1 Introduction

The total value of the U.S. commercial real estate market (CRE) is roughly equal to 100% of GDP, larger than the volume of Treasury certificates and corporate debt outstanding (Ghent *et al.*, 2019). A significant part of the portfolios of pensions funds, life insurance companies, and other institutional investors are allocated to commercial real estate, but 70% of the overall stock is owned by non-institutional private entities, accounting for 30% of their overall firm assets.

Unsurprisingly, the CRE market has therefore been at the center of the two most recent recessions. In 2008, the collapse of the system of mortgage securitization triggered widespread turmoil, ultimately impacting real output and employment. In 2020, the Covid-19 pandemic led to extensive periods of lockdown, effectively shifting the locus of economic activity away from physical space into an emerging ecosystem of virtual interactions, with a devastating impact on all industries for which the technological transition was either sluggish or infeasible.

This paper seeks to uncover the drivers of price and liquidity dynamics in the CRE market, exploiting newly available transaction-level data. To overcome limitations inherent in aggregate indices, we obtain information about the universe of realized commercial real estate transactions in the U.S. from Zillow's ZTRAX database, which covers the period between 1994 and 2020. The granularity of the data allows us to address the differential exposure of CRE to crisis-induced cash flow disruptions by looking into several dimensions of heterogeneity that would otherwise remain unobserved. In particular, this concerns the functional use of the property, where we isolate developments in the retail, office, industrial and hospitality sectors, and the geographic location, relative to the urban core.

First, our results confirm the segmentation documented by previous studies, but show remarkable consistency in the evolution of liquidity across these market segments: While a common time component explains 48% of the price change variation, it also explains 37% of the variation in volumes. This explains the resilience of the commercial real estate market, especially in the period immediately following the pandemic. The

underlying mechanism here is tightly linked to the fundamental nature of investor behaviour: since above 70% of the property stock is held by non-institutional investors, with an average collateralization level of below 15% (Ghent *et al.*, 2019; Ghent, 2021), in the absence of a supply shock that significantly affects asset valuations on the owners' side, fire sales are rare. Instead, in response to a demand shock, the extensive margin effect dominates—liquidity in the market decreases in response to increased uncertainty, but it quickly rebounds when market conditions change.

The evolution of CMBS prices further supports the interpretation of recent developments as driven by factors that affect the demand side of the market. Exploiting variation across tranches by issuance year and risk profile, we find that the magnitude of the risk premium is well explained by the exposure of the underlying collateral to the demand for space in its particular market segment.

Second, an important dimension of this micro-level evidence concerns spatial variation in prices and liquidity. Gupta *et al.* (2021) estimate the "spatial gradient" of residential property, and find significant price and rent increases away from the center, with larger effects in areas where working from home is more prevalent, housing markets are more regulated, and supply is less elastic. Ramani and Bloom (2021) validate these findings with additional migration data, showing that real estate demand has moved from dense central business districts (CBDs) towards lower density suburban areas, and virtually no reallocation of population across cities (the "donut" effect). We extend this analysis to the commercial real estate sector and document significant variation across property types, consistent with their exposure to such shifts of preferences of end users, and their revealed residential choices.

Third, relying on two granular datasets that cover over a million CRE transactions and over a hundred million data points on mobility trends during the pandemic, we demonstrate the stability in the relationship between footfall and realized transaction prices pre- and post-pandemic.[1] While this serves as validation for the role of demand

[1]Throughout the paper, "footfall" and "mobility" are used interchangeably. More specifically, we refer to mobility trends as the realized footfall at a specific place (e.g., shopping mall, restaurant, office) within a certain period of time (e.g., day, week, month).

shocks, it also suggests a path for recovery, consistent with significant increases in market valuations visible during the period in which lockdowns and restrictions have been largely lifted.

Finally, we also look at long-term drivers of CRE prices. Combining macro-level data at the national and state-level, we establish long-term relationships between the CRE market and national financial conditions, as well as local factors such as rental vacancies, business activity, and indebtedness level. Lessons from previous crises (particularly the global financial crisis (GFC)) and historical relationships point to a 0.5-0.6% temporary drop in CRE prices for each 1% increase in vacancy rates, over the following quarter. In addition, a one-standard deviation tightening in financial conditions is associated with a 2.5%-3% decline in CRE prices. These effects are found milder in states where households are less indebted relative to their incomes, and thus less financially constrained.

To isolate the contributions of these factors at aggregate level, we complement the reduced-form analysis described above by enriching a standard search-theoretic framework with a risk shock that affects valuations idiosyncratically in each period. In the model, the risk shock affects the market participants' reservation values. In the data, we proxy for these unobserved reservation values to financial market prices, as captured by commercial mortgage-backed security (CMBS) spreads. This allows us to contrast the very sharp adjustment of risk preferences during the financial crisis with a more cash-flow-driven pattern of market activity during and after the pandemic. When estimated against observed empirical patterns, our framework substantiates the predominant contribution of demand shocks in both crises episodes.

Overall, the paper aims to contribute to the recent emerging literature on the drivers of real estate market price cycles. Tuzel and Zhang (2017) and Duca *et al.* (2021) find remarkable diversity in the international and regional behavior of house prices, and document the need to improve the data tracking key local demand conditions. This is the motivating factor for our exploration of local demand using detailed mobility data. Our focus on the two major crisis episodes also complements recent work by Levitin

and Wachter (2013) and Duca and Ling (2020) on the 2008 period, and Chernozhukov *et al.* (2020), Agarwal *et al.* (2020), and D'Lima *et al.* (2020) on the 2020 events around the start of the Covid-19 pandemic.

The impact of adverse cash-flow developments on the commercial real estate market has received significant attention, because of the direct link between price and liquidity dynamics in this market —see Ghent *et al.* (2019) and Ghent (2021) for a review on the nature of commercial real estate as an asset class. Ling *et al.* (2020) provide a first look at the impact of Covid-19 on real estate prices, exploiting a novel measure of exposure to local health shocks. We complement their evidence with additional measures of local demand, and a longer time period that covers the staggered pace of reopening, with the ensuing rebound of liquidity in the market. Bergeaud *et al.* (2021) focus on the longer-term impact of the pandemic and find that increases in the magnitude of remote work are associated with higher vacancy rates, less construction and lower prices in the office sector. Analyzing the CRE market in Ireland, Kennedy *et al.* (2021) find consistent evidence that vacancies rates are an important determinant of downside risks to CRE prices, with a more pronounced impact on retail and office segments after the Covid-19 shock.

In our analysis, we address the differential exposure of CRE to pandemic-induced cash flow disruptions by looking at the composition of loan pools collaterialized with properties with different functional use. Buchak *et al.* (2020) point to the role of liquidity as a central determinant of the response of the real estate market to shocks, and the ability of potential technology-enabled intermediaries (iBuyers) to perform arbitrage functions. They find that iBuyers technology allows for additional supply liquidity, but only in sub-markets where this is least valuable. During the early days of the pandemic, this phenomenon became very transparent, with activity in the majority of local markets moving to a grinding halt. Deghi *et al.* (2021) quantify the vulnerabilities that arise as a consequence of the pandemic in the CRE sector and analyze how macroprudential policy can mitigate financial stability risks posed by the CRE sector. We contribute to this line of research by providing micro-level evidence to underpin

further estimations of aggregate impact in the post-pandemic period.

Finally, the pricing of CMBS instruments has received considerable attention in the wake of the financial crisis—see Titman and Tsyplakov (2010) and An *et al.* (2011), but not in the most recent period. We fill this gap, and exploit the dynamics of loan spreads to pin down the market's perceptions of the value of commercial real estate from the perspective of its owners and operators. This allows for a more precise identification of risk shocks.

The paper is structured as follows. Section 2 describes the data sources used to compute price and liquidity dynamics in the US commercial real estate market. Section 3 introduces a simple search model and estimates the contribution of supply, demand and risk shocks. Section 4 reports the results of several reduced-form estimation exercises, which cover the role of local cash flow variation, the evolution of spatial gradients, the long-run effects of crises, and the pricing of risk. Section 5 concludes.

2 Data

In tandem with other data sources, this paper relies on two comprehensive datasets to measure the impact of Covid-19 pandemic and the GFC on the United States commercial real estate sector.

2.1 Commercial Property Indices

Over the past couple of years, a number of alternative indices have emerged, to capture the evolution of property values in the commercial real estate market.

The first is the Green Street Commercial Property Price Index, an appraisal-based index covering the period since 1998. The index provides a limited view of the market, focusing on properties owned by Real Estate Investment Trusts. It also does not allow us to distinguish sectoral dynamics, weighting various types of commercial properties such as retail (20%), office (17.5%), apartment (15%), health care (15%), industrial (10%), lodging (7.5%), and other sectors (15%).

The second is the RCA US CRE property index, for the period since 2000, retrieved through the MSCI CPPI US report. The index captures the universe of traded US commercial property in the apartment, retail, industrial and office segments.

2.2 Commercial Property Transactions

To overcome the limitations posed by existing indices, we source actual CRE transactions from Zillow's ZTRAX database, which contains data from over 400 million detailed public deed records across 2,750 U.S. counties. The ZTRAX database represents a rich source of transaction-level data, spanning over 20 years and containing detailed information from deed transfers, mortgages, foreclosures, and property tax delinquencies. The information collected from these records includes property characteristics such as building square footage and land surface area. Additionally, the dataset contains geographic and valuation information. The geographic information includes data such as zip code and sale address, while the valuation variables refer to mortgage amount, sale price, and loan amount. These data are available for approximately 150 million parcels across 3,100 counties nationwide, making the ZTRAX data especially comprehensive and valuable.

Our final dataset includes 30-40 states that contain reliable, representative data and account for more than 80 percent of the U.S. population between 1994-2020.[2] To ensure we capture only CRE transactions, we consider only transactions greater than $250,000, leaving us with around 1.3 million real estate sale transactions. Daily transaction-level information is aggregated by quarter and zip-code. Through the lenses of land usage, we are able to identify which commercial sector each transaction belongs to. To enable identification of sector-specific trends, we aggregate transactions into six commercial real estate types: retail, office, industrial, multi-family living units, lodging, and other.

Part of our analysis controls for population density, while testing the hypothesis of the so-called "donut" effect. Amplified by the Covid-19 pandemic, working from home has negatively affected office occupancy rates, leading to a decline in CRE prices

[2]For more details see also Alter and Dernaoui (2020).

particularly in crowded areas (Ramani and Bloom (2021)). To proxy for population density, we rely on the 2013 urban-rural classification scheme provided by the National Center for Health Statistics (NCHS). Aggregated at the county level, the NCHS' survey data distinguishes between six types of areas: 1) Large central metropolitan (metro); 2) Large fringe metro; 3) Medium metro; 4) Small metro; 5) Micropolitan; 6) Noncore. The first two categories refer to counties that contain metropolitan statistical areas (MSA) of 1 million or more population. Below this threshold, the third and fourth categories contain MSAs with a population in excess or below 250 thousand, respectively, while the last two categories are non-metropolitan counties.

2.3 Local Economic Activity

In the literature, economic activity is typically captured in survey data sourced from the U.S. Census Bureau, including monthly retail sales and food services. We validate economic activity with granular visit data from SafeGraph which covers business listings and footfall data for over 6 million points of interest (POIs) across the U.S. and Canada. Some examples of POIs include major retail chains, shopping malls, convenience stores and airports. At the individual POI level, SafeGraph has daily data covering a variety of visitor analytics, including foot-traffic counts and demographic insights. This dataset can provide an insight into how frequently people visit these POIs, where they come from, and where else they go.

The raw dataset contains 150 million observations. After cleaning, we have almost 95 million observations representing 3,098 U.S. counties with an average of 125 POIs across each and a median of 21. Considering the coverage of POIs increased overtime, we normalized the data to obtain accurate foot-traffic counts. Using business activity codes, we are able to aggregate POIs into five different sectors: retail, auto, restaurants, manufacturing, and wholesale trade.

To validate the SafeGraph data, we compare changes in aggregated monthly visits in each individual sector (from SafeGraph) with changes in monthly sales for the entire US economy (from Census data), as depicted in Figure 3. In particular, the correlation

for the restaurant sector is found in excess of 90% (3c), suggesting a nearly perfect association between the trends found in SafeGraph and economic activity. Additionally, monthly series corresponding to retail sales (3a) and manufacturing sector (3d) were found strongly linked to SafeGraph data as well, with correlations around 70%. Perhaps to a lesser extent but still correlated in excess of 60%, the auto sector (3b) and wholesale trade (3e) confirm the relationship to aggregated Census data.

2.4 State- and National-Level Macroeconomic Activity

Macroeconomic factors can be important drivers of CRE prices. To test this relationship, we developed a model which includes a variety of state and national level indicators which can influence CRE prices. In general, characteristics at the state-level like GDP growth, population growth, inflation, imports and exports are important indicators of economic activity, thus driving CRE demand. More specific to CRE prices, state-level business elements like the cost of doing business, supply and demand factors, and employment opportunities can each have an impact on the prices of CRE within a state. To measure cost of entry, we use general corporation license and franchise tax year-on-year growth across states. To proxy for supply and demand factors, we use the year-on-year growth rates for business applications and rental vacancy rates. In addition, the private sector net job creation is used as an indicator of employment opportunities.

