BANK OF ENGLAND

Staff Working Paper No. 617

Dis-integrating credit markets: diversification, securitization, and lending in a recovery

Matthieu Chavaz

September 2016

BANK OF ENGLAND

Staff Working Paper No. 617

Dis-integrating credit markets: diversification, securitization, and lending in a recovery

Matthieu Chavaz[1]

Abstract

Using exogenous variation in exposure to hurricanes, this article explores how differently diversified US banks lend during the protracted recovery from a major downturn. Compared to diversified banks, local banks (i) originate a higher share of new mortgage and small business loans in affected areas, but (ii) sell a higher share of the new mortgages into the secondary market. These results suggest a pattern of specialization, whereby loans in affected areas are increasingly originated by banks with special abilities or incentives to seize opportunities in a distressed market, but increasingly transferred to agents which can better support the associated risk.

(1) Bank of England. Email: matthieu.chavaz@bankofengland.co.uk

This paper was previously circulated as: 'Riders of the storm — economic shock and bank lending in a natural experiment'. I thank the members of my thesis jury — Cedric Tille, Marc Flandreau, and Charles Calomiris — for guidance. For helpful comments, I also would like to thank Jean-Louis Arcand, Neil Bhutta, Benjamin Collier, Jess Cornaggia, Justin Gallagher, Solomon Hsiang, Vasso Ioannidou, Rustom Irani, Frederic Malherbe, David Martinez, Joseph Mason, Ugo Panizza, Amar Radia, Rodney Ramcharan, Kristle Romero Cortes, Farzad Saidi, Neeltje Van Horen, Razvan Vlahu, Tomasz Wieladek, as well as participants in the 2015 Atlanta Fed Real Estate conference, 8th FIRS conference, CEPR SwissWinter Financial Intermediation conference, Bocconi Carefin conference, 3rd Banco de Espana-World Bank conference, Erasmus Credit Conference, UniCredit Young Economists conference, De Nederlandsche Bank (DNB), Bank of England and Graduate Institute research seminars. This paper has benefited from financial support from the Swiss National Science Foundation (Sinergia project 'Macroeconomics of Financial Crises') and from the hospitality of De Nederlandsche Bank. All errors are mine. This work does not necessarily reflect the views of the Bank of England.

Information on the Bank's working paper series can be found at
www.bankofengland.co.uk/research/Pages/workingpapers/default.aspx

Publications Team, Bank of England, Threadneedle Street, London, EC2R 8AH
Telephone +44 (0)20 7601 4030 Fax +44 (0)20 7601 3298 email publications@bankofengland.co.uk

ISSN 1749-9135 (on-line)

1 Introduction

Access to bank credit can play a key role in an economy recovering from a major downturn. However, the ability or willingness of banks to lend in a recovery might be hampered by both (i) tightening financial constraints and (ii) declining or more uncertain profitability of new lending (Gilchrist et al., 2014). Scholars and policymakers have long been interested in whether local or geographically diversified banks are more likely to lend in such circumstances, be it in the case of the Great Depression, the 1980s farm debt crisis or, more recently, the protracted recovery from the 2007-2009 Great Recession (Bernanke, 2011).[1]

The recurrence of this interest reflects a theoretical puzzle. On the one hand, local banks in affected areas should be more vulnerable to losses in income or access to external finance arising from the shock, and thus to tightening financial constraints. This *financial capacity channel* suggests that lending to affected areas should stem from diversified banks.[2]

On the other hand, local banks may find it more profitable to keep on lending to affected areas due to their lending technology or ex-post incentives, relative to lending elsewhere. Given their superior local knowledge, local banks may have an advantage in screening, monitoring and pricing new loans despite depressed or uncertain collateral values.[3] They may also benefit more from doing so if originating-and-selling new loans yields immediate fee income, or if new loans have affect local house prices and activity positively.[4] This *relative profitability channel* suggests that lending to affected areas should stem from local banks.

[1]See Sprague (1903) for an early discussion, Carlson and Mitchener (2009) for a study of branching and bank performance in 1930s California, and Calomiris et al. (1986) for a discussion on branching restrictions during the 1980s agricultural bust.

[2]This effect is consistent with models featuring a bank lending channel, whereby banks' assets deteriorate in a downturn, lowering their lending capacity if they face frictions in raising external finance (Stein, 1998).

[3]This effect is consistent with models featuring a balance sheet channel (Bernanke and Gertler, 1989), whereby borrower collateral deteriorates during downturns, increasing lenders' need to invest in screening (Ruckes, 2004) or monitoring (Holmstrom and Tirole, 1997). That local banks may have an advantage at doing so is consistent with evidence that local lenders accumulate more knowledge of their core mortgage market in normal times and thus accept more information-intensive loans (Loutskina and Strahan, 2011).

[4]The former effect is consistent with models showing that financially constrained firms are more prone to invest in a project whose profitability becomes more uncertain, but yields an immediate cash-flow (Boyle and Guthrie, 2003). The second effect is consistent with evidence that credit supply has positive externalities, such that banks are more prone to keep on lending to an area in which they have a higher share of the outstanding loans (Favara and Giannetti, 2015).

Given these opposite effects, the issue of *who* lends in a recovery is an empirical one. Available evidence is scant, not least for the US. This may partly be due to the need to isolate empirically a prolonged shock to banks' financial capacity and loan profitability that affects a clearly identifiable yet randomly selected subset of the population, unlike downturns originating in part in the banking sector like the Great Recession.

This paper addresses this challenge by studying bank lending during the protracted recovery from the 2005 hurricane season - the costliest natural disaster in recorded US history. Together, Hurricanes Katrina, Rita, Wilma, and Dennis damaged 1.19 million housing units, a large part of which were insufficiently insured. Combined with policy mismanagement, environmental hazards, and the permanent displacement of 1.5 million persons, these exceptional destructions shed acute uncertainty about the ability of most affected areas to recover within less than a decade. This dire recovery prospect contrasts with the average US hurricane, which has little sustained effect on income, population or growth.[5]

Given the shock to collateral and economic prospects, the experiment exposes banks to the two key features of recovery periods, namely (i) potentially tightening financial constraints due to substantial income losses and asset impairment, and (ii) more costly or uncertain new lending opportunities, for instance owing to difficulties in appraising collateral values in devastated areas or monitoring borrowers with uncertain future creditworthiness. A crucial difference, however, is that the distribution, severity and timing of this shock are unambiguously exogenous and unpredictable (Nordhaus, 2010). This allows to identify the causal impact of a downturn on credit allocation for differently diversified banks, and thus to disentangle the two conflicting channels of interest.

The baseline test compares the way a bank's mortgage lending changes in affected counties - compared to elsewhere and before the shock - depending on its geographic diversification. If the financial capacity channel dominates (local banks have a smaller financial capacity after the

[5]See Kates et al. (2006) for an early assessment of the New Orleans area's recovery prospects in the aftermath of Katrina, and Deryugina (2013) and Strobl (2011) for evidence on the impact of average hurricanes.

shock), a local bank in the affected area should have a *lower* lending growth in affected counties than a better diversified bank. If the relative loan profitability channel dominates (local banks have better technology or higher incentives to lend in affected areas), the opposite should hold. I use wind speed to delineate affected counties, and the share of a bank's branches inside these counties to measure its diversification. I control for unobservable heterogeneities across banks and areas and for loan demand using bank-county and county-time fixed effects.

I find robust evidence that the loan profitability channel dominates. This effect is sizable. A 10% higher share of branches in affected counties is associated with a 9.2% higher (log) lending growth in affected counties. So, for instance, a New Orleans community bank has a 92% marginally higher (log) growth in affected counties compared to a bank without any branch in affected counties like Bank of America. This implies that the affected areas' mortgage markets become less geographically integrated, which I dub the *dis-integration effect*. This effect could be explained by local banks receiving more loan applications after the shock, or by lending incentives being distorted by government interventions. However, I find similar results when using the share of accepted loans as alternative dependent variable in order to control for borrower sorting more finely, as well as when controlling for regulatory forbearance and leniency, and dropping mortgages guaranteed or purchased by Government-Sponsored Enterprises (GSEs).

I find a similar dis-integration effect in a broader analysis of disasters spanning the 2000-2010 period, using a novel dataset of county-level flood insurance payouts, as well as when replicating the baseline regression using small business lending data. This suggests that the dis-integration effect is not unique to the post-2005 period or the mortgage market.

Having established *who* lends in affected areas, I then investigate *how* local banks adjust lending after the shock. I identify two main margins of adjustment. First, local banks accept a higher share of applications received in affected counties, but a lower share in unscathed counties. Second, local banks increase the share of applications from affected counties that they originate-and-sell into the secondary mortgage market. This suggests that loan sales allow local banks to accept more new loans in affected counties, which they have an advantage or greater incentive to originate according to the relative profitability channel, but a disadvantage to finance according to the financial capacity channel. Equivalently, loan sales allow local banks to exploit their comparative advantage in lending to affected markets while earning fee income, thus mitigating possible financial constraints, and transferring the associated risk to agents with a better financial capacity to bear it.

The third part of the paper discusses *why* local banks seem to find it more profitable than diversified banks to lend in affected areas. I investigate four non-mutually exclusive channels. I find evidence suggestive of local banks having both (i) a comparative advantage and (ii) a greater ex-post benefit to lend in affected areas. Consistently with the former motive, I find that local banks are most prone to accept information-intensive (non-prime) mortgage applications in affected counties, i.e. loans whose origination should be particularly costly in a distressed environment and which may thus benefit from local knowledge. Consistently with the latter motive, I find that local banks also, albeit to a lesser extent, increase acceptances of non-information-intensive (prime) applications, i.e. loans that can be sold easily and generate immediate fee income. Combined, these two results suggest that the possibility to originate and sell prime loans can help local banks to originate and retain information-intensive loans (their "traditional" role) even when being potentially constrained.

A third hypothesis is that the shock deteriorates local banks' charter value and capital, increasing their incentive to take risk. Inconsistent with a risk-shifting motive, I find that lower capitalized local banks do not accept more loans in affected counties. Fourth, lending in affected areas could be more beneficial for local banks if it has positive externalities on local house prices and economic activity (Favara and Giannetti, 2015). Inconsistent with this hypothesis, I find that a local bank does not accept more loans in an affected census tract in which it owns a higher share of outstanding mortgages.

2 Contributions to Existing Literature

The paper's main contribution is to document how how differently diversified banks contribute to lend in an economy recovering from an unambiguously exogenous downturn. The results suggest a new pattern of specialization in the two key steps in the loan production function. First, the origination of new loans in affected areas is increasingly taken on by banks whose local focus gives them special abilities and incentives to lend in distressed circumstances. Second, the financing of these loans is increasingly transfered to secondary market participants whose (presumed) diversification gives them an advantage in supporting the associated risk.

These findings contribute to three main strands of the literature. First, local and diversified banks' lending technologies are known to differ in normal times. Local banks specialize in serving information-intensive borrowers, such as small businesses (Berger et al., 2005) or non-prime mortgagors[6] (Loutskina and Strahan, 2011). They also tend to hold these loans on their balance-sheet rather than sell them. Thus, it is unclear whether they can also do so in a recovery period, during which they are more likely to be financially constrained. My findings suggest that they can, but must increase loan sales to do so. Local banks increase originations of both prime and non-prime mortgages, which suggests that the possibility to liquidate the former allows to finance the latter. This pattern contrasts with evidence that community banks curtailed lending during the Great Recession, which DeYoung et al. (2015) attribute to these banks' inability to liquidate outstanding small business loans in order to preserve their lending capacity.

Second, the results speak to a literature stressing the benefits of securitization in mitigating banks' financial frictions, such as shortages of cheap deposit funding (Loutskina and Strahan, 2009; Loutskina, 2011). My findings suggest that following a major shock, loan sales also allow

[6]These are mortgages which cannot be underwritten and sold into the secondary market using standardized information (such as credit scores) and screening techniques (such as automated underwriting softwares).

vulnerable banks to keep on lending while compensating income losses.

Third, the findings contrast with earlier literature suggesting that the geographic integration of regional US credit markets should increase after a regional shock, for instance because diversified banks should be better able to lend to distressed small businesses than local banks (Demyanyk et al., 2007).[7] Using disaggregated lending data in a quasi-experimental set-up, and also considering the role of securitization, I find that the *origination* of credit dis-integrates geographically (new loans are more likely to be issued by local banks) but its *funding* further integrates (these new loans are more likely to be sold to (presumably) diversified secondary market agents). This finding adds to evidence that securitization has increased the integration of regional US mortgage markets during the boom years (Loutskina and Strahan, 2012).

Finally, my findings are consistent with three papers developed in parallel to mine. Romero Cortés and Strahan (2014) show that small US banks exposed to milder hurricanes from 2000 to 2012 cut mortgage lending in unaffected areas. This suggests that these banks have an advantage in lending in affected areas, which is consistent with my findings. However, the paper does not discuss the reasons behind this advantage, nor studies lending in affected areas. Using the same shocks, Romero Cortés (2014) finds that job creation and retention is higher in affected areas with a larger presence of local banks. However, she does not use disaggregated loan data, nor explores the role of securitization. While their main focus is elsewhere, Gallagher and Hartley (2014) find that New Orleans neighborhoods flooded by Katrina that had a larger presence of local banks registered lower reductions in aggregate household mortgage debt and higher lending growth. This suggests that local banks have an interest in encouraging households to rebuild rather than to repay and emigrate. Again, my findings are consistent, albeit based on a different question and approach.[8]

[7] Morgan et al. (2004) show that markets could either integrate or dis-integrate following a regional shock, depending on the weight of the aggregate local shock to bank capital and borrower collateral. However, their model does not differentiate between differently diversified banks and does not consider loan securitization. My empirical model holds the local aggregate amount of bank capital and collateral fixed via fixed effects.

[8] Berg and Schrader (2012) and Lambert et al. (2015) also exploit natural disasters to explore questions around relationship lending in emerging markets and bank capital management, respectively.

