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* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

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Abstract

We employ a panel vector auto-regressive model to analyze the dynamic interactions between delinquency rates on bank loans, funding and market liquidity, and asset price movements in regional U.S. commercial real estate (CRE) markets. Our findings indicate that rising delinquency rates lead to tighter funding liquidity, which in turn negatively impacts asset prices and market liquidity. Importantly, funding liquidity and market liquidity reinforce one another, demonstrating that "liquidity spirals" are also relevant in CRE markets. Additionally, there is a negative feedback loop between market liquidity and default rates: good market liquidity allows borrowers with financially distressed loans to sell properties before becoming delinquent. This highlights the crucial role of market liquidity in CRE markets. Based on these insights, we recommend counter-cyclical loan policy standards. In hot markets, tighter funding liquidity may reduce future delinquency rates, while in cold markets, more relaxed lending standards could enhance market liquidity. This may facilitate restructuring and refinancing of distressed loans, helping to mitigate liquidity spirals.

Keywords— Funding liquidity, Market Liquidity, Commercial Real Estate, Delinquency Rates
JEL codes— R3, G21, G12

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1 Introduction

Acquiring and investing in commercial real estate (CRE) requires significant capital investment. It is common for investors to use a combination of equity and debt, rather than relying solely on equity. As such, the liquidity of financing, or the ease with which an asset can be financed, is critical in the decision-making process for CRE investments. Conventional funding sources for CRE include banks, life insurance companies, and pension funds (Geltner et al. 2014). Typically, the property is used as collateral and serves as security for the lender. A substantial portion of CRE investments is facilitated through portfolio loans, with commercial banks being the predominant financiers among these loans (Levitin and Wachter 2013, Black et al. 2017, 2020).

In 2007, the outbreak of the subprime mortgage crisis led to a significant contraction in the availability of credit in the housing market. This financial turmoil led to a pronounced collapse of the housing market. Subsequently, CRE prices experienced a substantial decline, approximately by 35%–40% over the period from 2008Q2 to 2009Q4 (Arsenault et al. 2013). An increase in the delinquency rates of CRE loans from 2007 to 2010 coincided with a significant tightening of bank lending standards and a notable decrease in market liquidity and property values.

In this paper, we analyze the dynamic relations between delinquency rates, funding liquidity, market liquidity, and asset prices in the private CRE sector, extending the framework of Ling et al. (2016) by including delinquency rates on CRE loans. Our paper offers two main contributions to the existing literature. First, we use regional data on market liquidity – the ease of trading a property – and asset price dynamics. Second, the literature has not extensively examined default risk as a channel through which the valuation of CRE assets affects funding liquidity. This study addresses this channel by analyzing the extent to which the change in banks' delinquency rates is affected by fluctuations in the CRE price index returns. Moreover, our findings confirm that the simultaneous drying up of funding and market liquidity, as previously observed in both the equity and bond markets, also holds true in the CRE sector. Our study identifies the delinquency rate as an important mechanism for revealing the dynamic interactions between funding liquidity, market liquidity, and asset valuation in the real estate sector.

We apply a Panel Vector Auto-Regressive (PVAR) model on quarterly data for 25 U.S. Metropolitan Statistical Areas (MSAs). Our sample covers the period from 2005 to 2018, including the booming CRE market until 2007, followed by the 2008 crisis and subsequent recovery. The delinquency rate ($deli$) is defined as the ratio of the amount of delinquent CRE loans to the total amount outstanding. We collect questionnaires on lending standards of commercial banks on CRE loans from the Senior Loan Officer Opinion Survey on Bank Lending Practices to obtain a measure of the change in funding liquidity ($\Delta tighten$). The real price index returns (r) are based on a repeat sales model. The measure for market liquidity ($mliq$) is the difference between the seller's and buyer's reservation price index relative to the repeat sales price index (Van Dijk et al. 2020). Both the price index and market liquidity are calculated per MSA and constructed from MSCI/RCA transaction-level data. We examine the dynamic interactions between delinquency rates, funding liquidity, market liquidity, and price index returns in the CRE asset market, as illustrated in Figure 1.

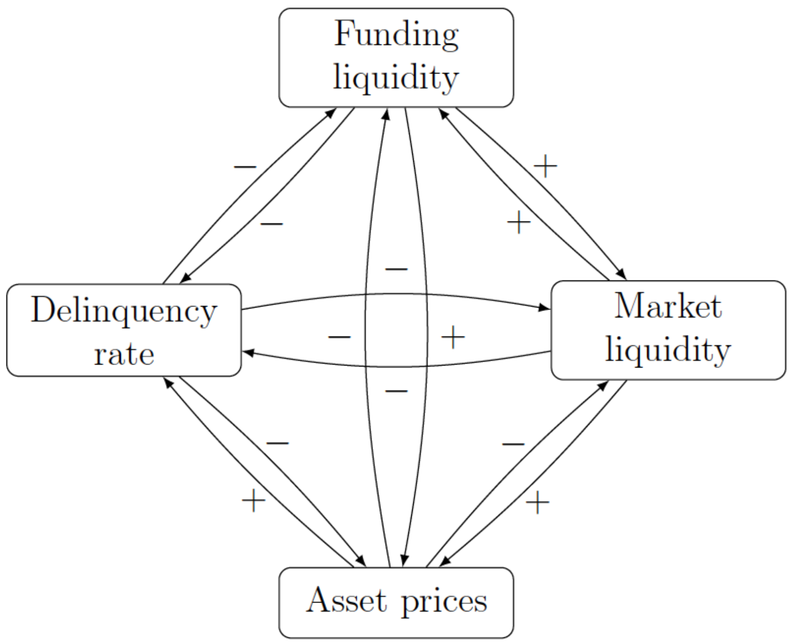


Figure 1. Feedback effects

We estimate generalized impulse response functions and perform a forecast error variance decomposition to analyze the interactions of the endogenous variables. Our findings show that an increase in the change of delinquency rates leads to a subsequent rise in the change of funding liquidity. The reverse relationship also applies. This phenomenon can be attributed to banks reducing the supply of loans in response to capital losses or increased credit risks of borrowers, as has also been shown in previous studies (Hancock and Wilcox 1994, 1997).

Consequently, a tightening liquidity scenario exacerbates the rise in delinquency rates, a correlation supported by many studies that use lending standards-related metrics (Archer et al. 2002, Seslen and Wheaton 2010, An and Sanders 2010).

Our analysis also shows a mutual reinforcement between changes of funding liquidity and market liquidity (i.e., liquidity spirals). This finding aligns with the theoretical framework of Brunnermeier and Pedersen (2009) for financial markets and is supported by CRE market studies (e.g. Ling et al. 2016, Wiley 2017, Clayton 2009).

We find that tighter funding liquidity leads to lower real price index returns, consistent with previous studies (Brown 2000, Ling et al. 2016, Wiley 2017). A decrease in funding liquidity reflects a reduction of CRE loan origination or more stringent lending criteria, thus diminishing the pool of prospective buyers and leading to a decline in transaction prices.

