Federal Reserve Bank of New York
Staff Reports

Bank Heterogeneity and Capital Allocation: Evidence from “Fracking” Shocks

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Staff Report No. 693
October 2014
Revised February 2015

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JEL classification: G21, E32

Abstract

This paper empirically investigates banks’ ability to reallocate capital. I use unconventional energy development to identify unsolicited deposit inflows and then I estimate how banks allocate these deposits over the recent business cycle. To condition on credit demand, I compare banks’ allocations within affected areas over time and in the cross section. When conditions deteriorate, liquid asset allocations increase and loan allocations decrease. Banks with fewer funding sources and higher capital ratios reduce loan allocations more than nearby peers. My results suggest that during adverse times, precautionary liquidity and risk aversion can impede capital reallocation by banks, even in a developed economy.

Key words: financial intermediation, banks, business cycles

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1 Introduction

The banking sector plays a crucial role in the allocation of capital by channeling funds from savers to borrowers. The ability of financial intermediaries to accomplish this task has become an important element in understanding the causes and consequences of business cycles.[1] In this paper, I empirically investigate how banks invest a positive funding shock over the recent business cycle. Doing so allows me to characterize the reallocation capabilities of banks in good and bad times. I find that during the Great Recession banks with inferior access to funding and high capital ratios lend a smaller share of incremental funds than their peers – even when they operate in relatively healthy economic areas. My findings suggest that an economy like the U.S., with a diverse mix of banks, could find capital trapped inside more isolated, less risk tolerant banks when a negative shock hits the economy.

Estimating these effects is challenging for several reasons: marginal allocation decisions can be obfuscated by a lack of access to funds, banks' financing choices can vary in response to changes in investment opportunities, and latent economic factors can influence both the demand for credit and the supply of bank financing. These issues are particularly thorny when analyzing banks where deposits and lending are geographically concentrated.

To address these concerns, I identify a positive, unsolicited shock to the credit supply of banks in a region, then trace banks' investment allocations in response to this shock, and finally compare these allocations across banks within similar credit demand climates. The unsolicited inflow reveals marginal investment allocations and the cross-sectional comparisons demonstrate how these decisions vary across banks, conditional on investment

[1]For example, theoretical work: Bernanke and Gertler (1995), Holmström and Tirole (1997), Lorenzoni (2008), Gertler and Kiyotaki (2010), Brunnermeier and Sannikov (2014), and empirical: Bernanke (1983), Hoshi, Kashyap and Scharfstein (1991), Gertler and Gilchrist (1994), Peek and Rosengren (2000), Lown and Morgan (2006), Campello, Graham and Harvey (2010).

opportunities. The empirical strategy is analogous to a difference-in-difference approach in which the first difference reveals a bank's exposure to a positive liquidity shock and the second compares the investment response across banks conditional on this exposure.

Since 2001, innovations in drilling technology have enabled the development of several new oil and gas fields throughout the United States. The development of these "fracking" fields generates windfalls to local landholders, who receive payments from drillers that they then deposit in nearby banks. As a result, this development has an outsized impact on local deposits. The stickiness of the typical retail deposit customer ensures that a broad swath of local banks receive funds. The accidental nature of the energy shock is plausibly exogenous to banks seeking deposits to advance bank-specific investment opportunities. Several facts indicate the changes are consistent with an unsolicited inflow of deposits rather than heightened demand for funds: deposit growth in energy counties is well in excess of economic activity, deposit growth within multi-branch banks is significantly greater in energy counties than in non-energy counties, non-deposit borrowing for affected banks does not increase, and deposit rates do not rise.

Using drilling and production data from state agencies, I identify fourteen unconventional energy fields that affect one hundred and twenty-six "treatment" counties from 2002-2012. I estimate the payments to mineral-rights owners and find they can be large, with some counties receiving as much as one billion dollars a year. I establish that energy payments are positively correlated with county-level deposit growth. I then use this county-level variation in deposit growth to generate a bank-level instrument for deposit inflows by calculating the weighted sum of treatment counties' excess deposit growth. The bank-level instrument impacts 389 banks between 2003 and 2012.

To estimate the allocation of these deposit inflows, I construct a panel of bank balance sheet data from U.S. regulatory filings. Using two-stage least squares (2SLS), I instrument for changes in deposits using the energy shock, and in the second-stage I estimate the impact of these incremental deposits on bank investments. In good times, 2003-2007, banks invest 38% of incremental deposits in loans. Lending declines at the onset of the financial crisis and then bottoms out in the 2009-2011 period. At the trough roughly 15% of incremental deposits are allocated to loans and 85% to liquid assets (Figure 3). During the downturn banks also reduce debt pay-down activity. The average allocation to liquid assets is higher than OLS results, particularly during the downturn, as the deposit shock reveals the investment choices of banks that might otherwise be barred funds or indisposed to seek them.

One confounding factor is that the deposit inflows can correspond with changes in investment opportunities for a region, which would bias the level of my estimates. While funding for energy projects is sourced from larger corporations and national markets, the wealth shock can influence demand for credit. I address this potential bias using two distinct strategies. The first relies on time-series comparisons to evaluate the dynamics in reallocation but not the level. If the impact of energy development on banks' local investment opportunities is consistent over time, then changes in investment allocations are well identified. The second strategy proxies for local changes in investment opportunities using county-year fixed effects in a sub-sample of single county banks. The resulting estimates rely on within-county variation in banks' exposure to the deposit shock. Both strategies reinforce the conclusion that lending and debt pay-down are pro-cyclical while allocations to liquid assets are counter-cyclical – consistent with higher demand for liquidity during the recession but not easily explained by lower loan demand.

Examining cross-sectional differences in the response provides further insight to banks' behavior. I generate additional instruments by interacting the deposit shock with bank characteristics and I estimate the heterogeneous response to the unsolicited inflows. In tandem with the decline in lending, significant differences emerge across banks. Two characteristics in particular correlate with lower loan allocations: lack of longer-term, non-deposit funding and high capital ratios. Banks with historical use of non-deposit funds lend 27% more during the recession and those with a *low* Tier 1 capital ratio ($< 12\%$) lend 39% more. These two characteristics capture independent variation that is not explained by the size or scope of the bank.

When I examine the types of liquid assets that gain at the expense of loan allocations, I find banks without long-term funding offset lower lending with higher cash holdings, which is consistent with an enhanced concern for liquidity. Given the Tier 1 capital ratio is effectively risk-weighted leverage, the choice of capital structure and asset mix reflects a bank's tolerance for risk. Congruent with this interpretation, the high Tier 1 capital banks invest more in securities as lending declines, which reflects a preference for safer, more liquid assets during the downturn.

The interaction estimates are identified using differences between exposed banks that operate in similar loan demand environments (i.e. unconventional energy counties). Nevertheless, it may be that investment opportunities in these areas are correlated with unsolicited deposits and change differentially between the types of banks I am looking at, particularly between single location banks and banks operating over larger areas. Therefore, I repeat the analysis while conditioning on single county banks and including county-year fixed effects. I also consider sub-categories of loans (e.g. real estate, commercial and industrial). In the fixed effects specification, I find similar cyclical patterns in overall lending and specific types of loans. The heterogeneous response demonstrates that local banks with different sources of financing exhibit divergent reallocation capabilities, even when constrained to the same geographies and loan categories.

In order for changing investment opportunities to bias these results, they would need to be correlated with the demand shock and the chosen bank characteristics within a specific location and loan category. In the most limiting specification, these are small, geographically constrained banks lending to borrowers in mostly rural geographies; therefore, there is little scope for significant differences in clientele. In addition, economic activity in unconventional energy areas is relatively stable over the business cycle, which suggests that changing allocations are driven by macroeconomic factors outside the local demand environment. Nonetheless, suppose that the observed patterns are explained by changing local demand across banks and over time: the results would suggest starkly segmented local lending markets whereby some banks are able to reallocate incoming deposits to loans and others cannot. The reallocation capabilities of these banks remain quite different under this explanation, albeit as a result of segmented clientele rather than the bank's access to funds.

Given these findings, I conclude that access to funding and risk tolerance are important factors in determining how banks allocate funds over the business cycle. This suggests that an economy like the U.S., with a diverse mix of banks, could find liquidity trapped inside banks during a downturn. Even in a well-developed economy, it seems the availability of liquid funds in the inter-bank markets is not enough to prevent some banks from hoarding liquidity or taking a more conservative investment posture. Banks' actions can have direct implications on the real side of the economy since capital does not flow as freely to users. Such impediments to capital reallocation can be particularly costly when they are correlated with aggregate conditions because they exacerbate downturns.

This paper contributes to our understanding of several topics related to banking. The first is the role of credit in the business cycle (i.e. Bernanke and Gertler (1989), Rajan (1994), Gorton and He (2008)) and the liquidity in financial crises (Diamond and Rajan, 2005). In contrast to prior empirical work comparing the average cross-sectional response to cyclical factors, like changing monetary policy (Kashyap and Stein (2000), Kishan and Opiela (2000)), my quasi-experimental approach compares marginal investment behavior of banks in both good and bad times conditional on a relatively stable local demand environment. The counter-cyclical lending patterns agree with macroeconomic evidence that capital reallocation is impeded during downturns (Eisfeldt and Rampini, 2006). I also demonstrate that the cyclicality of reallocation varies in the cross-section due to liquidity constraints and risk aversion. The greater sensitivity of risk intolerant banks suggests a role for uncertainty shocks (Bloom, 2009) when evaluating the interaction between financial intermediaries and business cycles, for example Adrian et al. (2010).

The second strain of literature is the role of liquidity in bank investment decisions. Banks in my sample choose liquid assets during the recession rather than disbursing the funds via pay-out or pay-down, suggesting heightened liquidity demand during the crisis (Brunnermeier, 2008). In particular, banks without ready access to long-term financing forego lending in exchange for cash, mirroring empirical results that show firms without credit lines bypassed positive investments during the downturn (Campello, Giambona, Graham and Harvey, 2011). The results are complementary to other empirical work focused on the liquidity motives of banks during the financial crisis (Ivashina and Scharfstein (2010), Cornett, McNutt, Strahan and Tehranian (2011), Iyer, Peydr, da Rocha-Lopes and Schoar (2013)) and emphasize demand for liquid assets. Unique to prior work, my results find rising demand for liquidity even in relatively healthy pockets of the economy.

The third is the impact of financing constraints on bank lending (Stein, 1998). In the context of investment-cash flow tests for banks, a positive lending sensitivity is considered a rejection of the Modigliani-Miller proposition (Modigliani and Miller, 1958), as unconstrained firms should invest inframarginal funds to lower their marginal cost of capital.

The fact banks lend some portion of their marginal deposit financing is consistent with an external financing friction. Indeed, various funding shocks in many countries have been shown to impact bank lending (capital: Peek and Rosengren (1997), credit: Paravisini (2008), deposits: Khwaja and Mian (2008), Jayaratne and Morgan (2000)). My results elaborate on the existence of lending sensitivities by emphasizing their heterogeneity – when are these sensitivities high and for which banks? My findings establish several previously undocumented state dependencies in the sensitivity of loans to funding shocks that emphasize banks' liquidity demand and risk tolerance.

Two concurrent papers also exploit the impact of unconventional energy on bank deposits. Gilje (2013) compares real outcomes in areas with different types of financial institutions. A more closely related paper, Gilje, Loutskina and Strahan (2013), tests for the role of branch networking in the reallocation of these funds by estimating the sensitivity of residential mortgage originations in non-energy branches. I do not find evidence that branch networks are an important driver in overall lending allocations; however, the two results are not mutually exclusive – exposed banks can originate more mortgages in non-energy counties but that need not increase their aggregate lending.

2 Empirical Strategy

The goal is to estimate the heterogeneous response of bank investment to changes in funding. I examine the following relation between a balance sheet account such as a change in loans, ΔL, and a change in deposits, ΔD, for bank i from time $t-1$ to t.

$$\Delta L_i^t = \lambda(\mathbf{c_i^{t-1}})\Delta D_i^t + \varepsilon_i^t \tag{2.1}$$

$\lambda_D(\mathbf{c_i^{t-1}})$ is the share of the deposit change allocated to the left-hand side variable. The share is a function of bank characteristics, $\mathbf{c_i^{t-1}}$ (i.e. size, scope, leverage) which reflect differences in the underlying production technology of the bank. The final term, ε_i^t, contains other factors that may impact investment, including shocks to loan demand.

I transform this relation in order to estimate a linear model. First, I scale the change in deposits and the left-hand side variable by the bank's total assets at time $t-1$, A_i^{t-1}, and denote them using lowercase designations Next, I parameterize the lambda term by linearizing with respect to the observable characteristic, $\mathbf{c_i^{t-1}}$. I use this additional term to estimate the difference in the allocation decision across banks. Finally, I include year fixed-effects, τ_t, to capture the impact of aggregate fluctuations, and a vector of controls for bank characteristics, $\mathbf{X_i^{t-1}}$, which includes $\mathbf{c_i^{t-1}}$. I exclude bank fixed effects from the estimation procedures due to the emphasis on cross-sectional differences.

