



Federal Deposit Insurance Corporation • Center for Financial Research

WORKING PAPER SERIES

Deposit Insurance and Bank Funding Stability: Evidence from the TAG Program

Ajay Palvia

Federal Deposit Insurance Corporation

George Shoukry

Federal Deposit Insurance Corporation

Anna-Leigh Stone

Samford University

April 2024

Last Updated: June 2025

FDIC CFR WP

2024-02 fdic.gov/cfr

The Center for Financial Research (CFR) Working Paper Series allows CFR staff and their coauthors to circulate preliminary research findings to stimulate discussion and critical comment. Views and opinions expressed in CFR Working Papers reflect those of the authors and do not necessarily reflect those of the FDIC or the United States. Comments and suggestions are welcome and should be directed to the authors. References should cite this research as a “FDIC CFR Working Paper” and should note that findings and conclusions in working papers may be preliminary and subject to revision.

Deposit Insurance and Bank Funding Stability: Evidence from the TAG Program

Ajay Palvia ^a, George Shoukry ^a, and Anna-Leigh Stone ^b

^a Federal Deposit Insurance Corporation, Center for Financial Research

^b Brock School of Business, Samford University

06/12/2025

Abstract

We study the unlimited deposit insurance provided by the Transaction Account Guarantee (TAG) Program. We find that size and financial performance were key drivers of program participation, with large banks and more solvent banks much more likely to opt out. We show that opting out of the program caused strong and persistent declines in noninterest-bearing deposits (NIBDs), showing that the additional insurance stabilized funding for program participants. Our results suggest that targeted deposit insurance protections are valued by banks, especially community banks and financially weaker banks, and can be successful in stemming deposit outflows during periods of stress.

Keywords: Deposit Insurance, Federal Deposit Insurance Corporation, Transaction Account Guarantee Program, Deposits

JEL Classification: G01, G21, G28

Views and opinions expressed in this paper reflect those of the authors and do not necessarily reflect those of the FDIC or the United States. We thank Rosalind Bennett, Rebel Cole, Pedro J. Cuadros-Solas, Christopher Martin, Alex Ufier, Luke Watson, and Manju Puri for helpful suggestions. We also thank seminar participants from the Federal Reserve Bank of Richmond, the American Bankers Association (ABA), the Federal Deposit Insurance Corporation (FDIC), and the International Association of Deposit Insurers (IADI), as well as conference participants from FDIC Bank Research Conference, Financial Management Association Annual Meeting, and Southern Finance Association Annual Meeting for helpful comments and suggestions. A. Palvia: 550 17th St NW, Washington, DC 20429, United States, apalvia@fdic.gov; G. Shoukry: 550 17th St NW Washington, DC 20429, gshoukry@fdic.gov; A. Stone: 800 Lakeshore Drive, Birmingham, AL 35229, United States, +1 205-726-4644, alstone@samford.edu.

1. Introduction

There has been considerable study of the potential moral hazard effects of deposit insurance, but the financial stability benefits of deposit insurance have been relatively understudied and are less often quantified empirically. This is partly because of a lack of data from settings with credible counterfactuals from similar banks exposed to different deposit insurance regimes. In this paper, we study the funding stability effects associated with a voluntary, significant expansion of deposit insurance that was implemented during the 2008 financial crisis.

Throughout 2007 and 2008, the federal government enacted several programs to help restore confidence in the banking system. Such programs included the U.S. Department of Treasury's Troubled Asset Relief Program (TARP), the Federal Reserve's Term Auction Facility, and the Federal Deposit Insurance Corporation (FDIC) Debt Guarantee Program. However, bankers and policymakers were also concerned about depositors pulling funding from banks, particularly small banks, and placing them at institutions perceived to be "too big to fail." Of particular concern were business-owned noninterest-bearing deposits (NIBDs) which often had balances greater than the FDIC insurance limit.¹ On October 14, 2008, the FDIC implemented the Transaction Account Guarantee (TAG) Program, which provided full FDIC insurance coverage on noninterest-bearing transaction accounts until December 31, 2010 when the program expired.² While this program did not provide unlimited insurance exclusively to small institutions, it was one of the few that purposefully included them.

To study the implications for bank funding, we exploit two unique features of the TAG Program. The first being that the program was mostly voluntary. Except for an initial period in which all insured banks were covered by the TAG Program, participation in the program was optional, and banks had three opportunities to opt out of the program and its extensions. The second feature is that the program's unlimited coverage applied to only certain kinds of deposits, allowing us to better isolate the effects of the program. Banks choosing to remain in the program had unlimited deposit insurance coverage for certain types of accounts (generally, noninterest

¹ See <https://www.fdic.gov/regulations/resources/TLGP/101608.html> for details.

² The Dodd-Frank Act created an unlimited insurance guarantee for noninterest-bearing transaction accounts, which was in effect from December 31, 2010 through December 31, 2012. The Dodd-Frank Act guarantee program differed from the TAG Program in important ways (see Section 2 in this paper for more details).

bearing transaction accounts), with a surcharge applying to amounts not otherwise covered by the standard FDIC insurance.³ In this paper, we use NIBDs reported on banks' public quarterly filings as a proxy for the types of deposits covered by the TAG Program.⁴

We begin the analysis by discussing aggregate trends in NIBDs from 2002 until 2010. We document that NIBDs, as well as the ratio of NIBDs to total deposits, increased during the period of unlimited insurance, primarily during the extensions of the TAG Program. Further dividing the data into small and large banks, defined by a cutoff of \$10 billion in total assets, we show that small institutions were losing NIBDs leading up to the unlimited insurance increase.⁵ At the same time, large institutions were gaining NIBDs, suggesting a flight to large institutions was taking place. During the unlimited insurance period, however, NIBDs at both small and large banks grew, particularly during the TAG Program extensions. In addition, we show that while participation in the program was initially very high, large banks began opting out of the program during the first extension. These large banks exiting the program drastically changed the percentage of deposits that were covered by unlimited insurance during the last year of the TAG Program.

Our primary analysis consists of three main parts. First, we assess the factors that drove banks to participate in the program focusing on the quarters in which banks had the choice to opt out. We find that bank size and financial condition were key drivers of opting out. In particular, banks with assets of \$10 billion or more were much less likely to stay in the program consistent with benefits of size including possible “too-big-to-fail” guarantees or economies of scale. In addition, better capitalized banks were much less likely to exit the program consistent with such banks having less need to reassure skittish depositors amidst the financial crisis. We find

³ Specifically, the coverage applied to noninterest bearing transaction accounts, low-interest Negotiable Order of Withdrawal (NOW) accounts, and Interest on Lawyers Trust Accounts (IOLTAs). For these accounts, the TAG Program insured only amounts above the limit of \$250,000; amounts below the limit were insured under the standard FDIC insurance. See <https://www.fdic.gov/regulations/resources/TLGP/faq.html> for details.

⁴ Reported totals for NIBDs make no distinction between amounts insured by the standard FDIC coverage and amounts above the standard FDIC limit that were insured by TAG. In addition, they may include uninsured amounts, such as matured time deposits that did not automatically renew or transfer to a different account (time deposits were not covered by the TAG program). Nevertheless, NIBDs are a convenient proxy for our analysis because noninterest-bearing transaction accounts covered by TAG were a subset of total NIBDs, and NIBDs were reported by both TAG participants and nonparticipants.

⁵ The cutoff of \$10 billion in total assets is used by the Federal Reserve to differentiate between community banks and larger institution. See <https://www.federalreserve.gov/supervisionreg/community-and-regional-financial-institutions.htm> for details.

some, albeit less economically significant evidence, that liquidity measures were drivers of opting out. In additional tests, we show that the results are robust to the subsample of smaller banks (less than \$10 billion and \$1 billion) and are driven more so by the first opt-out period.

Second, we study the direct effects of the unlimited insurance on bank funding. We exploit the voluntary periods of the program and compare TAG Program participants with non-participants to estimate the effects of opt-out decisions on NIBD levels. In this part of the analysis, we implement a trimming procedure to ensure that the TAG Program participants and non-participants in our sample are comparable. Using both difference-in-differences and the Callaway and Sant'Anna (2021) estimator, we document that NIBDs at banks that opted out declined compared to banks that never opted out. The results are stronger for banks that opted out at the start of the program and during the first extension. We find that NIBD declines were persistent, that is, NIBDs continued to decline over time for banks that opted out. Our results do not appear to be driven by pre-existing trends, specifically our results do not suggest pre-trends of declining NIBDs at banks that chose to opt out of the TAG Program.

Last, we use variation in risk-based TAG Program fees to instrument for the decision to opt out of the TAG Program, and we find results that further confirm the previous ones. During the extensions of the TAG Program, participants were charged different fees depending on their risk levels. We use confidential supervisory data on banks' risk categories, and we exploit differentials in TAG Program fees around risk category thresholds to instrument for the decision to opt out of the TAG Program. Restricting the sample to banks close to the thresholds, we find that banks facing higher premiums to remain in the TAG Program were more likely to opt out, and that the opt out decisions resulted in declines in NIBDs.

These results are unique in the literature, as empirical analysis on the TAG Program has been limited. Schich (2008) provides a summary of the full insurance guarantee (and the implications for extending the insurance). Hoskins (2012) discusses the unlimited insurance guarantee and the potential impact upon its expiration. In addition, both Bank of America and Goldman Sachs have published reports discussing the

implications of full insurance.⁶ However, these papers included limited empirical analysis and were published primarily to promote the TAG Program and provide evidence for its extension. While Boyle et al. (2015) do not directly examine the TAG Program, they examine whether the onset of deposit insurance during a crisis might help reduce the amount of runs at institutions. However, they find that additional insurance does not affect deposit withdrawals in the short run. Martin et al. (2022) find that the TAG Program reduced the outflow of deposits, but the results are for a single institution. This paper studies the effects of the TAG Program on all FDIC-insured institutions. While Stone (2020) finds that corporations might have provided most NIBDs covered by unlimited insurance, the implications for banks are not examined.

Some studies examine Massachusetts-chartered institutions covered by private deposit insurance and find evidence that privately insured institutions experienced relatively stronger deposit inflows during the financial crisis (Stone (2021) and Danisewicz et al (2022)). These studies differ from our analysis of the TAG Program in several ways. First, unlike the TAG Program, the insurers were private, industry-sponsored companies and not guaranteed by either the state or the federal government. Second, private insurers in Massachusetts insured only savings and cooperative institutions, and the institutions had to be Massachusetts-chartered, so the number and types of Massachusetts institutions that were privately insured during the crisis are necessarily limited. In contrast, the TAG Program was available to all FDIC-insured institutions.

Better understanding the impacts and effectiveness of the TAG Program's unlimited insurance is important for policymakers when deciding future actions that could be taken during financial crises. While not executed, in March 2020 during the Covid-19 pandemic, Section 4008 of the Coronavirus Aid, Relief, and Economic Security (CARES) Act temporarily provided the FDIC Congressional approval through December 31, 2020, to implement a debt guarantee program, to include a guarantee of deposits held in noninterest-bearing transaction accounts, as authorized under the FDI Act. After the failure of Silicon Valley Bank in March 2023, a discussion about deposit insurance reform was reignited. In a 2023 report, the FDIC concluded that if reform was necessary

⁶ Goldman Sachs Research Department published "US Daily: FDIC Deposit Guarantees: Another Year-End Risk" on September 4, 2012. See <http://www.goldmansachs.com/gsam/pdfs/GLM/research-FDIC-deposit-guarantees.pdf> for details. Bank of America published "Life After Full FDIC Insurance" in April 2012. See <https://corp.bankofamerica.com/documents/10157/67594/LifeAfterFDIC.pdf> for details.

for the deposit insurance system, a “targeted coverage” structure similar to the TAG Program could be the preferred approach to stabilize bank funding (FDIC (2023)). Thus, it is beneficial to study whether this type of program was helpful during the 2008 financial crisis to prevent deposit withdrawals and protect banks.

2. The Transaction Account Guarantee Program

The FDIC was established in response to the Great Depression, primarily to reassure the public that deposits held in financial institutions were safe, thus preventing future bank runs. However, during the 2008 recession and following a determination of systemic risk, to avoid or mitigate serious adverse effects on economic conditions or financial stability, the FDIC provided additional reassurances to depositors by implementing the TAG Program on October 14, 2008.⁷

The initial TAG Program coverage started October 14, 2008 and went through December 31, 2009. Figure 1 shows a timeline of the implementation of the TAG Program and its extensions. The program was extended twice for six-month increments: first to June 30, 2010 and ultimately to December 31, 2010. (A separate guarantee program, mandated by the Dodd-Frank Act and discussed further below, was in place from December 31, 2010 through December 31, 2012.) Under the TAG Program, all banks were automatically enrolled and covered free of charge until December 5, 2008 (extended from November 12, 2008). After this date, institutions could voluntarily opt out of the program, which meant insurance on these deposits returned to the \$250,000 limit.⁸ Once a bank opted out of the TAG Program, it was excluded through each subsequent extension.

The unlimited insurance offered by the TAG Program applied to noninterest-bearing transaction accounts, which were defined as accounts “with respect to which interest is neither accrued nor paid and on which the insured depository institution does not reserve the right to require advance notice of an intended withdrawal”, as well as low-interest Negotiable Order of Withdrawal (NOW) accounts, and Interest on Lawyers Trust Accounts (IOLTAs).⁹ As previously mentioned, we use noninterest-bearing deposits (NIBDs) to proxy for the types of accounts covered by the TAG Program.

⁷ 73 FR 64179 (Oct. 29, 2008). See <https://www.govinfo.gov/content/pkg/FR-2008-10-29/pdf/E8-25739.pdf> for details.