Our analysis shows that higher delinquency rates lead to a decrease in real price index returns. This finding supports the argument made by Calomiris et al. (2013) that increased delinquency rates can trigger foreclosures and fire sales, depressing market transaction prices. Additionally, delinquency rates, as indicators of capital loss, influence the supply of loans (Hancock and Wilcox 1994, 1997), affecting asset prices and market liquidity. This highlights the important role of credit risk in shaping market dynamics and asset valuation in the CRE market. Furthermore, our findings indicate that a positive shock in real returns results in higher delinquency rates and tighter credit. One explanation for this finding could be that rising prices during booms cause banks to monitor borrowers' credit risk less closely and lend more, which in turn drives up future default risk (Mian and Sufi 2009), an subsequently lowers funding liquidity.

Finally, our research identifies negative feedback effects between market liquidity and default rates, a relationship that, to our knowledge, has not been previously investigated in the CRE market. This finding is consistent with research in the equity market (Brogaard et al. 2017, Nadarajah et al. 2021) and the bond market (He and Xiong 2012, Chaumont 2020). Higher market liquidity enables the borrower of financially distressed loans to sell the property before becoming delinquent and going to foreclosure. This stresses the importance of liquidity in CRE markets.

This paper proceeds as follows. Section 2 provides an overview of the literature. Section 3 introduces the empirical model. Section 4 describes the data. Section 5 presents results. Section 6 concludes.

2 Related Literature

In this section, we discuss relevant studies on delinquency rates, funding liquidity, market liquidity, and asset prices, focusing on CRE-markets.

In real estate finance research, funding liquidity has been widely studied for its impact on asset values. Factors that relate to funding liquidity or credit availability have been shown to affect asset prices. Greater availability of debt flows (Chervachidze et al. 2009), mortgage capital flows (Clayton and Peng 2011), and overall capital flows (Chervachidze and Wheaton 2013) – key indicators of credit availability – enhances purchasing power in the real estate market, thereby driving up asset values. Capital structure, debt maturity, and the cost of funding liquidity (i.e., financially distressed costs) also significantly affect asset values (Brown 2000) and real estate investment trust (REIT) share prices (Sun et al. 2015). For example, Brown (2000) observed that the share prices of mortgage REITs decline in response to the cost of funding liquidity, and liquidations are more likely to occur to more highly leveraged mortgage REITs by selling foreclosure properties when they are financially distressed.

As one of the most related studies, Ling et al. (2016) address the dynamic interplay between funding liquidity, market liquidity, and asset prices across private and public CRE markets. They find that market liquidity can positively affect funding liquidity and vice versa. Similarly, asset returns and the tightening of funding liquidity are negatively related. Under certain market conditions, falling asset prices and the dry-up of market liquidity increase the risk of financing an acquisition, further tightening funding liquidity. Similarly, by exploring the dynamic interactions among net operating income growth, changes of underwriting restrictiveness, market liquidity, and price index returns within the CRE market, Wiley (2017) concludes that highly active investor participation positively affects subsequent asset price appreciation, while the tightening of commercial real estate lending standards has a negative impact on future asset appreciation. In addition, declining market liquidity and falling prices are found to adversely influence future credit availability. Relatedly, Van Dijk and Francke (2021) show that the integration of international capital markets – which to a large extent similar to funding liquidity – is the prime reason for strong international co-movement in market liquidity. Returns are also partly determined by global funding liquidity, but local space markets also play a crucial role here. Therefore, cross-market movements in returns are found the be smaller that movements in market liquidity.

Additionally, Clayton (2009) conceptually discusses a feedback loop between market liquidity, financial leverage, and property prices, suggesting that rising prices enhance liquidity and credit availability, reinforcing price appreciation. This paper also suggests that the easy supply of debt increases demand and encourages uninformed investors to overpay for a property, resulting in increased liquidity and high price levels in CRE markets. Similarly, Clayton and Peng (2011), Arsenault et al. (2013) find a positive feedback loop between CRE property prices and mortgage supply. Higher CRE returns ease funding liquidity constraints by increasing banks' willingness to allocate assets to CRE loans, thereby expanding credit availability (Hancock and Wilcox 1997). In their paper, they include the delinquency rate on real estate loans as a proxy for lenders' willingness to finance real estate projects.

These papers support the study by Brunnermeier and Pedersen (2009) in which market liquidity and funding liquidity are mutually reinforcing in the financial market. They provide a theoretical framework where decreased market liquidity increases default risk and triggers margin calls, further deteriorating funding liquidity conditions. A representative empirical study on the relationship between funding and market liquidity in real estate markets is conducted by Glascock and Lu-Andrews (2014). The authors find for REITs that this relationship varies over the business cycle, with funding liquidity as measured by debt-service coverage ratio, loan-to-value ratio, number of loans on commercial commitments, and adjustments in credit stringency having a positive effect on market liquidity during expansions but potentially worsening liquidity during recessions.

Numerous studies have examined how specific loan characteristics related to funding liquidity and banks' lending standards influence loan delinquency and other credit risk measurements. For instance, higher loan default risk – measured by the probability of default, delinquency rates, charge-off rates, or the probability of non-performing loans – has been found to be affected by higher loan-to-values (Vandell et al. 1993, Seslen and Wheaton 2010, An and Sanders 2010, Ghosh 2015, Gaudêncio et al. 2019, Seagraves and Wiley 2016), lower debt-service coverage ratios (Seslen and Wheaton 2010, An and Sanders 2010, Cremer 2020, Seagraves and Wiley 2016), lower original debt coverage ratio (Archer et al. 2002), and higher interest rates (Igan and Pinheiro 2010, Vandell et al. 1993). While these factors are often linked to funding liquidity, some studies, such as Glascock and Lu-Andrews (2014), explicitly define and analyze their role in this context, as discussed in the previous discussion.

In turn, default risk has been found to affect funding liquidity. Lenders tighten lending standards following experienced loss and credit risk (Hancock and Wilcox 1994, 1997, Black et al. 2020). Following an exogenous funding liquidity shock, the breakdown of the commercial mortgage-backed securities (CMBS) market, banks tightened lending standards by reducing loan-to-values and increased debt yield requirements, effectively limiting leverage in CRE loans (Black et al. 2020). Consistently, Hancock and Wilcox (1994) find that across regions, lower delinquency rates of banks' real estate loans were associated with stronger growth in real estate loans. Ghosh (2018) find that higher loan charge-offs – another proxy of loan default risk – can decrease the ability of banks to provide new loans.

Asset prices have been found to influence delinquency rates on real estate loans significantly. Igan and Pinheiro (2010) find an overall positive relationship between real estate prices and delinquency rates. However, when using residential and CRE indices, residential loan delinquencies increase with the residential price index, while CRE loan delinquencies exhibit an inverse relationship with the CRE price index. They argue that using real estate as collateral allows for more loans during real estate booms, which increases demand for real estate, drives prices even higher, and thus creates more loans. When the real estate cycle turns, nonperforming loans increase. An and Sanders (2010) find that the decline in property values is a major cause of the increased number of defaults on CMBS loans during the crisis. Mian and Sufi (2009) find that looser funding liquidity played a crucial role in the growth of mortgages, leading to higher home prices and more future defaults in residential real estate markets. Their study attributes the expansion of mortgage credit from 2002 to 2005 in mortgage supply – driven by securitization and weaker borrower screening – to an expectations-driven mechanism: banks' optimistic forecasts of house prices lower their perceived default risk, encouraging them to issue riskier loans.