The estimating equation is,

$$\Delta l_i^t = \lambda_D \Delta d_i^t + \lambda_{\mathbf{D,c}}'(\mathbf{c_i^{t-1}} * \Delta d_i^t) + \tau_t + \psi' \mathbf{X_i^{t-1}} + \varepsilon_i^t \tag{2.2}$$

The scaled change specification allows for easy comparisons across uses of funds by estimating the percentage of a deposit change allocated to the left-hand side variable, λ_D, and the variation in this allocation with bank characteristics, $\lambda_{\mathbf{D,c}}$.

2.1 Identification

OLS estimation of Equation 2.2 can result in biased estimates due to several factors. First, some banks will vary funding to reflect changing investment opportunities while others will lack access to funds despite opportunities. As a result, examining average changes in deposits excludes banks that do not and/or cannot change their deposit funding. This “bank selection” effect biases OLS estimates of the allocation of deposits into loans. Second, latent economic conditions can drive households and firms to change both their desired level of deposits and their demand for credit thereby changing banks’ investment opportunities. Distinct from a bank-level effect or macroeconomic conditions, changing local economic conditions reflect the areas in which the banks operate. I refer to this as “local demand” bias.

Denoting bank selection as ι_i^t and local demand as η_i^t, we can rewrite the error term as the sum of these factors and an orthogonal component, ν_i^t. Bias in the coefficients of interest can therefore be summarized as,

$$\hat{\lambda_D} = \lambda_D + \underbrace{\frac{\operatorname{cov}(\Delta d_i^t, \iota_i^t)}{\operatorname{var}(\Delta d_i^t)}}_{\text{Bank Selection}} + \underbrace{\frac{\operatorname{cov}(\Delta d_i^t, \eta_i^t)}{\operatorname{var}(\Delta d_i^t)}}_{\text{Local Demand}},$$

where conditioning information is repressed for brevity. A similar decomposition can be written for the interaction term, $\lambda_{D,c}$.

In order to address bank selection I introduce a positive deposit shock not sought by banks, Δd_i^{t*}, such that $\operatorname{cov}(\Delta d_i^{t*}, \iota_i^t) = 0$. The variation is estimated using a bank’s exposure to unconventional energy counties where landowners’ royalties lead to significant increases in deposits. I then estimate Equation 2.2 using 2SLS where exposure to the unsolicited inflow instruments for a change in deposits. The deposit shock ensures a set of banks have funds they must allocate, regardless of their desire for funds or ability to raise them. I also instrument for the second term using the interaction of the deposit shock with the characteristic of interest. Therefore, even if the deposit shock differentially impacts banks along the characteristic of interest, it will not bias the second-stage allocation estimate. I will expound on the deposit shock in the next section.

The unsolicited nature of the shock eliminates bank selection biases; however, local demand remains a confounding factor. The primary financing for unconventional energy development comes from corporations and national markets, but the wealth shock and changing employment opportunities can cause households to adjust credit demand positively or negatively, hence $\text{cov}(\Delta d_i^t, \eta_i^t) \neq 0$.[2] This is particularly true for the average allocation, λ_D.

Assuming the impact of the wealth shock on local demand is stable over time, the dynamics in the average response, λ_D, are well identified as time-series comparisons difference out the bias. This applies to the cross-sectional response as well. If the covariance between the unsolicited deposits and local demand is the same with respect to a bank characteristic, then the cross-sectional difference, $\lambda_{D,c}$, is immune to this bias (i.e. $\text{cov}(c_i^{t-1} * \Delta d_i^t, \eta_i^t) = 0$). The intuition of this approach is analogous to a difference-in-difference estimation where the first difference estimates the incremental change in deposits and lending in exposed counties and the second difference compares this response among exposed banks either across time or in the cross-section.

In addition, I conduct robustness tests in which I proxy for local demand. I restrict the sample to single-county banks and include county-year fixed effects to proxy for the average change in a county's lending. The resulting estimates are based on within county variation in the deposit shock based on the share of total funding banks receive from local branches. Any remaining bias would have to reflect differential exposure to local demand that banks similarly sized banks operating in similar areas cannot overcome when considering lending allocations. Implications for this alternative interpretation will be discussed along with the results.

[2]See the following for anecdotal evidence of both: Nossiter, Adam. "Gas Rush Is On, Louisianians Cash In." *The New York Times* July 29, 2008.

2.2 Unconventional Energy

Since 1999, rising energy prices and technological innovation have allowed drillers to recover oil and gas from "unconventional" geologic formations that were previously considered inaccessible or uneconomical. The magnitude of these developments is significant. As recently as 2000, shale natural gas was considered an inconsequential component of recoverable natural gas resources in the U.S. According to the Energy Information Administration (EIA), by 2011 major shale formations contained 827 trillion cubic feet (Tcf) of recoverable natural gas. At a recent price of $4.25 per thousand cubic-feet (Mcf) these reserves are worth approximately $3.5 trillion dollars.

Two advances in drilling technology have been critical to increasing recoverable resources: horizontal drilling and hydraulic fracturing ("fracking"). To exploit these technologies, drillers must first lease mineral rights from local landowners. These property owners receive payments in the form of an an upfront signing bonus based on the number of acres leased and a royalty on extracted resources. The signing bonus can vary anywhere from $10 to $30,000 per acre, the royalty from 10% to upwards of 25%. Generally, these terms vary depending on the established reserves of the field, the desirability of the location, and the latest energy prices.

2.2.1 Impact on Deposits

I identify fourteen of the largest unconventional energy formations during the period 2001-2012. For ten impacted states, I collect county-level measures of drilling and production activity from various state agencies and estimate the annual lease payments to local landowners. The cash-flow shock to landowners is calculated at the county-level each year and denoted CFS. I construct a relative measure of the payment shock by scaling the estimated payment by the level of deposits in a county from The Federal Deposit Insurance

Corporation (FDIC) *Summary of Deposits* (SOD). I designate counties as "treated" if the annual payments are large (maximum annual payment greater than $30m) *or* the relative impact is high (cumulative payments after four years are greater than 20% of the deposit base). This criteria excludes counties with little relative or absolute payment activity. Similar samples can be found by considering areas where production is high relative to county characteristics like population or employment.[3]

The resulting treatment sample includes 126 counties spanning 10 states. The estimated cash-flow to these counties is quite large, the maximum is in excess of $1 billion dollars a year or 700% of the deposit base for a county. On average, treatment county payments exceed $70m a year or 39% of the local deposit base. Figure 1 summarizes the geography of the impacted counties with gradations signifying the maximum annual cash-flow impact relative to local deposits ($CFS/Deposits$).

In order to characterize the impact of these payments on deposits, I compare treatment counties to 1,790 untreated counties in the same states and neighboring states. I exclude Wyoming and Colorado which have unconventional energy resources but for which I lack production data. To the extent there are unconventional energy counties that are not in the treatment sample, they will bias estimates of excess deposit growth downward.

Figure 2 illustrates the rise in payments corresponds to increased and persistent excess deposit growth. In the years after initial development (event year zero), cash payments relative to existing deposits rise and deposit growth relative to the untreated counties ranges from 4-5%. By year five, the average annual payment to landowners is 40% of the deposit base and the level of deposits is 20% higher than the control sample.

[3]The payment estimates are only used for county selection and do not enter into the primary analysis, hence I reserve the detailed procedure for the interested reader in a corresponding mimeo (Plosser, 2013). I research typical royalty rates and acreage bonuses and estimate county-level payments based on the number of drilling permits, the type of drilling permits, and output.

2.2.2 Regressions

I test the significance of the payment-deposit relation using a pooled cross-sectional regression. The dependent variable is deposit growth in county j at time t; the key independent variable is either a treatment dummy, $Energy_j^t$, or estimated payments to landowners relative to lagged deposits, CFS_j^t/D_j^{t-1}. For the former I consider deposit growth at the one-year horizon, denoted $\%\Delta$, for the latter the two-year horizon, $\%\Delta_2$.[4]

$$\%\Delta Deposits_j^t = \beta(Energy_j^t) + \psi Controls_j^t + \varepsilon_j^t \tag{2.3}$$

$$\%\Delta_2 Deposits_j^t = \beta_(CFS_j^t/D_j^{t-1}) + \psi Controls_j^t + \varepsilon_j^t \tag{2.4}$$

The coefficient on the payment shock can be interpreted as the average excess deposit growth for Eq. 2.3 and the percent of the shock allocated to local deposits in Eq. 2.4. Controls include year fixed effects, county fixed effects, the lagged log of deposits, and contemporaneous growth in private wages paid and number of business establishments. The final two measures of economic activity are from The Bureau of Labor and Statistics (BLS) *Quarterly Census of Employment and Wages* (QCEW). Standard errors are clustered by county to account for arbitrary serial correlation.

The results in Table 1 are consistent with a wealth shock resulting in increased local deposits. In Column (1), one-year deposit growth is 5.3% higher in energy counties conditional on corresponding changes in economic activity. A regression of two-year deposit growth on the estimated payment shock, (2), yields similar conclusions (Eq. 2.4). The payment shock is positively correlated with deposit growth, with 5.4% of the payments allocated to local deposits.

To verify these changes are not driven by bank demand for funds, I consider the impact

[4]The cash-flow shock is a calendar year variable, but deposits are as of June 30 each year. Therefore, two year deposit growth is used to cover the intervening calendar year.

of energy exposure on deposit growth *within* banks. If branches in energy areas grow faster than unexposed branches at the same bank, then this is a location specific phenomenon within banks. For each bank with a pre-existing presence in an energy county, I aggregate their branch deposits to the county-level. I then regress the growth in a bank's county-level deposits on exposure to energy counties and bank fixed effects, thereby focusing on within bank variation in deposit growth. By construction this analysis relies on banks that operate in multiple counties. Consistent with excess deposit growth particular to treatment areas rather than banks, both the treatment dummy, Column (3), and the payment shock, (4), are statistically significant and positive at the 5% level.

The evidence is consistent with an unsolicited inflow of deposits. The rise in deposits corresponds with estimated landowner payments and is not well explained by measures of economic activity. The increased level of deposits is persistent, which is important when interpreting banks' allocation decisions. And, the excess growth is specific to exposed branches rather than exposed banks, suggesting they do not reflect bank demand for funding.[5]

2.2.3 Aggregating to Banks

I use the sample of treatment counties to construct a bank-level measure of unsolicited deposits. The bank-level measure must take into account the varying impact energy exposure has on deposit growth, both at the the bank-level and the county-level. For example, a simple treatment dummy at the bank-level would fail to capture the differential exposure of a bank with a large deposit presence in an energy county relative to a bank with a small deposit presence nor would it reflect the varying impact of treatment for banks of different size. If these characteristics are correlated with my interaction terms

[5]Additional specifications and robustness tests can be found in Plosser (2013).

they will bias my results. Therefore, I require a continuous measure of energy exposure that can be scaled to reflect a bank's deposit presence and size.

One candidate for this measure is the estimated payment shock from the prior section. However, there are also significant sources of treatment heterogeneity at the county-level that are not well captured by the payment estimates, including the size, timing and taxation of payments. The estimated payment shock is a noisy signal of the ultimate impact on landowners earnings and deposit growth. To generate a more accurate measure of excess deposit growth, I use my treatment designation to identify county-years exposed to unconventional energy and I calculate excess deposit growth by differencing annual deposit growth for these counties, $\%\Delta D_j^{Treat,t}$, with the mean of three nearest neighbors from a propensity score matched sample, $\overline{\%\Delta D_j^{Match,t}}$.

$$\%\Delta D_j^{t*} = \%\Delta D_j^{Treat,t} - \overline{\%\Delta D_j^{Match,t}}$$

The excess deposit measure allows for cross-sectional and time-series differences in how treatment translates into a county's excess deposit growth.

The propensity score is calculated each year using the predicted values from a logit of a treatment dummy on county-level demographic information, banking sector characteristics, measures of economic activity, industry composition, and region fixed effects. Demographic data is from the 2000 U.S. Census and industry composition is based on establishment shares from the BLS QCEW using two-digit NAICS categories. For brevity I do not present the twelve sets of logit coefficients; Appendix A contains one set of illustrative estimates based on the entire sample period.

The resulting sample of positive excess deposit counties ranges from June 2004 to June 2012 and includes 123 unique counties. This varies from the payment shock sample in that the earliest development years (2002, 2003) do not exhibit excess deposit growth and three counties in the treatment sample never exhibit excess deposit growth. Otherwise, this estimate of unsolicited deposits retains the key properties observed earlier. It is not subject to reversals and it is associated with county deposit growth *within* banks (Appendix A.1).[6]

I link county excess deposit growth to banks using branch locations. For each bank, I aggregate the positive realizations of county excess deposit growth by weighting the county excess deposit growth, $\%\Delta D_j^{t*}$, by the share of the bank's total deposits held in the county and summing across all of the counties in which the bank has deposits. This generates a bank-level variable for bank i, from the county-level, j, shocks.

$$\%\Delta D_i^{t*} = \sum_{j=1}^{N} \%\Delta D_j^{t*} \left(\frac{D_{i,j}^{t-1}}{D_i^{t-1}} \right) \tag{2.5}$$

I exclude banks that open branches in a treatment county after the initial year.