⁸ Additionally, participating banks had until November 2, 2009 to make a decision regarding participation in the first extension and until April 30, 2010 to make a decision regarding participation in the second extension.

⁹ See <https://www.fdic.gov/regulations/resources/TLGP/faq.html> for details.

In her opening remarks during a teleconference held on October 16, 2008, then-chairman of the FDIC, Sheila Bair, clarified why the TAG Program did not apply to a wider range of deposit types. She stated, “we've seen a lot of stress in the business accounts, the payroll accounts, which typically need to be just by necessity of the nature of them over \$250,000. We're trying to stabilize this source of liquidity, especially for the smaller banks.”¹⁰

Bank participation in the program after December 5, 2008 was voluntary, and the insurance was funded by an additional fee paid by each bank. A summary of the TAG Program fees compared to the annual deposit insurance assessment rates is provided in Table 1. From December 6, 2008 until December 31, 2009, the additional assessment fee was a flat 10 basis points on deposits over the \$250,000 insurance limit, regardless of risk. Banks in the riskiest categories paid less for the additional insurance than their annual assessment rates. In the first quarter of 2009, when the FDIC raised annual assessment rates, the TAG Program fee was lower than the annual deposit insurance assessment rate across all risk categories. When annual assessment rates were changed again during the second quarter of 2009, the difference between the TAG Program fee and the annual assessment rates generally became even more stark. During the first and second extensions of the TAG Program in 2010, the additional fee was increased from a flat 10 basis points to a risk-varying 15–25 basis points. At that time, the TAG Program fees were higher than the annual assessment rates for some banks in the lowest risk categories, but remained lower than annual assessment rates for banks in the highest risk categories.¹¹

While the TAG Program was allowed to expire on December 31, 2010, Section 343 of the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank) extended the unlimited insurance on NIBDs from December 31, 2010 through December 31, 2012. However, this Dodd-Frank extension had some major differences from the original TAG Program. The most important for the purposes of this study is that the Dodd-Frank extension did not charge additional deposit insurance premiums on qualifying accounts over the FDIC limit, it covered all banks, and it did not allow banks to opt out of the insurance.¹² Because the Dodd-Frank

¹⁰ See <https://www.fdic.gov/regulations/resources/TLGP/101608.html> for details.

¹¹ The FDIC reported that they collected \$1.2 billion in fees under the TAG Program. Cumulative estimated losses due to bank failures under the TAG Program were \$1.5 billion in 2018. See <https://www.fdic.gov/regulations/resources/tlgp/> for details.

¹² The Dodd-Frank Act also changed the assessment base from adjusted total deposits to total liabilities.

extension applied to all banks, we would not be able to analyze the causes and consequences of banks' opt-out decisions in the same way as we do in the current paper. In addition, Stone (2022) finds that banks during the Dodd-Frank extension experienced an increase in deposit flows over the FDIC limit, but that NIBDs as a percentage of total deposits continued to increase despite the expiration of the unlimited insurance. Thus, Stone (2022) concludes that the Dodd-Frank unlimited insurance encouraged additional deposits to flow into banks. For these reasons, this paper focuses on the TAG Program prior to the Dodd-Frank extension. An exception to this is the analysis of Section 6.1, which extends beyond 2010, into the era of the alternate Dodd-Frank guarantee program.

3. Data and Descriptive Statistics

Our data is constructed primarily using quarterly bank Call Reports. Our sample includes all FDIC-insured institutions that filed Call Reports, with the exclusion of insured branches of foreign banks. Although they were allowed to participate in the TAG Program, we exclude insured branches of foreign banks because of missing data on key variables.¹³ Descriptive statistics at the bank-quarter level for key variables and other controls are shown in Table 2 for the three quarters in which banks could choose to opt-out (i.e., 2008Q4, 2009Q4, and 2010Q2).

The statistics show that over these quarters, about 9.5 percent of bank-quarters are classified as choosing to opt out of the TAG Program.¹⁴ The banks in the sample, represent the universe of banks over these quarters, and are typically quite small; Table 2 shows that only 1.3 percent and 8.8 percent of these banks have assets of \$10 billion or more and \$1 billion or more, respectively. On average, banks have a relatively high share of deposit funding (91.6 percent), low uninsured deposit ratios (17.2 percent), and low NIBD deposit ratios (13.8 percent).¹⁵ Banks also generally have adequate capital with average equity to assets of 10.8 percent and have

¹³ While our data includes both banks and thrifts, for brevity we often refer to these institutions as just banks.

¹⁴ Unreported tabulation by year shows substantially less participation during 2010 (76 percent) relative to 2009 (85 percent).

¹⁵ The level of uninsured deposits is an estimate, reported in Call Reports, of the amount in deposit accounts above the coverage limits, which were \$100,000 prior to late 2008 and \$250,000 thereafter. However, due to a lag in reporting requirements, the categorization thresholds did not change to \$250,000 until 2010Q1. Thus, during 2009, our estimate of uninsured deposits includes those above \$100,000 and will therefore overstate the true ratio of uninsured deposits. Note that the definition of "large" time deposits, which are excluded from core deposits, is also based on deposit insurance thresholds and suffers from the same limitation.

positive ROA levels on average; mean non-performing loans are also low at 2.5 percent. On the other hand, there is substantial variation in both liquidity and asset performance. For example, 5th percentile and 95th percentile uninsured deposits are about 2 percent and 43 percent. Similarly, equity capital ratios 5th and 95th percentiles range from 6.7 percent to 18.3 percent.

The statistics also show the median and average quarter-over-quarter asset growth is about 1 percent, though the bottom 5th banks shed at least 6 percent of assets and the 95th percentile grew assets by at least 11 percent. The mean log bank age is 3.74 suggesting an average age of about 42 years. Roughly 18 percent of banks are affiliated with multi-bank holding companies, 30 percent are organized as subchapter-s companies, and 7 percent have been involved with a merger in the prior 4 quarters. We winsorize all bank-level financial variables at the 1st and 99th percentiles.

Section 5 also uses variables based on the FDIC's Summary of Deposits (SOD), state-level economic data produced by the Bureau of Labor Statistics (BLS), and housing price index data from the Federal Housing Finance Agency (FHFA).¹⁶ In Section 6, we also use confidential supervisory data on banks' risk categories, which are based partly on confidential data on banks' CAMELS ratings.¹⁷

4. Trends in Aggregate Noninterest-Bearing Deposits

Figure 2 plots the sum of domestic NIBDs across FDIC-insured institutions that filed Call Reports, excluding insured branches of foreign banks from 2002 until 2010. The bars break the graphs into four sections: the pre-TAG Program era, the TAG Program, the first extension, and the second extension. We document that NIBDs slightly increased up until mid-2005, when aggregate deposits leveled off in the years leading up to the unlimited insurance. NIBDs then increased in the quarter prior to the TAG Program and continued to increase throughout the program and its extensions. The increase in NIBDs suggests the program may have not only prevented withdrawals, but may have encouraged growth in NIBDs.

4.1. Small Banks

¹⁶ BLS data is obtained through Haver.

¹⁷ CAMELS ratings are confidential supervisory ratings with six components: Capital Adequacy, Asset Quality, Management Quality, Earnings, Liquidity, and Sensitivity to Market Risk. In addition to the six components, each bank is assigned a composite CAMELS rating. Both the component and composite ratings range from 1 (best) to 5 (worst). The composite rating summarizes a bank's overall health and may differ from a simple average of the component ratings.

According to Sheila Bair, the TAG Program was implemented with the hope of preventing significant deposit withdrawals, particularly at small institutions. It is therefore necessary to examine if small banks benefited from the program by not seeing a further drawdown in funds in these accounts. Figure 3 provides total domestic NIBDs and the mean ratio of domestic NIBDs to total domestic deposits for small and large institutions. We define small banks as institutions with assets less than or equal to \$10 billion and large banks as institutions with assets greater than \$10 billion. Panels A and B show NIBDs for small and large banks. Prior to the unlimited insurance, NIBDs for small banks started declining around 2006 and continued until around 2008. When the unlimited insurance was implemented, deposits were slow to change but eventually increased during the second extension of the TAG Program. This finding is also consistent with findings in Acharya and Mora (2015). The trend for large banks is similar with the exception that large banks did not see a decline in NIBDs prior to the passage of unlimited insurance. In fact, there is even an increase in NIBDs immediately prior to the passage of the TAG Program, perhaps suggesting a flight to deposits at large institutions perceived to be “too big to fail.”

In Panel C, the mean measure of NIBDs to deposits is presented for both small and large banks. For small banks, a similar trend is seen as in Panel A. NIBDs become a smaller percentage of domestic deposits leading up to the crisis. NIBDs then start increasing around the passage of the extensions of the unlimited insurance. Despite the continual increase in aggregate NIBDs at large banks, NIBDs as a percentage of total domestic deposits at small banks declined until around 2007, leveled off, and then increased during the periods of unlimited insurance.

4.2. Participation in the TAG Program

Recall that the TAG Program provided unlimited insurance from October 14, 2008 until December 31, 2010 and allowed banks to exit the program voluntarily after December 5, 2008. By December 31, 2010, a total of 2,072 banks had opted out of the program: 1,110 banks during the original TAG Program, 521 during the first extension, and 441 during the second extension.¹⁸ Figure 4 presents the total domestic NIBDs held at institutions

¹⁸ These totals do not account for some activity, such as mergers, that may have occurred after opting out but before the end of the quarter in which opt-out decisions were submitted. In addition, de novo institutions may have submitted opt-out decisions prior to filing Call Reports. Consequently, opt-out counts in our empirical analysis differ slightly from the totals reported here. Because we rely heavily on Call Reports, our sample in each quarter includes FDIC-insured institutions that

that remained in the TAG Program. The dashed line provides the total amount of domestic NIBDs held at all institutions from the first quarter of 2009 until the fourth quarter of 2010, regardless of participation in the TAG Program. This is the same total provided in Figure 2. The solid line presents the sum of domestic NIBDs across only participating institutions. During the initial periods of the TAG Program, the two series are nearly identical, but after the first extension, the portion of total NIBDs held by TAG Program participants declines dramatically. At the end of the program, less than 20 percent of all NIBDs were held at institutions participating in the TAG Program.

One might next wonder which institutions were leaving the TAG Program. Table 3 provides statistics on bank participation separated by the size of the institutions. The total participation of smaller institutions remained very high throughout these periods. During the first quarter of full insurance protection, more than 85 percent of institutions with less than \$10 billion in assets participated and by the fourth quarter of 2010, close to 75 percent were still participating. Institutions with assets greater than \$10 billion had a very high participation rate of more than 93 percent during the initial periods of the program. The participation rate then fell to less than 65 percent during the first extension and experienced a further decline to around 32 percent during the final extension. The high participation rate of large institutions in the initial quarters shows that these banks judged the benefits of the program to outweigh the fees in the initial periods; however, their large decline in participation demonstrates that something caused large banks to reevaluate the benefits of the program.

The noticeable decline in participation by large banks is very interesting and could potentially bias an estimate of the effect that the TAG Program had on banks. Table 3 also presents statistics on the percentage of total NIBDs held by banks that participated based on bank size. Even though several thousand small institutions participated in the program, they held less than 20 percent of total NIBDs. On the other hand, despite the initial participation of only about 100 large institutions, they held 79 percent of all NIBDs. However, during the extensions, the portion of total NIBDs at participating large banks dropped to 18 percent and further to 4

filed Call Reports, and excludes insured branches of foreign banks. Insured branches of foreign banks were allowed to opt out of the TAG Program, but we exclude them because of missing data on key variables. The opt-out lists are provided online. See <http://www.fdic.gov/regulations/resources/TLGP/optout.html> for details. We assume that banks duplicated across lists opted out at the earliest listed date.

percent. Thus, there is a need to control for bank size when examining banks opting out of the program and the effect of the TAG Program. Figure 5 breaks down the NIBDs at TAG Program participants based on bank size. Whereas Figure 4 showed that the aggregate amount of NIBDs covered by the TAG Program declined, Figure 5 shows that the decline was due to large institutions opting out of the program, not smaller institutions.

In addition to exploring the size of the institutions that participated, we also examine if there was any regional variation in participation. Figure 6 provides state level average participation rates for all banks headquartered in that state across the TAG Program. Overall, participation in the program was very high at the state level—Idaho had the most banks participate at 100 percent while Kentucky had the lowest at around 71 percent. We see evidence to suggest some regional variation. For example, banks located in the Western United States had slightly higher participation rates at around 87 percent, whereas banks located in the Midwest had lower participation at around 80 percent.

5. What Drives TAG Participation?

In this section, we further consider the drivers of the participation decision in the TAG Program. Consistent with both theory and past literature we expect the decision to opt out to be driven by three key factors: size, liquidity needs, and financial condition. Size could drive banks' opt-out decisions because both implicit too-big-to-fail (TBTF) guarantees and economies of scale could provide advantages to larger banks in more easily maintaining deposit funding. Liquidity could impact TAG Program participation because banks facing declines or weak growth in their deposit funding, such as their NIBDs, amidst market stress are more likely to have incentives to seek out government safety nets to assure potential depositors and maintain such funding. Lastly, financial condition is likely to impact participation because distressed or financially troubled banks may be more susceptible to fleeing deposits and such banks may be inclined to provide fuller insurance to reassure nervous depositors. We assess the impact of these drivers on opt out decisions during the three quarters where banks could choose to opt out as summarized in Table 3.

