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Natural disasters and economic growth: The role of banking market structure

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ABSTRACT

Following a natural disaster, the rate of economic growth recovers faster in less competitive banking markets. A 10% reduction in competition increases the rate of economic growth by 0.3%. In less competitive markets, banks respond to a disaster by increasing the supply of real estate credit by refinancing mortgage loans, but do not lend more to businesses or consumers. Instead, government agencies provide disaster loans to affected businesses and households. Smaller, profitable and well-capitalized institutions that rely more on traditional retail banking originate most mortgage credit.

1. Introduction

Businesses and homeowners in the United States (US) are experiencing increasingly frequent and severe natural disasters (IPCC, 2012; MunichRE; Ivanov et al., 2020; Wagner, 2020). Reviving economic growth in areas hit by natural disasters often relies on bank lending due to the incompleteness of insurance markets (Froot, 2001; Koetter et al., 2020). This raises the question: who continues to lend in the aftermath of a disaster?

We conjecture that banking market structure plays a key role in determining the rate of economic recovery from a disaster. A large theoretical literature stresses the important role of asymmetric information in financial markets and how it can generate market failures such as credit rationing (Rothschild and Stiglitz, 1976; Stiglitz and Weiss, 1981; Tirole, 2006). Following a natural disaster, asymmetric information becomes acute in credit markets as borrowers are unable to post damaged or destroyed collateral, and employment becomes uncertain (Berg and Schrader, 2012). With perfect competition, banks price loans at average cost and respond to a disaster by setting higher interest rates as a riskier pool of borrowers implies greater loan losses (Einav and Finkelstein, 2011). This leads to adverse selection and credit rationing, which hinders economic recovery. However, market power allows banks to continue lending to the real economy without raising interest rates because their profitability allows them to absorb credit risk (Mahoney and Weyl, 2017; Lester et al., 2019), reducing the negative consequences of adverse selection. As bank market power increases, the credit rationing effects of asymmetric information become weaker and eventually turn positive (Crawford et al., 2018). Economic growth thus potentially recovers faster after a natural disaster in imperfectly competitive banking markets because financial institutions continue lending to firms and households when they most need credit.

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In this paper, we provide micro-level evidence that following a natural disaster, economic growth recovers faster in US counties with less competitive banking sectors. We focus on hurricanes (or tropical storms) that have sharp, adverse localized economic effects. Estimates show that a hurricane provokes a statistically significant 0.4 percentage-point decrease in the annual rate of economic growth. However, following a hurricane, a 10% reduction in banking competition leads to a statistically significant 0.32% increase in the rate of economic growth. The effect of market power on the recovery is most pronounced among profitable and better-capitalized banks, suggesting these banks deploy the retained earnings they accumulate during normal times to support the local economy after a disaster.

When we examine the credit supply channels that underpin this result, we find that banks increase the supply of real estate credit, especially refinancing of existing mortgages. This is consistent with market power allowing financial institutions to support distressed borrowers to prevent foreclosure by renegotiating mortgage terms. Conversely, we find no link between market structure and consumer or commercial and industrial (C&I) lending after a disaster. In these segments, banks intermediate disaster loans on behalf of the Small Business Administration (SBA). The supply of SBA disaster loans is invariant to bank market structure because it is the SBA that evaluates and approves loan applications.[1]

Our empirical strategy uses a triple-difference approach applied to county-level panel data. We exploit exogenous variation in the timing and location of hurricanes. The path and landing location of a hurricane is inherently difficult to predict and is independent of economic conditions. We thus compare the evolution of economic growth over time in counties affected by a hurricane relative to unaffected contiguous counties. To isolate the role of bank market structure in supporting the recovery to the long-run growth path, we exploit variation in the level of bank competition between treated and untreated counties following a hurricane. A host of robustness tests demonstrate our findings hold, irrespective of how we measure market structure, and we obtain similar inferences using a matching strategy to ensure ex-ante conditions within the control group mirror the treatment group.

Our paper contributes to several strands of literature. Scholars have documented contractions in economic growth following natural disasters using within (Strobl, 2011) and cross-country (Cavallo et al., 2013) data sets. None of these studies focuses on the role of banks, either before or during the recovery phase. A parallel literature shows how natural disasters affect credit supply and financial intermediaries' responses (Berg and Schrader, 2012; Cortés and Strahan, 2017; Koetter et al., 2020; Brown et al., 2021). Our work intersects these bodies of research and provides unique insights into how bank market structure influences economic growth following a natural disaster.

We also contribute to the literature on banking competition and economic growth. Economic theory suggests credit constraints hinder growth (Aghion et al., 2005). Market power in banking markets may increase interest rates and lead to credit rationing, resulting in slower economic growth (Diallo and Koch, 2018). However, the empirical literature has failed to reach a consensus on whether banking competition results in lower rates of economic growth. In fact, studies on the role of external financial dependence find that concentration in the banking market spurs growth in industrial sectors that rely more on external finance. Cetorelli and Gambera (2001), Bonaccorsi Di Patti and Dell'Ariccia (2004), and Rogers (2012) find a negative correlation between banking competition and firm creation. However, these results are at odds with those found by Claessens and Laeven (2005) and Cetorelli and Strahan (2006), who document a positive correlation between banking competition and growth. Moreover, de Guevara and Maudos (2011) argue that the link between bank market power and economic growth follows an inverted-U shape. Unlike this strand of literature, we focus specifically on how bank market structure influences post-disaster economic growth, rather than economic growth in "normal" times.

Last, we provide novel insights to the literature on real estate lending. Prior research shows that the economy is highly sensitive to housing finance and that the length and depth of the Global Financial Crisis was partly due to the slow recovery of the housing market (Loutskina and Strahan, 2015). Other studies have shown that financial institutions that concentrate lending in a particular area accept more risky loans compared to multimarket banks because they have an advantage in managing and processing new mortgage loan applications or renegotiating existing ones due to their superior screening and monitoring abilities. This allows these banks to promptly assess borrowers' repayment capacity in the face of temporarily depressed collateral values following a disaster (Loutskina and Strahan, 2011; Cortés and Strahan, 2017). These lenders also minimize foreclosures to avoid depressing the value of outstanding loans on their balance sheet (Favara and Giannetti, 2017). Our contribution to this strand of research is to demonstrate the important role played by bank market power in promoting recovery through an increase in real estate credit, rather than loans to businesses. This mechanism differs dramatically from other work that emphasizes the importance of C&I loans in provoking economic growth.

Policymakers are frequently concerned about the deleterious effect of market power in banking, both for consumer welfare and economic performance generally. Our findings highlight a dark side of competition, albeit one that arises after relatively rare natural disasters. We look at this debate from an angle indicating that, under certain circumstances, a reasonable degree of bank market power can benefit local economies. Our findings therefore align with new theoretical models that highlight how, depending on market conditions, bank market power can spur credit supply (Crawford et al., 2018).

The paper proceeds as follows. Section 2 provides institutional details. We outline the hypotheses in Section 3, describe the data set in Section 4, and the identification strategy in Section 5. Section 6 reports econometric results and discussion. We present robustness tests in Section 7 and draw conclusions in Section 8.

[1] The SBA does not provide credit directly to businesses or consumers. Rather, it partners with banks that originate the loans it approves on its behalf. The SBA offers a government guarantee that protects banks from losses in case of borrower default. While the SBA provides disaster loans to consumers, its lending criteria do not allow households to obtain credit to replace severely damaged property or mitigate cash flow issues. This is why bank market power plays an important role in the supply of real estate credit after a disaster.

2. Institutional background

The US government assists businesses and households that are adversely affected by natural disasters. SBA disaster loans are available to businesses of all sizes located in declared disaster areas. Eligible businesses may obtain different types of loans, in particular: "physical damage loans" to cover repairs and replacement of damaged physical assets, "mitigating assistance loans" to cover business operating expenses, "economic injury disaster loans" where an owner's home or personal property is damaged, and "military reservist loans" that cover operating expenses to make up for employees on active duty leave. From a business's perspective, an SBA loan is a potentially more attractive source of funding than a C&I loan because the interest rate is typically set below market prices.

The SBA also provides disaster loans to households. However, only households that are unable to obtain credit elsewhere are eligible to apply for a loan up to a maximum limit of $200,000. This may only be used to repair or replace damaged property. Unlike SBA disaster loans to businesses, the SBA does allow household borrowing to cover disaster-related cash flow problems or expenses.

It is important to note that the SBA guarantees loans to all eligible borrowers, and the extent of SBA support is unrelated to bank market structure. Borrowers apply to the SBA for a disaster loan and the SBA evaluates whether to approve an application. The SBA does not lend money directly to businesses and households, but instead, it sets guidelines for loans made by its partnering banks that, following approval, originate the loan. Banks have strong incentives to process SBA loans because these loans have a government guarantee which, from a bank's perspective, removes credit risk. In addition, banks earn non-interest income from processing SBA loans.

FEMA (Federal Emergency Management Agency) is the principal organization that coordinates the response to natural disasters in the United States. Specifically, FEMA deals with disasters that overwhelm the resources of local and State authorities, and it is regularly involved following Presidential Disaster Declarations (PDD), owing to their large adverse economic impacts. FEMA provides grant funds that are available for pre- and post-disaster related projects. These funds support critical recovery initiatives, research, and other programs, and are the principal funding mechanism FEMA uses to commit and award federal funding to eligible state, local, tribal, territorial authorities, certain private non-profits, individuals, and institutions of higher education.

3. Hypotheses development

The banking sector often plays a key role in the economic recovery from natural disasters because of incomplete disaster insurance markets and systematic underinsurance by borrowers (Koetter et al., 2020; Wagner, 2020). However, providing credit to disaster-affected borrowers is beset with frictions as banks become more concerned about the uncertainty of future repayment (Noy, 2009). Moreover, asset liquidation values play a key role in determining a firm's debt capacity (Shleifer and Vishny, 1992). Natural disasters that deteriorate collateral values can therefore reduce credit supply (Gan, 2007; Benmelech and Bergman, 2011; Cerqueiro et al., 2016; Calomiris et al., 2017), which depresses investment, leading to economic downturns (Chaney et al., 2012).

