capital constraint can limit the bank's credit supply response to a shock on deposits. To this end, I focus on two of the regulatory capital measures: Tier 1 risk-based capital ratio and leverage ratio.[55] I split the sample on the (lag) bank's capital, those banks in the bottom 10% of the distribution and those above the 10th percentile.[56] Table 9B reports the point estimates. The estimates show that only those banks above the 10th percentile of the capital ratio distribution for both regulatory measures significantly increase their lending after the winner's shock.

## 4.5 Regulatory mix and credit supply

### 4.5.1 Background on U.S. Banking Regulation

The regulatory structure in U.S. banking involves dual supervision of institutions by both state and federal regulators. Since the National Bank Act of 1863, commercial banks have faced a dual supervisory system, under which they are chartered and supervised both by federal and state-level entities. Banks can choose between a state and

[55]The other regulatory capital measure is total risk-based capital ratio.

[56]The findings are similar using, instead of 10% cut-off, 5% or 20% cut-offs.

national charter. With a state charter, they are able to choose whether or not to be members of the Federal Reserve System. There are three types of commercial bank charters which differ on the federal regulator associated with: the Office of the Comptroller of the Currency (OCC), the Federal Deposit Insurance Corporation (FDIC), and the Federal Reserve System (Fed). Federally chartered banks, also known as national banks are primarily supervised (and chartered) by the OCC. However, state banks are supervised by their chartering state banking departments, along with the Federal Reserve, in case that they have decided to be members of the Federal Reserve System (known as state-member banks). Those state banks which decide not to be a member of the Federal Reserve System (these banks are known as non-member banks) are supervised by their respective chartering state banking departments along with the FDIC.

Over the years, most part of the differences across requirements and charters have disappeared as regulatory and charters have converged. Many authors claim that the main drivers of charter choice now are direct regulatory costs and the bank's perception of the regulator's accessibility (Cyran (2009)).

Banking supervision relies on off- and on-site monitoring. Off-site monitoring requires all depository institutions to file quarterly Call Reports, which are examined to monitor a bank's financial conditions between on-site examinations. On-site examinations allows regulator to verify the content of Call Reports and the safety and soundness of the supervised entity as well as its compliance with regulations. In an on-site examination, supervisors also evaluate the loan portfolio and meet with the bank's management to discuss the need for informal or formal supervisory actions. Informal actions comprise a written commitment from the bank to solve any deficiencies found. Among formal actions are: cease-and-desist orders, suspensions or removals of banks' senior management, and/or terminations of insurance.

Federal bank supervisors are required to conduct on-site examinations every 12 months, unless their assets fall below a minimum threshold (since 2007 stands at $500 million for state-members and non-members banks), in which case the exams are conducted every 18 months. Since 1980, federal supervisors had begun coordinating with state banking departments so that they could share examination results.[57] This alternation system aims to reduce the regulatory burden on state chartered banks under dual supervision system, by substituting a federal examination with a state examination. Since 1995,

[57] Federal Financial Institutions Examination Council (FFIEC) has issued guidelines for determining the acceptability of state examination reports as substitutes for federal examinations.

acceptable state reports became eligible substitutes for federal reports. Thus, federal and state regulators could alternate their role as examiners every 12 months (or 18 months for small banks) for state chartered banks.

#### 4.5.2 Treatment heterogeneity relative to regulators

Related to the literature on regulatory shopping in the banking sector, Agarwal et al. (2014) find that regulators can implement identical rules inconsistently. Comparing federal and state regulator supervisory ratings within the same bank, they find that federal regulators are systematically tougher.

However, what are the real consequences of inconsistent regulators? Does the regulatory mix affect credit-supply? In particular, what is the effect of bank's choice between state or federal charter on credit supply? I should be worry that selection bias would affect the estimates since banks do not choose randomly between a state and national charter. However, Agarwal et al. (2014) find that the nature of unobservable factors that drive the bank sorting decision into and from the state charter might be time-invariant. Thus, bank quarter fixed effects may be a sufficient correction to account for charter shopping.

I split the sample according to whether the bank is a state or national chartered, then I estimate (2), for the set of non-large banks (those in the 99% of the asset distribution).[58] Table 10A shows that the winner's shock on total loans and small business loans is only significant for state-chartered banks. The interpretation of the findings in Table 10A is that the regulatory mix matters for the cost of external financing (i.e., the degree of adverse selection issue) following Stein (1998). In addition, finding no significance effect of the winner's shock for the set of federal-charted banks can be a possible benefit of facing tougher federal regulators (i.e., less adverse selection problem).

From Agarwal et al. (2014), we know that federal regulators are less lenient. Thus, there are several mechanisms that can explain the results in 10A. The first hypothesis is that only high type banks choose being federal chartered. This hypothesis is ruled-out since any selection issue is already accounted by the bank and quarter FE (Agarwal et al. (2014)). Thus, the estimates of 10A are the causal effect of winner's shock and the charter choice on lending origination.

[58]All the proceeding tests are for the set of non-large banks following the previous findings of no significant treatment effect on deposits and lending for the set of large banks, unless otherwise noted.

Second, the federal regulators provide a kind of certification that lessens the bank's adverse-selection problems. A potential problem may arise with this hypothesis, since federal regulators also control state chartered-banks. Why do they provide certification to a set of banks (federal chartered) and not to the other set of banks (state chartered)? A possible answer is that the OCC is the one that provides certification.

Third, the state regulators are more lenient which could increase the adverse-selection problems for the set of state chartered banks (i.e., increases the difficulty of replacing insured deposits with other forms of uninsured debt finance such as commercial paper, or medium-term notes). Why state regulators are laxer? There are several channels that can explain this question: i) state banks have influence on their state regulators (influence hypothesis), ii) state regulators care about the state of the local economy (local interest hypothesis), and iii) state regulators have capacity constraint relative to the federal regulator (weakness hypothesis). It's worth pointing out the these last two hypothesis can complement each other.

*Certification Channel*

A test of the second hypothesis related to the certification channel is to assess the market microstructure properties of federal and state chartered banking firm's equity. Since bank assets may be illiquid and hard to value, government regulations/regulators tend to mitigate their opaqueness. This potential opaqueness may lead to an adverse selection problem that increases the cost of external financing. If banks were relatively difficult for outsiders to understand, the literature on equity market microstructure indicates that their shares should exhibit distinctive trading characteristics in variables such as their bid–ask spreads, the adverse selection component of those spreads and their share turnover (Flannery, Kwanb, Nimalendran (2004)). In this case, if outsiders have more difficulty valuing state chartered than federal chartered banks, I would expect lower bid–ask spreads associated with federal chartered.[59]

Following the previous literature that has examined market data to determine whether banking firms are more opaque than non-banking firms(e.g., George, Kaul, Nimalendran

[59] Flannery et al. (2004) assess the market microstructure properties of U.S. banking firms' equity, to determine whether they exhibit more or less evidence of asset opaqueness than similar-sized non-banking firms. Their information asymmetry hypothesis underlies Kyle's (1985) conclusion that a "more opaque" asset trades with a larger bid–ask spread. Asset opacity could either raise or lower trading volume and turnover. Ceteris paribus, a higher spread (trading cost) would discourage uninformed traders from holding a stock, making it more difficult for informed traders to hide their information.

(1991); Huang and Stoll (1994); Flannery et al. (2004)) I focus on three different proxies for adverse selection. The first one is the adverse selection (AS) component of spreads from George et al. (1991).[60] The second measure, defined as SPREAD, is the bid–ask spread scaled by price. Finally, the third measure shares turnover (TOVER) is the number of shares traded divided by the number of shares outstanding.

I explore the correlation between the above adverse selection proxies measures and the fact that a bank is federal chartered, controlling by banks' characteristics and microstructure variables. Admittedly, interpreting these patterns causally would require further assumptions.[61] These caveats notwithstanding, I try to assess if federal regulators provide a kind of certification to federal chartered banks that lessens the bank's adverse-selection problems. Appendix Table 12 reports the correlation estimates of each measure on an indicator variable equal to one if the bank is federal chartered. As shown in column (1), there is a negative relation between being federal chartered and the first proxy measure AS, 3 percent higher relative to the mean. Column 2 reports that the there is no significant relation between federal chartered bank and bid–ask spreads. Because less frequently traded stocks can have more information problems, the literature hypothesize that the average shares turnover might be related to adverse selection. Column (3) reports that federal chartered banks have a share turnover 33 percent higher, relative to the mean, than state chartered banks. Finally, even if the above measures are proxies of potential adverse selection problems, this analysis suggests that there is a correlation between the bank's charter and potential adverse selection in the bank's equity, which provide suggestively support the second hypothesis about the OCC providing certification to those federal chartered banks.

