Bank Capital and Risk Taking: A Loan Level Analysis Online Appendix

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August 28, 2017

A Online Appendix - Not for Print

This online appendix is organized as follows. Section A.1 presents robustness checks to the main results, while Section A.2 presents supplemental analyses that add context or nuance to the main findings of the paper. Section A.3 gives more information on the regulatory background of bank capital and Section A.4 discusses details of data cleaning and construction.

A.1 Robustness Checks

I present the following set of robustness checks. Section A.1.1 considers additional bank-level controls to the main loan risk specifications. Section A.1.2 discusses validation exercises for the instrumental variables specification. Section A.1.3 considers additional measures of bank capital.

A.1.1 The Role of Additional Bank Variables

Section 6.2 in the body of this paper discusses the theory and methods behind the robustness checks that add additional bank-level variables to the main default analyses in this study. This section of the online appendix contains the main regression tables giving detailed results on these robustness checks. In particular, Table A.1 and Table A.2 present the key results of these analyses.[1] As noted in the body of the text, the results in these tables all closely match those in the main tables that omit these additional bank-level controls.

A.1.2 Instrument Validation

In order for my instrumental variables specification to satisfy the exclusion restriction short term changes in bank managers' strategic risk preferences must not be correlated with the geographic distribution of bank activities. In the body of the paper, I discuss results that show that banks are very stable in their geographic locations over time which lends credibility to the argument that banks are not shifting their geographic distributions of deposits in response to short-term changes in risk preferences. A way to more formally relate this to my particular instrumental variables specification is to use information on a bank's deposit distribution as of the year 2000 in order to construct my weighted house price change instrument, instead of as of the year 2006, as I do in the body of the paper. Table A.3 present the results of this analysis. The sample size is about 1/3 lower in this analysis as compared to the one in the body of the paper, due to the fact that the set of banks with branches in multiple CBSAs as of year 2000 is smaller than the same set measured as of year 2006. Nevertheless, these results confirm the effects documented in the body of the paper.

[1] For brevity, I omit analogous sets of results for home mortgage loans. The findings in them are very much the same as for the small business loans presented here.

A.1.3 Alternative Capital Metrics

The main analyses in this investigation consider five different measures of bank capital: the ratio of Tier 1 capital to total assets, the ratio of Tier 1 capital to risk weighted assets, the ratio of Tier 1 plus Tier 2 capital to risk weighted assets, the ratio of market capitalization to total assets and the ratio of market capitalization to risk weighted assets. There are, however, alternative possibilities. In particular, one could measure capital at the level of the bank holding company,[2] instead of the individual bank,[3] and one could consider a bank's capital level relative to other banks, rather than its absolute level of capital. As discussed briefly in Section 4 of the body of this paper, measuring capital with quantiles provides a kind of robustness check against distortions in measuring "true" capital from an economic perspective as compared to what is actually reported in regulatory filings.

Table A.4 and Table A.5 consider the main loan risk specifications for each of these alternative measures in turn. The results are all consistent with those in Table 3. The quantile metrics in Table A.5 are particularly informative, as they aid with interpreting the economic significance of the various estimates. For instance, the coefficient in column (6), panel D of Table A.5, which corresponds to the ratio of market capitalization to risk weighted assets, and includes both time and bank fixed effects is -0.003. In other words, moving from the 50th to the 51st percentile is associated with an approximately 0.3% reduction in the odds of default compared to not default. Put differently, a move from the 25th to the 75th percentile of capitalization, according to this metric, is associated with an approximately 15% reduction in the odds of default compared to not default. Evaluated at the mean default rate for the small business loans, this corresponds to a reduction of 2.2 percentage points, from 18.5% default probability to 16.3%.

A.2 Supplemental Analyses

In this portion of the appendix, I consider the following supplemental analyses. Section A.2.1 presents results for home mortgage loans, analogous to those presented in the body of the paper for small business loans. Section A.2.3 investigates the responses of bank supervisors to changes in loan risk. Section A.2.4 examines the extent to which differences in infrastructure investment may be a mechanism through which banks increase or decrease their risk exposure in response to the incentive influences of bank capital.

A.2.1 Mortgage Loan Risk and Bank Capital

The results presented so far for small business loans are striking in the picture they reveal regarding the relationship between bank capital and loan risk. Small business loans are an important component of bank lending, particularly for small and mid-sized banks. Mortgage lending is a far larger sector of the US financial landscape. Do the results presented for small business loans hold up when considering mortgage loans?

Table A.6 presents the basic analyses of the relationship between bank capital and loan risk for residential mortgages. The results are broadly consistent with those for the small business loans. The mean default rate on the home mortgage loans is 2.5%, as compared to 18.5% for the small business loans. Thus, this must be factored in when assessing the coefficients on these analyses, since the coefficients in their raw form represent, when exponentiated, the change in the *relative* probability of default as compared to the null outcome of not defaulting.

To take an example, the coefficient in column (6), panel C, corresponding to the ratio of Tier 1 plus 2 capital to risk weighted assets is -0.046. Evaluated at the mean default rate for home mortgage loans, this indicates that a one percentage point increase in that capital ratio is associated with a reduction in loan default probability from 2.5% to 2.4% (a 4% proportional reduction in risk) and a five percentage point increase in that capital ratio would be associated with a reduction from 2.5% to 2.0% mean default rate.

Figure A.1 presents the simple plots of bank capital against home mortgage risk, equivalent to those for small business loans in the body of this text, and Figure A.2 plots the coefficients for mortgage loans fit to five-year subsamples of the total study period. Figure A.3, Figure A.4 and Figure A.5 present basic descriptive plots of the home mortgage data equivalent to those given for the small business loan data in the body of the text.

[2] Technically, the market capital based metrics presented previously are already at the ultimate holding company level, since this will be the only institution with publicly traded stock.

[3] Specifically, I consider the capital level of the highest level holding company that controls a bank. In the event that a bank is not owned by a holding company, this metric simply equals the capital level of the bank itself.

A.2.2 Alternative Risk Metrics

Section 4.3 of the Empirical Methodology section of the body of this paper discusses several metrics of loan risk beyond just the probability of loan default. In Table A.7 I consider the losses suffered conditional on a small business loan's default. The analyses are of the specific form:

$$\log(1 + \text{LGD}_{it}) = \alpha + \beta \text{Capital}_{jt} + \Gamma X_t + \mu_j + \eta_t + \varepsilon_i \tag{A.1}$$

For brevity, I present the results just using the market capitalization based capital measures.[4] The coefficient estimate of -0.001 in each of the specifications indicates that a move of ten percentile points in either of the given capital metrics (e.g. a bank moving from the median capitalization to the 60th percentile of capitalization) is associated with a reduction of approximately 10% in the average losses suffered given default of a small business loan. All of these results are strongly statistically and economically significant.

So far, I have considered risk-taking based on ex-post measures - whether a loan will default and if so, how substantial the losses will be. It is also possible to consider risk from an ex-ante perspective. I do this in two ways. First, I consider the decision by banks of how much default insurance to purchase from the Small Business Administration on the small business loans in this sample. Clearly, purchasing more of this insurance will reduce the overall risks of the lending that a bank faces. Thus, a bank's decision on how much insurance to purchase can also be seen as a way of gauging its risk preferences. Secondly, I investigate the interest rates charged by banks for both small business and home mortgage loans.

Table A.8 considers models to predict the amount of default insurance banks purchase from the small business administration. The results show a statistically significant association between banks with higher capital levels and higher amounts of default insurance. For instance, each extra percentage point of the Tier 1 capital to risk weighted asset ratio is associated with an extra 2.3 percentage points of default insurance, on average. Given that the guaranteed percentages range largely from 50 to 85 percentage points, this is a fairly sizeable increase. The result is particularly interesting given that the prior analyses have already shown that banks with higher capital make *less* risky loans. Thus, it might have been natural to assume that banks making less risky loans might purchase less default insurance, but in fact the result is the reverse. Put conversely, banks with the least capital not only make riskier loans, they also double down on those risks by purchasing less default insurance on those loans when it is available.

I present the results of the analyses of loan interest rates in Table A.9. Although the results here are a tiny bit less consistent than in my default risk analyses, they still show consistent and frequently statistically significant negative relationships between capital levels and loan interest rates. In other words, as one would expect, banks that have lower capital levels make riskier loans, but those loans carry, on average, higher interest rates. In general, a one percentage point increase in capital ratios is associated with a decrease in two to six basis points of interest on loans. One caveat with these interest rate analyses is that not all of the loans in my sample have information on the interest rate charged.[5]

A.2.3 Bank Supervisor Responses to Risk Taking

The policy implications of a link between lightly capitalized banks and high loan risks are considerably different depending on whether bank regulators and supervisors are able to effectively monitor and respond to the added risks banks may be taking on to their balance sheets. In order to investigate this, I start by creating a bank-by-year panel that measures the average default rate for loans originated by a bank each year. For example, the data for 2003 and Bank of America in this panel will give the percentage of all loans originated by Bank of America in 2003 that eventually default at any point in the loan life. Given this construction, the panel explicitly

[4] As in many of my main specifications, these have the strongest and most consistently significant results. The results for the other variables are similar but have lower levels of statistical significance.

