Riders of the Storm: Economic Shock & Bank Lending in a Natural Experiment*

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Geographic diversification insulates bank capital from local downturns. Therefore, diversified banks should be better able to maintain lending in markets hit by a negative shock than local banks. Using recent U.S. hurricanes as a natural experiment, I show that the opposite holds. Mortgage credit demand in affected areas is predominantly satisfied by banks whose activities are concentrated in these markets. I show that these banks circumvent capital constraints by funding marginal lending through loan sales. Therefore, the benefits of diversification for access to credit seem to materialize through secondary markets rather than via diversified banks' lending. I argue that informational frictions are key to explain the prevalent role of local banks in serving distressed markets. Downturns exacerbate the opacity of borrowers and collateral values, thereby giving an advantage to lenders with a larger ability or incentive to process soft information. This also increases the probability of adverse selection.

KEYWORDS: Bank lending, diversification, information, securitization, mortgage market, Home Mortgage Disclosure Act (HMDA).

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1. Introduction

The ability of a local economy to overcome a negative shock may hinge on access to bank credit. The increasing prevalence of geographically diversified banks plays an ambiguous role in that context. On the one hand, diversified lenders should have an advantage in serving markets hit by a downturn compared to local lenders. This is because lending and borrowing across imperfectly correlated markets better insulates their capital from local shocks. On the other hand, these banks may face higher costs than local banks in doing so. In particular, if the shock also exacerbates the opacity of borrowers and collateral values, banks who concentrate on few markets may have a better capacity to collect and proceed relevant soft information, or to communicate it within the firm. This theoretical ambiguity makes clear that the role of diversification in shaping credit allocation following an adverse local shock is an empirical matter. Despite their importance in the still vivid debate about the merits of cross-market banking integration, there is little evidence about the relative accuracy of those conflicting hypotheses. This is not least so because identifying the causal effect of a local downturn on lending requires addressing the endogeneity of bank credit and economic activity.

This paper fills this gap by tracking the allocation of mortgage lending in the wake of an unambiguously exogenous local shock. I exploit the devastating 2005 U.S. hurricane season as a natural experiment. The shock results in severe losses of collateral in affected areas and, consequently, to downward pressure on the capital of banks with large exposure to these markets. I document that exposed banks also register substantial inflows of core deposits resulting from affected homeowners cashing in insurance payouts. This contradictory combination closely resembles patterns observed following financial crises (Acharya and Naqvi, 2012). Despite these remarkable similarities, hurricanes differ from crises in four important respects. First, they are assigned to borrowers and lenders in a way that is quasi-random by nature. Second, while crises may be caused in part by factors correlated with bank credit, hurricanes are unambiguously exogenous phenomena. Third, their occurrence and their severity are generally unpredictable (Nordhaus, 2010). Finally, their impact remains confined to a clearly identifiable subset of the cross-section of lenders and borrowers.

Combined, these factors enable to identify the causal effect of a local shock on bank lending by comparing the post-shock change in lending across differently exposed banks. This identification strategy exploits the fact that the shock should disproportionately affect banks with larger exposure to affected areas. To implement it, I first use information on the location-specific wind intensity of hurricanes to construct a *county-specific* binary variable determining which county suffers significant destruction. Second, using information on the county-specific location of bank branches prior to the shock, I aggregate this proxy to a continuous *bank-level* variable, measuring the extent to which a bank is exposed to the shock as a whole[1]. By interacting the county- and bank-level exposure proxies, I identify how differently exposed banks allocate credit across affected and unaffected markets in response to the shock. To evacuate confounding demand factors, I systematically include county-year fixed effects[2].

I assemble a panel of bank-county-level mortgage lending data collected under provisions of the Home Mortgage Disclosure Act (HMDA). The sample covers lending by 2475 commercial banks in eight U.S. states over the 2002-2007 period. Mortgage lending is an ideal testing ground for three main reasons. First, in contrast to the extensively studied small business lending market, it is not subject to any form of market-financed substitute. Second, the mortgage market accounts for 30% of U.S. credit markets (Gan and Riddiough, 2008), and the crisis has been a timely reminder of its pivotal importance for economic activity. Finally, the HMDA data permits to precisely track the county-specific distribution of the *flow* of loan originations.

Results The paper's main findings are the following. First, I test the two conflicting hypotheses on the effect of bank exposure to markets hit a by a negative economic shock on local credit supply. Under a "substitution" hypothesis, exposed banks are capital-constrained following the shock because of asset loses and increasing portfolio opacity. In contrast, their capital being largely shielded from the shock, banks with limited exposure to shocked markets can step in for shocked banks in serving borrowers in affected markets. Therefore, mortgage lending in affected counties *increases* with a bank's exposure to shocked counties. Under a "segmentation" hypothesis, the opposite occurs. The cost of lending in affected markets decreases with bank exposure to these markets. This is e.g. the case if banks with large exposure have access to a small range of alternative investment opportunities - thereby decreasing the opportunity costs of lending in markets characterized by heightened risk - or if those banks are more efficient in collecting, processing and communicating soft information necessary to screen borrowers in markets characterized by heightened opacity.

I find strong evidence in favor of the "segmentation" hypothesis. The growth of mortgage lending in counties hit by the hurricanes increases with banks' exposure to affected counties. This result is robust to a number of alternative sample and variables definitions. I further show that exposed banks ration credit in unaffected areas, consistently with the idea that local shocks are transmitted across areas via cross-market banks (Peek and Rosengren, 1997). Overall, this implies that exposed banks do not only lend more in affected areas, but also actively re-balance lending from non-affected to affected areas.

Second, I distinguish loans retained on the originator's balance sheet from loans sold into the secondary market. I show that the positive association between lending growth in affected coun-

[1] I find qualitatively similar results using the pre-shock county-specific location of bank mortgage lending flows.
[2] This identification set-up is close in spirit to Khwaja and Mian (2008) and Gilje et al. (2013).

ties and bank-level shock exposure is predominantly driven by the growth in *sold* loans. This shows that banks exposed to asset losses effectively circumvent capital constraints by making use of off-balance sheet loan funding. While local banks specialize in screening loan applicants in affected areas, they transfer the resulting credit risk to agents with a better ability to bear it. Therefore, while diversified banks' lending does not appear to support credit supply in affected markets, this result suggests the existence of *indirect* diversification benefits accruing from the existence large, diversified secondary market participants.

Third, I show evidence for the role of informational frictions in explaining the prevalence of the "segmentation" hypothesis. Under normal circumstances, mortgage loan underwriting is largely based on hard information such as credit scores, which is accessible to the entire cross-section of lenders (Stein, 2002). I conjecture that the shock overturns this symmetry. This is because the increase in correlated (local-level) risk and the inability of credit scores to accurately predict default risk in a distressed state-of-the-world reduce the precision of hard information as sole signal of creditworthiness. This increases the need to extract and process soft information on loan applicants, collateral values and local markets in affected areas. I argue that lenders with strong exposure to affected areas have both a larger ability and incentive to do so. Empirical evidence confirms this prior. Using the distance between the borrower and the bank's headquarter as a proxy for the ability of a bank to acquire and process soft information in a particular market, I find that exposed banks predominantly increase lending in those affected markets which are closer to their headquarter.

I investigate several alternative hypotheses to the informational channel. First, concerns about the negative externalities of a credit shortage may encourage locally dominant banks to maintain lending in distressed markets. Second, loan sales could constitute a way for banks exposed to a negative shock to restore balance sheet capitalization and liquidity. Third, borrowers in affected could match themselves to lenders in a non-random way. Finally, exposed banks may have been more sensitive to regulatory and political incentives designed to encourage lending in affected counties. I show that accounting for these alternative hypotheses does not invalidate the empirical significance of the informational channel.

Evidence for an increasing importance of soft information and loan sales in affected markets raises the question of adverse selection. Using the share of accepted loans as a proxy for lending standards (Dell'Ariccia et al., 2012), I find that exposed banks tighten lending standards on loans originated in affected areas they retain on their balance sheet, and loosen standards on loans they eventually sale. Hence, securitization not only improves the availability of credit because it relaxes capital constraints, but also because it goes along with more lax underwriting standards. Finally, I study why the secondary market for mortgage loans originated in affected markets does not break down because of the possibility of adverse selection. I find that the easing of credit quality requirements on loan purchases in affected areas by Government-Sponsored Enterprises (GSEs) can explain this outcome.

The remainder of this paper proceeds as follows. Section 2 reviews existing literature and highlights this paper's contribution in greater details. Section 3 provides background information on the experiment this study uses and describes related data. Section 4 develops the main hypotheses sketched in the introduction and outlines the identification strategy used to evaluate them. Section 5 discusses the paper's results and their robustness. Finally, Section 6 concludes.

2. Existing Literature & Contributions

The findings of this paper have links to four main active areas of research in both macroeconomics and finance.

First, the paper's results contributes to a large literature on the benefits of intra- and inter-state banking integration in the U.S.. A key expected benefit of integration is to reduce the severity of local shocks. Being more shielded from local shocks, geographically diversified banks can step in for capital-constrained local banks. Consistently, Morgan et al. (2004) show that inter-state banking has reduced State GDP volatility. More generally, geographically integrated credit markets provide households with an *indirect* way to smooth negative local shocks (Asdrubali et al., 1996; Demyanyk et al., 2007).

These studies rely on regional macroeconomic aggregates, thereby treating actual credit allocation patterns as a "black box". Moreover, the overall effect of banking integration for the severity of a local shock remains ambiguous from a theoretical point of view. Multi-market banks may also find it profitable to shift capital towards away from affected markets (Morgan et al., 2004). Telling conflicting hypotheses apart thus requires using highly disaggregated data. There is very limited relevant evidence. An exception is Keeton (2009), who shows that multi-market banks' small business lending is less responsive to local economic declines. Using mortgage lending data, I find the opposite result. Following a local shock, lending is predominantly devolved upon banks which are themselves heavily exposed to the shock. I also show that the bulk of this lending is funded by loan sales. Overall, the contribution of my paper is to show that in the case of the mortgage market, the gains of diversification may rather stem from the secondary market rather than from direct lending by diversified banks.