By focusing on CMBS loans, Seagraves and Wiley (2016) conclude that including the cap rate spread in combination with the loan-to-value and debt-service coverage ratio in underwriting criteria can reduce loan performance risk, with the cap rate spread and debt-service coverage ratio having a negative effect on the probability of non-performing loans, while the loan-to-value ratio has a positive effect. More broadly, rapid loan growth, coupled with less stringent borrower credit assessments, inflates transaction prices and increases future default risk and delinquency rates (Weinberg 1995, Keeton 1999, Mian and Sufi 2009).

3 Empirical Approach

3.1 The PVAR-model

In our empirical model, we analyze the dynamics and interactions of the variables delinquency rates, funding liquidity, market liquidity, and asset price index returns. To be precise, our endogenous variables of interest are given by $y_{i,t} = (\Delta deli_t, \Delta tighten_t, \Delta mliq_{i,t}, r_{i,t})'$. The variable *deli* denotes the delinquency rate, *tighten* is a measure of funding liquidity, *mliq* is a market liquidity metric, and r indicates the real asset price index return. The subscripts $i = 1, \ldots, N$ and $t = 1, \ldots, T$ denote the region and quarter, respectively. Note that the variables *deli* and *tighten* are measured at the national level, while *mliq* and r are measured at the regional level. The control variables $x_{i,t}$ are the U.S. term spread, the default spread, and the excess returns from the equity market. In our application, the control variables are measured at the national level and do not vary between regions, so $\mathbf{x}_{i,t} = \mathbf{x}_t$. More details on the panel data variables are provided in Section 4.

We use a Panel Vector Auto-Regressive (PVAR) model with p lags of m endogenous variables, given by:

$$y_{i,t} = \mu_i + \sum_{l=1}^{p} A_l y_{i,t-l} + B x_t + \varepsilon_{i,t}, \quad i = 1, \ldots, n, \quad t = 1, \ldots, T. \tag{1}$$

The m-vector $y_{i,t}$ contains the endogenous variables. The model includes lags $l = 1, \ldots, p$ of $y_{i,t}$, with corresponding $(m \times m)$ coefficient matrices A_l. The k-vector x_t contains exogenous control variables, with corresponding $(m \times k)$ coefficient matrix B. All variables are standardized. The m-vector μ_i contains fixed effects for region i. They are included to capture time-invariant regional heterogeneity. The m-vector $\varepsilon_{i,t}$ is the error term and has zero mean and a $(m \times m)$ positive semi-definite variance-covariance matrix $\mathrm{Var}(\varepsilon_{i,t}) = \Sigma_\varepsilon$. It is assumed that $\mathrm{Cov}(\varepsilon_{i,t}, \varepsilon_{k,s}) = 0$ for $i \neq k \vee s \neq t$.

The inclusion of fixed effects μ_i can introduce bias into the coefficient's estimate, because fixed effects may correlate with lagged dependent variables (i.e., Nickell's bias, see Nickell 1981). Therefore, ordinary least squares can lead to biased coefficients in dynamic models, especially for panel data having a rather large number of regions and a relatively small number of time periods (large N small T). To avoid Nickell's bias, the Arellano and Bover (1995) generalized method of moments (GMM) estimation technique is employed. This method leverages instrumental variables to construct moment conditions that help to obtain unbiased estimates in the presence of endogenous regressors. Specifically, the GMM technique uses lagged values of the variables as instruments, thereby effectively dealing with the endogeneity introduced by the lagged dependent variable. We apply a forward orthogonal deviations (FOD) transformation, as the first difference transformation may induce serial correlation (Arellano and Bover 1995). The FOD transformation is given by:

$$\ddot{z}_t \equiv \sqrt{\frac{T-t}{T-t+1}} \left(z_t - \frac{1}{T-t}(z_{t+1} + \cdots + z_T) \right), \quad t = 1, ..., T-1,$$

for z_t is $y_{i,t}$ or x_t. The transformed PVAR-model is given by

$$\ddot{y}_{i,t} = \sum_{l=1}^{p} A_l \ddot{y}_{i,t-l} + B\ddot{x}_t + \ddot{\varepsilon}_{i,t}. \tag{2}$$

We use "collapsed" instruments (Roodman 2009, Sigmund and Ferstl 2019) to make the computation more feasible by reducing the number of instruments, thus mitigating the potential problem of instrument proliferation that could weaken the GMM estimates. We apply a one-step system GMM estimation, which generally tends to be less biased than the two-step estimator in small samples (Arellano and Bover 1995).

3.2 Optimal Lag Length Selection

In this subsection, we consider the lag length selection in the PVAR-model, given by Eq. (2). First, we consider widely used selection information criteria to choose the optimal lag length (Andrews 1991). It is 11 for MMSC-BIC, and 15 for MMSC-AIC and MMSC-HQIC. MMSC-BIC and MMSC-HQIC are recommended by Andrews and Lu (2001) since "The MMSC-AIC does not fulfill its consistency criterion, as it has a positive probability even asymptotically of selecting too few over-identifying restrictions" (Sigmund and Ferstl 2019).

Next, we consider the performance of the orthogonalized impulse response function (OIRF), where non-convergence occurs for lag lengths greater than 5. As the lag length increases to 9, oscillation occurs. Thus, the PVAR-model is unstable or non-converging for lag lengths above 5. Furthermore, we apply the Jansen J-statistic to ensure that there are no overidentification issues, where the statistics suggest that the optimal lag length is not smaller than 3. Finally, we consider the *stability condition* of the PVAR-model. The VAR model is stable if all the roots z of the polynomial $|I_p - A_1 z - \cdots - A_p z^p| = 0$ have $|z| < 1$, so there are no roots in and on the complex unit circle (Lütkepohl 2005). The model is unstable if the lag length is greater than 12.

Therefore, we choose an optimal lag length of $p = 4$ quarters, considering seasonal effects over a year. Additionally, choosing a small lag length increases the estimation efficiency and minimizes the data loss (Abrigo and Love 2016). Also economically speaking, a lag length of 4 should be sufficient to capture the variable dynamics that we are interested in.

3.3 Ordering of Endogenous Variables

In the results section, we report the generalized impulse response functions (GIRFs) and the forecast error variance decompositions (FEVDs) to illustrate the dynamic interactions between the four endogenous variables. Unlike the GIRFs, the FEVDs are dependent on the order of the endogenous variables, due to the use of an order-sensitive Cholesky decomposition in the orthogonalized impulse response functions (OIRFs). In this decomposition, variables considered to influence other variables contemporaneously are placed earlier in the ordering (Chordia et al. 2005, Goyenko and Ukhov 2009). The last variable in the ordering is assumed to be affected by all others but does not affect others contemporaneously. In this study, the variables are ordered as $\Delta deli$, $\Delta tighten$, $\Delta mliq$, and r. We will test for robustness by using different orderings.

First, delinquency rates are considered an early indicator of financial distress, reflecting the risk of default for borrowers. As such, they are likely to influence funding conditions and market liquidity, as commercial banks adjust their lending standards on CRE loans. CRE investors adjust investment behavior accordingly in response to rising credit risk.

Second, the change in banks' lending standards for CRE loans, which serves as a proxy for credit conditions, is placed next. This variable captures variations in credit conditions and, by affecting funding liquidity, it can influence both market liquidity and asset returns. It is also likely to be contemporaneously affected by changes in CRE loan delinquency rates.

Third, market liquidity is placed after funding liquidity because it responds immediately to changes in funding conditions and delinquency rates, but does not contemporaneously affect these variables. As funding conditions tighten, market liquidity may decrease.