Amid a natural disaster, bank market power may spur or hinder economic recovery. Prior contributions to the literature provide contrasting predictions on the relationship between bank market structure and economic growth. Under the *market power hypothesis*, increasing banks' market power leads to slower rates of economic growth. In more competitive environments, banks increase credit availability, set lower interest rates, and provide more services both to the non-financial sector and households. This drives firm entry, innovation, employment and ultimately economic growth (Black and Strahan, 2002; Cetorelli and Strahan, 2006; Carbó-Valverde et al., 2009).

This strand of literature builds upon the so-called *quiet life hypothesis*, which posits that a low level of competition adversely affects the quality of products and services offered by the banking industry, and its propensity to innovate (Berger and Hannan, 1998; Bertrand and Mullainathan, 2003; Claessens and Laeven, 2005; Gormley et al., 2018). Jayaratne and Strahan (1998) show that in response to tougher competition bank performance improves, leading to cost efficiency gains and smaller loan losses that are passed on to borrowers through lower interest rates. More competitive environments lead banks to reduce opacity which increases the supply of credit, albeit only among large and profitable banks (Jiang et al., 2016).[2] However, while competition improves access to credit and the terms of credit, its effect on aggregate credit supply is limited. Jayaratne and Strahan (1996) report the bank branching deregulation episode that raised competition in local banking markets across the US, had no effect on overall lending volumes but instead led to a better allocation of bank portfolios due to the adoption of advanced lending technologies and improved screening and monitoring incentives.

However, articles also show that concentration in the banking sector may provoke faster rates of economic growth. Cetorelli and Gambera (2001) and Bonaccorsi Di Patti and Dell'Ariccia (2004) find that firms that are more dependent on external finance, or more informationally opaque grow more in concentrated banking sectors. Marquez (2002) and Zarutskie (2006) find similar results when borrowing firms are young and small, and thus, typically more informationally opaque than large and mature ones.[3] Thus, in the presence of high levels of asymmetric information, market power may be beneficial to economic growth.

A key feature of our study is the focus on the relationship between bank market power and economic growth after natural disasters, when economic agents may behave differently than in "normal" times. In this environment, market power could be beneficial for post-

[2] Laeven et al. (2015) show in a theoretical model that when the financial sector innovates, it can build better loan-screening models and that technological innovation spurs economic growth.

[3] Relatedly, Kick and Prieto (2014) show that market power gives banks incentives to behave prudently.

disaster economic growth through its moderating effect on asymmetric information.

Following a natural disaster, many borrowers are unable to post collateral, which has been damaged or destroyed, leading to an increase in asymmetric information between borrowers and lenders, and higher adverse selection costs (Berg and Schrader, 2012). In a competitive market, where banks set interest rates according to their average costs, an increase in adverse selection costs provokes higher interest rates (Einav and Finkelstein, 2011). Ultimately this makes the terms of credit unattractive to many borrowers leading to credit rationing and slower economic growth (Chaney et al., 2012; Mahoney and Weyl, 2017; Lester et al., 2019).

However, Crawford et al. (2018) show that the level of bank market power can mitigate and, under certain parameter configurations, reverse credit rationing when adverse selection costs are high. In less competitive markets, banks are more profitable which allows them to accumulate reserves during "normal" times. Following a disaster, these institutions can deploy their reserve buffer to absorb the greater credit risk and cover higher expected loss provisions without compromising regulatory capital requirements (Jiminez et al., 2017).[4] Crawford et al. (2018) also show that in the face of higher adverse selection costs, banks with market power can use their profitability to avoid raising interest rates. This prevents credit rationing as low-risk agents continue to borrow. Under this framework, following a disaster, the correlation between bank market power and economic growth is positive because banks with market power continue lending despite higher adverse selection costs. This prevents credit rationing and enables businesses and households to make investments that spur the recovery.

For the reasons outlined above, it is difficult to determine *a priori* whether market power should increase or decrease post-disaster economic growth, and developing an answer to this question is an empirical exercise. To reflect the conflicting theoretical and empirical evidence, we thus formulate two alternative hypotheses:

H1A: Post-disaster economic growth will be higher in regions with a more competitive bank market structure.

H1B: Post-disaster economic growth will be higher in regions with a less competitive bank market structure.

4. Data description

Our data set draws information from several sources. We collect quarterly county-level data on the growth rate of 1) real per capita personal income from the Bureau of Economic Analysis (BEA), and 2) the number of establishments from the Quarterly Census of Employment and Wages database (QCEW).[5] Using this information we construct the quarterly rate of per capita personal income growth (*Income growth*) and establishment growth (*Estab growth*) for the years 1995 to 2017. We restrict the sample to counties located in 15 states that are affected by hurricanes.[6]

To identify whether a county is subject to a hurricane, we retrieve data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) database. SHELDUS reports quarterly county-level information on personal injuries, fatalities, economic damage (e.g. the value of property destroyed), and whether there was a PDD following an environmental hazard (hurricane, drought, flood, tornado, and other events). To sharpen identification, we consider only major hurricanes, defined as those with a PDD.[7] Online Appendix Table A1 reports the number of hurricane events by state and year.

Treated counties are defined as those affected by a hurricane during the sample period. We define the variable $Disaster_{c,t}$ as equal to 1 in the three years following a hurricane and 0 in contiguous counties. Later we show our findings are invariant to using shorter post-disaster periods.[8]

Measuring banking market conditions in the county relies on quarterly bank-level Condition and Income Reports provided by the Federal Financial Institutions Examination Council (FFIEC). For each bank, this provides information on the natural logarithm of total assets (*Bank size*), the equity to total assets ratio (*Capital ratio*), interest and non interest income, and personnel and other operating expenses. To identify in which counties a bank operates branches, we rely on the Federal Deposit Insurance Company (FDIC) Summary of Deposits (SOD) database. This source provides annual information on the number of branches and deposit holdings of each bank in each county.

Using the bank-level data, we construct branch-level averages of each bank variable. Specifically, we calculate the mean of the variable across all banks that operate a branch in county c during year t. To capture other determinants of economic growth, we merge in additional control variables from a variety of sources. For example, county-level data on the population growth rate (US Census) and the natural logarithm of real (2017 US$) per capita income in the county (BEA). Annual state-level information on the top marginal personal income tax rate is taken from the National Bureau of Economic Research (NBER).

[4] Consistent with this view, Schüwer et al. (2018) show highly capitalized banks were able to extend credit to damaged firms and households following hurricane Katrina.

[5] Personal income includes the income the residents of a county receive from all sources, including payroll, rental income, dividend or interest income, and transfer receipts.

[6] The states are Alabama, Alaska, Arkansas, Connecticut, Delaware, Florida, Georgia, Louisiana, Maryland, Mississippi, New Jersey, North Carolina, South Carolina, Texas, and Virginia.

[7] A PDD indicates the affected state does not have sufficient resources to respond to the disaster promptly and that the Federal Government is required to intervene. If financial institutions aid the recovery, this should be most pronounced following PDD events. The average damage amount per capita from hurricanes in our sample is $27,000 at 2017 prices.

[8] Where a county is subject to multiple hurricanes within a three-year window, we follow Aretz et al. (2018) and consider only the first event because firms and households may take precautionary measures following the first hurricane, invalidating the exogeneity of subsequent hurricanes.

4.1. Market structure

Throughout most of the analysis we measure bank market structure using the Lerner Index (*Lerner*). The Lerner Index approximates banks' ability to extract rents using their market power to set prices above marginal costs.[9] To calculate the Lerner Index, we use a two-step procedure. Following Anginer et al. (2014) we first use bank-level data to estimate a bank's log-cost function

$$\log C_{i,t} = \alpha + \beta_1 \log A_{i,t} + \beta_2 \log A_{i,t}{}^2 + \beta_3 \log I_{i,t} + \beta_4 \log P_{i,t} + \beta_5 \log O_{i,t} + \beta_6 \log A_{i,t} {}^* \log I_{i,t} + \beta_7 \log A_{i,t} {}^* \log P_{i,t} + \beta_8 \log A_{i,t} {}^* \log O_{i,t} + \beta_9 \log I_{i,t}{}^2 + \beta_{10} \log P_{i,t}{}^2 + \beta_{11} \log O_{i,t}{}^2 + \beta_{12} \log I_{i,t} {}^* \log P_{i,t} + \beta_{13} \log I_{i,t} {}^* \log O_{i,t} + \beta_{14} \log P_{i,t} {}^* \log O_{i,t} + \gamma_t + \varepsilon_{c,t} \tag{1}$$

where $C_{i,t}$ is the sum of interest and non-interest expenses in bank i during quarter t; $A_{i,t}$ is total assets; $I_{i,t}$, $P_{i,t}$, and $O_{i,t}$ denote interest, personnel and other operating expenses normalized by total assets, respectively; γ_t are quarter fixed effects; $\varepsilon_{c,t}$ is the error term.

We impose 5 restrictions on the regression coefficients in Equation (1) to achieve homogeneity of degree one in input prices:

$$\beta_3 + \beta_4 + \beta_5 = 1,$$

$$\beta_6 + \beta_7 + \beta_8 = 0,$$

$$\beta_9 + \beta_{12} + \beta_{13} = 0,$$

$$\beta_{10} + \beta_{12} + \beta_{14} = 0,$$

$$\beta_{11} + \beta_{13} + \beta_{14} = 0.$$

In the second stage we use the parameter estimates from Equation (1) to estimate marginal costs for each bank-quarter using

$$\mathrm{MC}_{i,t} = \frac{C_{i,t}}{A_{i,t}} {}^* [\beta_1 + 2\beta_2 \log A_{i,t} + \beta_6 \log I_{i,t} + \beta_7 \log P_{i,t} + \beta_8 \log O_{i,t}]. \tag{2}$$

The right-hand side of Equation (2) is the first-order derivative of each bank's total cost with respect to total output (measured using total assets). The Lerner Index is then computed as:

$$L_{i,t} = \frac{R_{i,t} - \mathrm{MC}_{i,t}}{R_{i,t}}, \tag{3}$$

where $R_{i,t}$ is total revenues normalized by total assets for bank i at time t. To ensure outliers do not drive our inferences, we winsorize $L_{i,t}$ at the 1*st* and 99*th* percentiles.