Finally, I transform the estimate of deposit growth into an estimate of dollar changes in deposits scaled by prior period assets.

$$\Delta d_i^{t*} = \frac{\Delta D_i^{t*}}{A_i^{t-1}} = \%\Delta D_i^{t*} \frac{D_i^{t-1}}{A_i^{t-1}}$$

This will be the primary instrument in my estimation strategy. I restrict the sample to the range of bank sizes with a deposit shock of at least 1%, i.e. banks with less than $14 billion in real assets, as the deposit inflows are too small to impact the largest banks.

[6]A potential concern with this measure is that using county-level excess deposit growth rather than the payment estimates results in some-sort of selection bias. In unreported results I have conducted the analysis using a the payment shock and found qualitatively similar patterns, albeit at lower levels of statistical significance. This is consistent with the payment shock being a noisy signal of actual cash-flow to landowners and resulting deposits.

This reflects approximately 99.5% of U.S. banks and 50% of banking assets.[7]

3 Analysis of Bank Allocations

I begin my analysis by describing the set of treatment banks. I then estimate the average allocation of these banks before making time-series comparisons over the recent business cycle and conducting robustness tests on the dynamics of the average allocation. In the final section, I consider the heterogeneous response to the deposit inflows with respect to several bank characteristics related to the scale, scope, and capital structure.

3.1 Treatment Banks

I construct a panel of bank financials by combining data from various regulatory agencies from 1999 to 2012. Chartered commercial banks must provide detailed financials to the FDIC on a quarterly basis in *Call Reports of Income and Condition* (FFIEC Form 031). Bank holding companies (BHCs) file similar reports with the Federal Reserve (FR Y-9C, FR Y-9SP). As banks have been shown to establish internal capital markets (Houston, James and Marcus, 1997), I restrict the analysis to consolidated financial statements of high-holder institutions.[8]

I focus on the second quarter report as it coincides with the timing of the SOD and by extension the deposit shock; henceforth, years reflect values as of June 30. I include all banks with less than $14bn in assets and a branch presence in an energy state or a neighboring state. Extreme balance sheet changes can generate misleading regression results; therefore, I exclude bank-years with asset or deposit growth in the top or bottom

[7] Empirical results are similar for cutoffs as low as $1.5bn in real assets; 95% of relevant observations are below $1.5bn.

[8] See Appendix B for more details on panel construction.

50bps of the distribution for a given year, banks with non-traditional asset composition, and banks undergoing corporate transformations.[9] Banks are only designated treatment banks if the branch presence in a county precedes the onset of unconventional energy development.

For the period 2004-2012, Table 2 compares the financial characteristics of bank-years exposed to unsolicited deposits versus the broader sample. Treated banks have slightly more deposit financing and slightly lower allocations to loans. On average, the treatment group invests 58% of its balance sheet in loans with the bulk being categorized as real estate loans, 36%. There are several liquid asset categories. The largest is securities (26%), followed by cash (7%) and Federal Funds sold (FFS) and repurchase agreements (3%). The dollar change in deposits scaled by assets, Δd_i^t, is 7.8% for treatment banks and 4.9% for the full sample. This magnitude corresponds to the average estimated impact of the deposit shock, Δd_i^{t*}, of 3.2%.

3.2 Average Allocation of Deposits

I estimate the average impact of the unsolicited deposit shock on one-year changes in balance sheet quantities using 2SLS. The first stage regresses the the one-year change in deposits scaled by prior year assets, Δd_i^t, on the unsolicited deposit shock, Δd_i^{t*}. The second stage estimates how the deposit change is correlated with a specific balance sheet account, Δl_i^t.

$$\text{First Stage:} \quad \Delta d_i^t = \pi_D \Delta d_i^{t*} + \tau_1^t + \pi' \mathbf{X_i^{t-1}} + \epsilon_i^t \tag{3.1}$$

$$\text{Second Stage:} \quad \Delta l_i^t = \lambda_D \Delta d_i^t + \tau_2^t + \psi' \mathbf{X_i^{t-1}} + \varepsilon_i^t \tag{3.2}$$

[9] Notably *de novos* (< 3 years old), which exhibit extreme changes in size and balance sheet composition, and banks that have made an acquisition or sold assets according to the Merger Information file maintained by the Federal Reserve Bank of Chicago.

The coefficient of interest, λ_D, can be interpreted as the share of deposits allocated to the dependent variable. Year fixed effects, τ^t, control for aggregate variation over time. The vector of controls, $\mathbf{X_i^{t-1}}$, includes lagged observations of log real assets, loan share of assets, the Tier 1 capital ratio, leverage and indicators for the institution type (BHC, Financial Holding Company, Commercial Bank). Standard errors are robust to heteroskedasticity and clustered by bank.

The unsolicited deposit changes can primarily be attributed to three balance sheet categories: loans, liquid assets, and non-deposit borrowing. Liquid assets are comprised of cash, securities and "overnight" lending (FFS/repos). The allocation share, λ_D, for these three items should roughly sum to one, as deposit changes must be offset elsewhere on the balance sheet.[10]

Table 3 summarizes the OLS and 2SLS estimates for the period 2004-2012. OLS estimates of λ_D imply that for every dollar change in deposits, there is a \$0.60 change in loans, Panel A, Column 2 or (A.2). Liquid assets increase by \$0.44, (A.3), and non-deposit borrowing, a source of funds, increases by slightly, (A.4). Given the positive correlation between deposit growth and borrowing the OLS results are consistent with bank demand bias – banks with more (fewer) investment opportunities are raising (lowering) deposit financing.

Contrast these results to Panel B which contains the first- and second-stage estimates using the unsolicited deposit shock as an instrument. The first stage finds exposure to the deposit shock is highly correlated with changes in deposits, (B.1), with a coefficient of 0.98 on the instrument and an F-stat for the test of excluded instruments of 227. The second-stage estimates find the portion allocated to loans is 26% and the portion to liquid

[10]The residual of these three categories includes equity, fixed assets, and trading accounts, but these shocks are not significant sources/uses of the unsolicited deposits. This can be verified by observing that allocations to loans, liquid assets, and non-deposit borrowing sum to approximately one.

assets is 76%, (B.2) and (B.3) respectively. The differences between the OLS and 2SLS results are consistent with the presumed endogeneity, as the unsolicited shock results in a lower loan allocation. Given loans typically make-up around 60% of deposits, the results imply banks are reducing loans as a share of total assets.

The banks exposed to energy deposits do not appear to be soliciting funds. The excess deposit shock is negatively related to non-deposit borrowing (B.4), in contrast OLS estimates suggest deposits positively co-vary with other borrowing. I estimate the interest rate of the banks by dividing the last twelve months of interest expense by the average level of debt liabilities over the prior year. I expect banks seeking funds to pay higher rates, whereas banks receiving unsolicited deposits will have lower rates. In-line with this view, the OLS estimates (A.5) exhibit a positive relationship between deposit growth and the interest rate, whereas the unsolicited deposits (B.5) are *negatively* correlated.

In comparison to recent work on bank financial constraints, a dollar increase in deposits implies a relatively low \$0.26 increase in lending.[11] This may be the result of local demand bias where lending opportunities are suppressed in these counties. However, there are other important differences: my sample is in a developed financial system where financing constraints for banks are lower and the the majority of my observations are during a recession. Indeed, analysis over time differences out local demand bias and finds significant differences in investment behavior over the business cycle.

3.2.1 Time Variation

To characterize the dynamics of banks' investment choices, I repeat the estimation of Eq. 3.2 for two sub-periods: when the economy was growing, 2004-2007, and the recession

[11]For instance, Paravisini (2008) finds government funds lent to Argentine banks resulted in \$0.66 in lending for every government dollar provided to banks. Using Pakistani banks, Khwaja and Mian (2008) estimate a 1% decline in liquidity reduces lending by 0.6%, whereas my results imply a 1% increase in liquidity increases lending by 0.4%.

period, 2008-2012. In Table 4, OLS estimates of loan allocations fall slightly from 64% to 56% (1-3), but unsolicited deposit allocations exhibit more dramatic variation. The allocation of deposits to loans (5) falls from 38% to 22%. The allocation to liquid assets rises from 57% to 80%, (6), and debt pay-down falls from 9% of deposit inflows to 1%, (7). These latter two changes are statistically significant at 5% and 10% confidence levels, respectively.

Observing the alternative uses for funds informs the reason for the decline. All else being equal, declining investment opportunities should result in increased allocations to liquid assets and debt pay-down. However, the estimates show debt pay-down is *decreasing* as a use of funds. Banks maintain or increase non-deposit borrowing even as they increase their liquid asset holdings. This pattern is consistent with heightened liquidity demand during the recession.

If I examine the components of liquid assets, Table 5, the change corresponds with a large increase in the lowest yielding, safest, most liquid asset class – cash. In the earlier period (1-3), 7% of incremental deposits are allocated to cash versus 30% in the recession (4). Allocations to securities increase slightly, from 39% to 41%, (2) and (5), and FFS/repos are roughly unchanged around 10%, (3) and (6).

This is not a phenomenon localized to the peak of financial market disruptions. Figure 3 demonstrates the time-variation in the allocation of unsolicited deposits at a higher frequency by considering four time periods: the pre-recession period up to 2007, the financial crisis period 2008 to 2009, the recession period 2010 to 2011, and the post-recession 2012.[12] While estimated with less precision due to smaller sample sizes, the point estimates are illustrative. Horizontal bars reflect the period over which deposit flows occur and markers denote the midpoint of the estimation period. Average loan

[12]Estimate details can be found in Appendix Table 13.

allocations decline during the crisis and hit a nadir of 15% during the recession before rebounding slightly in the final period. Conversely, the allocation to liquid assets rises and peaks in the recession period at approximately 85%.

3.2.2 Robustness: Local Demand

Assuming the wealth shock has a similar demand impact over time, the dynamics are well identified. But we can employ alternative assumptions to determine how robust the dynamics are to alternative identification strategies. One possibility is that in response to their newfound wealth, households reduce their debts, depressing the sensitivity of lending to deposit shocks. I examine sub-categories of loans and find the lower propensity to lend is not restricted to household borrowers, but is pervasive across loan categories (Appendix Table 14). The unsolicited lending sensitivity is lower than the OLS estimates for C&I loans, small business loans, real estate loans, and consumer loans.

I also proxy for demand conditions using county-year fixed effects in Table 6. I exclude banks that operate in multiple counties so that fixed effects capture the average behavior of banks operating in a specific location. In this specification, differential exposure to the deposit shock is determined by within-county differences in local deposit funding. Consistent with Table 3, the average loan and liquidity allocations are 27% and 74%, respectively. However, the marginal loan allocation is higher in the pre-recession period, 53% versus 38%, which indicates local demand bias attenuates lending allocations in this time-frame. The allocations in the later period are very close to those in Table 4, with loan allocations falling to 21% and liquidity allocations rising to 80%. Proxying for local demand suggests that, if anything, the time-variation in bank behavior is *underestimated*, as local loan demand suppresses marginal lending in the pre-recession period but not during the downturn. Similar patterns emerge when performing these tests in a log specification (Appendix Table 16).

Does the time-variation reflect declining credit demand in these counties? As discussed, the change in non-deposit borrowing does not neatly conform to a loan demand narrative – banks choose to invest in liquid assets but they also stop paying-down debt. In addition, the decline in marginal lending is not restricted to a particular type of loan (Appendix Table 15). An examination of economic activity in energy areas shows that as national economic conditions deteriorate during the recession, unconventional energy counties remain relatively healthy. Figure 4 illustrates that in all four sub-periods average establishment growth in energy counties is positive and consistently above non-energy counties. In fact, establishment growth in energy counties is almost at pre-recession levels by 2009-2011 and exceeds them in 2012. Similar patterns emerge for other measures like employment or wages. During the recession, non-energy counties experience large, statistically significant declines in these measures, while energy counties generally experience modest, statistically insignificant declines (Appendix Table 17).

The change in debt pay-down behavior, the broad nature of the decreased lending allocations, and the limited time-variation in economic conditions, are difficult to reconcile with a simple time-varying loan demand narrative. While these results do not rule out time-varying loan demand as a factor, they suggest that additional mechanisms are at work. My examination of the heterogeneous response conditional on a loan demand environment identifies several alternative explanations.