Finally, consistent with previous studies (Chordia et al. 2005, Goyenko and Ukhov 2009), returns are ordered after market liquidity. In our framework, returns are driven by investor behavior responding to prevailing market conditions, including credit risk and liquidity, justifying their placement as the final variable.

It is also possible to argue for a different variable ordering. For example, in times when funding liquidity suddenly dries up, i.e., at the onset of the Global Financial Crisis or more recently with the Silicon Valley Bank failure). Funding liquidity may contemporaneously impact delinquency rates and the other variables in the system in those times. Hence, funding liquidity should be ordered before delinquency rates. We will consider this alternative ordering in the FEVD-analysis in Section 5.2.

Table 1. Description of variables

Variable	Description
$deli_t$	Delinquency rate on CRE loans (excluding farmland), booked in domestic offices of all commercial banks. Source: Federal Reserve Economic Data (FRED).
$\Delta tighten_t$	The net percentage of tightening standards for CRE loans (excluding farmland) of U.S. domestic and foreign commercial banks, see Eq. (3). Source: Senior Loan Officer Opinion Survey on Bank Lending Practices, Board of Governors of the Federal Reserve System.
$r_{i,t}$	CRE property price index real return, based on the methodology in Van Dijk et al. (2020). Source: MSCI/RCA for the construction on price indices and FRED for the inflation rate.
$mliq_{i,t}$	Market liquidity from Van Dijk et al. (2020), using transaction data from MSCI/RCA.
ts_t	Term spread, measured as 10-year Treasury bond yield − 90-day Treasury bill yield. Source: Center for Research in Security Prices (CRSP).
ds_t	Default spread, measured as Moody's Seasoned Baa corporate bond yield − Moody's Seasoned Aaa corporate bond yield. Source: FRED.
$r_t^m - r_t^f$	Equity market excess return: Equity market return $r_{m,t}$ − risk-free rate $r_{f,t}$, measured by the 30-day Treasury bill yield. Source: CRSP.

Notes: Subscripts i and t denote MSA and quarter, respectively.

4 Data

The data include quarterly observations from 2005 to 2018 in 25 US metropolitan statistical areas (MSAs).[1] This period notably includes the collapse of the commercial mortgage-backed securities market from late 2007 to 2008, a period marked by a severe liquidity crisis that impacted all asset-backed securities. This crisis, stems from a combination of lax lending standards, excessive risk-taking, and unsustainable levels of debt, as detailed in research by Black et al. (2020) and Gorton and Metrick (2012). Table 1 lists the endogenous and control variables used in this study, which we will explain in more detail in the following subsections.

4.1 Delinquency Rates and Funding Liquidity

We focus on the delinquency rates on CRE loans and the lending standards for CRE loans offered by commercial banks, as these loans are crucial for financing CRE investments. A bank's CRE lending strategy may target one or more of the five primary CRE sectors: office,

[1]The included MSAs are: Atlanta, Austin, Baltimore, Boston Metro, Charlotte, Chicago, Dallas, DC Metro, Denver, Detroit, Houston, LA Metro, Las Vegas, Miami/So Fla, Minneapolis, NYC Metro, Orlando, Philly Metro, Phoenix, Portland, Sacramento, San Diego, Seattle, SF Metro, and Tampa.

retail, industrial, hospitality, and residential.[2] The delinquency rates on CRE loans of all commercial banks are sourced from the Federal Reserve Economic Data (FRED).[3]

The delinquency rate *deli* reflects the percentage of loans within these sectors that are past due by thirty days or more. As a proxy for the default rate on CRE loans, it is a critical metric that reflects the risk of non-repayment of these loans, and thus signals potential capital losses to commercial banks. This rate not only measures financial distress but also serves as an important indicator that influences both the dynamics of CRE financing and overall market performance. First, banks rely heavily on the delinquency rate to adjust their lending standards. Second, the delinquency rate directly reflects the current performance of the CRE market, as the ability of borrowers to meet their loan obligations is closely tied to the income generated from their real estate investments, primarily through rental income.

Our measure of the change in funding liquidity is $\Delta tighten$. This variable is derived from the Senior Loan Officer Opinion Survey on Bank Lending Practices, sourced from the Board of Governors of the Federal Reserve System. The survey is collected quarterly from eighty large domestic banks and twenty-four U.S. branches or agencies of foreign banks. At each participating bank, one or more senior loan officers complete the survey via electronic submission. The survey question asks "Over the past three months, how have your bank's credit standards for approving applications for CRE loans, including construction and land development loans and loans secured by nonfarm nonresidential real estate changed?" Respondents can select one of the following options "Tightened considerably", "Tightened somewhat", "Remained basically unchanged", "Eased somewhat", and "Eased considerably".[4]

[2]The residential sector includes both multifamily and one- to four-family residential development and construction, as outlined in the Comptroller's Handbook on CRE Lending 2.0 (March 2022).

[3]Board of Governors of the Federal Reserve System (U.S.), Delinquency Rate on CRE Loans (Excluding Farmland), Booked in Domestic Offices, All Commercial Banks [DRCRELEXFACBS], retrieved from FRED, Federal Reserve Bank of St. Louis, `https://fred.stlouisfed.org/series/DRCRELEXFACBS`, August 10, 2021.

[4]Starting from 2013 Q4, the questionnaire for domestic banks divides one question into three subquestions: 1. "Over the past three months, how have your bank's credit standards for approving new applications for construction and land development loans or credit lines changed?" 2. "Over the past three months, how have your bank's credit standards for approving new applications for loans secured by nonfarm nonresidential properties changed?" 3. "Over the past three months, how have your bank's credit standards for approving new applications for loans secured by multifamily residential properties changed?" Two table files compile responses from the SLOOS: "Table 1" for domestic banks and "Table 2" for foreign banks. We take the average number of responses indicating "Tightened considerably" or "Tightened somewhat" and the total number of responses from these three questions in both "Table 1" and "Table 2". Participating domestic banks account for approximately 60% of all loans by U.S. banks and about 70% of all U.S. bank business loans (Lown and Morgan 2006).

We calculate the $\Delta tighten$ variable as follows

$$\Delta tighten_t = \frac{m_t - n_t}{N_t}, \tag{3}$$

where the subscript t denotes the quarter, m_t represents the number of banks that selected either "Tightened considerably" or "Tightened somewhat", while n_t is the number of banks that choose "Eased somewhat" or "Eased considerably". N_t is the total number of banks participating in the survey. An increase in $\Delta tighten$ implies a tightening of funding liquidity or credit conditions, which suggests a decrease in the availability of funds for CRE investments in that particular quarter (Ling et al. 2016).

The variable $\Delta tighten$ is widely recognized and used in financial research as an indicator of funding liquidity or availability of credit. For instance, this funding liquidity metric has been linked to private equity returns (Franzoni et al. 2012), the leverage of private equity investments (Axelson et al. 2009), changes in commercial loans at banks (Lown and Morgan 2006), and has been used as a measure of loan supply by banks (Leary 2009). Note that both delinquency rates and funding liquidity are measured at the national level.

4.2 Price Index Real Returns and Market Liquidity

The price index returns and measures of market liquidity are sourced from Van Dijk et al. (2020). The individual transaction data to estimate the indices is provided by MSCI/RCA. The price index returns are obtained by a structural time series repeat sales model, and are available by MSA on a quarterly basis. Price index returns are shown as percentage changes in the transaction price index $P_{i,t}$. They are then deflated by the consumer price index to get real returns $r_{i,t}$.