[5] In particular, I have interest rate information for only 30% of the small business loans and only 16% of the home mortgage loans. Why such low rates of these variables supplied in the data? From discussions with the Small Business Administration, I learned that in their internal records they do have more comprehensive interest rate information but that in the process of generating the data in response to the FOIA request, data errors prevented all of the interest rate information from being transferred. So far, I have been unable to recover fuller coverage on this variable. Regarding the home mortgage data - although it is necessary to file a record with the county registrar of deeds if a lender wants a legally enforceable lien on a property, it is generally not required that such a record include the interest rate on the loan. Individual counties, which each have their own administrative system for such records, have significantly different coverage rates for whether and how strictly they require this variable to be included in deed records. To my knowledge, there is no specific reason to believe that either of these data coverage issues would systematically bias my results, particularly given the extensive controls I already have in place.

incorporates information for its 2003 observations that is not yet knowable in 2003. But, the purpose of this is to assess whether regulators successfully identify and respond to changes in the riskiness of loans banks are taking on to their banking sheets *before* those loans actually default and reveal for certain their riskiness.[6]

I create this panel using the fifty lenders who are most active in the small business administration data set. Lenders who are less active are likely to have more sparse data, particularly in certain years, or even no loans in a given year, making calculations of average default rates more difficult and less reliable. Additionally, since large lenders tend to make more loans, and since it is risks to large banks that are in many respects of greatest concern from a policy perspective, this focus is sensible. Finally, the lenders in this panel account for 73% of all of the loans in the small business data.

Having created this panel, I consider two sets of panel regressions. For the first, I collect data on all formal enforcement actions brought against banks by any of the FDIC, Federal Reserve, Office of the Comptroller of the Currency, or the now dissolved Office of Thrift Supervision.[7] In total, there are 203 formal actions that are brought against these banks during the study period, indicating that they are actions that happen with some frequency. Enforcement actions can require various responses from banks. In some cases, they may explicitly require a bank to increase its capital position in order to respond to increased risks that supervisors perceive. In other instances, they may directly require a bank to take steps to constrain practices that regulators consider overly risky.[8] From these, I construct a panel regression of the following form:

$$\text{N Actions}_{it} = \alpha + \beta\Delta(\text{Default Rate}_{it}) + \eta_t + \varepsilon_{it} \tag{A.2}$$

Here N Actions_{it} represents the number of enforcement actions against bank i at time t. $\Delta(\text{Default Rate}_{it})$ represents the change in the default rate of a bank's loan's from year $t-1$ to year t. η_t is a time fixed effect common across all banks. Thus, I investigate whether bank supervisors respond with more enforcement actions when they perceive bank risk taking increasing.[9] Many times, however, supervisors may use informal actions to pressure banks to either increase their capital or change their practices in response to activity that the supervisors consider too risky. In order to account for these informal actions, I formulate a second panel regression of the form:

$$\Delta(\text{Bank Capital}_{it}) = \alpha + \beta\Delta(\text{Default Rate}_{it}) + \eta_t + \varepsilon_{it} \tag{A.3}$$

With this formulation then, I investigate whether changes in bank risk prompt increases in bank capital, potentially due to informal regulatory (or perhaps market) pressure.[10]

Table A.10 presents the results of these analyses of bank supervisor responses. The first column investigates whether changes in bank default rate predict increases in enforcement actions against banks. The coefficient estimate of 0.005 is neither statistically nor economically significant. It suggests, for instance, that if a bank went from the mean default rate for SBA loans of 18.5% and doubled that default probability, it would correspond with an increase in roughly an extra 0.1 enforcement actions for that bank. To contextualize this further, with 203 enforcement actions over the total 519 bank-year observations in the analysis, banks experience an average of 0.4 actions per year.

The next three columns of Table A.10 look for evidence of informal regulatory actions in which bank supervisors might require banks to increase capital levels without issuing formal enforcement actions. They likewise show no evidence of such informal actions. In general, they show that there is actually a small (but not generally significant) negative association in which banks that increase their loan risk slightly reduce their capital levels. Overall, these investigations of bank supervisor actions do not show evidence that such supervisors respond in noticeable ways to changes in bank loan risk.

Nevertheless, these results are best interpreted as suggestive rather than fully definitive. It is almost certain both that bank supervisors have some awareness of changes in bank risk taking and take some actions to address

[6] Indeed, a bank supervisor that is only able to perceive risks that have already fully been realized is really not a supervisor at all in any meaningful sense of the term.

[7] Each agency publishes a comprehensive list of these actions on their respective website.

[8] For the purposes of this analyses I do not directly consider the differences in type of enforcement action as indeed, each action is unique and tailored to the situation of a particular bank at a particular time.

[9] In alternate specifications I also consider the lagged default rate as a predictor, as well as the current default rate. The conclusions of these analyses are the same under those other specifications.

[10] Similar to Equation A.2 I also consider alternative specifications in which I lag the Δ for the default rate, i.e. so that I ask whether changes in default rate from 2003 to 2004 predict changes in capital from 2004 to 2005. I also consider specifications using the absolute default rate or lagged default rate. Again, these variations make no impact on the conclusions of the analyses.

those. It is also almost certain that such awareness is imperfect and such actions do not perfectly constrain unsafe bank practices that may exist. Where precisely supervisory responses genuinely lie on the spectrum between these two poles is a topic for further investigation. The results here suggest, however, that at least so far as these tests indicate, any supervisor perceptions of changes in risk and concurrent responses are not strong and consistent enough to produce statistically discernible impacts.

A.2.4 Bank Infrastructure Investments

What accounts for the greater losses given default observed in Table A.7? One possibility is that banks with lower capital made loans to businesses that inherently had a higher propensity to fail in more catastrophic ways that either left fewer business assets available to repay a portion of the loan due or that failed more quickly before very much of the loan's balance could be paid off. Another possibility, not exclusive of the first, is that banks with lower capital may have invested fewer resources in developing effective infrastructure to collect on defaulted loans.[11] Both possibilities reflect deliberate risk-taking decisions - investing less in infrastructure to recover on loans can hardly be seen as an accident. Indeed, the savings from lower infrastructure investments will likely yield higher profits in periods with low default rates and lower profits during more adverse conditions. But, each possibility lends a different nuance to the understanding of the way that bank capital influences risk taking.

One way to investigate this is through a variation on my loss given default (LGD) analyses described above. In the initial set of LGD analyses, as with all of my default analyses, I do not directly consider loan or borrower characteristics as predictors of default or loss given default. The reasons for this are straightforward. If a loan characteristic, such as the loan's interest rate, is a predictor of loan risk, then including it in an analysis of the effects of capital on loan risk amounts to conditioning on the outcome of interest, something that could bias the coefficient estimates for the capital variables towards zero. To take an extreme example, if banks could perfectly predict loan default rates, and set interest rates as a common function of default risk, then including loan interest rates in a default analysis would erroneously show zero predictive ability of a bank's capital ratio on risk, since all of the information on the bank's risk taking would already by captured in the interest rates it charges on its loans. Nevertheless, adding these additional variables can be useful for supplemental analyses.

In particular, I consider a version of my loss given default analyses in which I include all borrower and loan level information available on the small business loans,[12] plus fixed effects for the CBSA in which a loan is made and contemporaneous data on unemployment levels and property values in the area in which the loans are made. As with before, I also use bank and time fixed effects. The goal here is to capture, as closely as possible, the full set of information available to banks when they made the loans.

If I were able to perfectly measure all relevant ex-ante risk factors of loans, and if including all of those factors in a model to predict LGD still showed a significant effect of bank capital in predicting losses given default, then that would suggest that some of the excess losses of less capitalized banks were due to the ability of those banks to collect on losses and not due to the fact that the loans were to businesses that were inherently more likely to suffer larger losses with fewer recoverable assets afterwards. Conversely, if including loan-level risk factors eliminated or greatly reduced the statistical relation between capital and losses given default, it would suggest that lightly capitalized banks simply chose loans that were more likely to suffer large losses on default based on more clearly identifiable criteria. Because I am not able to perfectly observe the information set available to banks when originating loans, however, the results of these analyses and their implications for bank infrastructure are only suggestive.

The second column of Table A.7 presents the results of this LGD analyses with an expanded set of predictors. The adjusted R^2 of the regressions more than doubles with the inclusion of additional controls, demonstrating that they do contain a significant amount of information on the riskiness of the borrowers. Yet, interestingly, the coefficient estimates and standard errors for the bank capital variables are almost completely unchanged. There are two plausible explanations.

One possibility is that banks with lower capital are indeed investing less in infrastructure to recover on defaulted loans. Another possibility, not exclusive of the first, is that the differences in borrower risk (that pertains to LGD) that banks with lower capital select on are not directly observable with any of the controls. This could be

[11] On the importance of bank investments in infrastructure to, for instance, service existing loans, see generally Agarwal et al. (2017).

[12] Specifically this includes the loan's interest rate, the amount of default insurance purchased on the loan, the term of the loan in months, the type of business the loan is extended to, an indicator for whether the loan is a revolving line of credit, and the specific sub-program of the Small Business Administration's 7a loan program under which the loan is made. I also include an indicator variable set equal to one for loans that are missing their interest rates, and set the missing interest rate values to zero, as is done in similar analyses in Jiang et al. (2014).

because the set of controls leaves out key predictors that banks are indeed selecting on. It could also, however, be that banks with lower capital invest less in collecting soft information on borrowers, similar to the effects discussed for securitized loans by Keys et al. (2010). Even this case, however, would reflect a reduction in infrastructure investment by banks with lower capital, with the infrastructure in question pertaining this time to infrastructure for initially screening small business borrowers for risk characteristics.

A.2.5 The Role of Partial Default Insurance

Banks issuing SBA sponsored loans have the option of purchasing default insurance to cover up to 85% of the losses in the event of default. How does the relationship between capital and loan risk vary across loans for which banks purchase different amounts of insurance? To investigate this, I divide the data into three separate groups based on the amount of insurance purchased by the bank. I consider loans with 50% or less of the principal guaranteed, loans with between 50 and 75% guaranteed, and loans with between 75 and 85% of the principal guaranteed.