*State Regulators' Leniency Channel*

A first test of the third hypothesis of the regulatory mix, is using the cross-sectional variation in federal-state spreads in CAMELS from Agarwal et al. (2014) for the set of state chartered banks.[62] I split the sample according to the federal-state spread in quintiles and estimates the winner's shock effect on lending for those banks in the first

[60] The bid-ask spread, according to George et al. (1991), can be decomposed into two components (i.e., order processing and adverse selection). The AS measure captures the adverse selection component.

[61] Another caveat in this analysis is the small sample of public commercial banks.

[62] CAMELS rating summarizes the bank's condition in six components: capital adequacy, asset quality, management, earnings, liquidity, and sensitivity to market risk.

quintile (less laxity of state regulators relative to federal regulators) and those in the fifth quintile (more lax state regulators).[63] Table 10B shows that in those states with relative higher federal-state spread in their CAMELS are where the winner's shock has a significance effect for total and small business loans. These findings support the third hypothesis that the state regulators leniency can affect credit supply.

To further study the third hypothesis, I test for the possible channel of the more lax state regulators. It is well documented that a majority of states finance their prudential supervision efforts through the use of assessment fees proportional to bank assets (Blair and Kushmeider (2006)). As a result, large banks hold a disproportionate weight in the existence of state supervision, since they represent the largest revenue source for the state regulator itself. Under this hypothesis we should expect that the winner's shock has relative higher effect on those bigger banks since these banks could presumably have higher influence on the state regulator. Thus to test for the influence hypothesis for the set of state chartered banks, I split the sample according to the (lag) bank's asset size. Table 10C shows that the winner's shock effect is higher for the set of large state banks (those in the 90% of the asset distribution).

To further tests for the influence hypothesis, I use the state cross-sectional differences in institutional quality from previous papers. A first proxy for institutional quality is the ratio of convictions of government officials for corrupt practices divided by the state population to capture the relative institutional quality for each state. I split the sample according to those state above and below the median in convictions per capita. Table 11 Panel B reports the estimates. The winner's shock effect on total loans and small business lending is higher in those states above the median in terms of convictions. A second measure of institutional quality is state and local expenditures per-capita. Glaeser and Saks (2006) argue that states with poorer fiscal policy, and therefore higher expenditures compared to revenues, may have environments that are conducive to corrupt practices. Table 11C reports the results.[64] The treatment effect on lending is greater in those states in which the government expenditure per-capita is above the median. These finding supports the influence of regulators hypothesis of the state chartered banks since the fees to the state regulators are higher for the bigger

[63] The use of quintile is to increase the difference between groups since most federal-state spread are close to the median (see Agarwal et al. (2014) Figure 4).

[64] As a robust check of the tests of institutional quality. I do a similar test but for the set of federal banks. In this case, there should not be an effect since these banks only face federal regulators. Appendix Table 12 show that there is no difference between banks federal chartered in states above and below the median for the difference institutional qualities measures.

state charter banks.

State-chartered banks can choose between being members or not of the Federal Reserve System. Does it matter whether the bank is member or not of the Federal Reserve System for the treatment effect? Table 10D reports the estimates when I split the sample for those bank members or not of the Federal Reserve System. There is no difference between banks that are members or not of the Fed in both types of loans. This finding implies that there is no distinction between federal regulators for the set of state-chartered banks. In addition, these findings do not rule out the certification hypothesis since the state-chartered banks face a different federal regulator (i.e., OCC).

The above findings highlight differences in the response of treatment relative to regulators. Another possible channel to this heterogeneity could be that state regulators care about the local economy, and as a result are softer on the state banks, especially when the local economy is doing poorly. To assess whether the local interest hypothesis plays a role in explaining heterogeneity in the response of a supply shock, I test if state-chartered banks increase small-business loans more when they are hit by a shock and the unemployment rate in their states are more than the median. Table 11 Panel A reports no relation between the lending behavior and unemployment. Finally, the current version of the paper does not test for the weakness hypothesis. The next version of the paper will incorporate tests to study this channel.

Overall, this section's findings suggest that the regulatory mix in U.S. can affect credit supply. Moreover, the current results suggest support for the federal regulators certification mechanism and, moreover, the lax state regulators hypothesis. In addition, they highlight the potential influence of special interest groups on state regulators (influence channel).

# 5 Conclusion

This paper uses a novel natural experiment and dataset that allows inquiry into the causal effect of exogenous shocks in the supply of deposits on credit supply. The identification strategy utilizes the fact that having a jackpot winner, and the amount won, in a specific local area and at a time that is randomly assigned, conditional on lottery ticket sales. Additionally, the analysis is nationally representative of the U.S., and the identification condition at the local-level (i.e., in the absence of a winner shock, the changes in the outcome variable do not differ between the treatment and control group) is directly testable from features of the settings (e.g., unclaimed prizes). Furthermore, it is possible to determine the receiving branch, and thus the bank, that received the prize. This allows one to study the shock's effect at the bank-level, controlling for any unobservable time-varying effect at the CBSA-level (e.g., local demand conditions within a given CBSA-year).

The analysis finds that the jackpot winner shock leads to a significant increase in deposits and in small business lending at the CBSA-level (4.05% and 4.28%, respectively). The shock's effect is greater in those CBSAs in which small banks have high levels of local bank concentration (6.79%). In addition, the estimate of the elasticity of total small business lending with respect to deposits is 0.49. At the bank-level, banks in the treatment group experience a large growth in deposits, total lending, and small business lending. The winners' shock effect on the set of non-large banks is not persistent (i.e., only in the first three quarters of treatment). After controlling for demand conditions in the local markets, banks in the treatment group increase on average their small business loan origination (5.02% after a one-standard-deviation increase) across the different CBSAs in which they have locations. There is no evidence that the treated banks experience a relative increase in nonperforming loans and a decrease of interest revenues. Finally, the winners' shock does not affect the probability of lending. Thus, since the shock leads to great lending origination to small businesses, but not an increase in probability of lending, an interpretation of the findings is that on average the increase in lending is to current clients and not new clients.

The results at the local-level show that local deposit supply matters for small business loan origination, even after the developments in the financial sector of recent decades: intrastate and interstate branching deregulation (Kroszner and Strahan (1999); Johnson and Rice (2008)), increases in securitization (Loutskina and Strahan (2009)), and development of nonpersonal means of information transmission (Petersen and Rajan (2002)). Additionally, these results support previous findings that banks have an important role in mitigating frictions for small firms (e.g., banks obtain soft information on firms to help in credit decisions). The findings at the bank-level suggest that a set of banks (i.e., small banks and those with the most illiquid balance sheet) were financially constrained before experiencing the winners' shock, and thus are not consistent with the Modigliani–Miller proposition for banks. Finally, the bank's choice between a state and national charter seems to matter to the degree of adverse selection that the banks face, which could affect their lending behavior. This is plausible a cost for the banks that are voluntary choosing to be state-chartered banks. However, there should be benefits to choosing a state charter; apart from lower supervisory fees from state regulators, future research needs to document these benefits.

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Figure 1 States highlighted (gray) offer Mega Millions and Poweballs as of June 2013