The market liquidity measure $mliq$ is the difference between buyers' (P^b) and sellers' (P^s) reservation price indexes, as a percentage of the price index (P), given by

$$mliq_{i,t} = \frac{P^b_{i,t} - P^s_{i,t}}{P_{i,t}} \times 100, \tag{4}$$

where subscript i indicates an MSA. The buyers' and sellers' reservation price indexes P^b and P^s are estimated by the method of Van Dijk et al. (2020), which is based on a two-step Heckman selection model (Heckman 1979). First, a Probit model as a selection equation is used for the probability of sale. There is a sale only if the unobserved buyers' reserve price exceeds the unobserved sellers' reserve price. Second, the inverse Mills ratio is used as an additional regressor in the outcome equation, which, in this case, is a structural time series repeat sales model. Finally, from these estimation results, buyers' and sellers' log price indexes (in lower case, suppressing the dependence on MSAs) can be derived as $p_t^b = p_t + \hat{\gamma}_t \hat{\sigma}_t/2$ and $p_t^s = p_t - \hat{\gamma}_t \hat{\sigma}_t/2$, where $\hat{\gamma}_t$ are the coefficients of the time fixed effects in the selection equation, p_t is the log price index from the outcome equation, and $\hat{\sigma}_t^2$ is the estimate of the variance of the noise term in the outcome equation. More details can be found in Van Dijk et al. (2020).

The market liquidity measure *mliq* is closely related to other liquidity measures, such as time-on-market and the turnover ratio. A significant advantage of the liquidity measures used is that they do not require any additional information beyond that used to calculate the price index. An additional advantage is that these can be calculated at a disaggregated level per MSA per quarter.

4.3 Control Variables

In our analysis, we include three control variables to account for broader financial market conditions that may affect CRE market dynamics. These variables are the term spread and default spread, as well as the equity market excess return, measured at the national level, see Table 1.

The term spread ts is calculated as the difference between the yields of 10-year Treasury bonds and 3-month Treasury bills. It serves as an indicator of the yield curve's slope, providing insights into long-term versus short-term interest rate expectations and economic outlooks. The default spread ds is measured by the yield difference between BAA-rated and AAA-rated corporate bonds. Default spreads act as a proxy for the market's price of default risk, with wider spreads indicating higher perceived risk, which can affect market liquidity and investment behavior in CRE. The Treasury bill yield, term and default spreads are considered indicators related to the business cycle (Fama and French 1989, Avramov and Chordia 2006). They are frequently used in CRE pricing models to account for economic influences on real estate values (Ling and Naranjo 1999, Peng 2016).

The inclusion of equity market excess returns $r_t^m - r_t^f$ is based on the understanding that equity market conditions can significantly influence private equity returns, as highlighted in studies like Franzoni et al. (2012).

4.4 Descriptive Statistics

Figure 2 shows quarterly time series from 2005 to 2018 using eight panels (A-H). Each panel highlights a key aspect of the CRE market dynamics. The shaded area indicates a recession period.

Panel A shows that between 2006Q4 and 2010Q1, the delinquency rate (*deli*) increased from around 1% to 9%, reflecting aggressive lending practices for CRE loans during the earlier period. Panel B shows that from 2006Q2 to 2010Q1, the change in delinquency rates ($\Delta deli$) consistently increased. In particular, $\Delta deli$ rose sharply from 0.2% in 2007Q4 to 1.3% in 2009Q4, reflecting a growing volume of distressed loans during the Global Financial Crisis. This aligns with the findings of Downs and Xu (2015), which report historically high default and delinquency rates for commercial mortgages due to the Global Financial Crisis.

Panel C shows that banks tightened their lending standards for CRE loans ($\Delta tighten$) between 2006Q1 and 2010Q1, a period that also witnessed rising delinquency rates. This is in line with Lown and Morgan (2006), who suggest that considerate tightening of funding liquidity is typically associated with a recession and an increase in delinquency rates.[5]

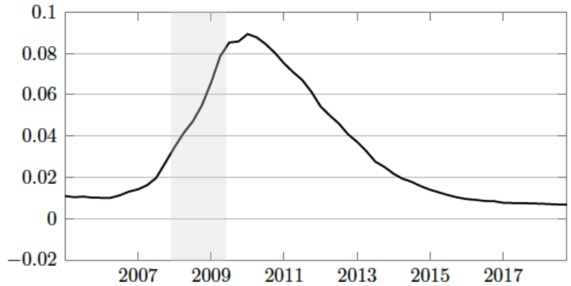
Panel D shows that the average amount of CRE loans in commercial banks steadily increased from 1,106 billion U.S. dollars in 2005Q1 to 1,725 billion U.S. dollars in 2008Q4. The contraction of CRE loans from 2009 to 2012 coincides with relatively high delinquency rates. The volume of CRE loans generally decreases when delinquency rates are high. During this period, banks gradually reduced their holdings of CRE loans, preceded by a tightening of lending standards on CRE loans.

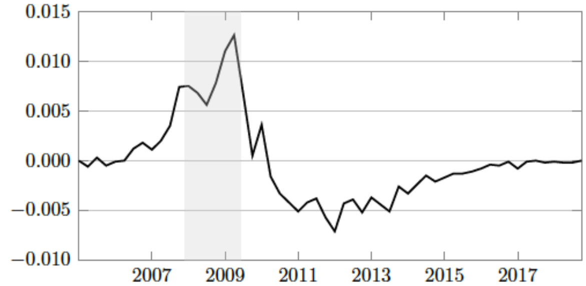
Panel E shows the nominal CRE repeat sale price index (P), averaged over MSAs. During the Global Financial Crisis, the price index experienced a significant decline from 2007Q3 to 2009Q4. This was followed by a stable period, with the index remaining around 100 until 2012, after which it rose rapidly to around 165 by 2018.

Panel F depicts the median CRE mortgage interest rate, averaged over MSAs. Mortgage interest rates fell from a fluctuating 6% in 2007 to 4% in 2013, in line with $\Delta tighten$.

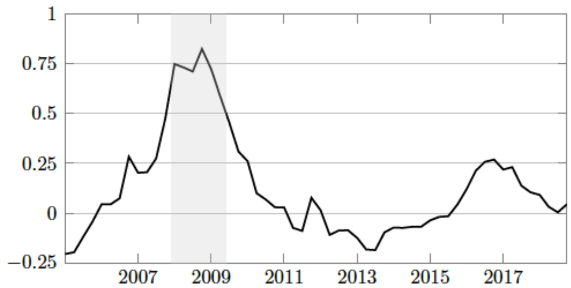
Panel G shows the market liquidity *mliq*, averaged over MSAs. Market liquidity experienced a sharp decline from 8.1 in 2007Q2 to -35.2 in 2009Q3, before gradually bouncing back to almost 12.9 in 2015Q4, where it then stabilized around 10.4. The time series of market liquidity *mliq* and the change in funding liquidity $\Delta tighten$ indicate that both market

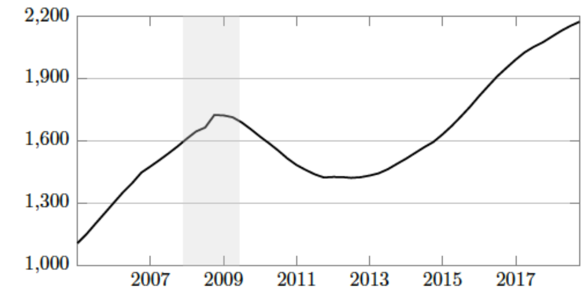
[5] One possible reason for banks' reluctance to lend during the 2008 financial crisis is that many borrowers were not creditworthy, making such loans a negative NPV investment. Additionally, due to debt overhang, banks find it challenging to raise the capital necessary to issue positive NPV loans (Berk and DeMarzo 2020).