Table A.11 presents the results of these model specifications. In the analyses that control for bank fixed effects and macro-economic variables, the relation between higher capital and lower loan risk is consistent and significant across categories of loan guarantee amounts, although the effects for the loans with the least amount of guarantee are stronger, often substantially stronger, than those for the higher guarantee amounts. For the loans with higher guarantee amounts, however, the effects lose magnitude and statistical significance when time fixed effects are added. On the other hand, the results remain strong and robust for the category of loans with the least amount of default insurance even as these additional controls are added. For instance, the coefficient of -0.054 in column (2), panel C (for the ratio of Tier 1 plus 2 capital plus risk weighted assets) indicates that an increase of this capital ratio by one percentage point is associated with a reduction in the probability of loan default (evaluated at mean loan default probability) of 0.8 percentage points. This pattern - of stronger effects for the loans with the least amount of default insurance, would indeed seem intuitive. If, for instance, the guarantee insurance were taken to its limit of 100%, then any impact of capital levels on willingness of banks to take risks (at least default risks) would be irrelevant, and so it would be sensible to see an attenuated or non-existent relation.

A.3 Bank Capital Regulation

The formal regulation of bank capital in the United States dates back to the mid 1980s. Prior to that, regulators considered various measures of capitalization as part of their overall safety and soundness reviews of banks, but did not base their efforts on any set of unified standards or even definitions of how precisely capital was to be calculated. The data in this study covers the period from 2002 until the present, as that is the time in which the major capital variables that I analyze are publicly available for US banks. Accordingly, I focus here on a brief overview of pertinent capital regulation over that time period only. For a more in-depth history of the topic, see Posner (2015).

Capital regulations focus on multiple definitions of capital, which I in turn examine separately throughout this study. Roughly speaking, Tier 1 capital includes the value of a bank's common stock, as well as certain types of reserves and preferred stock that is non-redeemable and non-cumulative. Tier 2 capital includes other types of reserves and preferred stock that do not qualify as Tier 1, as well as subordinated debt and other instruments that are designed to (arguably) offer similar loss absorbing benefits as Tier 1 capital and equity. "Total" capital refers to the sum of Tier 1 and Tier 2 capital.

Capital regulations govern several different capital ratios, which take a measure of capital and divide it by a measure of bank assets. The most prominent of these ratios is the ratio of Tier 1 capital to risk weighted assets. Complex regulations govern the calculation of a bank's risk weighted assets. In general, the goal of these regulations is to weight safer assets less heavily than riskier ones, thereby producing lower capital ratios for banks with comparatively riskier assets. In some situations, pre-specified rules govern this risk weighting but in other situations banks are able to use internal risk models (along with regulator supervision and approval of those models) in order to determine this risk weighting. Another ratio governed by regulations is the ratio of Tier 1 plus Tier 2 capital to risk weighted assets. A final ratio is that of Tier 1 capital to unweighted assets, sometimes referred to as the "leverage ratio." This ratio is designed in large part to set an absolute floor for capital levels in case the measure of risk weighted assets fails to adequately capture actual economic risk.

During the course of this study period, from 2002 to the present, there have been several changes in the specifics of US regulatory policy for bank capital. At the beginning of this period, the US was still operating under the framework of the Basel I accords. These set a minimum Tier 1 capital ratio of 4%, meaning that the ratio of Tier 1 capital to risk weighted assets must be greater than 4%. The minimum ratio of Tier 1 plus Tier 2 capital to risk weighted assets was set to 8%, and the "leverage ratio," or ratio of Tier 1 capital to unweighted assets was set to a minimum 3%.

Basel II capital guidelines were originally promulgated in 2004 and were formally adopted by US regulators in 2007. These regulations did not change the specific minimum thresholds for any of the key ratios discussed here. But, they did introduce many changes in how risk weighting of assets were assessed. One significant change was the explicit incorporation of market and operational risk into the risk calculations, alongside credit risk which had been the only consideration under Basel I. Another significant change was the expanded emphasis on using internal models to calculate risk, rather than more blunt and standardized guidelines (e.g. mortgage loans have a 50% risk weight) that were more prevalent in Basel I. Basel II, however, did continue to allow for banks to use the simple and standardized guidelines - a practice that was more common amongst smaller banks with less technically sophisticated risk modeling staff.

In the wake of the recent financial crisis, the Dodd-Frank Act (responding in part to the Basel III accords) called for increases in capital requirements.[13] Regulators finalized the first major Dodd-Frank capital rules in 2013, though the effective dates for them were not until 2014 for large financial institutions and 2015 for smaller ones. These raise the Tier 1 ratio to 6%, kept the Tier 1 plus Tier 2 ratio at 8% and raised the leverage ratio to 4%. The new regulations also introduce a new version of Tier 1 capital, called "Common Equity Tier 1" that excludes all components of Tier 1 capital except for common equity. The regulations set the minimum for the ratio of this to risk weighted assets at 4.5%. Finally, they establish a new "supplementary leverage ratio" that is similar to the prior leverage ratio but also includes off-balance sheet assets in the denominator. The supplementary leverage ratio is only applicable to very large bank holding companies and is set at 3%. As discussed in Section 3, the small business loan data that I use is exclusively for loans originated prior to 2014 and the home mortgage loan data is for mortgages originated prior to 2013. Thus, the impact of these new rules during the study period is relatively modest and in large part limited to anticipatory responses.[14]

Since their adoption, minimum capital ratios have served as absolute floors - if a bank fell below them it would become subject to "prompt corrective action" in which regulators would substantially restrict its activities and enforce a plan for it to raise its capital levels quickly. As such, banks have a natural incentive to target their capital levels above these minimum requirements. In addition, banks considered "well capitalized," which generally meant that they exceeded these minimum ratios by a couple of percentage points, would gain additional privileges, such as expanded abilities to accept brokered deposits. Hill (2012) discusses these issues, and related issues related to the discretion of regulators in enforcing capital adequacy, in considerably greater detail.

An additional regulatory consideration relevant to bank capital has been the stress test programs. The first of these was administered in 2009, with subsequent ones conducted following years according to rules formalized as part of the Dodd-Frank rulemaking processes. In a stress test, federal regulators announce an adverse economic scenario in which certain key economic factors, such as unemployment rates or property values, move towards more "stressed levels" (e.g. unemployment rates increase and property values drop). Banks then use their internal risk models to estimate the losses they would suffer under the stress scenario. If these losses bring a bank's capital below the minimum ratios described above, the bank's ability to pay dividends, buy back shares, and issue certain types of bonuses to executives will be reduced.

The restrictions on dividends and bonuses can range from, for instance, a total ban in extreme cases to a percentage cap on profits which can be used towards these purposes. The specific amount of restrictions for a given bank depends on the amount below the minimum capital ratios that the stress scenario brings the bank. These stress tests thus differ from the normal capital regulations in the sense that there is no specific minimum capital level they apply to all banks, and falling below minimum capital levels in a stress test scenario simply restricts the bank's abilities to make certain discretionary payments, rather than risking the bank being shut down or taken over by regulators in the case of a bank's actual capital falling below regulatory minimums. Nevertheless,

[13] Dodd-Frank did not specify the precise levels for new capital requirements, leaving that decision to regulators.

[14] Beyond these basic capital minimums, the regulations passed pertinent to Dodd-Frank call for several additional "buffers" that require bank organizations to exceed minimum capital ratios by a certain percentage in order to avoid restrictions on their ability to pay dividends to shareholders and discretionary bonuses to executives. These buffers are gradually phased in, starting in 2016 and continuing through 2019, and as a result, are not very relevant to this current study.

they are another relevant consideration in understanding the total picture of regulatory and supervisory factors that influence bank capital in the post-financial crisis period.

A.4 Data Cleaning and Construction

A.4.1 Creating Loan Records from County Registrar of Deeds Records

When a mortgage is initially taken out on a property, it is registered with the county and I observe the public filing of this transaction. The filing will contain information such as the amount of the mortgage, the lender, the term of the mortgage, and other similar data. I then track the outcome of this mortgage based on subsequent filings for the same parcel ID. For instance, if three years after a thirty-year mortgage is registered, I observe that the property has changed ownership through a foreclosure sale, then I can determine that the mortgage defaulted and was foreclosed upon (provided there were no other records filed for the given parcel ID between the loan's origination and the foreclosure sale). Similarly, if I instead observe that three years after the initial mortgage, the property changes hands through a regular arms-length sale, and again there were no other intervening records, then I can conclude that the mortgage was prepaid at the time of the resale. If, instead of a sale, I observe a new mortgage of a comparable size being taken out three years after an initial mortgage, than I can conclude that the initial mortgage was repaid via a refinance transaction.[15] On the other hand, if the second mortgage is substantially smaller than the initial one, then we record it not as repaying the first but as being a second lien mortgage that exists alongside the initial one. Overall, this construction of mortgage histories out of these public record filings is similar to the approach taken by Ferreira and Gyourko (2015).[16]

A.4.2 Matching Deed Records with HMDA

For the purposes of matching the deed mortgage records that I construct with those from the Home Mortgage Disclosure Act (HMDA) database, I use the following pieces of information which are common amongst both: census tract, loan amount, year of loan origination, lender name, whether the loan is a purchase or refinance loan, and whether the loan is a conventional mortgage, FHA backed, or VA backed. Census tracts are extremely small pieces of land, making them ideal for such a matching operation. The Census Bureau targets between 2000 and 8000 people in each tract, and readjusts their boundaries after each decennial census in order to maintain their populations within that range. As supplied by CoreLogic the deed data comes with the census tracts as designated by the 2010 census. For earlier mortgage records, I use ArcGIS software and geographic shape files designating the boundaries of the tracts in order to map the addresses in the deed records to census tracts from the appropriate census year. The shape files are obtained from the National Historical Geographic Information System (NHGIS). Because the names of lenders in the two databases are not precisely the same (for instance, one may contain "Bank of America" whereas the other lists "Bank of America, NA"), I use an algorithm based on the Levenshtein distance between strings in order to pair lender names that are not exact matches.