We utilize three measures of size including dummies denoting large banks (Gr \$10 B and Gr \$1 B) and a continuous indicator (Log Assets). Proxies for liquidity include the ratio of deposits to liabilities, the ratio of

NIBD to total deposits, and the ratio of uninsured deposits. We measure financial condition by considering solvency (equity to assets ratio), profitability (ROA), and loan performance (non-current loan ratio).

We begin the analysis by comparing means of the above mentioned measures between banks that did not opt out with banks that did. The results, shown in Table 4, document notable differences in size between such banks. Banks with assets of more than \$10 billion were three times more likely to opt out. Other than the largest banks, opt-outs had lower assets. The results suggest that TBTF liquidity guarantees and perhaps other benefits of size such as economies of scale reduce the need for banks to obtain additional insurance.¹⁹ Table 4 also shows that opt-out banks had statistically more deposits relative to liabilities and less uninsured deposits. However, NIBD ratios appear similar for opt-out vs non-opt-out banks. With respect to financial condition, banks opting out have notably higher equity to assets and ROA and notably better loan performance.

We next turn to our multivariate analysis of opt-out drivers using the proxies for size, liquidity, and financial condition used previously as well as a variety of other controls. Our modeling approach is summarized in equation 1:

$$\text{Opt-Out}_{(t)} = b_0 + b_1\text{SIZE}_{(t-1)} + b_2\text{LIQ}_{(t-1)} + b_3\text{FINCON}_{(t-1)} + b_4\text{STRUC}_{(t-1)} + b_5\text{LOCECON}_{(t-1)} + b_6\text{FE} + v \quad (1)$$

The dependent variable, $\text{Opt-Out}_{(t)}$, is a dummy variable equal to one if the bank opted out of the TAG Program that quarter and zero otherwise. The vectors SIZE, LIQ, and FINCON denote the various measures of size, liquidity, and financial condition that were described and summarized in Table 2. The vector STRUC includes bank structural controls measured as asset growth over the prior quarter, log of bank age, multi-bank holding company affiliation, subchapter-S status, and a dummy denoting a merger in the prior year.²⁰ The vector LOCECON includes state (local) economic controls proxying for competition (Herfindahl–Hirschman Index or

¹⁹ The thresholds used to define TBTF institutions are typically based on asset cutoffs mandating differential treatment for larger institutions in the Dodd-Frank-Act, which had a stated goal of ending "too-big-to-fail"; these thresholds vary from \$10 Billion to \$250 Billion. While the smallest of among these, the \$10 Billion asset threshold was used in Dodd-Frank in certain cases, such as the cutoff for mandating company run-stress tests (see <https://www.govinfo.gov/content/pkg/PLAW-111publ203/pdf/PLAW-111publ203.pdf>). We define large institutions as those with assets of greater than \$10 Billion, the smallest of the asset thresholds in Dodd-Frank, for empirical reasons as only about 1.3% of our bank-quarter observations are above \$10 Billion in assets.

²⁰ All banks within a multi-bank holding company were required to make uniform decisions in terms of participation in the program. <https://www.fdic.gov/regulations/resources/TLGP/faq.html> "All eligible entities within a U.S. Banking Holding Company or a U.S. Savings and Loan Holding Company structure must make the same decision regarding continued participation in each component of the program (the TAGP component and the DGP component) or none of the members of the holding company structure will be eligible for participation in that component of the program."

HHI) and for economic climate (Unemployment Rate, Per-Capita-Income, and HPI index).²¹ We include both levels and differences of the economic climate indicators to better control for economic factors that could influence opt out choices. Lastly, we include bank fixed effects and time fixed effects. The sample only covers the three quarters where banks were given the option to exit the program (2008Q4, 2009Q4, and 2010Q2). The results for the multivariate analysis are shown in Table 5; we do not show results for local economic indicators for brevity.

The results in columns 1 and 2 show that bank structural controls, local economic controls, and time/bank fixed effects explain at least some variation in the opt-out decision. Of the bank structural controls, bank age and multi-bank-holding company affiliation appear to, respectively, positively and negatively impact bank opt-out choices. Adding the size controls (column 3) reveals significant coefficients for all 3 indicators. The results suggest that very large banks (Gr \$10 B) are 27 percent more likely to opt out. The results are consistent with these banks, which make up only about 1 percent of all banks, being perceived as safer by depositors or having other size benefits that reduce the need to reassure depositors amidst contagion. The results also suggest that banks with assets greater than \$1 B are more likely to opt out, though the economic effect is smaller. Interestingly, size (log assets) is more generally negatively associated with opting out. It is noteworthy that the R-square increases by about 50 percent after including the size controls, which is also indicative of the relevance of size in explaining banks' opt-out choices.

The results in column 4 suggest that liquidity measures such as deposits to liabilities and NIBD ratio are also related to optout. Banks with more deposit funding relative to total funding appear to be more likely to opt out and banks with higher NIBD ratios are less likely to opt out. The latter could be because banks with sufficient NIBDs may have less need to stay in the program. An important caveat, however, is that the liquidity measures do not add much to the explanatory power of the regressions and thus their economic effects are small. Solvency levels appear relatively more important, however. The results shown in column 5 suggest that a one standard deviation movement in equity/assets is linked to a 2.5 percentage point increase in opt-out propensity,

²¹ HHI is estimated for the Combined Statistical Area (CSA) and non-CSA counties.

which is large relative to the mean of 9.5 percent.²² In column 6 we include other financial condition indicators, ROA and Non-Current Loan Ratio; these variables appear to also be strongly linked to opt-out decisions. Including the financial condition indicators improves the explanatory power of the regressions by about 17 percent.

Next, we further consider the impact of bank size by excluding larger banks from the analysis. Table 6 panel A shows the core results excluding banks above \$10 billion (column 1) and \$1 billion (column 2). The analysis shows that the results are largely unaffected if large banks are excluded, but it is notable that lower uninsured deposit ratios are linked to opting out in both columns 1 and 2. Taking into account the insignificant coefficients for uninsured deposit ratio in Table 5, the results in columns 1 and 2 of Table 6 suggest that lower levels of uninsured deposits drive opt-outs primarily for smaller banks. In panel B, we consider heterogeneity in our results by opt-out quarter. The results suggest that the impact of size is similar across opt-out quarter, but the impact of financial condition varies substantially. For example, the impacts of equity/assets and ROA are two to four times larger during the first opt-out period relative to the latter two. In addition, the impact of non-current loans is much stronger in the latter opt-out period.

Overall, the evidence suggests some level of adverse selection. Banks were more likely to opt out if they appeared to not need the program (i.e., if they were larger, better capitalized, more profitable, and if they had better asset quality). The effects are generally consistent but vary somewhat in magnitude and significance by opt-out round. Many banks that remained in the program initially decided to opt out in one of the later rounds. By the middle of 2010, it was known that a Dodd-Frank version of the program was going to start in 2011 and cover all banks. This may have also influenced banks' opt out decisions by reducing the downside from opting out (the irreversibility of opt-out decisions), for banks that did not have a strong need to remain in the program.

6. Effects of the TAG Program on NIBD Funding

In this section, we compare banks that opted out of the TAG Program with those that did not to see if participation in the TAG Program led to changes in banks' NIBDs. While the program was intended to stop the

²² This is estimated as $0.039 \times 0.64 = .025$.

withdrawal of deposits at banks, it is of interest to test if it was successful in achieving this or if it might have drawn in additional deposits.

6.1. Difference-in-Differences Estimates

Our sample in this section extends from the first quarter of 2007 through the fourth quarter of 2011. Over the lifetime of the TAG Program, there were three opt-out opportunities. Thus, banks can be classified into four groups, those that: (1) never opted out, (2) opted out in 2009Q1, (3) opted out in 2010Q1, and (4) opted out in 2010Q3.²³

To mitigate endogeneity from selection inherent in the opt-out decision, we trim the sample based on average propensity scores over 2007 to ensure the banks in the sample are comparable. We use a pooled logit model over all quarters of 2007 with the dependent variable being an indicator of whether a bank ever opted out of the TAG Program (1 for ever opt out, and 0 for never opt out). The regressors include the log of asset size, ROA, noncurrent loans to loans ratio, equity to assets ratio, RWA to assets ratio, core deposits to liabilities ratio, liquid assets to assets ratio, and the ratio of uninsured deposits to total deposits. Following Crump et al. (2009), we drop banks with average propensity score below 0.1 or above 0.9. The trimming procedure excludes 612 institutions, or about 6.9 percent of the sample of insured institutions. Our trimmed sample contains a total of 8,324 insured institutions, 2,011 of which opted out of the TAG Program at some point, and 6,313 that never opted out.

Our framework used in this analysis is difference-in-differences, where we use both OLS and more advanced estimators designed to address concerns with staggered treatment timing. Figure 7 shows that there is significant overlap in the average propensity scores between banks that opted out and those that never opted out. The overlap in Figure 7 shows that for a large mass of banks, the decision to opt out may have been largely driven by idiosyncratic factors, which supports the exogeneity of the opt-out decision in the difference-in-differences framework.

Our OLS specifications are of the following form:

²³ In this section, we define the opt-out quarter to be the first full quarter following the quarter in which opt-out decisions had to be submitted.

$$\text{Log}(NIBD_{it}) = \alpha + \beta(\mathbf{1}_{i \in G(t_0)} \times \mathbf{1}_{t \geq t_0}) + \gamma \mathbf{x}_{it} + c_i + d_t + \varepsilon_{it} \quad (2)$$

$$\text{Log}(NIBD_{it}) = \alpha + \sum_{k=2007Q2}^{2011Q4} \beta_k (\mathbf{1}_{i \in G(t_0)} \times \mathbf{1}_{t \geq k}) + \gamma \mathbf{x}_{it} + c_i + d_t + \varepsilon_{it} \quad (3)$$

where $\text{Log}(NIBD_{it})$ is the log of NIBDs for bank i in quarter t , $G(t_0)$ denotes all the banks that opted out in quarter t_0 , \mathbf{x}_{it} contains controls at the bank-quarter level (the same set of control variables used in the propensity score trimming), c_i is a bank fixed effect, and d_t is a quarter fixed effect. The coefficient of interest in specification (2) is β . Specification (3) is a dynamic version of (2) that allows for a time-varying coefficient β_k that we illustrate graphically. The opt-out quarter, t_0 , can be one of three values: 2009Q1, 2010Q1, or 2010Q3. In each case, the OLS specifications (2) and (3) only keep one of the three opt-out groups and exclude the other two; that is, the comparison group in these specifications is always the banks that never opted out of the TAG Program. However, in addition to OLS specifications (2) and (3), we use an estimator proposed by Callaway and Sant’Anna (2021), which allows us to combine all banks regardless of their opt out date while avoiding the biases discussed in Baker et al. (2022).²⁴

Table 7 reports the results from specification (2). It shows that NIBDs declined after opting out for banks that opted out in either 2009Q1, 2010Q1, or 2010Q3, when compared to banks that never opted out. The effects are stronger when considering banks that opted out in 2009Q1 or 2010Q1, and not very strong (though still directionally consistent) for banks that opted out in 2010Q3. This may be explained by the fact that the Dodd Frank Act of 2010 replaced the TAG Program and guaranteed NIBDs after 2010, so opting out of the TAG Program in 2010Q3 was effectively only an opt out for at most 6 months (the second half of 2010).

Figure 8 shows estimates from the Callaway and Sant’Anna (2021) estimator with all banks in the trimmed sample included regardless of their opt-out date. There is a clear and persistent negative effect from opting out of the TAG Program on the levels of NIBDs at banks that opt out. The magnitude of the decline is similar to the

²⁴ With several opt-out groups and opt-out dates, OLS is a weighted average of several comparisons between banks in the TAG Program and banks not in the TAG Program. These comparisons include groups of banks that opted out earlier as effective controls for groups of banks that opted out later, leading to a “bad comparisons” problem and causing bias if there is a time-varying effect of opting out. These problems do not exist in the case of only two groups and one opt out date, which is why the sample for specifications (1) and (2) is restricted to only banks that never opted out and one additional opt out group (all three opt out dates considered separately).

ones estimated by OLS in Table 7. The figure also reveals time-heterogeneity in the effect of opting out. NIBDs continue to decline over time for banks that opted out, and there is not simply a “one-time” decline followed by stabilization. This phenomenon likely explains why the OLS estimates in Table 7 are larger in magnitude for banks that opted out earlier.

Figure 9 shows the effects of opting out of the TAG Program on NIBDs for three samples, one for each of the three opt out groups, with each sample containing banks that never opted out as a comparison group. Figure 9 shows the dynamic estimates over time from both the Callaway and Sant’Anna (2021) estimator and the OLS specification (2). Consistent with the results above, the figures show a stronger negative effect of opting out on NIBDs for banks that opted out earlier. Interestingly, the figures suggest there may have even been a trend reversal after opting out, where NIBDs were relatively increasing at banks that opted out and started relatively declining at the same banks after they opted out of the TAG Program. Again, the weaker effects for banks that opted out later may be due to the expected implementation of the Dodd-Frank version of an alternate guarantee program after 2010.

6.2. Using Risk-Based TAG Program Fees to Instrument for Opt-Out Decisions

In this subsection, we consider an alternate source of variation that might have affected banks’ decisions to opt out of the TAG Program through an arguably exogenous channel—the insurance premiums that banks had to pay to remain in the TAG Program in 2010. We use this variation as an IV to isolate the effect of opting out of the TAG Program on NIBDs. Specifically, we exploit the implementation within the TAG Program of risk-based premiums—a pricing system that has been shown to have several benefits, such as limiting moral hazard (Shoukry (2024)).