3 The 2005 Hurricane Season

This section provides background information establishing that the 2005 hurricane season exposes banks to the two key features of a recovery period (Gilchrist et al., 2014), namely a shock to (i) banks' financial capacity and (ii) to the profitability of new lending.

The 2005 hurricane season stands out by its unprecedented magnitude. Katrina has been the deadliest and costliest natural disaster in recent US history (1900 onwards), with losses in excess of $ 108 billion (Blake et al., 2007). Wilma, Rita and Dennis have been respectively the fifth, seventh and 18th costliest hurricanes, with combined damages of $ 35.5 billion. The damages to the housing stock illustrate the scale of destructions most strikingly. Together, the 2005 hurricanes damaged 1.2 million housing units, of which 300,000 were totally destroyed or very seriously damaged (Department of Housing and Urban Development, 2006).

One first consequence of such destruction of collateral is to increase banks' financial vulnerability. Damages caused by an average US hurricane are typically covered by a combination of public and private insurance (Deryugina, 2013). After Katrina, in contrast, only 30 to 60% of affected Louisiana households were covered by flood insurance, such that 25% of mortgages in the state were past-due as of the third quarter of 2005 (Overby, 2007). Payment collection was made even more difficult by the displacement of around 1.5 million individuals after Katrina (Groen and Polivka, 2008). A majority of lenders introduced 30- to 90-day waivers on mortgage payments. Loan losses were compounded by parallel interruptions of interest payment on local government debt (Brown, 2005). Consistently with access to external finance suffering from heightened asset opacity (Stein, 1998), some banks also reported increasing difficulties in raising wholesale deposits or selling mortgages (The American Banker, 2006a). Appendix section A documents more formally that the shock has decreased banks' income and capitalization, and increased non-performing loans.

A second consequence of the shock is its impact on the profitability of lending in affected areas. In theory, lending costs increase in a downturn because depressed collateral exacerbates agency frictions between banks and borrowers, increasing the necessity and costs of screening and monitoring.[9] Anecdotal evidence suggests a number of concrete manifestations of this phenomenon. For instance, banks reported increasing difficulties in appraising property values in devastated areas due to the absence of comparable sales.[10] Some also reported a growing need to monitor construction works closely due to a surge in cases of fraud.[11] Finally, some potential secondary market buyers like GSEs required additional information from originators, for instance hard evidence for the impact of the hurricane on mortgage applicants.[12] In the immediate aftermath of the shock, these challenges were compounded by infrastructure damages. 98 bank branches had not re-opened as of December 2005 (Brown, 2005), some were looted, and premise destructions inflicted important damages on IT systems and paperwork.

One further unique feature of the shock compared to other hurricanes is that the damages it inflicted were particularly long-lasting. Population displacement and exogenous constraints around reconstruction (such as environmental hazards, delays in insurance payouts or uncertainties around planning restrictions) raised acute concerns around the ability of the region to recover in less than eight to 11 years (Kates et al., 2006). This prediction was reiterated later on as, three years after the shock, population and housing and labor markets had not returned to their pre-shock level (Vigdor, 2008). Thus, the shock should not only have altered the cost of lending in its immediate aftermath, but also the longer-term profitability of lending in areas with particularly uncertain recovery prospects.[13]

[9] See for instance Bernanke and Gertler (1989) and Holmstrom and Tirole (1997).

[10] The American Banker (2006a). Regulators and potential secondary market buyers routinely require appraisals to be based on evidence from comparable transactions - a mechanically rare occurrence in such a distressed environment. This issue was so acute that it prompted bank regulators to relax appraisal requirements for properties in affected areas under some specific conditions. In return however, banks had to provide other additional information (Department of the Treasury et al., 2005).

[11] The New York Times (2015), for instance, relates the strategy of New Orleans Liberty Bank in this context: "Liberty tried making loans in the Lower Ninth Ward. [...] employees needed to be just as hands-on there. Contractor fraud was rampant then, especially in lower-income communities, and Liberty's staff, as it did elsewhere in the city, would offer lists of recommended contractors and monitor their progress to make sure the work was being done".

[12] GSEs issued special guidelines requesting additional information for non-prime loans originated in affected areas (see section 6.1.2 for details). This suggests that a substantial share of loans in affected areas could not be originated using standardized data and screening techniques.

[13] While the shock unambiguously impacts the quality of new lending opportunities, it does not necessarily increase the aggregate demand volume in affected areas. Intuition suggests that housing damages must increase

4 Hypotheses & Identification Strategy

The previous section has shown that the 2005 hurricane season can be summed up as a shock to (i) banks' financial capacity and (ii) the profitability of new lending in affected areas relative to lending elsewhere. The puzzle raised in the introduction is that local banks in the affected areas should be more vulnerable to the former shock, but less to the latter. To see which of these effects dominates empirically, the baseline test investigates how a bank's mortgage lending growth changes in affected counties depending on how geographically diversified it is from the point of view of the affected area. The empirical model is as follows:

$$\begin{aligned} \Delta Loan_{b,c,t} &= \beta_1 \cdot Local_{b,t} + \beta_2 \cdot Affected_{c,t} \times Local_{b,t} \\ &+ \beta_3 \cdot BankControls_{b,t} + \beta_4 \cdot BorrowerControls_{b,c,t} \\ &+ CountyYearF.E._{c,t} + BankCountyF.E._{b,c} + \epsilon_{b,c,t}, \end{aligned} \tag{1}$$

where $\Delta Loan_{b,c,t}$ is the (log) growth of bank b's mortgage origination volume in county c and year t. $Affected_{c,t}$ is 0 until the shock (2003-2005), and 1 thereafter (2006-2008) if c is hit. $Local_{b,t}$ is 0 until 2005, and the pre-shock share of b's branches located inside affected counties thereafter.[14]

The variable of interest is $Affected_{c,t} \times Local_{b,t}$. If the financial capacity channel dominates, β_2 should be negative (the more local a bank, the lower its lending growth in affected counties). This effect is consistent with local banks being more vulnerable to losses in income (via payment arrears or outright defaults) and access to external finance (via increased asset opacity) than banks whose outstanding assets are diversified across geographic areas. That banks

mortgage demand. But this effect may be offset by out-migration from affected areas. Indeed, the number of severely or totally damaged housing units (300,000) is outweighed by the number of individuals permanently displaced from the New Orleans area (about 1,500,000).

[14] $Affected_{c,t}$ and $Local_{b,t}$ can be respectively decomposed as $Affected_c \times Post_t$ and $Local_b \times Post_t$, where $Post_t$ is 0 until 2005 and 1 thereafter, and $Affected_c$ and $Local_b$ are time-invariant county affectedness and bank-level diversification measures, respectively. $Affected_c$ and $Affected_{c,t}$ drop from the model due to the county-year fixed effect. $Local_b$ and $Local_b \times Affected_c$ drop because of the bank-county fixed effect.

cannot perfectly compensate these losses by raising external finance is consistent with various agency frictions embedded in models of the bank lending channel (e.g. Stein (1998)).

In contrast, if the relative profitability channel dominates, β_2 should be positive (the more local a bank, the higher its lending growth in affected counties). This effect is consistent with the shock to the profitability of lending in affected areas relative to that of lending elsewhere being comparatively smaller for a local bank. For instance, the shock to borrower collateral may increase the necessity or cost of screening (Ruckes, 2004) or monitoring (Bernanke and Gertler, 1989; Holmstrom and Tirole, 1997) borrowers. Local banks may have a technological advantage in doing so since they accumulate a better knowledge of local borrowers and mortgage markets in normal times (Loutskina and Strahan, 2011). Second, they may also have a greater incentive to exploit this advantage if it allows them to earn immediate cash from loan sales, thereby mitigating financial constraints, or if keeping on lending has positive externalities on local house prices and economic activity (Favara and Giannetti, 2015), thereby shoring up local banks' long-term profitability.

$BankControls_{b,t}$ is a set of time-varying bank controls (see section 5.3). $BorrowerControls_{b,c,t}$ is a set of borrower controls averaged by bank-county-year, including income, ethnicity, sex, loan size, loan-to-income, and neighborhood income and minority population (section 5.2).

The fixed effects address two distinct challenges for identification. A first concern is that the behaviour of banks with a different diversification may differ on average for reasons imperfectly correlated with $BankControls_{b,t}$ (e.g. differences in corporate governance or risk aversion), especially in areas regularly prone to hurricanes like coastal Louisiana. I control for such heterogeneities via $BankCountyF.E._{b,c}$, a matrix of bank-county fixed effects.

A second concern is that credit demand may differ across affected counties and time for reasons imperfectly correlated with $BorrowerControls_{b,c,t}$. In the baseline regression, I control for these via $BankCountyF.E._{b,c}$, a matrix of county-year fixed effects. This allows β_2 to identify a pure supply-side effect, unless (i) the volume of unsolicited mortgage applications in affected counties varies systematically with $Local_{b,t}$ within a county-year and (ii) it does so for reasons imperfectly captured by $BorrowerControls_{b,c,t}$.

A violation of this assumption may bias the estimate of the supply-side effect in an ambiguous direction. For instance, in affected areas, applicants of higher (lower) unobserved quality could chose the bank they apply with based on its diversification, be it because of its perceived lending capacity (consistent with the financial capacity channel), or benefit or incentive to lend in affected areas (consistent with the relative profitability channel).

To further mitigate this concern, section 6.2 estimates equation 1 using the share of accepted applications for a bank-county-year as the dependent variable. Since it is akin to modeling credit supply conditional on demand, this specification allows relaxing assumptions about the *volume* of unsolicited applications. In this case, β_2 identifies a pure supply-side effect unless (i) the *quality* of unsolicited applicants varies systematically with $Local_{b,t}$ within a county-year and (ii) for reasons not captured by $BorrowerControls_{b,c,t}$. Unlike the baseline regression, however, this set-up would not capture a bank's attempt to aggressively solicit applications following the shock, a strategy that local banks may have been prone to adopt following the shock according to anecdotal evidence.[15]

5 Data

5.1 Measuring Hurricane Exposure

The main challenge in implementing the identification strategy set out above is to measure the county-specific exposure to the 2005 hurricanes ($Affected_{c,t}$), and the bank-specific diversification from the point of view of the affected area ($Local_{b,t}$).

Figure 1 plots the track of (from left to right) Hurricanes Rita, Katrina, Dennis, and Wilma

[15] For instance, New York Times (2006) relates that "To further bolster his flagging loan business" New Orleans Liberty Bank CEO Alden McDonald "set in motion a plan to open loan centers in strip malls in other parts of Louisiana as well as Texas and Mississippi. "I needed those fees," he said. "I needed to get my interest income up." Libertys staff was able to qualify enough people to approve $10 million in loans in less than three months".

on a map of the Gulf of Mexico region. The insurance literature predicts that the magnitude of damage claims across affected areas is a function of the location-specific (i) storm intensity, (ii) capital stock quality (e.g. housing) and (iii) insurance coverage (Mendelsohn et al., 2012). My benchmark proxy exploits the only unambiguously exogenous component of these three, storm intensity. Specifically, I use the National Oceanic and Atmospheric Administration (NOAA)'s H*Wind data, which provides maximum wind speed estimates for a fine grid of geographical coordinates during each of the 2005 hurricanes under study.[16] I project this grid onto county borders, as figure 2 illustrates.

I then define $Affected_{c,t}$ as 0 until 2005, and 1 thereafter if the maximum wind in county c exceeds 96 miles per hour. This threshold corresponds to a category 2 hurricane, characterized by "extremely dangerous wind" and "extensive damage" according to the Saffir-Simpson Scale.[17] The upper panel in figure 1 shows the resulting set of affected counties. For robustness checks, I alternatively use county-level presidential disaster declarations from FEMA.[18] Panel 2 in figure 1 shows that the resulting set of affected counties is about twice as large, which is consistent with declarations over-estimating damaged areas.[19]

To measure a bank's geographic diversification from the point of view of the affected area, I use pre-shock (July 2005) branch location data from FDIC's Summary of Deposits. Specifically, $Local_{b,t}$ is 0 until 2005, and the share of b's branches located in affected counties thereafter. After the shock, $Local_{b,t}$ thus varies from 0 (e.g. Bank of America, which had no single branch in

[16] H*Wind data is collected at regular frequency during storms by a combination of land-, sea-, space- and airborne observation platforms. NOAA then consolidates the raw data into "maximum sustained wind swaths", which report the maximum wind speed observed during the storm for each of the grid points.

[17] This is the most common scale for hurricane wind-damages. See e.g. http://www.nhc.noaa.gov/aboutsshws.php. Wind-damage models may be less precise in predicting damages caused by storm surges. However, the bias should be moderate since wind speed is the strongest at landfall, and coastal areas are the most vulnerable to surges. Results are also robust to using a finer census-tract level distinction of flooded neighborhoods within the New Orleans area following Gallagher and Hartley (2014). Results are available upon request.

[18] I only consider declarations which trigger both Individual and Public Assistance aid programs. This for instance excludes counties, for instance, that are declared as disaster-struck for being crossed by an evacuation route.

[19] Declarations are issued immediately after hurricanes. Fannie Mae (2005) for instance states that "*As more information became available, we learned that most of the property damage occurred in a much smaller area within the FEMA Disaster areas*". Declarations can also be subject to political biases since they may be a condition for the provision of federal disaster aid.

affected counties) to 1 (e.g. an Orleans parish community bank). Since banks can also lend at arm's length, I alternatively use the share of a bank's retained mortgage loans given in affected counties before the shock in robustness checks.

As a further alternative to wind speed, I use a novel county-year-level dataset of National Flood Insurance Program (NFIP) payouts for the 2000-2010 period made available to me by FEMA. The NFIP is the main insurance provider in flood-prone regions, and floods are typically the costliest form of hurricane damages - especially in the case of Katrina.[20] I thus use this data to construct a continuous alternative to $Affected_{c,t}$ (see sections 6.1.1 and 6.1.3 for details).