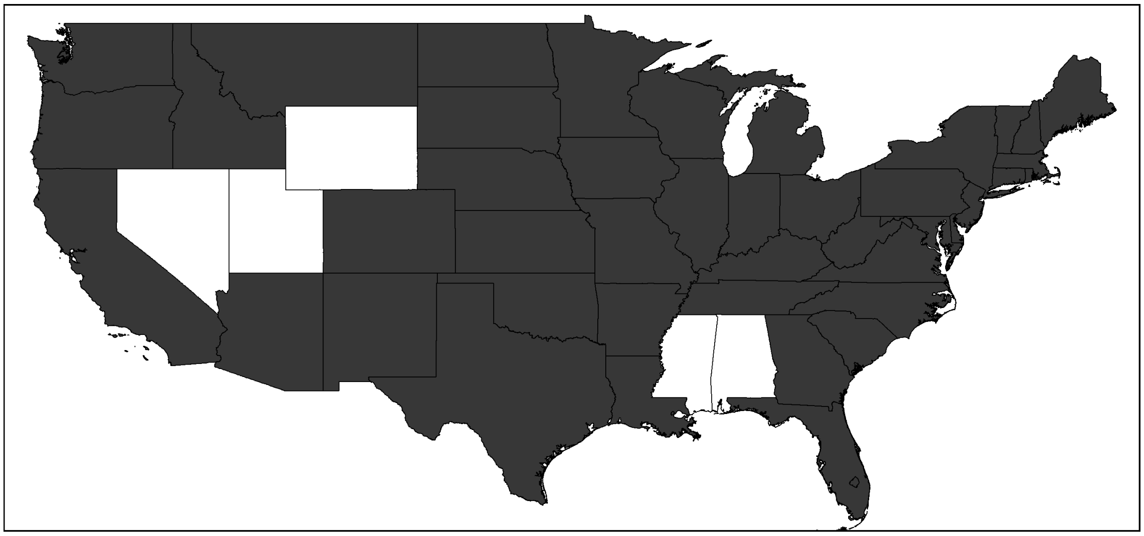

Figure 2 Mega Millions and Poweball jackpot winners (gray) by county, 2002-2013

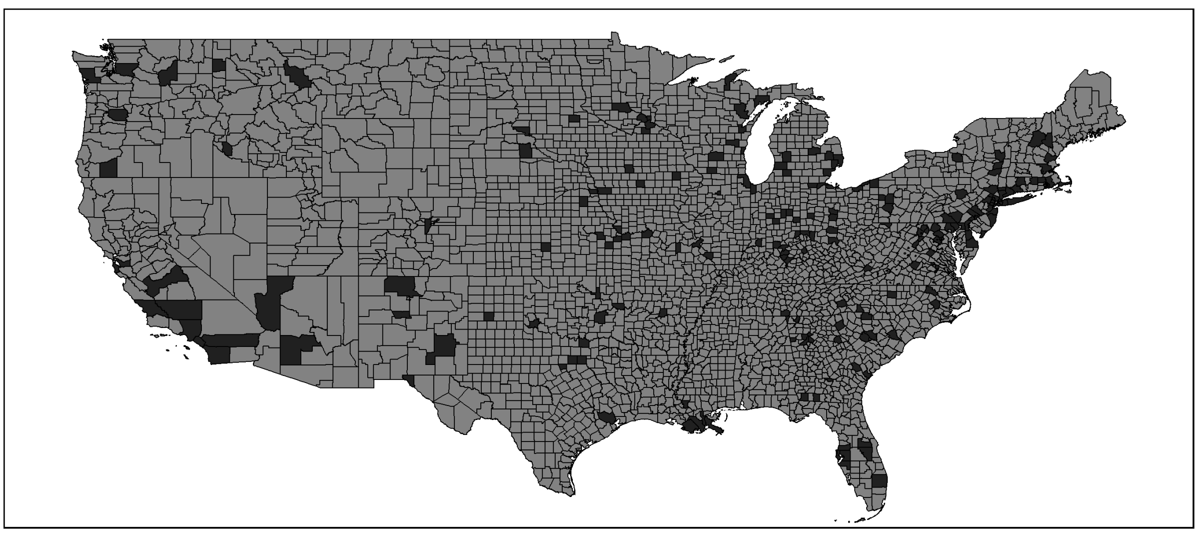

Table 1 Jackpot winners and CBSA characteristics

U.S. lotteries jackpot winners dataset comes from different public sources. Deposits data comes from the SOD. Population data is from the Census. Standard deviations in brackets.

| | | |
|---|---|---|
| Number of states where both lotteries are played (June 2013) | | 43 |
| | Mega Millions | 43 |
| | Powerball | 43 |
| Number of jackpot winners | | 284 |
| | Mega Millions | 139 |
| | Powerball | 145 |
| Number of different states with winners | | 41 |
| | Mega Millions | 16 |
| | Powerball | 38 |
| Number of different CBSA with winners | | 142 |
| | Mega Millions | 65 |
| | Powerball | 95 |
| Type of prize | | |
| | Cash | 263 |
| | Non-cash (annuity or unclaimed) | 21 |
| Winners' state of residence | | |
| | Same state | 255 |
| | Different state | 29 |
| Prize amounts (after-taxes in 1999 Dollars) | | |
| | Mean | $32,964,828 |
| | 25th percentile | $12,224,520 |
| | 75th percentile | $47,631,512 |

| CBSA characteristics | | | |
|---|---|---|---|
| | Winner | Non-winner | p-value on t-test for difference |
| Ln (population in 2001) | 13.247 | 11.239 | 0.000 |
| | [1.037] | [ 0.961] | |
| % white in 2001 | 0.785 | 0.802 | 0.037 |
| | [0.144] | [0.184] | |
| % male in 2001 | 0.489 | 0.493 | 0.000 |
| | [0.009] | [0.016] | |
| % over age 45 in 2001 | 0.346 | 0.358 | 0.000 |
| | [0.046] | [0.053] | |
| Deposit growth (%) 1994-2001 | 0.021 | 0.021 | 0.952 |
| | [0.073] | [0.311 ] | |

Table 2 Effect of Jackpot Winners' shock on Deposits and small business loans at the CBSA level

Data are from the SOD, 1999-2013, and FFIEC, 1999-2012. An observation is a CBSA by year cell. The dependent variable equals the Log Deposits at the CBSA level, log of the total small business loan originations, defined as loans under $1 million, and log small business loans originated with gross annual revenues $<$ 1 million at the CBSA level.. Winner is an indicator equal to one in those CBSA/year with Jackpot winners, that chooses the cash option and resides in the state where the ticket winning was bought, and zero otherwise. Log Prize is the amount won after withheld federal and state taxes in 1999 dollars. Prize/deposits equals the ratio of the amount won in CBSA $i$ and year $t$, and deposits in CBSA $i$ and year $t-1$ (year before treatment). Small bank equals one if the CBSA is in the 5th quintile of the yearly distribution of the ratio of the number of branches from banks with assets lower or equal to $1 billion (in 1999 dollars) to the total number of branches in each CBSA, and zero otherwise. State taxes is a dummy variable equal to 1 for those states with individual income state taxes. Winner $(t+1)$ is a lead variable equal to 1 year before the shock, in those CBSA with a winner at t, and zero otherwise. Winner (t+2), Winner (t+3), and Winner (t+4) are defined analogously. All specifications include lag CBSA characteristics (i.e., log(population), % white, % male, % over age 45, income per-capita), CSBA, state and year FE. Robust standard errors in parentheses, clustered at the CBSA level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| Panel A | Log Deposits | | | Log Small Business Loans Originated with Gross Annual Revenues < 1 | | | Log Total Amount of Small Business Loans | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (8) | (9) | (10) |
| Winner | 0.0313*** | | | 0.0431** | | | 0.0371** | | |
| | (0.0119) | | | (0.0185) | | | (0.0148) | | |
| Log Prize | | 0.0038*** | | | 0.0045** | | | 0.0040*** | |
| | | (0.0012) | | | (0.0018) | | | (0.0015) | |
| Prize / Deposit | | | 0.828** | | | 1.890** | | | 1.304* |
| | | | (0.413) | | | (0.930) | | | (0.789) |
| Small Bank | | | | | | | | | |
| Winner x Small Bank | | | | | | | | | |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| CBSA FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 11,802 | 12,588 | 11,802 | 10,916 | 10,912 | 11,420 | 10,916 | 10,912 | 11,420 |

Table 2 (Continued)

| Panel B | Log Small Business Loans Originated with Gross Annual Revenues < 1 | | Log Total Amount of Small Business Loans | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Winner | 0.0417** | 0.0758* | 0.0365** | 0.0454 |
| | (0.0186) | (0.0397) | (0.0150) | (0.0477) |
| Winner x State taxes | | -0.0353 | | -0.00740 |
| | | (0.0444) | | (0.0501) |
| Small Bank | -0.0363 | | -0.0272 | |
| | (0.0292) | | (0.0235) | |
| Winner x Small Bank | 0.131*** | | 0.0679*** | |
| | (0.0252) | | (0.0204) | |
| Year FE | Yes | Yes | Yes | Yes |
| CBSA FE | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes |
| Observations | 10,912 | 10,964 | 10,912 | 10,964 |

Table 2 (Continued)

| Panel C | Log Deposits | | | | Log Small Business Loans Originated with Gross Annual Revenues < 1 | | | | Log Total Amount of Small Business Loans | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Winner (-3y, -2y) | | -0.0157 | | | | -0.00424 | | | | 0.00563 | | |
| | | (0.0131) | | | | (0.0243) | | | | (0.0190) | | |
| Winner (-2y, -1y) | | 0.0126 | | | | 0.0273 | | | | 0.0269 | | |
| | | (0.00943) | | | | (0.0254) | | | | (0.0190) | | |
| Winner (-1y, 0y) | | 0.0142 | | | | 0.00855 | | | | 0.00633 | | |
| | | (0.0115) | | | | (0.0235) | | | | (0.0173) | | |
| Winner (0y, 1y) | | 0.0327** | 0.0329*** | 0.0392*** | | 0.0460** | 0.0428** | 0.0390* | | 0.0411** | 0.0384*** | 0.0334** |
| | | (0.0144) | (0.0120) | (0.0150) | | (0.0219) | (0.0183) | (0.0216) | | (0.0174) | (0.0148) | (0.0167) |
| Non-cash and winner out-of-state | -0.00803 | | | | -0.0105 | | | | -0.0115 | | | |
| | (0.0238) | | | | (0.0268) | | | | (0.0229) | | | |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| CBSA FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sample | Possible treated | | Treated states | States with less than 8 winners | Possible treated | | Treated states | States with less than 8 winners | Possible treated | | Treated states | States with less than 8 winners |
| Observations | 11,802 | 11,802 | 10,421 | 9,428 | 11,420 | 10,916 | 10,176 | 9,278 | 11,420 | 10,916 | 10,176 | 9,278 |

