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Spatially Mapping Banks' Commercial & Industrial Loan Exposures: Including an Application to Climate-Related Risks*

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Abstract

The correlation of the spatial distribution of banking exposures with changes in spatial patterns of economic activity (e.g., internal migration, changes in agglomeration patterns, climate change, etc.) may have financial stability implications. We therefore study the spatial distribution of large U.S. banks' commercial and industrial (C&I) lending portfolios. We construct a novel dataset that augments FR Y-14Q regulatory data with borrower microdata for a more granular understanding of where banks' exposures are located by looking beyond headquarters to the location of facilities. We find that banks are exposed to almost all U.S. counties, with clustered exposure in certain geographies. We then use our dataset for a climate-related application by analyzing what fraction of C&I loans have been extended to firms that operate in areas vulnerable to physical risks, identifying, for

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example, counties where both (i) banks are highly exposed via their lending portfolios, and (ii) physical risks have historically resulted in large losses. Results of this kind can help inform risk management and be used to improve resilience to future stresses.

Keywords: bank lending to firms, climate risks, mapping of firm facilities, spatial lending patterns

JEL Classification: R32, R11, Q54, G21

1 Introduction

Spatial characteristics of the economy matter for analyzing a wide array of issues, including the impacts of domestic internal migration, new infrastructure (for example, solar farms, ports, transportation corridors), changing patterns of industry and agricultural agglomeration, and climate change.[1] Identifying financial system exposures to these spatial aspects of the economy is therefore likely to be useful in assessing risks to financial stability. In particular, spatial lending patterns can reveal where financial investments are occurring, how they may be shifting over time, and to what extent financial risks are geographically diversified. Such analysis is nascent but advancing.[2]

Thus far, detailed data on U.S. banks' spatial exposures are sparse beyond residential real estate (RRE).[3] To address this gap, we create a novel dataset that augments the Federal Reserve's regulatory Y-14Q commercial and industrial (C&I) lending dataset with borrower microdata from the National Establishment Time Series database. While limited to commercial loans from large banks, this dataset offers a much more comprehensive picture of the banking sector's spatial exposures than previously possible, and

[1]See, for example, Burchfield, Overman, Puga, and Turner (2006), Buera, Kaboski, and Shin (2011), Rosenthal and Strange (2020), and Steijn, Koster, and Oort (2022) on agglomeration; Crescenzi and Rodríguez-Pose (2012) on infrastructure; and Jia, Molloy, Smith, and Wozniak (2023) on migration.

[2]The growing field of spatial finance, for example, integrates geospatial data into financial practice. See, for example, Caldecott, McCarten, Christiaen, and Hickey (2022), Cotugno, Monferrà, and Sampagnaro (2013), and https://www.cgfi.ac.uk/spatial-finance-initiative/.

[3]Some other jurisdictions have more detailed credit registries that can allow for better spatial mapping outside of RRE.

it can be used as a complement to existing data on RRE exposures. Depending on the policy question at hand, both the cross-sectional and time-series dimensions of our dataset may have distinct relevance. Point-in-time exposures are useful for assessing current risks, while time-series trends can be projected forward to assess resilience to future stresses and responsiveness to national imperatives.

This paper is organized as follows. In Section 2, we describe the methodology used to develop the dataset. Section 3 illustrates the benefits of our approach for mapping cross-sectional loan exposures. We then check that the time-series dimensions of our data are consistent with well-established economic trends, in particular the migration of economic activity from the Rust Belt to the Sun Belt. In Section 4, we highlight one possible application of this dataset; we overlay climate damages data and banks' financial exposures to study how borrowers' susceptibility to physical risks may impact their ability to repay financial obligations, which may have implications for financial stability. The benefit of this approach is that it explicitly accounts for the interlinkages between financial assets, business infrastructure, and physical risks. We conclude in Section 5 by discussing avenues for future research.

2 Methodology: Spatially Mapping Financial Exposures

To quantify banks' exposures over time, we leverage loan-level data from the Federal Reserve's Y-14Q Schedule H.1. form. This regulatory dataset contains information on corporate loans above $1 million for holding companies (banks) with $100 billion or more in total consolidated assets.[4] We subset the data to C&I loans originating in the U.S., adjust loan volumes to 2021 dollars, and select a sample period of 2013:Q1 to 2022:Q3.[5] These data are a rich source of information, as they shed light on loan and borrower characteristics for each corporate loan on a bank's balance sheet.

Researchers using the Y-14Q data are constrained to mapping spatial lending patterns using a borrower's headquarters location Zip code, which is the only geographic variable included in the dataset. A limitation of this ap-

[4]We study banks' committed exposures.

[5]The data become more reliable from 2013:Q1 onwards.

proach is that it does not account for a borrower's spatial operations beyond its headquarters; we find that this limitation matters because any disruptions to these operations may impact a borrower's revenue streams, and thus, its ability to repay loans. To remedy this issue, we conduct a novel and extensive merge to link each Y-14Q borrower to the 2020 National Establishment Time-Series (NETS) database, which contains information for over 78 million facilities and operations (establishments) in the U.S.[6,7] These microdata contain the address-level locations of facilities, allowing us to better understand the full scope of a borrower's geographic dependencies. We merge approximately 74% of loan volumes across all quarters.