For multimarket banks, the Lerner Index takes the same value in each county it operates. However, a multimarket bank's market power is likely greater in counties where they have a stronger presence. We, therefore, weight $L_{i,t}$ by the ratio of the bank's deposits in county c relative to the bank's total domestic deposits. We construct the weights using the SOD deposit data, similar to Danisewicz et al. (2018). Finally, we take the mean of the Lerner Index across banks operating in each county at time t.[10]

Table 1 describes each variable in the data set and reports the data source. Summary statistics are tabulated in Table 2.

5. Identification strategy

To identify how bank market structure influences the recovery from a natural disaster, we estimate the equation

$$y_{c,t} = \alpha_0 + \alpha_1 \mathrm{Lerner}_{c,t} + \alpha_2 \mathrm{Disaster}_{c,t} + \alpha_3 \mathrm{Lerner}^* \mathrm{Disaster}_{c,t} + \alpha_4 X_{c,t} + \gamma_c + \gamma_t + \varepsilon_{c,t}, \tag{4}$$

where $y_{c,t}$ is a dependent variable (either *Income growth* or *Estab growth*) in county c during quarter t; $Lerner_{c,t}$ is the mean Lerner Index of all banks in the county; $Disaster_{c,t}$ equals 1 in the three years following a hurricane in county c and 0 in contiguous counties; $X_{c,t}$ is a vector of control variables; γ_c and γ_t are county and quarter fixed effects, respectively; $\varepsilon_{c,t}$ is the error term. Standard errors are clustered at the county level.

[9] Other papers that use the Lerner Index to approximate market power include Carbó-Valverde et al. (2009) and de Guevara and Maudos (2011).

[10] Later, we conduct sensitivity checks using alternative market structure measures. For each county-year we use the annual state-level interstate branching restrictiveness index (*BRI*) from Rice and Strahan (2010), the three firm concentration index *CR3*, and a Herfindahl-Hirshman index based on banks' deposit market shares within the county (*HHI*).

Table 1
Variable descriptions.

Variable	Description	Source
Macroeconomic variables		
Income growth	Percentage change of income per capita at 2017 price levels	BEA
Estab growth	Percentage change of number of establishments in the private sector	QCEW
Unemployment rate	County unemployment rate	BLS
Commercial, consumer and real estate loans variables		
C&I loans	Natural log of commercial and industrial loans	FFIEC
Consumer loans	Natural log of consumer loans, other than real estate loans	FFIEC
Real estate - New	Natural log of new loans for home purchase	HMDA
Real estate - Improvement	Natural log of loans for home improvement	HMDA
Real estate - Refinancing	Natural log of loans refinanced	HMDA
Denial rate	Percentage of denied applications	HMDA
Sec rate	Percentage of real estate loans securitized through the GSEs	HMDA
Jumbo rate	Percentage of real estate loans that fall above the limit threshold set by GSEe	HMDA
Competition proxies		
Lerner	Lerner index	FFIEC
BRI	IBBEA Branch Restriction Index	Rice and Strahan (2010)
CR3	3-firm concentration ratio in the county	SOD
HHI	Herfindahl - Hirschman index of deposits	SOD
Bank level control variables		
Capital ratio	Equity over total assets	FFIEC
Bank size	Natural log of bank total assets	FFIEC
BD	Bank business diversification	Cetorelli and Goldberg (2014)
IR	C&I Loans' interest rates	FFIEC
County level control variables		
Income per capita (ln)	Natural log of county income per capita at the 2017 price level	BEA
Population growth	Percentage change of county population	U.S. Census
Tax rate	Maximum state wages tax rate	NBER
Market share of multimarket banks	Market share of multimarket banks in the county	SOD
SBA^B	SBA loans to businesses per capita	SBA
SBA^H	SBA loans to homeowners per capita	SBA
FEMA grants (ln)	FEMA grants to business and homeowners per capita	FEMA
Damage per capita	Total disaster damage per capita in the county at the 2017 price level	FEMA
Sample splits variables		
ROA	Dummy equal to one if the average bank net income to total assets in the county is above sample median and zero otherwise	FFIEC
Capitalization ratio	Dummy equal to one if the average bank equity to total assets in the county is above sample median and zero otherwise	FFIEC
Deposit to asset ratio	Dummy equal to one if the average bank deposits to total assets in the county is above sample median and zero otherwise	FFIEC
Non interest income	Dummy equal to one if the average bank non interest income to total assets in the county is above sample median and zero otherwise	FFIEC
Money market	Dummy equal to one if the average bank interest expense from non deposit liabilities to total assets in the county is above sample median and zero otherwise	FFIEC
Small vs. large bank	Dummy equal to one if the bank size in the county is below USD 500 million (at 2017 price level) and zero otherwise	FFIEC
External financial dependence	Dummy equal to one if the at least 50% of the establishments in the county belong to industries with a score of external financial dependence at the top 30% percentile and zero otherwise	QCEW and de Guevara and Maudos (2011)
County income	Dummy equal to one if the county personal income in real terms is above sample median and zero otherwise	BEA
Metro/Rural	Dummy equal to one if more than 50,000 people live in a metropolitan area in the county and zero otherwise	SOD
Crisis	Dummy equal to one if a observation falls in 2008 or 2009 and zero otherwise	FFIEC
PCA	Dummy equal to one if in the county there is a bank under PCA during the period 1995-2017 and zero otherwise	FDIC, OCC and FED

Notes: This table provides a description of each variable in the data set and its source. BEA denotes Bureau of Economic Analysis, QCEW denotes Quarterly Census of Employment and Wages, BLS denotes Bureau of Labor Statistics, FFIEC denotes Federal Financial Institutions Examination Council, OCC denotes the Office of the Comptroller of the Currency, FED denotes the Federal Reserve, HMDA denotes Home Mortgage Disclosure Act database, SOD denotes the FDIC Summary of Deposits database, NBER denotes the National Bureau of Economic Research, SBA denotes Small Business Administration, FEMA denotes Federal Emergency Management Agency.

The estimating equation includes a control for the average capital ratio of banks in the county because prior research shows that highly capitalized banks are able to absorb potential losses due to their capital buffers. The estimations condition on average bank size because small institutions face difficulties obtaining external finance through capital markets but could benefit from lower information

Table 2
Descriptive statistics.

	Obs	Mean	Std. Dev	Median	p25	p75
Income growth	47,919	0.017	0.037	0.018	-0.001	0.036
Estab growth	48,925	0.002	0.017	0.003	-0.006	0.011
Unemployment rate	29,920	0.069	0.031	0.064	0.047	0.086
C&I loans	20,069	16.582	1.539	16.560	16.686	17.481
Consumer loans	18,424	15.988	1.534	16.017	15.250	16.688
Real estate loans - All	46,684	17.633	2.129	17.490	16.241	19.140
Real estate - New	46,577	16.806	2.147	16.595	15.312	18.401
Real estate - Improvements	45,327	14.371	1.931	16.347	13.188	15.609
Real estate - Refinance	46,160	16.935	2.140	16.846	15.577	18.403
Denial rate	46,684	0.147	0.077	0.132	0.097	0.179
Sec rate	35,866	0.334	0.188	0.333	0.184	0.482
Jumbo rate	40,133	0.013	0.031	0.000	0.000	0.010
Lerner	49,021	0.119	0.282	0.211	0.059	0.278
BRI	49,021	1.177	1.651	0.000	0.000	3.000
CR3	49,021	0.771	0.191	0.779	0.623	0.971
HHI	49,021	0.309	0.199	0.254	0.169	0.389
Capital ratio	49,021	0.105	0.017	0.105	0.094	0.115
Bank size	49,021	21.283	1.785	21.404	20.048	22.481
BD	49,021	0.348	0.278	0.416	0.000	0.551
C&I interest rate	42,045	0.041	0.055	0.037	0.021	0.055
Income per capita (ln)	47,919	10.399	0.247	10.370	10.229	10.534
Population growth	47,919	0.007	0.017	0.005	-0.003	0.015
Tax rate	49,021	0.044	0.027	0.051	0.030	0.062
Market share of multimarket banks	45372	0.850	0.226	0.991	0.768	1.000
SBA^B	5,651	36.833	172.272	3.637	0.888	15.655
SBA^H	6,917	76.038	507.621	6.348	1.219	25.417
FEMA grants (ln)	4,932	15.413	12.123	24.514	2.865	27.006
Damage per capita	5,128	27,000	79,722	6,362	1,935	23,259
ROA	49,021	0.500	0.500	1.000	0.000	1.000
Capitalization ratio	49,021	0.505	0.499	1.000	0.000	1.000
Small vs. large bank	49,021	0.495	0.499	0.000	0.000	1.000
Deposit asset ratio	49,021	0.500	0.500	1.000	0.000	1.000
Non interest income	49,021	0.500	0.500	1.000	0.000	1.000
Money market	49,021	0.500	0.500	1.000	0.000	1.000
External financial dependence	49,021	0.480	0.499	0.000	0.000	1.000
County income	47,919	0.368	0.482	0.000	0.000	1.000
Metro/Rural	46,885	0.464	0.498	0.000	0.000	1.000
Crisis	49,021	0.087	0.282	0.000	0.000	0.000
PCA	49,021	0.011	0.108	0.000	0.000	0.000

Notes: This table reports summary statistics for each variable described in Table 1.

and agency costs through their superior relationship-lending technologies. We control for the top marginal personal income tax rate because Jayaratne and Strahan (1996) include taxes as controls in regressions of personal income growth on banking competition measured through intrastate deregulation. We also add bank diversification and government assistance as controls as these factors may influence the post-disaster recovery through borrowers' access to credit.

Isolating consistent estimates in Equation (4) rests on the exogeneity of natural disasters. The timing, intensity, and location of hurricanes are inherently difficult to predict. They are independent with respect to the rate of personal income growth and establishment growth. Estimates of α_2 are therefore likely to be unbiased. However, bank market structure may correlate with unobservables in the error term, leading to biased estimates of α_3. Standard econometric intuition suggests that in this case the sample estimate of α_3 will be biased because $E(Lerner_{c,t}|\varepsilon_{c,t}) \neq 0$.