[15] CoreLogic also applies a proprietary logic to identify certain mortgage transactions as refinances, and so I use this in my data construction as well.

[16] See also Diamond and McQuade (2016) for another use of such public records deed data.

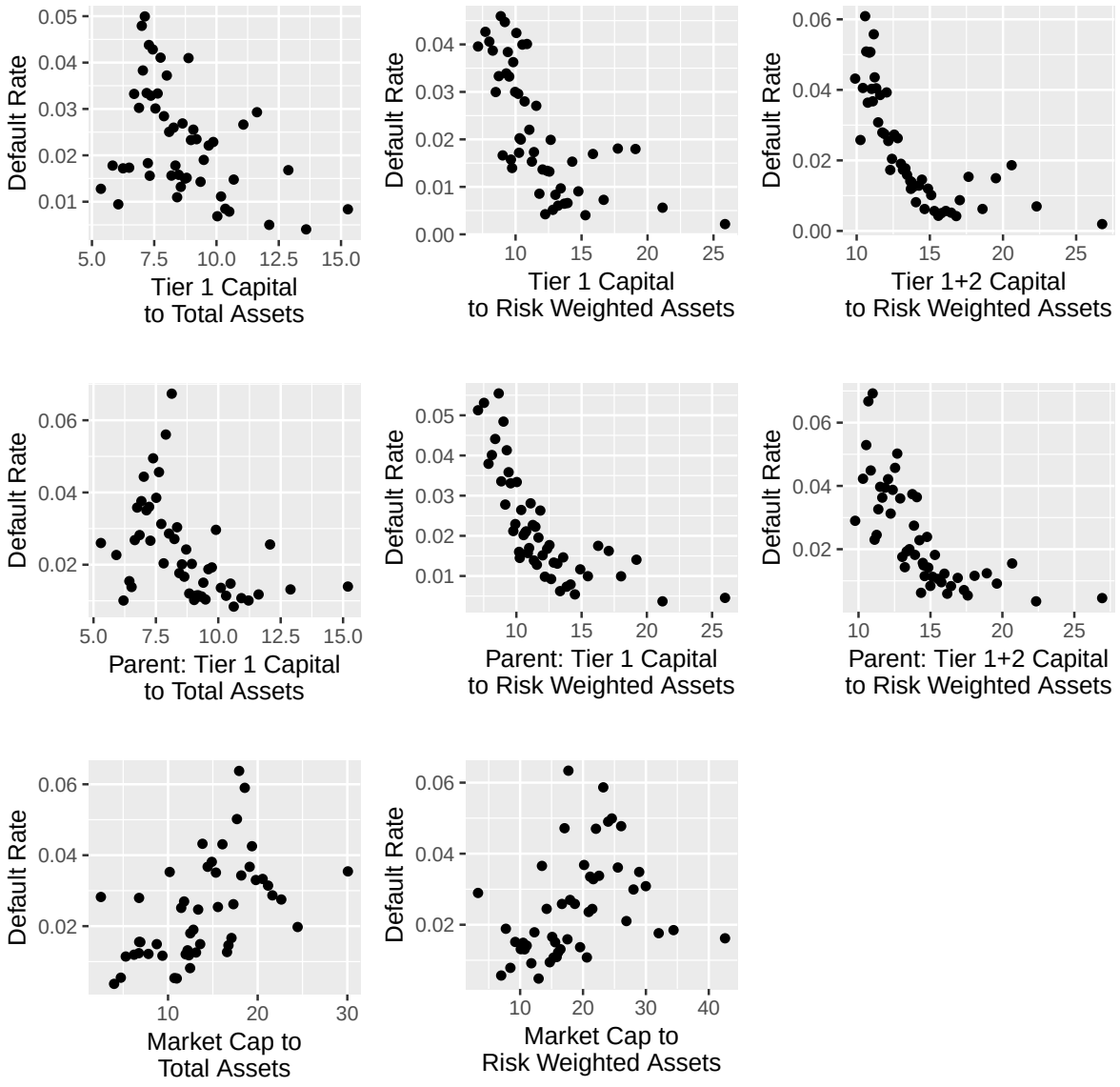

Figure A.1. Default risk against bank capital - residential mortgage loans. To create these plots, I discretize each of the continuous capital metrics into 50 separate bins, chosen such that each bin will contain roughly the same number of total loans. I then calculate the percentage of all loans in each bin that default and plot this against the middle of each bin in each of the respective graphs.

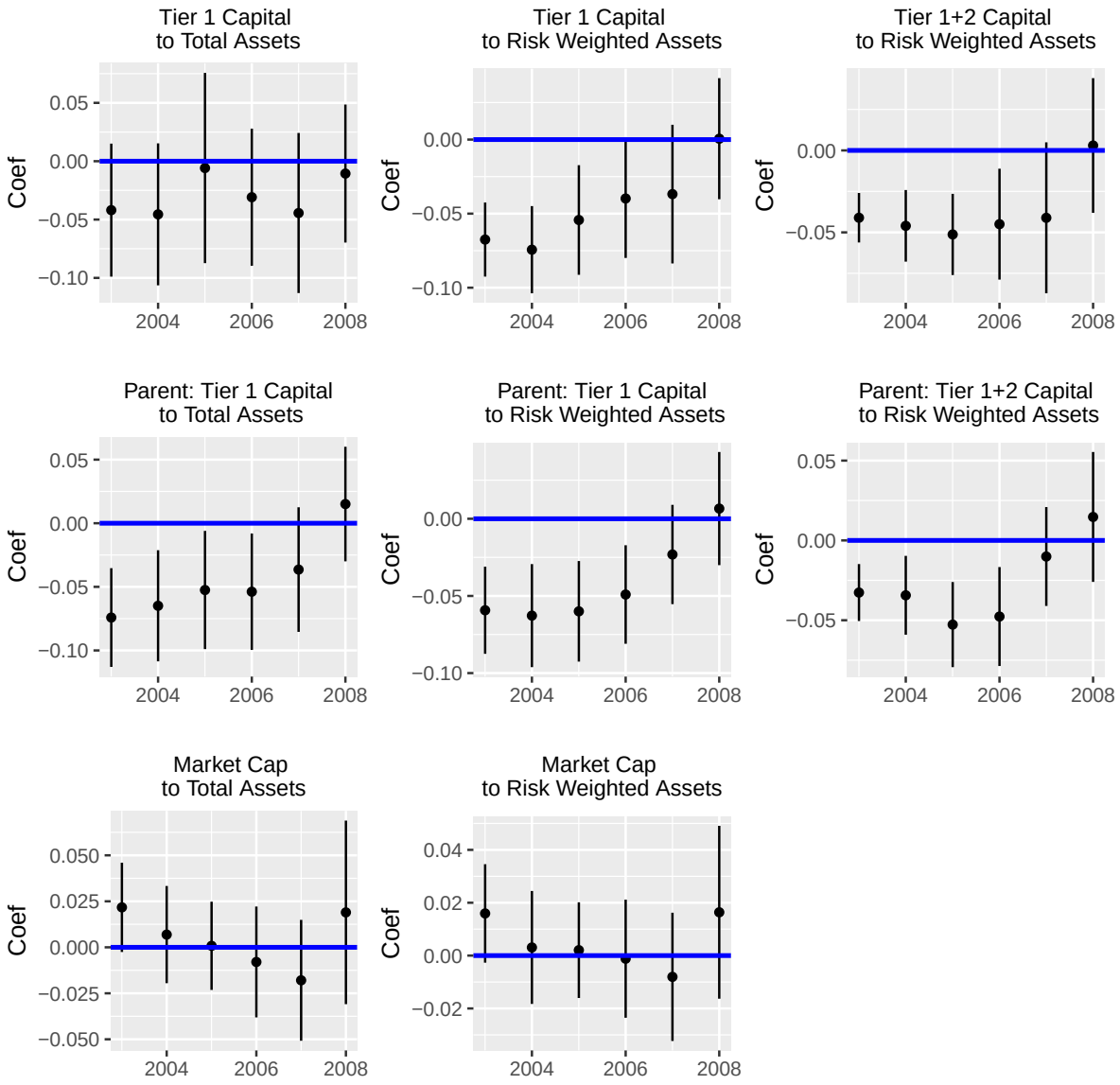

Figure A.2. Five-year subsets of data - home mortgage loans. These figures consider models fit over rolling, five-year long windows of time. For each time window, I calculate the coefficient estimate and confidence interval (95%) for the key capital variable. For instance, the coefficient and confidence interval associated with the year 2003 on these plots represents a model fit using data from 2003 to 2007. All specifications include macroeconomic controls plus bank and time fixed effects with robust errors clustered at the bank level.