To further ensure that we have a representative sample, we compare the distribution of borrower size (in terms of total assets[8]) and sector (in terms of two-digit NAICS codes) across the merged and unmerged samples – as shown by Figures 1 and 2[9] – and find no significant differences. For the reasons discussed below, these two characteristics strongly influence the number of facilities that a borrower has and the degree of geographic dispersion of those facilities and thus closely relate to the goal of the merge. To see this, we assume that borrowers in different sectors have fundamentally different business models. For example, a retailer needs to maximize the number of customers it reaches and is thus likely to: (1) operate multiple facilities (retail stores), and (2) strategically locate them in areas with larger populations (for example, metropolitan areas across the country). On the other hand, a company in the manufacturing sector that is producing a final good is unlikely to directly engage with customers and instead ships final goods to others for distribution. Given this business structure, they are likely to have a limited number of specialized production facilities that are located in geographically central areas for ease of shipping. They may also choose to locate facilities in areas where production inputs, such as labor, are less expensive.[10]

[6] In some cases, the NETS data are not very well connected, that is, all establishments of a particular entity may not be linked to the same headquarters facility. This disparity makes the merge process quite difficult, and we view our work as a first step in better understanding a firm's geographic dependencies.

[7] At the time of this analysis, the NETS data were last updated in 2020, so we assume that establishments active as of 2020 were still active as of 2022.

[8] We take the logarithm of borrowers' total assets.

[9] Figures 1 and 2 display data for June 2013, but the data do not change significantly across the quarters in our sample.

[10] See, for example, Austin and Lilley (2021) on how *right-to-work* legislation may have impacted firm location, and Austin, Glaeser, and Summers (2018) on other factors influ-

We also assume that as a borrower's asset size grows, they have greater financial resources available to expand their business and establish more facilities in new geographies. Thus, we expect that borrowers with higher levels of total assets are more likely to have multiple, geographically diverse facilities. We find no significant differences between the distributions of borrower size and sector across the merged and unmerged samples, giving us confidence that our merged sample is representative.[11]

encing choice of firm location.

[11]We also compare other financial variables — borrowers' *earnings before interest taxes, depreciation, and amortization* (EBITDA), total liabilities, net sales, leverage, *loss-given-default* (LGD), *exposure-at-default* (ED), and *probability-of-default* (PD) and find no significant differences between the merged and unmerged samples.

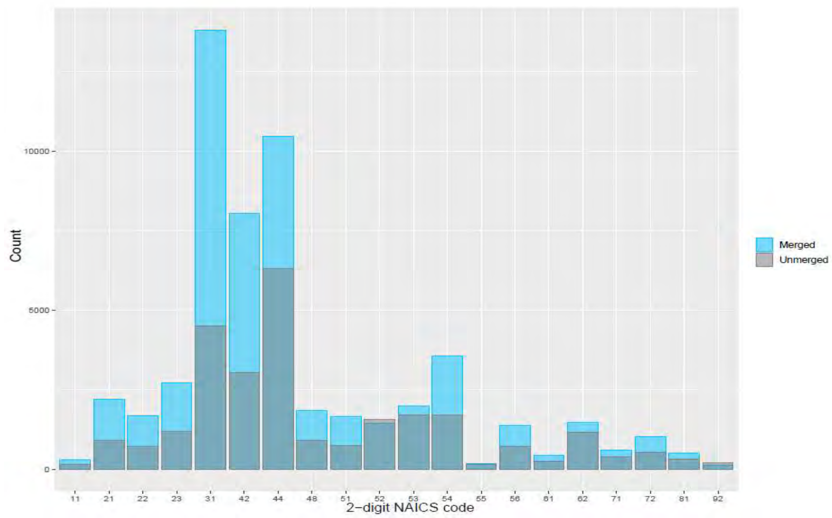

Figure 1: **Comparing Borrowers' 2-Digit NAICS Codes in the Merged and Unmerged Samples.** This figure overlays the distribution of borrowers' 2-digit NAICS codes in the merged and unmerged samples in June 2013. Data from the merged sample are shown in light blue, and data from the unmerged sample are shown in gray. Given that the shapes of the distributions are similar, we proceed with the merged sample for our analysis. Source: Federal Reserve Y-14Q.

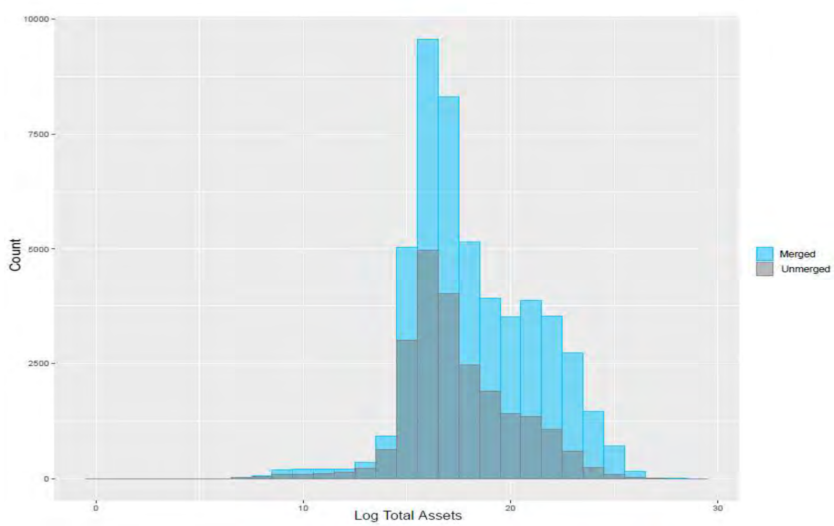

Figure 2: **Comparing Borrowers' Total Assets in the Merged and Unmerged Samples.** This figure overlays the distribution of borrowers' total assets (log) in the merged and unmerged samples in June 2013. Data from the merged sample are shown in light blue, and data from the unmerged sample are shown in gray. Given that the shape of the distributions are similar, we proceed with the merged sample for our analysis. Source: Federal Reserve Y-14Q.