However, prior literature shows that this is not the case. Suppose the estimating equation contains an endogenous variable (e.g. $Lerner_{c,t}$), an exogenous variable (e.g. $Disaster_{c,t}$) and an interaction between the two. Nizalova and Murtazashvili (2016) and Bun and Harrison (2019) show the bias of the interaction term's coefficient derives from the correlation between the interaction term and the omitted variable in the error term, minus the product of the correlation between the interaction term and the endogenous variable and the correlation between the endogenous variable and the omitted variable in the error term.[11] Despite the interaction term containing

[11] The results are not sensitive to the number of omitted variables the interaction term correlates with. Nizalova and Murtazashvili (2016) show the findings are robust to correlation between the interaction term and multiple omitted variables in the error term.

an endogenous variable, providing 1) the exogenous variable is independent of the endogenous variable (i.e. $E(Disaster_{c,t}|Lerner_{c,t} = 0)$, and 2) the exogenous variable is independent of the error term conditional on the endogenous variable (i.e. $E(Disaster_{c,t}, \varepsilon_{c,t}|Lerner_{c,t} = 0)$, OLS provides consistent estimates of the interaction coefficient. Bun and Harrison (2019) and Nizalova and Murtazashvili (2016) present evidence from Monte Carlo simulations that confirm this finding.[12]

In our setting, while there are valid reasons to believe the Lerner Index is correlated with unobservables in $\varepsilon_{c,t}$, it is plausible that hurricanes are exogenous with respect to bank market structure and unobservable determinants of $y_{c,t}$ in Equation (4), once we account for bank market structure. The joint independence conditions likely hold because a hurricane's location, timing and damage depend on meteorological conditions that are unrelated to bank market structure and determinants of economic growth in a county.[13] Estimates of α_3 in Equation (4) are therefore likely to be consistent.

5.1. Diagnostic checks

The control group consists of counties contiguous to each treated county that are not hit by a hurricane during the quarter the treated county is affected. The validity of the econometric setup relies on the parallel trends assumption to compute the implied counterfactual. We test this assumption by studying the pre-treatment evolution of the dependent variables in the treatment and control groups.

Figs. 1 and 2 depict economic growth and establishment growth in the four years on either side of a hurricane. In both cases, the pre-treatment evolution of the variables is similar across the groups. Table 3 presents formal statistical evidence on the parallel trends assumption. We use Wilcoxson tests to examine equality in the dependent variables over quarters *t*-8 and *t*-1 between the treatment and control groups. We cannot reject the null of equality for both variables. The complementary graphical and statistical evidence indicate the parallel trends assumption is satisfied.

Following a natural disaster, the federal government provides assistance to affected regions.[14] FEMA is the primary organization that coordinates the response to major disasters in the US by providing grant funds to eligible disaster related projects following an emergency. In addition, the SBA provides disaster loans to eligible businesses and households in areas with a disaster declaration. A question is whether these forms of government assistance correlate with bank market structure. This appears unlikely as FEMA and SBA assistance is available to eligible businesses and households regardless of conditions within the banking sector.

The data also support this view. Online Appendix Table A2 shows that the level of FEMA grants in county *c* during quarter *t* is not significantly related to bank market structure. In addition, the estimates in columns 2 and 4 of Table 5 show SBA disaster loans per capita are unrelated to bank market structure. This is consistent with the fact that the SBA, rather than a bank, decides whether to approve a borrower's application. Approved loans are then originated by a partner bank.[15]

6. Econometric results

We report estimates of Equation (4) using *Income growth* as the dependent variable in column 1 of Table 4. Following a hurricane, the rate of personal income growth contracts by 0.4 percentage points. This effect is statistically significant and equates to a 24% reduction relative to the mean.

The results also show bank market power has asymmetric effects on economic growth depending on whether a county is subject to a disaster. The *Lerner* coefficient estimate is -0.016 and is statistically significant at the 10% level. Increasing bank market power therefore has adverse effects on economic growth during "normal" times. However, the *Lerner*Disaster* interaction coefficient is positive and highly statistically significant, indicating that following a disaster economic growth recovers more quickly in counties where bank market power is strong. Economically, a 1% increase in the Lerner Index leads to a 0.032 percentage-point higher rate of growth in the average affected county during the recovery phase. Bank market structure thus offsets some of the negative consequences of natural disasters.[16] The results are consistent with *H1B*: during normal times bank market power imposes a deadweight loss on

[12] Other studies that exploit these properties to identify consistent estimates of the interaction between an exogenous and endogenous variable include Nunn and Qian (2014), Dreher et al. (2015), Nizalova and Murtazashvili (2016), Bun and Harrison (2019) and Buchholz et al. (2020). For example, Dreher et al. (2015) study how the interaction between the ideological distance between donors and recipients (the exogenous variable) and foreign aid (the endogenous variable) influence economic growth. Providing ideological distance is exogenous and independent of foreign aid, and the estimating equation controls for the endogenous variable, estimates of the interaction coefficient using OLS are consistent.

[13] Recent articles that emphasize the exogeneity of natural disasters, including hurricanes, with respect to economic outcomes include Aretz et al. (2018), Wagner (2020) and Brown et al. (2021).

[14] The hurricanes we study are those that provoke a PDD. A PDD indicates that the disaster is of such severity and magnitude that effective response is beyond the capabilities of the State and the affected local governments or Indian tribal government that federal assistance is necessary

[15] Online Appendix Table A3 shows that economic conditions and the level of banking market competition do not predict the location or timing of hurricanes. It is therefore unlikely that simultaneity bias is present in Equation (4).

[16] A reason why hurricanes affect economic growth within the same quarter is that SBA loans are originated within 3 weeks while mortgage underwriting takes between a few days and weeks. This allows households and businesses to access credit quickly and begin repair and reconstruction work. The key findings are unchanged when we include one quarter lags of the Lerner Index and Disaster variables in Equation (4).

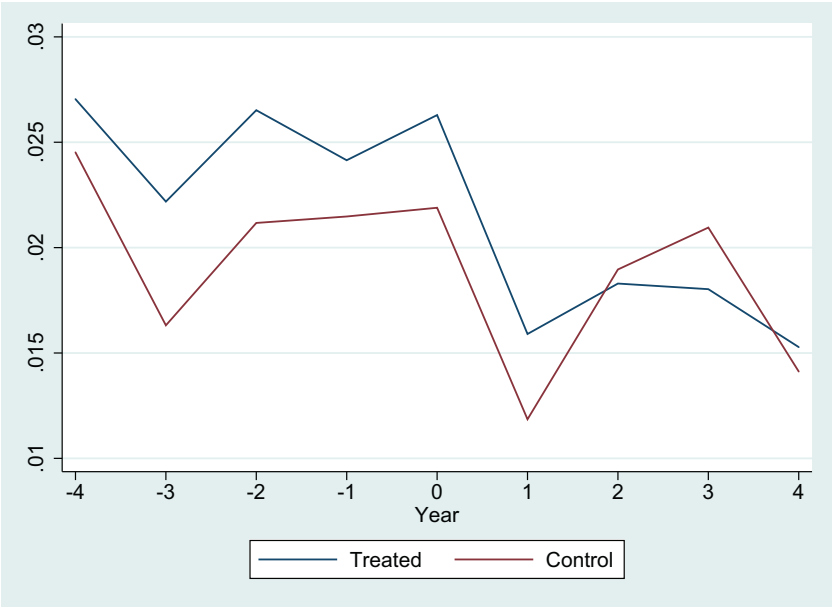

Fig. 1. Evolution of Economic Growth.
Notes: This figure plots the annual rate of growth of personal income within the treatment and control groups during the 4 years before and after a hurricane. Treated (Control) indicate counties subject (not subject) to a hurricane at time 0. Negative years indicate pre-disaster periods. 0 denotes the year during which the hurricane takes place.

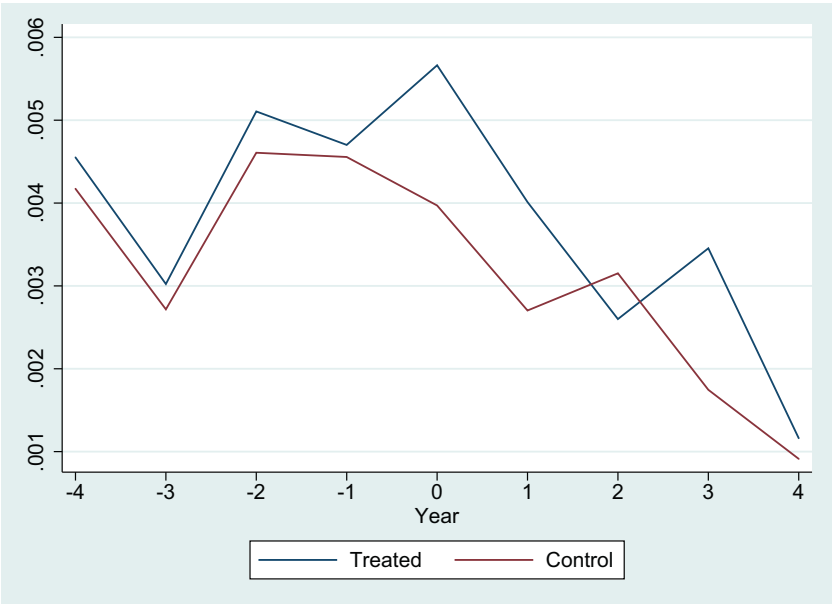

Fig. 2. Evolution of Establishment Growth.
Notes: This figure plots the annual rate of growth in establishments within the treatment and control groups during the four years before and after a hurricane. Treated (Control) indicate counties subject (not subject) to a hurricane at time 0. Negative years indicate pre-disaster periods. 0 denotes the year during which the hurricane takes place.

Table 3
Parallel trends.

	Mean change			
	Treated	Control	Difference	Wilcoxson p-value
Income growth	-0.089	-0.005	-0.084 (0.855)	-0.756
Estab growth	-0.75	-0.67	-0.08 (0.940)	-0.476

Notes: This table reports Wilcoxson tests for equality in quarterly growth rates over *t*-8 and *t*-1 between the treatment and control groups. Difference is the difference between the mean change in treated and control counties. Wilcoxson p-value is the p-value from the test that Difference equals 0. Variable definitions are provided in Table 1.

Table 4
Market structure and recovery following disasters.