Table 3 Two Stage Least Squares Model (2SLS) of the Relationship Between Total Small Business Loan Originations and Deposit Supply at the CBSA level

Data are from the FFIEC and SOD, 1999-2012. An observation is a CBSA by year cell. The dependent variable equals the log of small business loan originations to businesses with $1 million in annual gross revenue or less at the CBSA level. Log Deposits are the log deposits at the CBSA level for those banks that meet the CRA asset size threshold to be subject to data reporting requirements. Log Prize is the amount won after withheld federal and state taxes in 1999 dollars. All specifications include lag CBSA characteristics (i.e., log(population), % white, % male, % over age 45, income per-capita), CSBA, state and year FE. Robust standard errors in parentheses, clustered at the CBSA level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| | First Stage | OLS | RF | 2SLS |
|---|---|---|---|---|
| | Log Deposits | Log Total Amount of Small Business Loans | | |
| | (1) | (2) | (3) | (4) |
| Log Deposits | | 0.309*** | | 0.490*** |
| | | (0.0226) | | (0.188) |
| Log Prize | 0.00741*** | | 0.00364** | |
| | (0.00202) | | (0.00146) | |
| First Stage F-stat | 13.41 | | | |
| Year FE | Yes | Yes | Yes | Yes |
| CBSA FE | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes |
| Observations | 10,776 | 10,776 | 10,776 | 10,776 |

Table 4 Individual Detection Algorithm Summary Statistics

U.S. lotteries jackpot winners dataset comes from different public sources. Branch characteristics data comes from the SOD. Banks characteristics data comes from the Call Report. Standard deviations in brackets.

| | | | |
|---|---|---|---|
| Number of non-group jackpot winners | 191 | | |
| Winners matched | 134 | | |

| Winners matched | | Number of branches | |
|---|---|---|---|
| Single branch matched | 71 | 71 | |
| Multiple branches matched (up to three) | 63 | 146 | |
| Total | 134 | 217 | |
| | | | |
| Driving distance from retailer to branch (minutes) | | | |
| Mean | 16.23 | | |
| 25th percentile | 10.92 | | |
| 75th percentile | 25.98 | | |

| Branch characteristics | Winner | Non-winner | p-value on t-test for difference |
|---|---|---|---|
| Deposit growth (%) 1994-2001 | 0.05 | 0.12 | 0.000 |
| | [.163] | [.269] | |

| Banks characteristics | Winner | Non-winner | p-value on t-test for difference |
|---|---|---|---|
| Ln(Assets) | 14.11 | 11.12 | 0.000 |
| | [2.360] | [1.300] | |
| ROA | 0.0047 | 0.0050 | 0.003 |
| | [.008] | [.009] | |
| Equity/Assets | 0.100 | 0.110 | 0.000 |
| | [.040] | [.050] | |

Table 5 Effect of Jackpot Winners' shock on Deposits and Loans at the bank-level

Data are from the Call Report, 1999-2013. An observation is a bank by quarter cell. The dependent variable equals the Log Deposits at the bank level, and Log total loans. Prize/deposits (0m, 3m) equals the ratio, on the quarter of treatment, of the prize deposit in bank $i$ in quarter $t$ to and deposits in banks $i$ and quarter $t-1$ (quarter before treatment). Prize/deposits (0m, 12m) is the same ratio but takes the value of the ratio in the 12 months after treatment for the banks in the treatment group (0 m, 12 m), and zero otherwise. Prize/deposits($t+4$) (-12m, 0m) is the same ratio but takes the value of the ratio in the 12 months before the shock. Prize/deposits($t+1$) (-3m, 0m) is the same ratio but takes the value of the ratio in the 3 months before the shock. Prize/deposits($t+2$) (-6m, -3m) is the same ratio but takes the value of the ratio in the 6 months to 3 months before the shock. Prize/deposits($t-1$) (3m, 6m) is the same ratio but takes the value of the ratio in the 3 months to 6 months after the shock. Prize/deposits($t-2$), Prize/deposits($t-3$) are defined analogously. Bank controls include the lag of log(assets), ROA, and Equity/Assets. All specifications include bank, and quarter FE. Robust standard errors in parentheses, clustered at the bank level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| Panel A | Log Total Deposits | | | Log Total Loans | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Prize / Deposit (0m, 3m) | 0.0814* | | | 0.154* | | |
| | (0.0434) | | | (0.0813) | | |
| Prize / Deposit (0m, 12m) | | 0.124*** | | | 0.149*** | |
| | | (0.0209) | | | (0.0326) | |
| Prize / Deposit (-12m, 0m) | | | -0.0236 | | | -0.464 |
| | | | (0.0676) | | | (0.308) |
| Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 451,142 | 448,025 | 451,142 | 451,190 | 448,068 | 451,190 |

| Panel B | Log Total Deposits | | | Log Total Loans | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Prize / Deposit (-6m, -3m) | -0.0625 | -0.0566 | -4.345 | -0.748 | -0.749 | 8.052 |
| | (0.0748) | (0.0736) | (22.81) | (0.498) | (0.498) | (7.403) |
| Prize / Deposit (-3m, 0m) | 0.113 | 0.126 | -5.055 | -0.259 | -0.258 | 21.25 |
| | (0.0870) | (0.0900) | (32.97) | (0.163) | (0.164) | (16.47) |
| Prize / Deposit (0m, 3m) | 0.0808* | 0.0912** | -7.320 | 0.158* | 0.159* | 11.48 |
| | (0.0424) | (0.0429) | (18.18) | (0.0834) | (0.0837) | (10.20) |
| Prize / Deposit (3m, 6m) | | | | 0.179*** | 0.179*** | 2.116 |
| | | | | (0.0514) | (0.0515) | (6.712) |
| Prize / Deposit (6m, 9m) | | | | 0.191*** | 0.191*** | 14.10 |
| | | | | (0.0459) | (0.0459) | (9.292) |
| Prize / Deposit (9m, 12m) | | | | 0.0311 | 0.0308 | 3.349 |
| | | | | (0.0593) | (0.0594) | (13.10) |
| Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Sample (Size) | All | Bottom 99% | Top 1% | All | Bottom 99% | Top 1% |
| Observations | 436,078 | 433,027 | 3,051 | 435,027 | 431,984 | 3,043 |

Table 6 Effect of Jackpot Winners' shock on the intensive and extensive margin on Small Business Loans at the bank-level

Data are from the FFIEC and SOD, 1999-2012. An observation is a bank by year cell. The dependent variables are log of the total small business loan origination, defined as loans under $1 million, log of small business loan originations to businesses with $1 million in annual gross revenue or less at the bank level, and an indicator variable equal to one if a loan is originated (extensive margin). Prize/deposits equals the ratio, on the year of treatment, of the prize deposit in bank $i$ in year t to deposits in banks $i$ and year $t-1$ (year before treatment). Prize/deposit (t+3) is the same ratio but takes the value of the ratio three years before the shock, for those banks treated at $t$, and zero otherwise. Bank controls include the lag of ln(assets), ROA, and Equity/Assets, and the number of branches bank i in CBSA $j$ in year $t-1$. All specifications include CBSA by year FE. Robust standard errors in parentheses, clustered at the bank level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| | Log Small Business Loans with Annual Revenues < 1 | | Log Total Amount of Small Business Loans | | Y=1 if loan originated |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Prize / Deposit$_{t0}$ | 6.223** | | 5.304** | | 0.0287 |
| | (2.552) | | (2.264) | | (0.195) |
| Prize / Deposit $_{t+3}$ | | 1.432 | | 0.663 | |
| | | (2.073) | | (2.145) | |
| CBSA x Year FE | Yes | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes | Yes |
| Observations | 73,946 | 73,946 | 75,503 | 75,503 | 10,124,017 |

Table 7 Two Stage Least Squares Model (2SLS) of the Relationship Between Small Business Loans and Deposit Supply at the bank-level

Data are from the FFIEC and SOD, 1999-2012. An observation is a bank by year cell. The dependent variables are log of the total small business loan origination, defined as loans under $1 million, log of small business loan originations to businesses with $1 million in annual gross revenue or less at the bank level, and an indicator variable equal to one if a loan is originated (extensive margin). Prize/deposits equals the ratio, on the year of treatment, of the prize deposit in bank $i$ in year t to deposits in banks $i$ and year $t-1$ (year before treatment). Prize/deposit (t+3) is the same ratio but takes the value of the ratio three years before the shock, for those banks treated at $t$, and zero otherwise. Bank controls include the lag of ln(assets), ROA, and Equity/Assets, and the number of branches bank i in CBSA $j$ in year $t-1$. All specifications include CBSA by year FE. Robust standard errors in parentheses, clustered at the bank level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively. Column 1 Panel B reports the distribution of the population of commercial banks by tier 1 risk-based capital ratio and balance sheet liquidity, $P(X=x)$. Column 2 Panel B reports the distribution of compliers by tier1-liquidity groups, calculated as the ratio of the first stage for that subgroup to the overall first stage, multiplied by the proportion of the population in the group, $P(X=x \mid I_1 > I_0)$. Column 3 Panel B displays the relative likelihood of a bank belonging to a particular group, in the complier group compared to the population at large.