With the merged dataset, we compute county-level, operations-weighted exposures by multiplying a borrower's overall exposure (given by the committed exposure amount for each loan) and the share of their active establishments in a particular county.[12,13,14] For example, suppose a borrower receives a $10 billion loan, and has nine active establishments in county A and one active establishment in county B. Of the $10 billion in loan volume, our process assigns $9 billion in exposures to county A and $1 billion in exposures to county B, since 90 percent of the borrower's establishments are located in county A and 10 percent are located in county B. This method implicitly assumes that a higher number of establishments in a particular geography indicates greater importance for the borrower to fulfill its financial obligations.[15] Depending on the research question, our dataset may provide a more comprehensive view of where banks' exposures are located.

3 Dimensions of Spatial Mapping

Our approach results in a detailed panel dataset, which we use to explore cross-sectional and time-series dimensions of banks' C&I loan exposures as described below.

[12] We only use operations that are active during the time of the loan, that is, if a loan was on a bank's balance sheet in 2015:Q1 but NETS indicates that a borrower's establishment closed in 2014, we would not consider it an active facility in this computation.

[13] We assume that if a parent company experiences financial distress, this may impact the ability of its subsidiaries to fulfill their loan obligations. Similarly, if a subsidiary experiences financial distress, it may impact the ability of the parent company to fulfill its loan obligations if the subsidiary is involved in key financial flows. Thus, we account for firm structure as the data permit, that is, if the affiliation between a parent company and its subsidiary is apparent in NETS. For example, suppose that company B is a subsidiary of parent company A. If the Y-14Q data indicate that company B receives a loan, our merge process includes the operations of companies A and B in the list of operations when assigning loan volumes, if company A appears as the parent in NETS. We also do the reverse, that is, if the Y-14Q data indicate that company A receives a loan, our merge process includes the operations of companies A and B in the list of operations when assigning loan volumes, if company B appears as its subsidiary in NETS.

[14] The Y-14Q data also capture cross-border loan exposures, but as noted above, we only examine loans originated in the U.S. and only consider borrowers' operations in the U.S. Our computation of county-level, operations-weighted exposures could introduce distortions if there are large exposures to multinationals with significant operations abroad.

[15] This follows the methodology taken by Correa, He, Herpfer, and Lel (2022), which merges NETS with syndicated loan data.

3.1 Cross-Sectional C&I Exposures

We aggregate the data to the county level for greater legibility and show exposures to borrowers' *headquarters* by county; see Figure 3, which uses a randomly selected quarter as an example. Geographic exposures vary from one quarter to another in our sample, but the locations of concentrated exposures do not significantly change. As indicated by the dark red shading in Figure 3, exposures are concentrated in Harris County, Texas, New York County, N.Y., Cook County, Ill., Los Angeles County, Calif., and Dallas County, Texas. Gray cells indicate *no* exposures for a particular county. By contrast, the geographic distribution of C&I exposures using our methodology (accounting for borrowers' headquarters *and* additional operations) is strikingly different; the sum of exposures is unchanged between the two figures, but Figure 4 offers deeper insights. Given the confidential nature of this data, we do not disclose the quarter or county-level loan value. Rather, the county-level loan exposure values are visualized relative to other counties.

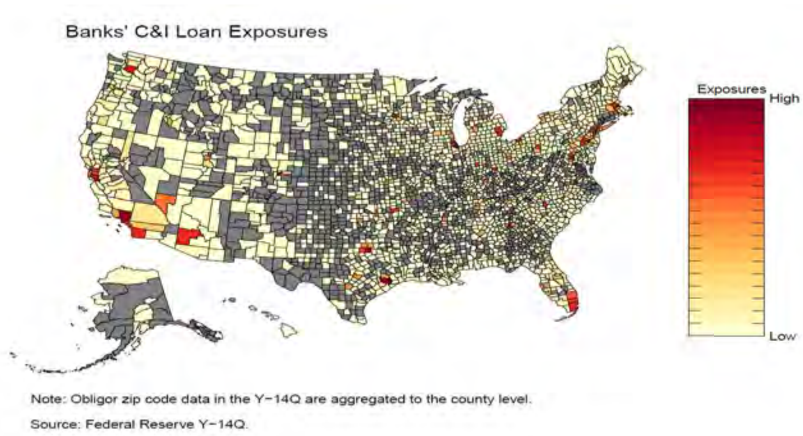

Figure 3: **Banks' C&I Loan Exposures.** This figure shows the spatial distribution of banks' C&I loan exposures in a randomly selected quarter. Borrower Zip code data are aggregated to the county level, and the colors correspond to the level of exposures (in billions). For example, light yellow shading indicates low levels of exposure whereas dark red indicates high levels of exposure. Source: Federal Reserve Y-14Q.