National-level variables also influence CRE prices across states- though the impact can vary depending on state characteristics like debt levels. Financial conditions, such as interest rates and credit availability, can have an impactful relationship on CRE prices because as interest rates increase, the cost of a loan increases, thus driving down the prices of real estate.[3] To test the impact of financial conditions at the state-level, we use the National Financial Conditions Index (NFCI) from the Federal Reserve Bank of Chicago and interact it with a dummy indicator of household indebtedness, with the

[3]For the residential sector, Alter and Mahoney (2021) find that financial conditions can be a good leading indicator of downside risks to house prices.

expectation that states with higher debt levels will be more sensitive to changes in financial conditions.

2.5 Commercial Mortgage-Backed Securities

To gauge the reaction in the financial market, we analyze the pricing of CMBX contracts. These contracts are typically a credit default swap (CDS) on an underlying portfolio of 25 CMBS deals.[4] Given that pricing is reliably available at the daily frequency, the CMBX data allows us to investigate how the financial market perceives valuations of commercial real estate assets during key events, similar to Driessen and Van Hemert (2012). Zooming into different CMBX series and tranches (see Panel A of Figure 7), we can identify the main factors driving prices of these contracts. For example, the CMBX AAA tranche regularly references super-senior CMBS with a credit enhancement (of about 30%). In contrast, CMBX AJ, AA, A, BBB, BBB- refer to increasingly lower seniority tranches in the capital structure of the same portfolio of CMBS. These data were provided by Markit and sourced through JP Morgan's Data-Query.

3 Prices and Volumes

3.1 Aggregate

To verify our data, we perform a variety of validation exercises. After identifying CRE transactions from the ZTRAX data, we compare it to the two major CRE price indices mentioned above. This allows us to verify that the aggregated ZTRAX CRE price data exhibits similar behavior to these price indices.[5] Figure 1a depicts the two CRE price indices tracked during the 2000-2021 period.

[4]Each CMBX series references a different portfolio of 25 CMBS deals. However, all tranches of the same CMBX refer to the same portfolio of 25 underlying CMBS.

[5]The appendix contains more details about alternative validation exercises and robustness checks.

3.2 Heterogeneity by property type

Figure 2 shows the evolution over time of different types of CRE properties, both for volumes and prices. Over the past two decades, CRE prices have generally doubled or tripled, with a slightly stronger growth for industrial spaces (2d). Although prices have substantially corrected after the GFC, particularly for retail (2a) and multi-family (2e), they recovered and reached new highs right before the pandemic hit. Interestingly, the cycles are even more visible for volumes, with the number of transactions substantially dropping around the two major crises. It is worth noting that transaction volumes peaked at the end of 2016 for most CRE types, while prices continued to rise. Importantly, volumes drop significantly for all segments during the pandemic, but prices show heterogeneous dynamics. While lodging, retail and multifamily prices were intuitively affected the most during the pandemic, given the nature of the crisis, industrial and other segments remained relatively stable. This aspect is a peculiar feature of the CRE market, which ensures its resilience. During crisis episodes, there are typically not many transactions, liquidity dries up, absorbing the price shocks. Once liquidity rebounds, prices recover as well (see e.g., Fig. 2b and 2f).

3.3 Heterogeneity across space

Beyond pure time-series effects, both the financial crisis of 2008 and the Covid-19 shock have important implications across various CRE segments. Figure 6 reports estimated spatial gradients of CRE prices by property type. To calculate the gradient, we regress the logarithm of the property price, controlling for hedonic characteristics, on a variable that captures the distance from the closest urban core. Across all property types, a clear trend is visible, toward higher prices close to the urban core, and lower prices outside.

Interestingly, the effects around the financial crisis and the Covid-19 period are rather similar, pointing towards a short-term inversion of that trend. For industrial and office properties, the gradient was increasing in 2009, but decreasing in 2020. For the office sector, our interpretation of the result is that the Covid-19 merely accelerated

a trend that was already visible before, in the sense that the sub-urban office had started to be more attractive already for a number of years ahead of the pandemic's impact.

For each property type, we estimate the following regression at the transaction level:

$$P_i = \alpha + \beta_0 X_i + \beta_1 UrbanCDC + \beta_2 UrbanCDC * \Gamma_t + \Gamma_t + \Phi_c + \varepsilon_i. \tag{1}$$

where the dependent variable P_i is either (ln) CRE price per built surface, or (ln) CRE price per land surface, or (ln) CRE price. When the price is not standardized, the vector X_i controls for property characteristics such as surface, building condition, and year when the property was built, which could influence property valuations. Along the lines described in Section 2.2, $UrbanCDC$ is an ordered categorical variable taking integer values from 1 to 6, thus ranging from (1) highest population density (i.e., in large central metropolitan areas) to (6) the lowest density (i.e, in rural or noncore areas). Γ_t and Φ_c refer to year and county fixed effects, respectively.

Table 2 provides transaction-level evidence on the quantification of spatial gradients in the commercial real estate market over the past two decades, as a counterpart to the results described above. The pronounced shift towards steeper spatial valuation of closeness to the urban core is clearly visible across a wide range of specifications. Consistent with the results of Gupta *et al.* (2021), we find a strong rebound of the spatial gradient for multifamily housing after the pandemic, from a value of -0.2 to roughly -0.16 within a single year. Such effects are only modestly visible in any other market segment, where our estimation suggests a continuation of trends that were building up over the previous years.

Taking the estimated coefficients in Table 2, the results therefore suggest that in the early 2000s prices are around 30% higher in the most rural areas, compared to the city core; to the contrary, in the early 2010s, they become 30% *lower* in the most rural areas, relative to the city core. We see this as an economically very important transition, consistent with an accumulating volume of past evidence, e.g., Dale-Johnson

et al. (2001) and Rosenthal *et al.* (2022).

3.4 Risk pricing

In Panel B of Figure 7 we analyze the two periods of market disruption through the lens of financial risk pricing. Using data on CMBX spreads tracked across vintages and risk pools, we see remarkable consistency in the degree to which the financial market responded to the two crises.

First, the left-hand plot reports changes in commercial spreads between June 2008 and December 2008, which is the period during which US financial markets have been most affected by the collapse of the subprime mortgage market. During this period, the average spread increased by roughly 12 percentage points, or 2.5 times higher than the long-run average. This extreme magnitude is not surprising, given the wide spread market panic that spilled over across markets during those months. Second, the right-hand plot shows changes in commercial spreads between December 2019 and June 2020. This captures the direct impact at the onset of the Covid-19 pandemic, the set of early lockdowns around the world, and the associated expectation of a major global economic downturn.

The surprising feature of these results is the very different impact of the two shocks across the risk rating spectrum. While the financial crisis affected low-risk tranches the most, the events surrounding the start of the Covid-19 pandemic have mostly impacted higher-risk tranches. This suggests the different nature of the two shocks as perceived by the market. The former was expected to have a pervasive impact on the universe of debt holders, while the latter was expected to materialize very heterogeneously, with default risk only increasing in the more vulnerable sectors.

This risk adjustment pattern is consistent with the underlying structure of the different loan cohorts. Panel A of Figure 7 reports the allocation of different loan pools across types of commercial real estate. The pools issued in earlier cohorts are more heavily exposed to the retail sector, with the corresponding collateralized retail asset share decreasing from around 40% to 25% in the latest cohort. This sector was most

intensely exposed to the effects of prolonged periods of lockdown and other mobility restrictions: CMBX 6 has a delinquency rate in June 2020 that is double compared to CMBX 12. This pattern is entirely consistent with the pricing of spreads during that period, with the adjustment of the spread for CMBX 6 amounting to slightly more than double the one for CMBX 12.

3.5 Long-run trends

Having explored the transaction-level drivers of value around two periods of significant market disruption, we now turn to an analysis at the aggregate level using state-level data. To formally gauge the long-run determinants, we estimate the following panel regression specification:

$$P_{st} = \alpha + \beta X_{st} + \delta HHDebt_s * NFCI_t + \Gamma_s + \Phi_i + \varepsilon_i. \tag{2}$$

where the dependent variable (P_{st}) is the median price (per square foot) in each state s at time t. In general, these regressions are estimated using state (Φ_s) and quarter (Γ_t) fixed effects, over 2002-2020 period.[6] X_{st} is a vector of local characteristics such as output growth, inflation, rental vacancies, business activity, net jobs creation, total exports, etc. The interaction between the state-specific dummy $HHDebt_s$ and nationwide $NFCI_t$ captures the heterogeneous effect of the financial conditions on the dependent variable, subject to the level of indebtedness in each state. $HHDebt_s$ takes value one in states where the level of indebtedness (proxied by household debt-to-income ratio and averaged over the entire period) is below the cross-state median (i.e., 1.5), and zero otherwise. Table 3 presents the results for all types of CRE properties, while Table 4 focuses only on retail properties.

Table 3 illustrates the fundamental drivers of CRE price dynamics, emphasizing the strong effect of local economic conditions as captured by GDP growth (with a marginal

[6] Table A.1 presents the summary statistics for the dependent variable and its determinants. All regressors are lagged by one quarter, with the exception of rental vacancy variable which is lagged four quarters. The latter choice is based on a higher goodness-of-fit and significance.

positive effect of 0.6% to 1% for each percentage point change in local output) and the vacancy rate (with a marginal negative rate of 0.5% to 0.6% for a one percentage point change in the rental vacancy rate). The local average inflation level has a very modest and statistically insignificant parallel impact on realized CRE prices, most likely because of the wider investor base present in the market.[7] In addition, the relationship between CRE prices and corporate license state tax (a proxy for firm creation) is statistically significant (with a marginal effect of 1%).

Consistent with the theory, the effects of national financial conditions (NFCI) are found negative (columns 11-15) and significant.[8] A one-standard deviation tightening in NFCI in the previous quarter leads to a drop of about 2.5% in CRE prices. Importantly, the effects are found milder in states where households are less indebted relative to their incomes (columns 14-15). These results can be interpreted as evidence of weaker transmission of financial conditions in the presence of less financially constrained households through the consumption channel. Intuitively, households with less debt relative to their incomes are able to maintain their consumption habits even when monetary policy or financial conditions are tightening. In economic terms, the impact of tighter financial conditions on CRE prices is about 1/3 of the average effect (0.8%) in states with lower debt levels.

As expected, these effects are different when we move to the retail sector (Table 4). For instance, local inflation is a paramount driver of CRE valuation, reflecting the concentrated exposure of the sector to cash flows generated locally. Similarly, the impact of the rental vacancy rate becomes even more pronounced in the retail sub-sample relative to the overall market, with a marginal effect of 0.9% price appreciation after a 1 percentage point drop in vacancy. As far as financial conditions are concerned, the effects are stronger on retail CRE prices than when all transactions are considered. A one-standard deviation tightening in NFCI in the previous quarter leads to

[7] Effects are found insignificant also for GDP deflator, population growth, business applications, net jobs creation and total exports (columns 4-10).

[8] These regressions do not include time fixed effects (FE), given that NFCI is at the national level. However, we introduce time FE in regression 15, and show that the interaction coefficient remains robustly significant.

a drop of about 3% in retail CRE prices. Likewise, the effects are milder in states where households are less indebted relative to their incomes, and thus less financially constrained (columns 14-15), with a drop in retail CRE prices of 1.5% in states with lower indebtedness levels.

3.6 Local cash-flow variation

The valuation of commercial real estate has a strong cash flow component. This is either a direct income from the tenant to the landlord, e.g., in the case of retail and hospitality, or an internal transfer price for the case of owner-occupied property, in the industrial or healthcare sectors. While the former is directly observed and measured in companies' profit and loss statements, the latter is an imputed quantity, and depends on the actual use of the property by its owner-occupant. The opportunity offered by footfall data is that it accurately captures the degree to which real estate space is actually being used (i.e., "consumed"), at any given point in time, and at any given location.

The series of Covid-19-related lockdowns provides a source of clean exogenous variation to the level of consumption of commercial real estate, and the associated cash flow variation across locations. Figure 4 plots the evolution of footfall, measured for various property types, across counties, and through time. The significant decrease of economic activity in the period after March 2020 is clearly visible, with remarkable consistency across counties. But more importantly, the plots show that for all property types, the cross-sectional variation of footfall is not materially affected by the overall level shift.

Focusing on the time dimension, Figure 4 shows changes in mobility trends across the full county distribution, expressed in year-over-year growth rates to avoid seasonality issues. Visits to retail locations dropped by 30% to 50% (Fig 4a) during the initial phase of the Covid-19 shock. Although these trends were reversed in the following months, the recovery was slightly below pre-Covid averages and the recovery started to falter by 2021, coinciding with the emergence of a new variant. Similarly, restaurants

(4b) and hotels (4c), along with healthcare (4e) and other contact-intensive services (4f), experienced substantial declines in visits. The recovery in mobility trends of the contact-intensive sectors seems to have been slower and well below pre-pandemic levels, in particular for healthcare and other services. Compared to pre-pandemic trends, visits to industrial places (4d) were generally less affected, with a much faster recovery. However, some counties experienced substantial declines in mobility even for industrial places, as suggested by the lower band (p25).