5.2 Bank Lending Data

The baseline test uses mortgage lending data. The sector accounts for 30% of US credit markets (Gan and Riddiough, 2008) and has a pivotal role for economic activity (Mian and Sufi, 2009). Furthermore, US mortgage data is unique in its comprehensiveness and granularity, notably in terms of the geographical location of borrowers.[21]

The data comes from an application-level mortgage register collected at yearly frequency under provisions of the Home Mortgage Disclosure Act (HMDA data). For each application, HMDA reports the lender identity, the geographic location of the borrower (up to the census tract level), whether the application was accepted, and whether an accepted loan was sold during the year of origination. HMDA also reports a number of borrower characteristics (loan size, income, loan-to-income, ethnicity, sex and census tract median income and minority population), which I average by bank-county-year to populate $BorrowerControls_{b,c,t}$, following Gilje et al. (2016). Table 1 provides further definition details.

[20] The 2005 hurricanes have generated claims in excess of \$ 20 billion under the NFIP, twice as much as the cumulated sum of claims from the program's launch in 1969 to 2004 (King, 2008).

[21] Only a few banks are exempted from reporting with HMDA, for two reasons. First, banks are exempted if their total assets fall below a time-varying threshold value, ranging from \$ 32 (in 2002) to \$ 36 million (in 2007). Second, banks which do not have at least one branch office in a Metropolitan Statistical Area are also exempted. These two criteria may reduce the quality of coverage in rural areas. HMDA data also reports loan purchases. I drop these since my interest is in the flow of new loans.

I use the raw HMDA data in two different ways. First, I aggregate a bank's origination volume by county and year to compute the dependent variable for the baseline test (1). I also calculate the share of accepted applications for a bank-county-year. Table 1 shows that the average lending growth and acceptance rate are 8.1% and 80.3%, respectively. Second, I keep the data at the application-level, and I use a dummy for whether the application was accepted as dependent variable. This specification accounts less precisely for lending volumes due to heterogeneous loan, bank and county sizes. However, it allows for finer exploration of loan-level heterogeneities, which I exploit in section 7.

I use three years worth of data before (2003-2005) and after the shock (2006-2008). The 2005 hurricanes struck between late August (Katrina) and mid-October (Wilma). I define 2006 as the start of the shock period since housing reconstruction in most affected areas did not start until early 2006 due to exceptional destructions, environmental hazards, delays in insurance payouts, planning restrictions and populations displacements (Kates et al., 2006). These exogenous factors also imply that, as correctly anticipated after the storms (Kates et al., 2006), housing reconstruction extended over several years, which requires a large post-shock estimation window.

I focus on lending in the three states in which the bulk of damages was concentrated (Alabama, Louisiana, and Mississippi) as well as four bordering states themselves subject to hurricanes (Georgia, Florida, South Carolina, and Texas). While themselves unscathed, a number of counties may not constitute adequate control groups because of large-scale in-migration from affected counties. I thus drop counties hosting a significant number of migrants (see Appendix B for details). Results are robust to alternative choices of time and geographic coverages, and when keeping out-migration counties inside the sample.

5.3 Bank Controls

To control for bank characteristics beyond diversification, I match HMDA with end-of-year regulatory filings (Call Reports) using unique identifiers reported in the two datasets.[22] I construct one-year lags of equity, liquid assets and deposits (all as share of total assets), as well as log total assets, asset quality (non-performing loans as share of total loans) and deposit costs (interest expenses over deposits). Table 1 reports summary statistics and definition details. Finally, I discard a bank if it is involved in a merger during year t.[23]

6 Main Results

6.1 The Dis-Integration Effect

Column 1 in table 2 reports the results of the estimation of benchmark model (1). The main explanatory variable of interest is $Local_{b,t} \times Affected_{c,t}$, which measures how a bank's mortgage lending growth in affected counties changes with the share of its branches in the affected area. I expect the corresponding parameter (β_2) to be negative if the financial capacity channel dominates (local banks in affected areas have a smaller lending capacity), and positive if the relative profitability channel dominates (local banks in affected areas have a technological advantage or greater benefit to lend in affected areas).

The results suggest that the latter channel dominates, with (log) lending growth in affected counties increasing by 9.22% when the bank's share of branches in affected counties increases by 10%. This suggests an economically meaningful effect. For instance, the (log) mortgage growth of a New Orleans community bank (for which $Local_{b,t} = 1$ after 2005) in a representative affected county increases by almost two times more (.92) than that of Bank of America (for which $Local_{b,t} = 0$ after 2005). As their lending growth is systematically higher, the market

[22] The HMDA data records applications with commercial banks, credit unions, savings associations and mortgage companies. Since Call Reports are available for commercial banks only, this matching discards the other lender categories. This entails eliminating around 20% of the flow of originated loans for the median county.

[23] Call Reports as well as a merger database can be downloaded from the Chicago Fed website.

share of banks with a more local focus must increase in affected areas. In other words, mortgage origination in affected areas becomes less geographically integrated. In the remainder of the paper, I refer to this result as the dis-integration effect.

A second variable of interest is $Local_{b,t}$, which measures the way a bank's mortgage lending growth in unaffected counties changes with the share of its branches in the affected area. The corresponding coefficient (β_1) is negative, suggesting that local banks rebalance some of their lending away from unaffected counties and into affected ones. This supports the hypothesis that such banks have a comparative advantage or greater benefit from lending in affected counties. However, the effect is statistically insignificant.

6.1.1 Robustness

Columns 2 to 8 in table 2 explore the robustness of the dis-integration effect. I start with three alternative definitions of $Local_{b,t}$ and/or $Affected_{c,t}$. First, a caveat of the baseline $Local_{b,t}$ proxy is that branch location may imperfectly capture exposure to loan losses after the shock since banks can also lend at arm's length. In column 2, I thus use the concentration of a bank's mortgages in affected counties instead. Specifically, $Local_{b,t}$ is 0 until 2005 and, thereafter, the share of b's total retained mortgages given in affected counties from 2002 to 2004. Second, the wind-based $Affected_{c,t}$ proxy may be prone to measurement error. In column 3, I thus use presidential disaster declarations instead. Specifically, $Affected_{c,t}$ is 0 until 2005, and 1 thereafter if FEMA reports a declaration for county c. The key estimate (β_2) changes little in both cases, albeit it is economically smaller in column 3, consistent with declarations overestimating actually affected areas.

A third caveat is that baseline proxies rely on a crude binary classification of affected counties. In column 4, I thus use flood insurance payouts instead of wind. Specifically, $Affected_{c,t}$ is 0 until 2005, and the ratio of 2005 payouts to total housing units in c thereafter. $Local_{b,t}$ is 0 until 2005 and, thereafter, the sum of $Affected_{c,t}$ for each c, weighted by the share of b's branches in c.[24] The key result also holds, albeit at a lower statistical significance (10%), which is consistent with the continuous treatment measure being noisier.

I then try alternative geographical and time coverages. Column 5 reduces the sample to the three most affected states only (Alabama, Louisiana, and Mississippi), and column 6 uses a shorter estimation window (2004-2007). Results are similar in both cases.

The dis-integration effect could reflect size- rather than diversification-related heterogeneities. I thus construct a variable *2005 Size*$_{b,t}$ which is 0 until 2005, and the pre-shock (2005 Q2) bank size thereafter. I add this control along with its interaction with $Affected_{c,t}$ into the baseline model. If size explains the dis-integration effect, this should make $Affected_{c,t} \times Local_{b,t}$ insignificant. Column 7 shows that this is not the case.

In Appendix section C and table 7, I show that the dis-integration effect is robust to a range of additional perturbations, including re-integrating in-migration counties, winsorizing extreme dependent variable values, dropping rural counties, dropping banks with limited experience in lending outside of the affected area, replacing bank controls by Bank-Holding Company controls, dropping unaffiliated banks, and replacing borrower controls by applicant controls. I also conduct a placebo experiment, assuming that the shock occurs three years earlier, finding no significant dis-integration effect in this case.

6.1.2 Government Intervention

The unprecedented destruction wrought by the 2005 hurricanes have prompted a number of extraordinary government initiatives. Such interventions may contribute to the dis-integration effect if they differently impact local and diversified banks' incentives to lend in affected areas. Some of the measures taken by (i) GSEs, (ii) the Federal Housing (FHA) and Veteran Administrations (VA) and (iii) bank regulators warrant discussion in this context.[25]

[24]For instance, the ratio of 2005 flood insurance payouts to total housing units is 29.2% in the Orleans Parish ($Affected_{c,t} = 0.292$), and 0 in the Dallas County ($Affected_{c,t} = 0$). Thus, for a bank with 50% of branches in each of the two counties, $Local_{b,t}$ is $0.292 \times 0.5 = 0.146$.

[25]Counties declared as disaster areas are routinely eligible for federal aid for public infrastructure repair and assistance to affected businesses and households (Deryugina, 2013). A number of additional initiatives were taken

Fannie Mae and Freddie Mac introduced two main measures to promote lending after Katrina and Rita. First, they allowed banks that used their automated underwriting softwares to abstract from two characteristics which could reduce an application's chance to be eligible for a GSE purchase,[26] namely (i) a recent deterioration in credit history or income, or (ii) ownership of another, typically damaged property which could not be sold before applying for a new loan.[27] In return however, originators were required to provide formal evidence that such deteriorations had been caused by the hurricanes. Second, GSEs re-classified affected counties as "undeserved", thus making them subject to loan purchase targets set by Congress (see for example Bhutta (2012)).

These measures may contribute to the dis-integration effect if GSEs, in addition to increasing purchases or relaxing underwriting standards in affected counties, target local banks in doing so.[28] To rule out this possibility, column 1 of table 3 estimates the baseline model while dropping all loans sold to GSEs. This does not change the results.

Loans to replace or repair damaged properties in declared disaster areas are eligible for FHA guarantees under certain conditions.[29] Column 2 thus drops loans guaranteed by FHA or the VA. This does not change the results either.

Third, federal and state bank regulators in Alabama (AL), Louisiana (LA) and Mississippi

in 2005, including programs to encourage homeownership in affected areas such as the Road Home Program. See http://www.state.gov/documents/organization/150082.pdf for a comprehensive overview. Since these schemes target individuals rather than banks, I do not discuss them further.

[26]Automated underwriting refers to the process of screening mortgage applications using standardized data and proprietary IT systems developed by GSEs. The borrower and loan characteristics are entered by the prospective lender into the system using standardized forms such as Fannie Mae's Uniform Residential Loan Application. Required information typically includes employment history, assets and liabilities and an appraisal of the property's present value. In return, a software such as Fannie Mae's Desktop Underwriter or Freddie Mac's Loan Prospector calculates whether the loan conforms to their underwriting standards and, if so, at what price it would be purchased. Automated underwriting is thought to have dramatically increased economies of scale in mortgage lending (Passmore et al., 2005).

[27]See Freddie Mac (2005) or Fannie Mae (2005). These guidelines stayed in place until at least 2007. GSEs introduced other measures such as short-term moratoria on interest payments and foreclosures, as well as exemptions to the reporting of derogatory post-storm credit history to credit bureaus. I do not discuss these further since they concern GSE's own legacy loans rather than those held or newly originated by banks.

[28]One could, for instance, imagine that this would be politically beneficial for GSEs if local banks in affected areas were connected with key representatives. A contentious overhaul of GSE regulation was underway in Congress in 2005. Some representatives submitted bills which would have given GSEs quantitative loan purchase targets in affected areas, but without success.

[29]Loans too risky to meet GSE standards may be eligible if they do not exceed a loan-to-value ratio of 100%. See for example Department of Housing and Urban Development (2005).

(MS) issued joint guidelines relative to the examination of the (i) capitalization and (ii) lending of banks ”directly affected” by Katrina. For the former, the guidelines encourage examiners to ”give appropriate recognition to the extent to which weaknesses are caused by external problems related to the hurricane”. For the latter, they advise accounting for ”legitimate reasons why management may have eased underwriting standards after Hurricane Katrina” (Federal Deposit Insurance Corporation, 2006).

The guideline’s definition of ”directly affected” banks is vague. However, Gruenberg (2006) suggests that the FDIC’s main concern was around institutions headquartered in states in which the bulk of damages was concentrated (AL, LA and MS). These banks may have a high $Local_{b,t}$ value. Thus, regulatory forbearance may contribute to the dis-integration effect if (i) regulators are systematically more lenient with these banks[30] and (ii) more so regarding these banks’ behavior in affected counties. To control for a bank’s eligibility for these forbearance guidelines, I define $Local\ Headquarter_{b,t}$ as 0 until 2005, and 1 thereafter if b is headquartered in AL, LA or MS. Column 3 in table 3 shows that adding this proxy and its interaction with $Affected_{c,t}$ does not materially change the estimate of the dis-integration effect ($Local_{b,t} \times Affected_{c,t}$).

Banks with a high $Local_{b,t}$ value may also be more likely to have state charters. Since state regulators tend to be less severe than federal regulators (Agarwal et al., 2014), these banks could be regulated more leniently irrespective of forbearance guidelines. I thus define $Local\ Regulator_{b,t}$ as 0 until 2005, and 1 thereafter if b is state-chartered and headquartered in AL, LA or MS. Column 4 shows that adding this control and its interaction with $Affected_{c,t}$ does not change the conclusions either.[31]

[30] This is ambiguous, since anecdotal evidence suggests these banks were also subject to *greater* scrutiny out of concerns for their safety (Gruenberg, 2006).

[31] A final potential source of government distortions stems from the Community Reinvestment Act (CRA). CRA regulation incentivizes banks to lend in areas in which they raise deposits (so-called ”Assessment Areas” (AA)). Banks’ lending in AA is examined every five years on average. Regulators can factor in the result of these assessments when for instance, evaluating a bank’s merger or branch opening plans. To encourage lending after the 2005 hurricanes, regulators have added disaster areas to AA in post-storm examinations (see for example The American Banker (2006b).) For this to contribute to the dis-integration result, the incentive to comply with CRA regulation must be higher for local banks. This is counterintuitive. If anything, CRA regulation should be more binding for

6.1.3 External Validity

The dis-integration effect could be unique to (i) the macroeconomically benign environment and booming mortgage market prevailing in 2005, (ii) the exceptional scale of Katrina and (iii) the socio-economic profile of the affected areas, such as the disproportionate share of low-income and ethnic minority households.