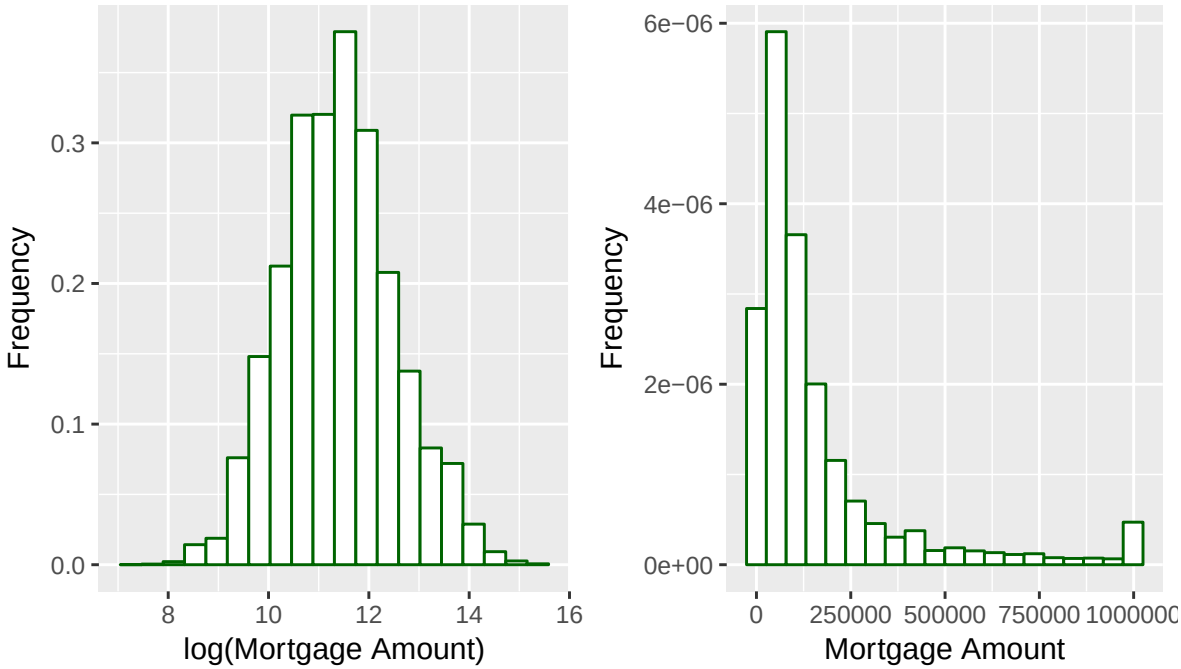

Figure A.3. Home mortgage data - descriptive plots. For interpretability of the plot, loans above $1 million are represented as $1 million in this plot.

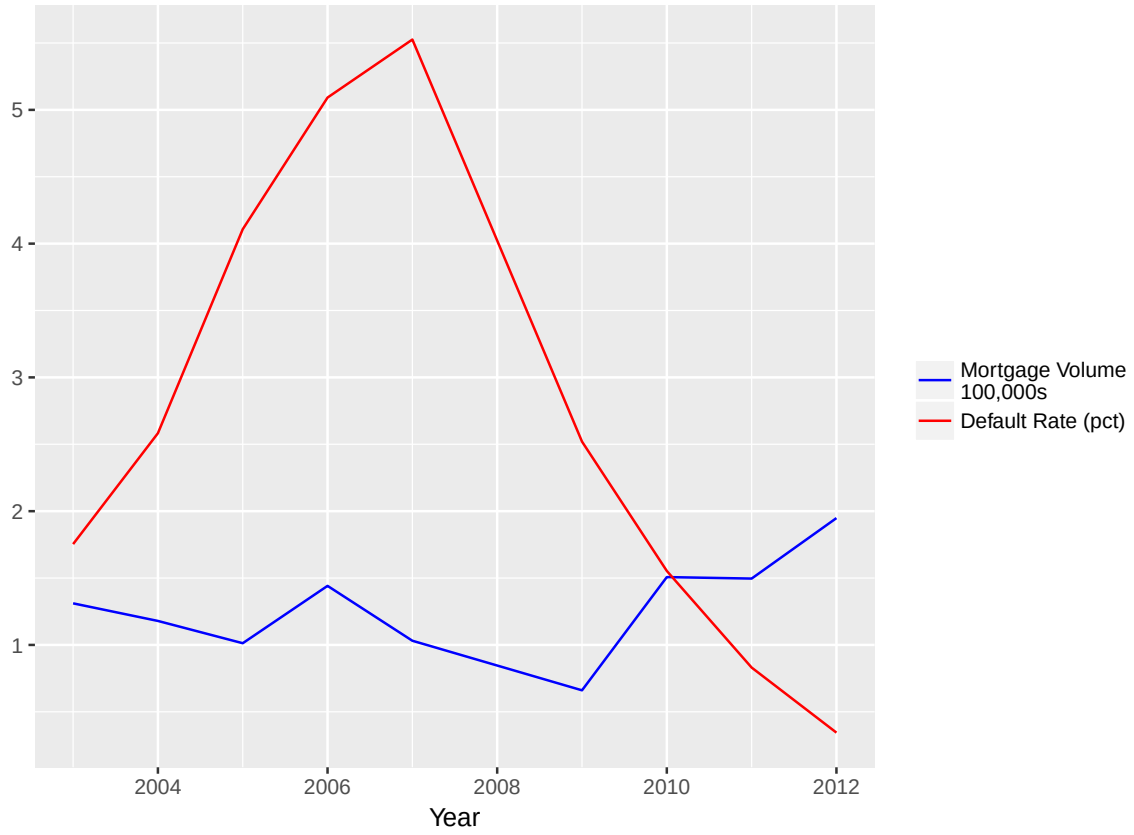

Figure A.4. Home mortgage data - origination and default rates by time.

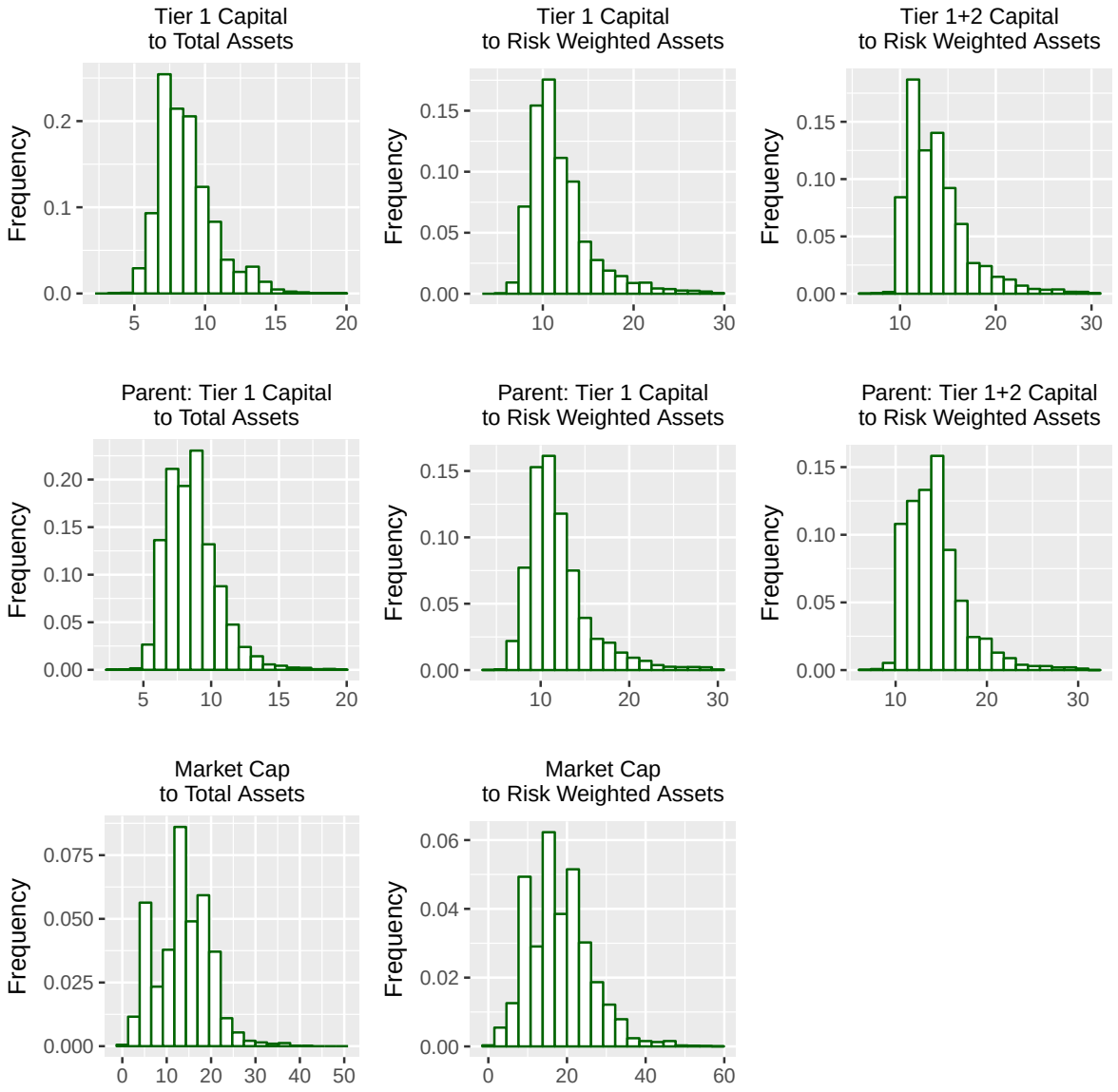

Figure A.5. For each home mortgage loan, this plot considers the capital level of the bank that originated the loan at the time of the origination and plots the empirical distribution of those capital levels.