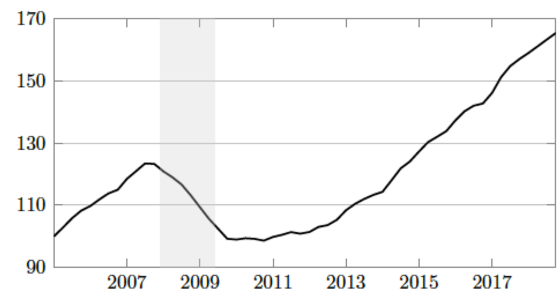


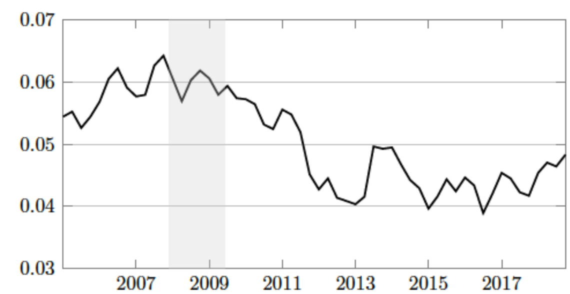
(A) $deli$ (B) $\Delta deli$



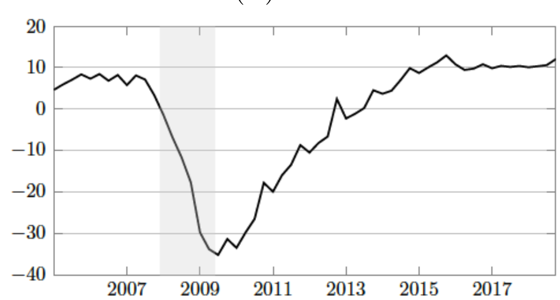


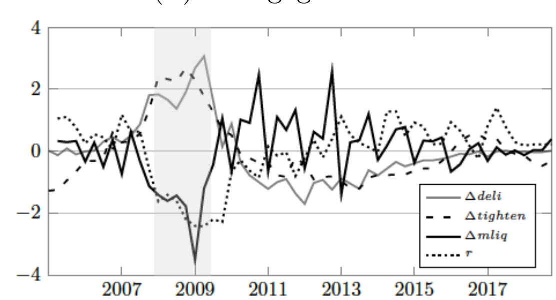
(C) $\Delta tighten$ (D) Average of CRE loans, in billions





(E) P (F) Mortgage rate





(G) $mliq$ (H) Standardized endogenous variables

Figure 2. Quarterly commercial real estate data: 2005–2018

Panel A, $deli$: The delinquency rate on CRE loans. Panel B, $\Delta deli$: The change in delinquency rates on CRE loans. Panel C, $\Delta tighten$: The change in funding liquidity. Panel D, Average of CRE Loans: The average of CRE loans (seasonally adjusted, in billions), all commercial banks. Panel E, P: The nominal sale price index at the MSA level, averaged across 25 MSAs. Panel F, mortgage rate: The median mortgage interest rate, averaged across 25 MSAs. Source: RCA. Panel G, $mliq$: The market liquidity, averaged across 25 MSAs. Panel H, $\Delta deli$, $\Delta tighten$, $\Delta mliq$ and r, standardized. The shaded area indicates a recession period. Source: FRED.

and funding liquidity dried up during the subprime mortgage crisis.

Finally, panel H provides a direct comparison of the dynamics of four standardized endogenous variables. Panel H presents standardized aggregate time series of the four endogenous variables, averaged across MSAs. While not formally identifying causal relationships, the figure illustrates differences in the timing and volatility of these variables at the national level. Specifically, $\Delta deli$ tends to display earlier and sharper fluctuations during the crisis period, followed by $\Delta tighten$ and $\Delta mliq$, while r moves more gradually. These observed patterns inform the ordering used in the Cholesky decomposition. Nevertheless, this ordering is only a baseline based on market-wide dynamics and may not reflect regional heterogeneity across MSAs.

Table 2. Descriptive statistics

	N	Mean	Median	Min	Max	Std.Dev.
r	$1,375$	0.0044	0.0053	-0.1294	0.1186	0.0321
$\tilde{r}$	$1,375$	0	-0.0009	-0.1230	0.1205	0.0266
$mliq$	$1,375$	-1.5550	3.5180	-52.2400	27.4300	15.0900
$\Delta mliq$	$1,375$	0.1347	0.3166	-24.2900	18.9100	4.8020
$\widetilde{\Delta mliq}$	$1,375$	0	-0.0215	-14.0771	13.2052	3.3470
$deli$	55	0.0327	0.0194	0.0070	0.0893	0.0276
$\Delta deli$	55	-0.000075	-0.0005	-0.0071	0.0126	0.0042
$\Delta tighten$	55	0.1327	0.0449	-0.1970	0.8261	0.2588
ts	55	0.0081	0.0014	-0.0600	0.1120	0.0362
ds	55	0.0111	0.0096	0.0056	0.0337	0.0049
$r^m - r^f$	55	0.0199	0.0315	-0.2223	0.1640	0.0768

Notes: Our sample covers the period from 2005Q2 to 2018Q4 in 25 MSAs. Because of the first differencing, we lose the observations in 2005Q1. Table 1 provides the descriptions of the variables. $\tilde{r}_{it}$ is defined as $r_{it} - \bar{r}_{.t}$ and $\widetilde{\Delta mliq}_{it}$ as $\Delta mliq_{it} - \overline{\Delta mliq}_{.t}$.

Table 2 provides descriptive statistics for the main variables over the period from 2005Q2 to 2018Q4. The sample includes 1,375 observations, 55 quarters times 25 MSAs. The quarterly price index real returns r range from -12.9% to 11.9%, with an average of 0.44%. The change in market liquidity metric, $\Delta mliq$, is on average close to zero, and varies between -24.3 and 18.9. There is substantial variation in real returns between MSAs; the real returns in deviation from their time series means ($\tilde{r} = r_{it} - \bar{r}_{.t}$) vary between -0.123 to 0.120 with a standard deviation of 0.027. The same holds for change in market liquidity metrics in deviation from their time series means ($\widetilde{\Delta mliq}_{it} = \Delta mliq_{it} - \overline{\Delta mliq}_{.t}$), they vary between -14.1 and 13.2. See also Figures 3 and 4. The variables $deli$ and $\Delta tighten$ have an average of 0.0327 and 0.1327, with a standard deviation of 0.0276 and 0.2588, respectively.