For the first five quarters of the TAG Program from 2008Q4 until 2009Q4 the additional fee for the program was a flat 10 basis points, however, during the extensions in 2010 the rate varied from 15 to 25 basis points based on risk. Throughout 2010, there were four “risk categories” (RCs) that served as a classification of banks based on their risk levels. These RCs ranged from 1 to 4, with 1 being the best, and were defined by capital

group and CAMELS rating.²⁵ There were three different premium levels, with two risk-category-dependent thresholds between them. One threshold separated RC 1 banks from RC 2 banks (we call this the “first” threshold), and the other threshold separated RC 2 banks from banks with RC 3 or 4 (we call this the “second” threshold). Figure 10 illustrates the risk-based TAG Program premiums of 2010.

In this section we focus on the banks close to one of the two thresholds at which the TAG Program premiums change (see below for the precise definition of our chosen distance metric). With sufficient controls, banks close to a particular threshold are arguably similar except for facing different premiums on TAG Program participation. We thus use the premiums as an instrument for the opt-out decision to estimate the effect of opting out of the TAG Program on NIBDs within an IV framework.

One difficulty with this approach is defining a metric of “closeness” to a risk category threshold. As previously mentioned, RCs were defined clearly based on a bank's capital ratios and composite CAMELS rating (a bank's CAMELS ratings are known only by the bank and its regulators). Thus, each bank knew its own RC, and could easily infer how its RC would change as a result of a hypothetical change in its own capital ratios or composite CAMELS rating. However, within each RC there were potentially many banks with varying levels of risk. For our purpose, understanding the relative riskiness of those banks (i.e., how “close” each of them was to a particular threshold) requires further analysis.²⁶

To obtain a closeness metric, we build a separate machine learning model for each threshold that predicts the probability that a particular bank will be misclassified as being on the other side of the threshold. This misclassification probability will naturally increase as a bank becomes more similar to banks on the other side of the threshold (illustrated by the bell curves in Figure 10), allowing us to measure closeness in a data-driven,

²⁵ The risk assessment structure for the FDIC is based on two items. The first is the Capital Group in which there are three groups: 1 (Well Capitalized), 2 (Adequately Capitalized), and 3 (Under Capitalized). The second is the Supervisory Subgroup. There are three subgroups based on a bank’s CAMELS rating: A, B, and C. Where A includes banks with a rating of 1 or 2, B includes banks with a rating of 3, and C includes banks with a rating of 4 or 5.

²⁶ Consider, for instance, two hypothetical banks with a composite CAMELS rating of 3, but bank A’s component ratings are 1-1-3-3-2-4 and bank B’s component ratings are 1-2-3-1-3-4. It is unclear which of the two banks in this hypothetical example is closer to becoming 4-rated (having a composite rating of 4). As previously mentioned, composite ratings reflect a bank’s overall health and may differ from a simple average of the component ratings. In this hypothetical example, bank A has two component ratings that are better than bank B’s (Asset Quality and Liquidity), but has one component rating that is significantly worse (Earnings). Although both banks have the same composite rating of 3, the likelihood of each of the two banks being downgraded to a composite rating of 4 depends on the weightings assigned to each of the component ratings by bank examiners, which may in turn depend on several qualitative and historical characteristics of the banks.

objective way. For each threshold, the machine-learning model (a random forest) is estimated with a dependent variable being an indicator for whether a bank’s RC is “above” or “below” the threshold. Predictors in the model include the financial variables from Section 6.1, as well as the six CAMELS components and three capital ratios that are used in the determination of the RCs. Because we know the true RC for each bank in each quarter, we use the estimated model to predict the probability that the bank would be misclassified as being on the “wrong” side of the threshold; and this can be done for any quarter of interest.

Our sample is the quarter-end snapshot of banks in the TAG Program at 2009Q3. This is the quarter immediately preceding the deadline to opt out of the first extension of the TAG Program (the deadline was November 2, 2009). The machine learning model is estimated on the true RCs from the prior quarter (2009Q2), and it’s used to make predictions of RCs in the 2009Q3 quarter to obtain closeness metrics as described above. We restrict the sample to banks close to one of the two premium thresholds and study whether opting out of the TAG Program in either of the program’s 2010 extensions caused a decline in NIBDs.

The second stage dependent variable of interest is the percent change in NIBDs between 2009Q3 and 2010Q4. This time period spans 2010, the year in which the TAG Program fees were risk-based, and ends in 2010Q4 with the end of the TAG Program. We control for the percent change in assets between 2009Q3 and 2010Q4. A bank is counted as an opt-out if it opted out during either the second or the third extensions of the program. Our instrument for this opt-out variable is the risk-based TAG Program fee that the bank would pay given its RC in 2009Q3, interacted with the bank’s NIBD dependence (NIBD to assets ratio). We keep banks with a misclassification probability of at least 0.2, and we also report results with different probability cutoffs (0.25 and 0.3).

The two stages of the IV regression are defined as follows:

$$OPT - OUT_i = \alpha_1 + \beta_1 IV_i + \gamma_1 \mathbf{x}_i + \epsilon_i \quad (4)$$

$$\text{Log}\left(\frac{1 + NIBD_{i,2010Q4}}{1 + NIBD_{i,2009Q3}}\right) = \alpha_2 + \beta_2 \widehat{OPT - OUT}_i + \gamma_2 \mathbf{x}_i + \epsilon_i \quad (5)$$

where $OPT - OUT_i$ is an indicator with a value of 1 if bank i opted out of the TAG Program at either of its 2010 extensions, IV_i is the instrument for bank i as described above, \mathbf{x}_i is a vector of controls containing the same set

of variables used in Section 6.1 as well as asset growth between 2009Q3 and 2010Q4 and an indicator with a value of 1 if bank i is among the sample of banks “close” to the first threshold (the threshold separating RC 1 from RC 2 banks) with the metric of closeness defined by the output from the machine learning models as described above.

Table 8 shows the results from the IV regression. The odd-numbered columns show the first stage regressions, and the even-numbered columns show the second stage. First stage results suggest that banks facing higher premiums are significantly more likely to opt out of the TAG Program, and the effect is consistent across different cutoff probabilities. The second stage regressions show a strong and negative effect of opting out of the TAG Program on institutions’ NIBDs.

Overall, the IV regression results are consistent with results from Section 6.1: opting out of the TAG Program results in declines in NIBDs, suggesting that the increased insurance provided by the TAG Program provided funding stability for participants. Moreover, the first stage regressions also show that banks with better risk category classifications (i.e., those close to the first threshold) were significantly more likely to opt out, further confirming results from Section 5 on the drivers of participation. Better-rated banks, those that seemed to have less need to reassure depositors, were more likely to opt out of the program.

7. Conclusion

This paper examines the periods of unlimited FDIC insurance guarantee provided by the TAG Program. To start, we show that aggregate NIBDs increased during the periods of unlimited insurance as well as NIBDs as a percentage of total deposits. Leading up to the passage of the TAG Program, deposits were leaving smaller banks and entering larger banks suggesting a flight to institutions perceived to be “too big to fail” was taking place. We show that the TAG Program stabilized NIBDs as a source of funding for banks. However, we document that the percentage of deposits covered by unlimited insurance declined over the TAG Program as large banks exited the program.

To understand banks’ decisions to opt out or remain in the TAG Program we study the drivers of participation. We find that banks were more likely to opt out of the program if they were larger, better capitalized, more profitable, and if they had better asset quality. These results point to adverse selection, but

they also imply that banks choosing to remain in the TAG Program and pay the associated fees found the program sufficiently valuable in its reassurance to depositors.

Next, we examine if banks that opted out of the TAG Program had significant subsequent differences in NIBDs. Using both difference-in-differences and the Callaway and Sant’Anna (2021) estimator, we document that NIBDs at banks that opted out declined compared to banks that never opted out. In a separate two-stage instrumental variable model that exploits the risk-based TAG Program premiums to instrument for the opt out decision, we find that banks facing higher premiums were more likely to opt out and again show that opting out of the TAG Program led to reductions in NIBDs. These results confirm that the TAG Program stabilized funding for banks choosing to participate in it.

These results have implications for policymakers. As revealed in legislation such as the CARES Act of 2020, policymakers continue to consider targeted, temporary extensions of deposit insurance as part of their crisis response toolkit. In addition, with the renewed interest in examining potential reform to the deposit insurance system after the March 2023 bank failures, the FDIC recommended that a viable approach might be one similar in structure to the TAG Program (FDIC (2023)). The approach that the FDIC (2023) indicated was the most promising, “targeted coverage,” would significantly expand the coverage for business payment accounts. However, as noted in the FDIC’s report, targeted coverage faces challenges, including being able to distinguish between deposits used for business payments and other deposits, and limiting avenues of arbitrage. Any reform of deposit insurance design faces a unique set of challenges and opportunities, giving rise to a need for a full consideration of the tradeoffs involved. Our results directly inform the debate on deposit insurance reform by providing a deeper understanding of the economic outcomes of the TAG Program.

REFERENCES

- Acharya, V. V. and N. Mora, 2015, A Crisis of Banks as Liquidity Providers. *Journal of Finance*, 70, 1-43.
- Baker, Andrew C, David F Larcker, and Charles CY Wang (2022), How much should we trust staggered difference-in-differences estimates?, *Journal of Financial Economics*, 144, 370–395.
- Boyle, G., R. D. Stover, A. Tiwana, and O. Zhylyevskyy, 2015, The impact of deposit insurance on depositor

- behavior during a crisis: A conjoint analysis approach, *Journal of Financial Intermediation*, 24, 590-601.
- Callaway, Brantly and Pedro HC Sant'Anna (2021), Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225, 200–230.
- Crump, Richard K, V Joseph Hotz, Guido W Imbens, and Oscar A Mitnik (2009), Dealing with limited overlap in estimation of average treatment effects. *Biometrika*, 96, 187–199.
- Danisewicz, Piotr, Chun Hei Lee, and Klaus Schaeck (2022), Private deposit insurance, deposit flows, bank lending, and moral hazard. *Journal of Financial Intermediation*, 52, 100967.
- Federal Deposit Insurance Corporation, 2023, Options for Deposit Insurance Reform, <https://www.fdic.gov/analysis/options-deposit-insurance-reforms/>.
- Hoskins, S. M., 2012, An overview of the Transactions Account Guarantee (TAG) program and the potential impact of its expiration or extension, Congressional Research Service, R42787.
- Martin, C., M. Puri, and A. Ufier, 2022, Deposit inflows and outflows in failing banks: The role of deposit insurance, FDIC Center for Financial Research Working Paper 2018-02.
- Schich, A., 2008, Financial crisis: Deposit insurance and related financial safety net aspects, *Financial Market Trends*, 2, 1–39.
- Shoukry, G. F., 2024, Insurance Pricing, Distortions, and Moral Hazard: Quasi-Experimental Evidence from Deposit Insurance, *Journal of Financial and Quantitative Analysis*, 59, 896–932.
- Stone, A. L., 2020, Unlimited FDIC insurance and the implications for corporate cash, *Quarterly Journal of Finance*, 10, 2040001.
- Stone, A. L., 2021, Double the insurance, double the funds? *Journal of Banking & Finance*, 133, 106284.
- Stone, A. L., 2022, Dodd-Frank and unlimited deposit insurance, *Finance Research Letters*, 47, 1–7.

Fig. 1 Timeline of the TAG Program

This figure shows a timeline of the Transaction Account Guarantee (TAG) Program. The top portion of the timeline notes events of particular relevance for our analysis. The bottom portion notes the TAG Program fee structure for initial TAG Program and its extensions. For more details on the events surrounding the implementation of the TAG Program and its extensions, see <https://www.fdic.gov/regulations/resources/TLGP/archive.html>.

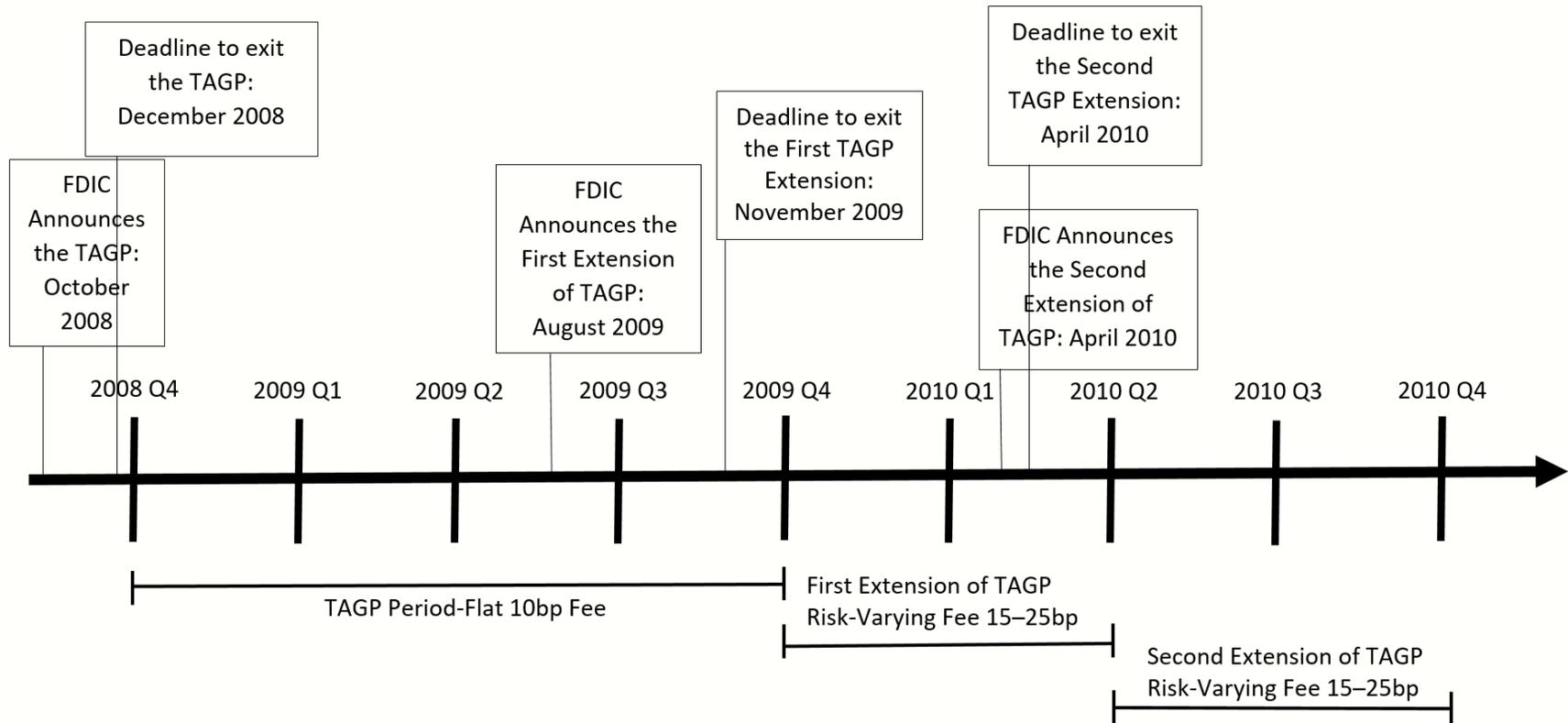


Fig. 2 Domestic Noninterest-Bearing Deposits

This figure plots the aggregate amount of domestic NIBDs, reported in billions of dollars, as reported by all FDIC-insured banks from January 2002 until December 2010. The vertical bars separate the initial TAG Program and its first and second extensions and denote the quarters with opt-out decision deadlines.