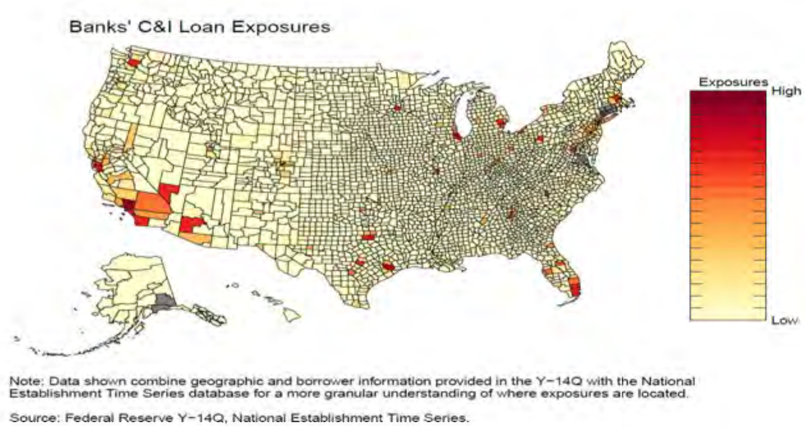

Figure 4: **Banks' C&I Loan Exposures Merged with NETS.** This figure shows the spatial distribution of banks' C&I loan exposures in the same quarter once the Y-14Q data are supplemented with borrower microdata from NETS. The colors correspond to the level of exposure (in billions). For example, light yellow shading indicates low levels of exposure whereas dark red indicates high levels of exposure. Source: Federal Reserve Y-14Q, NETS.

First, while exposures are still concentrated in many of the same economic hubs as Figure 3, additional counties such as San Bernardino County, Calif., Clark County, Nev., and Pima County, Ariz. appear to be important geographies for borrowers' operations. This suggests that banks have greater exposure to Southern California, Nevada, and Arizona than indicated by the Y-14Q in isolation. Second, exposures are spread across many more counties, as shown by significantly more yellow shading; crucially, we can quantify exposures in almost all counties that were previously shown in gray in Figure 3, demonstrating that banks are at least somewhat exposed to almost every county in the U.S.

3.2 Dynamic Time-Series C&I Exposure

We examine loan inflows and outflows over our sample period to better understand how banks' C&I loan exposures have been shifting over time. We calculate the percent change in county-level exposures and find that the median change is effectively zero (0.0014 percent) while the mean is 3.67 percent, implying a distribution skewed toward loan growth. Though these figures are informative, the variation in economic activity across counties creates comparison challenges; for instance, small counties that experience large shifts in loan volumes relative to their small economies are significant outliers in the data. To account for this, we apply weights based on the share of national loans located within that county and find that the weighted-average percent change in loan exposure is 0.19 percent, implying that loan growth has been positive on average. Within our sample of counties, just over half experience a positive weighted percent change in loan exposure from 2013, whereas the rest experience a negative change. Many counties experience a negligible change, with 10.12 percent of counties experiencing a weighted percent change within one millionth (.000001) of zero.

To confirm that our data are consistent with well-established economic trends, we explore the weighted-average percent change of banks' exposures to Rust Belt and Sun Belt states over our sample period.[16] Since the end of WWII, economic activity and employment within the heavy manufacturing zone known as the Rust Belt has declined, with the share of U.S. manufacturing workers located in this region shifting from one-half in 1950 to one-third in 2000. Between 2000 and 2010, the manufacturing sector suffered a loss

[16]For this analysis, we define the Rust Belt states as Illinois, Indiana, Michigan, Missouri, New York, Ohio, Pennsylvania, and West Virginia. Sun Belt states are defined as Alabama, Arizona, California, Florida, Georgia, Louisiana, Mississippi, Nevada, New Mexico, North Carolina, South Carolina, Tennessee, and Texas.

of 1.6 million jobs, further impacting the region, and the financial crisis of 2008 and subsequent recession further resulted in high unemployment rates that stuck in the years to follow (Alder, Lagakos, and Ohanian (2023)). The Sun Belt, however, has experienced rapid growth over the past 50 years, with its share of the national population jumping from 48 percent in 1970 to 62 percent in 2020 (Frey (2021)). Moreover, the top 10 metros with the highest employment growth between 2021-22 were all Sun Belt metro areas, with Portland, Ore. as the lone exception (Benzow (2023)). We observe patterns consistent with these historical shifts in economic activity in our dataset; the average weighted percent change in exposures to Rust Belt states is lower than the overall mean at 0.16 percent whereas the average weighted percent change in exposures to Sun Belt states is higher than the overall mean at 0.21 percent.

Figure 5 explores how the weighted percent change in loan exposures at the county level interacts with the initial level of loan exposure at the beginning of our sample period.