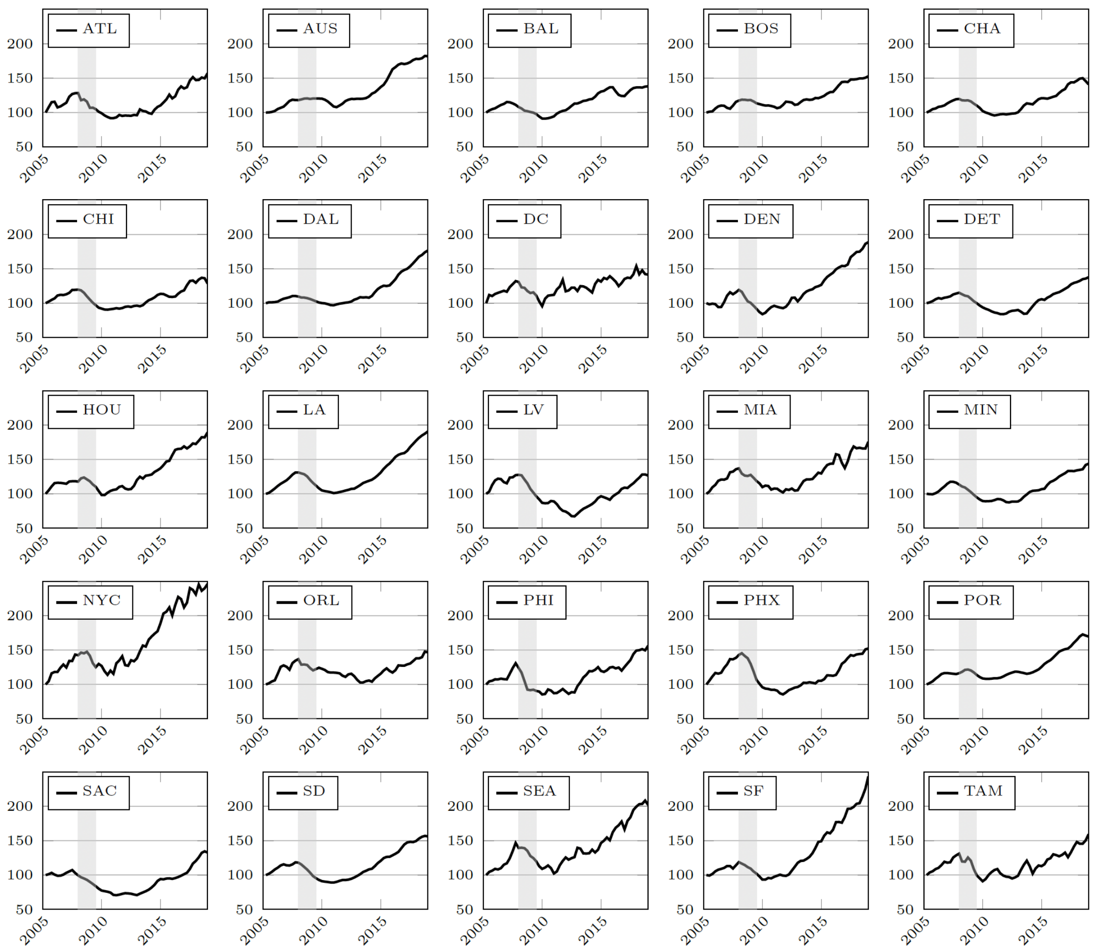


Figure 3. Nominal sale price indice (P) for 25 MSAs: 2005–2018

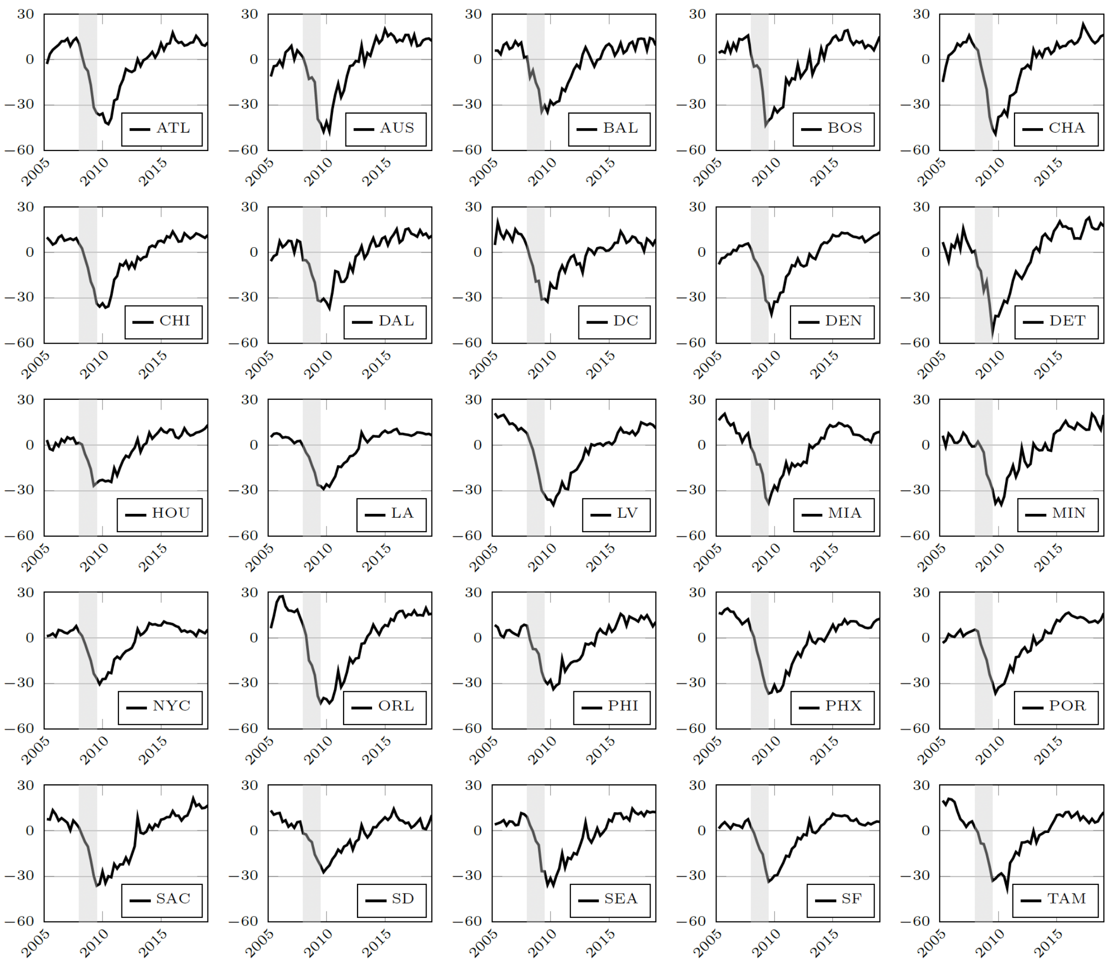


Figure 4. Market liquidity metric (*mliq*) for 25 MSAs: 2005-2018

Before estimating the PVAR-model, we test whether the endogenous variables are stationary. Appendix Table A.1 presents the results of three types of unit root tests, where the null hypothesis indicates non-stationarity. Market liquidity, real returns and the control variables are found to be stationary according to all three tests. The change in funding liquidity ($\Delta tighten$) is found to be non-stationary in the ADF test, but the Madalla-Wu and Im-Pesaran-Shin tests indicate stationarity. Changes in delinquency rates ($\Delta deli$) are found to be non-stationary in all three tests. However, we still include this variable in our model as the variable (both in levels and differences) has lower and upper bounds in practice, making non-stationarity less likely. Furthermore, even if some variables exhibit unit roots, the model remains suitable for dynamic analysis as long as the eigenvalue analysis confirms system stability.[6] To capture broader interactions, we will perform impulse response analysis in the next section.