I thus first consider a broader set of disasters across time and space. I again use the county-level flood insurance payouts data (section 6.1.1) to do so.[32] This time however, I use the entire panel (2000-2010) instead of the sole 2005 season. I make two changes to the baseline approach. First, I adapt the geographic coverage of the mortgage lending panel to the spatial distribution of the most significant (typically hurricane-driven) flood events. Specifically, I include all US states that account for a combined 75% of all payouts over the period.[33] Second, I consider counties to be affected for one year only (as opposed to three in the baseline regression) since, unlike Katrina, reconstruction can start shortly after most hurricanes (Romero Cortés and Strahan, 2014). Consistently, $Affected_{c,t}$ is the one-year lagged number of payouts in c, t as a ratio to the number of housing units in c. $Local_{b,t}$ is the sum of $Affected_{c,t}$ for all counties, weighted by the share of b's branches located in c. Finally, to avoid the 2005 season contaminating results, I drop the year 2006 altogether.

The results in column 1 of table 4 show a similar dis-integration effect, with mortgage growth increasing with a bank's weighted share of branches in affected counties. Note that this does not necessarily mean that the effect holds for the average hurricane. Since the treatment proxies ($Local_{b,t}$ and $Affected_{c,t}$) are continuous and largely right-skewed, these results are likely driven by the most destructive hurricanes in the sample.

Second, I replicate the analysis of the 2005 hurricanes to the small business lending market,

diversified banks given their spatially dispersed branch networks and lending activities.

[32] Since NOAA wind swathes data is available for selected major hurricanes only, I cannot replicate the baseline approach to other disasters.

[33] These are (sorted by number of payouts): Louisiana, Florida, Texas, New Jersey, New York, North Carolina, Pennsylvania and Mississippi. Results are robust when using the baseline set of states instead.

using data collected under the Community Reinvestment Act (CRA). The raw data shows the total lending volume for a given bank-county-year. This allows the replication of the baseline mortgage regression, while using bank-county yearly small business growth as the dependent variable.[34]

The model is otherwise similar to the baseline set-up, with two exceptions. First, given the level of aggregation, borrower characteristics cannot be controlled for (other than via a county-year fixed effect).[35] Second, while housing reconstruction post-Katrina did not start before 2006, infrastructure repair and debris removal started within two weeks after the storm (Kates et al., 2006). Small business credit demand may thus already have changed during the second half of 2005. Unlike in the baseline regression, I thus use data for the 2002-2007 period (against 2003-2008), and define 2005 (against 2006) as the first shock year.

Column 2 of table 4 shows a similar dis-integration effect, with (log) small business lending growth in affected counties increasing by 2.39% when the share of a bank's branches in affected counties increases by 10%. This effect is economically smaller than that found for the mortgage market. One hypothesis is that small business loans cannot be sold, which increases the importance of post-shock financial constraints or, equivalently, the weight of the financial capacity channel. A second difference is that the coefficient for $Local_{b,t}$ is both negative and strongly statistically significant. This suggests that local banks rebalance small business lending away from unaffected counties to affected ones. The marginal drop in lending to unaffected counties (-65%) is stronger than the increase in affected counties (24%). This suggests either that the shock decreases the overall financial capacity of local banks (consistently with binding financial constraints), or that cutting lending to unaffected counties allows accomodating more new mortgage lending in affected counties. The next section formally investigates further margins of adjustment.

[34]The data is less representative than HMDA because reporting with CRA is voluntary and biased toward banks' so-called Assessment areas. See footnote 31.

[35]This also implies that publically guaranteed loans such as the Small Business Administration's disaster loans cannot be filtered out.

6.2 Margins of Adjustment

The previous section has addressed the question of *who* lends in affected counties, pointing to the importance of local banks. I now explore *how* these banks re-adjusted mortgage lending after the shock. Table 5 investigates three potential margins of adjustment.

Column 1 estimates the baseline model, but uses the share of accepted applications in a bank-county-year as the dependent variable. This allows to evaluate how supply adjusts *conditional on demand*, while making weaker assumptions about endogenous sorting of unsolicited applications (see section 4). Again, the coefficient for $Local_{b,t} \times Affected_{c,t}$ is positive and significant, suggesting that at least a portion of the dis-integration effect can be ascribed to supply only. Controlling for their characteristics, the share of applications from an affected county which are accepted increases by 1.45% on average when the bank's share of branches in affected counties increases by 10%. There is a significant, opposite effect in unaffected counties ($\beta_1 = -0.13$), suggesting that the higher acceptation volume in affected counties is compensated by an equal share of denied applications in unaffected counties. This re-balancing constitutes a second margin of adjustment.

Finally, since local banks have a presumably lower financial capacity following the shock, selling some of the newly originated loans may allow financing yet more lending. To test this hypothesis, columns 2 and 3 respectively decompose the share of accepted applications into (i) the share of applications accepted-and-sold and (ii) the share of applications accepted-and-retained.[36] The coefficient of $Local_{b,t} \times Affected_{c,t}$ is positive and significant for the former only. Specifically, controlling for their characteristics, the share of applications accepted-and-sold by a bank increases by 2.49% when the share of its branches in affected areas increases by 10%. In contrast, the share of applications accepted-and-retained *decreases* by 1.05% when

[36] HMDA data records an application as sold (or securitized) if it was sold by the originator during the year of origination. Since selling loans may take up to three months, this may bias results in an unknown direction - especially for loans that were originated during the last months of a year (Favara and Giannetti, 2015). This also implies that I cannot measure sales of loans originated before the shock, which could constitute a further way for local banks to finance new lending.

$Local_{b,t}$ increases by 10%.

Together, these results indicate that the increase in accepted applications is attributable to loans sold into the secondary market rather than kept on the originator's balance sheet. This suggests that while local banks play a key role in supplying loans to affected areas, some of this lending is actually financed by secondary market participants.

7 Channels

The previous section has shown that local banks (i) originate more loans in affected areas (and fewer elsewhere) compared to more diversified banks, but (ii) increasingly resort to loan sales in doing so. The latter outcome supports the notion that securitization allows banks to circumvent tightening financial constraints (Loutskina and Strahan, 2009). The former result (the dis-integration effect) suggests that local banks have either a comparative advantage or greater benefit to lend in affected counties. However, the reason behind this effect is more ambiguous.

This section explores four non-mutually exclusive explanations for the dis-integration effect. For this exercise, I switch to the application-level model, with a dummy for an accepted application as the dependent variable. The key benefit of this approach is that it allows for finer exploitation of loan characteristics than the baseline county-level model, while further attenuating identification challenges around credit demand (see section 4). The model is as follows:

$$\begin{aligned} Accepted_{a,b,c,t} &= \beta_1 \cdot Local_{b,t} + \beta_2 \cdot Local_{b,t} \times Affected_{c,t} \\ &+ \beta_3 \cdot Local_{b,t} \times Affected_{c,t} \times Channel \\ &+ \beta_4 \cdot BankControls_{b,t} + \beta_5 \cdot BorrowerControls_{a,b,c,t} \\ &+ CountyYearF.E._{c,t} + BankCountyChannelF.E._{b,c} + \epsilon_{a,b,c,t}, \end{aligned} \tag{2}$$

where $Accepted_{a,b,c,t}$ is 1 if bank b accepts mortgage application a in county c and year t, and 0 otherwise. Explanatory variables are similar to that of the baseline model, with two exceptions. First, the parameter of interest is $Local_{b,t} \times Affected_{c,t} \times Channel$, which captures the way the dis-integration effect ($Local_{b,t} \times Affected_{c,t}$) varies with competing explanations proxied by $Channel$.[37] Second, $BankCountyChannelF.E._{b,c}$ is the standard set of bank-county fixed effects, augmented with a second interaction term to evacuate time-invariant heterogeneities in a bank's behavior for a particular $Channel$, where appropriate.[38]

7.1 Lending Technology

Loutskina and Strahan (2011) show that local and diversified banks use different mortgage lending technologies. Local banks accumulate specific knowledge about a given market, thus earning rents from originating information-intensive loans more effectively. Diversified banks generate economies-of-scale by originating loans which can be underwritten using standardized data and techniques across multiple markets.

The background information in section 3 suggests that new lending opportunities in affected counties should have become more information-intensive, or, more generally, more costly to evaluate and process using standardized data and techniques as a result of the exceptional destruction of collateral and heightened uncertainty around future house prices and economic activity. Concrete examples of such increasing costs include increasing difficulties in appraising house values in devastated areas, a higher necessity to monitor construction works closely due to rampant fraud concerns, and requests for additional information by potential secondary market purchasers such as GSEs.[39]

[37] For simplicity, equation 2 does not show all possible combinations between $Local_{b,t}$, $Affected_{c,t}$ and $Channel$ that do not drop because of fixed effects. All these terms are controlled for in the actual estimation model.

[38] If $Channel$ is a dummy for a high-income applicant for instance, $BankCountyChannelF.E._{b,c}$ is a matrix of bank-county-high-income fixed effects. See footnotes 41, 44 and 46 for details. Following existing empirical models of loan approval (Duchin and Sosyura, 2014; Puri et al., 2010), I estimate equation 2 using a linear probability model. The key motivation for this choice is that non-linear models produce biased estimates in the presence of a large number of fixed effects and interaction terms (Wooldridge, 2010).

[39] The increase in origination costs or information-intensity stressed in this section is not necessarily tantamount to an increasing need to collect *soft* information, i.e. information that cannot be transmitted to potential purchasers.

Since they specialize in such information-intensive loans in good times, a first hypothesis is that local banks have a comparative technological advantage in screening, monitoring or pricing loans in affected counties, and thus a higher opportunity cost to lend elsewhere.

If this hypothesis holds, local banks should accept in particular more applications for which they have the greatest comparative advantage, i.e. information-intensive or, more generally high-origination cost loans. I use two alternative proxies to distinguish these loans. First, $\textit{Moderate-to-high Income}_{a,b,c,t}$ is 1 if a's income is above 80% of the Metropolitan Statistical Area (MSA) median family income, and 0 otherwise. Second, $Conforming_{a,b,c,t}$ is 1 if a meets all the criteria for a GSE purchase perfectly observable in HMDA, and 0 otherwise.[40] Both proxies exploit the heterogeneous ease of selling different mortgages. High-income and conforming mortgages are more likely to qualify for a GSE purchase. Hence, these "prime" loans can be underwritten using standardized data and tools such as GSE's automated softwares, even after the shock. In contrast, non-prime mortgages might be more affected by the increasing origination costs described above.[41]

Since local banks should thus be most prone to accept non-prime loans, I expect the parameter for $Local_{b,t} \times Affected_{c,t} \times Channel$ (β_3) to be negative. Columns 1 and 2 in table 6 show that this is the case. This confirms that the dis-integration effect (the higher propensity of a more local bank to accept an application in an affected county) decreases marginally when $Channel$ changes from 0 (a non-prime application) to 1 (a prime application). Specifically, the dis-integration effect decreases by 0.786 and 1.08% when the application changes to a moderate-to-high-income (column 1) and a conforming application (colum 2), respectively.

For instance, the additional information requested by GSEs (such as hard evidence for the link between an applicant's house value and the hurricane destructions) was precisely meant to be transmitted. However, it might have been *costly* to collect and process.

[40] First, the loan must be for a house purchase, rather than for a house improvement or a loan refinancing. Second, the loan must be for a one-to-four person house. Third, the loan must not be guaranteed by the FHA or VA. Fourth, the loan size must be below the jumbo-loan size threshold.

[41] One concrete example of this mechanism is that GSEs requested additional information for loans from affected areas which did not qualify for a prime loan (see section 6.1.2). More generally, Ergungor (2010) shows that lending in low-to-moderate income neighborhoods necessitates costly local information collection. In these regressions, $BankCountyChannelF.E._{b,c}$ is a bank-county-moderate-to-high-income (column (1)) and bank-county-conforming (column (2)) fixed effect, respectively. This controls for time-invariant heterogeneities in bank behavior across areas and types of applicants.

A second variable of interest is $Local_{b,t} \times Affected_{c,t}$, which measures the magnitude of the dis-integration effect when $Channel = 0$ (i.e. when the application is non-prime). The corresponding parameter (β_2) is positive and significant for both proxies. Specifically, column 1 shows that the probability of a low-income application in an affected county being accepted (controlling for its other characteristics) increases by 1.86% when the share of b's branches in affected areas increases by 10%. Column 2 suggests that acceptation probability for a non-conforming applicant increases by 1.72% when $Local_{b,t}$ increases by 10%. Together, these results suggest that local banks are most prone to accepting applications if they are relatively more information-intensive (or costlier to process), hence giving a potential comparative advantage to lenders with a good knowledge of affected markets.

7.2 Marginal Benefit of Cash

A non-mutually exclusive hypothesis is that local banks have a greater ex-post benefit to increase originations in affected counties with a view to sell these loans and generate fee income, since they are more exposed to losses in income or access to external finance.[42]

In this interpretation, local banks would also have an incentive to originate easily sellable "prime" (high-income or conforming) loans. Results in the previous section have shown that the dis-integration effect is marginally *smaller* for such loans. However, this does not yet mean that local banks originate fewer such loans after the shock (relative to diversified banks). This can be seen by adding the coefficients for $Local_{b,t} \times Affected_{c,t} \times Channel$ and $Local_{b,t} \times Affected_{c,t}$ in columns 1 and 2 of table 6. This sum captures the marginal effect of the dis-integration effect ($Local_{b,t} \times Affected_{c,t}$) when $Channel = 1$, i.e. for prime applicants.

This sum is positive in both columns. Specifically, controlling for her characteristics, the chance of a high-income applicant in an affected county being accepted increases by 1.1%

[42] Malherbe (2014) shows that cash-poor banks have an incentive to sell loans to generate cash. They are able to do so despite the threat of adverse selection since the buyer understands that the seller seeks to overcome financial constraints rather than to sell lemons. Boyle and Guthrie (2003) show that when uncertainty about the profitability of an investment increases, financially constrained firms prefer to invest (thus realizing early cash) than to "wait-and-see" (i.e. delaying investment while waiting for new information to reduce uncertainty).