There is no clear expectation for how the cross-sectional variation in mobility should be affected. One possibility is that a national lockdown leads to a similar response across all markets, reducing any amount of heterogeneity that would have been visible before the impact of the shock. Alternatively, if some locations are more affected by the health component of the pandemic, they should respond more strongly, which magnifies the initial heterogeneity. Perhaps reflecting the combined effect of these two opposing forces, we do not see any significant change in cross-county variation, throughout the sample.

In Figure 5 we run yearly regressions of average CRE prices and county-level visits, focusing on the retail sector. For a change in footfall of 10%, we find a marginal effect of a price adjustment equal to roughly 1.5%. While this is a significant economic magnitude, more importantly, the size of the effect is remarkably stable across time, and only very modestly higher in 2020.

The observed stability of the cross-sectional relationship between footfall and prices provides an important validation opportunity for our hypothesis that the main driver of Covid-19 market dynamics is a demand shock. At the same time, this result also indicates a direct path for recovery, which was observed as a pervasive feature across all locations, once economic activity has recovered, and once the associated footfall has increased back to roughly pre-pandemic levels.

4 Structural Estimation

4.1 Theoretical framework

We start with a standard search framework (see Diaz and Jerez (2013)), in which buyers of mass m scan the available set of property listings of mass s for potential opportunities. Upon a successful match, buyer and seller valuations determine the trade surplus, and the allocation of the surplus is determine by a competitive equilibrium.

In each period t, we assume the model is driven by three exogenous shocks: (i) a demand shock ε_t^B, (ii) a supply shock ε_t^S, and (iii) a risk shock ε_t^R, all of which are normally distributed with mean zero and standard deviations σ^B, σ^S and σ^R, respectively. Before turning to the estimation procedure, we describe the dynamics of transaction volumes, value functions, and equilibrium realized prices.

4.1.1 Transaction volumes

In a typical period t, the stock of sellers evolves according to the following flow equation, where $\overline{S}$ is the steady state mass of properties listed for sale:

$$s_t = \overline{S} + \varepsilon_t^S. \tag{3}$$

The corresponding stock of buyers comes from two sources: first, a fraction $1 - \pi_{t-1}^B$ of buyers in period $t-1$ have not been able to find a match; second, a fraction α of buyers n_t that were not interested in a purchase in period $t-1$, but become interested in period t:

$$b_t = (1 - \pi_{t-1}^B)b_{t-1} + \alpha n_{t-1} + \varepsilon_t^B. \tag{4}$$

We assume a constant total stock of properties, with no construction activity, which implies that at any given point in time, any given individual will be either a buyer, a seller, or a matched owner not listing a property for sale. The corresponding market

clearing condition for a total housing stock with mass N is given by:

$$n_t + b_t + s_t = N. \tag{5}$$

This allows us to define market thinness θ_t as the relative mass of buyers and sellers, consistent with the broader search literature:

$$\theta_t = \frac{b_t}{s_t} \tag{6}$$

Importantly, in this simple framework, market thinness θ_t is the single state variable which determines the transition path of transaction volumes. In particular, it determines the probability that buyer and seller search will be successful, conditional on the probability of a trade q, which we model as a constant structural parameter, and the matched mass of buyers and sellers m_t:

$$\pi_t^S = q \times m_t \text{ and } \pi_t^B = \frac{q \times m_t}{\theta}. \tag{7}$$

Here, π_t^S is the probability that any given seller with find a match, and π_t^B is the probability that any given buyer will find a match. This implies that transaction volumes are then given by:

$$v_t = \pi_t^S \times s_t, \tag{8}$$

for a per-period matching function which takes the form of a standard non-linear transformation of market thinness:

$$m_t = 1 - e^{-\theta_t}. \tag{9}$$

4.1.2 Valuations and prices

Given a particular structure of the market, prices arise in competitive equilibrium as a function of individual buyer and seller valuations. The division of the surplus from the transaction is captured by the variable η_t, which de facto indicates the seller's relative

bargaining power in each period.

$$\eta_t = \frac{e^{-\theta_t}}{1 - e^{-\theta_t}} \theta_t. \tag{10}$$

In a thin market, i.e., in a situation where $b_t << s_t$, η_t will be low, and equilibrium prices will reflect buyer reservation values. In a hot market with $b_t >> s_t$, each listing has a large number of potential buyers lined up, and equilibrium prices will reflect seller reservation values.

The following system describes the value functions for the three types of agents:

$$W_t^N = v^B + \beta\alpha E_t[W_{t+1}^B] + \beta(1-\alpha)E_t[W_{t+1}^N], \tag{11}$$

$$W_t^B = v^S + \beta E_t[W_{t+1}^B] + \beta\pi_t^B \eta_t S_t, \tag{12}$$

$$W_t^S = v^S + \beta E_t[W_{t+1}^S] + \beta\pi_t^S(1-\eta_t)S_t + \varepsilon_t^R. \tag{13}$$

Here, the magnitude of the total surplus S_t is given by:

$$S_t = v^B - v^S + \beta E_t[W_{t+1}^N - W_{t+1}^B], \tag{14}$$

and finally, equilibrium prices p_t solve the following non-linear equation:

$$\frac{v^B - v^S - p_t + \beta E_t[W_{t+1}^S - W_{t+1}^B]}{p_t + \beta E_t[W_{t+1}^N - W_{t+1}^S]} = \frac{\eta_t}{1-\eta_t}. \tag{15}$$

4.2 Time variation in the data

We match three sets of moments in the model and the data: transaction volumes v_t, prices p_t, and seller valuations W_t^S. While the former two are standard in the real estate literature on search models (see, e.g., Genesove and Han (2012)), our contribution is to include the average value of the CMBX spread as a novel financial variable in the set of observed empirical moments. The CMBX spread allows us to identify the risk shock separately. We calculate year-on-year quarterly differences for all variables, both in the model and the data.

Panel A of Figure 8 reports the three sets of moments that help pin down the values of each of the exogenous shocks that drive equilibrium decisions and outcomes in the model. Figure A.7 in the appendix illustrates the identification approach that allows us to map these shocks onto the set of observable variables.

Supply shocks ε_t^S are identified by situations in which prices and volumes move in opposite directions. Demand shocks correspond to situations in which prices and volumes are positively correlated, with valuation spreads moving in the opposite direction. Risk shocks generate a similar positive correlation between prices and volumes, with corporate spreads moving in the same direction as well. Before turning to the results of the model, we briefly discuss the evolution of CMBX spreads, since they are the novel element in our estimation.

4.3 Estimated shocks

We numerically linearize the model around its steady state and use a Bayesian Kalman filter technique (see Herbst and Schorfheide (2015)) to match theoretical moments to those observed in the data. The identification approach that we propose is equivalent to a sign-restrictions method in a traditional VAR framework, in that the structure of the model imposes restrictions on the direction of the impact of each shock. In addition, we opt for a Bayesian estimation approach because it allows us to specify prior distributions for the parameters, and is therefore analytically more tractable.[9]

Panel B of Figure 8 reports the estimated time series of the three shocks. During the financial crisis of 2008-2009, both demand and supply were at elevated levels, suggesting an overall equilibrium in which high prices reflect high valuations and a high propensity of trade. This is a period that is also characterized by an unusually low level of the risk shock. This latter conclusion is particularly interesting, because we did not feed the *level* of the CMBX rate to the model, and the spread itself is not much lower during this period compared to the more recent years. The model therefore

[9] The model solution and estimation are implemented in Matlab, using Dynare version 5.2. (see Adjemian *et al.* (2011)).

correctly attributes the pre-2008 developments to an extreme level of risk tolerance in the market.

The situation before and after the Covid-19 pandemic is very different. First, the pre-pandemic period sees a slow deterioration in supply entering the market, and an increase in uncertainty. Especially after 2018, the decrease in demand is quite pronounced as well, which suggests that even before the major disruption that ensued in the early months of 2020, the commercial real estate market had entered a cooling period. An additional reason for this development has to do with the monetary policy regime, and the subsequent waves of proposed tightening.

Turning to the Covid-19 period itself, the strength of the risk shock is evident, alongside the very dramatic collapse of demand. Indeed, this is the most significant result from our structural estimation exercise—attributing the collapse of volumes and prices in the 2020 and 2021 to a negative demand shock of a magnitude that is very similar to the one observed during the financial crisis of 2008. In the next section, we explore the nature and mechanics of this demand shock in more detail.

5 Conclusion

Historically, the CRE market has been highly intertwined with financial conditions and the business cycle. During the recent downturns such as the GFC and the Covid-19 pandemic, the initial collapse in transaction volumes, a liquidity proxy, led to steep declines in valuations. However, the transmission mechanisms of these two crises have been different. While valuations swiftly rebounded during the pandemic, helped by substantial policy support, the GFC had a more long-lasting impact, with prices returning to pre-crisis levels after a some years.

To better understand these dynamics, we first test a few hypotheses in a reduced-form setup, relying on two rich datasets covering over a million CRE transactions and over a hundred million mobility patterns. This granular analysis allows us to establish long-run relationships between the CRE market and local factors. Next, we investigate

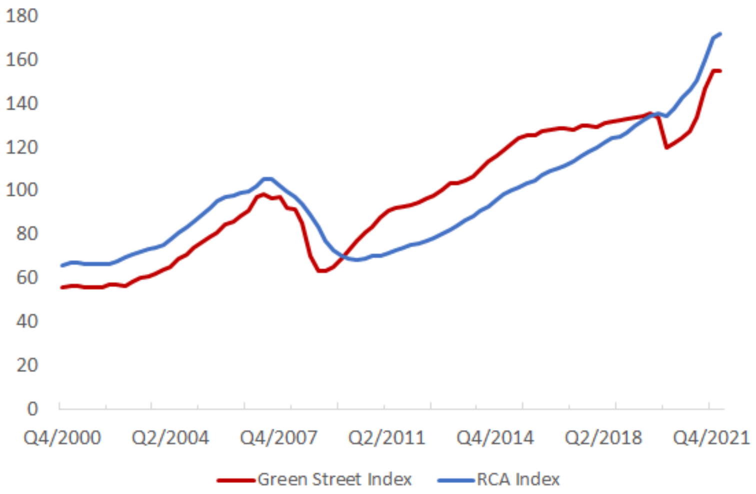
the behaviour of CMBS spreads during the GFC and the Covid-19 pandemic. Finally, we built a structural model which differentiates between risk shocks and fundamental factors, allowing us to contrast the adjustment of risk preferences during the GFC with a more cash-flow-sensitive market observed during the pandemic.

Our main contributions to the existing literature are threefold. First, our findings suggest that patterns observed during the pandemic were broadly similar to those experienced during the GFC. However, both demand and supply were found elevated prior to the GFC and the overall market equilibrium reflected high valuations and propensity to trade. In contrast, the CRE market was marked by a slow deterioration in supply and increased uncertainty prior to the pandemic. Second, the stability of cross-sectional relationships between retail traffic and prices suggests that the CRE market during the pandemic was primarily driven by a demand shock. As far as the office segment is concerned, our results point to an accelerated trend during the pandemic that was already visible a few years before, with sub-urban office spaces becoming relatively more attractive. Third, focusing on the long-run trends, we find that a 1% increase in vacancy rates leads to a temporary drop of 0.5%-0.6% in CRE prices over the following quarter. Importantly, a one-standard deviation tightening in financial conditions is associated with a 2.5%-3% decline in CRE prices. These effects are found stronger for the retail sector, which has typically been more sensitive to the financial cycle, and milder in states with less financially constrained households.

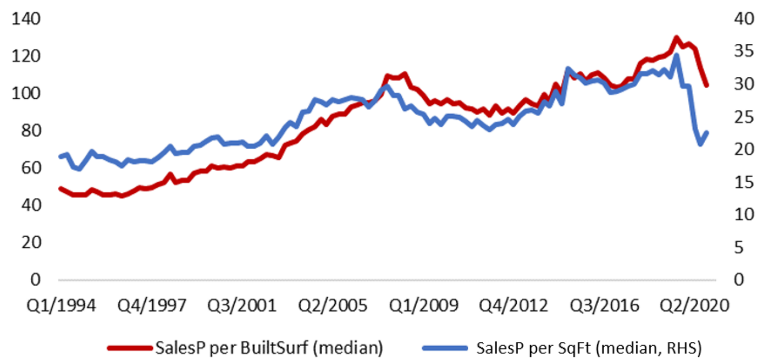
Based on the long-run relationships, we conclude that the sensitivity to financial conditions depends also on other macro-financial factors and local aspects such as the level of leverage in the economy. Going forward, the transmission of monetary policy tightening could be reflected in CRE prices through direct and indirect channels, including higher vacancy rates, an increase in tenant bankruptcies, and tighter financial conditions for investors.