| Panel A | First Stage | OLS | RF | 2SLS |
|---|---|---|---|---|
| | Log Deposits | Log Total Amount of Small Business Loans | | |
| | (1) | (2) | (3) | (4) |
| Log Deposits | | 0.362*** | | 0.934** |
| | | (0.0358) | | (0.418) |
| Prize / Deposit | 5.394*** | | 5.036** | |
| | (1.657) | | (2.177) | |
| First Stage F-stat | 10.60 | | | |
| CBSA x Year FE | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes |
| Observations | 75,486 | 75,486 | 75,486 | 75,486 |

| Panel B | Compliance for different bank groups | | |
|---|---|---|---|
| | $P(X=x)$ | $P(X=x \mid I_1 > I_0)$ | $\frac{P(X=x\mid I_1>I_0)}{P(X=x)}$ |
| | (1) | (2) | (3) |
| Tier 1: Bottom 5% | | | |
| Liquidity: Bellow 50% | 0.042 | 0.005 | 0.121 |
| Liquidity: Above 50% | 0.007 | 0.004 | 0.612 |
| Tier 1: Top 95% | | | |
| Liquidity: Bellow 50% | 0.451 | 0.482 | 1.069 |
| Liquidity: Above 50% | 0.501 | 0.435 | 0.869 |

Table 8 Effect of Jackpot Winners' shock on Loan Performance

Data are from the Call Report, 1999-2013. An observation is a bank by quarter cell. The dependent variables are the ratio of nonperforming loans (past due 90+ days plus nonaccrual) to total loans at the bank level, and interest and fee income from loans to total loans at the bank level. Prize/deposits (0m, 12m) equals the ratio, on the year of treatment, of the prize deposit in bank $i$ in year $t$ to deposits in banks $i$ and year $t-1$ (quarter before treatment). Prize/deposits (0m, 24m) and Prize/deposits (0m, 36m) are defined analogously. All specifications include bank, and quarter FE. Robust standard errors in parentheses, clustered at the bank level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| | Nonperforming Loans to Total Loans | | | | Interest Revenues to Total Loans | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Prize / Deposit (0m, 12m) | -0.00493 | | | | -0.000707 | | | |
| | (0.00651) | | | | (0.000996) | | | |
| Prize / Deposit (0m, 24m) | | -0.0121 | | | | -9.97e-05 | | |
| | | (0.0118) | | | | (0.000655) | | |
| Prize / Deposit (0m, 36m) | | | -0.0111 | | | | 0.000744 | |
| | | | (0.0135) | | | | (0.000794) | |
| Prize / Deposit (0m, 48m) | | | | -0.0105 | | | | 0.000694 |
| | | | | (0.0202) | | | | (0.000772) |
| Quater FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 448,060 | 448,021 | 438,646 | 438,607 | 413,547 | 413,508 | 373,556 | 373,517 |

## Table 9 Bank-attributes and credit supply

Data are from the Call Report, 1999-2013. An observation is a bank by quarter cell. The dependent variable equals the Log Deposits at the banks level, and Log total small business loans. Prize/deposits equals the ratio, on the year of treatment (0m, 12m), of the prize deposit in bank $i$ in quarter $t$ to and deposits in banks $i$ and quarter $t-1$ (quarter before treatment). Columns (1) and (3) in panel A are those banks in the 99% of the quarterly asset distribution. Columns (5) and (7) in Panel A are those banks bellow the median of the ratio (Cash+Assets)/Total Assets distribution, Bank controls include the lag of log(assets), ROA, and Equity/Assets. All specifications include bank, and quarter FE. Robust standard errors in parentheses, clustered at the bank level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively..

| Panel A | Size | | | | Balance Sheet Liquidity | | | |
|---|---|---|---|---|---|---|---|---|
| | Log Total Loans | | Log Total Small Business Loans | | Log Total Loans | | Log Total Small Business Loans | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Prize / Deposit | 0.151*** | 6.278 | 0.229* | 9.956 | 0.100** | 0.139*** | 0.285* | 0.0592 |
| | (0.0312) | (5.748) | (0.132) | (14.32) | (0.0445) | (0.0225) | (0.148) | (0.119) |
| Percentile | Bottom 99% | Top 1% | Bottom 99% | Top 1% | Bellow 50% | Above 50% | Bellow 50% | Above 50% |
| Quater FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 431,984 | 3,043 | 424,564 | 2,665 | 215,502 | 219,525 | 211,324 | 215,905 |

| Panel B | Log Total Loans | | | | Log Total Small Business Loans | | | |
|---|---|---|---|---|---|---|---|---|
| | Tier 1 Risk-Based Capital Ratio | | Leverage Capital Ratio | | Tier 1 Risk-Based Capital Ratio | | Leverage Capital Ratio | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Prize / Deposit | 0.0759 | 0.166*** | 0.241 | 0.182*** | 0.0440 | 0.233*** | 0.441 | 0.282** |
| | (0.183) | (0.0280) | (0.191) | (0.0312) | (0.429) | (0.0858) | (0.427) | (0.110) |
| Percentile | Bottom 10% | Top 90% | Bottom 10% | Top 90% | Bottom 10% | Top 90% | Bottom 10% | Top 90% |
| Quater FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 36,896 | 337,128 | 36,943 | 337,081 | 36,768 | 330,237 | 36,491 | 330,514 |

Table 10 Banks' charters and credit supply

Data are from the Call Report, 1999-2013. An observation is a bank by quarter cell. The dependent variable equals the Log Deposits at the banks level, and Log total small business loans. Prize/deposits equals the ratio, on the year of treatment (0m, 12m), of the prize deposit in bank $i$ in quarter $t$ to and deposits in banks $i$ and quarter $t-1$ (quarter before treatment). Columns (1) and (3) are those state-chartered banks. Columns (2) and (4) are those federal-chartered banks. Panel B are those state charter banks, and panel C are those state-chartered banks regulated by the FED (members of the Federal Reserve System) and by FDIC (non-members the Federal Reserve System). Bank controls include the lag of log(assets), ROA, and Equity/Assets. All specifications include bank, and quarter FE. Robust standard errors in parentheses, clustered at the bank level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| Panel A | Charter classification | | | |
|---|---|---|---|---|
| | Log Total Loans | | Log Total Small Business Loans | |
| | (1) | (2) | (3) | (4) |
| Prize / Deposit | 0.191*** | -0.0383 | 0.253** | 0.407 |
| | (0.0285) | (0.284) | (0.124) | (0.419) |
| Charter | State | Federal | State | Federal |
| Quater FE | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes |
| Observations | 335,289 | 97,744 | 328,701 | 95,826 |

| Panel B | Federal and State Camels' Spread | | | |
|---|---|---|---|---|
| | Log Total Loans | | Log Total Small Business Loans | |
| | (1) | (2) | (3) | (4) |
| Prize / Deposit | 0.163*** | 0.293 | 0.409** | 2.946 |
| | (0.0157) | (2.364) | (0.161) | (2.158) |
| Charter | State | | | |
| Federal and State Spread quantile | Top 20% | Bottom 20% | Top 20% | Bottom 20% |
| Quater FE | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes |
| Observations | 55,399 | 54,554 | 55,394 | 54,551 |

Table 10 (Continued)

| Panel C | Size | | | |
|---|---|---|---|---|
| | Log Total Loans | | Log Total Small Business Loans | |
| | (1) | (2) | (3) | (4) |
| Prize / Deposit | 0.279*** | 0.178*** | 0.590** | 0.239* |
| | (0.0864) | (0.0347) | (0.269) | (0.123) |
| Charter | | State | | |
| Percentile Size | Top 10% | Bottom 90% | Top 10% | Bottom 90% |
| Quater FE | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes |
| Observations | 31,059 | 290,255 | 29,922 | 285,099 |

| Panel D | State-chartered banks members and non-members of the Federal Reserve | | | |
|---|---|---|---|---|
| | Log Total Loans | | Log Total Small Business Loans | |
| | (1) | (2) | (3) | (4) |
| Prize / Deposit | 0.176** | 0.185*** | 0.186 | 0.242* |
| | (0.0854) | (0.0328) | (0.184) | (0.124) |
| Federal regulator | Fed | FDIC | Fed | FDIC |
| Quater FE | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes |
| Observations | 47,386 | 273,928 | 47,090 | 267,931 |