3.3 Heterogeneous Response

To investigate the heterogeneous response across banks I interact the change in deposits with observable characteristics. As this creates a non-linear IV, I instrument for both the change in deposits, Δd_i^t, and the interaction term between deposits and characteristics,

$(c_i^{t-1} * \Delta d_i^t)$, using the unsolicited deposit shock, Δd_i^{t*}, and an interaction term, $(c_i^{t-1} * \Delta d_i^{t*})$. I estimate the following pooled cross-sectional regressions using 2SLS.

$$\text{First Stage:} \qquad \Delta d_i^t = \pi_{D,1}\Delta d_i^{t*} + \pi_{D,c,1}(c_i^{t-1} * \Delta d_i^{t*}) + \tau_0^t + \boldsymbol{\pi_1}'\mathbf{X_i^{t-1}} + \epsilon_{i,1}^t \tag{3.3}$$

$$(c_i^{t-1} * \Delta d_i^t) = \pi_{D,2}\Delta d_i^{t*} + \pi_{D,c,2}(c_i^{t-1} * \Delta d_i^{t*}) + \tau_1^t + \boldsymbol{\pi_2}'\mathbf{X_i^{t-1}} + \epsilon_{i,2}^t \tag{3.4}$$

$$\text{Second Stage:} \qquad \Delta l_i^t = \lambda_D \Delta d_i^t + \lambda_{D,c}(c_i^{t-1} * \Delta d_i^t) + \tau_2^t + \psi'\mathbf{X_i^{t-1}} + \varepsilon_i^t \tag{3.5}$$

Variables are the same here as in Equations 3.1 and 3.2. The primary coefficient of interest, $\lambda_{D,c}$, estimates how the average allocation varies with the characteristic. The two first-stage regressions allow the instrument's impact on bank deposits to differ depending on the characteristic of interest. Hence, the second stage is conditional on this impact which eliminates the potential for differential deposit flows across banks to bias $\lambda_{D,c}$.[13] Year fixed effects, τ^t control for aggregate time variation. The vector of controls, $\mathbf{X_i^{t-1}}$, includes lagged observations of log real assets, loan share of assets, the Tier 1 capital ratio, leverage and indicators for the institution type. Standard errors are robust to heteroskedasticity and clustered by bank.

Given the extensive role of bank size in the literature,[14] I begin the investigation with an indicator for banks above the median in real assets (approximately \$110m in 2004). Panel A of Table 7 summarizes the heterogenous impact for the recession period. First stage results are suppressed for brevity, but F-stats are provided to infer the strength of the two instruments.[15] The smallest banks lend 14% of the unsolicited deposits, (A.1),

[13]For example, assume that there are two types of bank in a county and that banks of Type A receive more of a county's deposits on average relative to Type B banks. A single first stage regression, or a reduced form regression, will fail to account for the differential impact of the shock on the banks' deposits which will result in biased estimates of marginal allocations in the second stage.

[14]For instance, Diamond (1984) argues the costs of delegated monitoring are minimized by diversification – a characteristic that larger banks can deliver – and Stein (2002) suggest small banks have a comparative advantage when lending to borrowers with more "soft" information.

[15]In each case, first stage results suggest the average exposure to the deposit shock is similar across the characteristics I examine and statistically indistinguishable from one as shown in Table 3, B.1.

compared with larger banks that lend 16% more or 30% of deposits, with a symmetric response for liquid assets, (A.2).

Size is a broad characteristic correlated with many mechanisms that may impact banks' allocation decisions. Larger banks have more scope and may be able to reallocate funds to a greater set of potential projects. Variation with scope would be consistent with a low demand environment where banks with more scope are better able to allocate incremental funds. Larger banks also typically have easier access to financing, and they are more levered relative to the riskiness of their balance sheets – two characteristics that capture banks sensitivity to the funding environment. In sample, scope and non-deposit financing are positively correlated with asset size, while the Tier 1 capital ratio is negatively correlated.

I consider each of these characteristics as interactions: a dummy variable for banks that operate in more than one county, *location*; an indicator for firms with non-deposit borrowing, *borrow*; and an indicator for banks with Tier 1 capital less than 12%, $tier1$. I use dummy variables due to their ease of interpretation; however, similar conclusions result from continuous measures of scope and Tier 1 capital. Approximately 50% of banks in my sample are single location banks, 70% have non-deposit borrowing, and 30% have low Tier 1 capital. Non-deposit borrowing in this sample is primarily comprised of longer term debentures such as subordinated debt and Federal Home Loan Bank Loans as well as some shorter term Federal Funds Purchased (FFP). For brevity, I restrict the dependent variable to loans.

Having more than one location is associated with 5% more lending (A.3), but the difference is not statistically significant. Banks with non-deposit borrowing or low Tier 1 capital display statistically significant differences in investment allocations. Banks without other borrowing only lend 4% of the incremental funding, whereas those with external longer-term borrowing lend 39% (A.4). High Tier 1 capital banks allocate 13% to loans versus 51% for low banks (A.5). In this final specification I suppress the Tier 1 capital ratio as a control variable given the dummy is included as a control. These results present a pattern of heterogeneity related to funding sources rather than investment opportunities (scope).

One concern is that these characteristics can be endogenously impacted by the sequence of shocks; therefore, I repeat the analysis using five-year lagged characteristics and controls (B.1-B.3). I find larger banks lend 8% more, non-deposit borrowers lend 26% more, and low Tier 1 capital banks lend 40% more. Each of these differences is statistically significant at levels of 10% or lower. I also test whether these characteristics explain the heterogeneity implied by size. I simultaneously estimate the size interaction in the presence of the borrowing and Tier 1 dummies in specifications (B.4) and (B.5), respectively. Both the lagged borrowing dummy and the Tier 1 capital dummy retain their magnitude and statistical significance in the presence of the size interaction; however, allocations do not meaningfully differ with size conditional on these additional interactions.

Interpreting the reasons for these differentials requires a view as to why these characteristics differ across banks. Non-deposit borrowing and capital ratios are endogenous outcomes related to underlying fundamentals at these institutions. In the case of borrowing, banks' historical use of non-deposit financing might result from being less well-connected to financial markets or more aggressive in seeking financing. In either case, their non-deposit borrowing reflects their ready access to funds as well as their relative exposure to liquidity shocks. When I examine the types of liquid assets these banks choose in response to the shock, Table 8, I find banks without non-deposit borrowing allocate more funds to cash (A.1) rather than securities or FFS, consistent with a desire to insure themselves against future liquidity shocks. While the classic investment-cash flow test interprets a positive lending sensitivity as evidence of an external financing constraint, my results underscore that this need not be the case if liquidity is the use with the highest expected return Holmström and Tirole (2000).

All else equal, the Tier 1 ratio, a measure of risk-weighted leverage, determines the riskiness of equity. In the data, Tier 1 capital ratios are negatively correlated with standard deviation of return on equity (Appendix Table 18). Similarly, Baker and Wurgler (2013) show public banks with high capital ratios exhibit less return volatility. Prior research has shown that banks actively target Tier 1 capital ratios in excess of regulatory thresholds (Berger et al., 2008). Given these facts, a bank's Tier 1 target reflects its tolerance for risk – the higher the Tier 1 ratio the lower the bank's risk tolerance. This is particularly true for banks like those in my sample that operate in similar geographies and hold similar assets. This intolerance may stem from the perceived cost of raising new equity Froot et al. (1993) or from the underlying preferences of existing shareholders (Saunders et al., 1990).

In the context of these results, banks with a high tolerance for risk, a low Tier 1 ratio, are less sensitive to changes in macroeconomic conditions, as their lending propensity is high despite the developing crisis. In contrast, the banks with a low risk tolerance have larger capital cushions but choose safer, more liquid assets during the recession. Table 8 shows high Tier 1 banks choose mostly securities rather than loans (B.2), in-line with a differential demand for risk. Typically, low Tier 1 capital banks are considered more sensitive to business conditions as they are more likely to experience distress in a downturn and be forced to reduce lending. However, my treatment banks operate in relatively healthy areas; therefore, their investment choices reflect their desire for risk rather than the necessities of their financial condition. Examining estimates at higher frequencies provides additional evidence.

3.3.1 Time Variation

To better understand the role of this heterogeneous response over time, I plot point estimates of allocations for four sub-periods. Estimates are based on the lagged characteristic specifications (Table 7, B.2 and B.3), restricted to four sub-periods. Note that the combination of cross-sectional interactions and smaller periods result in weak instruments for the earliest period.[16] The instrument weakness in the earlier period limits my ability to credibly test for these differentials changing over time; however, we know the sum of these differences is significant, as shown in Section 3.2.1, and the pattern of point estimates can provide insight as to potential causes.

For borrowers versus non-borrowers a clear difference forms at the onset of the financial crisis (Figure 5). Non-borrowers reduce their lending allocation relative to the pre-period and borrowers maintain roughly similar loan allocation levels. Non-borrowers slightly increase their lending allocation in 2012 from a low of almost 0%. For high versus low Tier 1 capital banks, Figure 6, the allocation difference peaks during the financial crisis in period two. High Tier 1 banks further reduce their lending allocation for the period from 2007-2011 before slightly rebounding in 2012. In contrast, low Tier 1 banks *increase* the propensity to lend for the 2008-2009 period and then return to their pre-recession levels by 2012. The differential response mirrors broader market measures of risk such as the VIX index which peaked in the crisis period before moderating.

[16] F-stats: 8.6 for Tier 1 capital and 5.1 for non-borrowers.

3.3.2 Robustness: Local Demand

When estimating the average allocation, as in Table 3, the relevant comparison is between exposed and unexposed banks. However, when estimating the heterogeneous response, the comparison is between differentials of exposed and unexposed banks. Therefore, the identification concern is whether local demand is impacted differently for exposed banks with different ex ante characteristics. For example, multi-location banks operate in different geographies with different demand environments, and scope is correlated with both interaction effects; hence, these banks may be differentially exposed to demand shocks during the recession. In order to further condition the analysis on banks exposed to the same local demand conditions, I restrict the sample to single location banks and include county-year fixed effects in the interaction regression, Table 9.

In-line with the broader sample, single county banks with non-deposit borrowing lend 26% more than those without (1), and Low Tier 1 capital banks lend 51% more (2). A simultaneous estimate of both non-deposit borrowing and low Tier 1 capital suggest the two effects capture distinctly different dimensions of heterogeneity in the sample, with non-deposit borrowers lending 19% more and low Tier 1 banks lending 46% more (3). These forces are not restricted to the sub-sample of single county banks, as multi-location banks exhibit similar patterns (4), albeit at lower levels of statistical significance. These cross-sectional patterns are repeated in log specifications (Appendix Table 20).

If bank characteristics are correlated with specific clientele, and the demand of those clientele is correlated with the deposit shock, then the observed patterns can result from differential exposure to local demand conditions within a county. While it is not obvious what might drive these clientele differences, I can observe sub-categories of loans to see if the lending patterns are broad-based or unique to a particular type of loan. When I examine C&I, real estate, small business, and consumer loans using the within-county specification, I find that the differential lending behavior shows up in every category for both characteristics, Table 10. Hence, I find clientele effects to be a particularly convoluted explanation to the differing behavior – clientele demand would need to vary with the bank characteristic within counties and within loan categories. The more direct explanation is that the variation is attributable to bank-level differences in investment posture. Bank-level differences suggest bank-level frictions such as liquidity demand and risk intolerance.

4 Conclusion

This paper provides a window into the intermediation capabilities of banks over the business cycle. I compare marginal investment allocations over time and in the cross-section by exploiting deposit windfalls from unconventional energy development. When aggregate economic conditions deteriorate, impacted banks increase investments in liquid assets at the expense of lending and debt pay-down. The cross-sectional allocations of banks during the recession are consistent with both a flight to liquidity as less connected banks choose cash and a flight to safety as less risk tolerant banks choose securities. The divergence appears even in the presence of location-time fixed effects, implying that banks with the same nearby investment opportunities but varying characteristics have disparate reallocation capabilities.

These comparisons are primarily among small banks operating in a single county, significantly limiting the potential for differential loan demand dynamics across banks. In addition, the evidence suggests that loan categories co-vary and liquid asset allocations rise at the expense of both loans and debt pay-down. Two facts that are difficult to reconcile with loan demand hypotheses. Therefore, I interpret these patterns using bank-level frictions such as risk intolerance and demand for precautionary liquidity rather than factors related to loan demand. If, on the other hand, variation in loan demand causes these patterns, the results suggest that some banks are severely constrained by their clientele despite the lending opportunities of nearby banks. In either interpretation, heterogeneity in banks' ability to reallocate loans over the business cycle results in capital becoming trapped in certain banks during downturns.

The quasi-experimental approach employed here necessitates a couple of caveats. The first is that these results are the product of a natural experiment on a sub-sample of banks. They do not reflect the average response of banks during the recession, but the response of smaller banks operating in relatively healthy areas. Nevertheless, these banks exhibit a sensitivity to aggregate conditions – similar banks in less healthy areas should be more responsive. Moreover, smaller banks are especially relevant when thinking about disruptions to relationship lending and, consequently, firms (Berger, Miller, Petersen, Rajan and Stein, 2005). And while larger banks can tap many more financing options, heterogeneity in capital ratios and funding sources even for the largest banks suggests that access to funds and risk posture vary in the wider population.