My paper also adds to a subset of this literature which stresses that U.S. credit markets are still subject to geographic segmentation despite the dramatic increase in cross-market banking integration and the diffusion of hard information. Becker (2007) uses the share of elderly population in U.S. metropolitan areas to demonstrate that local deposit supply influences local economic outcomes. Gilje (2012) exploits shale gas discoveries to show that local deposit supply affects the number of business start-ups. The effect is the strongest in industries with high reliance on external finance and in counties with large presence of small banks. Those two papers focus on small business lending, a market in which segmentation appears as a more natural outcome given its informational intensity. Also using shale gas booms, Gilje et al. (2013) complete these findings by showing that deposit-rich banks increase mortgage lending in neighboring, non-boom states. Critically however, these spillovers are limited to those markets where they have a branch presence, consistently with the existence of informational frictions.

The novelty of my paper is to exploit a natural experiment in which a positive deposit shock coincides with a local macroeconomic downturn. This allows me to make two additions to this literature. First, in the case of a counter-cyclical deposit shock, the findings of Gilje et al. (2013) are reversed. Specifically, banks exposed to deposit windfalls do not "export liquidity" to outside counties, but rather increase lending in those counties where the shock originates. Second, banks exposed to a deposit shock rather finance incremental lending by selling loans than by using deposits. Combined, those two findings imply that a negative shock in a subset of counties increases the geographical segmentation credit market, but that this effect is limited to loan *origination*. In contrast, the segmentation of loan *financing* effectively decreases in affected markets, with secondary market participants funding the bulk of post-shock lending.

Second, while the focus of the present paper is on *intra-national* banking integration, my paper adds to a burgeoning literature focusing on international banks as vehicles for the transmission of financial shocks across borders. First, banks transmit shocks originating in home countries to host markets, whether funding shortages (Schnabl, 2012), asset losses (Peek and Rosengren, 1997) or both (Popov and Udell, 2012). Second, shocks in host markets are transmitted to home markets, whether funding shocks in international markets (Aiyar, 2012) or losses on foreign assets (Puri et al., 2010). I add to these findings by showing that banks exposed to a negative financial shock in a subset of U.S. counties ration lending in counties left unscathed by the shock. While most aforementioned studies use the recent crisis as laboratory, my results reinforce the credibility of the underlying exogeneity assumption by exploiting an adverse event which clearly originates outside the banking sector. Moreover, while the financial and economic crises have ultimately impacted substantial number of markets, the shock I exploit is clearly localized, which enables a cleaner experimental set-up.

Typically, these studies concentrate on the spillover of financial shocks into regions distant from that where the shock originates as a way to attenuate confounding demand factors. This leaves with little evidence as to credit allocation patterns in distressed markets. In this paper, I concentrate on the latter dimension. I ensure that demand-specific factors are controlled for using county-year fixed effects. My contribution is to show that banks exposed to a negative shock may ration credit in unaffected markets because lending in a distressed market becomes more profitable for banks with strong local ties. This finding coincides with Giannetti and Laeven (2012). Using syndicated lending data, they show that banks hit by a negative shock in their home market *increase* home lending (a ”flight home effect”). The pattern is even more striking in my case, given the magnitude of the shock experienced by borrowers in home markets.

Third, this paper also relates to the literature focusing on loan sales and securitization. A group of studies stresses the agency problems resulting from the originate-to-distribute model and their role in deteriorating credit quality during the run-up to the recent crisis (Keys et al., 2009). Banks selling loans have both a smaller incentive to screen and monitor lenders (moral hazard problem), and an incentive to sell the lowest quality loans (adverse selection problem). Another string of the literature argues that securitization is beneficial because it allows lenders to circumvent local funding shortages (Loutskina and Strahan, 2009).

This paper contributes to this literature by providing evidence for both the ”bright” and ”dark” sides of securitization in a state-of-the-world characterized by heightened uncertainty about borrower creditworthiness. First, loan sales improve credit availability in an area suffering a negative shock because they allow local banks to exploit their knowledge of local markets while circumventing their smaller ability to bear the associated credit risk. This is consistent with the model of Carlstrom and Samolyk (1995), whereby local banks have a comparative advantage in screening local lenders, but have a disadvantage in retaining the associated loans. To my knowledge, there is no existing empirical evidence for this hypothesis. Second, I show that banks accept a larger share of loans they eventually sell, consistently with a deterioration in lending standards.

Fourth, my results add to a literature focusing on the role of the state-contingent allocation of information in credit markets. In Dell'Ariccia and Marquez (2006), the degree of asymmetric information across lenders is higher during economic downturns. Consistently, Dell'Ariccia and Marquez (2004) suggest that banks concentrate on their most opaque borrowers when confronted with an exogenous cost shock (”fly-to-captivity”). Those two papers focus on small business lending, a market where soft information - and thus, borrower captivity - is key. The contribution of my paper is to provide consistent evidence in the case of mortgage lending, a market presumed to largely rely on hard information under normal circumstances (Stein, 2002). I argue that the increase in borrower and market opacity in shocked areas rises the return to collecting soft information about local borrowers and markets[3].

[3] From a methodological point of view, this paper also adds to a small literature focusing on the effect of natural shocks on bank-specific outcomes. Kaoru et al. (2012) exploit the 1994 Kobe earthquake to show that a bank-level negative shock affects lending to firms outside the disaster area. Berg and Schrader (2012) investigate the impact of natural disasters on emerging market banks. They show that banks shield those firms with which they maintain lending relationships. My findings are consistent with those two results, with banks exposed to the hurricane rationing credit in unaffected markets and increasing lending in ”core” home markets. My contribution is to document the existence of similar patterns in a market and a country where informational frictions are presumed to be much less prevalent.

3. Background Information & Data

This Section provides background information about hurricanes and their effect on lenders and borrowers. It then describes the data and method uses to measure exposure county- and bank-level exposure to the hurricanes.

3.1. Hurricanes & Banks

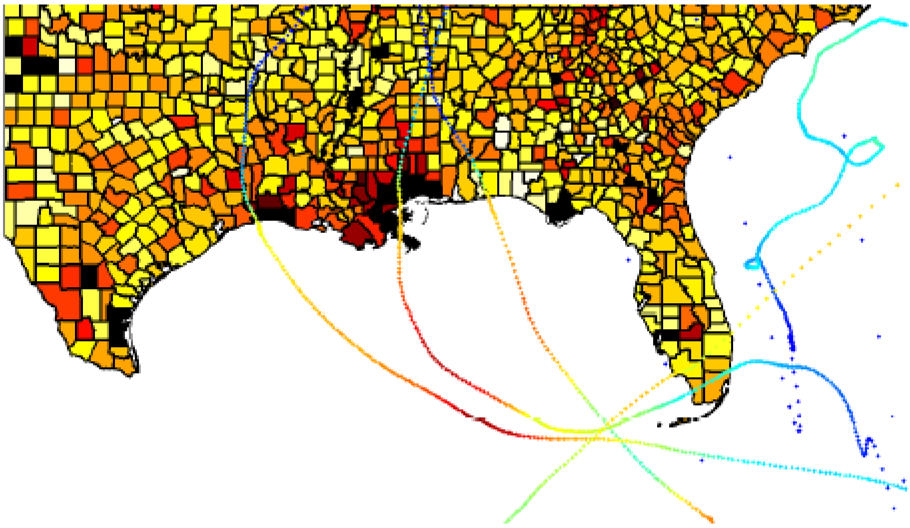
In this article, I concentrate on the 2005 U.S. hurricane season[4]. It has entered record books for having caused the costliest damages in a century. Hurricane Katrina alone is estimated to have destroyed 210'000 houses (Brown, 2005) and caused monetary losses of 108 Bio. USD (Blake et al., 2007). Hurricanes Wilma, Rita and Dennis have generated damages amounting respectively to 21, 12 and 2.5 Bio, which ranks them all in the top 20 of costliest hurricanes from 1851 onwards (Pielke Jr et al., 2008).

Anecdotal evidences suggest that banks with substantial exposure to affected areas have been confronted with three main challenges (Brown, 2005). First, the deterioration of local housing stocks has impaired local banks' assets. In the months following Katrina, mortgage delinquency has e.g. culminated to 24.6% in the New Orleans area. This partly because of households' imperfect insurance coverage. The share of housing insured for flooding damages in FEMA-disaster zones was between 30 and 60% in Louisiana and 10% in Mississippi (Brown, 2005). Second, the downward pressure on capital exterted by asset losses has been compounded by simultaneous surges in deposits. Counties exposed to hurricane-strength winds have registered a median deposit growth of 24% during the year following the shock. This is all the more striking given that those counties have also experienced substantial drops in population. Figure 1 helps to vizualise the spatial distribution of abnormal county-level deposit growth numbers. This makes clear that affected counties are located in the vicinity of hurricane landfalls. Anecdotal evidence suggests that deposit surges are explained by an influx of transfer payments into affected areas (Brown, 2005). Katrina alone has generated claims in excess of 23 Bio. USD under the National Flood Insurance Program (NFIP), more than the entire NFIP claim history (Bagstad et al., 2007).

Deposit surges in affected counties have not only proved sizable, but also lasting. For a majority of counties, the surge observed in 2006 does not appear to have reversed during subsequent years. This suggests that a substantial share of insurance pay-outs could not be immediately re-invested to replace damaged housing. There were widespread doubts as to whether severely affected regions would ever recover from the shock (Vigdor, 2008). The associated uncertainty may have induced households to increase precautionary savings. If this is the case, a third chal-

[4]Hurricanes are formally defined as a class of tropical cyclones forming in the Atlantic or North Eastern Pacific oceans and generating winds in excess of 74 miles-per-hour.

FIGURE 1: 2005 HURRICANES & COUNTY DEPOSIT GROWTH



Notes: This figure plots county-level median deposit growth from 2005 to 2006. Darker shades indicate stronger deposit growth. Tracks of 2005 hurricanes season (multicolored lines intensity is a function of wind speed) are from NOAA best track estimates.

lenge for exposed banks comes in the form of a deterioration of their long-run franchise value.