Table A.1
Default Risk - Additional Bank Variables - Bank-level Capital. This table presents the results of a conditional logit regression with the dependent variable being a binary indicator of whether or not a loan defaults. The analyses here consider additional variables not included in the main analyses presented in this paper. Loan:Deposit ratio represent the ratio of a bank's total loan volume to it's total deposit volume. log(Total Assets) represents the logarithm of a bank's total (unweighted) assets. Deposits/Liabilities represents the ratio of a bank's total deposits to its total liabilities. Officer Loans/Total Assets represents all loans made by the bank to officers and directors divided by the bank's total (unweighted) assets. The macro controls used in these specifications include the national unemployment rate, the five-year returns on the S&P 500 index and the 5-year US treasury rate. These are the same macro variables used in all other regression specifications in this paper. Error clustering is at the bank level.

	(Small Business)	(Home Mortgage)
Panel A		
Tier 1 Capital to Total Assets	-0.006	-0.039
	(0.0102)	(0.0261)
Loan:Deposit Ratio	0.047	-0.014 *
	(0.2893)	(0.008)
log(Total Assets)	0.099	0.095
	(0.0883)	(0.1392)
Deposits/Liabilities	-0.315	-0.277
	(0.4034)	(0.5574)
Officer Loans/Total Assets	0.726	-4.962
	(2.28)	(3.1735)
Observations	571684	1158798
AUC	0.775	0.803
Panel B		
Tier 1 Capital to Risk Weighted Assets	-0.011	-0.051 ***
	(0.0136)	(0.0119)
Loan:Deposit Ratio	-0.002	-0.018 ***
	(0.2864)	(0.0059)
log(Total Assets)	0.1	0.078
	(0.0878)	(0.142)
Deposits/Liabilities	-0.343	-0.235
	(0.4153)	(0.5519)
Officer Loans/Total Assets	0.85	-5.091
	(2.2421)	(3.1812)
Observations	571684	1158798
AUC	0.775	0.803
Panel C		
Tier 1+2 Capital to Risk Weighted Assets	-0.01	-0.044 ***
	(0.0123)	(0.0092)
Loan:Deposit Ratio	0.005	-0.018 ***
	(0.283)	(0.0059)
log(Total Assets)	0.1	0.119
	(0.0878)	(0.1479)
Deposits/Liabilities	-0.331	-0.328
	(0.4175)	(0.5806)
Officer Loans/Total Assets	0.809	-4.93
	(2.2112)	(3.1558)
Observations	571684	1158798
AUC	0.775	0.803
Banks FEs	yes	yes
Time FEs	yes	yes
Macro Controls	yes	yes

Cluster robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2
Default Risk - Additional Bank Variables - Market Cap based Capital Metrics. This table presents the results of a conditional logit regression with the dependent variable being a binary indicator of whether or not a loan defaults. The analyses here consider additional variables not included in the main analyses presented in this paper. Loan:Deposit ratio represent the ratio of a bank's total loan volume to it's total deposit volume. log(Total Assets) represents the logarithm of a bank's total (unweighted) assets. Deposits/Liabilities represents the ratio of a bank's total deposits to its total liabilities. Officer Loans/Total Assets represents all loans made by the bank to officers and directors divided by the bank's total (unweighted) assets. The macro controls used in these specifications include the national unemployment rate, the five-year returns on the S&P 500 index and the 5-year US treasury rate. These are the same macro variables used in all other regression specifications in this paper. Error clustering is at the bank level.

	(Small Business)	(Home Mortgage)
Panel A		
Market Cap to Total Assets	-0.012 **	0.016
	(0.0045)	(0.0109)
Loan:Deposit Ratio	-0.363	-0.009
	(0.4404)	(0.0097)
log(Total Assets)	0.066	-0.157
	(0.1037)	(0.2281)
Deposits/Liabilities	-0.405	0.862
	(0.5326)	(0.8825)
Officer Loans/Total Assets	2.291	-18.766 *
	(5.7828)	(9.5824)
Observations	382225	598128
AUC	0.756	0.788
Panel B		
Market Cap to Risk Weighted Assets	-0.007 *	0.014
	(0.0044)	(0.0087)
Loan:Deposit Ratio	-0.359	-0.009
	(0.4644)	(0.0097)
log(Total Assets)	0.074	-0.16
	(0.1047)	(0.2287)
Deposits/Liabilities	-0.482	0.882
	(0.5282)	(0.8827)
Officer Loans/Total Assets	2.608	-18.263 *
	(5.4974)	(9.3374)
Observations	382225	598128
AUC	0.756	0.788
Banks FEs	yes	yes
Time FEs	yes	yes
Macro Controls	yes	yes

Cluster robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3
Small business loans - IV specification (year 2000 geographic weights). This table presents the results of an instrumental variables specification for a linear probability model. The response variable is a binary classifier of whether or not a loan defaults during its term. The capital variables are instrumented for using the weighted change in house price index in the areas in which banks operate. Bank market shares for the purposes of this instrument are assessed as of 2000. The macro controls used in these specifications include the national unemployment rate, the five-year returns on the S&P 500 index and the 5-year US treasury rate. These are the same macro variables used in all other regression specifications in this paper. Errors are clustered at the bank level.

	(Naive)	(IV)
Panel A		
Tier 1 Capital to Total Assets	-0.012 ***	-0.058 **
	(0.0044)	(0.0263)
Observations	39199	39199
Adjusted R^2	0.087	0.064
Panel B		
Tier 1 Capital to Risk Weighted Assets	-0.007 **	-0.051 ***
	(0.0036)	(0.0132)
Observations	39199	39199
Adjusted R^2	0.086	0.056
Panel C		
Tier 1+2 Capital to Risk Weighted Assets	-0.004	-0.095 ***
	(0.0028)	(0.0298)
Observations	39199	39199
Adjusted R^2	0.085	0.034
Banks FEs	yes	yes
Time FEs	yes	yes
Macro Controls	yes	yes

Cluster robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4
Small business loans - Parent Regulatory Capital. This table presents the results from a conditional logistic regression. The dependent variable is whether an individual loan defaults or not. The capital variables in this analysis are taken from the highest company in a bank's corporate hierarchy for which capital information is available through the Call Reports. If a bank is not owned by any bank holding company, then the parent capital metrics are identical to those of the bank itself. Capital ratios are represented in percentage units. Thus, if a parent company's tier 1 capital divided by total assets yields 0.12, then the value of the corresponding dependent variable would be 12. Errors are clustered at the bank level.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Parent: Tier 1 Capital to Total Assets	-0.142 ***	-0.051 *	-0.136 *	-0.048 ***	-0.042	-0.013
	(0.0455)	(0.0287)	(0.0776)	(0.0101)	(0.0303)	(0.0119)
S&P 500 Five-Year Return		0.228 ***		0.262 ***		0.156 ***
		(0.0821)		(0.0615)		(0.039)
5 Year Treasury Rate		0.24 ***		0.223 ***		0.038 **
		(0.041)		(0.0314)		(0.0186)
Unemployment Rate		-0.278 ***		-0.211 ***		-0.219 ***
		(0.0413)		(0.0344)		(0.0253)
Observations	540384	540384	540384	540384	540384	540384
AUC	0.599	0.714	0.716	0.765	0.719	0.77
Panel B						
Parent: Tier 1 Capital to Risk Weighted Assets	-0.17 ***	-0.061 ***	-0.204 ***	-0.06 ***	-0.046 ***	-0.011
	(0.03)	(0.0165)	(0.0577)	(0.0133)	(0.0169)	(0.0133)
S&P 500 Five-Year Return		0.189 **		0.25 ***		0.152 ***
		(0.0832)		(0.0641)		(0.0418)
5 Year Treasury Rate		0.236 ***		0.222 ***		0.038 **
		(0.0377)		(0.0293)		(0.0187)
Unemployment Rate		-0.26 ***		-0.188 ***		-0.217 ***
		(0.0369)		(0.0313)		(0.0254)
Observations	540384	540384	540384	540384	540384	540384
AUC	0.638	0.716	0.729	0.766	0.72	0.77
Panel C						
Parent: Tier 1+2 Capital to Risk Weighted Assets	-0.209 ***	-0.082 **	-0.177 ***	-0.047 ***	-0.065 **	-0.014
	(0.0459)	(0.032)	(0.0644)	(0.01)	(0.0288)	(0.0117)
S&P 500 Five-Year Return		0.222 **		0.259 ***		0.152 ***
		(0.0893)		(0.0674)		(0.0402)
5 Year Treasury Rate		0.24 ***		0.219 ***		0.038 **
		(0.0358)		(0.0294)		(0.0186)
Unemployment Rate		-0.252 ***		-0.199 ***		-0.217 ***
		(0.0381)		(0.0333)		(0.0257)
Observations	540384	540384	540384	540384	540384	540384
AUC	0.648	0.718	0.727	0.765	0.723	0.77
Banks FEs	no	no	yes	yes	no	yes
Time FEs	no	no	no	no	yes	yes
Macro Controls	no	yes	no	yes	no	yes