(0.186-0.0786) when the share of b's branches in affected areas increases by 10%. Column 2 suggests that for a non-conforming applicant, this probability increases by 0.64% (0.172-0.108) when $Local_{b,t}$ increases by 10%.

Combined with the previous section, these results suggest that in affected areas, local banks accept both more prime and non-prime applications. While they may have a relatively higher comparative advantage in catering to non-prime borrowers, they may also have a weaker financial capacity to do so since these loans are harder to sell. Since prime loans can be sold easily, however, fees potentially generated from these sales can increase local banks' financial capacity to retain non-prime loans.[43]

7.3 Preventing Negative Externalities

Literature shows that mortgage supply has positive externalities for local house prices and economic activity, for instance by reducing the incidence and contagion of foreclosures (Mian et al., 2015). Thus, banks have an incentive to keep lending to an area in which they have a key stake. Consistently, zip codes where a concentrated set of banks own a large share of outstanding mortgages have fewer foreclosures (Favara and Giannetti, 2015).

In this interpretation, the dis-integration effect would reflect local banks' attempt to protect indirectly their outstanding investments and long-term profitability. Following the reasoning in Favara and Giannetti (2015), this motive should increase with a bank's share of outstanding loans in a given neighborhood. The higher this share, the more new lending may benefit the bank's own loan portfolio and profitability. Accordingly, I construct a variable $Share_{b,c}$, defined as the share of all retained mortgages in census tract c originated by b during the pre-shock period (2002-2004).[44]

Column 3 in table 6 shows that the parameter of interest ($Local_{b,t} \times Affected_{c,t} \times Share_{b,c}$)

[43] I am indebted to Charles Calomiris for suggesting this interpretation.

[44] In this case, $BankCountyChannelF.E._{b,c}$ is a bank-census-tract fixed effect. This controls for time-invariant heterogeneities in bank behavior across census tracts.

is not statistically significant. Thus, a local bank is not more likely to accept an application from an affected census tract in which it owns a higher share of outstanding mortgages. This does not necessarily mean that this channel is not a work, but perhaps that it is outweighed by countervailing effects. For instance, a local bank may prefer to lend in an affected neighborhood in which it does not yet own mortgages in order to diversify its portfolio marginally, while still exploiting its advantage or benefit of lending inside the affected area.[45]

7.4 Risk-Shifting

Several theoretical mechanisms imply a link between a bank's risk-taking incentives and its expected long-term profitability or leverage. A deterioration in future profitability (or "charter value") leads to higher risk-taking if shareholders seek to maximize the implicit subsidy provided by deposit guarantee (Keeley, 1990) or if managers seek to convince shareholders of their managerial skills (Gorton and Rosen, 1995). More generally, firms highly levered or close to failure increase risk-taking since the downside risk is borne mostly by bondholders (Jensen and Meckling, 1976).

These theories speak to the present case, since local banks in affected areas contemplate both lower long-term profits (e.g. because of depressed economic and population growth prospects) and higher leverage and risk of failure (e.g. because of income losses). In this interpretation, the dis-integration effect would reflect distressed local banks lending more in affected areas because it increases their risk-taking.

To evaluate this channel, I create a variable $Equity_b$, defined a bank's ratio of equity to total assets immediately before the shock (June 2005). The lower $Equity_b$, the more b's leverage and proximity to default should increase after the shock. The variable of interest is $Local_{b,t} \times Affected_{c,t} \times Equity_b$, which measures whether the dis-integration effect decreases with a

[45] This can be seen by looking at the estimate for $Local_{b,t} \times Affected_{c,t}$, which captures the way a bank's probability of accepting an application changes with its share of branches in affected counties *if its pre-existing tract market share is zero*. The corresponding parameter is positive and significant.

bank's capitalization.[46] Column 4 in table 6 shows that this is not the case. The corresponding parameter is not only statistically insignificant, but also positive. Again, this does not necessarily mean that risk-shifting incentives are absent altogether; they may be offset by countervailing effects. For instance, a low-capitalized local bank might have a smaller financial capacity to accept an application from an affected area because it is more likely to face binding financial constraints in doing so.

To disentangle these two effects, I repeat the same regression while keeping only non-conforming applications, i.e. those harder to sell and thus more likely to mobilize originator capital. Column 5 shows that the parameter for $Local_{b,t} \times Affected_{c,t} \times Equity_b$ is positive and statistically significant in this case. In other words, local banks are more prone to accept non-prime applications from affected areas if they are better capitalized before the shock. This reinforces the interpretation that, if anything, a low capitalization constrains rather than encourages local banks' risk-taking.

8 Conclusion

More than 400 banks with assets below $1 billion have failed between 2007 and 2012 (DeYoung et al., 2015). These banks typically had local geographic footprints. The literature is inconclusive as to whether the resulting increase in US banks' average diversification will affect credit allocation in a context of protracted recovery. While local banks should be financially more vulnerable to localized downturns, they may also have special abilities or ex-post incentives to seize lending opportunities in a distressed market in which they have a key stake.

This paper uses major hurricane strikes to evaluate which of these two opposite channels dominates empirically during the recovery from an unambiguously exogenous downturn. The results show that local banks originate a higher share of mortgages in affected areas, but in-

[46] I use the baseline bank-county fixed effect in this case since $Equity_b$ does not add a new layer of variation unlike the *Channel* proxies in the three previous sections.

creasingly use loan sales to finance these loans.

These results are important for two reasons. From an academic point of view, they suggest a new pattern of specialization whereby, following a major downturn, credit supply is re-allocated to agents with different degrees of diversification. Consistent with their abilities and incentives, the origination of new loans in affected areas is increasingly taken on by local banks. Consistent with local banks' financial vulnerability in such circumstances, however, the financing of these loans is increasingly transfered to (presumably) better diversified secondary market participants.

From a policy perspective, the results suggest that local banks may keep an important role in a geographically integrated banking system, despite their greater vulnerability to financial constraints in adverse circumstances. However, local banks' ability to perform this role after a major downturn may hinge on the existence of a liquid, nationwide secondary market for mortgages loans. Thus, post-crisis changes in the geographical footprint of US banks should be discussed jointly with parallel changes in the operations and regulation of mortgage securitization.

References

Agarwal, S., D. Lucca, A. Seru, F. Trebbi, et al. (2014). Inconsistent regulators: Evidence from banking. *The Quarterly Journal of Economics 129*(2), 889–938.

Berg, G. and J. Schrader (2012). Access to credit, natural disasters, and relationship lending. *Journal of Financial Intermediation 21*(4), 549–568.

Berger, A. N., N. H. Miller, M. A. Petersen, R. G. Rajan, and J. C. Stein (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics 76*(2), 237–269.

Bernanke, B. and M. Gertler (1989). Agency costs, net worth, and business fluctuations. *The American Economic Review 79*(1), 14–31.

Bernanke, B. S. (2011). Community banking in a period of recovery and change. In *Speech, Independent Community Bankers of America National Convention, San Diego, California*.

Bhutta, N. (2012). GSE activity and mortgage supply in lower-income and minority neighborhoods: The effect of the affordable housing goals. *The Journal of Real Estate Finance and Economics 45*(1), 238–261.

Blake, E. S., C. W. Landsea, and E. J. Gibney (2007). *The deadliest, costliest, and most intense United States tropical cyclones from 1851 to 2006 (and other frequently requested hurricane facts)*. NOAA/National Weather Service, National Centers for Environmental Prediction, National Hurricane Center.

Boyle, G. W. and G. A. Guthrie (2003). Investment, uncertainty, and liquidity. *The Journal of Finance 58*(5), 2143–2166.

Brown, R. A. (2005). Unique challenges face FDIC-insured institutions after Katrina. *FDIC Outlook*.

Calomiris, C. W., R. G. Hubbard, and J. Stock (1986). The farm debt crisis and public policy. *Brookings Papers on Economic Activity 1986*(2), 441–485.

Carlson, M. and K. J. Mitchener (2009). Branch banking as a device for discipline: Competition and bank survivorship during the Great Depression. *Journal of Political Economy 117*(2), 165–210.

Demyanyk, Y., C. Ostergaard, and B. E. Sørensen (2007). US banking deregulation, small businesses, and interstate insurance of personal income. *The Journal of Finance 62*(6), 2763–2801.

Department of Housing and Urban Development (2005, August 31st). Underwriting and servicing policies to assist victims of presidentially-declared major disaster areas. *Mortgagee Letter*.

Department of Housing and Urban Development (2006, February). Current housing unit damage estimates; Hurricanes Katrina, Rita and Wilma.

Department of the Treasury, Office of the Comptroller of the Currency, Federal Reserve System, Federal Deposit Insurance Corporation, Office of Thrift Supervision, and National Credit Union Administration (2005). Real estate appraisal exceptions in major disaster areas. *Federal Register 70*.

Deryugina, T. (2013). Disaster insurance versus social insurance in the aftermath of hurricanes. *Mimeo*.

DeYoung, R., A. Gron, G. Torna, and A. Winton (2015). Risk overhang and loan portfolio decisions: Small business loan supply before and during the financial crisis. *The Journal of Finance 70*(6), 2451–2488.

Duchin, R. and D. Sosyura (2014). Safer ratios, riskier portfolios: Banks response to government aid. *Journal of Financial Economics 113*(1), 1–28.

Ergungor, O. E. (2010). Bank branch presence and access to credit in low-to moderate-income neighborhoods. *Journal of Money, Credit and Banking 42*(7), 1321–1349.

Fannie Mae (2005, October 14th). Hurricane-related mortgage servicing and underwriting policies. *Lender Letter*.

Favara, G. and M. Giannetti (2015). Forced asset sales and the concentration of outstanding debt: Evidence from the mortgage market. *CEPR working paper* (10476).

Federal Deposit Insurance Corporation (2006, February 3rd). Interagency supervisory guidance for institutions affected by Hurricane Katrina. *Financial Institutions Letters*.

Freddie Mac (2005, September). Temporary selling & servicing requirements for mortgages secured by properties located in eligible disaster areas. *Freddie Mac Bulletin*.

Gallagher, J. and D. Hartley (2014). Household finance after a natural disaster: The case of Hurricane Katrina. *Federal Reserve Bank of Cleveland Working Paper 1406*.

Gan, J. and T. J. Riddiough (2008). Monopoly and information advantage in the residential mortgage market. *Review of Financial Studies 21*(6), 2677–2703.

Gilchrist, S., J. W. Sim, and E. Zakrajšek (2014). Uncertainty, financial frictions, and investment dynamics. *NBER Working Paper* (20038).

Gilje, E., E. Loutskina, and P. Strahan (2016). Exporting liquidity: Branch banking and financial integration. *The Journal of Finance 71*.

Gorton, G. and R. Rosen (1995). Corporate control, portfolio choice, and the decline of banking. *The Journal of Finance 50*(5), 1377–1420.

Groen, J. A. and A. E. Polivka (2008). Hurricane Katrina evacuees: Who they are, where they are, and how they are faring. *Monthly Labor Rev. 131*, 32.

Gruenberg, M. J. (2006, February). Impact of recent hurricanes on financial institutions in the Gulf Coast. Statement before the Committee on Banking, Housing and Urban Affairs of the U.S. Senate.

Holmstrom, B. and J. Tirole (1997). Financial intermediation, loanable funds, and the real sector. *The Quarterly Journal of Economics 112*(3), 663–691.

Jensen, M. C. and W. H. Meckling (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics 3*(4), 305–360.

Kates, R. W., C. E. Colten, S. Laska, and S. P. Leatherman (2006). Reconstruction of New Orleans after Hurricane Katrina: A research perspective. *Proceedings of the National Academy of Sciences 103*(40), 14653–14660.

Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *The American Economic Review 80*(5), 1183–1200.

King, R. O. (2008). National Flood Insurance Program: Treasury borrowing in the aftermath of Hurricane Katrina. In *The Library of Congress, Order Code RS22394*.

Lambert, C., F. Noth, and U. Schüwer (2015). How do banks react to catastrophic events? Evidence from Hurricane Katrina. *SAFE Working Paper 94*.

Loutskina, E. (2011). The role of securitization in bank liquidity and funding management. *Journal of Financial Economics 100*(3), 663–684.

Loutskina, E. and P. Strahan (2011). Informed and uninformed investment in housing: The downside of diversification. *Review of Financial Studies 24*(5), 1447–1480.

Loutskina, E. and P. Strahan (2012). Financial integration, housing and economic volatility. *Mimeo*.

Loutskina, E. and P. E. Strahan (2009). Securitization and the declining impact of bank finance on loan supply: Evidence from mortgage originations. *The Journal of Finance 64*(2), 861–889.

Malherbe, F. (2014). Self-fulfilling liquidity dry-ups. *The Journal of Finance 69*(2), 947–970.

McIntosh, M. F. (2008). Measuring the labor market impacts of Hurricane Katrina migration: Evidence from Houston, Texas. *The American Economic Review 98*(2), 54–57.

Mendelsohn, R., K. Emanuel, and S. Chonabayashi (2012). The impact of climate change on hurricane damages in the United States. *Nature Climate Change 2(3)*, 205–209.

Mian, A. and A. Sufi (2009). The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis. *The Quarterly Journal of Economics 124*(4), 1449–1496.

Mian, A., A. Sufi, and F. Trebbi (2015). Foreclosures, house prices, and the real economy. *The Journal of Finance 70*(6), 2587–2634.

Morgan, D., B. Rime, and P. Strahan (2004). Bank integration and State business cycles. *The Quarterly Journal of Economics 119*(4), 1555–1584.

New York Times (2006, September 3d). A bank survives Katrina. Now, the hard part. *New York Times*.

New York Times (2015, August 18th). Why New Orleans black residents are still underwater after Katrina. *New York Times*.

Nordhaus, W. D. (2010). The economics of hurricanes and implications of global warming. *Climate Change Economics 1*(01), 1–20.

Overby, A. B. (2007). Mortgage foreclosure in post-Katrina New Orleans. *Boston College Law Review 48*(4), 851.