Table 11 State-chartered banks and local regulators

Data are from the Call Report, 1999-2013. An observation is a bank by quarter cell. The dependent variable equals the Log Deposits at the bank level, and Log total small business loans. Prize/deposits equals the ratio, on the year of treatment (0m, 12m), of the prize deposit in bank $i$ in quarter $t$ to and deposits in banks $i$ and quarter $t-1$ (quarter before treatment). Prize/Deposit*Unemployment is the interaction of the treatment variable with the median of unemployment for the state in which the treated bank is incorporated. In panel B the sample is sorted by the ratio of convictions of government officials for corrupt practices divided by the state population. In panel C, the sample is sorted by the ratio of state expenditure per-capita. Bank controls include the lag of log(assets), ROA, and Equity/Assets. All specifications include bank, and quarter FE. Robust standard errors in parentheses, clustered at the bank level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A

| | Log Total Loans | Log Total Small Business Loans |
|---|---|---|
| | (1) | (2) |
| Prize / Deposit | 0.191*** | 0.259** |
| | (0.0339) | (0.111) |
| Prize deposit * Unemployment | -0.0167 | -0.0267 |
| | (0.0162) | (0.0457) |
| Unemployment | -0.00770*** | 0.0313*** |
| | (0.00202) | (0.00435) |
| Charter | State | |
| Quater FE | Yes | Yes |
| Bank FE | Yes | Yes |
| Additional controls | Yes | Yes |
| Observations | 335,289 | 328,701 |

Panel B

| | Log Total Loans | | Log Total Small Business Loans | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Prize / Deposit | 0.160*** | 0.793*** | 0.318** | 0.447*** |
| | (0.0215) | (0.178) | (0.125) | (0.126) |
| Charter | | State | | |
| Convictions per capita | Bellow 50% | Above 50% | Bellow 50% | Above 50% |
| Quater FE | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes |
| Observations | 228,712 | 92,602 | 224,608 | 90,413 |

Panel C

| | Log Total Loans | | Log Total Small Business Loans | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Prize / Deposit | -0.0221 | 0.196*** | 0.0746 | 0.269** |
| | (0.294) | (0.0362) | (0.982) | (0.122) |
| Charter | | State | | |
| Government size | Bellow 50% | Above 50% | Bellow 50% | Above 50% |
| Quater FE | Yes | Yes | Yes | Yes |
| CBSA FE | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes |
| Observations | 181,089 | 129,289 | 177,577 | 126,727 |

# Appendix A: Call Report

I compile a data set with quarterly balance sheet and income statements information for all reporting banks over the period 1999 through 2013. I exclude all the bank-quarters with missing information on total assets, total loans, and liquid funds. I exclude the acquiring bank in the quarters before and after a merger using bank mergers data from the Federal Reserve Bank of Chicago. To make sure that outliers are not driving the results, I eliminate all bank-quarters with asset growth over the last quarter in excess of 60%, those with total loan growth exceeding 150%, and those with total loans-to-asset ratio below 10%. In the regression analysis of Small Business lending (SB), I omit all banks that have less than 5% of their loan portfolio in SB to avoid distortions from banks that do negligible amount of SB lending.

To construct the variables, whenever possible, I follow the "Notes on forming consistent time series" from Federal Reserve Bank of Chicago:

Total Assets: is item RCFD2170.

Total Securities: are items RCFD 1754 and RCFD 1773.

Total Loans and Leases: is item RCFD1400.

Small business lending: are items RCFD1766, RCFD1590 and RCON1480. [65]

Total Deposits: is item RCFD2200.

Nonperforming Total Loans: are items RCFD1403 and RCFD1407.

Interest and Fee Income from Loans: is item RIAD4010.

[65] Item RCFD1600 (Commercial and Industrial Loans) is no longer reported after 2000, thus I used RCFD1766 (Commercial and Industrial Loans - Other).

## Appendix B: Individual detection algorithm

Given that the SOD provides deposit data for each branch, and I estimate the amount received by each jackpot winner. Therefore, on principle I can identify the possible branch, and bank, that received the prize. The assumptions of the procedure are that i) the winner deposits in her respective CBSA and ii) the winner deposits in those branches that are closest in driving distance to where she bought the ticket.[66] The results in Table 2 support the first assumption, and the second assumption is plausible from conversations with state lottery representatives. In each CBSA/year where there was a non-group winner, prizes that were claimed by a single person , I do the following procedure.[67] First, I estimate the fitted value in deposits year t for each branch.[68] Then, I estimate the difference between the realized deposit at year $t$ and the predicted deposit for each branch. Subsequently, I create an interval of the prize claimed in the CBSA, this is to estimate the possible change in deposits for the branch. Then, I checked for each branch in the CBSA that experienced a change in deposits in the interval of the prize. Next, for those match branches from the last step I focus on those branches for which the growth in deposits in year t was the maximum experienced since 1994, the idea is to focus on those branches that experienced a shock in their deposits. Finally, since I have data on the zip code from the retailer that sold the winning ticket and the location of each branch, I estimate the driving distance in time from the zip code of the retailer to the branch, I focus on those branches that are closer in driving distance in the same CBSA (up to a maximum of 45 min). In those cases, in which there are multiple branches that could have received the prize, I leave the three branches closets to the address of the retailer.

[66]Only the city of residence for each winner is available, not their specific address. However, usually the winner buys their tickets close to their place of residence.

[67]See footnote 38.

[68]Since the SOD has data since 1994, I can estimate the fitted value for each branch.

Appendix Table 1 Jackpot winners characteristics

U.S. lotteries jackpot winners dataset comes from different public sources. Prize amounts are after-taxes and in 1999 Dollars.

| | | |
|---|---|---|
| Mega Millions | Mean | $33,264,070 |
| | 25th percentile | $12,590,042 |
| | 75th percentile | $48,586,876 |
| | | |
| Powerball | Mean | $32,704,618 |
| | 25th percentile | $10,408,372 |
| | 75th percentile | $47,440,084 |
| Year of winning | | |
| | 2002 | 7 |
| | 2003 | 28 |
| | 2004 | 21 |
| | 2005 | 23 |
| | 2006 | 22 |
| | 2007 | 32 |
| | 2008 | 22 |
| | 2009 | 29 |
| | 2010 | 30 |
| | 2011 | 29 |
| | 2012 | 31 |
| | 2013 | 10 |

## Appendix Table 2 Effect of Jackpot Winners' shock on Deposits at the CBSA level

Data are from the SOD, 1999-2013. An observation is a CBSA by year cell. The dependent variable equals the Log Deposits at the CBSA level. Winner is an indicator equal to one in those CBSA/year with Jackpot winners, that chooses the cash option and resides in the state where the ticket winning was bought, and zero otherwise. Log Prize is the amount won after withheld federal and state taxes in 1999 dollars. Prize in top quartile is equal to one if there was a jackpot winner and the amount received is in the top quartile of the prize distribution and zero otherwise, and Prize below top quartile is equal to one if there was a winner and the amount is not in the top quartile of the distribution and zero otherwise. Prize/deposits equals the ratio of the amount won in CBSA $i$ and year $t$, and deposits in CBSA $i$ and year $t-1$ (year before treatment). Non-cash Winner equal to 1 if there is a jackpot winner but the prize was unclaimed or the winner choose the annuity option and zero otherwise. Winner out-of-state equal one if the winner lives in a state different where the winning tickets was sold and zero otherwise. Winner (t+1) is a lead variable equal to 1 a year before the shock, in those CBSA with a winner at $t$, and zero otherwise. All specifications include lag of log(population), CSBA, state and year FE. Robust standard errors in parentheses, clustered at the CBSA level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| Panel A | Log Deposits | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Winner | 0.0315*** | | | |
| | (0.0117) | | | |
| Log Prize | | 0.00384*** | | |
| | | (0.414) | | |
| Prize / Deposit | | | 0.844** | |
| | | | (0.413) | |
| Prize in top quartile | | | | 0.0873*** |
| | | | | (0.0289) |
| Prize below top quartile | | | | 0.0117 |
| | | | | (0.0133) |
| Year FE | Yes | Yes | Yes | Yes |
| CBSA FE | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes |
| Observations | 11,802 | 12,588 | 11,802 | 11,802 |

## Appendix Table 3 Effect of Jackpot Winners' shock on Deposits and small business loans at the CBSA level

Data are from the SOD, 1999-2013, and FFIEC, 1999-2012. An observation is a CBSA by year cell. The dependent variable equals the Log Deposits at the CBSA level, log of the total small business loan originations, defined as loans under $1 million, and log small business loans originated with gross annual revenues $< 1$ million at the CBSA level.. Prize in top quartile is equal to one if there was a jackpot winner and the amount received is in the top quartile of the prize distribution and zero otherwise, and Prize below top quartile is equal to one if there was a winner and the amount is not in the top quartile of the distribution and zero otherwise. Non-cash Winner equal to 1 if there is a jackpot winner but the prize was unclaimed or the winner choose the annuity option and zero otherwise. Winner out-of-state equal one if the winner lives in a state different where the winning tickets was sold and zero otherwise. All specifications include lag CBSA characteristics (i.e., log(population), % white, % male, % over age 45, income per-capita), CSBA, state and year FE. Robust standard errors in parentheses, clustered at the CBSA level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| | Log Deposits | | | Log Small Business Loans Originated with Gross Annual Revenues < 1 | | | Log Total Amount of Small Business Loans | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Prize in top quartile | 0.0875*** | | | 0.0517** | | | 0.0452* | | |
| | (0.0297) | | | (0.0234) | | | (0.0235) | | |
| Prize below top quartile | 0.0113 | | | 0.0398* | | | 0.0340* | | |
| | (0.0132) | | | (0.0223) | | | (0.0174) | | |
| Non-cash Winner | | -0.0062 | | | -0.0143 | | | 0.0268 | |
| | | (0.0369) | | | (0.0460) | | | (0.0484) | |
| Winner out-of-state | | | -0.00884 | | | -0.00568 | | | -0.0270 |
| | | | (0.0304) | | | (0.0321) | | | (0.0204) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| CBSA FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 11,802 | 11,802 | 11,802 | 11,420 | 10,916 | 10,912 | 11,420 | 10,916 | 10,912 |