The second caveat is that I do not know the welfare consequences of banks' behavior. The nature of the shock limits my ability to disentangle real effects in this context, nor can I speak to the efficiency of marginal lending from from the bank's perspective. In unreported analysis, I do not find a significant relation between differences in marginal lending and future profitability or provisioning, which leaves the benefits of this incremental lending ambiguous. Despite these limitations, the results can be useful when targeting policy interventions designed to minimize variation in access to credit, either by mitigating banks' sensitivity to economic conditions or by providing funds to banks that are more willing to lend. Integrating these frictions into general equilibrium models is an important step in quantifying the role of intermediaries' liquidity demand and risk intolerance to the length and depth of business cycles.

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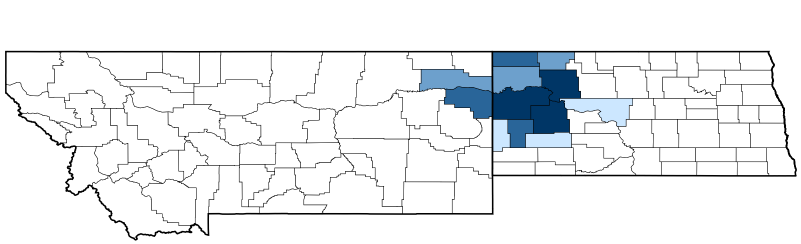
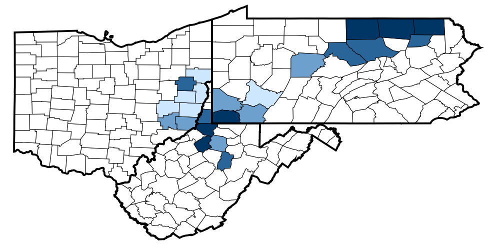
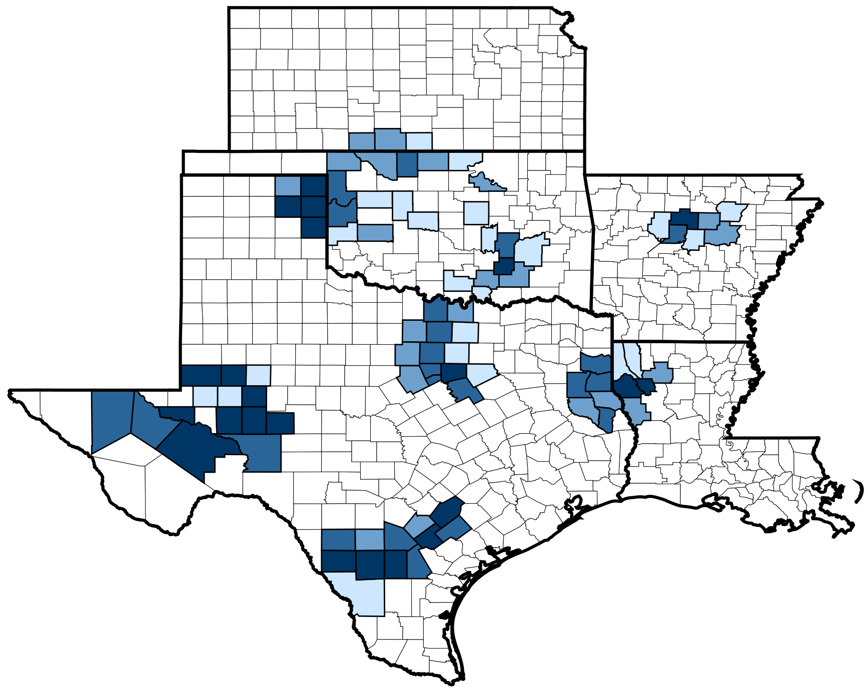


(a) Montana, North Dakota



(b) Ohio, Pennsylvania, West Virginia



(c) Arkansas, Kansas, Louisiana, Texas

Figure 1: Counties Impacted by Unconventional Energy

Figure 1 illustrates the location of counties impacted by unconventional energy development. Shaded counties are divided into quartiles based on the maximum annual payments to landowners relative to lagged deposits.

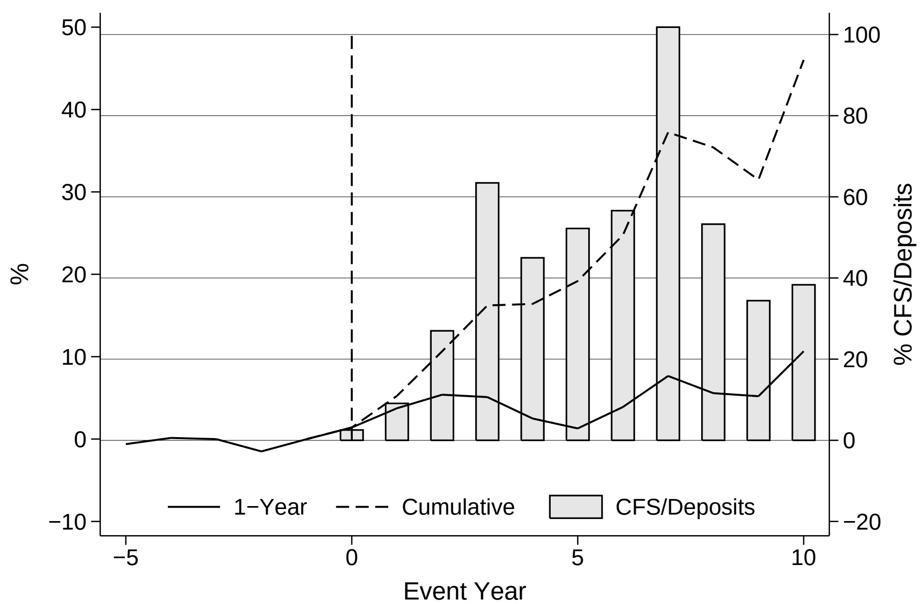


Figure 2: Energy Payments and Excess Deposit Growth

Figure 2 illustrates event time averages for *CFS/Deposits*, excess deposit growth and cumulative excess deposit growth for treatment counties. Year 0 indicates the first year of unconventional energy development. Excess deposit growth is the deposit growth rate demeaned by the average growth rate for counties in nearby states each year. Excess cumulative growth is the product of excess growth rates starting at time 0. Note that the treatment sample is shrinking over event time, only the earliest developments are observed in the final years.

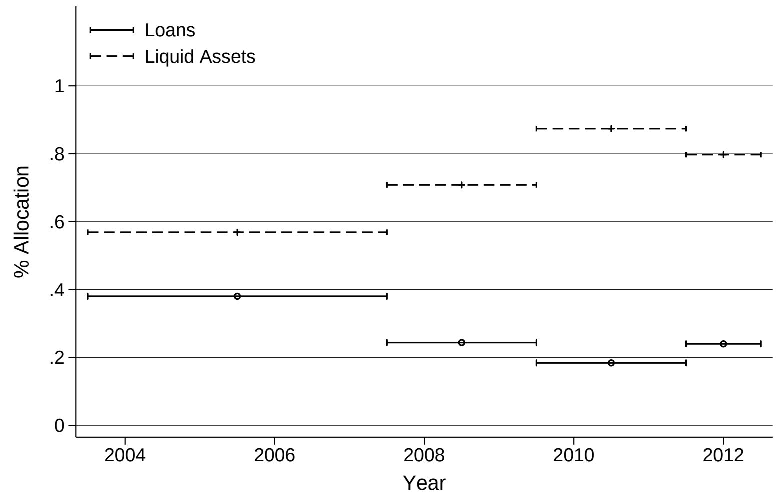


Figure 3: Allocation of Deposits Over Time

Figure 3 illustrates estimated allocations of unsolicited deposit shocks to loans and liquid assets for four separate time periods (λ_d from Equation 3.2). Time periods are from June to June. The first includes one year changes from 2004-2007; the second 2008-2009; the third 2010-2011, and the fourth 2012.

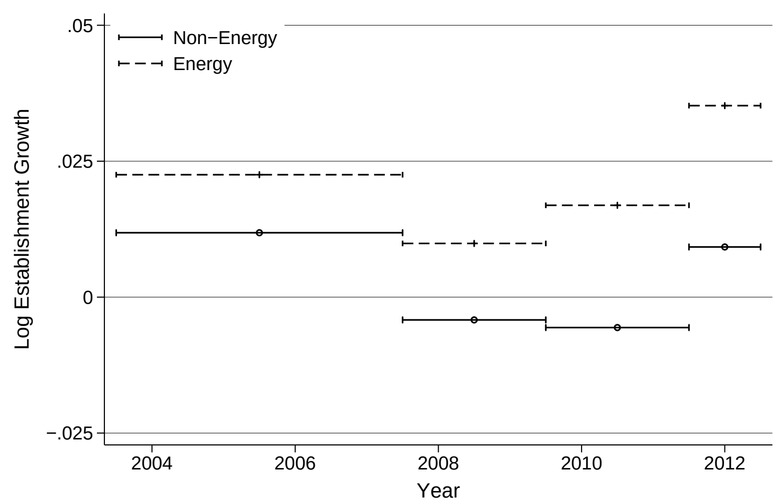


Figure 4: Log Establishment Growth Over Time

Figure 4 illustrates the average change in log establishments for energy and non-energy counties for four separate time periods. Time periods are from June to June. The first includes one year changes from 2004-2007; the second 2008-2009; the third 2010-2011, and the fourth 2012.

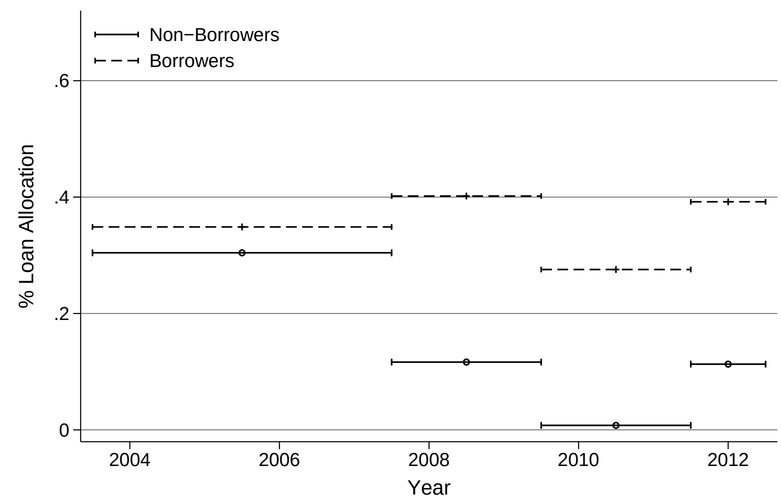


Figure 5: Allocations of Deposits Over Time: Borrowers vs. Non-Borrowers

Figure 5 illustrates estimated loan allocations for banks with non-deposit borrowing (Borrowers) and those without (Non-Borrowers) ($\lambda_d + \lambda_{d,c}$ and λ_d from Equation 3.5). Time periods are from June to June. The first includes one year changes from 2004-2007; the second 2008-2009; the third 2010-2011, and the fourth 2012.

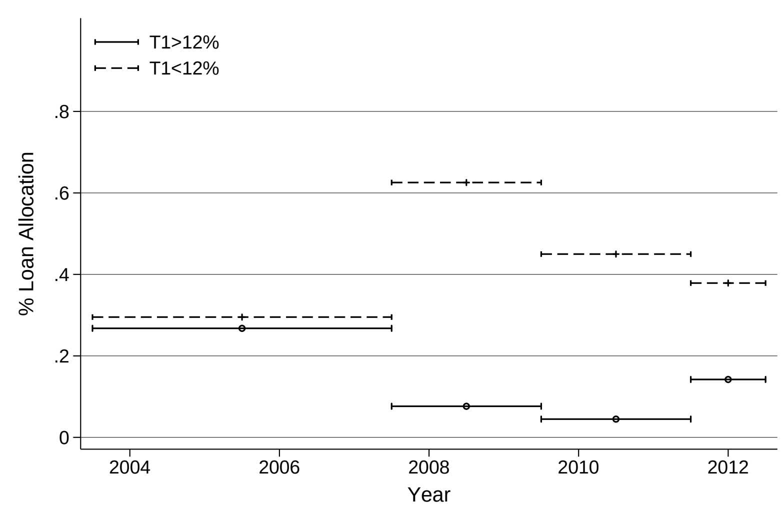


Figure 6: Allocations of Deposits Over Time: High vs. Low Tier 1 Ratios

Figure 6 illustrates estimated loan allocations for high and low Tier 1 capital ratio banks for four separate time periods (λ_d and $\lambda_d + \lambda_{d,c}$ from Equation 3.5). Indicators are based on Tier 1 capital ratio 5 years prior. Time periods are from June to June. The first includes one year changes from 2004-2007; the second 2008-2009; the third 2010-2011, and the fourth 2012.