	(1)	(2)	(3)	(4)
	Baseline results		Matched sample estimates	
Dependent variable:	Income growth	Estab growth	Income growth	Estab growth
Lerner	-0.016*	-0.002	-0.014	-0.008**
	(-1.710)	(-0.692)	(-1.148)	(-2.178)
Disaster	-0.004**	0.000	-0.005**	0.001
	(-2.189)	(0.668)	(-2.464)	(0.716)
Lerner*Disaster	0.032**	0.003	0.025*	0.007*
	(2.563)	(1.126)	(1.685)	(1.799)
Capital ratio	0.029	-0.009	0.049*	-0.018
	(1.023)	(-1.342)	(1.709)	(-1.606)
Bank size	-0.000	-0.000*	-0.001	-0.000
	(-0.034)	(-1.789)	(-1.174)	(-0.590)
Income per capita (ln)	0.154***	0.011***	0.167***	0.013***
	(10.237)	(7.535)	(13.034)	(6.586)
Population growth	-0.734***	0.052***	-0.558***	0.064***
	(-10.966)	(5.485)	(-10.940)	(5.030)
Tax rate	-0.336***	-0.011	-0.505***	-0.008
	(-4.020)	(-0.750)	(-4.766)	(-0.481)
Market share of multimarket banks	-0.001	0.000	-0.001	0.000
	(-0.515)	(0.631)	(-0.401)	(0.438)
SBA^H	0.000	-0.000	0.001	-0.000
	(0.287)	(-1.120)	(1.595)	(-0.307)
SBA^B	0.001***	0.000	0.000	0.000
	(3.056)	(1.644)	(0.363)	(0.291)
FEMA grants	-0.000	0.000***	-0.000*	0.000**
	(-0.419)	(3.076)	(-1.719)	(2.200)
County FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Counties	522	522	351	351
Observations	45,372	45,279	25,363	25,329
R-squared	0.292	0.113	0.321	0.120

Notes: This table reports estimates of Equation (4). Columns 1 and 2 contain observations from the whole sample. In columns 3 and 4 we run propensity score matching to build a matched sample. Bank competition is proxied by *Lerner*. The dependent variable is *Personal income growth* in columns 1,3 and *Establishment growth* in columns 2,4. Variable definitions are provided in Table 1. Standard errors are clustered at the county level and the corresponding cluster-robust t-statistics are reported in parentheses. ***,**,* indicate statistical significance at the 1%, 5%, and 10% level, respectively.

growth, but following a hurricane it aids recovery.[17]

Among the control variables we find personal income growth is positively associated with income per capita whereas higher rates of population growth and tax rates have a negative effect. Some elements of disaster-related government support matter for personal income growth. We find a positive and statistically significant relationship between SBA loans per capita to business and the rate of personal income growth. In contrast, the SBA loans per capita to households and FEMA grants coefficients are insignificant. These findings demonstrate that measures of government assistance do not confound the effect of bank market power on the economic recovery.[18] We find no significant relationships between personal income growth, the market share of multimarket banks, the mean capital ratio or bank size within the county.[19]

The estimates in column 2 of the table use the establishment growth rate as the dependent variable in Equation (4). We find bank market structure has no effect on establishment growth. The *Lerner* and *Lerner*Disaster* interaction coefficients are insignificant. This finding implies the effect of bank market structure on recovery is not transmitted through the creation of new businesses in the private sector.

Difference-in-difference estimates are most credible where the treatment and control groups strongly resemble each other before treatment. Level differences in ex ante conditions do not pose a threat to the parallel trends assumption or the validity of difference-in-difference estimates because the county fixed effects eliminate these differences (Whited and Roberts, 2013). However, while treated and control counties are statistically similar in terms of *Income growth*, *Estab growth*, *Lerner*, *BRI*, and *Bank size*, Online Appendix Table A6 shows some pre-disaster differences when it comes to other explanatory variables. We therefore follow Aretz et al. (2018) and use propensity score matching with replacement to match each treated county to the most similar control county.[20] Next, we estimate Equation (4) using the matched sample. Despite the reduction in sample size, the estimates reported in columns 3 and 4 of Table 4 are similar to the baseline results and support *H*1*B*.

6.1. Mechanisms

In this section, we disentangle the credit market mechanisms through which bank market power leads to faster personal income growth following a hurricane.

Column 1 in Table 5 reports estimates of Equation (4) using the natural logarithm of C&I loans in the county. We find that following a hurricane, banks do not increase C&I lending in affected counties and the *Lerner*Disaster* interaction coefficient is statistically insignificant. Alternatively, banks may support disaster-affected businesses by lowering C&I loans' interest rates. Online Appendix Table A7 shows this is not the case.

Rather, the SBA is the most important source of business finance following a hurricane. In column 2 of Table 5, we find that after a disaster SBA lending to businesses increases by approximately 14%. However, the *Lerner*Disaster* interaction coefficient is insignificant. This is consistent with the fact that SBA support is available to all eligible borrowers and is independent of bank market structure.

A key insight from the analysis is that SBA loans rather than on balance sheet C&I loans are the primary source of credit for disaster-affected firms. The SBA does not lend money directly to businesses. Rather, it provides a government guarantee on loans at below market interest rates to eligible borrowers that banks originate on its behalf.[21] The low interest rate potentially makes SBA loans more attractive to borrowers, and explains why among disaster-affected firms, SBA loans are the most important source of credit.[22] Banks have incentives to process SBA loans because the government guarantee removes credit risk while they can earn non interest income through processing fees.

The SBA lending channel also helps to explain why bank market structure does not influence establishment growth after a disaster. The *Estab growth* variable captures net entry of establishments (i.e. the difference between entering and exiting firms). The insignificant

[17] Online Appendix Table A4 reports tests using a continuous disaster measure. Rather than using the *Disaster* dummy variable in Equation (4), we capture hurricanes using the damage caused by a hurricane in natural logarithms. Despite this change, we continue to find that income growth recovers more quickly from hurricane damage in concentrated banking markets.

[18] The relative importance of SBA disaster lending to business compared to households for personal income growth is consistent with SBA disaster loans' status as the primary source of finance for disaster-affected firms. Businesses can use SBA loans to replace damaged physical capital, cover business operating expenses, repair damage to home or personal property, and to cover operating expenses due to employees on active duty leave. In contrast, the SBA limits funding to households that are unable to obtain credit elsewhere, and it imposes borrowing limits and restricts loans for the repair and replacement of damaged property to eligible households.

[19] In Online Appendix Table A5 we consider an alternative definition of bank diversification. Specifically, we follow Cetorelli and Goldberg (2014) and measure the extent of a bank's diversification across business lines (e.g. retail banking, insurance, mutual and pension funds, other financial subsidiaries and non-financial subsidiaries). We do not find that the extent of banks' business diversification correlates with either income or establishment growth in columns 1 and 2 of Online Appendix Table A5.

[20] We run a probit regression where the dependent variable is *Treated* and the independent variables are *Lerner*, *HHI*, *Capital Ratio*, *Population growth*, *Income per capita (ln)*, *Tax rate*, *Bank size*, and *Unemployment rate*. Then, we construct the matched sample using a caliper equal to 0.0001, and exclude the observations falling outside of the common support.

[21] The SBA provides disaster loans up to $2 million to businesses of all sizes located in declared disaster areas. A firm may use an SBA disaster loan to cover 1) repair and replacement of physical assets, 2) business operating expenses, 3) damage to business premises, and 4) operating expenses to make up for employees on active duty leave.

[22] Evidence from the Small Business Credit Survey shows that 48% of disaster-affected firms apply for credit, with 45% of these firms applying for SBA loans.

Table 5
Commercial lending and household finance.

Loan type	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Business		Personal		Mortgage						
Dependent variable	C&I	SBA^B	Consumer	SBA^H	All	New	HI	Refinancing	Denial	Securitization	Jumbo
	Baseline results										
Lerner	0.007	0.240	0.961**	0.274	-0.534**	-0.370	-0.694**	-0.764***	0.055**	0.103**	0.011
	(0.587)	(1.477)	(2.437)	(1.495)	(-2.343)	(-1.630)	(-1.998)	(-3.045)	(2.357)	(2.411)	(1.591)
Disaster	-0.000	0.132***	0.091	0.167***	0.038	0.057	0.044	0.041	0.001	0.017*	0.001
	(-0.468)	(3.141)	(0.813)	(2.866)	(0.630)	(1.038)	(0.644)	(0.668)	(0.417)	(1.932)	(0.465)
Lerner*Disaster	-0.005	-0.054	-0.500	-0.357	0.684***	0.528**	0.630	0.813***	-0.026	-0.142***	-0.014*
	(-0.491)	(-0.274)	(-0.709)	(-1.475)	(2.625)	(2.001)	(1.628)	(2.781)	(-0.907)	(-2.744)	(-1.899)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,016	47,919	16,909	47,919	43,087	42,984	41,850	42,615	42,699	45,372	45,372
R-squared	0.177	0.126	0.288	0.146	0.736	0.610	0.484	0.766	0.227	0.737	0.507

Notes: The dependent variables are commercial loans in logs (column 1), SBA loans to businesses per capita in logs (column 2), consumer loans in logs (column 3), SBA loans to homeowners per capita in logs (column 4), total home mortgages in the county in logs (columns 5), total new mortgages in the county in logs (column 6), loans for home improvement in the county in logs (column 7), refinancing home loans in the county in logs (column 8), average denial rates in the county (column 9), securitized loans as percentage of total home loans in the county (column 10), and jumbo loans as percentage of total home loans (column 11). Variable definitions are provided in Table 1. The unreported control variables are the capital ratio, bank size, income per capita (ln), population growth, tax rate, Market share of multimarket banks, SBA^H, SBA^B, and FEMA grants. Standard errors are clustered at the county level and the corresponding cluster-robust *t*-statistics are reported in parentheses. ***,**,* indicate statistical significance at the 1%, 5%, and 10% level, respectively.

interaction term in Table 4 indicates bank market structure has no effect on the total number of establishments operating in a county after a disaster. A reason why the number of establishments does not increase in counties where banks have market power is that the SBA lends exclusively to existing businesses. Entrepreneurs that wish to start-up firms in disaster regions are therefore ineligible for SBA loans and banks are unwilling to extend C&I loans. This limits firm creation and growth in the number of establishments.