Cluster robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.5
Small business loans - Basic Regulatory Capital - Quantiles. This table presents the results from a conditional logistic regression. The dependent variable is whether an individual loan defaults or not. Each capital variable represents the percentile rank of a bank as compared to all other banks in the Call Reports for a given capital metric. Thus, a value of 65 for 'Tier 1 Capital to Risk Weighted Assets' indicates that a bank had a higher ratio of tier 1 capital to risk weighted assets than 65 percent of all other banks in the Call Reports data. Errors are clustered at the bank level.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Quantile: Tier 1 Capital to Total Assets	-0.015 ***	-0.005 *	-0.019 ***	-0.007 ***	-0.004	0.0
	(0.0035)	(0.0026)	(0.0029)	(0.0015)	(0.0027)	(0.0009)
S&P 500 Five-Year Return		0.21 ***		0.26 ***		0.162 ***
		(0.0762)		(0.0589)		(0.0399)
5 Year Treasury Rate		0.234 ***		0.215 ***		0.038 **
		(0.0386)		(0.0301)		(0.0177)
Unemployment Rate		-0.282 ***		-0.208 ***		-0.221 ***
		(0.0383)		(0.0345)		(0.0233)
Observations	571685	571685	571685	571685	571685	571685
AUC	0.597	0.718	0.725	0.77	0.723	0.775
Panel B						
Quantile: Tier 1 Capital to Risk Weighted Assets	-0.025 ***	-0.011 ***	-0.029 ***	-0.01 ***	-0.009 ***	-0.002
	(0.0028)	(0.0018)	(0.0047)	(0.0016)	(0.0018)	(0.0025)
S&P 500 Five-Year Return		0.188 **		0.26 ***		0.156 ***
		(0.0779)		(0.0608)		(0.0404)
5 Year Treasury Rate		0.231 ***		0.217 ***		0.039 **
		(0.0373)		(0.0284)		(0.0176)
Unemployment Rate		-0.263 ***		-0.193 ***		-0.221 ***
		(0.0344)		(0.0334)		(0.0239)
Observations	571685	571685	571685	571685	571685	571685
AUC	0.624	0.722	0.732	0.77	0.725	0.775
Panel C						
Quantile: Tier 1 + Tier 2 Capital to Risk Weighted Assets	-0.031 ***	-0.013 ***	-0.031 ***	-0.01 ***	-0.01 ***	-0.002
	(0.0034)	(0.0029)	(0.0046)	(0.0014)	(0.0025)	(0.0021)
S&P 500 Five-Year Return		0.207 **		0.265 ***		0.158 ***
		(0.0896)		(0.0672)		(0.0398)
5 Year Treasury Rate		0.232 ***		0.217 ***		0.038 **
		(0.0369)		(0.0284)		(0.0177)
Unemployment Rate		-0.247 ***		-0.184 ***		-0.22 ***
		(0.032)		(0.0316)		(0.0237)
Observations	571685	571685	571685	571685	571685	571685
AUC	0.651	0.723	0.737	0.77	0.727	0.775
Panel D						
Quantile: Market Cap to Risk Weighted Assets	0.005 **	-0.005 ***	0.008	-0.008 ***	-0.004 **	-0.003 ***
	(0.0021)	(0.0017)	(0.0052)	(0.001)	(0.0018)	(0.0007)
S&P 500 Five-Year Return		0.121		0.055		0.129 ***
		(0.0767)		(0.109)		(0.0482)
5 Year Treasury Rate		0.204 ***		0.221 ***		0.052 ***
		(0.0449)		(0.0314)		(0.0195)
Unemployment Rate		-0.351 ***		-0.299 ***		-0.244 ***
		(0.0456)		(0.035)		(0.0294)
Observations	382225	382225	382225	382225	382225	382225
AUC	0.549	0.707	0.697	0.752	0.711	0.756
Panel E						
Quantile: Market Cap to Total Assets	0.005 **	-0.005 ***	0.006	-0.007 ***	-0.004 **	-0.002 **
	(0.0025)	(0.0018)	(0.0044)	(0.0009)	(0.0018)	(0.0007)
S&P 500 Five-Year Return		0.087		0.06		0.146 ***
		(0.0801)		(0.1092)		(0.0503)
5 Year Treasury Rate		0.208 ***		0.217 ***		0.046 **
		(0.043)		(0.0319)		(0.0189)
Unemployment Rate		-0.351 ***		-0.287 ***		-0.235 ***
		(0.0454)		(0.0377)		(0.0298)
Observations	382225	382225	382225	382225	382225	382225
AUC	0.545	0.707	0.695	0.752	0.71	0.756
Banks FEs	no	no	yes	yes	no	yes
Time FEs	no	no	no	no	yes	yes
Macro Controls	no	yes	no	yes	no	yes

Cluster robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.6

Home mortgage loans - Basic Regulatory Capital. This table presents the results from a conditional logistic regression. The dependent variable is whether an individual loan defaults or not. Capital ratios are represented in percentage units. Thus, if a bank's tier 1 capital divided by total assets yields 0.12, then the value of the corresponding dependent variable would be 12. AUC measures the area under the receiver operator characteristic (ROC) as a measure of goodness of fit. Errors are clustered at the bank level.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Tier 1 Capital to Total Assets	-0.063	0.007	-0.114 *	-0.072 **	0.013	-0.047
	(0.0417)	(0.0257)	(0.0622)	(0.0295)	(0.0246)	(0.0286)
S&P 500 Five-Year Return		-0.38 **		-0.207 *		-0.18
		(0.1674)		(0.1157)		(0.1727)
5 Year Treasury Rate		0.544 ***		0.443 ***		0.004
		(0.0386)		(0.0396)		(0.0373)
Unemployment Rate		-0.016		-0.002		-0.098 *
		(0.0287)		(0.0304)		(0.0509)
Observations	1158798	1158798	1158798	1158798	1158798	1158798
AUC	0.534	0.698	0.777	0.799	0.71	0.803
Panel B						
Tier 1 Capital to Risk Weighted Assets	-0.108 ***	-0.049 ***	-0.162 ***	-0.082 ***	-0.044 ***	-0.054 ***
	(0.0246)	(0.0135)	(0.0381)	(0.0139)	(0.0128)	(0.013)
S&P 500 Five-Year Return		-0.277 *		-0.173 *		-0.202
		(0.1608)		(0.0986)		(0.1776)
5 Year Treasury Rate		0.512 ***		0.423 ***		0.005
		(0.0368)		(0.0385)		(0.0376)
Unemployment Rate		-0.017		0.002		-0.093 *
		(0.0279)		(0.0289)		(0.0514)
Observations	1158798	1158798	1158798	1158798	1158798	1158798
AUC	0.594	0.704	0.782	0.799	0.713	0.803
Panel C						
Tier 1+2 Capital to Risk Weighted Assets	-0.126 ***	-0.044 *	-0.174 ***	-0.07 ***	-0.037 *	-0.046 ***
	(0.0451)	(0.0225)	(0.0322)	(0.0139)	(0.0203)	(0.0091)
S&P 500 Five-Year Return		-0.303 *		-0.191 *		-0.196
		(0.1703)		(0.1091)		(0.179)
5 Year Treasury Rate		0.517 ***		0.421 ***		0.004
		(0.0382)		(0.0407)		(0.0376)
Unemployment Rate		-0.011		0.003		-0.094 *
		(0.0293)		(0.0294)		(0.0511)
Observations	1158798	1158798	1158798	1158798	1158798	1158798
AUC	0.613	0.703	0.782	0.799	0.712	0.803
Panel D						
Market Cap to Total Assets	0.051 ***	-0.038 **	0.076 ***	0.009	-0.037 *	0.015
	(0.0123)	(0.0181)	(0.015)	(0.0134)	(0.0201)	(0.0118)
S&P 500 Five-Year Return		-0.655 ***		-0.337 *		-0.105
		(0.2255)		(0.1811)		(0.2982)
5 Year Treasury Rate		0.556 ***		0.498 ***		0.046
		(0.063)		(0.0684)		(0.0583)
Unemployment Rate		-0.128 *		-0.008		-0.202 **
		(0.0739)		(0.0624)		(0.0837)
Observations	598128	598128	598128	598128	598128	598128
AUC	0.603	0.73	0.76	0.783	0.735	0.788
Panel E						
Market Cap to Risk Weighted Assets	0.027 ***	-0.035 ***	0.05 ***	0.006	-0.035 ***	0.014
	(0.01)	(0.0089)	(0.0125)	(0.0089)	(0.0096)	(0.0093)
S&P 500 Five-Year Return		-0.724 ***		-0.33 *		-0.099
		(0.2487)		(0.1944)		(0.2966)
5 Year Treasury Rate		0.557 ***		0.499 ***		0.048
		(0.0648)		(0.0689)		(0.0586)
Unemployment Rate		-0.131 **		-0.011		-0.205 **
		(0.0587)		(0.0592)		(0.0837)
Observations	598128	598128	598128	598128	598128	598128
AUC	0.59	0.733	0.76	0.783	0.737	0.789
Banks FEs	no	no	yes	yes	no	yes
Time FEs	no	no	no	no	yes	yes
Macro Controls	no	yes	no	yes	no	yes

Cluster robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.7
Loss Severity. This table presents the results of linear regression specifications designed to measure the severity of losses suffered upon loan default of small business loans. In both cases, the dependent variable is the logarithm of the loss severity plus 1. Loss severities range from 0 to 125 and represent the percentage of the loan's total value that is lost upon default. Values over 100 are possible where more money is spent trying to collect on a loan than is actually recovered on the loan. Errors are clustered at the bank level.