Table 1: Regression of Deposit Growth on Exposure to Unconventional Energy

Table 1 contains coefficient estimates from pooled cross-sectional regressions from 2000-2012. (1) regresses one-year county-level deposit growth on a treatment dummy, *Energy*. (2) regresses two-year deposit growth on estimated payments to landowners scaled by lagged deposits, CFS_j^t/D_j^{t-1}. $\%\Delta Wage$ is the percent change in private wages paid in the county. $\%\Delta Establishments$ is the percent change in the number of business establishments. All growth rates are calculated, June to June. Standard errors reported in parentheses are clustered by county. (3) and (4) estimate the impact of energy exposure on bank j deposit growth in county i. The sample includes all banks with at least one treatment branch and one non-treatment branch. County controls include the lagged log of deposits, the log of the population density, and demographic characteristics. Deposit growth trimmed at the top and bottom half percent. Standard errors reported in parentheses are clustered by bank. t-stats reported in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
	County		**County-Bank**	
Dependent Variable:	$\%\Delta D_i^t$	$\%\Delta_2 D_i^t$	$\%\Delta D_{i,j}^t$	$\%\Delta_2 D_{i,j}^t$
$Energy$	0.053***		0.021***	
	(0.0052)		(0.0049)	
$CFS/Deposits$		0.054***		0.049***
		(0.017)		(0.014)
$log(Deposits)$	-0.20***	-0.39***		
	(0.015)	(0.025)		
$\%\Delta Wage$	0.064***	0.055***		
	(0.012)	(0.012)		
$\%\Delta Establishments$	0.068***	0.11***		
	(0.020)	(0.024)		
Year FE	+	+		
County FE	+	+		
Year-Bank FE			+	+
County Controls			+	+
Observations	24,744	24,724	12,339	12,324
R-squared	0.193	0.334	0.310	0.351

Table 2: Summary of Bank-Year Statistics 2004-2012

	Treatment Sample				**Full Sample**			
	N	Mean	Median	σ	N	Mean	Median	σ
Asset Composition:								
Cash	1,527	6.6%	4.5%	5.9%	28,892	6.0%	4.1%	6.0%
Securities	1,527	25.8%	23.4%	16.0%	28,892	24.4%	22.1%	14.9%
Fed Funds Sold	1,527	3.3%	1.5%	4.6%	28,892	3.1%	1.3%	4.7%
Total Loans	1,527	58.2%	60.0%	16.4%	28,892	61.8%	63.9%	15.6%
C&I Loans	1,527	10.6%	8.9%	7.1%	28,892	9.6%	8.0%	6.9%
Real Estate Loans	1,527	35.6%	34.1%	15.5%	28,892	39.7%	40.4%	16.2%
Loans to Individuals	1,527	6.1%	4.9%	5.3%	28,892	5.6%	4.4%	5.1%
Small Business Loans	1,526	16.6%	14.7%	8.6%	28,867	16.7%	15.3%	9.3%
Liabilities Composition:								
Deposits	1,527	83.5%	84.6%	6.6%	28,892	82.7%	84.0%	6.7%
Other Borrowings	1,527	4.8%	2.5%	6.4%	28,892	5.4%	3.3%	6.5%
Equity	1,527	10.4%	9.5%	4.3%	28,892	10.7%	9.8%	4.5%
Other Statistics:								
Assets ($mm)	1,527	671.2	178.9	1,653.0	28,892	313.7	111.5	879.9
Log(Assets)	1,527	12.30	12.15	1.35	28,892	11.77	11.68	1.21
Tier 1 Capital Ratio	1,524	14.2%	12.6%	7.5%	28,859	16.1%	13.9%	8.3%
Δd_i^t	1,527	7.8%	6.4%	9.5%	28,892	4.9%	3.7%	10.2%
Δd_i^{t*}	1,527	3.2%	1.8%	4.0%	28,892	0.2%	0.0%	1.2%
% BHC	1,527	85.3%	100.0%	35.4%	28,892	79.5%	100.0%	40.4%

Table 2 summarizes the treatment sample and the full sample of bank-years. Asset and Liabilities are shares of assets at $t-1$. Securities, FFS, & Repos is the sum of security holdings, federal funds sold (FFS) and securities purchased with an agreement to resell. Small business lending is a subset of real estate and C&I loans with a principal smaller than $1m. Log(Assets) is the log of bank real assets in thousands. % BHC is the percent of banks that are bank holding companies. Δd_i^t is the dollar change in deposits from $t-1$ to t divided by assets at $t-1$. Δd_i^{t*} the sum of excess deposit growth in unconventional energy counties weighted by the percentage of a bank's deposit in that county at $t-1$.

Table 3: OLS & 2SLS: Allocation of Deposits

Table 3 reports coefficient estimates from regressions of changes in balance sheet accounts on deposit changes, Δd_i^t. Both changes are scaled by assets at time $t-1$. Panel A contains OLS estimates. Panel B contains 2SLS estimates using excess deposits in unconventional energy counties as an instrument, Δd_i^{t*}, where (1) includes results from the first stage regression. *loans* denotes total loans, *liquid* is cash, securities and overnight lending, *debt* is non-deposit borrowings, and *intrate* the ratio between interest expense for the LTM and average liabilities. Suppressed controls include year fixed effects and lagged observations of log real assets, loan share of assets, Tier 1 capital ratio, leverage and indicators for organization type. Standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
Panel A		**OLS**			
Dependent Var.:		$\Delta loans_i^t$	$\Delta liquid_i^t$	$\Delta debt_i^t$	$intrate_i^t$
Δd_i^t		0.60***	0.44***	0.0036	0.0028***
		(0.017)	(0.013)	(0.0041)	(0.00042)
Observations		28,859	28,859	28,859	28,859
R-squared		0.513	0.402	0.056	0.591
Panel B	**First**	**Second Stage**			
Dependent Var.:	Δd_i^t	$\Delta loans_i^t$	$\Delta liquid_i^t$	$\Delta debt_i^t$	$intrate_i^t$
Δd_i^{t*}	0.98***				
	(0.065)				
Δd_i^t		0.26***	0.76***	-0.020	-0.027***
		(0.046)	(0.044)	(0.015)	(0.0044)
Observations	28,859	28,859	28,859	28,859	28,859
R-squared	0.043				
F-stat		227	227	227	227

Table 4: OLS & 2SLS: Sub-Period Allocation of Deposits

Table 4 reports coefficient estimates from regressions of changes in balance sheet accounts on deposit changes, Δd_i^t, for two time periods. Both changes are scaled by assets at time $t-1$. The top panel consider the period 2004-2007, the bottom 2008-2012. (1)-(3) contain OLS estimates. (4) contains the first stage estimates using excess deposits in unconventional energy counties as an instrument, Δd_i^{t*}. (5)-(7) contain second stage estimates. *loans* denotes total loans, *liquid* is cash, securities and overnight lending, and *debt* is non-deposit borrowings. Suppressed controls include year fixed effects and lagged observations of log real assets, loan share of assets, Tier 1 capital ratio, leverage and indicators for organization type. Standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2004-2007		**OLS**		**First**		**Second**	
Dependent Var.:	$\Delta loans_i^t$	$\Delta liquid_i^t$	$\Delta debt_i^t$	Δd_i^t	$\Delta loans_i^t$	$\Delta liquid_i^t$	$\Delta debt_i^t$
Δd_i^{t*}				0.91***			
				(0.18)			
Δd_i^t	0.64***	0.41***	0.0090		0.38***	0.57***	-0.089*
	(0.031)	(0.021)	(0.0067)		(0.13)	(0.12)	(0.050)
Observations	13,184	13,184	13,184	13,184	13,184	13,184	13,184
R-squared	0.529	0.360	0.033	0.063			
F-stat					25.1	25.1	25.1
2008-2012		**OLS**		**First**		**Second**	
Dependent Var.:	$\Delta loans_i^t$	$\Delta liquid_i^t$	$\Delta debt_i^t$	Δd_i^t	$\Delta loans_i^t$	$\Delta liquid_i^t$	$\Delta debt_i^t$
Δd_i^{t*}				0.96***			
				(0.068)			
Δd_i^t	0.56***	0.46***	-0.0047		0.22***	0.80***	-0.011
	(0.018)	(0.015)	(0.0047)		(0.046)	(0.044)	(0.015)
Observations	15,675	15,675	15,675	15,675	15,675	15,675	15,675
R-squared	0.475	0.396	0.072	0.057			
F-stat					199	199	199
t-stat $\beta_D^{Boom} = \beta_D^{Bust}$					1.23	1.92	1.53

Table 5: 2SLS: Sub-Period Allocation of Deposits into Liquid Assets

Table 5 reports second stage coefficient estimates from regressions of changes in liquid asset accounts on deposit changes, Δd_i^t, using excess deposits in unconventional energy counties as an instrument, Δd_i^{t*}. Changes are scaled by assets at time $t-1$. $cash$ is the sum of cash and deposit balances at other institutions, sec is the total of securities AFS and HTM, and $ffs\&repos$ denotes Fed Funds sold and securities purchased under agreement to resell. Suppressed controls include year fixed effects and lagged observations of log real assets, loan share of assets, Tier 1 capital ratio, leverage and indicators for organization type. Standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
2nd Stage	**2004-2007**			**2008-2012**		
Dependent Var.:	$\Delta cash_i^t$	Δsec_i^t	$\Delta ffs\&repos_i^t$	$\Delta cash_i^t$	Δsec_i^t	$\Delta ffs\&repos_i^t$
Δd_i^t	0.071	0.39***	0.11	0.30***	0.41***	0.086***
	(0.056)	(0.099)	(0.076)	(0.055)	(0.047)	(0.023)
Observations	13,184	13,184	13,184	15,675	15,675	15,675
F-stat	25.1	25.1	25.1	199	199	199

Table 6: 2SLS: Allocation of Deposits within County

Table 6 reports second stage coefficient estimates from regressions of changes in balance sheet accounts on deposit changes, Δd_i^t, in the presence of county-year fixed effects, using excess deposits in unconventional energy counties as an instrument. Changes are scaled by assets at time $t-1$. The sample is restricted to single county banks. $loans$ denotes total loans, and $liquid$ is cash, securities and overnight lending. Suppressed controls include county-year fixed effects and lagged observations of log real assets, loan share of assets, Tier 1 capital ratio, leverage and indicators for organization type. Standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	2004-2012		**2004-2007**		**2008-2012**	
Dependent Var.:	$\Delta loans_i^t$	$\Delta liquid_i^t$	$\Delta loans_i^t$	$\Delta liquid_i^t$	$\Delta loans_i^t$	$\Delta liquid_i^t$
Δd_i^t	0.27***	0.74***	0.53***	0.42**	0.21***	0.80***
	(0.078)	(0.075)	(0.18)	(0.17)	(0.072)	(0.069)
County-Year FE	+	+	+	+	+	+
Observations	14,023	14,023	6,844	6,844	7,179	7,179
F-stat	89.6	89.6	9.10	9.10	83.9	83.9

Table 7: 2SLS: Heterogeneous Response, 2008-2012

Table 7 reports second stage coefficient estimates from regressions of changes in balance sheet accounts on deposit changes, Δd_i^t, and an interaction with bank characteristic, $(c_i^{t-1} * \Delta d_i^t)$. I instrument for both the change in deposits, Δd_i^t, and the interaction term, $(\tilde{c}_i^{t-1} * \Delta d_i^t)$, using the deposit shock, Δd_i^{t*}, and an interaction between the characteristic and the deposit shock, $(c_i^{t-1} * \Delta d_i^{t*})$. (A.1) and (A.2) interact deposits with a dummy indicating real assets above \$110m, *size*; (A.3) with an indicator equal to one if the bank operates in more than one county, *location*; (A.4) with an indicator for firms with non-deposit borrowing, *borrow*; and (A.5) with an indicator for Tier 1 capital ratio below 12%, $tier1$. Suppressed controls include year fixed effects, interaction dummies, lagged observations of log real assets, loan share of assets, Tier 1 capital ratio, leverage and indicators for organization type. (B.1), (B.2), and (B.3) interact deposits with 5-year lagged dummies for *size*, *location*, and $tier1$, respectively; (B.4) and (B.5) consider combinations of these characteristics. Suppressed controls are also lagged in Panel B. Standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A	(1)	(2)	(3)	(4)	(5)
c_i:	**Size**		**Locations**	**Borrowing**	**Tier 1**
Dependent Var.:	$\Delta loans_i^t$	$\Delta liquid_i^t$	$\Delta loans_i^t$	$\Delta loans_i^t$	$\Delta loans_i^t$
Δd_i^t	0.14**	0.88***	0.20***	0.044	0.13***
	(0.068)	(0.065)	(0.075)	(0.058)	(0.045)
$(c_i^{t-1} * \Delta d_i^t)$	0.16*	-0.16**	0.051	0.35***	0.38***
	(0.085)	(0.083)	(0.096)	(0.092)	(0.097)
Observations	15,675	15,675	15,675	15,675	15,675
F-stat	61.3	61.3	46.0	69.6	47.2