Next, we consider how consumer lending evolves in the aftermath of a natural disaster. Column 3 of Table 5 reports estimates of Equation (4) using the logarithm of bank loans to consumers. We find that a disaster has no significant effect on banks' consumer lending, and the *Lerner*Disaster* interaction coefficient is insignificant. However, column 4 of the table shows that SBA loans to households significantly increases after a disaster but this effect does not vary according to bank market structure.

In the remainder of Table 4 we study the response of mortgage lending following a hurricane. Column 5 provides estimates of Equation (4) using the natural logarithm of real estate lending (regardless of the nature of these loans) as the dependent variable. The *Lerner*Disaster* interaction coefficient is economically large and statistically significant. We estimate that within the treatment group following a disaster, a 10% increase in the Lerner Index leads to a 6.8% increase in real estate credit. In contrast, during normal times bank market structure has a negative effect on real estate lending.

Columns 6 to 8 of Table 5 provide disaggregated insights into the type of real estate credit supply that bank market structure influences after a disaster. The *Lerner*Disaster* interaction coefficient is statistically significant when the dependent variable is the volume of new mortgages (column 6) or refinancing loans (column 8). Economically, the coefficient is approximately 50% larger for refinancing loans compared to new mortgage loans. Interestingly, the *Lerner*Disaster* interaction parameter is insignificant for home improvement loans (column 7). These findings suggest that in the aftermath of a hurricane, banks with high market power support borrowers by providing new mortgage credit and refinancing existing mortgages. This may alleviate credit constraints, cash flow shocks and disaster-related expenses, and is consistent with banks seeking to prevent foreclosure following a natural disaster (Favara and Giannetti, 2017).

Why might bank market structure matter after a disaster for mortgage credit rather than consumer loans? The SBA only extends disaster loans to households that are unable to obtain credit elsewhere. Many households are therefore ineligible for SBA disaster loans. Furthermore, SBA-eligible households face a borrowing limit of $200,000, which may only be used to repair or replace damaged property. This may be insufficient if a property is extensively damaged and also prevents borrowers from covering cash flow (e.g. lost employment income) or expenditure shocks. Mortgage finance may alleviate these frictions. For example, repairing an extensively damaged property may require a new mortgage due to limits on SBA and banks' home improvement loans. Mortgage refinancing may allow consumers to reduce their cost of debt to manage cash flow shocks and disaster-related expenses. At a time of acute uncertainty when consumers potentially lack collateral, banks with market power are best placed to provide credit due to their profitability and information advantages.

A related question is whether hurricanes lead banks to strengthen or loosen credit standards in the real estate market. To test this hypothesis we use the denial rate on mortgage applications as the dependent variable in Equation (4). In column 9 of Table 5 the *Lerner* coefficient is positive and significant at the 1% level. This is consistent with banks using market power to limit credit supply during normal times. However, the *Lerner*Disaster* interaction is insignificant.

Banks may respond to a disaster by securitizing loans at a higher frequency to mitigate credit risk arising due to the weaker financial position of borrowers in disaster areas (McGowan and Nguyen, 2021a,b). In column 10 of Table 5 we find evidence that supports this mechanism. The *Disaster* coefficient is positive and significant at the 10% level, and indicates the securitization rate is 1.7% higher relative to the implied counterfactual. The interaction coefficient is negative and significant at 1%. Hence, while banks are more likely to securitize mortgage loans after a disaster, they are less likely to do so when operating in concentrated markets. This is consistent with the informational advantages of banks with market power and their preference for retaining high default risk loans to earn higher returns (Agarwal et al., 2012).

Finally, we investigate how lending to different segments of the mortgage market responds to bank market structure following disasters. The presence of the GSEs in the secondary market creates differences in the information intensity of loans around the conforming limit threshold.[23] Loans that meet the GSEs' underwriting criteria have relatively low information intensities as banks can easily sell them to a GSE. However, jumbo loans do not benefit from the GSEs' purchase guarantees and are thus more informationally intensive. We therefore test how the jumbo share of loan originations responds to a disaster. In column 11 of Table 5 we find the *Lerner-Disaster* coefficient is negative and significant at 10%.

Hence, following a hurricane, banks embrace a more prudent risk management strategy by originating fewer jumbo loans. This finding is consistent with Chavaz (2016), who shows that in the aftermath of the 2005 hurricane season banks accepted more loan applications that qualified for a GSE purchase. Our results also corroborate the view that credit supply subsidies offered by GSEs spur economic growth in local markets by smoothing capital supply shocks (Loutskina and Strahan, 2015).

6.2. Bank profitability and resilience

A potential reason why banks with market power can maintain credit supply in the face of natural disasters is that they are more profitable and resilient (Jayaratne and Strahan, 1998; Jiang et al., 2016; Schüwer et al., 2018; Crawford et al., 2018; Danisewicz et al., 2021). We therefore investigate whether the results differ according to ex ante conditions in the banking industry within a county by

[23] The baseline limit for a conforming loan according to GSE guidelines is adjusted each year to reflect changes in the national average home price, https://www.fhfa.gov/DataTools/Downloads/Pages/Conforming-Loan-Limits.aspx

Table 6
Banking profitability and resilience.

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA		Capital ratio		Bank size	
Sample split	Low	High	Low	High	Low	High
Panel A: income growth						
Lerner	0.007	-0.032**	-0.010	-0.018	-0.026*	-0.015
	(0.641)	(-2.055)	(-0.782)	(-1.336)	(-1.862)	(-1.189)
Disaster	-0.002	-0.006*	-0.005*	-0.002	-0.006**	-0.003
	(-0.712)	(-1.828)	(-1.916)	(-0.786)	(-1.969)	(-1.088)
Lerner*Disaster	0.007	0.045**	0.020	0.028*	0.035**	0.029
	(0.358)	(2.541)	(1.188)	(1.723)	(2.004)	(1.414)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,852	22,512	22,794	22,570	22,623	22,742
R-squared	0.396	0.279	0.358	0.294	0.293	0.352
	ROA		Capital ratio		Bank size	
Sample split	Low	High	Low	High	Low	High
Panel B: estab growth						
Lerner	0.002	-0.003	-0.002	-0.002	0.004	-0.006*
	(0.714)	(-0.836)	(-0.506)	(-0.529)	(1.161)	(-1.923)
Disaster*	0.001	-0.000	0.001	0.000	-0.000	0.002
	(1.080)	(-0.142)	(0.942)	(0.325)	(-0.338)	(1.202)
Lerner*Disaster	-0.001	0.005	0.002	0.005	0.000	0.007*
	(-0.252)	(1.172)	(0.427)	(1.193)	(0.044)	(1.906)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,797	22,474	22,745	22,526	22,587	22,685
R-squared	0.136	0.123	0.141	0.109	0.115	0.133

Notes: The dependent variables are *Personal income growth* (Panel A), and *Establishment growth* (Panel B). Column 1 (2) contains observations from counties below (above) the median bank ROA. Column 3 (4) contains observations from counties below (above) the median bank capital ratio. Column 5 (6) contains observations from counties below (above) bank assets of $500 million (at 2017 prices). Variable definitions are provided in Table 1. The unreported control variables are the capital ratio, bank size, income per capita (ln), population growth, tax rate, market share of multimarket banks, SBA^H, SBA^B, and FEMA grants. Standard errors are clustered at the county level and the corresponding cluster-robust *t*-statistics are reported in parentheses. ***,**,* indicate statistical significance at the 1%, 5%, and 10% level, respectively.

focusing on indicators of profitability and resilience such as return on assets, capital ratios, and bank size. For each variable we calculate the median county value during the two years before a disaster. Then we split the sample at the median value of each variable.

Panel A of Table 6 reports estimates of Equation (4) using personal income growth as the dependent variable. We find the *Lerner*Disaster* interaction coefficient is significant for counties where there is a higher presence of banks with above-median ROA (column 2), capital ratios (column 4), and smaller size (column 5). Better capitalized banks are potentially able to increase lending without breaching regulatory capital limits, while more profitable banks can extend credit using the reserves they have accumulated without provoking adverse selection. Personal income growth may recover faster in counties with a larger share of small banks with market power because of these banks' relationship lending technologies. Through their existing borrower relationships, small lenders have superior information about a customer's true credit risk which allows them to quickly evaluate the value of destroyed collateral and extend credit to affected households by quickly assessing their repayment capacity. These institutions tend to concentrate lending in particular areas (Degryse and Ongena, 2005) and thus have an advantage in managing riskier loans due to their screening and monitoring abilities (Berger et al., 2005; Loutskina and Strahan, 2011; Cortés and Strahan, 2017).

In Panel B of Table 6 we use establishment growth as the dependent variable. The interaction coefficient is insignificant in all but one cell of the panel (column 6), but even here it is economically small and significant only at the 10% level. Again, this suggests that bank market structure aids the recovery from a disaster through the household rather than industrial sector.

6.3. Traditional banking activities

The link between bank market power and economic conditions could be affected by the focus of bank activities. For example, small institutions that specialize in traditional retail banking could benefit from a higher degree of market power and thus extend credit at better terms compared to larger and diversified institutions. Hakenes et al. (2014) find that these banks are more successful at spurring economic growth especially in situations of severe credit rationing.

We capture traditional banking activities using the total deposits to asset ratio, non interest income to total assets and interest expenses from non-deposit liabilities to total assets (*Money market*). For each variable, we calculate the mean bank value for each

Table 7
Bank reliance on traditional activities.