Figure 1: US Commercial Real Estate Indices

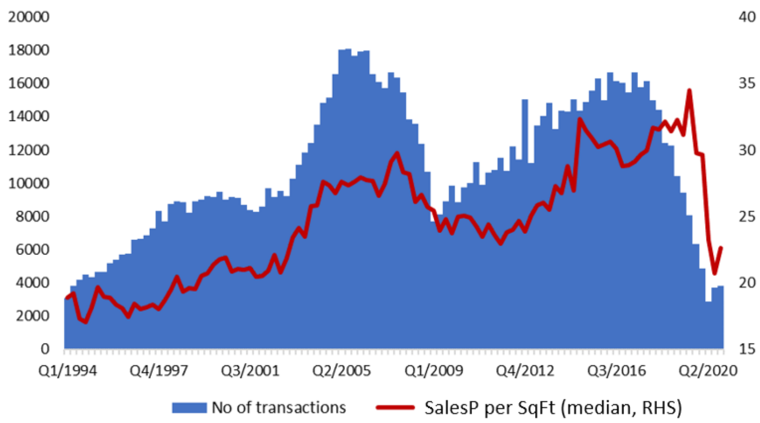
(a) CRE Price Index Comparison



(b) CRE Price Index
(Transaction-level estimates)



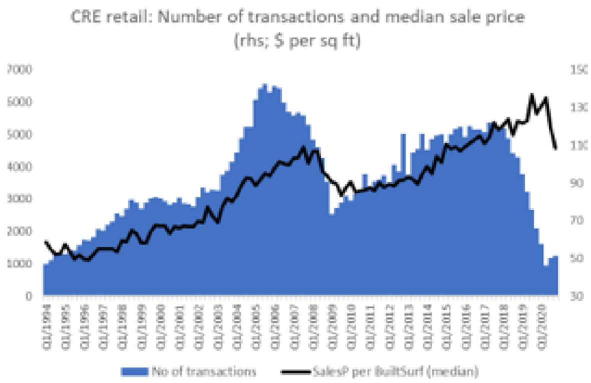
(c) CRE all transactions



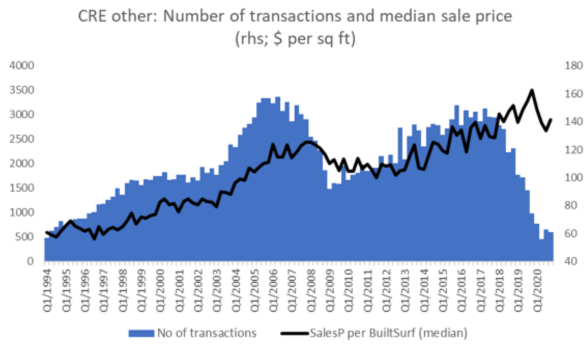
Source: Ztrax, Authors' calculations. Note: Panel A depicts two aggregated CRE indices. Panel B compares estimates of median Sales Price per built property surface with median Sales Price per property land surface, obtained from the ZTRAX transaction-level data. Panel C depicts total transaction volume (LHS) and median Sales Price per property land surface (RHS).

Figure 2: Ztrax Data

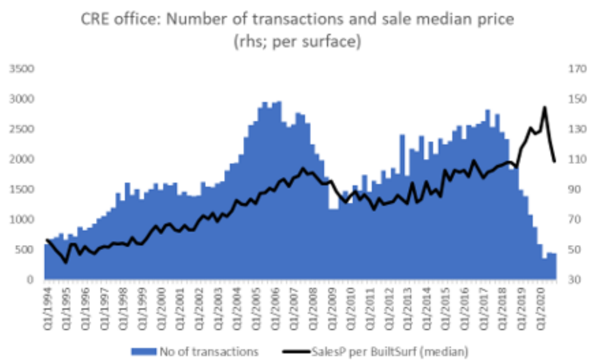
(a) CRE Retail



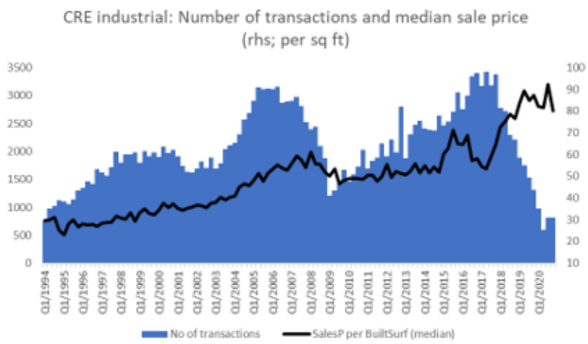
(b) CRE Other



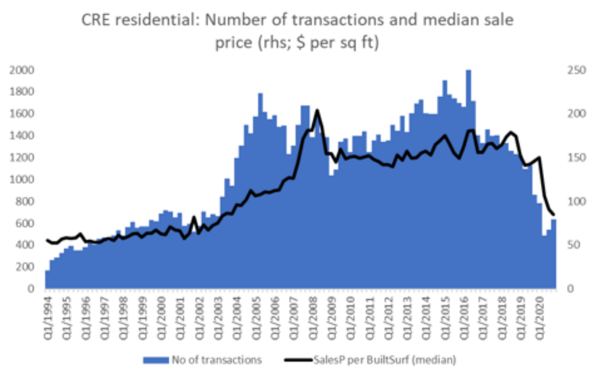
(c) CRE Office



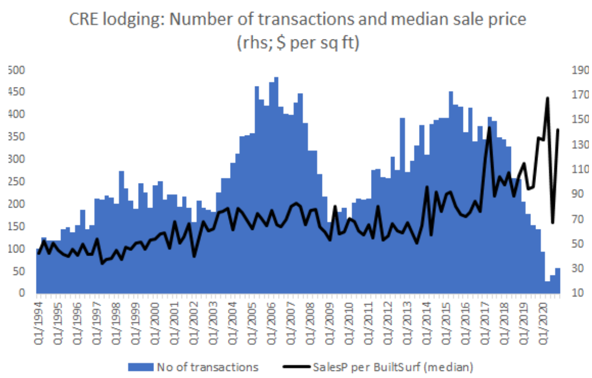
(d) CRE Industrial



(e) CRE Multi-family



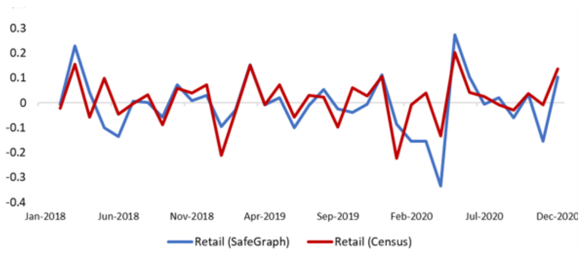
(f) CRE lodging



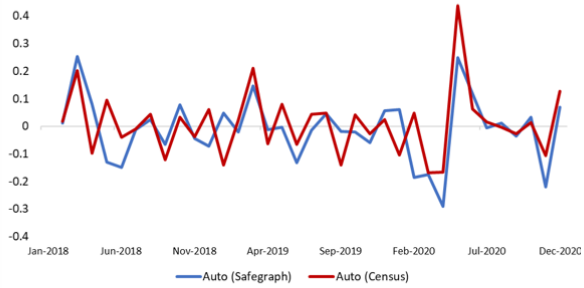
Source: SafeGraph, Authors' calculations. Note: YoY percent change

Figure 3: SafeGraph Data Validation

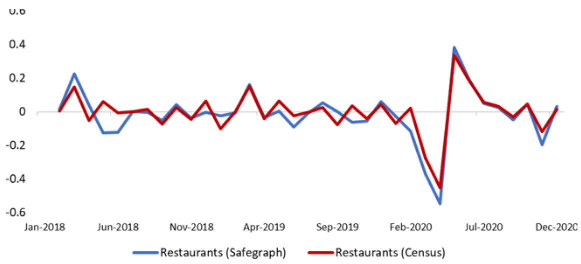
(a) Change in monthly visits and sales (Retail Sector)



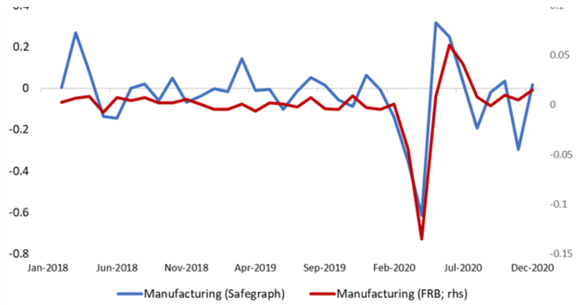
(b) Change in monthly visits and sales (Auto Sector)



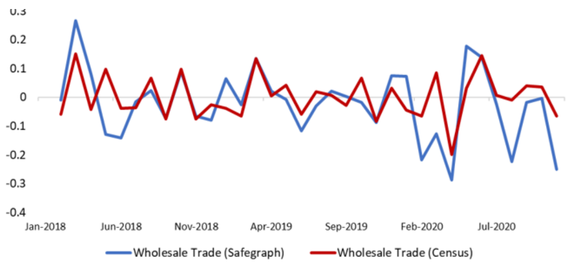
(c) Change in monthly visits and sales (Restaurant Sector)



(d) Change in monthly visits and sales (Manufacturing Sector)



(e) Change in monthly visits and sales (Wholesale Trade Sector)



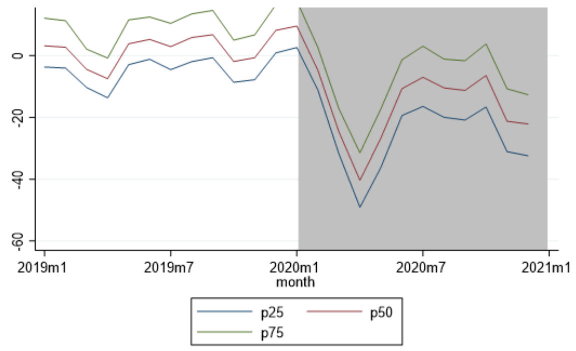
(f) Correlations

Retail	68%
Auto	64%
Restaurants	92%
Manufacturing	73%
Wholesale Trade	61%
Average	72%

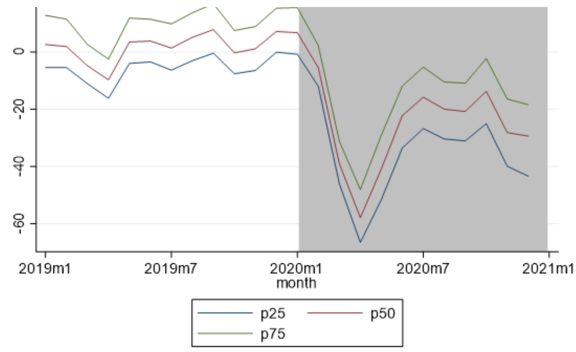
Source: SafeGraph, Authors' calculations, Census. Note: Log percent change