Panel B					
Dependent Var.:	$\Delta loans_i^t$	$\Delta loans_i^t$	$\Delta loans_i^t$	$\Delta loans_i^t$	$\Delta loans_i^t$
Δd_i^t	0.25***	0.087	0.098**	0.087	0.097
	(0.041)	(0.056)	(0.047)	(0.062)	(0.060)
$(size_i^{t-5} * \Delta d_i^t)$	0.081*			-0.0067	0.011
	(0.045)			(0.10)	(0.089)
$(borrow_i^{t-5} * \Delta d_i^t)$		0.26***		0.27**	
		(0.087)		(0.11)	
$(tier1_i^{t-5} * \Delta d_i^t)$			0.40***		0.39***
			(0.081)		(0.096)
Observations	14,648	14,648	14,648	14,648	14,648
F-stat	60.4	57.2	87.6	19.9	29.1

Table 8: 2SLS: Heterogeneous Response and Liquid Assets, 2008-2012

Table 8 reports second stage coefficient estimates from regressions of changes in liquid assets on deposit changes, Δd_i^t, and an interaction with bank characteristic, $(c_i^{t-1} * \Delta d_i^t)$. I instrument for both the change in deposits, Δd_i^t, and the interaction term, $(\tilde{c}_i^{t-1} * \Delta d_i^t)$, using the deposit shock, Δd_i^{t*}, and an interaction between the characteristic and the deposit shock, $(c_i^{t-1} * \Delta d_i^{t*})$. The interaction term in Panel A considers the 5-year lagged dummies for firms with non-deposit borrowing, $borrow^{t-5}$, and in Panel B firms with Tier 1 capital ratio below 12%, $tier1^{t-5}$. $cash$ is the sum of cash and deposit balances at other institutions, sec is the total of securities AFS and HTM, and $ffs\&repos$ denotes Fed Funds sold and securities purchased under agreement to resell. Suppressed controls include year fixed effects, interaction dummies, lagged observations of log real assets, loan share of assets, Tier 1 capital ratio, leverage and indicators for organization type. Standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A	(1)	(2)	(3)
Dependent Var.:	$\Delta cash_i^t$	Δsec_i^t	$\Delta ffs\&repos_i^t$
Δd_i^t	0.39***	0.47***	0.063
	(0.089)	(0.072)	(0.039)
$(borrow_i^{t-5} * \Delta d_i^t)$	-0.21**	-0.038	0.019
	(0.11)	(0.10)	(0.046)
Observations	14,648	14,648	14,648
F-stat	57.2	57.2	57.2

Panel B			
Dependent Var.:	$\Delta cash_i^t$	Δsec_i^t	$\Delta ffs\&repos_i^t$
Δd_i^t	0.32***	0.53***	0.062**
	(0.075)	(0.059)	(0.029)
$(tier1_i^{t-5} * \Delta d_i^t)$	-0.11	-0.23**	0.021
	(0.094)	(0.095)	(0.047)
Observations	14,648	14,648	14,648
F-stat	87.6	87.6	87.6

Table 9: 2SLS: Heterogeneous Response within County, 2008-2012

Table 9 reports second stage coefficient estimates from regressions of changes in balance sheet accounts on deposit changes, Δd_i^t, and an interaction with bank characteristic, $(c_i^{t-1} * \Delta d_i^t)$. I instrument for both the change in deposits, Δd_i^t, and the interaction term, $(\tilde{c}_i^{t-1} * \Delta d_i^t)$, using the deposit shock, Δd_i^{t*}, and an interaction between the characteristic and the deposit shock, $(c_i^{t-1} * \Delta d_i^{t*})$. The sample is restricted to single county banks in (1)-(3) and multi-location banks in (4). Interaction terms are 5-year lagged dummies for firms with non-deposit borrowing, $borrow^{t-5}$, and firms with Tier 1 capital ratio below 12%, $tier1^{t-5}$. *loans* denotes total loans. Suppressed controls include interaction dummies, county-year fixed-effects, lagged observations of log real assets, loan share of assets, Tier 1 capital ratio, leverage and indicators for organization type. Standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Dependent Var.:	$\Delta loans_i^t$	$\Delta loans_i^t$	$\Delta loans_i^t$	$\Delta loans_i^t$
Δd_i^t	0.091	0.12*	0.048	-0.061
	(0.075)	(0.064)	(0.070)	(0.090)
$(borrow_i^{t-5} * \Delta d_i^t)$	0.26**		0.19*	0.19
	(0.13)		(0.11)	(0.13)
$(tier1_i^{t-5} * \Delta d_i^t)$		0.51***	0.46**	0.31***
		(0.18)	(0.18)	(0.11)
County-Year FE	+	+	+	+
Observations	6,521	6,521	6,521	8,127
F-stat	26.1	13.6	18.8	7.34

Table 10: 2SLS: Heterogeneous Response within County and Loan Category, 2008-2012

Table 10 reports second stage coefficient estimates from regressions of changes in liquid assets accounts on deposit changes, Δd_i^t, and an interaction with bank characteristic, $(c_i^{t-1} * \Delta d_i^t)$. I instrument for both the change in deposits, Δd_i^t, and the interaction term, $(\tilde{c}_i^{t-1} * \Delta d_i^t)$, using the deposit shock, Δd_i^{t*}, and an interaction between the characteristic and the deposit shock, $(c_i^{t-1} * \Delta d_i^{t*})$. The interaction term in Panel A considers the 5-year lagged dummies for firms with non-deposit borrowing, $borrow^{t-5}$, and in Panel B firms with Tier 1 capital ratio below 12%, $tier1^{t-5}$. $c\&i$ is commercial and industrial loans, re total real estate loans, sbl is small business loans, and li is loans to individuals. The sample is restricted to single location banks. Suppressed controls include county-year fixed effects and lagged observations of log real assets, loan share of assets, Tier 1 capital ratio, leverage and indicators for organization type. Standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A	(1)	(2)	(3)	(4)
Dependent Var.:	Δci_i^t	Δre_i^t	Δsbl_i^t	Δli_i^t
Δd_i^t	0.044**	0.070	0.0094	0.0070
	(0.020)	(0.057)	(0.036)	(0.0089)
$borrow_i^{t-5} * \Delta d_i^t$	0.11*	0.051	0.13**	0.028**
	(0.059)	(0.080)	(0.064)	(0.014)
County-Year FE	+	+	+	+
Observations	6,521	6,521	6,504	6,521
F-stat	26.1	26.1	26.5	26.1
Panel B				
Dependent Var.:	Δci_i^t	Δre_i^t	Δsbl_i^t	Δli_i^t
Δd_i^t	0.069**	0.055	0.049*	0.017*
	(0.028)	(0.044)	(0.029)	(0.0092)
$tier1_i^{t-5} * \Delta d_i^t$	0.11**	0.25**	0.086	0.012
	(0.057)	(0.10)	(0.13)	(0.016)
County-Year FE	+	+	+	+
Observations	6,521	6,521	6,504	6,521
F-stat	13.6	13.6	13.6	13.6

A Results Appendix

A.1 Unconventional Energy: Aggregating to Banks

Table 11: Propensity Score Matching Coefficients

	Coefficient	SE
Log Deposits	0.38	(0.12)
Population Density	0.00	(0.00)
% Hispanic	-1.51	(0.31)
% Black	-5.11	(0.62)
% HS Graduates	1.86	(0.70)
% Working Age	8.69	(1.68)
Log Total Population	-0.38	(0.14)
Log Total Wages Paid	0.15	(0.10)
Deposit HHI	0.06	(0.32)
$\%\Delta Wage$	3.19	(0.46)
$\%\Delta Employment$	0.98	(0.47)
$\%\Delta Establishments$	4.76	(0.94)
Establishments %:		
Agriculture	2.51	(2.03)
Construction	4.62	(2.25)
Manufacturing/Utilities	-2.68	(2.80)
Wholesale & Retail Trade	11.07	(2.34)
Energy	16.46	(2.14)
Business Services	-1.19	(2.40)
Finance/Real Estate	-3.63	(2.73)
Education	-14.15	(12.83)
Healthcare	6.33	(2.09)
Misc. Services	7.73	(2.02)
Tranport./Warehousing	17.62	(2.48)
Year FE	+	
Census Division FE	+	
Observations	17,669	

Table 11 displays estimated coefficients from a logit where the dependent variable is a treatment dummy. Covers the period 2000-2012. The unit of observation is the county-year where the treatment dummy indicates whether the county is exposed to unconventional energy.

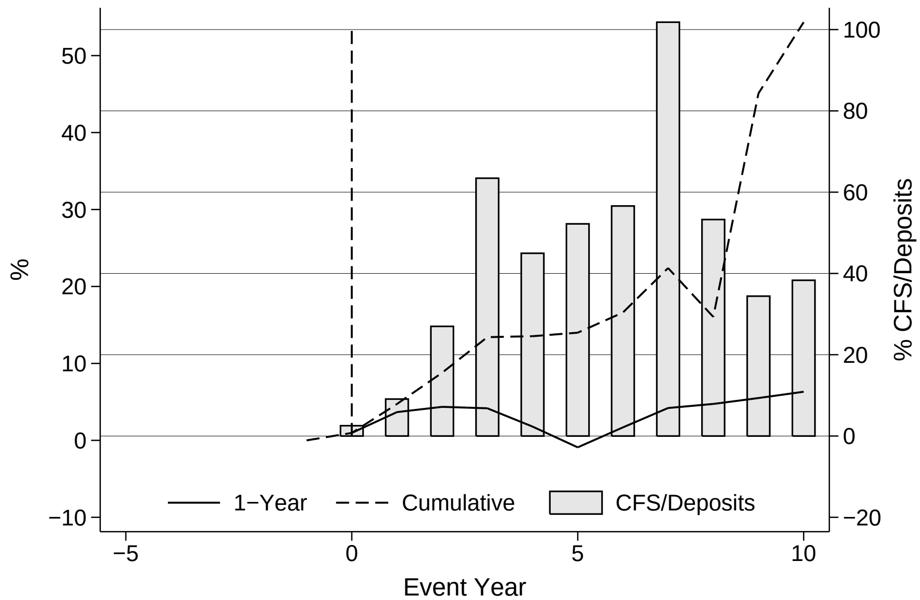


Figure 7: Energy Payments and Excess Deposit Measure

Figure 7 illustrates event time averages for $CFS/Deposits$, excess deposit growth and cumulative excess deposit growth for treatment counties. Year 0 indicates the first year of unconventional energy development. Excess deposit growth is the difference between a treatment county growth rate and 5 nearest neighbors based on propensity score matching. Excess cumulative growth is the product of excess growth rates starting at time 0. Note that the treatment sample is shrinking over event time, only the earliest developments are observed in the final periods.

Table 12: Regression of Bank-County Deposit Growth on Excess Deposit Measure

Table 12 contains coefficient estimates from pooled cross-sectional regressions from 2000-2012. The coefficients estimate the impact of energy exposure on bank j deposit growth in county i. The sample includes all banks with at least one treatment branch and one non-treatment branch. County controls include the lagged log level of deposits, the lagged log of the population density, and demographic characteristics. Bank-county deposit growth trimmed at the top and bottom half percent. Standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)
Dependent Variable:	$\%\Delta D_{i,j}^{t}$	$\%\Delta D_{i,j}^{t}$
$\%\Delta Deposits^{*}$	0.76***	0.67***
	(0.049)	(0.062)
Year FE	+	
Bank FE	+	
Year-Bank FE		+
County Controls		+
Observations	12,343	12,339
R-squared	0.153	0.318

A.2 Allocation of Deposits

Table 13: 2SLS: Average Allocation Time Variation

Table 13 reports the coefficient estimates used to construct Figure 3. Estimates are from a 2SLS regression of balance sheet changes on deposit changes, Δd_i^t using excess deposits in unconventional energy counties as an instrument. Changes are scaled by assets at time $t-1$. Suppressed controls include year fixed effects and lagged observations of log real assets, loan share of assets, Tier 1 capital ratio, leverage and indicators for organization type. Standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Panel A	**'03-'07**	**'08-'09**	**'10-'11**	**'12**
Dependent Var.:	$\Delta loans_i^t$	$\Delta loans_i^t$	$\Delta loans_i^t$	$\Delta loans_i^t$
Δd_i^t	0.38***	0.24***	0.18***	0.24***
	(0.13)	(0.087)	(0.068)	(0.067)
Observations	13184	6197	6338	3140
F-stat	25.1	102	85.6	58.6
Panel B	**'03-'07**	**'08-'09**	**'10-'11**	**'12**
Dependent Var.:	$\Delta liquid_i^t$	$\Delta liquid_i^t$	$\Delta liquid_i^t$	$\Delta liquid_i^t$
Δd_i^t	0.57***	0.71***	0.87***	0.80***
	(0.12)	(0.081)	(0.060)	(0.067)
Observations	13184	6197	6338	3140
F-stat	25.1	102	85.6	58.6