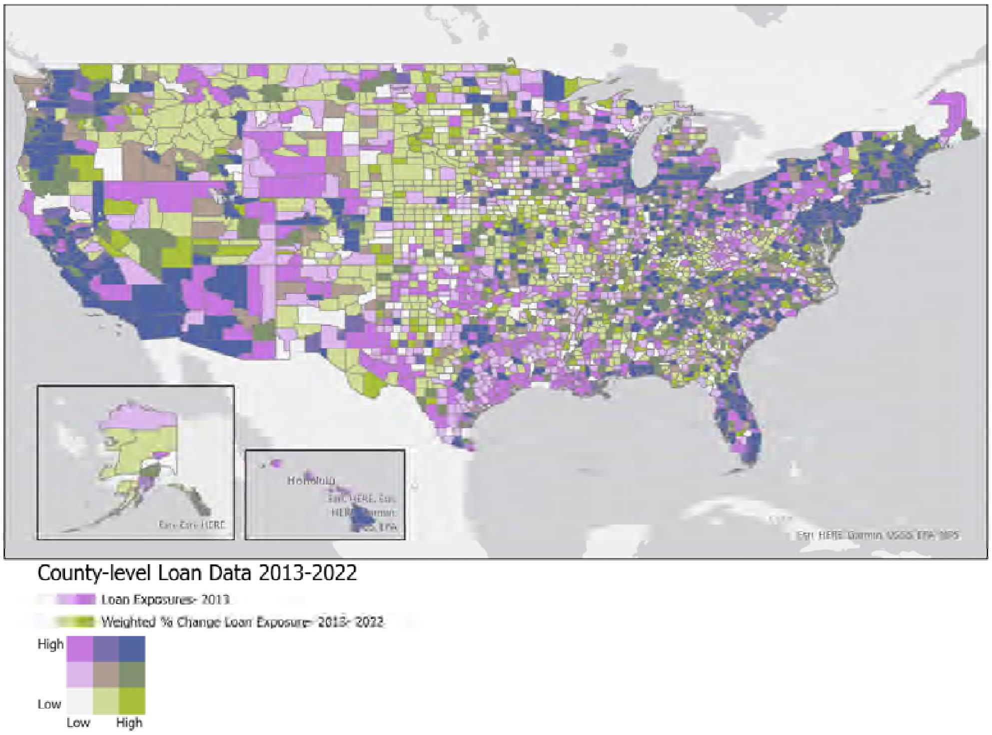

Figure 5: **Weighted Loan Exposure Dynamics.** This map shows the interaction between initial loan exposure levels in 2013 and the weighted percent change in loan exposure over our sample period at the county level. The colors correspond to the different cells in the 3x3 grid to the bottom left of the map. For example, purple counties (the northwest cell of the matrix) are counties that initially had a high level of loan exposure but subsequent loan growth stagnation or decline. By contrast, green counties (the southeast cell of the matrix) are counties that had a low initial level of loan exposure but experienced high levels of loan growth. Dark blue counties (the northeast cell) are those that had an initial high level of loan exposure counties and continued to experience rapid loan growth, in keeping with agglomeration forces. Source: Federal Reserve Y-14Q, NETS.

As shown by the blue shading in Figure 5, we find clusters of counties with high initial levels of loan exposure and high loan inflows, in keeping with patterns of agglomeration of economic activity; these counties are primarily in Florida, California, Arizona, the Greater Chicago Area, the Northeast, and the Pacific Northwest.[17] Other counties, particularly in the Midwest, have low initial loan exposure levels but high loan inflows, as shown in green. Finally, counties with high initial loan exposure levels but subsequent loan growth stagnation or decline are shown in purple. These counties tend to be concentrated in the hinterland but also in unexpected locations such as western Texas, suggesting disparate within-state economic growth in the Sun Belt.

4 Climate Application

As explored in previous sections, the Y-14Q-NETS merged dataset allows analysts to better understand the spatial distribution of firm C&I lending and how this lending behavior may be changing over time. These additional data can be applied to a variety of spatially relevant research questions. As an example, we describe an application to climate change. In recent years, attempts to quantify climate-related financial risks – which, in some cases, are highly localized – have been hampered by a lack of granular climate and financial data.[18] To demonstrate the utility of our new dataset, we merge our detailed, asset-level Y-14Q-NETS dataset with climate damages data to assess banks' credit risk exposure to climate hazards. Specifically, we examine what fraction of C&I loans have been extended to firms that operate in areas vulnerable to physical risks.

4.1 Climate Damages Data

To translate damages caused by climate hazards into possible losses for banks, we use the "Spatial Hazard Events and Losses Database for the United States," (SHELDUS) version 22, launched in February 2024. SHELDUS is a county-level hazard dataset that covers 18 hazard types including thunderstorms, hurricanes, floods, wildfires, and tornadoes. The purpose of our exercise is to quantify climate change-related risks for the financial system, so we exclude damages from earthquakes and volcanoes because the climate science is inconclusive on whether climate change impacts the frequency and intensity of such events.

[17] See, for example, Glaeser and Gottlieb (2009) on forces of agglomeration.
[18] See, for example, NGFS (2022) on localization of risks.

SHELDUS contains information on the month and year of an event, the duration,[19] the counties affected, and the direct losses caused by the event (property and crop losses, injuries, and fatalities) as well as insured crop losses (indemnity payments by the U.S. Department of Agriculture). Crop and property damage figures are reported in current U.S. dollars, inflation-adjusted U.S. dollars (base year, 2022), and *per capita* terms. Although SHELDUS data are available from 1960 to 2022, the National Climate Data Center (NCDC) changed its reporting procedures in 1995, resulting in an effective beginning date of 1996 for data consistency (SHELDUS (2024)). Since the Y-14Q data are only available from 2013, our fully merged dataset begins in 2013:Q1 and spans 3,143, or 100 percent, of counties and equivalents. Note, we aggregate SHELDUS monthly figures to a quarterly frequency to match the Y-14Q data. The total damage value varies widely from year to year depending on the incidence of natural hazard events that year.