Figure 4: Distribution of SafeGraph Monthly Visits Across Counties

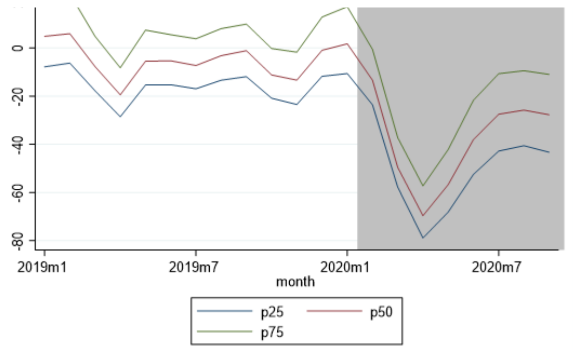
(a) Retail Visits



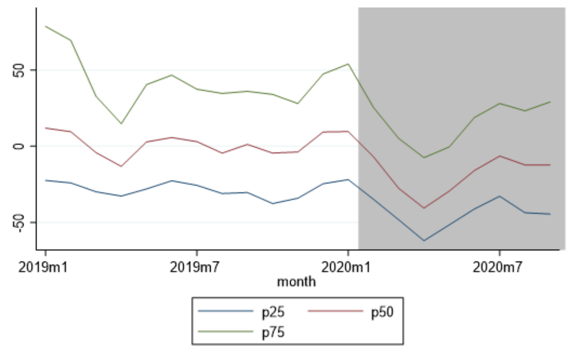
(b) Restaurant Visits



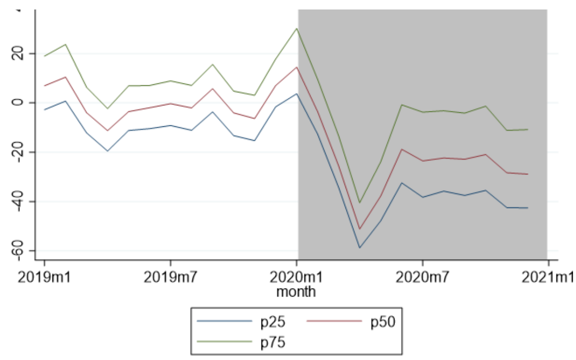
(c) Hotel Visits



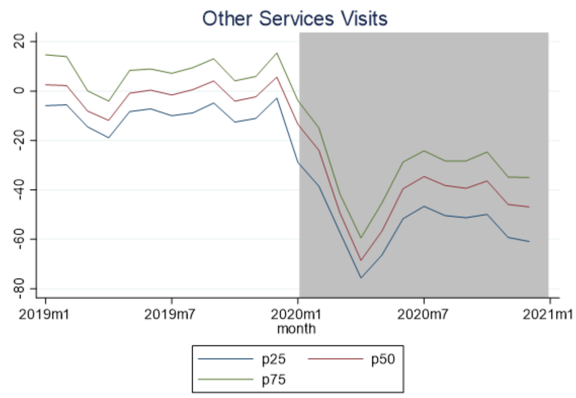
(d) Industrial Visits



(e) Healthcare Visits

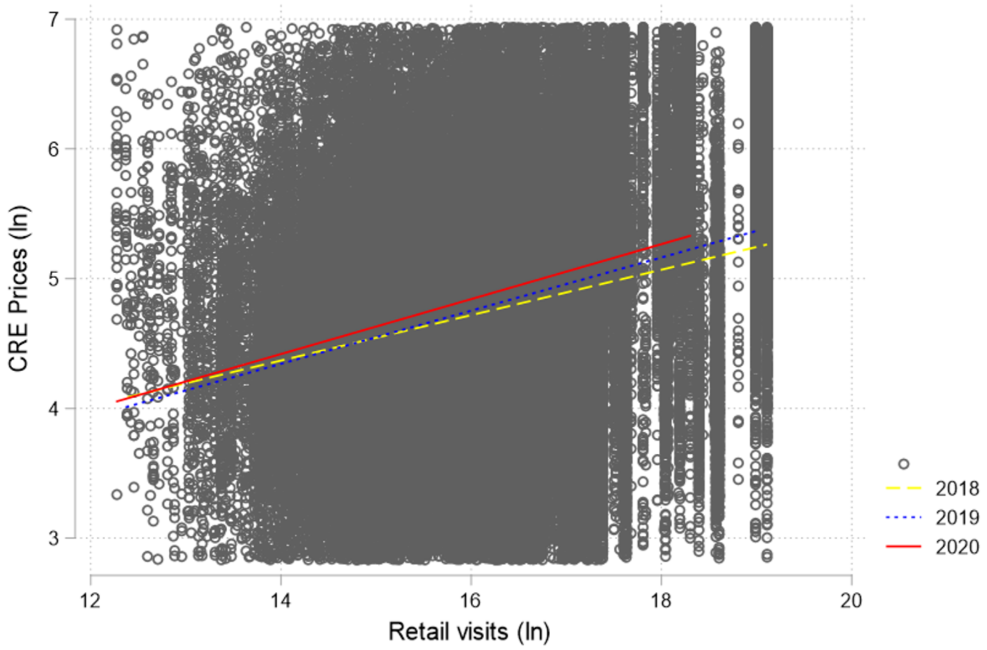


(f) Other Services Visits



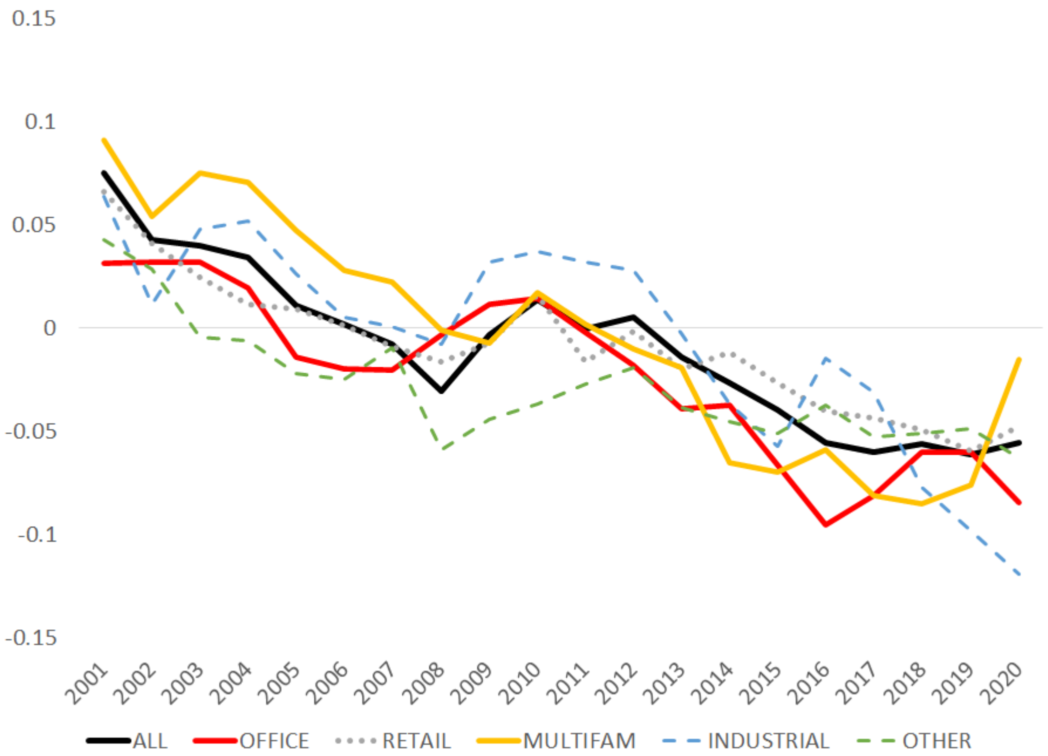
Source: SafeGraph, Authors' calculations. Note: YoY percent change

Figure 5: Transaction-level relationship between CRE prices and county-level retail visits in 2018, 2019, and 2020



Source: Authors' calculations.
Note: This scatter plot depicts yearly relationships between CRE prices and number of retail visits. The retail visits are aggregated by zipcode in a specific year.

Figure 6: Spatial Gradients



Source: Authors' calculations.
Note: This figure plots the interaction coefficients between the location (or distance to city center proxied by the $URBAN_{CDC}$ variable) and the yearly dummy, as presented in Table 2 columns (13)-(18). The coefficient of $URBAN_{CDC}$ is added to the interaction coefficients.

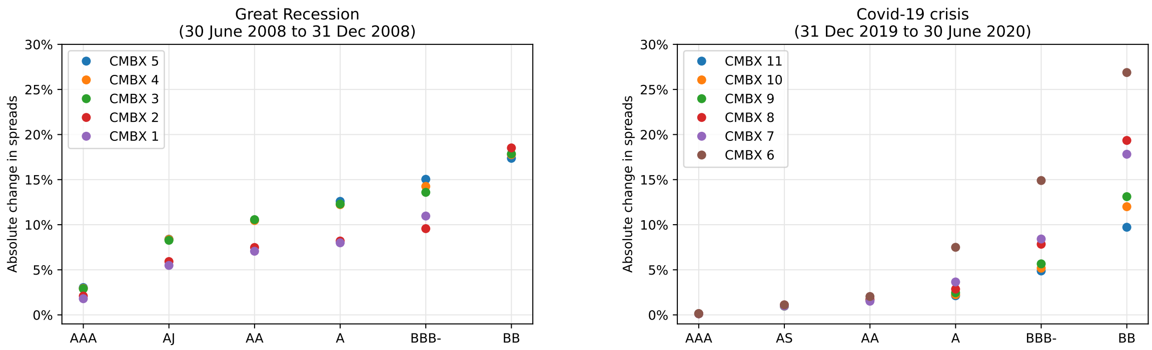
Figure 7: CMBX Spreads and Composition

Panel A

	CMBX 6	CMBX 7	CMBX 8	CMBX 9	CMBX 10	CMBX 11	CMBX 12
Multifamily	5.2%	11.7%	12.9%	14.7%	6.8%	8.3%	9.2%
Retail	39.9%	35.9%	28.5%	25.4%	30.3%	21.3%	24.9%
Office	26.9%	18.1%	25.9%	23.5%	30.6%	31.1%	31.6%
Lodging	10.4%	12.2%	13.6%	16.8%	13.7%	15.9%	13.7%
Industrial	4.1%	4.0%	3.3%	5.5%	4.6%	6.2%	7.7%
Delinquency Rate (2020/June)	10.3%	10.2%	10.1%	9.8%	9.2%	7.1%	5.5%
Total loans (bn USD)	21.40	20.60	22.30	22.32	22.50	23.20	22.80

Source: Trepp

Panel B

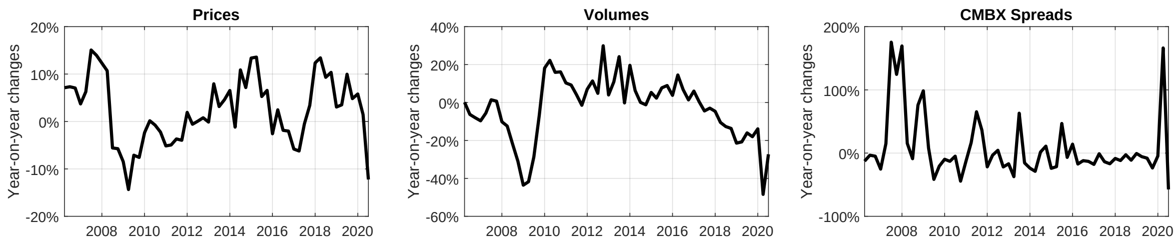


Source: JP Morgan DataQuery, Authors' calculations.
Note: YoY percent change; CMBX 1 to 12 represent different vintages of CMBS pools, covering the years 2007–2019.

Figure 8: Data and shocks

Panel A

Overview of the data



Panel B

Estimated structural shocks

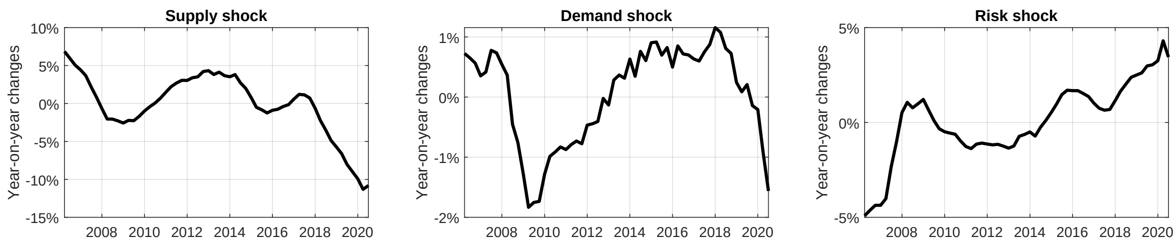


Table 1: Summary Statistics (ZTRAX, transaction-level)

Variable	Number of observations	Mean	Standard deviation	Minimum	25th percentile	Median	75th percentile	Maximum
SalesPriceAmount	1292551	2,135,863	14396319.6	250000	392500	668000	1450000	2,140,000,000
SalesPerSurface	1184900	449.68	106313.25	0.0	10.8	25.3	63.1	98,000,000
SalesPerBuiltSurf	885737	2,796.88	569777.8	0.03	38.72	86	187.27	460,000,000
BuildingAreaSqFt	885904	29,710	9.82E+04	0	3917	8632	21966	12,657,192
LotSurface	1184942	1,294,529	106716048	0	11940	33726	85378	35,200,000,000
CashTrans	1292551	0.61	0.49	0	0	1	1	1
Mortgage	1292551	0.39	0.49	0	0	0	1	1
LoanAmount	514155	2,645,936	20593250	0	300000	515500	1100000	1,000,000,000
BankLender	423570	0.7	0.46	0	0	1	1	1
NonBankLender	416498	0.13	0.33	0	0	0	0	1
CorpCash	1292551	0.01	0.09	0	0	0	0	1
Corp	1292551	0.7	0.46	0	0	1	1	1
OutBuyers_cash	1292551	0.03	0.18	0	0	0	0	1
OutBuyers	1292551	0.32	0.47	0	0	0	1	1
LTV	469113	0.76	0.23	0.00	0.65	0.78	0.90	1.5
BankLTV	263251	0.76	0.22	0	0.65	0.77	0.86	1.5
NonBankLTV	45950	0.74	0.25	0	0.61	0.75	0.9	1.5
Flippers	1292551	0.07	0.26	0	0	0	0	1
Retail	1292551	0.34	0.47	0	0	0	1	1
Office	1292551	0.16	0.37	0	0	0	0	1
Industrial	1292551	0.19	0.39	0	0	0	0	1
Residential	1292551	0.02	0.14	0	0	0	0	1
Mixt	1292551	0.09	0.28	0	0	0	0	1
Lodging	1292551	0.02	0.15	0	0	0	0	1
Restaurant	1292551	0.03	0.18	0	0	0	0	1
# transactions (per owner)	909877	8.68	49.54	1	1	1	2	839

Source: Ztrax, Authors' calculations.
Note: This table presents summary statistics of all CRE transactions, sourced from ZTRAX data. The minimum sale price was set to USD 250,000. To avoid outliers, other variables such as LTV were truncated at 1.5. p25 and p75 are the 25th and 75th percentile of the distribution, respectively.