The magnitude of the increase in deposits raises the question of whether the availability of credit was an issue at all in affected regions. There is substantial anecdotal evidence that credit supply was considered insufficient to meet the needs brought about by the devastation. The post-disaster months saw the emergence of a myriad of governmental program designed at encouraging small business and mortgage lending in disaster areas[5].

3.2. Measuring Hurricane Exposure

Identifying the mechanism of interest rests on delineating those counties and banks that are exposed to the shock. I now outline the strategy followed to do so.

County-Level Exposure Insurance literature provides with a broad array of techniques to predict the magnitude of local-level economic damages caused by a hurricane. Mendelsohn et al. (2012) argue that it should be a function of the local-specific (i) hurricane intensity, (ii) vulnerability of the capital stock and (iii) degree of insurance coverage. In the context of the present paper, there at least two good reasons for abstracting from the second and third dimensions. First, relevant variables, whether observable or unobservable, may be correlated with explana-

[5]Office of the Comptroller of Currency (2011): ”Rebuilding the Gulf Coast: How Banks Can Help”.

tory variables of interest. For instance, banks located in a county with poor quality housing may also have weaker balance-sheets *ex ante*. Second, if any, those variables should be time-invariant. Since my main model includes county-year fixed effects, I allow for both a heterogeneous direct and indirect, non-supply-driven impact of hurricanes over the whole window under study.

My main proxy for the magnitude of local-level economic therefore uses the sole local-specific physical strength of hurricanes. I use the most common metric, wind intensity. Related studies restrict themselves to measuring wind speed along the eye of the hurricane (Belasen and Polachek, 2008). However, economic damage can largely spill over that narrow band (Strobl, 2011). I thus use H*Wind field estimates computed by NOAA, which reconstruct wind speed over a comprehensive grid of points located around hurricane tracks. I then map the grid onto county borders. Figure 2 illustrates the result of this exercise.

To link the county-specific wind speed to the predicted magnitude of economic damages, I rely on dummy variables based on the most universal damage scale. The Saffir-Simpson Scale (SSC) ranks storms based on their maximum wind speed. It predicts "moderate" damages when wind exceeds 94 miles-per-hour (mph). I consider a county as affected if the maximum wind speed in its territory exceeds this threshold. Wind-damage models typically under-estimate hurricane damages brought about by storm surges. This is a significant omission, since flooding damages are typically much more devastating than wind damages (Brown, 2005). I thus additionally consider a county as affected if some surge is observed within its borders. I use the Southern Climate Impacts Planning Program's (SCIPP) SURGEDAT database to do so. The resulting subset of counties considered as affected is displayed in Figure 3.

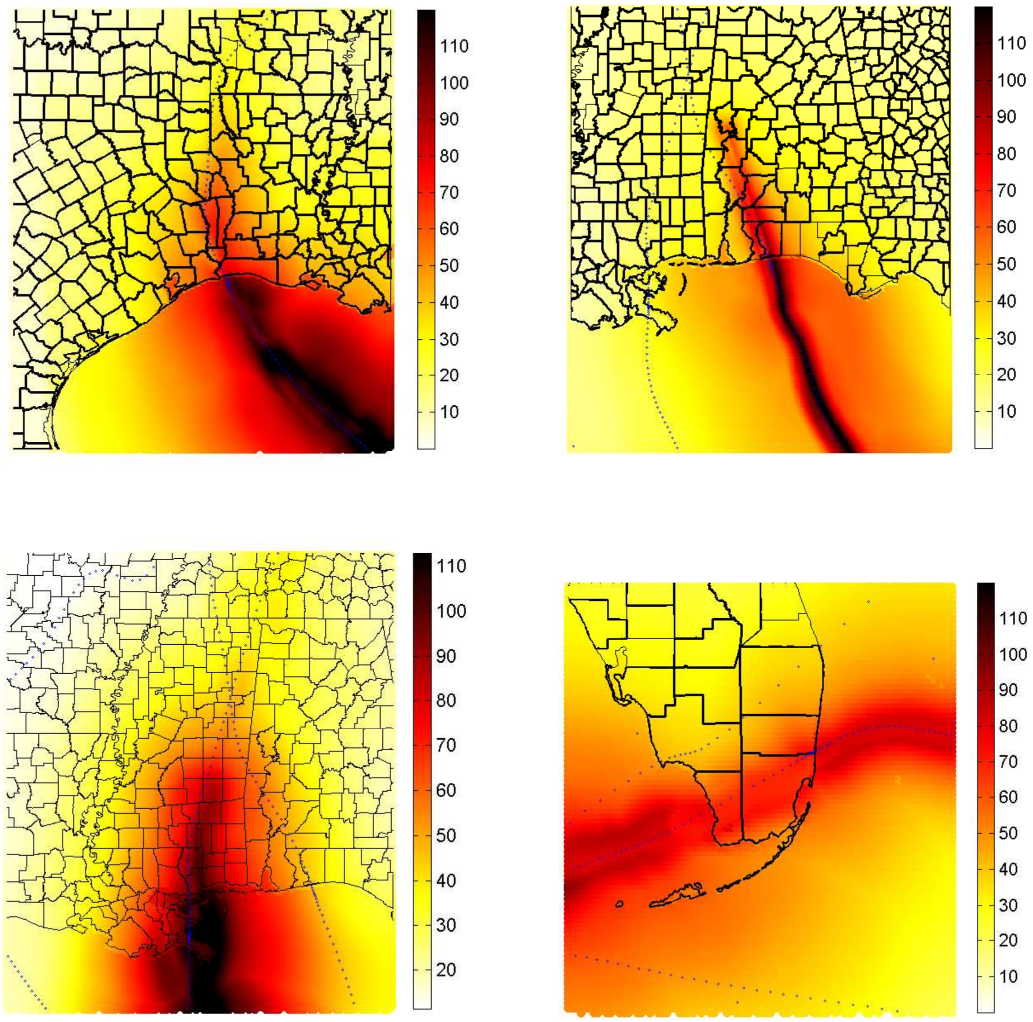
Bank-Level Exposure I assume that credit allocation decisions are made at the bank headquarter-level. I therefore aggregate the county-level exposure proxy to a bank-level variable. To do so, I use information about branch locations from the FDIC's Summary of Deposits. Specifically, I calculate the share of b's branches in county c as

$$Share_{b,c,pre} = \frac{Branches_{b,c,pre}}{Branches_{b,pre}}. \tag{1}$$

Banks may open ad hoc branches following a hurricane, e.g. in an attempt to collect insurance money flowing into disaster area. To rule out this possibility, I use branch locations data from the year preceding the disaster (July 30, 2005 vintage). I then aggregate this variable at the bank level using a simple weighting such as

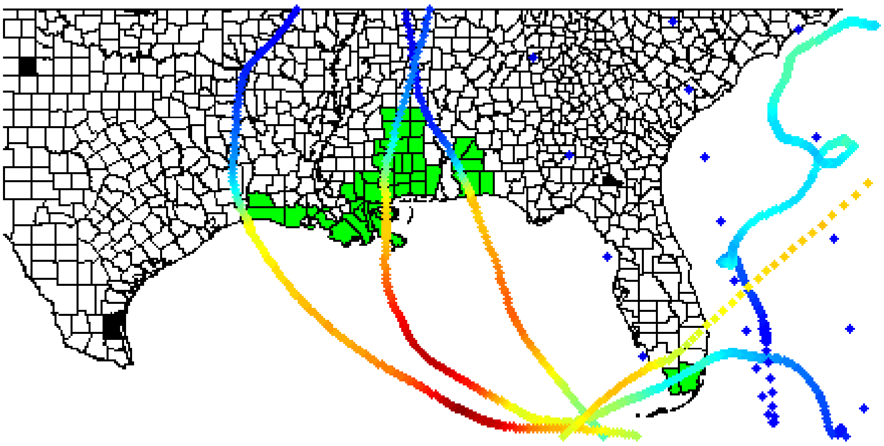
$$Exposure_{b,t} = \sum_{b=1}^{B} Share_{b,c,pre} \cdot Affected_{c,t}. \tag{2}$$

FIGURE 2: LOCAL-SPECIFIC WIND INTENSITY



Notes: This figure plots local-level wind intensity estimates from NOAA's H*Wind field model. The four panels respectively display field estimates for hurricanes Rita, Dennis, Katrina (Louisiana landfall) and Katrina (Florida landfall). The right scale corresponds to the wind strength estimate, recorded in miles-per-hour.

FIGURE 3: AFFECTED COUNTIES: BASELINE DEFINITION



Notes: This figure plots counties classified as $Affected_c$ according to the baseline definition (hurricane-force winds and surges). Hurricane tracks (multicolored lines) are from NOAA's best track estimates.

3.3. Lending & Bank Data

I construct a panel of bank-county-year mortgage loan originations for the 2002-2007 period. The baseline panel includes lending in eight states located in the broad region of 2005 hurricane landfalls, and which are themselves also subject to hurricane strikes : Texas, Louisiana, Mississippi, Alabama, Georgia, Florida, South Carolina and North Carolina. Since hurricanes struck from August to September 2005, the panel covers three years and a half before the shock, and two years and a half after. Adopting a large window may be necessary to fully capture credit reallocation dynamics in the aftermath of the shock.

I use data from a transaction-based mortgage lending registry collected under provisions of the Home Mortgage Disclosure Act (HMDA dataset). The unfiltered 2002-2007 sample of HMDA contains a total of 204.7 million transactions. HMDA data covers lending by commercial banks, credit unions, savings associations and mortgage companies. Since branching information is available for commercial banks only, I discard the remaining lender categories. This entails eliminating 20% of the flow of originated loans for the median county. The representativity of the resulting sample for the population of commercial banks with mortgage lending activity is high[6].

[6] A few banks only do not meet the criteria for mandatory reporting under HMDA. First, banks are exempted if their total assets falls below a threshold value. The latter changes over years, ranging to 32 (in 2002) to 36 Mio. USD (in 2007). Second, banks which do not have at least one branch office in a Metropolitan Statistical Area (MSA) are also dispensed to report. Overall, those two excluding criteria result in a less precise coverage of the behavior of small institutions active in rural areas.