Passmore, W., S. M. Sherlund, and G. Burgess (2005). The effect of housing government-sponsored enterprises on mortgage rates. *Real Estate Economics 33*(3), 427–463.

Puri, M., J. Rocholl, and S. Steffen (2010). Global retail lending in the aftermath of the US financial crisis: Distinguishing between supply and demand effects. *Journal of Financial Economics 100*(3), 556–578.

Romero Cortés, K. (2014). Rebuilding after disaster strikes: How local lenders aid in the recovery. *FRB of Cleveland Policy Discussion Paper* (14-28).

Romero Cortés, K. and P. E. Strahan (2014). Tracing out capital flows: How financially integrated banks respond to natural disasters. *FRB of Cleveland Working Paper*.

Ruckes, M. (2004). Bank competition and credit standards. *Review of Financial Studies 17*(4), 1073–1102.

Sprague, O. M. (1903). Branch banking in the United States. *The Quarterly Journal of Economics 17*(2), 242–260.

Stein, J. (1998). An adverse-selection model of bank asset and liability management with implications for the transmission of monetary policy. *The Rand Journal of Economics 29*(3), 466–486.

Strobl, E. (2011). The economic growth impact of hurricanes: Evidence from US coastal counties. *Review of Economics and Statistics 93*(2), 575–589.

The American Banker (2006a, March 3rd). Bankers on Gulf Coast seek help from around the country. *The American Banker*.

The American Banker (2006b, January 19th). Bankers seek more CRA credit for disaster lending. *The American Banker*.

Vigdor, J. (2008). The economic aftermath of Hurricane Katrina. *The Journal of Economic Perspectives 22*(4), 135–154.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

A The 2005 Hurricanes as a Shock to Bank's Financial Capacity

This section establishes empirically that the 2005 hurricane season exposes banks to a negative shock to their financial capacity, complementing the anecdotal evidence provided in section 3. Specifically, I measure the short-term impact of the shock for three proxies for financial capacity - income, non-performing loans, and capitalization[47] - using Call Reports data for all commercial banks for which I can observe the June 2005 branching network. For each of these proxies, I then estimate the following cross-sectional model:

$$\Delta Y_{b,t} \quad = \quad \gamma_1 \cdot Local_b + \gamma_2 \cdot BankControls_b + StateF.E._b + \epsilon_{b,t}, \tag{3}$$

where $\Delta Y_{b,t}$ is the change in b's income, non-performing loans, or capitalization between quarter t and the quarter immediately preceding the shock (2005q2). $Local_b$ is the same diversification proxy used in the baseline regression, i.e. the share of a bank's total branches located in counties affected by the 2005 hurricane season, as measured in June 2005. The parameter of interest is γ_1, which measures how a bank's financial capacity changes depending on its diversification from the perspective of the affected area. The financial capacity channel predicts that a more local bank should be more vulnerable to losses generated by the shock. I thus expect γ_1 to be negative for income and capitalization, and positive for non-performing loans.[48]

I estimate the cross-sectional model 3 for each quarter from 2004 to end 2006, and for each of the three proxies. The estimate for γ_1 (bold lines) and its confidence intervals (dashed lines) obtained from the regressions are plotted in the upper (income), middle (non-performing loans) and bottom (capitalization) panels of figure 3.

A first observation is that γ_1 is not significantly different from zero during the pre-shock

[47] Consistently with the baseline set-up, income and capitalization are measured as percentage of total assets, and non-performing loans is measured as percentage of total loans.

[48] $BankControls_b$ include (log) size, deposit funding, liquid assets, total loans, and deposit funding costs, all measured immediately before the shock, and defined consistently with the baseline set-up (see table 1 for definitions). $StateF.E._b$ is a set of dummies for banks' headquarter states. All dependent variables are winsorized at the bottom and top 1%.

period (from 2004q1 to 2005q1) for all three proxies. This suggests that there are no heterogeneous trends in financial capacity across local and diversified banks before the shock. In contrast, β_1 becomes significant immediately after the shock. Specifically, all three proxies suggest that a higher geographical focus in the affected areas ($Local_b$) is associated with a decrease in income and capitalization, and an increase in non-performing loans after the shock. This effect is significant for two quarters after the shock for income and non-performing loans, and four quarters for capitalization.

The largest effect on capitalization is found for 2006q1. Specifically, the corresponding parameter estimate suggests that a bank's capitalization decreases by 7.4 basis points (0.74%) when $Local_b$ increases from zero (for instance Bank of America) to 100% (for instance a community bank in the New Orleans area), compared to its pre-shock value. This corresponds to a 7.3% decline in the capitalization of the average bank in the sample, the latter amounting to 10.1% of total assets. Equivalenty, this would correspond to a 35.2% decline of this average bank's hypothetical capital buffer over a typical capital requirement of 8% of total assets.[49]

B Tracking Hurricane Katrina Migrants

Hurricane Katrina has led more than 1.5 million people to be permanently displaced from the most severely affected areas (Groen and Polivka, 2008). Migrants might need access to mortgage credit upon re-settling. This implies that areas with a substantial migrant presence are not adequate control groups for affected areas. Thus, such "out-migration counties" are excluded from the baseline regression.

To delineate out-migration counties, I use county-to-county migration data compiled by the Internal Revenue Service (IRS). The data records in- and outflows of residents broken down by

[49] Lambert et al. (2015) find that banks exposed to Hurricane Katrina increase their risk-weighted capital ratio in the longer run (up to 2007q4). However, this only holds for unaffiliated banks, which account for 23.9% of banks in my sample as of 2005q2. Further, they do not consider the period immediately after the shock (2005q3 and 2005q4), for which I find strong negative effects. Finally, they rely on a binary rather than continuous definition of exposed banks.

departure and relocation county.[50] I use the 2006 vintage, which tracks postal address changes from fiscal years 2005 to 2006. Since the vast majority of migrants relocated from the New Orleans area, I limit myself to tracking evacuees from this metropolitan area.[51]

For each US county, I calculate *Migrant Number*$_{c,t}$ as the log number of households relocating from the New Orleans area, net of the number of households relocating *to* the New Orleans area during the same period (this helps to filter out temporary displacements). Figure 4 plots *Migrant Number*$_{c,t}$ for all US counties, with darker shades indicating a larger presence of migrants. The Houston and Dallas areas stand out, consistently with evidence that they hosted the largest number of migrants (McIntosh, 2008).

Figure 4 shows that almost all counties in the sample of seven states used for the baseline sample host a positive number of evacuees. Thus, some arbitrary line must be drawn to exclude only the most significant out-migration counties. I remove all counties that host a combined 75% of all evacuees. The main results are robust when not excluding these counties.

C Additional Robustness Checks

Appendix table 7 reports eight additional checks for the robustness of the dis-integration effect (column (1) of table 2), as well as a placebo test.

A first caveat of the baseline set-up is that the classification of out-migration counties set out in section B is bound to be imprecise given the likely imperfect coverage of Katrina evacuees in IRS data. In column (1), I thus re-integrate the counties excluded from the baseline sample because they receive a substantial number of in-migrants from the New Orleans area following Katrina. This does not affect results. A second caveat is that bank-level controls such

[50] IRS Migration Data is based on postal address changes as recorded in income tax declarations (see irs.gov/uac/SOI-Tax-Stats-Migration-Data). It covers 95 to 98% of the income tax filing population (itself an unknown proportion of the population of migrant households). Since migrants may be disproportionately unemployed, this may bias the estimates downwards.

[51] Using alternative data, Groen and Polivka (2008) show that the entire population of evacuees came from the states of Louisiana, Mississippi, and Alabama. Morever, nearly all migrants from the two latter states had returned to their original residency before the end of 2005. A large majority of Louisiana evacuees came from the New Orleans area.

as income or capitalization might change endogenously after the shock as a result of lending decisions, thus biasing results in an unknown direction. In column (2), I drop the bank-level controls, again with little effect on results.

The baseline results could be driven by abnormally high mortgage growth numbers. In column (3), I thus winsorize the top and bottom 1% of the dependent variable. This decreases the economic magnitude of the dis-integration effect only marginally, suggesting that outliers do not inflate results significantly. One further caveat is that the coverage of HMDA data is less comprehensive in rural areas. In column (4), I thus drop counties that are not part of a metropolitan statistical area. If anything, this slightly increases the economic magnitude of the dis-integration effect.

The dis-integration effect could be driven by banks with little initial experience in lending outside of the affected areas, and thus no realistic prospect of substantially re-balancing their lending elsewhere after the shock. In column (5), I thus drop banks whose total mortgage lending in affected counties before the shock (2003-2005) represents less than 20% of their total mortgage lending. This increases the economic magnitude of the dis-integration effect. Further, unlike in the baseline regression, the parameter estimate for $Local_{b,t}$ is not only negative, but also statistically significant. This suggests that there is a significant re-balancing away from unaffected counties to affected ones.

Banks affiliated to a Bank-Holding Company (BHC) could receive equity or liquidity support from their parent bank following the shock. The baseline set-up would overlook this channel since it only includes bank-level controls. In column (6), I thus replace all bank-level controls by Bank-Holding Company (BHC) controls for affiliated banks.[52] I also compute $Local_{b,t}$ using the BHC's share of branches inside the affected areas instead of the bank's. This does not materially affect results. To further probe the role of financial transfers within groups, column (7) drops unaffiliated banks altogether. This decreases the economic magnitude of the

[52] I construct BHC controls by aggregating bank-level Call Reports to the regulatory high-holder level. This means that BHC controls will be similar with bank-level controls for independent (unaffiliated) banks.

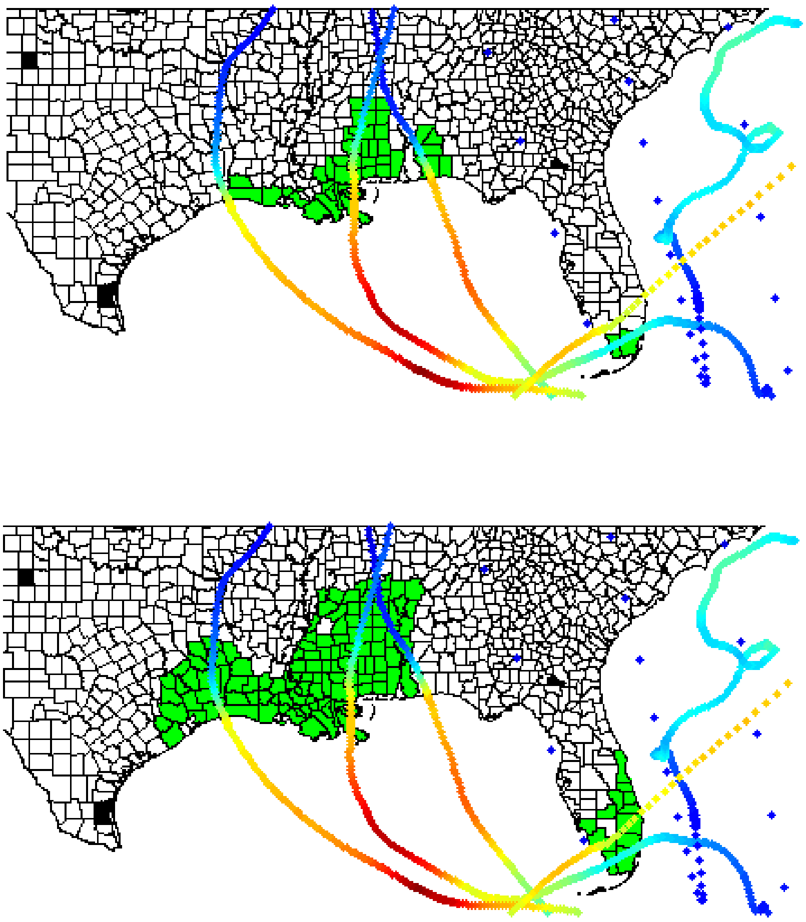
dis-integration effect only marginally.

The average quality of applicants from affected areas could change after the shock depending on whether a bank is local or diversified. The baseline set-up would capture such sorting only imperfectly since it controls for average borrower (i.e. accepted applicants) characteristics. In column (8), I thus replace borrower controls by applicant controls, again averaged by bank-county-year using application size as weights. This does not materially change results.

Finally, the dis-integration effect could be driven by heterogeneous pre-shock mortgage growth trends across local and diversified banks. In column (9), I thus conduct a placebo experiment, where I assume that the shock occurs three years earlier. I then define 2000-2002 as the pre-shock period, and 2003-2005 as the post-shock period. The estimate for the dis-integration effect is strongly insignificant in this specification.