4.2 Banks' Exposures and Climate Damages

Climate damages reflect four factors: (1) frequency, or the number of hazard events; (2) hazard, or the intensity of the event itself; (3) exposure, or the number of households and firms affected by the event; and (4) vulnerability, or the resilience of each firm, household, or local economy to the event (see, for example, Brunetti, Dennis, Kotta, and Smith (2023)). Over the past several decades, increases in population and material wealth have paved the way for greater exposures, as there are more structures, people, and assets susceptible to damage. Such changes have been concentrated in large metropolitan hubs and thus it is reasonable to expect that total climate-related damages will be highest in these locations, where there is simultaneously a large amount of lending *and* a large amount of commercial property to be damaged (NOAA (2024); Clark, Nkonya, and Galford (2022)). Against this backdrop, we examine how physical risks may impact banks' credit risk exposure. Of primary interest are counties where banks have extended high levels of C&I loans *and* physical risks have historically caused the most damage.[20] Although this relationship is intuitively circular, it is informative to understand from a financial risk perspective.

[19] SHELDUS reports on the length of the hazard event in number of days with a reported loss.

[20] Note, it is important to consider that metropolitan areas may have decreased their vulnerability by advanced adaptation (hardening) to climate risks. (Shi and Moser (2021)).

Since the impacts of damages in one county do not necessarily stay within county borders, we apply a clustering technique to account for regional spillover effects. For example, suppose floods damage roads in one particular county. There may be associated economic effects in neighboring counties owing to transportation disruptions. We thus use a clustering approach that groups a county with those immediately adjacent to it when computing damages: for each county, we assign the average damage and loan exposure value for itself and all neighboring counties that share a side or corner. By grouping in this way, clusters of counties that all experience high volumes of damage or loan exposure will lead to a higher clustered mean.

Using this approach, we identify regions where there are, on average, high volumes of damages and loan exposures over our sample period.

As shown by the brown shading in Figure 6, California, Arizona, Florida, the Pacific Northwest, the Tri-State area, and clusters of counties in Appalachia, the Denver area, and the Midwest stand out – these regions face high levels of damages from physical risks and house entities that received large amounts of C&I loans. If damages and lending patterns follow current trends, banks may be susceptible to increasing credit risk, especially as climate change is expected to exacerbate the impacts of physical risk events in coming decades. We note in passing that Figure 6 also highlights counties primarily in the Midwest that experience high levels of damages but where banks face low levels of exposure (shown in teal) and counties primarily in the Northeast and parts of the West (shown in red) that experience low levels of damages but where banks face high levels of exposure.

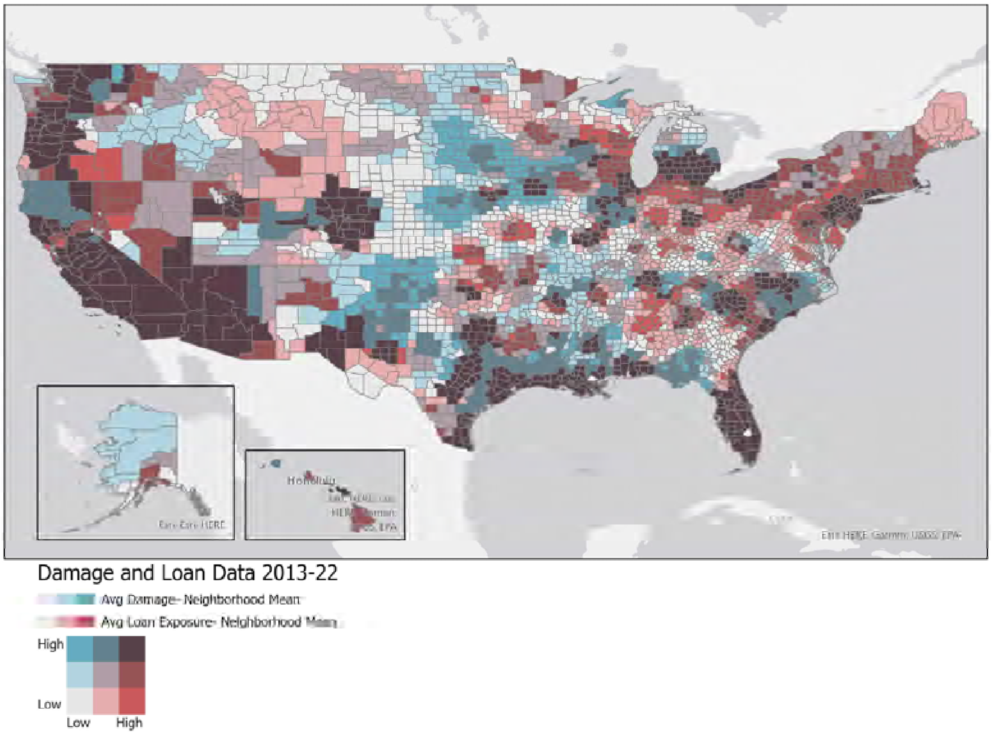

Figure 6: **Clustered Damages and Loan Exposures.** In this figure, we present the relationship between the mean hazard damages and loan exposures for each county over our sample period using our clustering approach. The colors correspond to the different cells in the 3x3 grid to the bottom left of the map. For example, dark brown counties (the northeast cell of the matrix) are counties that averaged high levels of loan exposures and damages from physical risks. By contrast, light gray cells (the southwest corner of the matrix) indicate counties with low levels of loan exposures and damages from physical risks. Source: Federal Reserve Y-14Q, NETS, SHELDUS.