Table 14: OLS & 2SLS: Allocation of Deposits into Types of Loans

Table 14 reports coefficient estimates from regressions of changes in loan accounts on deposit changes, Δd_i^t. Both changes are scaled by assets at time $t-1$. Panel A contains OLS estimates. Panel B contains 2SLS estimates using excess deposits in unconventional energy counties as an instrument, Δd_i^{t*}. $c\&i$ is commercial and industrial loans, re total real estate loans, sbl is small business loans, and li is loans to individuals. Suppressed controls include year fixed effects and lagged observations of log real assets, loan share of assets, Tier 1 capital ratio, leverage and indicators for organization type. Standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Panel A	**OLS**			
Dependent Var.:	$\Delta c\&i_i^t$	Δre_i^t	Δsbl_i^t	Δli_i^t
Δd_i^t	0.12***	0.41***	0.17***	0.039***
	(0.0060)	(0.015)	(0.0095)	(0.0039)
Observations	28,859	28,859	28,829	28,859
R-squared	0.165	0.422	0.183	0.078
Panel B	**Second Stage**			
Dependent Var.:	$\Delta c\&i_i^t$	Δre_i^t	Δsbl_i^t	Δli_i^t
Δd_i^t	0.080***	0.16***	0.086***	0.020***
	(0.016)	(0.033)	(0.021)	(0.0054)
Observations	28,859	28,859	28,829	28,859
F-stat	227	227	228	227

Table 15: 2SLS: Sub-Period Allocation of Deposits into Loan Categories

Table 15 reports second stage coefficient estimates from regressions of changes in loan accounts on deposit changes, Δd_i^t, using excess deposits in unconventional energy counties as an instrument, Δd_i^{t*}. Changes are scaled by assets at time $t-1$. $c\&i$ is commercial and industrial loans, re total real estate loans, sbl is small business loans, and li is loans to individuals. Suppressed controls include year fixed effects and lagged observations of log real assets, loan share of assets, Tier 1 capital ratio, leverage and indicators for organization type. Standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Panel A	**2004-2007**			
Dependent Var.:	$\Delta c\&i_i^t$	Δre_i^t	Δsbl_i^t	Δli_i^t
Δd_i^t	0.11**	0.26**	0.13**	0.032**
	(0.042)	(0.10)	(0.066)	(0.014)
Observations	13,184	13,184	13,184	13,184
F-stat	25.1	25.1	25.1	25.1
Panel B	**2008-2012**			
Dependent Var.:	$\Delta c\&i_i^t$	Δre_i^t	Δsbl_i^t	Δli_i^t
Δd_i^t	0.072***	0.13***	0.071***	0.019***
	(0.018)	(0.032)	(0.022)	(0.0058)
Observations	15,675	15,675	15,645	15,675
F-stat	199	199	202	199

Table 16: 2SLS: Allocation of Deposits, Log Specification

Table 16 reports second stage coefficient estimates from regressions of log changes in balance sheet accounts on log deposit changes, $\Delta \log(d_i^t)$, on deposit changes, $\Delta \log(d_i^t)$, using log excess deposits in unconventional energy counties as an instrument. *loans* denotes total loans, and *liquid* is cash, securities and overnight lending. Suppressed controls year fixed effects, lagged observations of log real assets, loan share of assets, Tier 1 capital ratio, leverage and indicators for organization type. Panel A contains all observations, Panel B includes county-year fixed effects and the sample is restricted to single county banks. Standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	**2004-2012**		**2004-2007**		**2008-2012**	
Log changes:	$\Delta loans_i^t$	$\Delta liquid_i^t$	$\Delta loans_i^t$	$\Delta liquid_i^t$	$\Delta loans_i^t$	$\Delta liquid_i^t$
$\Delta \log(d_i^t)$	0.39***	1.44***	0.52***	1.36***	0.35***	1.56***
	(0.073)	(0.084)	(0.13)	(0.30)	(0.085)	(0.081)
Observations	28,844	28,859	13,181	13,184	15,663	15,675
F-stat	258	257	32.0	31.9	231	229
Panel B	**2004-2012**		**2004-2007**		**2008-2012**	
Log changes:	$\Delta loans_i^t$	$\Delta liquid_i^t$	$\Delta loans_i^t$	$\Delta liquid_i^t$	$\Delta loans_i^t$	$\Delta liquid_i^t$
$\Delta \log(d_i^t)$	0.40***	1.18***	0.69***	0.85**	0.32**	1.34***
	(0.12)	(0.13)	(0.22)	(0.43)	(0.14)	(0.12)
County-Year FE	+	+	+	+	+	+
Observations	13,716	13,728	6,684	6,686	7,032	7,042
F-stat	94.4	93.8	11.2	11.1	92.2	90.2

Table 17: Variation in County-Level Economic Growth, 2002-2012

Table 17 reports the average growth of energy and non-energy counties prior to and during the recession. Estimates are the result of regressing county-year employment, wage or establishment growth on dummy variables indicating them as energy counties, energy counties in recession years (2008-2012), and non-energy counties in recession years. Columns (1)-(3) are percent change, columns (4)-(6) are log changes. Energy counties exhibit modest declines during the recession, while non-energy counties show significantly lower growth in all three measures. Regressions include county-fixed effects. Standard errors reported in parentheses are clustered by county. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.:	$\%\Delta Emp.$	$\%\Delta Wages$	$\%\Delta Estab.$	$\Delta LogEmp.$	$\Delta LogWages$	$\Delta LogEstab.$
Constant	0.016***	0.053***	0.013***	0.013***	0.050***	0.012***
	(0.00055)	(0.00066)	(0.00034)	(0.00053)	(0.00059)	(0.00034)
$Energy$	0.028**	0.051***	0.0072	0.030**	0.048***	0.0093
	(0.012)	(0.017)	(0.0074)	(0.012)	(0.014)	(0.0064)
$Energy * Recess.$	0.0071	-0.011	0.0015	-0.00023	-0.019	-0.0011
	(0.010)	(0.017)	(0.0084)	(0.0090)	(0.014)	(0.0072)
$Non\text{-}Energy * Recess.$	-0.023***	-0.032***	-0.014***	-0.023***	-0.031***	-0.014***
	(0.00086)	(0.0011)	(0.00061)	(0.00082)	(0.00099)	(0.00060)
County FE	+	+	+	+	+	+
Observations	28,113	28,030	28,269	28,113	28,030	28,269
R-squared	0.129	0.203	0.166	0.122	0.187	0.163

A.3 Heterogeneous Response

Table 18: OLS: Standard Deviation of ROE on Tier 1 Capital Ratio

Table 18 reports coefficients estimates from a regression of ROE standard deviation on average Tier 1 capital over the period 2000-2012. The unit of observation is the bank. The dependent variable in (1) is the standard deviation of ROE, σ_{ROE}, in (2) and (3) it is the log of this quantity. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
Dependent Var.:	σ_{ROE}	$\log(\sigma_{ROE})$	$\log(\sigma_{ROE})$
Tier 1 Ratio	-1.56***	-4.56***	
	(0.32)	(0.31)	
Log Tier 1 Ratio			-1.11***
			(0.055)
Observations	4,063	4,063	4,062
R^2	0.003	0.082	0.123

Table 19: 2SLS: Heterogeneous Response Time Variation

Table 19 reports the coefficient estimates used to construct Figures 5 and 6. Estimates are from a 2SLS regression of loan changes on deposit changes, Δd_i^t, and an interaction with bank characteristic, $(c_i^{t-1} * \Delta d_i^t)$. using excess deposits in unconventional energy counties as an instrument. I instrument for both the change in deposits, Δd_i^t, and the interaction term, $(\tilde{c}_i^{t-1} * \Delta d_i^t)$, using the deposit shock, Δd_i^{t*}, and an interaction between the characteristic and the deposit shock, $(c_i^{t-1} * \Delta d_i^{t*})$. Suppressed controls include year fixed effects and lagged observations of log real assets, loan share of assets, Tier 1 capital ratio, leverage and indicators for organization type. Standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Panel A	**'04-'07**	**'08-'09**	**'10-'11**	**'12**
Dependent Var.:	$\Delta loans_i^t$	$\Delta loans_i^t$	$\Delta loans_i^t$	$\Delta loans_i^t$
Δd_i^t	0.27**	0.076	0.045	0.14*
	(0.13)	(0.095)	(0.062)	(0.076)
$(tier1_i^{t-5} * \Delta d_i^t)$	0.028	0.55***	0.41***	0.24*
	(0.24)	(0.21)	(0.092)	(0.12)
Observations	12,218	5,787	5,893	2,968
F-stat	8.57	34.0	35.7	15.7
Panel B	**'04-'07**	**'08-'09**	**'10-'11**	**'12**
Dependent Var.:	$\Delta loans_i^t$	$\Delta loans_i^t$	$\Delta loans_i^t$	$\Delta loans_i^t$
Δd_i^t	0.30**	0.12	0.0077	0.11
	(0.15)	(0.13)	(0.060)	(0.084)
$(borrow_i^{t-5} * \Delta d_i^t)$	0.044	0.29	0.27***	0.28**
	(0.22)	(0.20)	(0.092)	(0.12)
Observations	12,196	5,787	5,893	2,968
F-stat	5.05	25.5	20.8	32.2

Table 20: 2SLS: Heterogeneous Response, 2008-2012, Log Specification

Table 20 reports second stage coefficient estimates from regressions of changes in log balance sheet accounts on log deposit changes, $\Delta\log(d_i^t)$, and an interaction with bank characteristic, $(c_i^{t-1} * \Delta\log(d_i^t))$. I instrument for both the change in deposits, $\Delta\log(d_i^t)$, and the interaction term, $(\tilde{c}_i^{t-1} * \Delta\log(d_i^t))$, using the deposit shock, $\Delta\log(d_i^{t*})$, and an interaction between the characteristic and the deposit shock, $(c_i^{t-1} * \Delta\log(d_i^{t*}))$. Interaction terms are 5-year lagged dummies for firms with non-deposit borrowing, $borrow^{t-5}$, and firms with Tier 1 capital ratio below 12%, $tier1^{t-5}$. *loans* denotes total loans. (1)-(3) include all observations, (4)-(6) include county-year fixed effects and the sample is restricted to single location banks. Suppressed controls include interaction dummies, lagged observations of log real assets, loan share of assets, Tier 1 capital ratio, leverage and indicators for organization type. Standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Log changes:	(1) $\Delta loans_i^t$	(2) $\Delta loans_i^t$	(3) $\Delta loans_i^t$	(4) $\Delta loans_i^t$	(5) $\Delta loans_i^t$	(6) $\Delta loans_i^t$
$\Delta\log(d_i^t)$	0.17	0.20*	0.092	0.19	0.20	0.11
	(0.14)	(0.11)	(0.14)	(0.19)	(0.15)	(0.19)
$(borrow_i^{t-5} * \Delta\log(d_i^t)$	0.36**		0.25*	0.30		0.22
	(0.16)		(0.15)	(0.22)		(0.20)
$(tier1_i^{t-5} * \Delta\log(d_i^t)$		0.52***	0.44***		0.77***	0.72***
		(0.14)	(0.13)		(0.23)	(0.21)
County-Year FE				+	+	+
Observations	14,644	14,644	14,644	6,517	6,517	6,517
F-stat	113	113	30.3	28.2	12.8	16.3

B Data

Summary of Deposits, FDIC: Provides deposits by bank branch as of June 30 of each year. This data is used to aggregate deposits for each county as well as to estimate the relative exposure of a bank to deposit shocks.

The SOD is based on banks' assignment of deposits to specific branches. Main offices, particularly of large banks, can experience significant changes in deposits as on-line or brokered deposits are reallocated across branches. This behavior creates volatility in deposits unrelated to local deposit accounts.

I remove branches from county-level estimates that experience extreme outlier movements relative to the deposit holdings in the county (an absolute annual change in a single branch that is greater than \$10m and 19% of a county's total deposits) in counties with multiple branches experiencing similarly signed outlier growth rates (>40% change or 2 standard deviations from average county-level deposit growth). This removes approximately .04% of branches. The result is that extreme county-level growth rates are reduced without losing the observation entirely.

Bank Regulatory Filings (FFIEC Form 031, FR Y-9C, FR Y-9SP): Chartered commercial banks must provide detailed financials to the FDIC on a quarterly basis in *Call Reports of Income and Condition* (FFIEC Form 031). Bank holding companies (BHCs) file similar reports with the Federal Reserve (FR Y-9C, FR Y-9SP). I focus on the second quarter report so as to correspond to the deposit shocks constructed using the SOD.

I only retain those filings that apply to the highest holder in an institution. When available I attribute ownership to the financial high-holder (RSSD9364), otherwise I use the regulatory direct holder (RSSD9379). Because some BHCs holders are themselves subsidiaries, I iterate on this process until I identify each bank's ultimate parent.

If the high-holder is a BHC with assets more than \$150m prior to 2006 or more than \$500m post-2006, the BHC is required to report consolidated financials on form *FR Y-9C*. I use the consolidated entity's financials for these firms. However, if the high holder is below these thresholds or a non-bank financial institution, the high-holder may not report consolidated financials. For these FR Y-9SP filers, I consolidate accounts across the parent bank's unconsolidated balance sheets and their subsidiaries to generate a consolidated high-holder balance sheet.