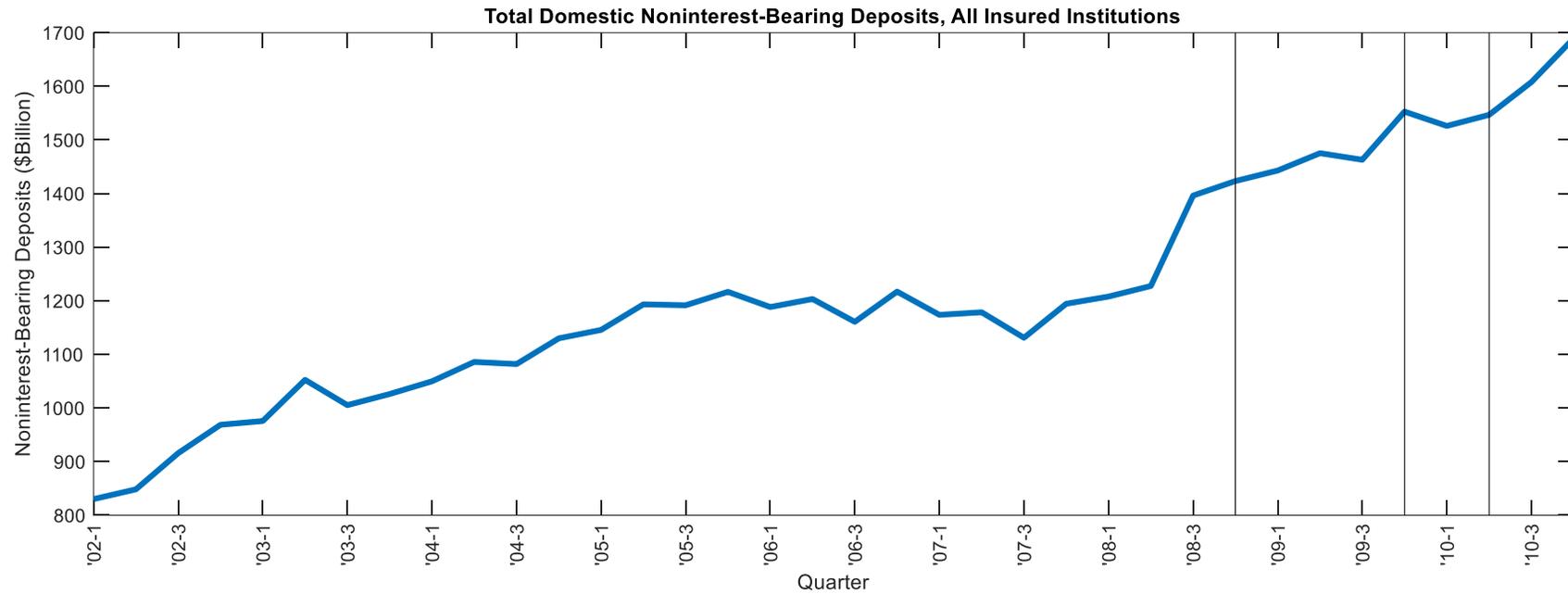


Fig. 3 NIBDs for Banks Based on Size

This figure plots multiple measures of NIBDs from January 2002 until December 2010. Panels A and B plot the aggregate amount of domestic NIBDs broken down by small and large banks. Small (large) banks are defined as having total assets less than or equal to (greater than) \$10 billion. Panel C plots the mean ratio of domestic NIBDs to total domestic deposits. The vertical bars separate the initial TAG Program and its first and second extensions, and denote the quarters with opt-out decision deadlines.

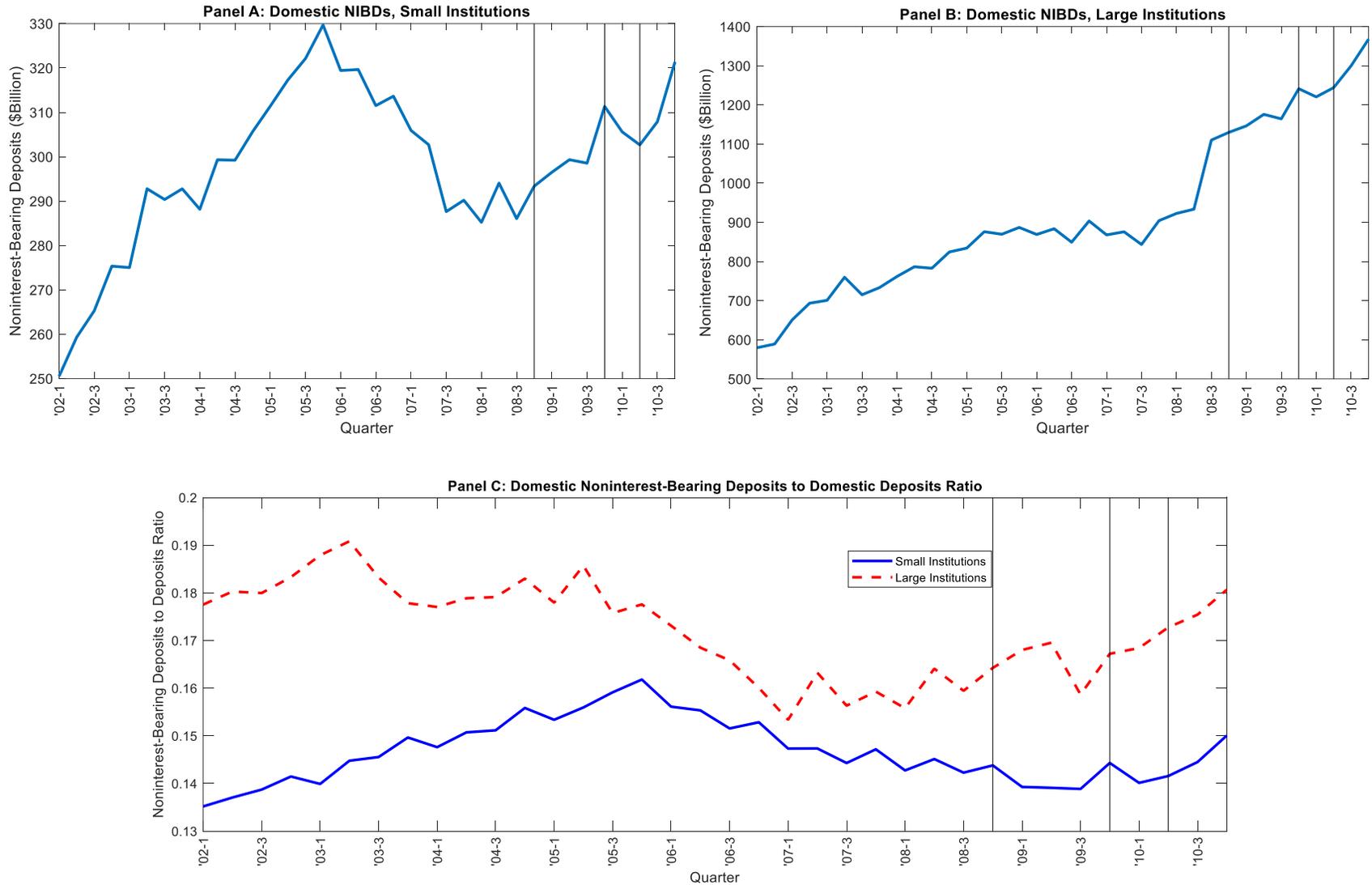


Fig. 4 Domestic NIBDs during the TAG Program

This figure plots total domestic NIBDs at all institutions in our sample and at the subset of institutions that participated in the TAG Program. Both series are reported in billions of dollars.

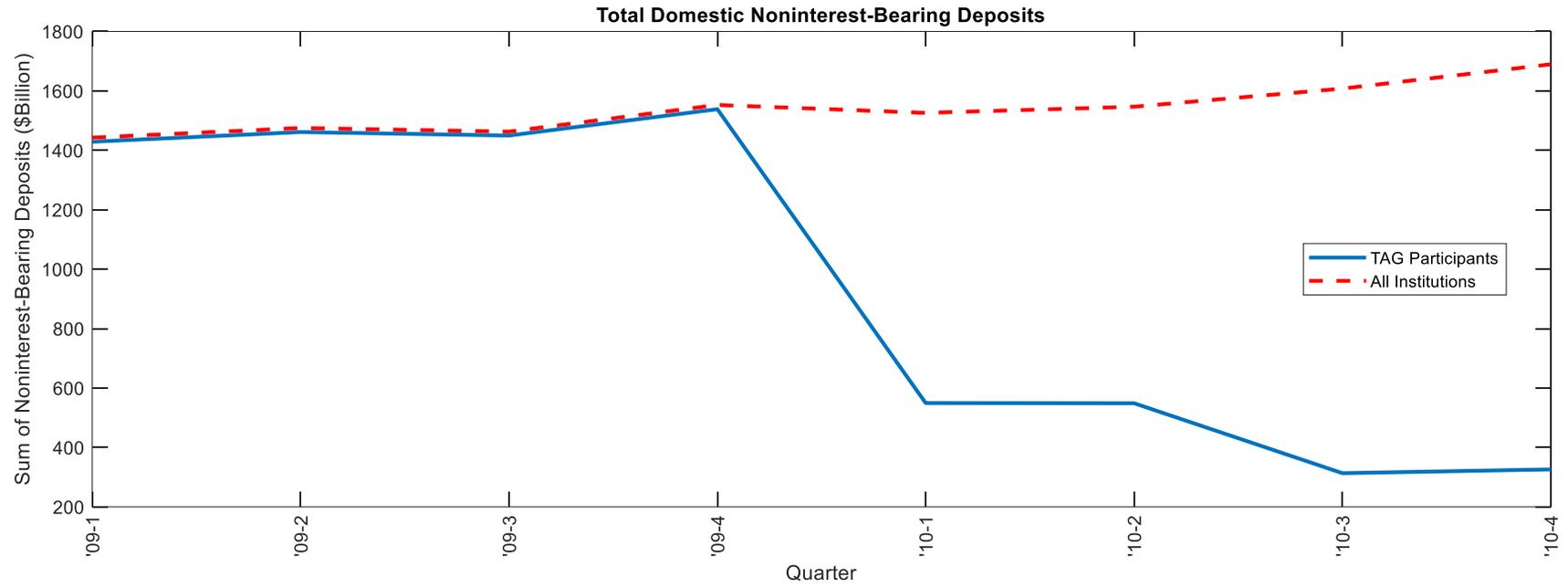


Fig. 5 Domestic NIBDs at TAG Participants Based on Size

This figure plots aggregate amounts of domestic NIBDs, reported in billions of dollars, held at banks that participated in the TAG Program and broken down by bank size. Small (large) banks are defined as having total assets less than or equal to (greater than) \$10 billion.