4.2.1 Time-series dimension of banks' exposures in high damage counties

We also explore how the level of loan exposures changes within counties that experience relatively high levels of damage from physical risks. One could imagine that, within counties that experience the highest volume of damages, loans are increasing, as these regions need to invest in adaptation infrastructure and fund recovery efforts after disasters. Alternatively, one might expect lending to shift away from these counties as firms relocate to less hazardous geographies. As a third possibility, lending may increase in counties with high damages simply due to general migration trends toward coastal regions and the Western U.S., where amenity values are higher.

To explore what trends are evident in the data, we look at the top 50th percentile of counties with the highest amount of damage volumes from physical risks over our sample period. As shown by Figure 7, the share of loan exposure to high-damage counties has been generally flat, with a slight increase from 0.816 to 0.823 over our time frame. Thus, the data do not suggest that economic activity and therefore financial investments are shifting away from or toward these climate-impacted regions.

Since the top 50th percentile of counties with the highest damage costs over our time frame also hold over 80 percent of the total loan volume, we also explore if the time trend looks different within counties that comprise the top 10th percentile of total damages over our time frame. This analysis, shown in Figure 8, indicates that the share of loan exposure to the highest damage counties is also relatively flat over the time frame. The share varies slightly from year to year within a tight range of 0.373 to 0.377.

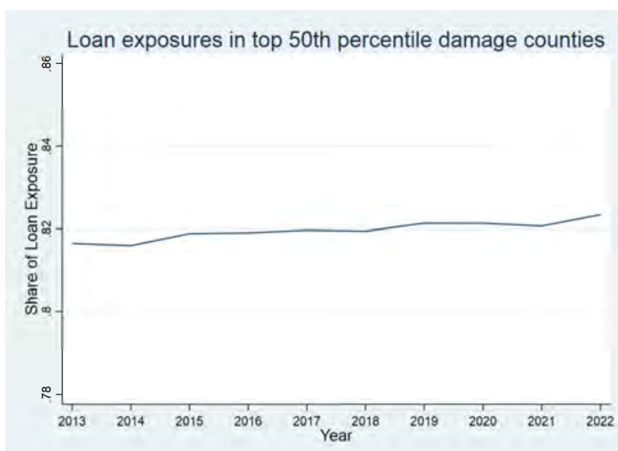

Figure 7: **Loan Exposures Over Time.** This figure shows the evolution of the share of loan exposures over time within the top 50th percentile of counties with the highest amount of damage from climate events within our sample. Source: Federal Reserve Y-14Q, NETS.

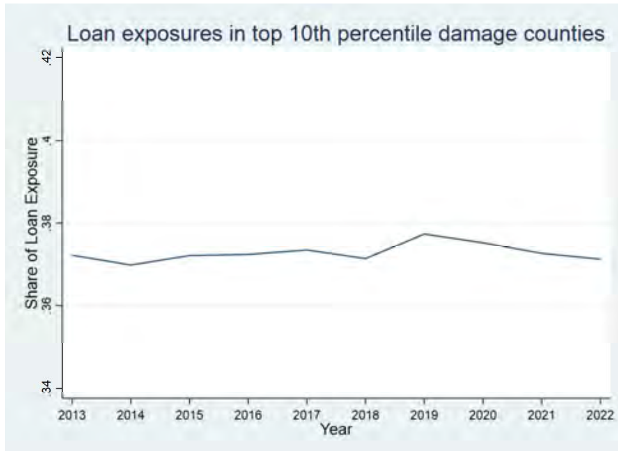

Figure 8: **Loan Exposures Over Time.** This chart shows the evolution of the share of loan exposures over time within the top 10th percentile of counties with the highest amount of damage from climate events within our sample. Source: Federal Reserve Y-14Q, NETS.

This analysis indicates that the financial system as a whole is not substantively changing lending behaviors within regions subject to high volumes of climate damage.

From the individual lender perspective, if the share of lending within a particular geography is high relative to the rest of the lender's portfolio, then that lender is likely to be more impacted by the occurrence of a damaging natural hazard event in that location. This is particularly true if the spatial distribution of lending takes into account the economic activity of the borrower as one can do when using the Y-14Q-NETS data. In this way, assessing what fraction of financial institutions' lending is financing borrower activity in a particular county can help shed light on the exposure of the banking system to hazardous geographies. It's also important to note that there are different financial protective layers in place for different hazards.[21] For example, large hurricane events may receive higher levels of government aid; alternatively, inland flooding may impact properties with inadequate flood insurance coverage due to policy exclusions and low flood insurance uptake rate. Thus, variation in financial protection layers across hazards can make

[21] See, for example, Brunetti et al. (2023) and Dennis (2023).

banks more or less vulnerable to certain types of losses. One could also supplement this analysis by decomposing damages by hazard type to understand which natural hazard banks are most exposed to.

Beyond simply looking at damage volume, we can consider the damage intensity certain regions face when controlling for exposed commercial property (plant and equipment) within that region. We therefore calculate a damage intensity measure using damage per dollar of lending, where loan exposures are used to proxy for the size of vulnerable firm assets. Figure 9 shows damage rate data from 2017 and 2022 at the county level. The spatial pattern of counties with relatively high damages per dollar of loan volume varies between these two sample years, with counties in Florida experiencing especially large damage volumes per dollar of lending in 2017. Counties scattered throughout the Northeast, Southeast, and Western U.S. experienced high levels of damage per dollar of lending in both years. These regions are different than those with the highest volume of damages overall, suggesting that controlling for economic activity is informative for analyzing these risks.