Appendix Table 4 Effect of Jackpot Winners' shock on Deposits and Small Business Loans at the CBSA level sorted by population

Data are from the SOD, 1999-2013. An observation is a CBSA by year cell. The dependent variable equals the Log Deposits at the CBSA level., log of the total small business loan origination, defined as loans under $1 million, log of small business loan originations to businesses with $1 million in annual gross revenue or less at the bank level Winner is an indicator equal to one in those CBSA/year with Jackpot winners, that chooses the cash option and resides in the state where the ticket winning was bought, and zero otherwise. Log Prize is the amount won after withheld federal and state taxes in 1999 dollars. Prize/deposits equals the ratio of the amount won in CBSA $i$ and year $t$, and deposits in CBSA $i$ and year $t-1$ (year before treatment). To save space, each cell represents the coefficient of interest of a different regression. All specifications include lag CBSA characteristics (i.e., log(population), % white, % male, % over age 45, income per-capita), CSBA, state and year FE. Robust standard errors in parentheses, clustered at the CBSA level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| | Log Deposits | | Log Small Business Loans with Annual Revenues < 1 | | Log Total Amount of Small Business Loans | |
|---|---|---|---|---|---|---|
| Winner | 0.0205* | -0.0066 | 0.0534** | -0.0162 | 0.0387* | 0.0011 |
| | (0.0107) | (0.0144) | (0.0270) | (0.0198) | (0.0225) | (0.0153) |
| Log Prize | 0.00197* | -0.0005 | 0.00507* | -0.00206 | 0.0034* | -0.00015 |
| | (0.0011) | (0.0014) | (0.0027) | (0.0020) | (0.0020) | (0.0015) |
| Prize / Deposit | 0.585* | 1.119 | 1.699* | -4.049 | 0.991 | -1.422 |
| | (0.3520) | (2.950) | (0.896) | (6.400) | (0.777) | (6.219) |
| Sample | Pop < 500 | Pop > 500 | Pop < 500 | Pop > 500 | Pop < 500 | Pop > 500 |
| Year FE | | | | Yes | | |
| CBSA FE | | | | Yes | | |
| Additional controls | | | | Yes | | |

Appendix Table 5 Effect of Jackpot Winners' shock on Total Small Business Loan Originations at the CBSA level

Data are from the FFIEC, 1999-2012. An observation is a CBSA by year cell. The dependent variable equals the log of the total small business loan originations, defined as loans under $1 million, and log small business loans originated with gross annual revenues < 1 million at the CBSA level. Winner is an indicator equal to one in those CBSA/year with Jackpot winners, that chooses the cash option and resides in the state where the ticket winning was bought, and zero otherwise. Small bank equals one if the CBSA is in the 5th quintile of the yearly distribution of the ratio of the number of branches from banks with assets lower or equal to $1 billion (in 1999 dollars) to the total number of branches in each CBSA, and zero otherwise. All specifications include lag CBSA characteristics (i.e., log(population), % white, % male, % over age 45), CSBA, state and year FE. Robust standard errors in parentheses, clustered at the CBSA level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| | Log Small Business Loans Originated with Gross Annual Revenues < 1 | | Log Total Loan Amount of Small Business Loans | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Winner | 0.0417** | 0.0460** | 0.0365** | 0.0382** |
| | (0.0186) | (0.0187) | (0.0150) | (0.0151) |
| Small bank ($2 Billion) | -0.0363 | | -0.0272 | |
| | (0.0292) | | (0.0235) | |
| Winner x Small bank ($2 Billion) | 0.131*** | | 0.0679*** | |
| | (0.0252) | | (0.0204) | |
| Small bank ($1 Billion) | | -0.131*** | | -0.112*** |
| | | (0.0310) | | (0.0256) |
| Winner x Small bank ($1 Billion) | | 0.154*** | | 0.0905*** |
| | | (0.0230) | | (0.0188) |
| Year FE | Yes | Yes | Yes | Yes |
| CBSA FE | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes |
| Observations | 10,912 | 10,912 | 10,912 | 10,912 |

Appendix Table 6 Effect of Jackpot Winners' shock on Total Small Business Loan Originations at the CBSA level

Data are from the FFIEC, 1999-2012. An observation is a CBSA by year cell. The dependent variable equals the log of the total small business loan originations, defined as loans under $1 million, and log small business loans originated with gross annual revenues < 1 million at the CBSA level. Winner is an indicator equal to one in those CBSA/year with Jackpot winners, that chooses the cash option and resides in the state where the ticket winning was bought, and zero otherwise. Small bank equals one if the CBSA is in the 5th quintile of the yearly distribution of the ratio of the number of branches from banks with assets lower or equal to $1 billion (in 1999 dollars) to the total number of branches in each CBSA, and zero otherwise. Winner (t+3) is a lead variable equal to 1 a three years before the shock, in those CBSA with a winner at $t$, and zero otherwise. All specifications include lag CBSA characteristics (i.e., log(population), % white, % male, % over age 45, income per-capita), CSBA, state and year FE. Robust standard errors in parentheses, clustered at the CBSA level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| | Log Small Business Loans Originated with Gross Annual Revenues < 1 | | Log Total Amount of Small Business Loans | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Winner $_{t+3}$ | -0.00621 | -0.00845 | -0.00178 | -0.00231 |
| | (0.0207) | (0.0205) | (0.0168) | (0.0167) |
| Small bank (2000)$_{t+3}$ | -0.0385 | | -0.0302 | |
| | (0.0290) | | (0.0231) | |
| Winner x Small bank (2000)$_{t+3}$ | -0.391 | | -0.112 | |
| | (0.371) | | (0.288) | |
| Small bank (1000) $_{t+3}$ | | -0.130*** | | -0.112*** |
| | | (0.0309) | | (0.0256) |
| Winner x Small bank (1000) $_{t+3}$ | | -0.245 | | -0.0531 |
| | | (0.421) | | (0.282) |
| Year FE | Yes | Yes | Yes | Yes |
| CBSA FE | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes |
| Observations | 10,912 | 10,912 | 10,912 | 10,912 |

Appendix Table 7 Effect of Jackpot Winners' shock on outcome variables at the county level (within a given cbsa-year)

The dependent variable equals the Log Deposits at the county level, and log of the total small business loan originations, defined as loans under \$1 million, and log small business loans originated with gross annual revenues $<$ 1 million at the county level. Prize/deposits (0m, 3m) equals the ratio, on the quarter of treatment, of the prize deposit in bank $i$ in year $t$ to and deposits in banks $i$ and quarter $t-1$ (quarter before treatment). Prize/deposits (0y, 1y) is the same ratio but takes the value of the ratio in the year after treatment for the banks in the treatment group (0y, 1y), and zero otherwise. Prize/deposits($t+3$) (-3y, 2y) is the same ratio but takes the value of the ratio in the 3 years to 2 years before the shock. All specifications include lag county characteristics (i.e., log(population), % white, % male, % over age 45, income per-capita), CSBA x year FE. Robust standard errors in parentheses, clustered at the county level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively..

| | △ Log Deposits | | Log Small Business Loans Originated with Gross Annual Revenues $<$ 1 | | Log Total Amount of Small Business Loans | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Prize/Deposit $_{t0}$ (0y, 1y) | 0.324** | | 0.429 | | 0.463 | |
| | (0.159) | | (1.512) | | (1.498) | |
| Prize/Deposit $_{t+3}$ (-3y, -2y) | | -0.0811 | | 0.199 | | 0.481 |
| | | (0.129) | | (1.443) | | (1.326) |
| CBSA-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 16,981 | 16,979 | 14,334 | 12,282 | 14,336 | 12,284 |