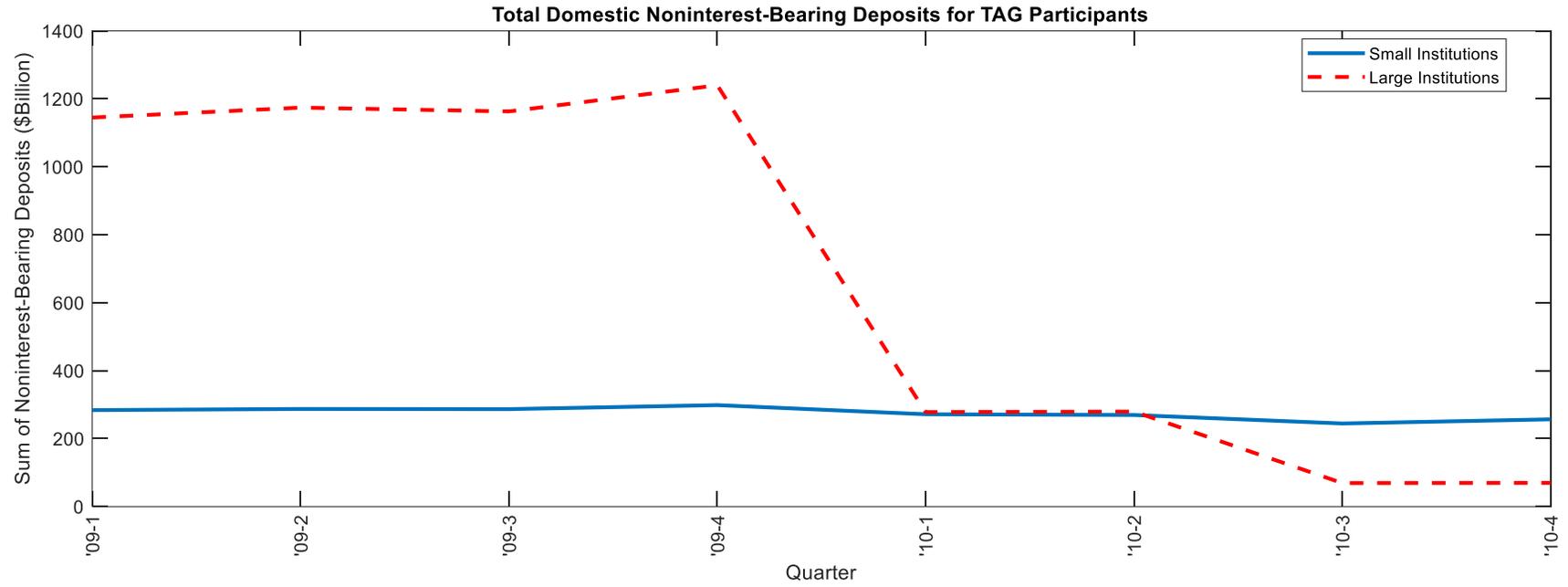


Fig. 6 Program Participation by State

This figure plots the TAG program participation rate by state. Participation rates are averaged between the first quarter of 2009 and the fourth quarter of 2010 based on banks headquartered in the state. While United States territories were allowed to participate in the TAG Program, they are not represented on the map.

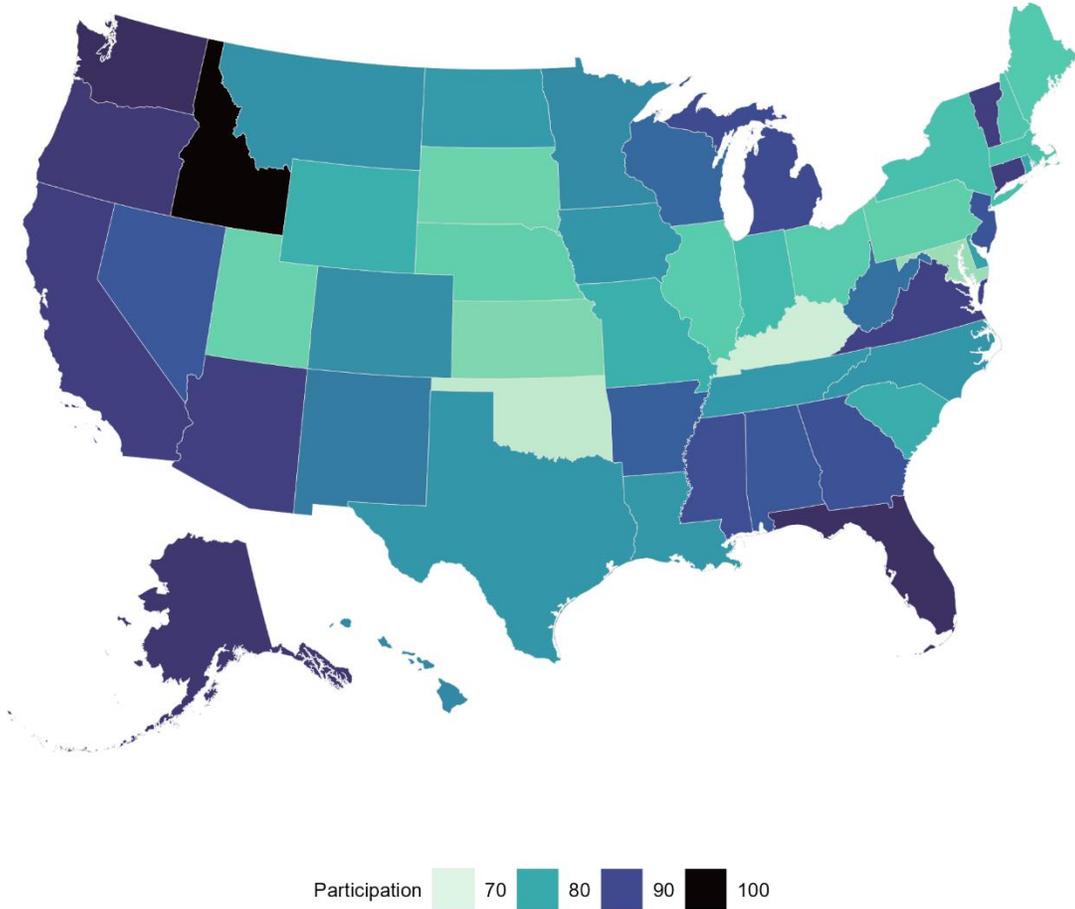


Fig. 7 Average Propensity Score Distributions

Propensity scores are derived from a pooled logit model with a dependent variable being an indicator for whether the institution ever opted out, and regressors include core financial ratios used throughout this paper. The sample for the logit regression is 2007, and each institution's average propensity score is the in-sample average of its predictions from the logit model over all the quarters of 2007. The left panel shows a kernel density estimate of the average propensity scores, and the right panel shows the histograms for banks that ever opted out and those that never opted out.

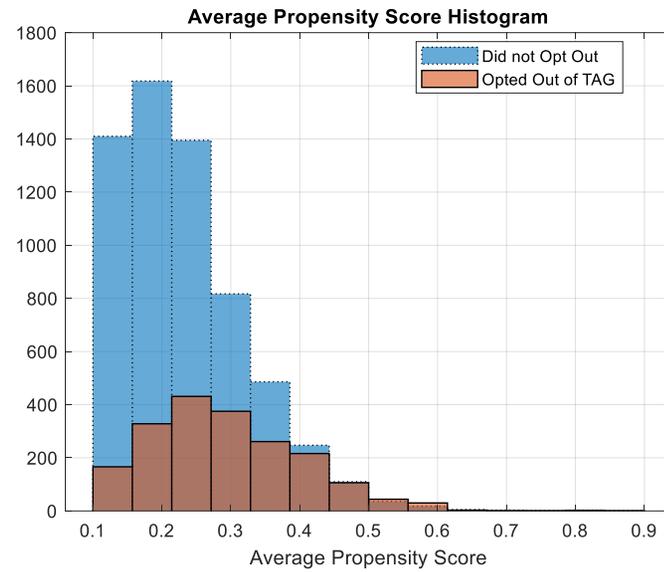
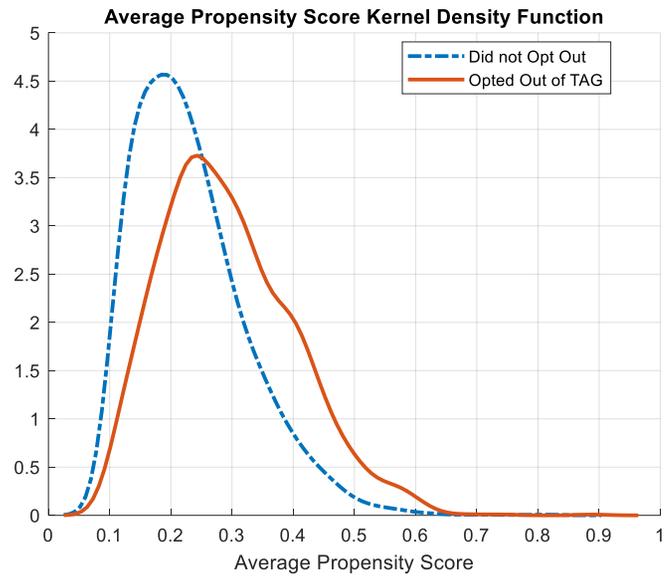


Fig. 8 Combined Effect of Opting Out of TAG on NIBDs

The figure shows the effect of opting out of the TAG Program on institutions' NIBDs (in log form), from the Callaway and Sant'Anna (2021) estimator. Controls include the core financial variables. The sample combines all institutions regardless of their opt-out choices.

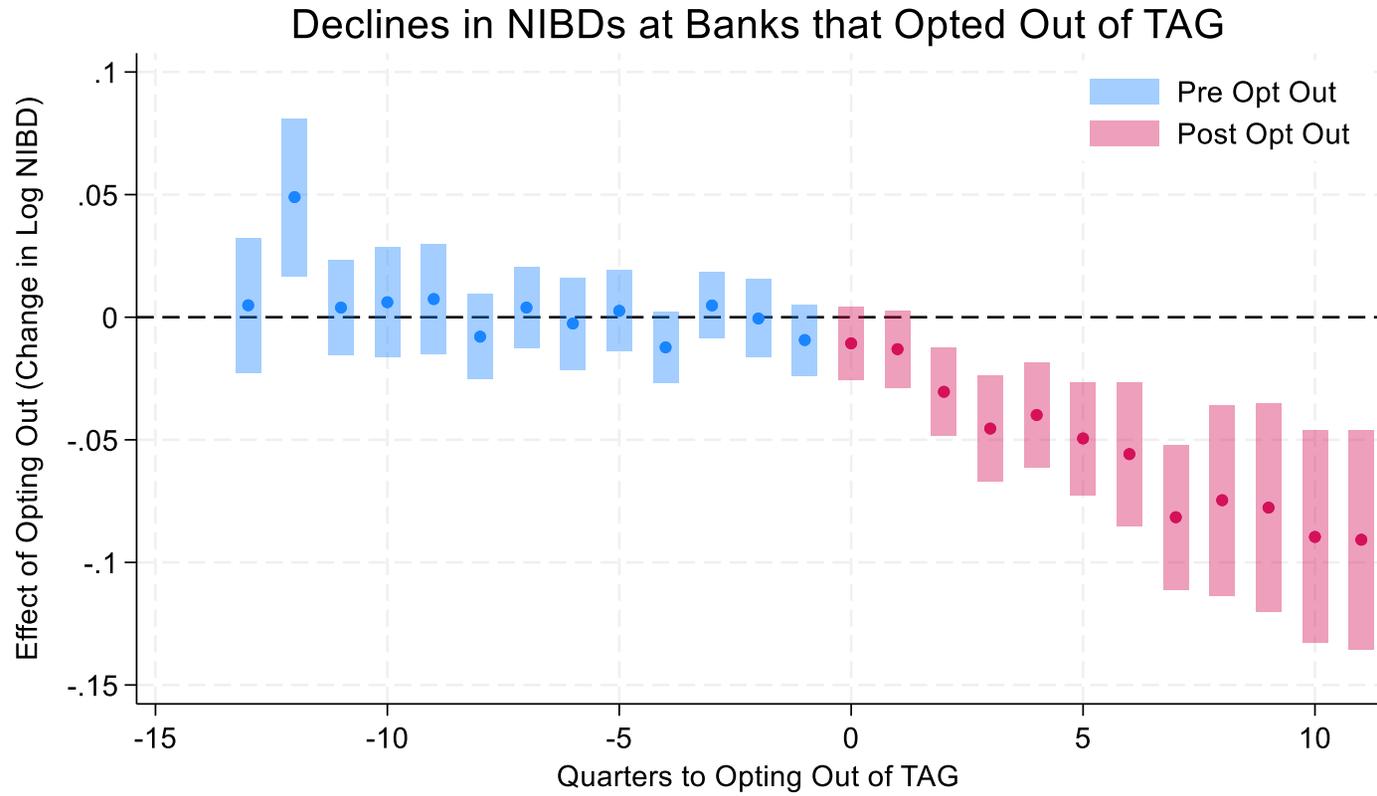
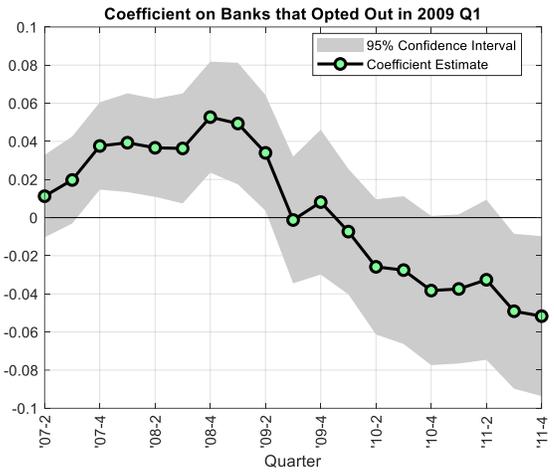
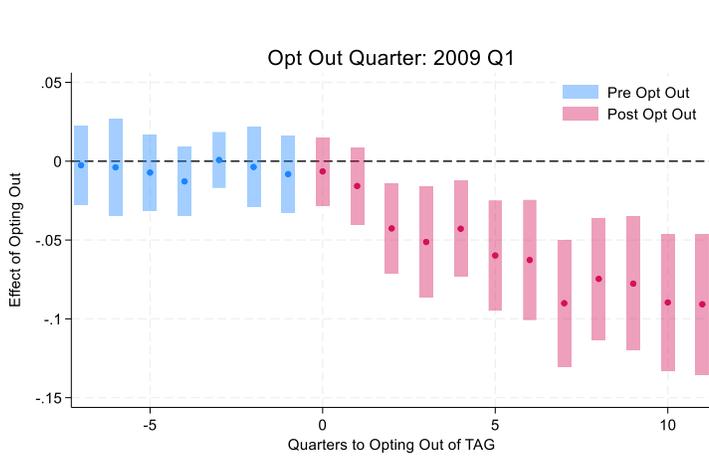