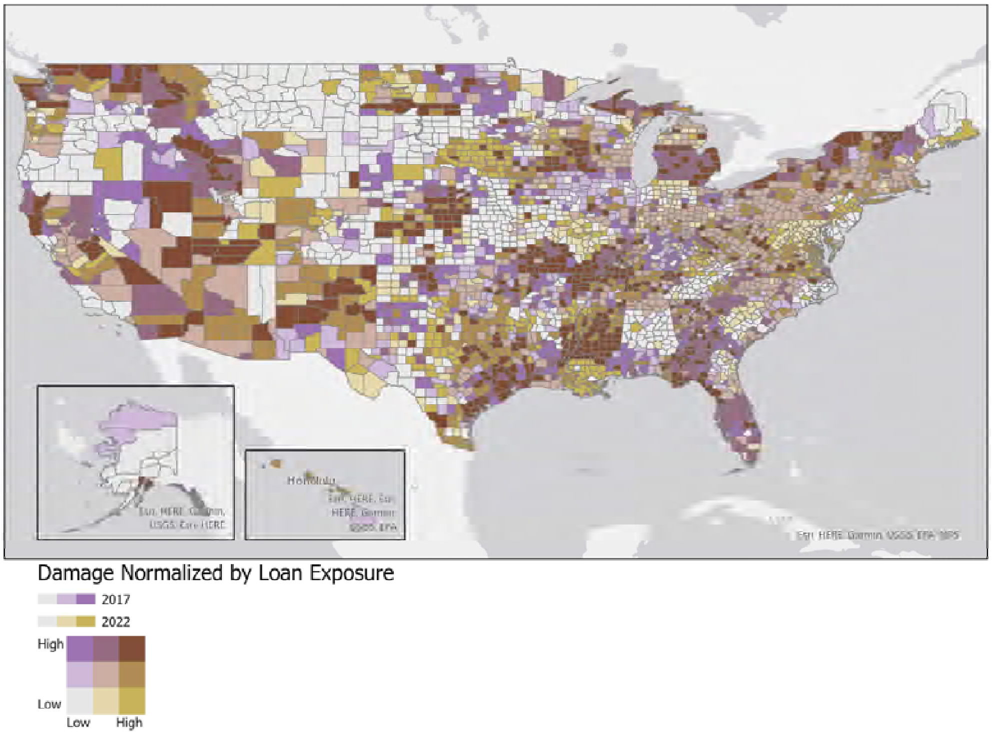

Figure 9: **County Level Damages Normalized by Loan Exposure.** In this figure, we present the relationship between county-level damage normalized by loan exposure for the years 2017 and 2022. The colors correspond to the different cells in the 3x3 grid to the bottom left of the map. For example, brown counties (the northeast cell of the matrix) are counties that experience large volumes of damage per dollar of lending in both 2017 and 2022. By contrast, purple counties (the northwest corner of the matrix) experience high volumes of damage per dollar lending in 2017 but not 2022. Source: Federal Reserve Y-14Q, NETS, SHELDUS.

5 Conclusion

We propose a data methodology that significantly advances the scope of spatial financial analysis by considering how a borrower's operations beyond its headquarters are relevant for assessing banks' credit risks. Indeed, once regional dependencies are accounted for, we find that financial institutions are exposed to almost all counties in the U.S. via their C&I lending portfolios, a result previously unknown from using the Y-14Q dataset in isolation. Whether financial institutions use spatial diversification as part of their risk mitigation strategy, if at all, is opaque, but assessing the geographic profile of borrowers may allow banks to better capture credit risk associated with natural disasters.

This novel dataset has several potential applications, and we study how banks' credit risk exposure may be impacted by climate change. We find that there are certain "counties of interest": regions where banks are highly exposed via their C&I lending portfolios and where physical risks have historically resulted in high losses. Such regions may pose financial stability risks, as the impacts of climate change are likely to become more salient in coming decades.

With greater data availability, we suggest two avenues for future work pertaining to the Y-14Q-NETS merge, two regarding the scope of financial loan exposures, and one concerning the spatial concentration of borrower operations. First, refinements to how a firm's revenues are allocated across facilities should move beyond taking a simple average. One possibility is to use a data source that maps a borrower's revenue streams to specific facilities as a weighting mechanism. Alternatively, employment data could be used to compute the relative share of a borrower's employees at each of its facilities. A higher share of workers at a facility might suggest that location has greater importance for revenue generation (and should thus be assigned a higher weight).

Second, future work can generate even more precise mappings of geographic exposures by integrating information on firm supply chain dependencies. To capture a larger amount of financial exposures, researchers can include loan-level data from community and regional financial institutions as well as nonbank financial institutions. This approach would also account for any cross-lending between these institutions for a better understanding of systemic risks. Additionally, future analysis could merge in information on financial institutions' CRE and RRE lending. Such a dataset would then account for the majority of financial institutions' lending and could be used to create an even more complete mapping of spatial financial exposures.

Finally, future work could assess if the share of borrowers' operations is highly concentrated within a particular geography that may be subject to high physical risks. If so, a hazard event in that region would likely have a larger impact on borrowers' operations and their ability to repay.

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