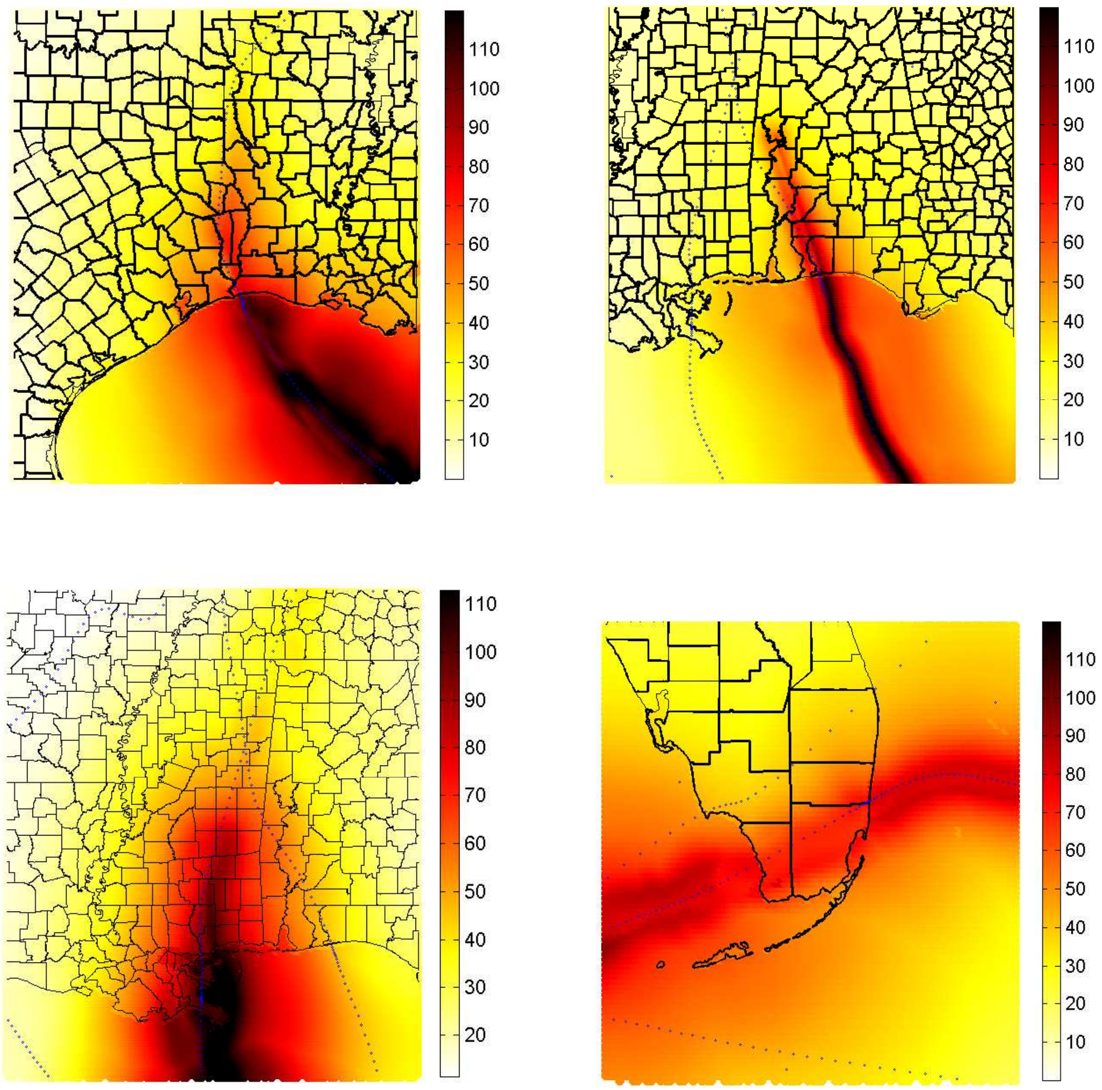
D Figures

FIGURE 1: COUNTIES AFFECTED BY THE 2005 HURRICANES



This figure compares counties considered as affected by the 2005 hurricanes according to baseline and alternative definitions. Green shading indicates that county *c* is considered as affected. In the upper panel, affected counties are those exposed to winds faster than 96 miles per hour. In the lower panel, affected counties are those for which FEMA reports a major disaster declaration. Hurricane tracks are from NOAA's best track estimates. The shade of tracks is a function of local-specific hurricane wind speed.

FIGURE 2: WIND SPEED DURING 2005 HURRICANES



This figure plots local-level wind intensity estimates from NOAA's H*Wind field model 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.

E Tables

TABLE 1: SUMMARY STATISTICS

Level of variation: b = Bank, c = County, t = Year

Variable	Definition	Mean	Std.
Dependent Variables			
Δ Mortgage$_{b,c,t}$	Log mortgage volume growth	0.081	1.151
% Accepted$_{b,c,t}$	Accepted mortgage volume/Total application volume	0.803	0.249
% Accepted-and-Sold$_{b,c,t}$	Accepted-and-sold mortgage volume/Total application volume	0.326	0.365
% Accepted-and-Retained$_{b,c,t}$	Accepted-and-retained mortgage volume/Total application volume	0.477	0.395
Treatment Proxies			
Local$_{b,t}$	0 before 2005; % of b's branches in affected counties thereafter	0.037	0.154
Affected$_{c,t}$	0 before 2005; 1 if wind in c exceeds 96 miles per hour thereafter	0.063	0.243
Local$_{b,t}$ $\times$ Affected$_{c,t}$	Interaction of Local$_{b,t}$ and Affected$_{c,t}$	0.019	0.125
Bank Controls			
Size$_{b,t}$	Log total assets	14.51	2.86
Liquid Assets$_{b,t}$	(Cash+Liquid securities)/Total assets)	0.189	0.12
Deposits$_{b,t}$	Deposits/Total assets)	0.722	0.166
Loans$_{b,t}$	Loans/Total assets	0.689	0.141
Capital$_{b,t}$	Equity capital/Total assets	0.102	0.04
Income$_{b,t}$	Net income/Total assets	0.012	0.009
Loan Quality$_{b,t}$	Non-performing loans/Total loans	0.009	0.01
Deposit Costs$_{b,t}$	Interest expense/Total Deposits	0.022	0.024
Borrower Controls			
Race$_{b,c,t}$	Non-Caucasian dummy	0.091	0.2
Sex$_{b,c,t}$	Non-male dummy	0.196	0.257
Loan/Income$_{b,c,t}$	Loan size over income	1.682	3.572
Income$_{b,c,t}$	Log income ($ Thousand)	4.463	0.811
Minority Population$_{b,c,t}$	% non-Caucasian households in borrower tract	23.71	17.92
Median Family Income$_{b,c,t}$	Median income in borrower tract over median income in MSA	1.104	0.289

This table reports the name (column 1), definition (column 2), average (column 3) and standard deviation (column 4) of the variables in the baseline bank-county-year dataset. Dependent variables and borrower controls are from HMDA. Bank controls are from Call Reports (all values are lagged by one year). Borrower controls correspond to the average borrower characteristic in a bank-county-year, weighted by loan size.

TABLE 2: MAIN RESULTS: THE DIS-INTEGRATION EFFECT
Dependent variable: Δ *Mortgage Lending*$_{b,c,t}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	**Robustness**					
		Local is % loans in *Affected*	*Affected* is FEMA declaration	*Affected* is NFIP payouts	Most affected states only	Smaller window (2004-2007)	*Size* $\times$ *Affected* control
$\text{Local}_{b,t} \times \text{Affected}_{c,t}$	0.922***	0.790***	0.672**	9.577*	0.797**	0.772**	1.001***
	(0.345)	(0.297)	(0.333)	(5.363)	(0.325)	(0.382)	0.348
$\text{Local}_{b,t}$	-0.401	-0.208	-0.338	-1.178	-0.238	-0.365	-0.458*
	(0.267)	(0.268)	(0.215)	(1.347)	(0.299)	(0.320)	0.263
2005 $\text{Size}_{b,t} \times \text{Affected}_{c,t}$							-.003
							(0.909)
2005 $\text{Size}_{b,t}$							0.046*
							(0.053)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank $\times$ County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63504	61165	63504	61759	29510	43850	59998
Adjusted R^2	0.421	0.418	0.421	0.416	0.420	0.409	0.487

This table reports OLS regressions relating a bank b's mortgage lending growth in county-year c, t depending on (i) whether c is affected by the 2005 hurricanes at t and (ii) how geographically diversified b is from the perspective of the affected area. The sample covers the 2003-2008 period in seven US states (AL, FL, GA, LA, MS, SC, and TX), except Katrina out-migration counties (see section B). $Affected_{c,t}$ is 0 until 2005, and 1 thereafter if wind speed during 2005 hurricanes exceed 96mph in c. $Local_{b,t}$ is 0 until 2005, and the share of b's branches in affected counties (as per June 2005) thereafter. *Bank controls* include one-year lag of (log) size, income, liquid assets, loan quality, deposits, equity and deposit costs. *Borrower controls* include bank-county-year loan size-weighted averages of race, sex, loan-to-income, (log) income, census tract income and tract share of minority population. Columns (2) to (8) change the following elements of the baseline specification. In column (2), $Local_{b,t}$ is 0 until 2005, and the share of b's retained mortgage in affected counties (2002-2004) thereafter. In column (3), $Affected_{c,t}$ is 0 until 2005, and 1 thereafter if FEMA reports a disaster declaration for c. In column (4), $Affected_{c,t}$ is 0 until 2005, and the number of 2005 flood insurance payouts in c (as % total housing units) thereafter. $Local_{b,t}$ is 0 until 2005, and the sum of $Affected_{c,t}$ for all c weighted by the share of b's branches in c thereafter. In column (5), the sample of states is AL, LA, and MS. In column (6), the estimation window is 2004-2007. Heteroskedasticity-robust standard errors clustered at the bank level are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE 3: DO GOVERNMENT INTERVENTIONS EXPLAIN THE DIS-INTEGRATION EFFECT?
Dependent variable: Δ *Mortgage Lending*$_{b,c,t}$

	(1) Drop loans purchased by GSEs	(2) Drop FHA-guaranteed loans	(3) Eligible for forbear-ance	(4) Regulatory leniency
$\text{Local}_{b,t} \times \text{Affected}_{c,t}$	0.873***	0.953***	0.942**	1.010***
	(0.332)	(0.349)	(0.394)	(0.363)
$\text{Local}_{b,t}$	-0.311	-0.427	-0.408	-0.424
	(0.270)	(0.270)	(0.314)	(0.274)
$\text{Local Headquarter}_{b,t} \times \text{Affected}_{c,t}$			-.039	
			(0.182)	
$\text{Local Headquarter}_{b,t}$			0.009	
			(0.226)	
$\text{Local Regulator}_{b,t} \times \text{Affected}_{c,t}$				-0.263
				(0.248)
$\text{Local Regulator}_{b,t}$				0.217
				(0.198)
Bank controls	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes
County $\times$ Year FE	Yes	Yes	Yes	Yes
Bank $\times$ County FE	Yes	Yes	Yes	Yes
Observations	60367	62382	63504	63504
Adjusted R^2	0.418	0.423	0.421	0.421

This table reports OLS regressions relating a bank b's mortgage lending growth in county-year c, t depending on (i) whether c is affected by the 2005 hurricanes at t (ii) how geographically diversified b is from the perspective of the affected area. The sample covers the 2003-2008 period in seven US states (AL, FL, GA, LA, MS, SC, and TX), except Katrina out-migration counties (see section B). $Affected_{c,t}$ is 0 until 2005, and 1 thereafter if wind speed during 2005 hurricanes exceed 96mph in c. $Local_{b,t}$ is 0 until 2005, and the share of b's branches in affected counties (as per June 2005) thereafter. *Bank controls* include one-year lag of (log) size, income, liquid assets, loan quality, deposits, equity and deposit costs. *Borrower controls* include bank-county-year loan size-weighted averages of race, sex, loan-to-income, (log) income, census tract income and tract share of minority population. In column (1), all loans sold to a GSE during the year of origination are excluded. In column (2), all loans guaranteed by the Federal Housing Administration or the Veterans Administration are excluded. $Local\ Headquarter_{b,t}$ is 0 until 2005, and 1 thereafter if b's headquarter is in Alabama, Louisiana, or Mississippi. $Local\ Regulator_{b,t}$ is 0 until 2005, and 1 thereafter if b has a state charter from Alabama, Louisiana, or Mississippi. Heteroskedasticity-robust standard errors clustered at the bank level are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE 4: EXTERNAL VALIDITY OF THE DIS-INTEGRATION EFFECT

	(1) 2000-2010 floods panel	(2) Small business lending
Dependent variable:	Δ Mortgage Lending$_{b,c,t}$	Δ Small Business Lending$_{b,c,t}$
Local$_{b,t}$ $\times$ Affected$_{c,t}$	115.76**	0.239*
	(47.31)	(1.72)
Local$_{b,t}$	-14.28	-0.647***
	(6.58)	(-4.33)
Bank Controls	Yes	Yes
Borrower Controls	Yes	No
County $\times$ Year FE	Yes	Yes
Bank $\times$ County FE	Yes	Yes
Observations	127948	42900
Adjusted R^2	0.487	0.375

Column (1) reports an OLS regression relating a bank b's mortgage lending growth in county-year c, t depending on (i) the degree to which c is affected by floods at t and (ii) how geographically diversified b is from the perspective of the affected areas. The sample covers the 2000-2010 period in eight US states (FL, LA, MS, NC, NJ, NY, PA, and TX). $Affected_{c,t}$ is the lagged number of flood insurance payouts (as % total housing units) in c and year t. $Local_{b,t}$ is the sum of $Affected_{c,t}$ for all c weighted by the share of b's branches in c. Column 2 reports an OLS regression relating a bank b's small business lending growth in county-year c, t depending on (i) whether c is affected by the 2005 hurricanes at t and (ii) how geographically diversified b is from the perspective of the affected area. The sample covers the 2002-2007 period in seven US states (AL, FL, GA, LA, MS, SC, and TX), except Katrina out-migration counties (see section B). $Affected_{c,t}$ is 0 until 2004, and 1 thereafter if wind speed during 2005 hurricanes exceeds 96mph in c. $Local_{b,t}$ is 0 until 2004, and the share of b's branches in affected counties (as per June 2005) thereafter. In both columns, *Bank controls* include one-year lag of (log) size, income, liquid assets, loan quality, deposits, equity and deposit costs. *Borrower controls* include bank-county-year loan size-weighted averages of race, sex, loan-to-income, (log) income, census tract income and tract share of minority population. Heteroskedasticity-robust standard errors clustered at the bank level are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE 5: MARGINS OF ADJUSTMENT

Dependent Variable:	(1) $\frac{Accepted}{Applications}$	(2) $\frac{Accepted-and-Sold}{Applications}$	(3) $\frac{Accepted-and-Retained}{Applications}$
$\text{Local}_{b,t} \times \text{Affected}_{c,t}$	0.145**	0.249*	-0.105
	(0.072)	(0.146)	(0.099)
$\text{Local}_{b,t}$	-0.132*	-0.225	0.0934
	(0.078)	(0.149)	(0.091)
Bank controls	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
Bank × County FE	Yes	Yes	Yes
Observations	63504	63504	63504
Adjusted R^2	0.783	0.827	0.844