For each transaction, banks are required to provide with an array of loan- and applicant-level information. I use those to compute borrower controls (see Table 3 for definitions).

I complement mortgage data by collecting a series of standard bank-level controls defined under Table 3. Data comes from regulatory filings (Call Reports), which I match with HMDA data using banks' regulatory identification numbers.

4. Hypotheses & Identification

In this Section, I outline the main hypotheses that this paper tests, before explaining the identification strategy I use to investigate them.

Hypotheses The overall effect of bank exposure to the hurricane shock on lending in affected counties should depend on the relative weight of two conflicting hypotheses. On the one hand, exposure to affected areas should go along with a smaller ability to finance profitable investment opportunities in affected counties. If the shock decreases the value of their loan portfolio, exposed banks may lack the necessary capital to sustain lending to borrowers with a higher average risk (lower collateral value). Moreover, they may have difficulties raising additional outside capital if they cannot credibly communicate the value of their outstanding assets to investors (Stein, 1998). In comparison, banks with more geographically diversified sources of funding and loan portfolios may be in a better position to absorb losses and to channel capital into affected areas through internal capital markets (Morgan et al., 2004). Under this hypothesis, we have that:

> H1: **Substitution** - Lending growth in affected counties *decreases* with bank-level exposure to the shock.

Following Berrospide et al. (2013), I label this hypothesis "substitution" because under this scenario, affected borrowers are predominantly served by diversified (unexposed) lenders.

On the other hand, more diversified (less exposed) banks face higher opportunity costs in extending lending to borrowers with lower collateral value if they have a better access to profitable investment opportunities in unaffected counties (Morgan et al., 2004). Alternatively, banks with limited exposure to shocked markets may be less efficient in collecting, processing and communicating soft information necessary to screen borrowers in markets characterized by heightened opacity. Regardless of the underlying mechanism, more exposed (less diversified) banks have a comparative advantage in lending in affected counties. They predominantly increase lending in affected counties or, equivalently, ration less in affected counties. Either way, we have that:

> H2: **Segmentation** - Lending growth in affected counties *increases* with bank-level exposure to the shock.

I label this hypothesis ”segmentation” because under this scenario, exposed borrowers are predominantly served by local (exposed) lenders. Formally, the ”substitution” (”segmentation”) hypothesis predicts that the marginal effect of $Exposure_b$ on lending in $Affected_c$ counties is negative (positive). This paper does not claim that either of these is true in a binary fashion, but rather tries to evaluate which one is quantitatively dominant.

Identification Strategy The empirical model used to test the ”substitution” and ”segmentation” hypotheses writes:

$$\begin{aligned} \Delta Loan_{b,c,t} &= \beta_1 \cdot Exposure_{b,t} + \beta_2 \cdot Affected_{c,t} \times Exposure_{b,t} \\ &+ \beta_3 \cdot BankControls_b + \beta_4 \cdot BorrowerControls_{b,c,t} \\ &+ CountyF.E._{\cdot c,t} + \epsilon_{b,c,t}. \end{aligned} \tag{3}$$

$\Delta Loan_{b,c,t}$ measures the yearly change in bank b's total mortgage loan originations in county c. $Exposure_b$ is a proxy for the sensitivity of bank b to the hurricane shock, as measured by the share of bank b's branches located inside affected counties before the shock (Section 3.2). $Affected_c$ is a county-level proxy for the local severity of the hurricane. It is equal to one for years 2005 to 2007 if county c is located within the geographical zone considered as significantly affected (Section 3.2)[7].

The interaction term $Affected_{c,t} \times Exposure_{b,t}$ identifies whether banks that differ along their relative exposure to the shock re-balance lending differently across affected vs. unaffected counties. If higher $Exposure$ decreases the ability of banks to provide credit in affected counties (H1 - ”Substitution”), I expect β_2 and $\beta_1 + \beta_2$ to be significant and negative. If higher $Exposure$ increases the tendency of banks to reallocate credit away from affected counties (H2 - ”Segmentation”), I expect β_2 and $\beta_1 + \beta_2$ to be positive and significant. Taken in isolation, β_1 quantifies how banks change their lending in non-affected counties following an exogenous balance-sheet shock.

$CountyF.E._{\cdot c,t}$ is a county-year fixed effect. There are two main reasons to include them. First, the magnitude of county-level economic destruction for a given hurricane intensity should depend on local economic characteristics such as the quality of local housing or the degree of insurance coverage. This could deem the assumption that $cov(\Delta Loan_{b,c,t}, \epsilon_{b,c,t}) = 0$ to be violated. If banks with substantial exposure to those counties e.g. also have less healthy balance-sheets ex

[7]Since model 3 systematically includes county-year fixed effects, the county-level proxy for the local impact of the shock is effectively dropped from the model. An unfortunate characteristic of HMDA data is the lack of timing information beyond the sole year of origination. Since the hurricanes I consider struck from late August (Katrina) to mid October (Wilma), I cannot distinguish those 2005 loans originated after the storm from those issued before. If any, considering 2005 as a post-storm year should be more conservative since any relevant post-hurricane change may be blurred by developments in the earlier part of the year

ante and ex post, this introduces a positive bias between $\Delta Loan_{b,c,t}$ and $\epsilon_{b,c,t}$. Focusing on variation across banks within a same county-year pair allows to avoid these two caveats by ensuring that I compare how different banks react *to a same shock*.

Unbiased estimation of β_1 β_2 using Ordinary Least Square (OLS) is warranted if $Affected_c$ and $Exposure_b$ are both credibly exogenous to any observable or unobservable variable which potentially belongs in 3, and truly unexpected. The stochastic nature of hurricane strikes in both time and spatial dimensions ensures that this should not be any cause for concern. However, the spatial distribution of hurricanes is not entirely random. In the U.S., they systematically hit a certain portion of the territory, which consists of the Gulf of Mexico and North-Atlantic coasts. Credit market participants in those regions may systematically differ from the population of interest. If any however, this heterogeneity should be time-invariant, such that county fixed-effect alleviate any related concern. A second concern is that the the occurrence of hurricanes over the years follows a vaguely deterministic pattern. For instance, hurricanes hit the New Orleans about each 11 years (Kates et al., 2006). However, their magnitude, path and destructiveness ultimately remain unpredictable. Moreover, there is no generally documented pattern of lasting effect of hurricane on banks before the 2005 season which could justify concerns about anticipation (Brown, 2005).

5. Results

This Section outlines the paper's results. First, I show that borrowers in affected markets are predominantly served by banks with large exposure to the shock, consistently with the ”segmentation” hypothesis (Section 5.1). Second, I show that this incremental lending is financed through loan sales rather than by marginal deposit inflows (Section 5.2) . Third, I show that informational frictions are key to explain the dominance of the ”segmentation” hypothesis (Section 5.3). Fourth, I discuss alternative explanations (Section 5.4). Finally, I discuss the implications of the increasing usage of soft information for adverse selection and the liquidity of secondary mortgage markets (Section 5.5).

5.1. Main Results: Substitution vs. Segmentation

Table 4 displays the main results of OLS estimation of model 3. I look for evidence for the ”substitution” and ”segmentation” hypotheses by focusing on the interaction of county- and bank-level exposure to the hurricane shock ($Affected_c \times Exposure_b$), as well as by the sum of $Affected_c \times Exposure_b$ and $Exposure_b$, which captures the effect of bank-level shock exposure *in affected counties*. Negative (positive) corresponding coefficients indicates that the ”substitution” (”segmentation”) dominates. Across a range of different variants of model 3, I find consistent support for the hypothesis that borrowers in affected counties are predominantly served by banks with a large exposure to affected regions ("segmentation" hypothesis).

Starting with Column (1), the interaction term $Affected_c \times Exposure_b$ is positive and statistically significant (.305***)[8]. Adding the corresponding coefficient to $Exposure_b$ shows that in affected counties, lending increases with $Exposure_b$ by a factor of 18.6% (.186**). Columns (2) and (3) repeat the same regression adding bank-level controls and county fixed-effects, respectively. These different specifications yield similar findings. Results show that lending in affected counties *increases* with bank-level exposure by a factor of .216*** and .137*, respectively. This suggests that observable heterogeneity across differently exposed banks, or unobservable heterogeneity across counties does not drive the main finding. Finally, Column (4) displays the results of the preferred specification, i.e. the within-county-year model 3. Results make it clear that my main result is robust to controlling for any variables affecting all lenders and borrowers within a same county-year pair. The coefficient on the interaction of interest is again statistically significant and economically sizable (.260***). Adding the coefficient on $Exposure_b$ implies that in affected markets, lending growth increases linearly with $Exposure_b$ by a factor of .119*. Overall, adding county-year fixed effects decreases the significance of bank-level exposure and the interaction between $Exposure_b$ and $Affected_c$. This suggests that county-year-level factors such as, in first line, changes in credit demand and collateral quality account for a non-negligible share of the observed relationship between lending growth and bank-level shock exposure.

Since it does not include county fixed effects, the regression in Column (1), provides with a parametric estimate for the county-level affectedness proxy ($Affected_c$). I find that lending growth decreases by 15.9%*** in affected counties, holding bank-level exposure fixed. A simple calculation indicates that lending growth in affected counties *increases* after the shock for banks with $Exposure_b$ larger than 52% (.159***/.305***), which lies below mean exposure among treated banks (71%).

Results simultaneously allow investigating whether banks confronted with a negative shock in a subset of markets transmit the shock to unaffected markets, in line with a large literature starting with Peek and Rosengren (1997). I look for corroborating evidence by focusing on the coefficient of $Exposure_b$, which captures the effect of bank-level shock exposure on lending growth *in unaffected counties*. Bank-level exposure enters with a negative sign and is statistically significant in all four specifications. The magnitude ranges from -.118* to -.164**. This suggests that in unaffected counties, exposed banks ration credit compared to unexposed banks.

Robustness I now show that the main results in Table 4 are not sensitive to various changes in variable definitions and the specification of the panel. First, I have so far implicitly assumed that credit allocation decisions are made at the bank level. This does not have to be true. The number

[8]*, ** and *** indicate significant at 10, 5 and 1%, respectively.