Table 2: Regression results: Spatial gradient (transaction-level)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Price per Built Surface (ln)					
Building Surface (ln)						
Building Condition						
Year Built						
URBAN_CDC	0.0862***	0.0670***	0.0710***	0.109***	0.0922***	0.0247
	(0.00752)	(0.0168)	(0.0133)	(0.0242)	(0.0181)	(0.0162)
2001.year x URBAN_CDC	-0.00480	-0.0356**	0.00503	-0.0168	-0.0197	0.0220
	(0.00880)	(0.0179)	(0.0157)	(0.0267)	(0.0219)	(0.0186)
2002.year x URBAN_CDC	-0.0369***	-0.0287*	-0.0201	-0.0682***	-0.0646***	0.00535
	(0.00851)	(0.0171)	(0.0148)	(0.0262)	(0.0206)	(0.0185)
2003.year x URBAN_CDC	-0.0406***	-0.0362**	-0.0389***	-0.0354	-0.0499**	-0.0155
	(0.00811)	(0.0169)	(0.0138)	(0.0243)	(0.0196)	(0.0182)
2004.year x URBAN_CDC	-0.0481***	-0.0464***	-0.0575***	-0.0443**	-0.0386**	-0.0242
	(0.00775)	(0.0157)	(0.0135)	(0.0215)	(0.0191)	(0.0175)
2005.year x URBAN_CDC	-0.0727***	-0.0807***	-0.0615***	-0.0662***	-0.0589***	-0.0445***
	(0.00723)	(0.0150)	(0.0127)	(0.0204)	(0.0174)	(0.0161)
2006.year x URBAN_CDC	-0.0842***	-0.0872***	-0.0694***	-0.0861***	-0.0920***	-0.0485***
	(0.00725)	(0.0149)	(0.0127)	(0.0211)	(0.0174)	(0.0160)
2007.year x URBAN_CDC	-0.0916***	-0.0866***	-0.0796***	-0.0947***	-0.0918***	-0.0280*
	(0.00726)	(0.0149)	(0.0128)	(0.0207)	(0.0174)	(0.0161)
2008.year x URBAN_CDC	-0.116***	-0.0677***	-0.0876***	-0.121***	-0.104***	-0.0804***
	(0.00743)	(0.0158)	(0.0132)	(0.0206)	(0.0178)	(0.0163)
2009.year x URBAN_CDC	-0.0865***	-0.0492***	-0.0736***	-0.126***	-0.0583***	-0.0674***
	(0.00784)	(0.0170)	(0.0140)	(0.0210)	(0.0190)	(0.0174)
2010.year x URBAN_CDC	-0.0726***	-0.0504***	-0.0582***	-0.103***	-0.0613***	-0.0614***
	(0.00771)	(0.0163)	(0.0135)	(0.0211)	(0.0189)	(0.0174)
2011.year x URBAN_CDC	-0.0845***	-0.0740***	-0.0874***	-0.117***	-0.0537***	-0.0446***
	(0.00768)	(0.0164)	(0.0135)	(0.0214)	(0.0187)	(0.0171)
2012.year x URBAN_CDC	-0.0783***	-0.0800***	-0.0751***	-0.130***	-0.0624***	-0.0397**
	(0.00749)	(0.0158)	(0.0132)	(0.0213)	(0.0179)	(0.0169)
2013.year x URBAN_CDC	-0.0957***	-0.104***	-0.0865***	-0.136***	-0.0927***	-0.0582***
	(0.00743)	(0.0158)	(0.0132)	(0.0213)	(0.0174)	(0.0166)
2014.year x URBAN_CDC	-0.110***	-0.106***	-0.0846***	-0.183***	-0.127***	-0.0677***
	(0.00741)	(0.0156)	(0.0129)	(0.0209)	(0.0182)	(0.0165)
2015.year x URBAN_CDC	-0.122***	-0.132***	-0.0964***	-0.185***	-0.146***	-0.0721***
	(0.00732)	(0.0153)	(0.0130)	(0.0208)	(0.0177)	(0.0163)
2016.year x URBAN_CDC	-0.143***	-0.162***	-0.111***	-0.182***	-0.121***	-0.0528***
	(0.00717)	(0.0152)	(0.0129)	(0.0212)	(0.0166)	(0.0164)
2017.year x URBAN_CDC	-0.147***	-0.148***	-0.117***	-0.199***	-0.137***	-0.0710***
	(0.00716)	(0.0151)	(0.0129)	(0.0207)	(0.0167)	(0.0163)
2018.year x URBAN_CDC	-0.144***	-0.132***	-0.125***	-0.199***	-0.172***	-0.0729***
	(0.00732)	(0.0155)	(0.0129)	(0.0210)	(0.0175)	(0.0161)
2019.year x URBAN_CDC	-0.149***	-0.130***	-0.129***	-0.197***	-0.196***	-0.0712***
	(0.00757)	(0.0162)	(0.0134)	(0.0210)	(0.0180)	(0.0168)
2020.year x URBAN_CDC	-0.144***	-0.151***	-0.120***	-0.137***	-0.219***	-0.0851***
	(0.00809)	(0.0179)	(0.0142)	(0.0223)	(0.0187)	(0.0183)
Constant	2.179***	1.642***	1.432***	1.616***	3.223***	2.780***
	(0.302)	(0.106)	(0.0843)	(0.0604)	(0.255)	(0.0446)
Observations	763,860	131,235	230,800	95,020	132,677	149,779
R-squared	0.366	0.454	0.394	0.465	0.487	0.358
Errors	robust	robust	robust	robust	robust	robust
TIME FE	✓	✓	✓	✓	✓	✓
COU FE	✓	✓	✓	✓	✓	✓
TYPE	ALL	OFFICE	RETAIL	MULTIFAM	INDUSTRIAL	OTHER

VARIABLES	(7)	(8)	(9)	(10)	(11)	(12)
	Price per Land Surface (ln)					
Building Surface (ln)						
Building Condition						
Year Built						
URBAN_CDC	-0.0924***	-0.178***	-0.0987***	-0.246***	-0.0288*	-0.106***
	(0.00685)	(0.0168)	(0.0119)	(0.0271)	(0.0162)	(0.0140)
2001.year x URBAN_CDC	-0.0108	-0.00901	-0.0109	-0.0396	-0.0522***	0.0254
	(0.00824)	(0.0189)	(0.0143)	(0.0296)	(0.0201)	(0.0165)
2002.year x URBAN_CDC	-0.0248***	-0.0153	-0.0138	-0.0292	-0.0604***	0.00869
	(0.00802)	(0.0180)	(0.0139)	(0.0294)	(0.0190)	(0.0161)
2003.year x URBAN_CDC	-0.0335***	0.00470	-0.0321**	-0.0280	-0.0652***	-0.00282
	(0.00765)	(0.0174)	(0.0131)	(0.0270)	(0.0181)	(0.0158)
2004.year x URBAN_CDC	-0.0500***	-0.0302*	-0.0471***	-0.0303	-0.0830***	-0.0125
	(0.00723)	(0.0163)	(0.0125)	(0.0254)	(0.0174)	(0.0151)
2005.year x URBAN_CDC	-0.0520***	-0.0347**	-0.0420***	-0.0242	-0.0917***	-0.0184
	(0.00679)	(0.0156)	(0.0117)	(0.0244)	(0.0162)	(0.0140)
2006.year x URBAN_CDC	-0.0655***	-0.0502***	-0.0522***	-0.0702***	-0.125***	-0.00754
	(0.00678)	(0.0156)	(0.0116)	(0.0250)	(0.0162)	(0.0141)
2007.year x URBAN_CDC	-0.0677***	-0.0438***	-0.0558***	-0.0926***	-0.127***	-0.0117
	(0.00682)	(0.0156)	(0.0118)	(0.0246)	(0.0161)	(0.0142)
2008.year x URBAN_CDC	-0.0475***	-0.0395**	-0.0470***	-0.0231	-0.115***	-0.0361**
	(0.00707)	(0.0163)	(0.0121)	(0.0253)	(0.0168)	(0.0147)
2009.year x URBAN_CDC	-0.0278***	-0.000403	-0.0245*	0.00858	-0.0836***	-0.00414
	(0.00740)	(0.0178)	(0.0128)	(0.0260)	(0.0177)	(0.0154)
2010.year x URBAN_CDC	-0.0344***	-0.00561	-0.0286**	0.00293	-0.0748***	-0.00513
	(0.00725)	(0.0170)	(0.0124)	(0.0257)	(0.0175)	(0.0152)
2011.year x URBAN_CDC	-0.0361***	-0.0230	-0.0302**	-0.0232	-0.0885***	-0.00681
	(0.00720)	(0.0170)	(0.0124)	(0.0258)	(0.0169)	(0.0151)
2012.year x URBAN_CDC	-0.0371***	-0.0156	-0.0240**	0.00127	-0.0925***	-0.00378
	(0.00705)	(0.0166)	(0.0122)	(0.0251)	(0.0164)	(0.0148)
2013.year x URBAN_CDC	-0.0581***	-0.0341**	-0.0449***	-0.0731***	-0.0980***	-0.0224
	(0.00698)	(0.0165)	(0.0121)	(0.0253)	(0.0163)	(0.0146)
2014.year x URBAN_CDC	-0.0690***	-0.0544***	-0.0484***	-0.0665***	-0.128***	-0.0368**
	(0.00699)	(0.0164)	(0.0120)	(0.0251)	(0.0167)	(0.0145)
2015.year x URBAN_CDC	-0.0882***	-0.0877***	-0.0554***	-0.107***	-0.152***	-0.0425***
	(0.00696)	(0.0161)	(0.0121)	(0.0247)	(0.0164)	(0.0145)
2016.year x URBAN_CDC	-0.109***	-0.0846***	-0.0691***	-0.128***	-0.143***	-0.0600***
	(0.00687)	(0.0161)	(0.0121)	(0.0247)	(0.0158)	(0.0144)
2017.year x URBAN_CDC	-0.109***	-0.0767***	-0.0840***	-0.107***	-0.165***	-0.0523***
	(0.00685)	(0.0159)	(0.0120)	(0.0249)	(0.0158)	(0.0144)
2018.year x URBAN_CDC	-0.104***	-0.0719***	-0.0802***	-0.155***	-0.187***	-0.0612***
	(0.00702)	(0.0165)	(0.0120)	(0.0254)	(0.0167)	(0.0145)
2019.year x URBAN_CDC	-0.119***	-0.0895***	-0.102***	-0.196***	-0.186***	-0.0796***
	(0.00757)	(0.0179)	(0.0130)	(0.0269)	(0.0175)	(0.0161)
2020.year x URBAN_CDC	-0.128***	-0.114***	-0.0701***	-0.279***	-0.209***	-0.124***
	(0.00927)	(0.0243)	(0.0160)	(0.0309)	(0.0194)	(0.0208)
Constant	2.186***	3.270***	3.180***	3.257***	2.302***	1.619***
	(0.424)	(0.114)	(0.106)	(0.0676)	(0.188)	(0.0365)
Observations	997,403	160,947	339,071	105,163	177,989	185,139
R-squared	0.415	0.381	0.415	0.587	0.495	0.313
Errors	robust	robust	robust	robust	robust	robust
TIME FE	✓	✓	✓	✓	✓	✓
COU FE	✓	✓	✓	✓	✓	✓
TYPE	ALL	OFFICE	RETAIL	MULTIFAM	INDUSTRIAL	OTHER