	(1)	(2)
Panel A		
Quantile: Market Cap to Risk Weighted Assets	-0.001 ***	-0.001 ***
	(0.0004)	(0.0004)
Observations	93173	93173
Adjusted R^2	0.076	0.162
Panel B		
Quantile: Market Cap to Total Assets	-0.001 **	-0.001 **
	(0.0004)	(0.0005)
Observations	93173	93173
Adjusted R^2	0.075	0.161
Banks FEs	yes	yes
Time FEs	yes	yes
Macro Controls	yes	yes
Borrower and Geographic Controls	no	yes

Cluster robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.8
Small Business Loans - Guaranteed Percent. This table presents the results of linear regressions in which the dependent variable is the percentage of default insurance that banks chose to purchase from the Small Business Administration. The goal is to determine whether, conditional on all observable risk factors, banks with higher (lower) capital purchase more (less) default insurance. Macroeconomic variables, and all other models specifications, are the same as those for the other analyses throughout this paper. The specifications also contain all available loan level information as well as CBSA fixed effects in order to capture as much information on the objective risk characteristics of loans. Errors are clustered at the bank level.

	(Naive)	(IV)
Panel A		
Tier 1 Capital to Total Assets	0.001	0.017 ***
	(0.0018)	(0.0052)
Observations	64194	64194
Adjusted R^2	0.524	0.516
Panel B		
Tier 1 Capital to Risk Weighted Assets	0.0	0.016 ***
	(0.0013)	(0.0047)
Observations	64194	64194
Adjusted R^2	0.524	0.512
Panel C		
Tier 1+2 Capital to Risk Weighted Assets	-0.001	0.027 *
	(0.001)	(0.0143)
Observations	64194	64194
Adjusted R^2	0.524	0.49
Banks FEs	yes	yes
Time FEs	yes	yes
Macro Controls	yes	yes
Borrower and Geographic Controls	yes	yes

Cluster robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.9
Interest Rate Analyses. This table presents the results of linear regressions where the dependent variable is the interest rate charged on small business and home mortgage loans. Sample sizes are smaller here than in the main analyses on loan default because not every loan comes with interest rate information. The macro controls used in these specifications include the national unemployment rate, the five-year returns on the S&P 500 index and the 5-year US treasury rate. These are the same macro variables used in all other regression specifications in this paper. Error clustering is at the bank level.

	(Small Business)		(Home Mortgage)	
	(1)	(2)	(3)	(4)
Panel A				
Tier 1 Capital to Total Assets	-0.028	-0.01	-0.051 *	-0.0
	(0.0303)	(0.0272)	(0.0301)	(0.0235)
Observations	148204	148204	157413	157413
Adjusted R^2	0.294	0.297	0.63	0.66
Panel B				
Tier 1 Capital to Risk Weighted Assets	-0.024	-0.012	-0.057 ***	0.001
	(0.0169)	(0.0151)	(0.0196)	(0.0135)
Observations	148204	148204	157413	157413
Adjusted R^2	0.294	0.297	0.631	0.66
Panel C				
Tier 1+2 Capital to Risk Weighted Assets	-0.031 *	-0.024 *	-0.057 ***	-0.006
	(0.0157)	(0.0145)	(0.0188)	(0.0126)
Observations	148204	148204	157413	157413
Adjusted R^2	0.294	0.297	0.631	0.66
Panel D				
Parent: Tier 1 Capital to Total Assets	0.004	0.008	-0.094 ***	-0.051 **
	(0.0289)	(0.028)	(0.0271)	(0.0212)
Observations	138135	138135	155340	155340
Adjusted R^2	0.293	0.296	0.629	0.658
Panel E				
Parent: Tier 1 Capital to Risk Weighted Assets	-0.005	0.002	-0.063 ***	-0.018
	(0.0174)	(0.0174)	(0.0172)	(0.0128)
Observations	138135	138135	155340	155340
Adjusted R^2	0.293	0.296	0.629	0.658
Panel F				
Parent: Tier 1+2 Capital to Risk Weighted Assets	-0.013	-0.01	-0.051 ***	-0.011
	(0.0179)	(0.0178)	(0.0178)	(0.0121)
Observations	138135	138135	155340	155340
Adjusted R^2	0.293	0.296	0.629	0.658
Panel G				
Market Cap to Total Assets	-0.054 **	-0.062 ***	-0.03	-0.012
	(0.0232)	(0.0227)	(0.019)	(0.0168)
Observations	97015	97015	91368	91368
Adjusted R^2	0.26	0.265	0.584	0.612
Panel H				
Market Cap to Risk Weighted Assets	-0.037 **	-0.042 **	-0.021 *	-0.003
	(0.0164)	(0.0169)	(0.0116)	(0.0112)
Observations	97015	97015	91368	91368
Adjusted R^2	0.259	0.263	0.584	0.612
Banks FEs	yes	yes	yes	yes
Time FEs	no	yes	no	yes
Macro Controls	yes	yes	yes	yes

Cluster robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.10
Regulatory Responses to Bank Risk. This table investigates whether regulators respond to changes in bank risk with either formal or informal regulatory actions. For each model, I consider the 50 lenders with the most loans in the small business data set. For each lender, I calculate the percentage (measured 0 to 100) of loans originated each year that default. I then look at whether changes in this rate, labeled Δ(Bank Default Rate) predict regulatory actions. The first column considers whether changes in default rate predict formal enforcement actions (e.g. whether the change in default rate from 2004 to 2005 predicts enforcement actions in 2005). The second through fourth columns consider the possibility of informal regulatory responses. They examine whether changes in default rate prompt changes in regulatory capital, under the theory that regulatory may more informally respond to changing risk behaviors of banks by informally pressuring them to increase capital in response to increased risk. All specifications include year fixed effects. All results here are also robust to lagging the differences, e.g. looking at whether changes in default rate from 2004 to 2005 predict enforcement actions in 2006 or changes in capital from 2005 to 2006. Errors are clustered at the bank level.

	Enforcement Actions	Change in Capital		
	(Enforcement Actions)	Δ(Leverage Ratio)	Δ(Tier 1 Ratio)	Δ(Total Ratio)
Δ(Bank Default Rate)	0.005	-0.007	-0.02 *	-0.013
	(0.0036)	(0.0072)	(0.0115)	(0.0101)
Observations	519	519	519	519
Adjusted R^2	0.026	0.115	0.241	0.244

Cluster robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.11
Guaranteed percent groups - small business loans. This table presents the results of a conditional logistic regression where the response variable is a binary indicator of whether a given loan defaults. The data is broken up into three separate groups based on what percentage of insurance coverage the bank originating the loan purchased from the Small Business Administration. Macroeconomic variables, and all other models specifications, are the same as those for the other analyses throughout this paper. Errors are clustered at the bank level.

% SBA Guarantee:	(≤ 50%)		(50-75%)		(75-85%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Tier 1 Capital to Total Assets	-0.11 ***	-0.009	-0.061 ***	-0.003	-0.051 ***	-0.011
	(0.0314)	(0.0255)	(0.0206)	(0.0184)	(0.0129)	(0.0091)
Observations	354390	354390	109634	109634	107661	107661
AUC	0.747	0.75	0.794	0.803	0.824	0.83
Panel B						
Tier 1 Capital to Risk Weighted Assets	-0.119 ***	-0.05 **	-0.074 ***	-0.007	-0.054 ***	0.005
	(0.015)	(0.0249)	(0.0166)	(0.0138)	(0.0116)	(0.0124)
Observations	354390	354390	109634	109634	107661	107661
AUC	0.748	0.75	0.795	0.803	0.824	0.829
Panel C						
Tier 1+2 Capital to Risk Weighted Assets	-0.102 ***	-0.054 **	-0.065 ***	-0.003	-0.046 ***	0.008
	(0.0161)	(0.0237)	(0.0141)	(0.0124)	(0.0113)	(0.0131)
Observations	354390	354390	109634	109634	107661	107661
AUC	0.747	0.75	0.795	0.803	0.824	0.829
Panel D						
Parent: Tier 1 Capital to Total Assets	-0.052 ***	-0.027 **	-0.049 ***	-0.003	-0.025	0.01
	(0.0133)	(0.0132)	(0.0185)	(0.0167)	(0.0155)	(0.0116)
Observations	344987	344987	98895	98895	96502	96502
AUC	0.743	0.746	0.788	0.796	0.82	0.827
Panel E						
Parent: Tier 1 Capital to Risk Weighted Assets	-0.067 ***	-0.034 **	-0.071 ***	-0.01	-0.036 **	0.017
	(0.02)	(0.0144)	(0.0157)	(0.0138)	(0.0172)	(0.017)
Observations	344987	344987	98895	98895	96502	96502
AUC	0.743	0.746	0.788	0.796	0.821	0.827
Panel F						
Parent: Tier 1+2 Capital to Risk Weighted Assets	-0.055 ***	-0.037 ***	-0.06 ***	-0.005	-0.027	0.02
	(0.0139)	(0.0099)	(0.0138)	(0.0124)	(0.0176)	(0.0177)
Observations	344987	344987	98895	98895	96502	96502
AUC	0.743	0.746	0.788	0.796	0.821	0.827
Panel G						
Market Cap to Total Assets	-0.035 ***	-0.017 ***	-0.032 ***	-0.006	-0.031 ***	-0.008
	(0.0056)	(0.0057)	(0.006)	(0.0057)	(0.0033)	(0.0049)
Observations	260541	260541	60664	60664	61020	61020
AUC	0.732	0.734	0.759	0.766	0.804	0.809
Panel H						
Market Cap to Risk Weighted Assets	-0.028 ***	-0.012 **	-0.028 ***	-0.006	-0.024 ***	-0.004
	(0.0052)	(0.0051)	(0.0044)	(0.0045)	(0.004)	(0.006)
Observations	260541	260541	60664	60664	61020	61020
AUC	0.732	0.734	0.759	0.766	0.804	0.809
Banks FEs	yes	yes	yes	yes	yes	yes
Time FEs	no	yes	no	yes	no	yes
Macro Controls	yes	yes	yes	yes	yes	yes

Cluster robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$