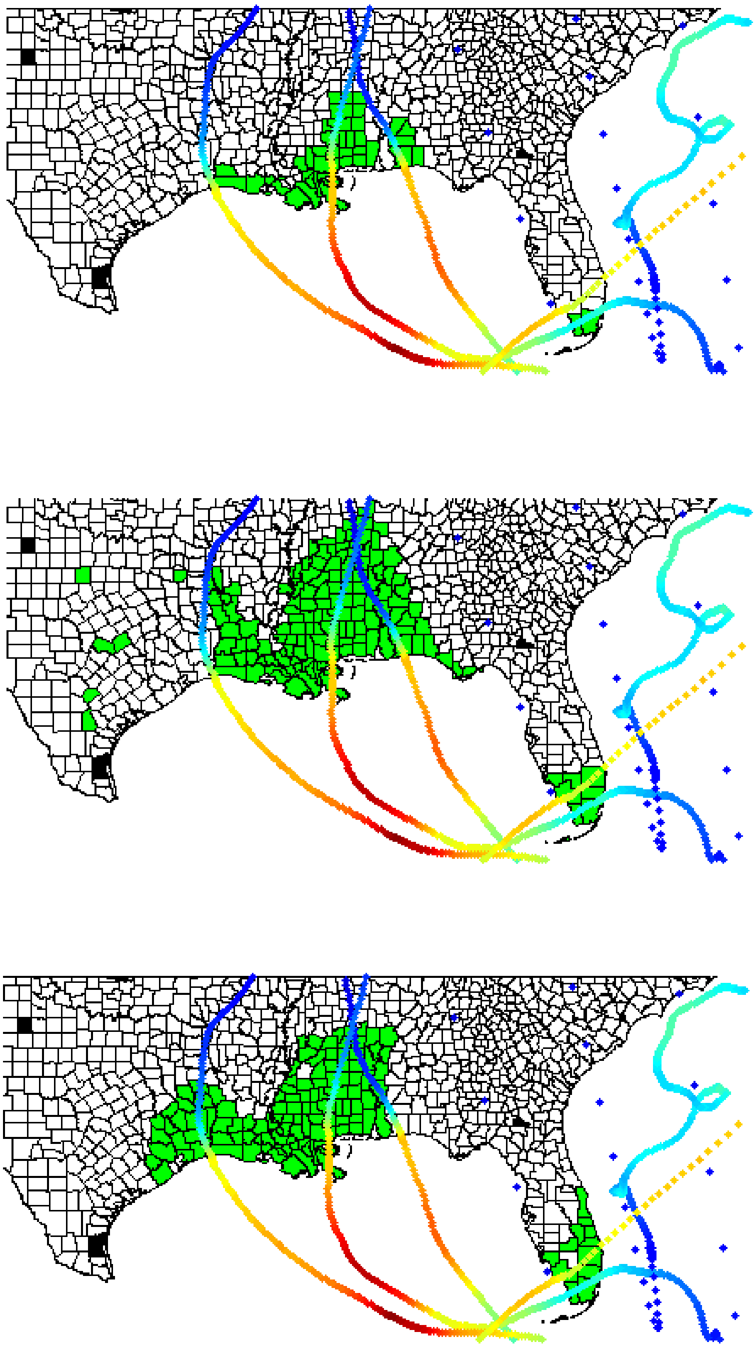
of U.S. banks affiliated to a Bank-Holding Company (BHC) has increased drastically over the last three decades. This may impact my findings along two dimensions. First, access to a BHC-level Internal Capital Market (ICM) insulates banks from changes in the availability or price of external funding (Houston et al., 1997). Therefore, assuming that bank-level shock exposure goes along with lower ability to finance lending may be inaccurate. Second, the assumption that the ability to re-allocate capital across market depends negatively on bank-level exposure may be equally inexact. Column (1) in Table 5 thus re-estimates the main equations of interest, assuming that $Exposure_b$ is determined at the BHC-level. I re-calculate $Exposure_b$ using information on the geographical distribution of bank branches across all banks within a same BHC[9]. Conclusion are robust to this change in both magnitude and significance.

Second, the explanatory variables could be subject to measurement error due to the non-linear nature of hurricane damages (Nordhaus, 2010). I re-estimate model 3 using two alternative definitions of the affected counties dummy and, by extension, of the bank-level shock exposure. In Column (2) of Table 5, I lower the threshold wind speed value from which counties are considered affected from 94 mph ("moderate damages" in the Saffir-Simpson Scale (SSC)) to 74 mph ("minimal damages" in the SSC). While results remain qualitatively similar, they are no longer statistically significant, which indicates that pooling severely hit areas with mildly damaged one weakens the results. Column (3) uses counties belonging to the Gulf Opportunity (GO) Zone as a dummy variable for $Affected_c$. The GO Zone has been enacted in December 2005 to encourage investment in counties severely affected by 2005 Katrina and Rita. This measure may be subject to political biases. On the other hand, the lag could provide with more accurate definitions of those counties having effectively suffered substantial damage. Either or, results of interest remain intact.

Third, results may be driven by pre-shock trends across differently exposed banks. I thus conduct a simple falsification exercise. I assume that the hurricanes impact the same areas, but that they strike in January 2003. My panel now compares lending growth in 2001-2002 to 2003-2004. Column (5) in Table 5 shows that the explanatory variables of interest are not statistically different from zero. This rules out any role for pre-shock trends. The significance of my results could further be spuriously boosted by serial correlation across individual observations. Bertrand et al. (2004) show that collapsing panels into pre- and post-shock periods provide with standard errors that more conservatively account for this possibility. Column (4) in Table 5 thus re-estimates the baseline model using such a two-period panel. Coefficients of interest remain statistically significant and quantitatively comparable.

[9] The definition of $Exposure_b$ does not change for unaffiliated banks.

Figure 4: Alternative definitions of Affected_c



Notes: This figure compares counties classified as $Affected_c$ according to baseline and alternative definitions. Panel 1 uses the baseline definition, i.e. counties exposed to winds faster than 94mph (”moderate damages” according to the Saffir-Simpson Scale (SSC)). Panel 2 adds counties counties exposed to winds faster than 74mph ”minimal damages” according to the SSC. Panel 3 uses membership in the Gulf Opportunity (GO) Zone. Green shading indicates that county c is considered as affected. Hurricane tracks are from NOAA’s best track estimates. The color is a function of local-specific hurricane wind speed.

5.2. Retained vs. Sold Loan Growth

I have so far implicitly assumed that all mortgage loans are funded on-balance sheets. This is clearly at odds with the drastic changes in the way in which banks finance loans brought about by securitization and loan sales. Loutskina (2011) shows that securitization transforms illiquid loans into tradable ones, allowing banks to insulate lending from shocks to external finance. Consistently with the prior that shock exposure compresses bank capital, I conjecture that the positive effect of $Exposure_b$ in affected counties should predominantly be driven by the growth in sold loans. To test this hypothesis, Table 6 repeats estimation of model 3 while distinguishing between loans which are subsequently sold in the secondary market from those which are retained on the originating bank's books[10].

Column (2) uses the change in sold bank-county-year lending as dependent variable. Results show that in affected counties, sold loan growth increases with bank-level exposure by a factor of 28.3%**. This is more than twice the corresponding coefficient using total loans (0.119*). Column (3) uses the change in retained bank-county-year lending as dependent variable. Results show that the marginal impact of $Exposure_b$ in affected counties is almost zero and statistically insignificant (0.01). Together, these result confirm that the positive effect of $Exposure_b$ on lending in affected counties is primarily driven by sold loans.

A potential caveat of these results is that they use a smaller number of observations than the baseline results in Column (1). This is because observing the change in sold (retained) lending requires a bank to have non-zero sold (retained) lending in a particular county for two consecutive years. Column (4) thus repeats the same regression using the change in the bank-county-year *share* of loans. Results show that the share of mortgages subsequently sold to secondary market participants similarly increases with $Exposure_b$. This reinforces the conclusion that banks exposed to the shock re balance lending towards off-balance sheet funding in affected counties.

5.3. Informational Frictions

Results from Table 4 suggest that banks exposed to a negative shock find it profitable to increase lending in counties affected by the hurricanes. Moreover, results from Table 6 suggest that the bulk of this additional lending is financed by loan sales. Combined, those two findings imply that the cost-benefit trade-off of screening borrowers in affected counties changes differently depending on bank exposure.

I argue that a central explanation for this heterogeneity lies in a differential ability or willingness to overcome informational frictions in a market characterized by increasing uncertainty about borrower creditworthiness. I conjecture that the shock exacerbates the dispersion of infor-

[10]This information is given in the HMDA dataset. However, it is only the case if the sale occurs within the same year as the loan origination. This biases results in an unknown direction.

mation across lenders. In a normal state-of-the-world, soft information should have little value in mortgage market underwriting (Stein, 2002), especially concerning the segment of loans which are typically sold[11]. The widespread usage of Automated Credit Evaluation is thought to have largely eroded the informational advantage of originators. First, credit scores may constitute a sufficient signal of borrower default risk. Second, large and sophisticated banks and secondary market participants may be better at aggregating and processing large-scale information, thereby being more able to assess external conditions and portfolio risks than smaller local lenders.

There are several reasons why the value of soft information may increase following a severe local downturn. First, the magnitude of the shock and the associated rise in correlated risk should increase the importance of assessing *local* risk, as opposed to idiosyncratic (borrower-specific) risk. This should decrease the accuracy of the sole credit score as a signal of default risk. In contrast, an intimate knowledge of local collateral values or recovery prospect should become more valuable. Second, pre-shock credit history may be a poor predictor of creditworthiness in a distressed state-of-the-world[12]. Therefore, knowledge of local customers beyond that derived from hard information should become more valuable. Finally, sophisticated models used by large banks and secondary market participants may lack the necessary data to evaluate increases in correlated (local-level) credit risk following a devastating local shock.