VARIABLES	(13)	(14)	(15)	(16)	(17)	(18)
	Price (ln)					
Building Surface (ln)	0.425***	0.553***	0.434***	0.445***	0.487***	0.301***
	(0.00132)	(0.00339)	(0.00263)	(0.00559)	(0.00338)	(0.00274)
Building Condition	0.0132***	0.0150***	0.0155***	1.43e-05	0.00435	0.0247***
	(0.00121)	(0.00291)	(0.00216)	(0.00444)	(0.00327)	(0.00250)
Year Built	0.00630***	0.00455***	0.00726***	0.00298***	0.00535***	0.00855***
	(3.82e-05)	(0.000100)	(6.94e-05)	(0.000110)	(0.000113)	(9.09e-05)
URBAN_CDC	0.0499***	0.0411***	0.0405***	0.119***	0.0791***	0.00587
	(0.00551)	(0.0137)	(0.0103)	(0.0194)	(0.0137)	(0.0110)
2001.year x URBAN_CDC	-0.00821	-0.0331**	-0.00486	-0.0202	-0.0143	0.00681
	(0.00647)	(0.0145)	(0.0121)	(0.0217)	(0.0171)	(0.0126)
2002.year x URBAN_CDC	-0.0239***	-0.0317**	-0.0159	-0.0740***	-0.0281*	-0.00924
	(0.00624)	(0.0140)	(0.0116)	(0.0209)	(0.0155)	(0.0124)
2003.year x URBAN_CDC	-0.0333***	-0.0315**	-0.0313***	-0.0525***	-0.0547***	-0.0186
	(0.00595)	(0.0130)	(0.0107)	(0.0186)	(0.0149)	(0.0123)
2004.year x URBAN_CDC	-0.0382***	-0.0375***	-0.0381***	-0.0641***	-0.0535***	-0.0173
	(0.00568)	(0.0127)	(0.0105)	(0.0168)	(0.0143)	(0.0117)
2005.year x URBAN_CDC	-0.0666***	-0.0858***	-0.0588***	-0.0909***	-0.0783***	-0.0193*
	(0.00532)	(0.0124)	(0.00985)	(0.0162)	(0.0131)	(0.0109)
2006.year x URBAN_CDC	-0.0771***	-0.0930***	-0.0634***	-0.109***	-0.0995***	-0.0358***
	(0.00538)	(0.0124)	(0.00988)	(0.0162)	(0.0132)	(0.0109)
2007.year x URBAN_CDC	-0.0884***	-0.102***	-0.0727***	-0.132***	-0.114***	-0.0442***
	(0.00540)	(0.0126)	(0.0100)	(0.0164)	(0.0132)	(0.0111)
2008.year x URBAN_CDC	-0.0816***	-0.0745***	-0.0756***	-0.134***	-0.110***	-0.0560***
	(0.00548)	(0.0131)	(0.0103)	(0.0164)	(0.0134)	(0.0112)
2009.year x URBAN_CDC	-0.0596***	-0.0488***	-0.0662***	-0.101***	-0.0696***	-0.0389***
	(0.00572)	(0.0138)	(0.0108)	(0.0165)	(0.0144)	(0.0117)
2010.year x URBAN_CDC	-0.0628***	-0.0651***	-0.0632***	-0.0994***	-0.0794***	-0.0396***
	(0.00571)	(0.0137)	(0.0105)	(0.0171)	(0.0144)	(0.0120)
2011.year x URBAN_CDC	-0.0784***	-0.0892***	-0.0892***	-0.119***	-0.0845***	-0.0419***
	(0.00571)	(0.0137)	(0.0105)	(0.0168)	(0.0144)	(0.0117)
2012.year x URBAN_CDC	-0.0757***	-0.103***	-0.0821***	-0.116***	-0.0926***	-0.0405***
	(0.00561)	(0.0132)	(0.0104)	(0.0174)	(0.0136)	(0.0116)
2013.year x URBAN_CDC	-0.0876***	-0.115***	-0.0867***	-0.130***	-0.111***	-0.0560***
	(0.00557)	(0.0133)	(0.0104)	(0.0170)	(0.0133)	(0.0114)
2014.year x URBAN_CDC	-0.101***	-0.113***	-0.0893***	-0.175***	-0.135***	-0.0666***
	(0.00558)	(0.0132)	(0.0103)	(0.0168)	(0.0139)	(0.0114)
2015.year x URBAN_CDC	-0.130***	-0.146***	-0.114***	-0.198***	-0.175***	-0.0958***
	(0.00558)	(0.0132)	(0.0103)	(0.0170)	(0.0136)	(0.0115)
2016.year x URBAN_CDC	-0.153***	-0.170***	-0.122***	-0.208***	-0.176***	-0.0748***
	(0.00546)	(0.0130)	(0.0103)	(0.0173)	(0.0127)	(0.0115)
2017.year x URBAN_CDC	-0.158***	-0.171***	-0.127***	-0.223***	-0.187***	-0.0762***
	(0.00545)	(0.0130)	(0.0103)	(0.0169)	(0.0128)	(0.0115)
2018.year x URBAN_CDC	-0.149***	-0.145***	-0.130***	-0.235***	-0.196***	-0.0898***
	(0.00555)	(0.0134)	(0.0102)	(0.0171)	(0.0136)	(0.0113)
2019.year x URBAN_CDC	-0.151***	-0.141***	-0.137***	-0.229***	-0.193***	-0.0945***
	(0.00577)	(0.0141)	(0.0105)	(0.0173)	(0.0140)	(0.0119)
2020.year x URBAN_CDC	-0.135***	-0.136***	-0.115***	-0.167***	-0.202***	-0.107***
	(0.00616)	(0.0155)	(0.0112)	(0.0179)	(0.0146)	(0.0129)
Constant	-4.439***	-2.292***	-6.234***	1.522***	-2.386***	-7.378***
	(0.177)	(0.210)	(0.149)	(0.221)	(0.275)	(0.180)
Observations	722,422	125,970	212,196	92,188	125,895	142,706
R-squared	0.436	0.568	0.439	0.473	0.528	0.327
Errors	robust	robust	robust	robust	robust	robust
TIME FE	✓	✓	✓	✓	✓	✓
COU FE	✓	✓	✓	✓	✓	✓
TYPE	ALL	OFFICE	RETAIL	MULTIFAM	INDUSTRIAL	OTHER

Source: Ztrax, Authors' calculations.
Note: Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *URBANCDC* takes integer values from 1 to 6, with 1 being the most urban area (e.g., closest to the city center).

Table 3: Regression results: Long-run - All CRE segments (state-level)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Median CRE price per SqFt (Δ%, yoy, all sectors)														
GDP (Δ%, yoy, all sectors)	1.507***	0.708***	0.617***	0.627***	0.617***	0.620***	0.737***	0.683**	0.614***	0.621***	1.075***	1.074***	1.123***	1.099***	0.688***
	(0.231)	(0.182)	(0.182)	(0.182)	(0.182)	(0.186)	(0.217)	(0.249)	(0.193)	(0.184)	(0.188)	(0.191)	(0.195)	(0.200)	(0.222)
Rental vacancies (level, in %)			-0.561**	-0.567**	-0.561**	-0.565**	-0.560**	-0.761***	-0.625***	-0.569**		-0.624***	-0.602***	-0.579***	-0.533**
			(0.212)	(0.208)	(0.212)	(0.212)	(0.241)	(0.233)	(0.214)	(0.210)		(0.176)	(0.184)	(0.189)	(0.250)
Population (Δ%, yoy)				-0.166											
				(0.415)											
GDP deflator (Δ%, yoy)					22.23										
					(21.52)										
Consumer price index (Δ%, yoy)						-0.111									
						(1.385)									
Corporate license state tax (Δ%, yoy)							0.0104**						0.0104*	0.0102*	0.0103**
							(0.00435)						(0.00546)	(0.00547)	(0.00438)
Business applications (Δ%, yoy)								-0.0701							
								(0.104)							
Net jobs creation (Δ%, yoy, private sect									0.00132						
									(0.00135)						
Total Exports (Δ%, yoy)										0.0308					
										(0.0304)					
Financial conditions index (level, NFCI)											-0.0423***	-0.0392***	-0.0332***	-0.0458***	
											(0.00848)	(0.00879)	(0.00829)	(0.0109)	
Low Debt (dummy) x NFCI (level)														0.0304*	0.0332*
														(0.0169)	(0.0180)
Constant	0.00106	0.0468	0.0919**	0.0937**	-0.339	0.0941*	0.0945**	0.111**	0.0955**	0.0972**	-0.00309	0.0504***	0.0490***	0.0476***	0.0979**
	(0.00533)	(0.0363)	(0.0420)	(0.0432)	(0.388)	(0.0536)	(0.0426)	(0.0480)	(0.0416)	(0.0408)	(0.00481)	(0.0160)	(0.0167)	(0.0169)	(0.0419)
Observations	1,697	1,697	1,697	1,697	1,697	1,697	1,596	1,344	1,595	1,697	1,697	1,697	1,596	1,596	1,596
R-squared	0.063	0.137	0.140	0.140	0.140	0.140	0.147	0.146	0.141	0.141	0.078	0.084	0.089	0.091	0.150
Number of id	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	×	×	×	✓

Source: Authors' calculations.
Note: Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. All regressors are lagged.

Table 4: Regression results: Long-run - Retail Space (state-level)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Median CRE price per SqFt (Δ%, yoy, retail & auto sectors)														
GDP (Δ%, yoy, retail & auto sectors)	0.706***	0.386**	0.337*	0.332*	0.337*	0.295	0.286	0.309	0.201	0.296	0.287**	0.161	0.161	0.120	0.230
	(0.134)	(0.175)	(0.179)	(0.188)	(0.179)	(0.182)	(0.198)	(0.197)	(0.208)	(0.183)	(0.131)	(0.127)	(0.127)	(0.126)	(0.185)
Rental vacancies (level, in %)			-0.652**	-0.657**	-0.652**	-0.612**	-0.607**	-0.611**	-0.665**	-0.617**		-0.793***	-0.793***	-0.785***	-0.593**
			(0.00271)	(0.00273)	(0.00271)	(0.00258)	(0.00263)	(0.00258)	(0.00264)	(0.00257)		(0.00192)	(0.00192)	(0.00197)	(0.00269)
Population (Δ%, yoy)				-0.363											
				(0.696)											
GDP deflator (Δ%, yoy)					2.844										
					(3.970)										
Consumer price index (Δ%, yoy)						2.553*	3.689***	2.535*	2.892**	2.522*	0.954	1.080*	1.080*	1.050*	2.355*
						(1.323)	(1.115)	(1.334)	(1.353)	(1.302)	(0.601)	(0.606)	(0.606)	(0.607)	(1.348)
Corporate license state tax (Δ%, yoy)							-0.00302								
							(0.0158)								
Business applications (Δ%, yoy)								-0.0429							
								(0.139)							
Net jobs creation (Δ%, yoy, private sect									0.000441						
									(0.00246)						
Total Exports (Δ%, yoy)										0.0410					
										(0.0549)					
Financial conditions index (level, NFCI)											-0.0496***	-0.0477***	-0.0477***	-0.0603***	
											(0.00853)	(0.00807)	(0.00807)	(0.00932)	
Low Debt (dummy) x NFCI (level)														0.0267*	0.0240
														(0.0146)	(0.0159)
Constant	0.0158***	0.0741**	0.134***	0.137***	0.0465	0.0404	-0.0121	0.0447	0.0362	0.0356	-0.0115	0.0531***	0.0531***	0.0529***	0.0544
	(0.00110)	(0.0329)	(0.0329)	(0.0329)	(0.108)	(0.0517)	(0.0478)	(0.0605)	(0.0479)	(0.0517)	(0.0118)	(0.0159)	(0.0159)	(0.0159)	(0.0533)
Observations	1,296	1,296	1,296	1,296	1,296	1,296	1,226	1,296	1,234	1,296	1,296	1,296	1,296	1,296	1,296
R-squared	0.018	0.089	0.092	0.092	0.092	0.094	0.099	0.094	0.093	0.094	0.040	0.046	0.046	0.048	0.095
Number of id	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	×	×	×	✓

Source: Authors' calculations.
Note: Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. All regressors are lagged.

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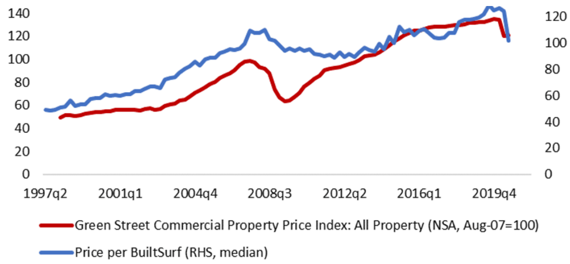
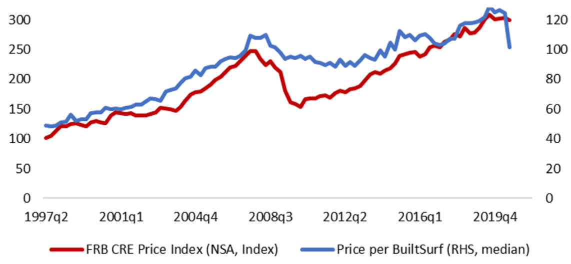
6 Appendix

Figure A.1: Ztrax Data Validation

(a) Green St. Vs ZTRAX



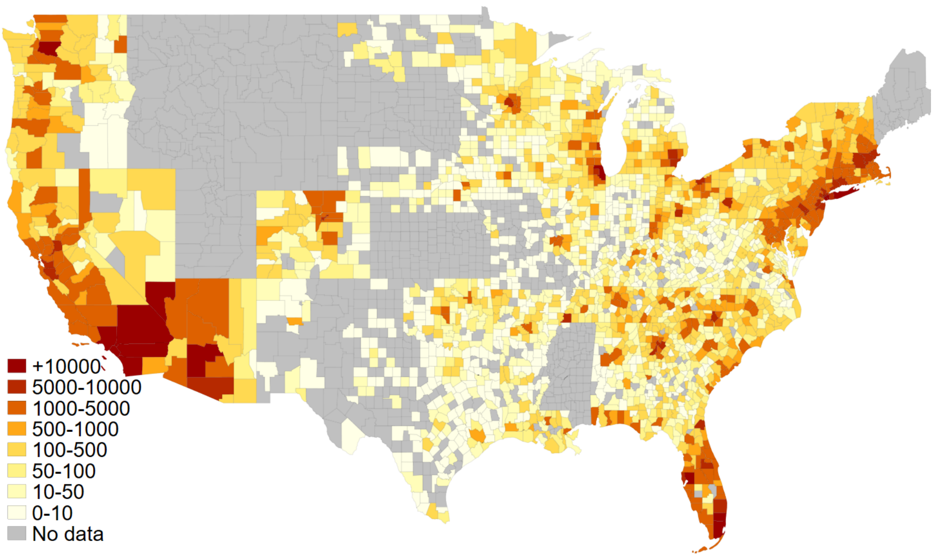
(b) FRB vs. Ztrax



Source: Ztrax, Green St., Federal Reserve Board, Authors' calculations.