Appendix Table 8 Collateral channel and credit supply

Data are from the FFIEC, 1999-2012. An observation is a MSA by year cell. The dependent variable equals the log of the total small business loan originations, defined as loans under $1 million, and log small business loans originated with gross annual revenues < 1 million at the MSA level. Winner is an indicator equal to one in those MSA/year with Jackpot winners, that chooses the cash option and resides in the state where the ticket winning was bought, and zero otherwise. Winner*Saiz Elasticity is the interaction variable between winner indicator and housing supply elasticity using data from Saiz (2010). All specifications include lag MSA characteristics (i.e., log(population), % white, % male, % over age 45, income per-capita), CSBA, state and year FE. Robust standard errors in parentheses, clustered at the MSA level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| | Log Small Business Loans Originated with Gross Annual Revenues < 1 | | | Log Total Amount of Small Business Loans | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Winner | 0.0385 | | | 0.0317 | | |
| | (0.0266) | | | (0.0200) | | |
| Winner*Saiz Elasticity | -0.0383 | | | -0.0394 | | |
| | (0.0368) | | | (0.0283) | | |
| Log Prize | | 0.00392 | | | 0.00323* | |
| | | (0.00259) | | | (0.00193) | |
| Log Prize*Saiz Elasticity | | -0.00362 | | | -0.00381 | |
| | | (0.00354) | | | (0.00270) | |
| Prize / Deposit | | | 2.177** | | | -0.731 |
| | | | (1.001) | | | (1.162) |
| Prize / Deposit*Saiz Elasticity | | | -1.989 | | | -1.682 |
| | | | (3.006) | | | (2.381) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| CBSA FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,625 | 3,709 | 3,709 | 3,625 | 3,709 | 3,709 |

Appendix Table 9 Effect of Jackpot Winners' shock on total securities at bank-level

Data are from the Call Report, 1999-2013. An observation is a bank by quarter cell. The dependent variable equals the Log Total Securities. Prize/deposits (0m, 3m) equals the ratio, on the quarter of treatment, of the prize deposit in bank $i$ in quarter $t$ to and deposits in banks $i$ and quarter $t-1$ (quarter before treatment). Prize/deposits (0m, 12m) equals the ratio, on the year of treatment, of the prize deposit in bank $i$ in quarter $t$ to and deposits in banks $i$ and quarter $t-1$ (quarter before treatment). Bank controls include the lag of log(assets), ROA, and Equity/Assets. All specifications include bank, and quarter FE. Robust standard errors in parentheses, clustered at the bank level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| | Log Total Securities | |
|---|---|---|
| | (1) | (2) |
| Prize / Deposit$_{t0}$ (0m, 3m) | -0.00313 | |
| | (0.256) | |
| Prize / Deposit $_{t0}$ (0m, 12m) | | 0.279 |
| | | (0.297) |
| Quarter FE | Yes | Yes |
| Bank FE | Yes | Yes |
| Additional controls | Yes | Yes |
| Observations | 443,545 | 441,049 |

## Appendix Table 10 Effect of Jackpot Winners' shock on Total Small Business Loans at the bank-level

Data are from the Call Report, 1999-2013. An observation is a bank by quarter cell. The dependent variable equals the log of total small business loans at the bank level. Prize/deposits (12 months) equals the ratio of the prize deposit in bank $i$ in quarter $t$ and deposits in banks $i$ and quarter $t-1$ (quarter before treatment) in the 12 months after treatment for the treated banks (0 m, 12 m), and zero otherwise. Prize/deposits (12 months) (t+4) is a lead variable equal to one in the 12 months before the shock (-12 m, 0 m), for the banks in the treatment group, and zero otherwise. Winner (t+1) is a lead variable equal to 1 a quarter before the shock (-3 m, 0 m), for the banks in the treatment group at $t$, and zero otherwise. Bank controls include the lag of ln(assets), ROA, and Equity/Assets. All specifications include bank, and quarter FE. Robust standard errors in parentheses, clustered at the bank level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| | Log Total Small Business Loans | |
|---|---|---|
| | (1) | (2) |
| Prize / Deposit$_{t0}$ (0m, 12m) | 0.242* | |
| | (0.133) | |
| Prize / Deposit $_{t+4}$ (-12m, 0m) | | -0.160 |
| | | (0.282) |
| Quarter FE | Yes | Yes |
| Bank FE | Yes | Yes |
| Additional controls | Yes | Yes |
| Observations | 438,922 | 441,696 |

Appendix Table 11 Federal and State charter banks characteristics

Data are from the Call Report, 1999-2013. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| | Federal | State |
|---|---|---|
| Number of banks | 3,372 | 8,861 |
| Median assets | 209,074 | 165,643 |
| Fraction of total system assets at Dec 2013 | 53.96% | 46.04% |
| Winners (treated banks) | 43% | 57% |

| | Below 95th percentile | | | Between 95th and 99th percentile | | |
|---|---|---|---|---|---|---|
| | Federal | State | p-value on t-test for difference | Federal | State | p-value on t-test for difference |
| Total deposits | 0.8332 | 0.8335 | 0.000 | 0.7061 | 0.7351 | 0.001 |
| Transaction deposits | 0.2346 | 0.2174 | 0.000 | 0.0976 | 0.088 | 0.389 |
| Non-transaction deposits | 0.5929 | 0.6083 | 0.000 | 0.5774 | 0.5867 | 0.000 |
| Large deposits | 0.1419 | 0.1457 | 0.000 | 0.1155 | 0.1512 | 0.000 |
| Brokered deposits | 0.0167 | 0.0229 | 0.085 | 0.0331 | 0.0543 | 0.551 |
| Federal funds borrowed | 0.0187 | 0.0161 | 0.000 | 0.0781 | 0.0718 | 0.000 |
| Subordinated debt | 0.0002 | 0.0001 | 0.000 | 0.0036 | 0.0024 | 0.000 |
| Other liabilities | 0.0079 | 0.0071 | 0.046 | 0.0156 | 0.0143 | 0.227 |
| Equity | 0.1097 | 0.1087 | 0.000 | 0.1072 | 0.1071 | 0.045 |

## Appendix Table 12 Federal-chartered banks and adverse selection proxies

Data are from the Call Report, 1999-2013. An observation is a bank by quarter cell.. Column (1) dependent variable (AS) is average adverse selection cost component of trading stock $i$ during quarter $t$ based on George et al. (1991) decomposition. Column (2) dependent variable SPREAD, is the bid–ask spread at $t$ scaled by price at $t-1$. Column (3) dependent variable (TOVER) is shares turnover, the number of shares traded at $t$ divided by the number of shares outstanding at $t-1$. All specifications include lag total assets, lag roa, lag equity ratio, net income scaled by market value of equity lagged (PROFIT), market value of assets held in trading accounts scaled by the lag of market value of equity, lag real estate loans scaled by assets, other real estate owned scaled by market value of equity lagged, book value of premises and fixed assets plus other hard-to-value assets scaled by market value of equity lagged, non-interest income scaled by market value of equity lagged, sum of liabilities' book value plus equity's market value at the end as proportion of equity market value and inverse of the stock's average quarterly price. All specifications include state and quarter FE. Robust standard errors in parentheses, clustered at bank level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| | AS | SPREAD | TOVER |
|---|---|---|---|
| | (1) | (2) | (3) |
| Federal-chartered | -0.109* | -0.0005 | 1.150*** |
| | (0.0604) | (0.0079) | (0.2561) |
| Quarter FE | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes |
| Observations | 410 | 542 | 543 |

Appendix Table 13 Federal-chartered banks: placebo tests

Data are from the Call Report, 1999-2013. An observation is a bank by quarter cell. The dependent variable equals the Log Deposits at the bank level, and Log total small business loans. In panel A the sample is sorted by the ratio of convictions of government officials for corrupt practices divided by the state population. In panel B, the sample is sorted by the ratio of state expenditure per-capita. Bank controls include the lag of log(assets), ROA, and Equity/Assets. All specifications include bank, and quarter FE. Robust standard errors in parentheses, clustered at the bank level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

| Panel A | | | | |
|---|---|---|---|---|
| | Log Total Loans | | Log Total Small Business Loans | |
| | (1) | (2) | (3) | (4) |
| Prize / Deposit | -1.084 | 0.127 | -0.475 | 0.553 |
| | (1.051) | (0.151) | (0.754) | (0.404) |
| Charter | Federal | | | |
| Convictions per capita | Bellow 50% | Above 50% | Bellow 50% | Above 50% |
| Quater FE | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes |
| Observations | 56,355 | 55,401 | 55,294 | 54,249 |

| Panel B | | | | |
|---|---|---|---|---|
| | Log Total Loans | | Log Total Small Business Loans | |
| | (1) | (2) | (3) | (4) |
| Prize / Deposit | -0.130 | 0.0122 | -0.503 | 0.521 |
| | (0.297) | (0.290) | (0.726) | (0.446) |
| Charter | Federal | | | |
| Government size | Bellow 50% | Above 50% | Bellow 50% | Above 50% |
| Quater FE | Yes | Yes | Yes | Yes |
| CBSA FE | Yes | Yes | Yes | Yes |
| Additional controls | Yes | Yes | Yes | Yes |
| Observations | 54,600 | 57,156 | 53,277 | 56,266 |