If originating loans in affected counties requires extracting soft information, screening local applicants becomes relatively costlier than in unaffected counties. However, this increase should be felt differently across banks. In particular, banks with large exposure to affected counties may have a cost advantage or a larger relative benefit in screening applicants in affected counties. This is so because banks concentrating on few mortgage markets invest more in soft information under normal circumstances (Loutskina and Strahan, 2011). In doing so, they may accumulate a better knowledge of local borrowers and housing markets, hence better able to evaluate collateral values and economic prospects in a distressed environment.

A large number of studies focusing on small business lending use the distance between borrowers and lenders , starting with Petersen and Rajan (2002). Since this paper assumes that credit allocation decisions are made at the bank-level, I use the distance between the borrower and the bank's headquarter as a proxy for the ability of a bank to extract soft information in a particular market. I then define a dummy $Close_{c,b}$ equal to 1 if county c belongs to the bottom quartile of all bank's b distance pairs[13] To do so, I use a database of county-to-county distance matrices provided by the CTA Transportation Network. I conjecture that the positive effect of exposure on

[11] Stein (2002) defines soft information as "information that cannot be directly verified by anyone other than the agent who produces it".

[12] Credit scores typically only concentrate on credit history while neglecting other personal characteristics (income, wealth, etc.). There is anecdotal evidence that the validity of pre-Katrina credit scores indeed was a concern for banks. See The American Banker (2006): "Bankers on Gulf Coast Seek Help from Around the Country", March 3d.

[13] Conclusions drawn from using $Close_{c,b}$ are robust to using alternative definitions of the threshold, such as the lowest 10, 33 and 50% of the distribution of a bank's headquarter-county distance pairs.

lending growth in affected counties should be larger in markets closer to the bank's headquarter. Using $Close_{c,b}$ as an additional explanatory variable and as a triple interaction term, Column (1) in Table 7 confirms that exposed banks have a comparatively larger tendency to increase lending in those affected counties that are the closest to their headquarter.

5.4. Alternative Explanations

I now study four alternative hypotheses to the information story.

Non-Atomistic Banks First, banks may have a stronger interest in maintaining lending in affected areas if their franchise value is closely linked to the fate of the local economy. In particular, they may internalize the negative externalities of a shortage of credit on local households' decision to emigrate or default, e.g. on local house prices (Harding et al., 2009) or crime (Immergluck and Smith, 2006). If this is the case, banks may find it profitable to extend lending to counties characterized by low creditworthiness. To the extent that they could forgo short-run profit in doing so, banks would de facto act as insurer against negative temporary shocks, consistently with their role in the risk sharing literature (Demyanyk et al., 2007). If any, the incentive to act as insurer should be stronger for those exposed banks which have a substantial market share in their respective areas. Therefore, I define a bank b as being *non-atomistic* in county c if it ranks among the top quartile in terms of mortgage origination market share before the shock (2002-2004)[14]. Using this variable as a triple interaction, Column (2) in Table 7 confirms that the effect of $Exposure_b$ in affected counties is larger for bank-county pairs in which bank b is non-atomistic (0.568*). Controlling for this explanation does not invalidate the effect of distance (0.588**). The two effects appear to be quantitatively similar.

Balance Sheet Management & Regulatory Incentives Second, my results could be explained by the desire of banks exposed to a negative financial shock to restore their balance sheet. First, if exposure to the shock results in negative pressure on capitalization or increasing difficulty in raising capital, loan sales may constitute a way to generate fees, boost income and improve capitalization. Second, exposure also goes along with substantial inflows of deposits. Banks may have regarded these flows as transitory. Against that backdrop, loan sales help banks constituting a buffer against sudden deposit outflows. Under both hypotheses, the fact that exposed banks predominantly increase sold lending in affected counties may just reflect the larger quantitative importance of these markets for exposed banks. The desire to restore balance sheet liquidity and capitalization may not only reflect the objective of bank managers, but also regulatory pressures. There is anecdotal evidence that the FDIC closely scrutinized banks located in areas affected by

[14] I explored alternative, potentially more conservative measures (top 10% and top 5%), finding similar results.

Hurricanes Katrina and Rita[15].

To evaluate the importance of this channel, I construct two additional bank-level dummy variables. *LowCap* is equal to 1 if the capitalization of bank b belongs to the bottom quartile of the cross-section of banks in the pre-shock period. Similarly, *LowLiq*, is equal to 1 if the share of liquid assets of bank b belongs to the bottom quartile of the distribution of banks in the pre-shock period. I then use these two variables as triple interaction. Column (3) and (4) in Table 7 show that accounting for low capitalization and liquidity does not alter the significance of the informational channel.

Non-Random Borrower Matching Third, if banks with large exposure to shocked counties are "special" in overcoming informational asymmetries in a downturn, borrowers could systematically adapt their behavior. Econometrically, this raises the concern that borrowers are not matched randomly to lenders. The extent to which borrower controls may rule out endogenous matching is probably limited, since (i) it only comprises of a limited set of observable characteristics (sex, race, income, loan-to-income) and (ii) it is a mere average over all borrowers in a bank-county-year pair. To evaluate the existence of any bias, I re-estimate model 3 using the yearly growth in mortgage loan *applications* reached to bank b in county c as dependent variable. Column (5) in Table 7 shows the effect of bank $Exposure_b$ on application growth in affected and *Close* counties is not significantly different from zero (0.0289).

Community Reinvestment Act Finally, my results could be explained by a web of regulatory, political and reputational incentives designed to encourage lending in affected areas. Among others, these may stem from Community Reinvestment Act (CRA) regulation. Under CRA regulation, banks volunteer to undergo a systematic inquiry of their lending practices each five years on average. A key evaluation criteria is the extent to which deposits tapped from local markets are reinvested locally. There is ample anecdotal evidence that regulators have considered lending in disaster areas very favorably in post-storm CRA assessments[16]. If there are regulatory benefits in extending lending to affected counties, any bank should find it profitable to exploit it. However, more exposed banks may have a stronger incentive to conform because of reputational concerns. While CRA ratings are not associated with pecuniary penalties, a bad rating may entail substantial reputational costs. This may be particularly detrimental for those banks whose franchise value is more closely linked to affected markets.

[15] In a 2005 paper (Brown, 2005), the FDIC states that "*over time [banks] may actually face challenges related to excess liquidity. As insurance proceeds and other forms of disaster assistance flow into the regions, customers can be expected to accumulate large balances at their banks until those funds can be put to use in the rebuilding effort. During this stage of recovery, banks could accumulate more deposits than they would under normal conditions. Such an inflow of funds could cause these institutions to grow their balance sheets faster than usual, forcing them to make some important strategic decisions with regard to how they manage their asset portfolios. All things being equal, this balance sheet growth could also have the effect of lowering capital and reserve ratios.*"

[16] See e.g. The American Banker (2006), "Bankers Seek More CRA Credit for Disaster Lending", Jan 19.

To evaluate the relevance of incentives associated with CRA ratings, I exploit the fact that a prime goal of CRA regulation is to foster credit supply in low income areas. Specifically, particular attention is given to lending in census tracts where median household income lies below 80% of the median household income in the respective Metropolitan Statistical Area (”qualified census tract”). Within counties, I therefore distinguish between loans issues in qualified vs. unqualified tracts. Since many lenders concentrate on either segment, using the yearly change in lending to qualified tracts result in a massive loss of observations. I therefore use the yearly change in the share of loan applications from qualified tracts, as a share of the total bank-year-county applications from qualified tracts. I conjecture that, if regulatory incentives matter, exposed banks should accept a larger share of applicants from qualified tracts. In unreported regressions, I show that this is not the case.

5.5. Adverse Selection

The hypothesis that banks with large exposure to shocked markets re-gain an informational advantage suggests that they should have a similar advantage with respect to secondary market participants. This raises the following two specific questions. First, did exposed banks exploit their advantage to sell loans of poorer quality? Second, should not this possibility have led the secondary market for loans originated in affected counties to collapse?

Lending Standards I first look for evidence suggestive of adverse selection by comparing how lending standards change across differently exposed banks following the shock. Accurately evaluating the existence of adverse selection would require tracking the loan performance of sold loans over time (Keys et al., 2009; Purnanandam, 2011), which HMDA data does not allow. It however enables to construct measures of *ex ante* adverse selection. This is because the dataset does not only record loan originations, but also those loan applications which were denied. In both cases, the data records information on the applicant’s characteristics (income, loan amount, race, sex, etc.). Therefore, it is possible to observe how banks approve loan applications based on ex ante risk characteristics. Using the same dataset, Dell’Ariccia et al. (2012) show that the bank-specific share of accepted loans is an adequate proxy for bank risk-taking.

Under the hypothesis of asymmetric information, $Exposure_b$ goes along with both lower bank capital and better information about borrower creditworthiness in affected counties. Consistent with a capital channel, I first conjecture that the share of loans accepted *and* retained on the originator’s balance sheets should *decrease* with $Exposure_b$. Second, consistently with an informational channel, the share of loans and sold into the secondary market should *increase* with $Exposure_b$.

Table 8 confirms these priors. Column (1) uses the yearly change in bank-county share of accepted loans. There is no evidence that bank-level shock exposure explains post-shock variation in the acceptance rate. Column (2) shows that the yearly change in the share of loan applications which are accepted and retained is *negatively* related with $Exposure_b$. Thus, holding applicant characteristics fixed, exposed banks tend to tighten lending standards following the shock. This confirms that exposed banks become more conservative in their risk evaluation owing to their lower ability to bear risk. In contrast, Column (3) shows that the share of loan applications which are accepted and sold *increases* with $Exposure_b$. This suggests that exposed banks ease lending standards on those loans which they eventually sale. This last result may be seen as suggestive evidence for adverse selection, assuming that the propensity of a loan to be sold can be assessed ex ante based on applicant characteristics.

The Role of Government-Sponsored Enterprises If exposed banks accept a larger share of loan applications in affected counties holding borrower characteristics fixed, the proportion of loans granted to "lemons" (risky borrowers) should increase. Secondary market participants should internalize this possibility. One may thus wonder why lenders with an informational advantage are nonetheless able to sell a larger amount and a larger share of loans originated in affected counties. A likely explanation to this apparent inconsistency is that some secondary market participants were given incentives to purchase loans from affected markets. There is anecdotal evidence that Government-Sponsored Enterprises (GSEs) were encouraged by public authorities to ease underwriting standards on the purchase of loans originated in markets affected by Hurricanes Katrina and Rita[17]. This is significant, since GSEs account for 28.4% of mortgage loan purchases on average in my sample.