Figure A.2: Ztrax Data County-level Coverage

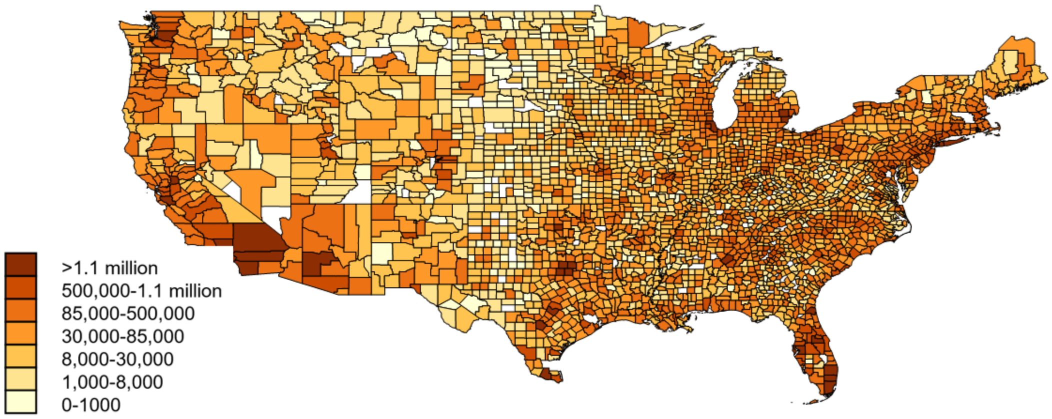
(a) (2000-2020)



Source: Authors' calculations.
Note: Number of transactions by county

Figure A.3: SafeGraph Data County-level Coverage

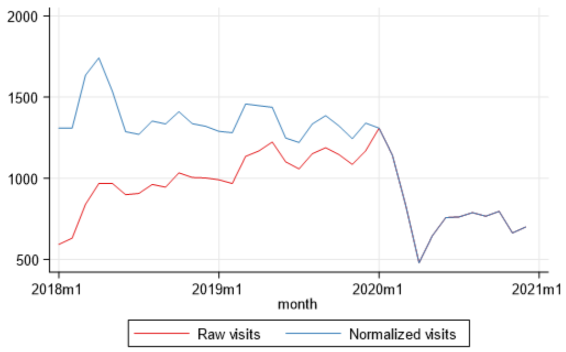
(a) Number of normalized retail visits by county (January 2020)



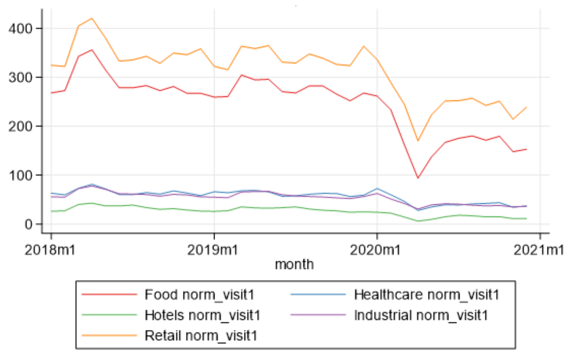
Source: SafeGraph; Authors' calculations.
Note: This figure depicts number of visits aggregated by county in January 2020.

Figure A.4: Stylized Facts (SafeGraph)

(a) Number of Visits by Month (All CRE types, in millions)



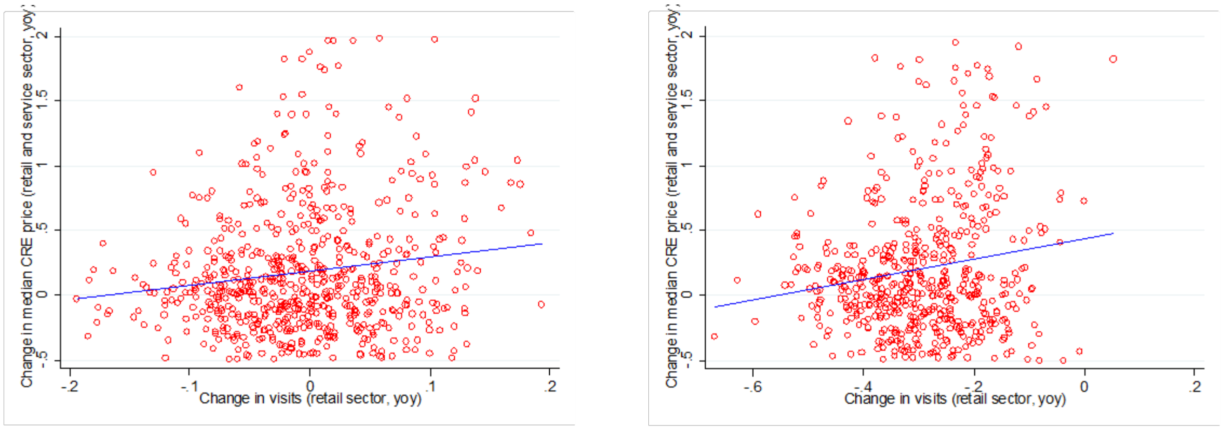
(b) Number of Visits by Sector (Normalized, in millions)



Source: SafeGraph, Authors' calculations.

Figure A.5: County-level relationship between visits and CRE prices in 2019 and 2020 (Dropping outliers and states lacking observations)

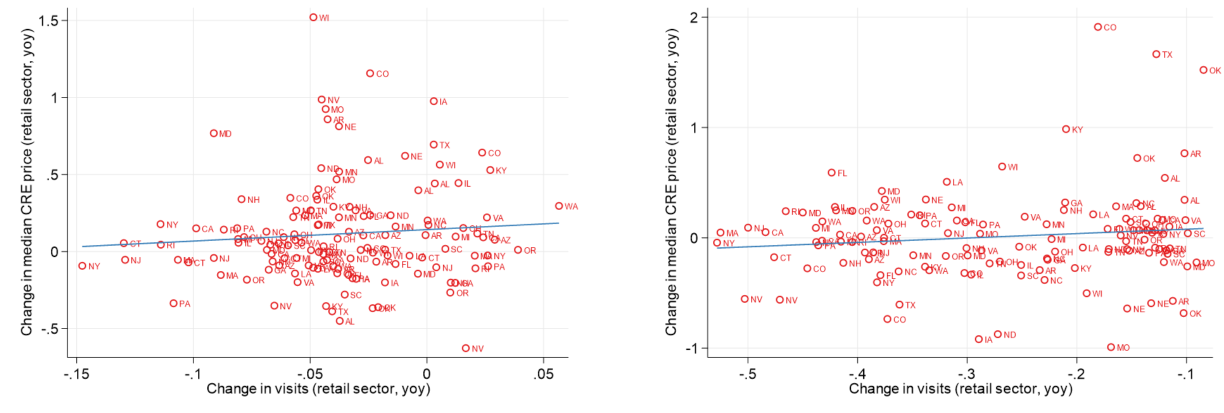
(a) 2019 (b) 2020



Source: SafeGraph, Authors' calculations.

Figure A.6: State-level relationship between visits and CRE prices in 2019 and 2020 (Dropping outliers and states lacking observations)

(a) 2019 (b) 2020



Source: SafeGraph, Authors' calculations.

Table A.1: Summary Statistics (state-level)

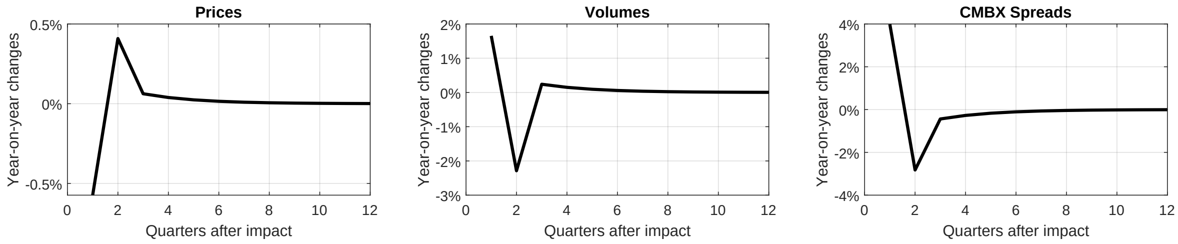
Variable	Observations	Mean	Std. deviation	Minimum	p25	Median	p75	Maximum
Median CRE price per SqFt (Δ%, yoy, all sectors)	1888	0.037	0.178	-0.501	-0.065	0.043	0.142	0.561
Median CRE price per SqFt (Δ%, yoy, retail & auto sector	1888	0.036	0.224	-0.560	-0.102	0.038	0.176	0.661
GDP (Δ%, yoy, all sectors)	1896	0.025	0.030	-0.127	0.010	0.024	0.043	0.155
GDP (Δ%, yoy, retail & auto sectors)	1320	0.009	0.040	-0.139	-0.013	0.013	0.033	0.187
Rental vacancies (level, in %)	1992	0.082	0.030	0.010	0.059	0.079	0.103	0.194
Population (Δ%, yoy)	1896	0.007	0.007	-0.085	0.003	0.007	0.012	0.037
GDP deflator (Δ%, yoy)	1896	0.019	0.007	0.001	0.016	0.019	0.024	0.032
Consumer price index (Δ%, yoy)	1896	0.021	0.012	-0.020	0.015	0.021	0.030	0.053
Corporate license state tax (Δ%, yoy)	1786	0.013	0.633	-5.651	-0.079	0.026	0.123	5.631
Business applications (Δ%, yoy)	1368	0.022	0.070	-0.365	-0.020	0.021	0.065	0.437
Net jobs creation (Δ%, yoy, private sector)	1779	0.335	3.155	-27.000	-0.333	0.417	1.200	38.000
Total Exports (Δ%, yoy)	1896	0.044	0.179	-1.368	-0.032	0.055	0.129	1.769
Financial conditions index (level, NFCI)	1992	-0.327	0.534	-0.766	-0.623	-0.485	-0.236	2.567
Low debt (dummy)	1992	0.5	0.5	1.0	1.0	1.0	0.0	0.0
Household debt to income (ratio)	1992	1.5	0.5	0.4	1.2	1.5	1.8	2.1

Source: US Census, ZTRAX, Chicago Fed, Authors' calculations. Note: The low debt dummy variable is created based on state-level debt-to-income data from the Federal Reserve; A state with an average debt-to-income ratio over the time period below 1.5 is considered a state with low debt. The median CRE prices were winsorized by 1 percent. The CPI is regional, rather than state-level.

Figure A.7: Illustration of identification

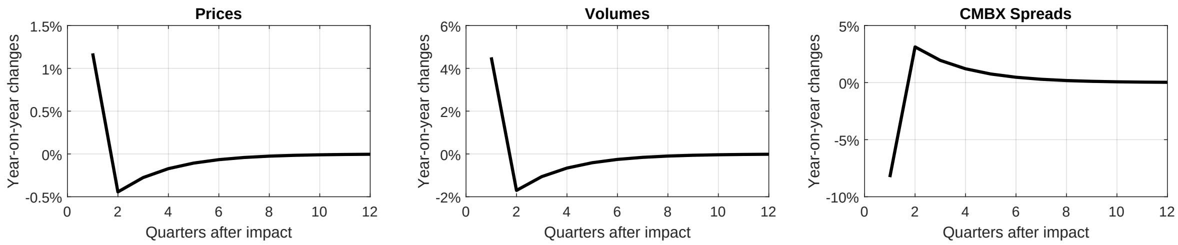
Panel A

Supply shocks



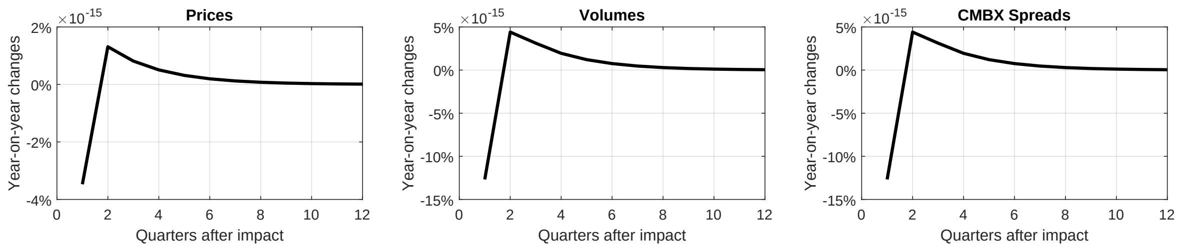
Panel B

Demand shocks



Panel C

Risk shocks



PUBLICATIONS

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