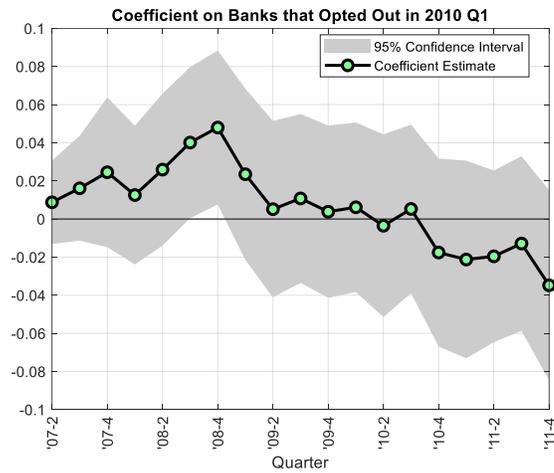
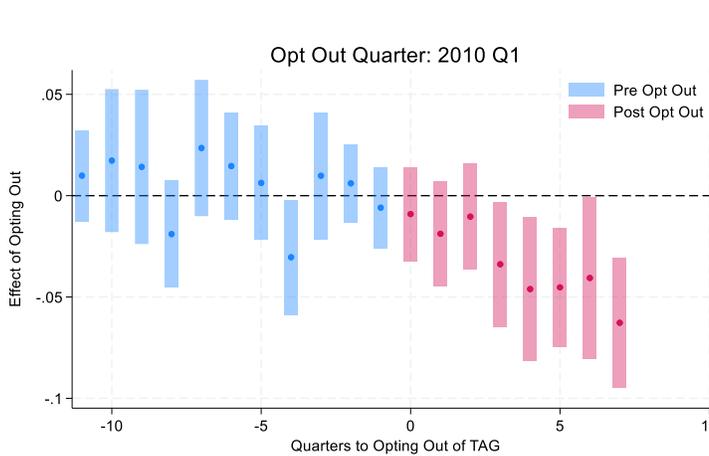
Fig. 9 Effect of Opting Out of TAG on NIBD

The dependent variable is the log of an institution's noninterest bearing deposits, and the controls for all panels include the core financial variables. The left figures show estimates from the Callaway and Sant'Anna (2021) estimator. The right figures show estimates from specification (2) with quarter and institution fixed effects, and with standard errors clustered at the institution level.

Panel A. 2009Q1 Opt-Out Sample



Panel B. 2010Q1 Opt-Out Sample



Panel C. 2010Q3 Opt-Out Sample

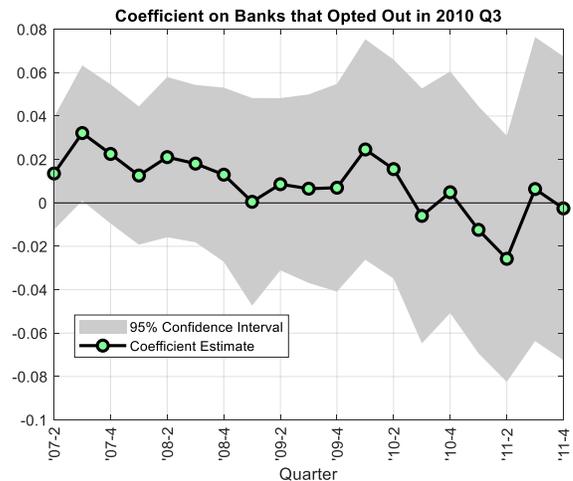
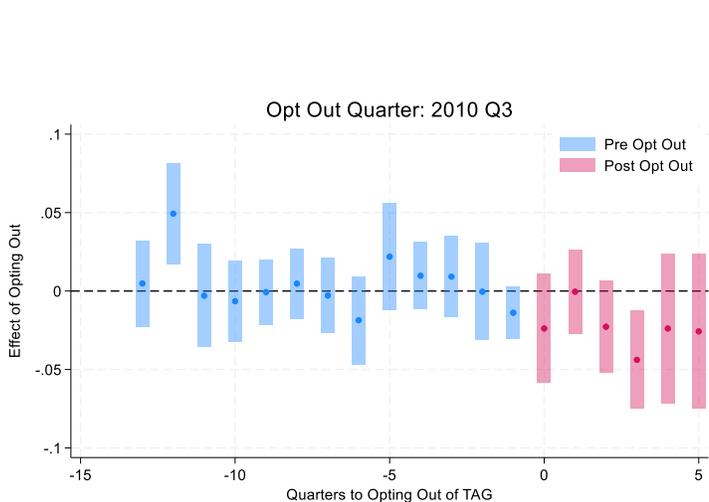


Fig. 10 Illustration of Risk Categories (RC) and TAG Program Premiums in 2010

This figure illustrates the risk-based premiums for TAG Program participation that banks faced in 2010. Premiums increased based on Risk Category (RC). There were two thresholds, one separating RC 1 banks from RC 2 banks and the other separating RC 2 banks from RC 3 or 4 banks. The bell-shaped curves around each threshold illustrate the misclassification probability distribution that we obtain from a machine-learning model (estimated separately for each threshold). These probabilities allow us to obtain an objective, data-driven metric to measure the closeness of banks to each of the thresholds.

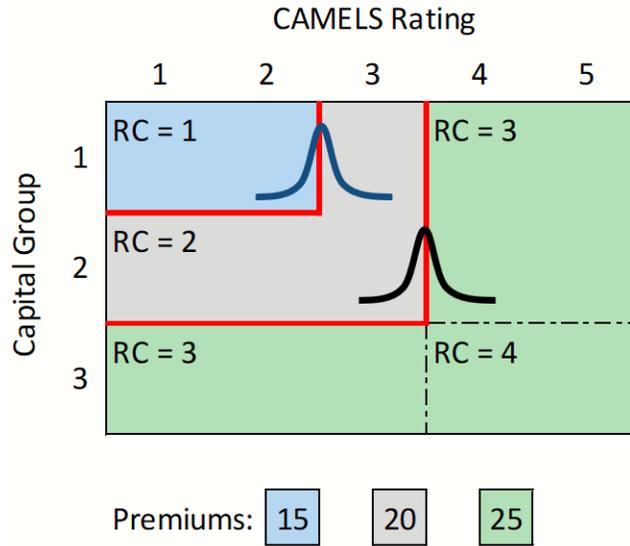


Table 1 FDIC Deposit Insurance Premiums

The table presents a summary of regular annual assessment rates and TAG Program fees for deposit insurance where bps stands for basis points. Beginning in April 2009, Annual Assessments Rates reflect the Total Base Assessment Rate. All data is gathered from the FDIC. See <https://www.fdic.gov/deposit/insurance/historical.html#20070101> for details.

		Risk Category 1	Risk Category 2	Risk Category 3	Risk Category 4
12/6/2008-12/31/2008	Annual Assessment Rates	5-7 bps	10 bps	28 bps	43 bps
	TAG Program	10 bps			
1/1/2009-3/31/2009	Annual Assessment Rates	12-14 bps	17 bps	35 bps	50 bps
	TAG Program	10 bps			
4/1/2009-12/31/2009	Annual Assessment Rates for Established Institutions (Insured 5 years of More)	7-24 bps	17-43 bps	27-58 bps	40-77.5 bps
	Annual Assessment for Newly Insured Institutions (Insured Less Than 5 years Without a CAMELS Rating)	14-21 bps	22-43 bps	32-58 bps	45-77.5 bps
	Annual Assessment for Newly Insured Institutions (Insured Less Than 5 years With a CAMELS Rating)	12-24 bps	22-43 bps	32-58 bps	45-77.5 bps
	TAG Program (4/1/2009-12/31/2009)	10 bps			
1/1/2010-12/31/2010	Annual Assessment Rates for Established Institutions (Insured 5 years of More)	7-24 bps	17-43 bps	27-58 bps	40-77.5 bps
	Annual Assessment for Newly Insured Institutions (Insured Less Than 5 years)	16-24 bps	22-43 bps	32-58 bps	45-77.5 bps
	TAG Program (1/1/2010-12/31/2010)	15bps	20 bps	25 bps	

Table 2 Descriptive Statistics

The table reports the descriptive statistics for key variables (Panel A) and other bank controls (Panel B) over the three opt-out quarters (2008Q4, 2009Q4, and 2010Q2). All variables are defined in Appendix Table A.1.

Panel A- Key Variables								
Variable	N	mean	sd	p5	p25	p50	p75	p95
Opt-Out	21211	9.5%	29.3%	0.0%	0.0%	0.0%	0.0%	100.0%
Assets Gr \$10 B	21211	1.3%	11.3%	0.0%	0.0%	0.0%	0.0%	0.0%
Assets Gr \$1 B	21211	8.8%	28.3%	0.0%	0.0%	0.0%	0.0%	100.0%
Log Assets	21211	12.1	1.3	10.3	11.3	12.0	12.8	14.4
Deposits/Liabilities	21211	91.6%	8.2%	74.9%	87.5%	93.6%	98.5%	99.7%
Uninsured Deposits Ratio	21211	17.2%	13.0%	2.0%	7.7%	14.1%	23.2%	43.2%
NIBD Ratio	21211	13.8%	8.2%	2.6%	8.2%	12.7%	17.8%	29.1%
Equity/Assets	21211	10.8%	3.9%	6.7%	8.5%	9.9%	12.1%	18.3%
ROA	21211	0.2%	-1.9%	3.4%	0.0%	0.6%	1.1%	2.0%
Noncurrent Loans/Total Loans	21211	2.5%	3.1%	0.0%	0.5%	1.5%	3.3%	8.9%

Panel B- Other Bank Variables								
Variable	N	mean	sd	p5	p25	p50	p75	p95
Log Assets Change	21211	0.02	(0.08)	(0.06)	0.02	0.01	0.03	0.11
Log Bank Age	21211	3.74	1.24	1.13	3.07	4.34	4.65	4.89
MBHC	21211	17.9%	38.4%	0.0%	0.0%	0.0%	0.0%	100.0%
Subchapter-S	21211	30.3%	46.0%	0.0%	0.0%	0.0%	100.0%	100.0%
Merger Prior Year	21138	7.2%	25.8%	0.0%	0.0%	0.0%	0.0%	100.0%

Table 3 Statistics on Banks Participating in the TAG Program by Size

The table presents statistics on depository institutions separated by bank assets and participation in the TAG Program each quarter. *Participants* are banks that participated in the TAG Program and *Non-Participants* are banks that opted out. A bank that opted out is counted as a non-participant in the first quarter in which opt-out decisions became effective (2008 Q4 for the initial program, 2010 Q1 for the first extension, and 2010 Q3 for the second extension). *Number of Observations* is the number of observations each quarter for each category. *Percent of NIBDs* is the ratio of domestic NIBDs in each category to total domestic NIBDs by quarter. *Percent Participating* is the percentage of each asset group that participated in the TAG Program.

Time	Depository Institutions with Assets ≤ \$10 Billion					Depository Institutions with Assets > \$10 Billion				
	Participants		Non-Participants		Percent Participating	Participants		Non-Participants		Percent Participating
	Number of Observations	Percent of NIBDs	Number of Observations	Percent of NIBDs		Number of Observations	Percent of NIBDs	Number of Observations	Percent of NIBDs	
2008 Q4	7093	19.75%	1098	0.86%	86.60%	107	79.31%	7	0.08%	93.86%
2009 Q1	7032	19.67%	1100	0.88%	86.47%	108	79.36%	7	0.09%	93.91%
2009 Q2	6981	19.47%	1098	0.82%	86.41%	109	79.60%	7	0.11%	93.97%
2009 Q3	6893	19.60%	1094	0.81%	86.30%	105	79.50%	7	0.09%	93.75%
2009 Q4	6817	19.22%	1088	0.83%	86.24%	99	79.86%	8	0.09%	92.52%
2010 Q1	6267	17.80%	1562	2.23%	80.05%	67	18.21%	38	61.76%	63.81%
2010 Q2	6175	17.42%	1550	2.15%	79.94%	66	18.07%	39	62.36%	62.86%
2010 Q3	5705	15.20%	1947	3.95%	74.56%	36	4.30%	73	76.55%	33.03%
2010 Q4	5643	15.19%	1908	3.83%	74.73%	34	4.12%	73	76.85%	31.78%

Table 4 Preliminary Analysis—Comparison of Opt-Out and Non-Opt-Out Banks

The table summarizes the various measures of size, liquidity, and performance for banks that did not and did opt out during the three quarters where they had the choice to opt out (2008Q4, 2009Q4, and 2010Q2). Statistical significance is denoted by *, **, and *** which corresponds to p-values of below 10 percent, 5 percent, and 1 percent respectively.