If this holds, I conjecture that the ability of exposed banks to sell loans from affected counties should be larger when the purchaser is a GSE. Table 9 provides consistent evidence. Column (2) shows that the positive effect of $Exposure_b$ on sold lending growth vanishes once loans sold to GSEs are excluded from the sample. Column (4) shows similar findings for the share of sold loans. Overall, this evidence suggests that the apparent inconsistency between the assumption of a growing importance of private information for affected counties' loans and their continued liquidity in secondary market can be rationalized by the existence of public subsidies operating through GSE's purchasing policy. This result should lead to caution when assessing the external validity of this paper's results.

6. Concluding Remarks

This paper has found that borrowers suffering an adverse shock are predominantly served by banks with a strong exposure to the shock (local banks). While those banks have a higher propen-

[17] The American Banker (2006): "Bankers on Gulf Coast Seek Help from Around the Country", March 3d.

sity to be capital-constrained following a local downturn, they also have a comparative advantage in screening loan applications in a distressed area. The existence of a liquid secondary market for mortgage loans allows circumventing capital constraints. This result suggests that the benefits of diversification rather operate through secondary markets rather than by diversified banks' lending. While this points to a bright side of credit risk transfer, this paper has also documented suggestive evidence that increasing usage of private information may lead to adverse selection.

The results suggest a series of potential complementary questions. In particular, while the uncovered evidence suggests that banks concentrating on affected regions improves access to credit in affected regions, the ultimate effect on both (i) the overall volume of credit and (ii) its impact on economic activity remain unclear. Is the positive effect of the shock on local lending offset by its negative impact on lending by diversified banks? Is local lending targeted towards investment opportunities which are conducive to long-run economic recovery? To shed more light on real effects, additional tests using market-level aggregates should be conducted. In particular, the focus should be on the central cross-sectional prediction that arises from the uncovered results: those market characterized *ex ante* by a larger presence of banks which concentrate on local lending should face better recovery prospects ceteris paribus.

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A. Tables

TABLE 1: HURRICANES & COUNTY-LEVEL CHARACTERISTICS

	#	Δ Dep^{Tot}	Δ Dep^{Med}	Δ Income	Δ Pop	Δ IncPC
Non-Affected counties						
None	295	0.08	0.08	0.04	0.01	0.03
Coastal	35	0.11	0.10	0.08	0.02	0.05
Affected counties						
Mild	67	0.06	0.06	0.04	0.00	0.04
Strong	47	0.24	0.24	0.05	-0.03	0.12

Notes: This table reports summary statistics of county-level outcomes across counties with different degrees of exposure to the 2005 hurricane season. "Mild" and "Strong" correspond to counties with tropical storm- and hurricane-force winds, respectively. "Coastal" designs counties considered coastal by the Census Bureau. Δ Dep^{Tot} is the percentage change in county total deposits between 2005 and 2006. Δ Dep^{Med} is the median percentage change across all county's bank branches between 2005 and 2006. Data are from the FDIC's Summary of Deposits. Δ Income Δ IncPC are the percentage change in county income and county per capita income between 2005 and 2006, respectively. Δ Pop is the percentage change in county population between 2005 and 2006. Income and population data is from the U.S. Census Bureau.

TABLE 2: AFFECTED COUNTIES

	Affected$_c$ (mild)	**Affected**$_c$ (strong)	**Total**
Alabama	21	4	67
Florida	14	5	67
Georgia	0	0	159
Louisiana	44	17	64
Mississippi	64	21	82
North Carolina	0	0	100
South Carolina	0	0	46
Texas	6	0	252

Notes: Columns (2) and (3) show the state-specific number of counties considered as *affected* according to the two different definitions outlined in Section 3. Column (3) shows the total number of counties in the respective states. Source: own calculation based on NOAA H*Wind field model.

TABLE 3: SUMMARY STATISTICS

	Treated banks		Untreated banks	
Bank-county-year observations	10538		39590	
	Mean	Std	Mean	Std
Δ Loan	0.15	1.06	0.14	1.11
Exposure$_b$	0.12	0.28	0.00	0.00
Bank controls				
Size	16.98	2.71	13.87	2.00
Loans	0.66	0.10	0.71	0.13
Liquid	0.20	0.07	0.18	0.12
NPL	0.01	0.00	0.01	0.01
Income	0.01	0.00	0.01	0.01
Equity	0.10	0.02	0.10	0.03
Deposits	0.72	0.09	0.74	0.20
Borrower controls				
Sex	0.23	0.21	0.22	0.26
Race	0.12	0.19	0.10	0.21
Loan/Income	0.24	0.56	0.22	0.67
Income	4.43	0.58	4.44	0.66

Notes: This table displays summary statistics of the main dependent and explanatory variables of interest across treated (positive Exposure) and non-treated (zero Exposure) banks. $\Delta Loan$ is the annual growth in bank-county mortgage loan originations. $Exposure_b$ is that share of b's deposits located in counties classified as severely affected according to the definition in Section 3. *Size* is the log of total assets. *Loans* is the share of loans in total assets. *Liquid* is measures the amount of liquid assets (cash and government bonds) as percentage of total assets. NPL measures the amount of Non-Performing-Loans as share of total loans. *Income* measures the net income over total assets. *Equity* is the bank's capital over total assets. *Deposits* measures the amount of core (insured) deposits as a percentage of total liabilities. All bank-level controls correspond to pre-shock numbers (June 2005 Call Report). Borrower controls are from HMDA and correspond to the average borrower in a bank-county-year, weighted by loan amount. *Sex* is the percentage of female borrowers. *Race* is the percentage of borrowers from ethnic minority. $Loan/Income$ is the average ratio of loan value over borrower's income. Finally, *Income* is the average borrower income in logarithms.

TABLE 4: MAIN RESULTS

	(1) Δ Loan	(2) Δ Loan	(3) Δ Loan	(4) Δ Loan
Affected$_c$	-0.159***	-0.172***	-0.167***	
	(0.046)	(0.045)	(0.050)	
Exposure$_b$	-0.118*	-0.125*	-0.164**	-0.141*
	(0.072)	(0.074)	(0.076)	(0.076)
Affected$_c$ $\times$ Exposure$_b$	0.305***	0.341***	0.301***	0.260***
	(0.078)	(0.087)	(0.095)	(0.098)
Exposure$_b$ in Affected$_c$	0.186**	0.216***	0.137**	0.119*
	(0.0774)	(0.0674)	(0.0688)	(0.0702)
Bank controls				
Size		0.00684	0.00397	0.00558
		(0.012)	(0.013)	(0.013)
Loans		0.133	0.229	0.234
		(0.332)	(0.360)	(0.344)
Liquid		0.345	0.305	0.304
		(0.269)	(0.277)	(0.267)
NPL		2.778	2.390	2.635
		(2.432)	(2.759)	(2.699)
Income		-0.924	-0.789	-0.849
		(0.781)	(0.796)	(0.779)
Equity		-0.0244	-0.0818	0.0167
		(0.766)	(0.759)	(0.733)
Deposits		0.00532	-0.0997	-0.0994
		(0.259)	(0.267)	(0.254)
Borrower controls				
Sex	-0.0649***	-0.0729***	-0.0139	-0.00950
	(0.024)	(0.022)	(0.022)	(0.022)
Race	0.0781***	0.0752***	0.0821***	0.0807***
	(0.027)	(0.026)	(0.028)	(0.030)
Loan/Income	0.396***	0.399***	0.501***	0.492***
	(0.022)	(0.026)	(0.025)	(0.025)
Income	0.335***	0.336***	0.496***	0.488***
	(0.013)	(0.015)	(0.019)	(0.019)
Year F.E.	Yes	Yes	Yes	
County F.E.	No	No	Yes	
County-Year F.E.	No	No	No	Yes
N	53384	52638	52638	52638
R^2	0.122	0.121	0.150	0.0968

Notes: This table shows results of OLS estimation of different specifications of model 3. $Affected_c$ is a dummy variable equal to one if county c is classified as severely affected according to the definition in Section 3. $Exposure_b$ is the percentage of b's branches in affected counties before the storm (June 2005). Exposure$_b$ in Affected$_c$ is the sum of $Exposure_b$ and $Affected_c$. Bank and borrower controls are defined under Table 3. Heteroskedasticity-robust standard errors clustered at the bank level are reported in parentheses. *, ** and *** indicate significant at 10, 5 and 1%.

TABLE 5: ROBUSTNESS CHECKS

	(1) **BHC**	(2) **Mild+Strong**	(3) **GO-Zone**	(4) **Collapsed**	(5) **Placebo**
	Δ Loan	Δ Loan	Δ Loan	Δ Loan	Δ Loan
$\text{Affected}_c \times \text{Exposure}_b$	0.325**	0.214**	0.287***	0.662**	-0.0576
	(0.127)	(0.091)	(0.110)	(0.273)	(0.169)
Exposure_b	-0.169*	-0.136*	-0.194*	-0.325	0.0314
	(0.094)	(0.081)	(0.100)	(0.205)	(0.141)
Exposure_b in Affected_c	0.156*	0.0775	0.0924*	0.337*	-0.0263
	0.0933	0.0471	0.0526	0.194	0.0926
Included Controls					
Bank controls	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes
County-Year F.E.	Yes	Yes	Yes	Yes	Yes
N	52638	52638	52638	10106	28799
R^2	0.0968	0.0968	0.0970	0.0390	0.105

Notes: This table reports results of OLS regression of model 3. In Column (1), $Exposure_b$ is the share of branches in $Affected_c$ counties belonging to the Bank-Holding Company (BHC) which bank b is affiliated to. In Column (2), $Affected_c$ counties are all counties registering hurricane force-winds (>74mp). In Column (3), $Affected_c$ counties as those belonging to the Gulf Opportunity (GO) Zone. Column (4) collapses the panel into pre- and post-periods. Column (5) reports estimate of a placebo test, whereby it is assumed that 2005 hurricanes same hit the same subset of counties in 2002. The corresponding panel covers the 2000-2004 period. Exposure_b in Affected_c is the sum of $Exposure_b$ and $Affected_c$. Bank and borrower controls are defined under Table 3. Heteroskedasticity-robust standard errors clustered at the bank level are reported in parentheses. *, ** and *** indicate significant at 10, 5 and 1%.