	(1)	(2)	(3)	(4)	(5)	(6)
	Deposit asset ratio		Non interest income		Money market	
Sample split	Low	High	Low	High	Low	High
Panel A: income growth						
Lerner	-0.004	-0.033**	-0.023	-0.016	-0.026*	-0.009
	(-0.314)	(-2.460)	(-1.548)	(-1.325)	(-1.812)	(-0.768)
Disaster	-0.007***	-0.002	-0.002	-0.005**	-0.001	-0.006***
	(-2.742)	(-0.523)	(-0.762)	(-2.046)	(-0.428)	(-2.857)
Lerner*Disaster	0.028	0.030*	0.033*	0.026	0.019	0.027
	(1.373)	(1.812)	(1.837)	(1.559)	(1.212)	(1.395)
Control variables, County FE, Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,541	22,818	22,637	22,731	22,658	22,697
R-squared	0.362	0.309	0.313	0.347	0.299	0.382
	Deposit asset ratio		Non interest income		Money market	
Sample split	Low	High	Low	High	Low	High
Panel B: estab growth						
Lerner	-0.004	0.003	-0.001	0.001	0.002	-0.004
	(-1.628)	(0.604)	(-0.159)	(0.419)	(0.429)	(-1.515)
Disaster	0.000	0.001	0.003**	-0.001	-0.000	0.001
	(0.267)	(0.915)	(2.062)	(-1.587)	(-0.116)	(0.635)
Lerner*Disaster	0.004	0.002	0.002	0.001	0.003	0.004
	(1.505)	(0.463)	(0.393)	(0.226)	(0.597)	(1.287)
Control variables, County FE, Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,507	22,759	22,592	22,683	22,603	22,659
R-squared	0.147	0.104	0.099	0.156	0.100	0.161

Notes: The dependent variables are *Personal income growth* (Panel A), and *Establishment growth* (Panel B). Column 1 (2) contains observations from counties below (above) the median bank deposit-to-asset ratio. Column 3 (4) contains observations from counties below (above) the median bank non interest income to total assets ratio. Column 5 (6) contains observations from counties below (above) the median bank interest expenses on non-deposit liabilities ratio. Variable definitions are provided in Table 1. The unreported control variables are the capital ratio, bank size, income per capita (ln), population growth, tax rate, market share of multimarket banks, SBA^H, SBA^B, and FEMA grants. Standard errors are clustered at the county level and the corresponding cluster-robust *t*-statistics are reported in parentheses. ***,**,* indicate statistical significance at the 1%, 5%, and 10% level, respectively.

variable during the two years preceding each hurricane and then collapse these values to the county level. Subsequently we split the sample at the median level of each indicator and estimate Equation (4) using the split samples. The results are shown in Table 7.

Panel A (B) of Table 7 reports estimates of Equation (4) using personal income growth (establishment growth) as the dependent variable. The estimates in Panel A show bank market power benefits economic growth following a disaster when a county's banks focus primarily on traditional activities. For example, the *Lerner*Disaster* interaction coefficient is positive and significant when the deposit to asset ratio is above the median, and when non interest income is below the median. In contrast, in the money market splits the interaction coefficient is insignificant in both cases. The results of Panel B are consistent with previous estimates and show that bank market power does not affect establishment growth in the aftermath of a disaster.

7. Robustness tests

In this section, we test the sensitivity of our findings to potential omitted variables and consider alternative measures of market structure.

7.1. County conditions

Does market structure affect the recovery from a disaster differently depending on the type of establishments in a county? For example, bank market structure may provoke larger responses where the private sector is more dependent on external finance. Panel A of Table 8 reports estimates of Equation (4) using sample splits at the median level of external financial dependence.[24] When we use personal income growth as the dependent variable, the *Lerner-Disaster* interaction parameter is similar in economic magnitude across columns 1 (high external financial dependence) and 2 (low external financial dependence) of the panel. However, it is only significant at conventional levels in counties where businesses are highly dependent on external finance.

The extent of a natural disaster may differ according to the ex ante level of income in a county. Households and firms in higher-

[24] In order to build this variable we retrieve from the *QCEW* database the number of establishments for each *NAICS* two digit industry in each county/quarter. Then we adopt the procedure explained in de Guevara and Maudos (2011) to construct an indicator of external financial dependence.

Table 8
County characteristics.

	(1)	(2)	(3)	(4)
Dependent variable	Income growth		Estab growth	
Panel A: External financial dependence				
Sample	High	Low	High	Low
Lerner	-0.019	-0.001	0.001	-0.003
	(-1.486)	(-0.055)	(0.413)	(-0.874)
Disaster	0.002	-0.009***	0.000	0.001
	(0.727)	(-2.763)	(0.704)	(0.478)
Lerner*Disaster	0.028*	0.024	-0.001	0.007
	(1.650)	(1.409)	(-0.387)	(1.351)
Control variables, County FE, Quarter FE	Yes	Yes	Yes	Yes
Observations	21,972	23,390	21,945	23,325
R-squared	0.351	0.296	0.155	0.105
Panel B: County income				
Sample	High	Low	High	Low
Lerner	-0.018	-0.009	-0.001	-0.002
	(-1.408)	(-0.761)	(-0.410)	(-0.601)
Disaster	-0.006**	-0.003	0.001	0.000
	(-2.052)	(-1.121)	(1.233)	(0.256)
Lerner*Disaster	0.029*	0.031**	0.002	0.004
	(1.682)	(1.980)	(0.683)	(1.005)
Control variables, County FE, Quarter FE	Yes	Yes	Yes	Yes
Observations	16,912	28,460	16,881	28,398
R-squared	0.398	0.288	0.158	0.098
Panel C: Metropolitan and rural counties				
Sample	Metro	Rural	Metro	Rural
Lerner	-0.006	-0.030*	-0.001	-0.002
	(-0.685)	(-1.723)	(-0.430)	(-0.480)
Disaster	-0.003	-0.005*	0.000	0.000
	(-1.428)	(-1.709)	(0.812)	(0.341)
Lerner*Disaster	0.019	0.040**	0.001	0.005
	(1.274)	(2.292)	(0.419)	(1.070)
Control variables, County FE, Quarter FE	Yes	Yes	Yes	Yes
Observations	20,707	24,665	20,678	24,601
R-squared	0.415	0.258	0.155	0.084

Notes: The dependent variables are *Personal income growth* (columns 1 and 2), and *Establishment growth* (columns 3 and 4). In Panel A we split the sample according to whether external financial dependence is above (High) or below (Low) the median level of external financial dependence. In Panel B we split the sample according to whether county income is above (High) or below (Low) the median level of county income. In Panel C we split the sample according to whether a county is metropolitan or rural following the FDIC SOD definitions. Variable definitions are provided in Table 1. The unreported control variables are the capital ratio, bank size, income per capita (ln), population growth, tax rate, market share of multimarket banks, SBA^H, SBA^B, and FEMA grants. Standard errors are clustered at the county level and the corresponding cluster-robust *t*-statistics are reported in parentheses. ***,**,* indicate statistical significance at the 1%, 5%, and 10% level, respectively.

income counties may be less susceptible to a hurricane because they can afford insurance as well as environmental protections to mitigate economic damage. In Panel B of Table 8 we find hurricanes have a negative effect on personal income growth irrespective of initial income levels, although the *Disaster* coefficient is only significant for counties with above-median income levels. The *Lerner*Disaster* interaction parameters show the recovery is faster where the banking market is less competitive irrespective of ex ante income levels.

Finally, in Panel C of Table 8 we investigate whether the results differ across metropolitan and rural counties.[25] We find bank market structure only exerts a positive and significant effect on the recovery in rural counties. For metropolitan counties we find no significant effects. This result is consistent with DeYoung et al. (2004) who present evidence that lenders in rural areas are smaller, there are fewer branches per inhabitant, and there is greater interaction between banks and their borrowers. This allows banks to establish superior information about borrowers' credit risk. In metropolitan areas where there are more banks, the elasticity of substitution is higher and banks are less able to establish long-term relationships.

7.2. Alternative market structure variables

A number of measures have been proposed to capture bank market structure. To ensure measurement error does not contaminate

[25] Following the FDIC SOD database, we designate a county as "metropolitan" if at least 50,000 people live in a metropolitan area. Otherwise, we define a county as "rural".

Table 9
Alternate measures of market structure.

Dependent variable	(1) Income growth	(2) Estab growth
Panel A: three firm concentration index		
CR3	-0.004	0.001
	(-0.801)	(1.299)
Disaster	-0.015***	-0.000
	(-3.520)	(-0.242)
CR3*Disaster	0.016***	0.001
	(3.073)	(0.856)
Control variables	Yes	Yes
County FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	45,372	45,279
R-squared	0.292	0.113
Panel B: Herfindahl-Hirschman index		
HHI	-0.002	0.003**
	(-0.255)	(2.467)
Disaster	-0.007**	-0.000
	(-2.541)	(-0.109)
HHI*Disaster	0.012*	0.002*
	(1.810)	(1.665)
Control variables	Yes	Yes
County FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	45,372	45,279
R-squared	0.292	0.114
Panel C: IBBEA branching restrictiveness index		
BRI	-0.001***	-0.000
	(-2.961)	(-0.939)
Disaster	-0.005***	0.000
	(-2.790)	(0.372)
BRI*Disaster	0.002***	0.000**
	(4.673)	(2.519)
Control variables	Yes	Yes
County FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	45,372	45,279
R-squared	0.293	0.114

Notes: The dependent variables are *Personal income growth* in column 1 and *Establishment growth* in column 2. In Panel A we proxy bank market competition using the 3-firm concentration index. In Panel B we proxy bank market competition using the Herfindahl-Hirschman index. In Panel C we proxy bank market competition using the IBBEA branching restriction index. Variable definitions are provided in Table 1. The unreported control variables are the capital ratio, bank size, income per capita (ln), population growth, tax rate, market share of multimarket banks, SBA^H, SBA^B, and FEMA grants. Standard errors are clustered at the county level and the corresponding cluster-robust *t*-statistics are reported in parentheses. ***,**,* indicate statistical significance at the 1%, 5%, and 10% level, respectively.

our findings, in Panel A of Table 9 we report estimates of Equation (4) that use the three-firm concentration index (*CR3*). The findings are robust to measuring bank market structure in this way. In Panel B of the table we proxy bank market structure using the Herfindahl–Hirshmann Index (*HHI*).[26] Our inferences remain robust.

As an alternative approach, we exploit the deregulation of interstate bank branching as an exogenous shock to market structure.[27] By granting states the authority to restrict interstate branching, the IBBEA increases the degree of market contestability more in some states. Owing to the staggered and chaotic nature of deregulation, changes in the number of interstate branching restrictions (the *BRI* index) are exogenous with respect to economic growth and conditions within the banking industry (Goetz, 2018).

Panel C in Table 9 presents estimates of Equation (4) using the *BRI* index to measure bank market structure. The findings are insensitive to this change. We find that during "normal" times counties in states with higher *BRI* values have significantly lower rates of personal income growth. However, after a disaster high *BRI* jurisdictions recover faster from a hurricane. The *BRI*Disaster* coefficient estimate is statistically significant in column 2 of the panel when the dependent variable is establishment growth. However, the economic magnitude of the coefficient is close to zero.