	(1) No Optout N=19,206	(2) Optout N=2,005	(3) Diff (2) - (1)	
Assets Gr \$10 B	1.1%	3.4%	2.3%	***
Assets Gr \$1B	8.7%	8.9%	0.2%	
Log Assets	12.14	11.84	-0.30	***
Deposits/Liabilities	91.5%	92.5%	1.1%	***
Uninsured Deposits Ratio	17.2%	16.4%	-0.8%	***
NIBD Ratio	13.8%	13.9%	0.1%	
Equity/Assets	10.7%	12.0%	1.3%	***
ROA	0.1%	0.7%	0.5%	***
Noncurrent Loans/Total Loans	2.6%	1.7%	-0.9%	***

Table 5 Opt-Out Decision Drivers

This table summarizes regressions considering the role of various drivers of optout choices of our indicators of NIBD growth on market NIBD growth measures from t to t-1. The control variables are measured at time t-1 and are defined in Appendix Table A.1. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Optout Decision (t)					
Assets Gr 10 B (t-1)			0.2762*** (0.025)	0.2810*** (0.025)	0.2622*** (0.025)	0.2650*** (0.025)
Assets 1B to 10B (t-1)			0.0596*** (0.009)	0.0603*** (0.009)	0.0486*** (0.009)	0.0530*** (0.009)
Log Assets (t-1)			-0.0343*** (0.003)	-0.0319*** (0.003)	-0.0248*** (0.003)	-0.0257*** (0.003)
Deposits/Liabilities (t-1)				0.1297*** (0.029)	0.10308*** (0.029)	0.10229*** (0.029)
Uninsured Deposits Ratio (t-1)				0.0087 (0.020)	-0.0050 (0.020)	-0.0159 (0.020)
NIBD Ratio (t-1)				-0.0790** (0.032)	-0.0777** (0.032)	-0.0918*** (0.032)
Equity/Assets (t-1)					0.6403*** (0.067)	0.5871*** (0.067)
ROA (t-1)						0.7257*** (0.112)
Noncurrent Loans/Total Loans (t-1)						-0.1347** (0.067)
Log Assets Change (t-1, t-2)		0.0118 (0.023)	0.0075 (0.022)	0.0068 (0.022)	-0.0084 (0.023)	-0.0260 (0.023)
Log Bank Age (t-1)		0.0193*** (0.002)	0.0214*** (0.002)	0.0218*** (0.002)	0.0225*** (0.002)	0.0200*** (0.002)
MBHC (t-1)		-0.0101** (0.005)	-0.0116** (0.005)	-0.0103** (0.005)	-0.0116** (0.005)	-0.0123** (0.005)
Subchapter-S (t-1)		-0.0031 (0.005)	-0.0042 (0.005)	-0.0038 (0.005)	0.0009 (0.005)	-0.0029 (0.005)
Merger Prior Year		-0.0069 (0.008)	0.0113 (0.008)	0.0106 (0.008)	0.0043 (0.008)	0.0060 (0.008)
Local Economic Controls	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
Observations	21161	21089	21089	21089	21089	21089
R-squared (Adjusted)	0.025	0.029	0.043	0.045	0.050	0.053
rmse	0.289	0.288	0.286	0.286	0.285	0.285

Table 6 Opt-Out Drivers – Subsample Analysis

This table shows results for our additional models considering opt-out drivers. Panel A (columns 1 and 2) present results excluding very large (greater than \$10 Billion in assets banks) and large (greater than \$1 Billion in asset banks) respectively. Panel B (columns 3,4, and 5) depict results for each of the optout periods separately (2008Q4, 2009Q4, and 2010Q2). The control variables are measured at time t-1 and are defined in Appendix Table A.1. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	<u>Panel A</u>		<u>Panel B</u>		
	Assets ≤\$10B	Assets ≤\$1B	Initial Optout	Second Optout	Final Optout
	<u>Optout Decision (t)</u>		<u>Optout Decision (t)</u>		
Assets Gr \$10 B (t-1)			0.2714*** (0.029)	0.2050*** (0.048)	0.3308*** (0.063)
Assets Gr \$1 B (t-1)	0.0581*** (0.009)		0.1018*** (0.013)	0.0020 (0.015)	0.0092 (0.017)
Log Assets (t-1)	-0.0272*** (0.003)	-0.0293*** (0.003)	-0.0734*** (0.005)	-0.0008 (0.004)	0.0203*** (0.005)
Deposits/Liabilities (t-1)	0.0981*** (0.029)	0.1047*** (0.030)	0.0500 (0.045)	-0.0562 (0.050)	0.1748*** (0.047)
Uninsured Deposits Ratio (t-1)	-0.0407** (0.020)	-0.0451** (0.022)	-0.0729** (0.031)	0.0723** (0.037)	0.0359 (0.037)
NIBD Ratio (t-1)	-0.0990*** (0.032)	-0.1253*** (0.033)	-0.2893*** (0.056)	0.0273 (0.052)	0.0056 (0.047)
Equity/Assets (t-1)	0.5760*** (0.068)	0.5415*** (0.070)	0.8769*** (0.108)	0.1936* (0.099)	0.2283** (0.100)
ROA (t-1)	0.7095*** (0.112)	0.7779*** (0.119)	0.9736*** (0.211)	0.3544** (0.158)	0.5036*** (0.177)
Noncurrent Loans/Total Loans (t-1)	-0.1362** (0.067)	-0.1213* (0.070)	-0.0320 (0.175)	-0.2739*** (0.092)	-0.5270*** (0.087)
Log Assets Change (t-1, t-2)	-0.0202 (0.023)	-0.0264 (0.036)	0.0114 (0.037)	-0.0016 (0.034)	-0.0311 (0.035)
Log Bank Age (t-1)	0.0196*** (0.002)	0.0200*** (0.002)	0.0372*** (0.003)	0.0097*** (0.003)	0.0075*** (0.003)
MBHC (t-1)	-0.0134*** (0.005)	-0.0208*** (0.005)	-0.0604*** (0.008)	0.0076 (0.008)	0.0419*** (0.010)
Subchapter-S (t-1)	-0.0025 (0.005)	-0.0035 (0.005)	-0.0093 (0.009)	0.0256*** (0.008)	-0.0193** (0.008)
Merger Prior Year	0.0074 (0.008)	0.0125 (0.010)	-0.0301*** (0.011)	0.0058 (0.014)	0.0130 (0.015)
Local Economic Controls	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES
Observations	20825	19262	8092	6815	6182
R-squared (Adjusted)	0.053	0.059	0.117	0.039	0.076
rmse	0.282	0.284	0.319	0.254	0.244

Table 7 Effect of Opting Out of TAG on Noninterest Bearing Deposits

This table shows estimates from specification (1), comparing institutions that opted out of the TAG Program to those that never opted out. Three samples are considered, one for each of the three opt-out dates. Variables are winsorized at the 1 percent and 99 percent levels within each quarter. Standard errors clustered at the bank level in parentheses.

*** p <0.01, ** p <0.05, * p <0.1.

	Dependent Variable: Log(Noninterest Bearing Deposits)					
	Opt Out in 2009 Q1		Opt Out in 2010 Q1		Opt Out in 2010 Q3	
Post Opt Out of TAG	-0.062*** (0.014)	-0.043*** (0.012)	-0.037** (0.017)	-0.030** (0.013)	-0.042** (0.021)	-0.020 (0.019)
Asset Size (log)		0.858*** (0.022)		0.867*** (0.023)		0.857*** (0.023)
ROA		0.981*** (0.104)		0.927*** (0.101)		0.985*** (0.098)
Noncurrent Loans/Total Loans		-0.271** (0.116)		-0.267** (0.112)		-0.232** (0.113)
Equity/Assets		-1.498*** (0.129)		-1.435*** (0.141)		-1.528*** (0.133)
RWA/Assets		0.068 (0.063)		0.086 (0.070)		0.088 (0.069)
Core Deposits/Liabilities		0.548*** (0.053)		0.567*** (0.059)		0.532*** (0.055)
Liquid Assets/Total Assets		-0.054 (0.060)		-0.051 (0.067)		-0.032 (0.072)
Uninsured Deposits Ratio		0.236*** (0.051)		0.182*** (0.052)		0.211*** (0.052)
Observations	131,277	130,976	120,597	120,260	119,184	118,843
R-squared	0.942	0.961	0.939	0.961	0.942	0.962
Bank FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
R-squared (Adjusted, Within)	0.00111	0.287	0.000220	0.315	0.000211	0.311

Table 8 Effect of Opting Out of TAG on NIBDs (IV Estimates)

This table shows estimates from an IV regression where the decision to opt out of the TAG program is instrumented by an IV composed of the TAG premiums interacted with NIBD dependence (NIBD/Assets). The sample includes only banks close to either the threshold separating Risk Category 1 banks from Risk Category 2 banks (First Threshold), or the threshold separating Risk Category 2 banks from Risk Categories 3 and 4 banks (Second Threshold). The table shows estimates for three different cutoffs for the misclassification probability, which is a measure of closeness derived from a machine learning classification model as described in Section 6. Odd-numbered columns show the first stage results (specification (4)) and even-numbered columns show the second stage results (specification (5)). Standard errors clustered at the state level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

	(1) <u>Cutoff Probability: 0.20</u>		(3) <u>Cutoff Probability: 0.25</u>		(5) <u>Cutoff Probability: 0.30</u>	
	Opt Out	NIBD %Change	Opt Out	NIBD %Change	Opt Out	NIBD %Change
Opt Out		-2.979** (1.212)		-2.569** (1.037)		-2.435** (1.134)
IV	0.0228** (0.0088)		0.0298** (0.0127)		0.0314** (0.0149)	
Asset Size (log)	0.0263** (0.0130)	0.0526 (0.0481)	0.0171 (0.0140)	0.0353 (0.0534)	0.0185 (0.0159)	0.0300 (0.0596)
ROA	0.0293 (0.506)	1.649 (2.015)	0.671** (0.293)	3.825* (2.046)	0.682* (0.387)	3.589* (1.960)
Noncurrent Loans/Total Loans	-0.231 (0.175)	-1.011 (0.949)	-0.279 (0.168)	-1.661* (0.931)	-0.248 (0.186)	-0.845 (1.104)
Equity/Assets	0.0434 (0.149)	-1.039 (1.877)	0.0247 (0.123)	-1.064 (1.849)	0.0362 (0.143)	-3.174 (1.963)
RWA/Assets	0.116 (0.135)	0.484 (0.553)	0.160 (0.165)	1.037** (0.437)	0.200 (0.231)	1.364** (0.575)
Core Deposits/Liabilities	-0.0840 (0.0988)	-1.362** (0.607)	-0.236** (0.111)	-1.768*** (0.656)	-0.165 (0.102)	-1.460** (0.722)
Liquid Assets/Total Assets	0.0771 (0.153)	0.751 (0.531)	0.113 (0.184)	1.267*** (0.463)	0.120 (0.253)	1.360*** (0.456)
Uninsured Deposits Ratio	-0.214 (0.143)	-0.616 (0.454)	-0.229 (0.164)	-1.011* (0.554)	-0.216 (0.187)	-1.098* (0.599)
Asset Size %Change	0.0405 (0.0399)	1.228*** (0.246)	0.0583 (0.0381)	1.247*** (0.225)	0.0577 (0.0447)	1.452*** (0.192)
First Threshold Indicator = 1	0.0703*** (0.0200)	0.149 (0.106)	0.0594*** (0.0217)	0.0434 (0.108)	0.0552** (0.0245)	0.0528 (0.137)
Observations	359	359	283	283	231	231
Probability Cutoff	.2	.2	.25	.25	.3	.3
First Stage F- Statistic	8.577		10.84		10.86	

Appendix

Table A.1 Variable Definitions

Variable	Definition
Log(NIBD)	Natural log of domestic noninterest-bearing deposits (NIBDs)
NIBD Ratio	Total domestic NIBDs to total domestic deposits
Change in Log(NIBD)	One quarter change in log NIBD
Change in NIBD Ratio	One quarter change in the NIBD ratio
Market-Change in Log(NIBD)	Average market NIBD growth
Decline- Market NIBD	Dummy variable equal to one if the market experienced a decline in average NIBD growth and zero otherwise
Market Opt-Out Rate	The opt-out rate of other banks in the markets in which a given bank operates
Opt-Out	A dummy variable equal to one if the bank did not participate in the TAG program that quarter and zero otherwise
Log Assets	Natural log of total assets
Assets Gr 10 B	A dummy variable equal to one for banks with asset size of at least \$10 billion, and zero otherwise
Log Assets Change	One quarter change in Log Assets
ROA	Net income after securities gains or losses, extraordinary gains or losses, and applicable taxes divided by total assets
Noncurrent Loans/Total Loans	Loans 30 or more days past due plus nonaccruals to total loans
Equity/Assets	Total equity to total assets
RWA/Assets	Risk-weighted assets to total assets
Core Deposits/Liabilities	Core deposits divided by total liabilities where core deposits are defined as all domestic deposits less brokered deposits and large time deposits.
Liquid Assets/Total Assets	Liquid assets divided by total assets where liquid assets are defined as the total of cash balances, fed funds and repos sold, and US treasuries.
Uninsured Deposit Ratio	Uninsured deposits to total deposits where the level of uninsured deposits is an estimate, reported in Call Reports, of the amount in deposit accounts above the coverage limits, which were \$100,000 prior to late 2008, and \$250,000 thereafter.
Log Bank Age	Natural log of bank age
MBHC	Dummy variable equal to one if the bank is an affiliate of a multi-bank-holding company and zero otherwise
Subchapter-S	Dummy variable equal to one if the bank has a subchapter-S status and zero otherwise
Merger Year	Dummy variable equal to one if the bank was involved in a merger in the prior year.
HHI	The weighted average HHI based on the bank's county-level deposit market area as defined by the FDIC's Summary of Deposits
Unemployment Rate	The weighted average percentage of the state unemployment rate based on the bank's market area as defined by the FDIC's Summary of Deposits
Per-capita income (PCI)	The weighted average per-capita income based on the bank's market area as defined by the FDIC's Summary of Deposits
Housing price index	The weighted average state housing price index based on the bank's market area as defined by the FDIC's Summary of Deposits