TABLE 6: RETAINED VS. SOLD LOANS

	(1) Δ Loan	(2) Δ Sold	(3) Δ Retained	(4) Δ Sold (%)	(5) Δ Pf Share (%)
$\text{Affected}_c \times \text{Exposure}_b$	0.260***	0.605***	0.0845	0.0942**	-0.019***
	(0.098)	(0.177)	(0.112)	(0.040)	(0.007)
Exposure_b	-0.141*	-0.322**	-0.0738	-0.0431	0.0170***
	(0.076)	(0.143)	(0.072)	(0.038)	(0.006)
Exposure_b in Affected_c	0.119*	0.283**	0.0107	0.0511**	-0.00209
	0.0702	0.126	0.0906	0.0251	0.00414
Included Controls					
Bank controls	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes
County-Year F.E.	Yes	Yes	Yes	Yes	Yes
N	52638	24139	42503	56685	62722
R^2	0.0968	0.0429	0.0993	0.0164	0.00829

Notes: This table reports results of OLS regression of model 3 with different dependent variables. Column (1) uses the baseline dependent variable, the yearly growth of total bank-county mortgage originations. Column (2) uses the growth of originations retained on the originator's balance sheet during the origination year. Column (3) uses the growth of originations sold in the secondary market during the origination year. Column (4) uses the yearly change of the percentage of originations sold in the secondary market during the origination year. Column (5) uses the yearly change in retained lending allocated to county c as a percentage of bank b total retained lending. Exposure_b in Affected_c is the sum of $Exposure_b$ and $Affected_c$. Bank and borrower controls are defined under Table 3. Heteroskedasticity-robust standard errors clustered at the bank level are reported in parentheses. *, ** and *** indicate significant at 10, 5 and 1%.

TABLE 7: INFORMATIONAL FRICTIONS & ALTERNATIVE EXPLANATIONS

	(1) Δ Sold	(2) Δ Sold	(3) Δ Sold	(4) Δ Sold	(5) Δ Appl
Alternative Explanation:		**Non-Atomistic**	**Low Capital**	**Low Liquidity**	
$\text{Affected}_c \times \text{Exposure}_b \times \text{Close}_{b,c}$	0.831*	0.693*	0.723*	0.807*	-0.0176
	(0.448)	(0.405)	(0.394)	(0.450)	(0.260)
$\text{Affected}_c \times \text{Close}_{b,c}$	-0.345	-0.330	-0.336	-0.332	0.0333
	(0.224)	(0.215)	(0.223)	(0.223)	(0.156)
$\text{Affected}_c \times \text{Exposure}_b$	0.514***	0.505***	0.708**	0.621***	0.222**
	(0.181)	(0.178)	(0.275)	(0.191)	(0.110)
$\text{Exposure}_b \times \text{Close}_{b,c}$	-0.539*	-0.432*	-0.424*	-0.524*	-0.0365
	(0.290)	(0.260)	(0.237)	(0.293)	(0.125)
Exposure_b	-0.183	-0.178	-0.287	-0.310**	-0.112***
	(0.120)	(0.117)	(0.214)	(0.091)	(0.027)
$\text{Close}_{b,c}$	-0.0681*	-0.0694**	-0.0821**	-0.0747**	
	(0.035)	(0.035)	(0.035)	(0.036)	
$\text{Affected}_c \times \text{Exposure}_b \times \text{AltExpl}$		1.201**	-0.401	-0.694*	
		(0.486)	(0.333)	(0.388)	
$\text{Affected}_c \times \text{AltExpl}$		-0.169	0.0842	0.256*	
		(0.142)	(0.176)	(0.139)	
$\text{Exposure}_b \times \text{AltExpl}$		-0.960**	0.0975	0.805**	
		(0.376)	(0.240)	(0.314)	
AltExpl		0.0256	0.177*	-0.259*	
		(0.058)	(0.095)	(0.141)	
Exposure_b in Affected_c , $\text{Close}_{b,c}$=1	0.623**	0.588**	0.720***	0.594***	0.0289
	0.245	0.244	0.277	0.239	0.168
Exposure_b in Affected_c , AltExpl=1		0.568*	0.118	0.421**	
		0.301	0.271	0.245	
Included Controls					
Bank controls	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes
County-Year F.E.	Yes	Yes	Yes	Yes	Yes
N	24139	24139	24139	24139	60660
R^2	0.0445	0.0448	0.0469	0.0479	0.0863

Notes: This table reports results of OLS regression of model 3 including additional interaction terms. $Close_{b,c}$ is equal to one if the distance between county c and bank b's headquarter is in the bottom quartile of all b's county-headquarter distance pairs. In Column (3), $AltExpl$ is $NonAtom$, which is equal to 1 if bank b belongs to the top quartile of c lenders in the pre-shock period (2002-2004). In Column (4), $AltExpl$ is $LowCap$, which is equal to 1 if the capitalization of bank b belongs to the bottom quartile in the pre-shock period. In Column (5), $AltExpl$ is $LowLiq$, which is equal to 1 if the share of liquid assets of bank b belongs to the bottom quartile in the pre-shock period. Δ Appl is the yearly growth in mortgage loan applications reached to bank b in county c. Exposure_b in Affected_c is the sum of $Exposure_b$ and $Affected_c$. Bank and borrower controls are defined under Table 3. Heteroskedasticity-robust standard errors clustered at the bank level are reported in parentheses. *, ** and *** indicate significant at 10, 5 and 1%, respectively.

TABLE 8: LENDING STANDARDS

	(1)	(2)	(3)
	Δ Acc (%)	Δ Acc (%)	Δ Acc (%)
Loans:	**All**	**Retained**	**Sold**
$\text{Affected}_c \times \text{Exposure}_b$	0.0142	-0.112***	0.100**
	(0.023)	(0.034)	(0.047)
Exposure_b	-0.0116	0.0302	-0.00684
	(0.022)	(0.027)	(0.054)
Exposure_b in Affected_c	0.00257	-0.0822***	0.0935***
	(0.0137)	(0.0198)	(0.0323)
Included Controls			
Bank controls	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes
County-Year F.E.	Yes	Yes	Yes
N	60015	48936	30918
R^2	0.00368	0.00674	0.00538

Notes: This table reports results of OLS regression of model 3 with alternative dependent variables. Δ Acc (%) is the yearly change in bank-county-year accepted loan applications as a share of total loan applications. Column (1) uses the share of all accepted loans. Column (2) uses the share of loans accepted and retained during the year of origination. Column (3) uses the share of loans accepted and sold during the year of origination. Exposure_b in Affected_c is the sum of $Exposure_b$ and $Affected_c$. Bank and borrower controls are defined under Table 3. Heteroskedasticity-robust standard errors clustered at the bank level are reported in parentheses. *, ** and *** indicate significant at 10, 5 and 1%.

TABLE 9: THE ROLE OF GOVERNMENT-SPONSORED ENTERPRISES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ Sold	Δ Sold	Δ Sold (%)	Δ Sold (%)	Δ Sold	Δ Sold	Δ Sold (%)	Δ Sold (%)
With loans sold to GSEs?	Yes	No	Yes	No	Yes	No	Yes	No
$\text{Affected}_c \times \text{Exposure}_b$	0.605***	0.382**	0.0942**	0.0663***	0.494***	0.316	0.0783**	0.0608**
	(0.177)	(0.167)	(0.040)	(0.024)	(0.181)	(0.192)	(0.035)	(0.027)
Exposure_b	-0.322**	-0.232**	-0.0431	-0.0332	-0.163	-0.140	-0.0308	-0.0282
	(0.143)	(0.110)	(0.038)	(0.027)	(0.114)	(0.116)	(0.033)	(0.026)
$\text{Affected}_c \times \text{Exposure}_b \times \text{Close}_{b,c}$					0.920**	0.433	0.176***	0.0860*
					(0.456)	(0.336)	(0.067)	(0.049)
$\text{Affected}_c \times \text{Close}_{b,c}$					-0.388*	-0.0542	-0.139***	-0.0697**
					(0.228)	(0.158)	(0.040)	(0.031)
$\text{Exposed} \times \text{Close}_{b,c}$					-0.628**	-0.392*	-0.0500	-0.0215
					(0.288)	(0.225)	(0.033)	(0.024)
$\text{Close}_{b,c}$					-0.0253	-0.0276	-0.00901**	-0.0103***
					(0.025)	(0.030)	(0.004)	(0.004)
Exposure_b in Affected_c	0.283**	0.150	0.0511**	0.0331	0.331**	0.176	0.0474*	0.0326
	0.126	0.137	0.0251	0.0251	0.162	0.173	0.0260	0.0258
Exposure_b in Affected_c , $\text{Close}_{b,c}$=1					0.622**	0.216	0.174***	0.0971***
					0.245	0.230	0.0425	0.0366
Included Controls								
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	24139	17427	56685	56685	24139	17427	56685	56685
R^2	0.0429	0.0332	0.0164	0.0118	0.0442	0.0337	0.0172	0.0123

Notes: This Table reports results of OLS regression of model 3 with alternative dependent variables. Δ Sold is the yearly change in bank-county-year loans which are sold during the year of origination. Δ Sold (%) is the yearly change in bank-county-year loans which are sold during the year of origination as a share of total bank-county-year originations. In Columns (2), (4) and (6), the share is calculated excluding all loans sold to Government-Sponsored Entreprises (GSEs). $Close_{b,c}$ is equal to one if the distance between county c and bank b's headquarter is in the bottom quartile of all b's county-headquarter distance pairs. Exposure_b in Affected_c is the sum of $Exposure_b$ and $Affected_c$. Bank and borrower controls are defined under Table 3. Heteroskedasticity-robust standard errors clustered at the bank level are reported in parentheses. *, ** and *** indicate significant at 10, 5 and 1%, respectively.