[26] Articles that use these measures of market power include Cetorelli and Gambera (2001) and Anginer et al. (2014).

[27] The Interstate Banking and Branching Efficiency Act (*IBBEA*) in 1994 granted banks the right to establish branch networks across state lines. The Act also gave states the authority to impose four types branching restrictions that raise barriers to entry. States therefore deregulated to different extents, and at different points in time.

7.3. Sensitivity tests

To ensure our findings are not driven by the Financial Crisis, we remove observations from the years 2008 and 2009. We continue to observe similar coefficient estimates to before in columns 1 and 2 of Table 10. A large number of banks failed or were acquired during the crisis. This may lead to greater market concentration after the crisis. We thus test whether there exists a structural change in the relationship between bank market structure and income growth between the pre- and post-crisis periods. Online Appendix Table A8 shows this is not the case. Rather the *Lerner*Disaster* interaction coefficient is positive and statistically significant during both periods.

A potential threat to identification are prompt corrective actions (PCA) that are issued to banks that exhibit deteriorating capital ratios. PCAs often trigger reductions in credit supply as banks seek to avoid further penalties (Danisewicz et al., 2018). We therefore exclude counties in which a bank is subject to a PCA to ensure our findings are not confounded by tightening credit supply. The number of banks subject to a PCA is small, and our findings in columns 3 and 4 of Table 10 are invariant to this change.

So far, we have defined the recovery period as the three years following a hurricane. We therefore test the sensitivity of the results to using a shorter duration. Columns 5 and 6 of Table 10 present estimates of Equation (4) in which $Disaster_{c,t}$ is equal to 1 during the two years after a hurricane, 0 otherwise. We continue to observe similar results to before.

The initial level of per capita personal income in a county may influence the speed of recovery from a disaster. For example, ex ante income levels may affect the reconstitution of capital due to increases in capital's marginal productivity. We therefore interact initial income with the disaster dummy variable and include this as an additional control variable in Equation (4). The estimates in column 1 of Online Appendix Table A9 show the *Income-Disaster* coefficient is statistically insignificant whereas the *Lerner*Disaster* coefficient remains positive and significant.

A concern could be that following a disaster small banks are more likely to fail or be acquired. In this case, the banking market becomes mechanically more concentrated. To examine whether this is the case, we generate $FMA_{b,c,t}$, a dummy variable that equals 1 if a small bank either fails or is acquired in a merger during quarter t, 0 otherwise. We then restrict the sample to include only small banks (defined as those with assets of less than $250 million) and estimate the baseline equation using a logit model. The estimates of this test are shown in Online Appendix Table A10. We find no evidence that small banks are more likely to fail after a disaster, or that this varies according to the level of competition in the market. It therefore appears unlikely that our findings are driven by the disappearance of small banks after a disaster.

In Table 11 we report the results of a bootstrapping exercise to investigate to what extent our results are driven by chance rather than a genuine relationship between the main variables. We randomize the assignment of the natural disasters to existing counties that are actually *untreated*, as well as the timing of the simulated assignment, and we run again our main regressions reported in Table 4 400 times. For each of the 400 replications, we estimate the *t*-statistic with clustered standard errors at the county level.[28] In Table 11 we report the bootstrapped percentiles of the *t*-statistics for three variables, *Lerner*, *Simulated disaster* and *Lerner*Simulated disaster*. We consider the percentiles for the 1% (0.005 and 0.995), 5% (0.025 and 0.975) and 10% (0.050 and 0.950) significance levels for two-tailed tests. Notably, *Lerner* is still the original one for each bank in the sample (not simulated), to ensure that the randomization involves only the assignment of natural disasters. In Table 11 we also report, for convenience, the estimated *t*-statistics for Table 4, to ease comparison ("Estimated t-statistics").

The results reported in Table 11 are consistent with those reported in Table 4 for both *Disaster* and *Lerner*Disaster*. Specifically, for *Income growth* the estimated *t*-statistic for *Disaster* (-2.189) is larger (in magnitude) than the critical value for the corresponding bootstrapped *t*-statistics at the 5% level (-1.7402) but not for the one at the 1% level (-2.3961). Similarly, the estimated *t*-statistic for *Lerner*Disaster* (2.563) is larger than the critical value for the corresponding bootstrapped *t*-statistic at the 5% level (2.1972) but not for the one at the 1% level (2.6146). The results for *Estab growth* are insignificant for both *Disaster* and *Lerner*Disaster*, consistent with Table 4. These findings paint a consistent picture, and suggest that it is very unlikely to obtain large *t*-statistics by chance in our setting. Thus, our findings are unlikely to be due to sampling error.

8. Conclusions

In this paper, we investigate whether bank market structure helps or harms the economic recovery from a natural disaster. Theory provides conflicting predictions on any possible relationship. We find that the rate of recovery is faster in areas with less competitive banking markets. This result is consistent with banks with market power using their greater profitability to continue lending in the face of higher expected loan losses and adverse selection costs (Crawford et al., 2018).

When we dig into the credit market mechanisms underlying this result, we find these effects are primarily transmitted through real estate lending. Banks with market power increase the supply of new mortgages and refinance existing mortgage loans at a higher frequency. This is consistent with financial institutions supporting borrowers to avoid foreclosure. Consistent with part of the existing literature, we find that well capitalized, and profitable institutions which rely more on traditional retail banking are primarily responsible for the increase in credit supply and contribute more to the economic recovery.

[28] First, we eliminate from our dataset the counties for which *Treated* = *1*, to ensure that we assign the simulated treatment only to counties for which the null hypothesis is true. Second, we generate a simulated variable, *Simulated disaster*, on the basis of pseudo-random numbers. *Simulated disaster* is generated by creating a variable identifying counties that are treated (untreated), on the basis of pseudo-random numbers. Then, we multiply this binary variable by a randomized version of *Post*, which takes on the value one in correspondence to the quarter of the simulated treatment and all subsequent quarters. Thus, both the county and the quarter in which a county is assigned the simulated disaster is randomized.

Table 10
Sensitivity checks.

Sample	(1)	(2)	(3)	(4)	(5)	(6)
	Excluding 2008–2009		*Excluding banks under PCA*		*Two year treatment window*	
Dependent variable	Income growth	Estab growth	Income growth	Estab growth	Income growth	Estab growth
Lerner	-0.019**	-0.001	-0.016*	-0.002	-0.017*	-0.002
	(-2.007)	(-0.453)	(-1.739)	(-0.692)	(-1.814)	(-0.993)
Disaster	-0.004**	0.001	-0.003*	0.000	0.001	0.000
	(-2.043)	(0.956)	(-1.824)	(0.716)	(0.328)	(0.814)
Lerner*Disaster	0.029**	0.001	0.031**	0.003	0.034***	0.004*
	(2.458)	(0.263)	(2.513)	(1.013)	(2.853)	(1.695)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43,288	43,195	44,812	44,719	45,372	45,279
R-squared	0.282	0.106	0.292	0.113	0.292	0.113

Notes: The dependent variables are *Personal income growth* in columns 1, 3, and 5 and *Establishment growth* in columns 2, 4, 6. In columns 1–2 we exclude the Global Financial Crisis effect by removing observations from 2008Q1 to 2009Q4. In columns 3–4 we remove counties where at least one bank was subject to a PCA. In columns 5–6 we use a two-year treatment window instead of a three-year window. Variable definitions are provided in Table 1. The unreported control variables are the capital ratio, bank size, income per capita (ln), population growth, tax rate, market share of multimarket banks, SBA^H, SBA^B, and FEMA grants. Standard errors are clustered at the county level and the corresponding cluster-robust *t*-statistics are reported in parentheses. ***,**,* indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 11
Bootstrap simulations.

Panel A: *Personal income growth*						
	Estimated t-statistics					
Lerner	-1.710					
Disaster	-2.189**					
*Lerner*Disaster*	2.563**					
	Bootstrapped t-statistics					
Percentile	**0.005**	**0.025**	**0.050**	**0.950**	**0.975**	**0.995**
Lerner	-3.7420	-3.0284	-2.5568	0.4875	0.7656	1.7152
Simulated disaster	-2.3961	-1.7402	-1.4890	1.4452	1.7634	2.2366
*Lerner*Simulated disaster*	-3.2120	-2.1738	-1.8609	2.0418	2.1972	2.6146
Panel B: *Estab growth*						
	Estimated t-statistics					
Lerner	-0.692					
Disaster	0.668					
*Lerner*Disaster*	1.126					
	Bootstrapped t-statistics					
Percentile	**0.005**	**0.025**	**0.050**	**0.950**	**0.975**	**0.995**
Lerner	-1.8439	-1.4119	-1.1669	1.9943	2.2451	3.1532
Simulated disaster	-2.0515	-1.7095	-1.5381	1.2354	1.3960	2.0015
*Lerner*Simulated disaster*	-3.1755	-2.0292	-1.5270	2.1436	2.4889	3.2198

Notes: To construct the bootstrapped *t*-statistics, we proceed as follows. First, we eliminate from our dataset the counties for which *Treated* = *1*, to ensure that we assign the simulated treatment only to counties for which the null hypothesis is true. Second, we generate a simulated variable, named *Simulated disaster*, on the basis of pseudo-random numbers. *Simulated disaster* is generated in two steps. First, we create a variable identifying counties that are treated (untreated) by assigning a value equal to one (zero), on the basis of pseudo-random numbers. Second, we multiply this binary variable by a randomized version of *Post*, which takes on the value one in correspondence of the quarter of the simulated treatment and all subsequent quarters. Thus, both the county and the quarter in which a county is assigned the simulated disaster is randomized. The original *Lerner* and the interaction terms *Simulated disaster* and *Lerner*Simulated disaster* are then used to construct the critical values for the t-statistics by running the original regression specifications as per Equation (4), but with the new variables.

In contrast, following a natural disaster banks do not increase the supply of C&I or consumer loans and this effect is invariant to banking market concentration. Instead businesses and consumers borrow from the SBA, a government agency that provides loans to firms and individuals in declared disaster areas at below-market interest rates. While banks intermediate these loans on behalf of the SBA, it is the SBA that screens loan applications and decides whether to approve a loan. Bank market power therefore has little bearing on the supply of credit in these market segments after a natural disaster.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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