This table reports OLS regressions relating different lending outcomes by bank b in county-year c, t depending on (i) whether c is affected by the 2005 hurricanes at t and (ii) how geographically diversified b is from the perspective of the affected area. The sample covers the 2003-2008 period in seven US states (AL, FL, GA, LA, MS, SC, and TX), except Katrina out-migration counties (see section B). $Affected_{c,t}$ is 0 until 2005, and 1 thereafter if wind speed during 2005 hurricanes exceeds 96mph in c. $Local_{b,t}$ is 0 until 2005, and the share of b's branches in affected counties (as per June 2005) thereafter. In column (1), the dependent variable is the volume of accepted applications as a percentage of all applications received by b in c, t. In column (2), the dependent variable is the volume of applications accepted and sold as a percentage of all applications received by b in c, t. In column (3), the dependent variable is the volume of applications accepted and retained by b as a percentage of all applications received by b in c, t. *Bank controls* include one-year lag of (log) size, income, liquid assets, loan quality, deposits, equity and deposit costs. *Borrower controls* include bank-county-year loan size-weighted averages of race, sex, loan-to-income, (log) income, census tract income and tract share of minority population. Heteroskedasticity-robust standard errors clustered at the bank level are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

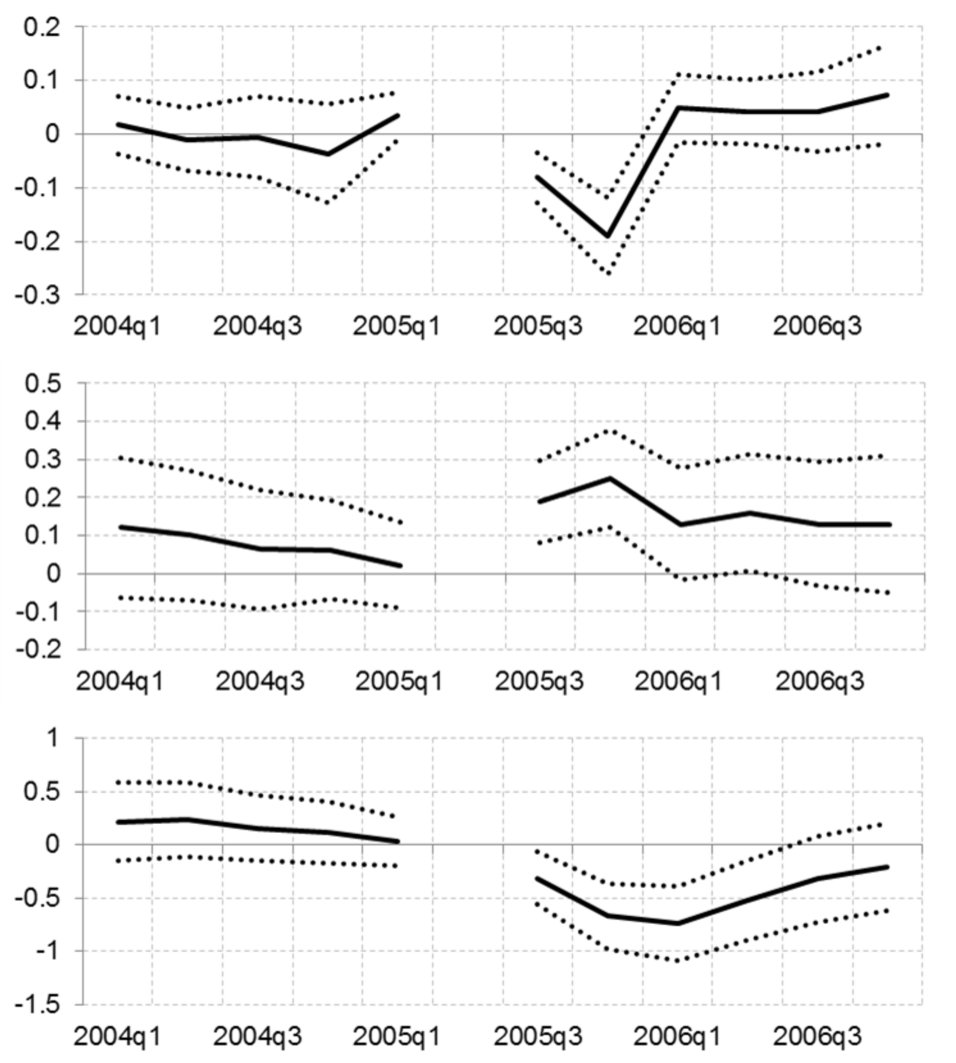
TABLE 6: THEORETICAL CHANNELS OF THE DIS-INTEGRATION EFFECT
Dependent variable: $Accepted_{a,b,c,t}$

	(1)	(2)	(3)	(4)	(5)
Channel:	**Moderate-to-high income applicant**	**Conforming application**	**Census tract market share**	**Pre-shock bank equity**	**Pre-shock bank equity**
Included applications:	All	All	All	All	Non-conforming
$\text{Local}_{b,t} \times \text{Affected}_{c,t}$	0.186***	0.172**	0.115*	-0.018	-0.0313
	(0.0658)	(0.068)	(0.0601)	(0.086)	(0.083)
$\text{Local}_{b,t}$	-0.192**	-0.158**	-0.128*	-0.0009	0.023
	(0.076)	(0.077)	(0.073)	(0.049)	(0.049)
$\text{Local}_{b,t} \times \text{Affected}_{c,t} \times \text{Channel}$	-0.0786*	-0.108**	-0.0502	1.701	2.716**
	(0.043)	(0.051)	(0.150)	(1.121)	(1.151)
$\text{Local}_{b,t} \times \text{Channel}$	0.0885**	0.0793*	0.0599	-1.648**	-2.339**
	(0.044)	(0.046)	(0.183)	(1.121)	(0.912)
Bank controls	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes
Bank × County × Channel FE	Yes	Yes	Yes	No	No
Observations	3177564	3177564	3177564	3176909	1740757
Adjusted R^2	0.165	0.166	0.243	0.164	0.188

Notes: This table reports OLS regressions relating a dummy for whether mortgage application a was accepted by bank b in county-year c, t depending on (i) whether c is affected by the 2005 hurricanes at t, (ii) how geographically diversified b is from the perspective of the affected area, and (iii) an additional theoretical channel. The sample covers the 2003-2008 period in seven US states (AL, FL, GA, LA, MS, SC, and TX), except Katrina out-migration counties (see section B). $Affected_{c,t}$ is 0 until 2005, and 1 thereafter if wind speed during 2005 hurricanes exceeds 96mph in c. $Local_{b,t}$ is 0 until 2005, and the share of b's branches in affected counties (as per June 2005) thereafter. In column (1), *Channel* is 1 if a's income is above 80% of the MSA median family income, and 0 otherwise. In column (2), *Channel* is 1 if a is a non-jumbo loan for the purchase of a one-to-four persons house not guaranteed by the Federal Housing Administration or Veteran Administration. In column (3), *Channel* is the share of all retained mortgages in census tract c between 2002 and 2004 originated by b. In column (4) and (5), *Channel* is b's equity (as % of total assets in the second quarter of 2005. $Bank \times County \times ChannelFE$ is a bank-county-moderate-to-high-income fixed effect in column (1), a bank-county-conforming fixed effect in column (2) and a bank-census-tract fixed effect in column (3). The model controls for all possible combinations between $Local_{b,t}$, $Affected_{c,t}$ and *Channel* that do not drop because of fixed effects. *Bank controls* include one-year lag of (log) size, income, liquid assets, asset quality, deposits, equity and deposit costs. *Borrower controls* include race, sex, loan-to-income, and (log) income. Heteroskedasticity-robust standard errors clustered at the bank level are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

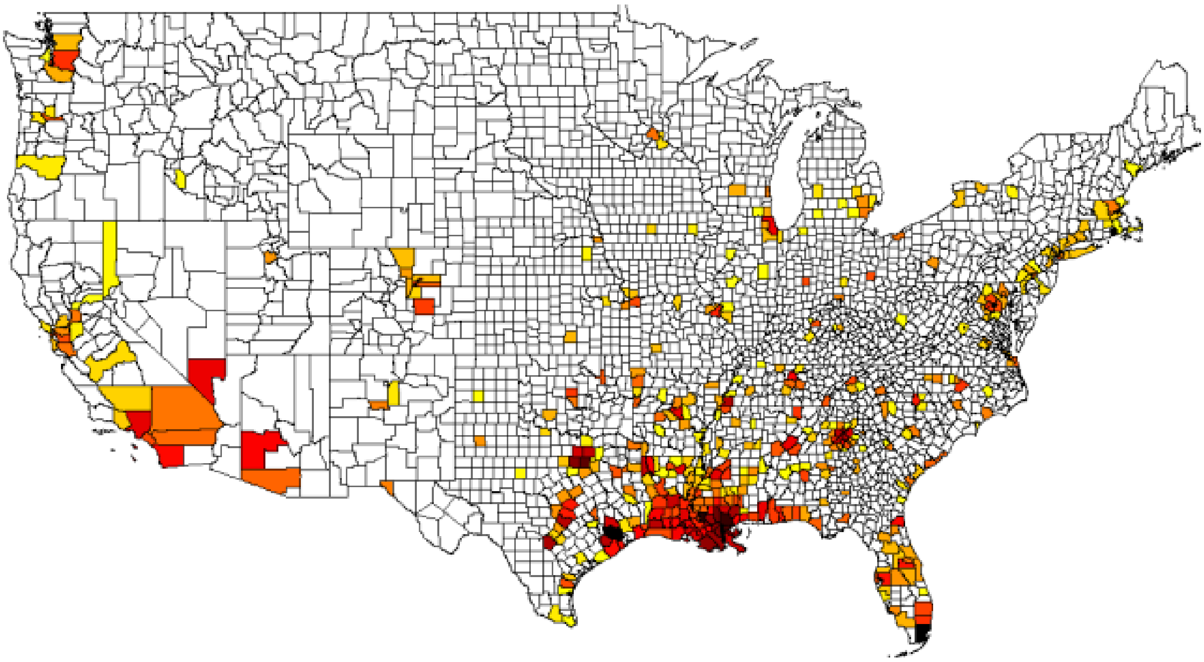
F Appendix Figures & Tables

FIGURE 3: THE 2005 HURRICANES AS A SHOCK TO FINANCIAL CAPACITY



This figure shows the estimate (bold line) and confidence intervals (dashed lines) of parameter γ_1, obtained from the regression: $\Delta Y_{b,t} = \gamma_1 \cdot Local_b + \gamma_2 \cdot BankControls_b + StateF.E._b + \epsilon_{b,t}$. $\Delta Y_{b,t}$ is the change in bank b's income (upper panel), non-performing loans (middle panel), and capitalization (upper panel) between quarter t and 2005q2. $Local_b$ is the share of b's branches located in counties affected by the 2005 hurricanes, as measured in June 2005. $BankControls_b$ include (log) size, deposit funding, liquid assets, total loans, and deposit funding costs, all measured in 2005q2 (see table 1 for definitions). $StateF.E._b$ is a set of dummies for b's home state. Dependent variables are winsorized at the bottom and top 1%.

FIGURE 4: HURRICANE KATRINA MIGRANT HOUSEHOLDS BY COUNTY



This figure shows the county-level log number of households relocating from the New Orleans metropolitan area (NOLA) in 2006, net of households relocating to NOLA during the same year. A darker shade indicates a higher number of households. *Source:* author's calculations based on IRS Migration Data (2006 vintage).

TABLE 7: ADDITIONAL ROBUSTNESS CHECKS
Dependent variable: Δ Mortgage Lending$_{b,c,t}$

	(1) Keep Evacuation Counties	(2) No Bank Controls	(3) Winsorize Dependent Variable	(4) Drop Rural Counties	(5) Drop Focused Banks	(6) BHC Controls	(7) Drop Independent Banks	(8) Applicant Controls	(9) Placebo
Local$_{b,t}$ × Affected$_{c,t}$	0.825***	0.882***	0.849***	0.976**	1.102**	0.860**	0.816**	0.892***	-0.0313
	(0.320)	(0.326)	(0.327)	(0.383)	(0.447)	(0.339)	(0.350)	(0.325)	(0.240)
Local$_{b,t}$	-0.323	-0.345	-0.353	-0.421	-0.652**	-0.445	-0.320	-0.393	-0.00873
	(0.235)	(0.253)	(0.257)	(0.306)	(0.329)	(0.291)	(0.252)	(0.258)	(0.203)
Bank Controls	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank × County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	71088	63507	63504	50472	61607	60905	58025	65424	78871
Adjusted R^2	0.411	0.415	0.421	0.404	0.425	0.458	0.430	0.407	0.442

This table reports OLS regressions relating a bank b's mortgage lending growth in county-year c, t depending on (i) whether c is affected by the 2005 hurricanes at t and (ii) how geographically diversified b is from the perspective of the affected area. The sample covers the 2003-2008 period in seven US states (AL, FL, GA, LA, MS, SC, and TX), except Katrina out-migration counties (see section B). $Affected_{c,t}$ is 0 until 2005, and 1 thereafter if wind speed during 2005 hurricanes exceed 96mph in c. $Local_{b,t}$ is 0 until 2005, and the share of b's branches in affected counties (as per June 2005) thereafter. *Bank controls* include one-year lag of (log) size, income, liquid assets, loan quality, deposits, equity and deposit costs. *Borrower controls* include bank-county-year loan size-weighted averages of race, sex, loan-to-income, (log) income, census tract income and tract share of minority population. Columns (1) to (9) change the following elements of the baseline specification. Column (1) re-integrates out-migration counties. Column (2) drops bank-level controls. Column (3) winsorizes the top and bottom 1% of the dependent variable. Column (4) drops counties not part of a metropolitan statistical area. Column (5) drops banks for which pre-shock (2003-2005) total mortgage lending in affected counties is less than 20% of total mortgage lending. Column (6) replaces bank controls by Bank-Holding Company (BHC) controls for affiliated banks. Column (7) drops banks unaffiliated to a BHC. Column (8) replaces borrower controls by applicant controls. Column (9) assumes that the shock occurs in 2002. Heteroskedasticity-robust standard errors clustered at the bank level are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.