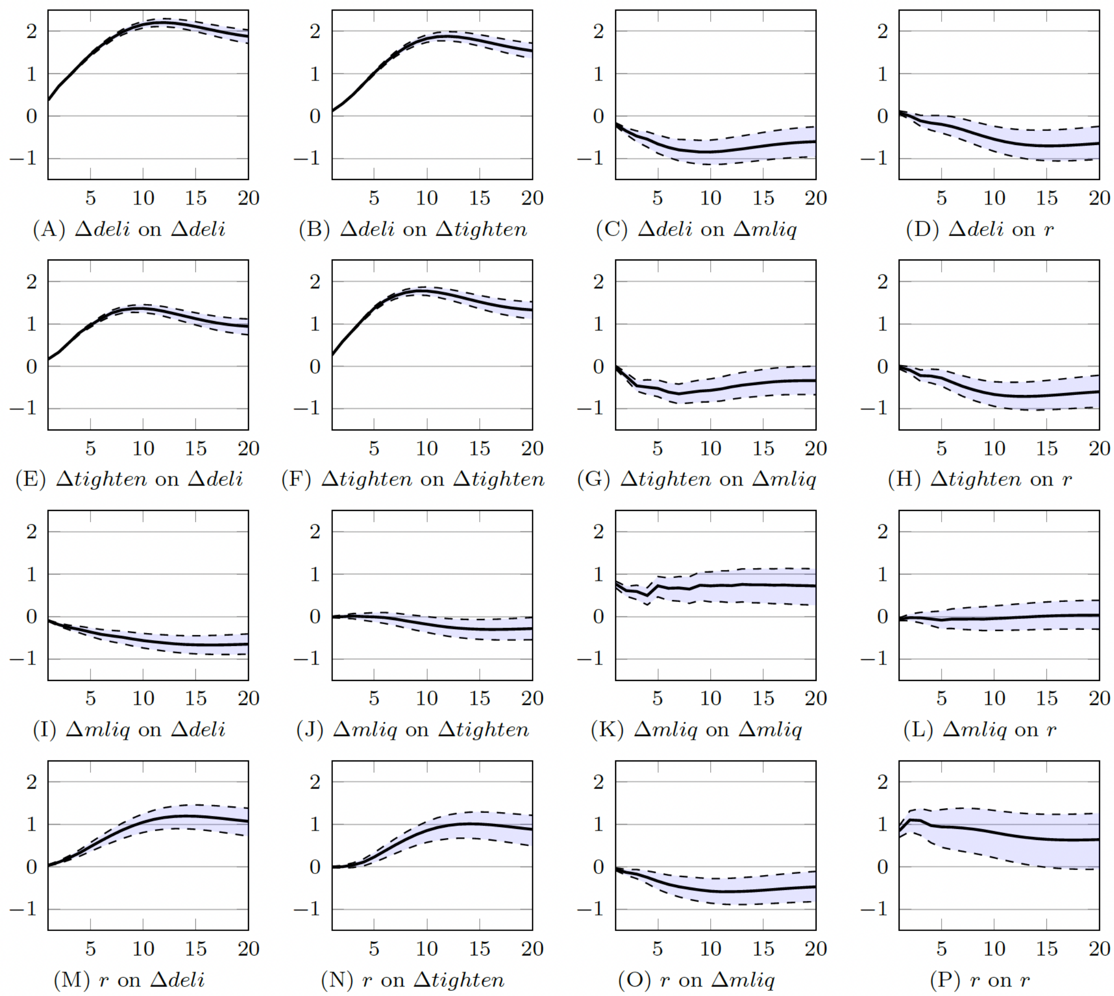
5 Empirical Results

The discussion of the empirical results will focus on the cumulative generalized impulse response functions in Section 5.1 and the forecast error variance decomposition in Section 5.2. Full coefficient estimation results are provided in Appendix Table A.2. Our PVAR-model has an optimal lag length of four and the estimation results are stable and show no evidence of overidentification problems, see Section 3.2.

5.1 Cumulative Generalized Impulse Response Functions

We estimate generalized impulse response functions (GIRFs) to examine how our endogenous variables respond after receiving an isolated unit shock to a specific variable. Figure 5 presents cumulative GIRFs for $y_{i,t} = (\Delta deli_t, \Delta tighten_t, \Delta mliq_{i,t}, r_{i,t})'$. Each solid line indicates the estimated changes in the response variable, and the shaded curves give the 95% confidence interval generated by 1,000 bootstrap replications. Because all variables are standardized, the vertical axis in each panel indicates the cumulative standard deviation change in the values of the response variable when the impulse variable is shocked by one standard deviation, which makes interpreting the economic significance of the results easier. We will discuss the GIRFs pairwise. Table 3 summarizes the results.

[6] If the PVAR system passes the eigenvalue test (all roots have moduli less than 1), unit root testing of individual variables is no longer necessary because the VAR model aims to analyze the relationship between variables instead of parameter estimation.



(A) $\Delta deli$ on $\Delta deli$ (B) $\Delta deli$ on $\Delta tighten$ (C) $\Delta deli$ on $\Delta mliq$ (D) $\Delta deli$ on r

(E) $\Delta tighten$ on $\Delta deli$ (F) $\Delta tighten$ on $\Delta tighten$ (G) $\Delta tighten$ on $\Delta mliq$ (H) $\Delta tighten$ on r

(I) $\Delta mliq$ on $\Delta deli$ (J) $\Delta mliq$ on $\Delta tighten$ (K) $\Delta mliq$ on $\Delta mliq$ (L) $\Delta mliq$ on r

(M) r on $\Delta deli$ (N) r on $\Delta tighten$ (O) r on $\Delta mliq$ (P) r on r

Figure 5. Cumulative generalized IRF for $y_{i,t} = (\Delta deli_t, \Delta tighten_t, \Delta mliq_{i,t}, r_{i,t})'$

Cumulative generalized impulse response functions. Shaded areas are 95% confidence intervals. Standard errors from re-sampling simulation with 1,000 repetitions. This GIRF corresponds to the estimates given in Table A.2.

Table 3. Summary of cumulative GIRF results

Pairs	Feedback channel	Effect
1	$\Delta deli \rightarrow \Delta tighten$	+
	$\Delta tighten \rightarrow \Delta deli$	+
2	$\Delta tighten \rightarrow \Delta mliq$	−
	$\Delta mliq \rightarrow \Delta tighten$	−
3	$\Delta mliq \rightarrow r$	(+)
	$r \rightarrow \Delta mliq$	−
4	$r \rightarrow \Delta deli$	+
	$\Delta deli \rightarrow r$	−
5	$r \rightarrow \Delta tighten$	+
	$\Delta tighten \rightarrow r$	−
6	$\Delta deli \rightarrow \Delta mliq$	−
	$\Delta mliq \rightarrow \Delta deli$	−

Notes: The cumulative generalized impulse response functions (GIRFs) are provided in Figure 5. + indicates a positive effect, while − denotes a negative effect. (+) suggests a positive but statistically insignificant relationship.

Panels B and E present the interactions between the change in delinquency rates $\Delta deli$ and the change in funding liquidity $\Delta tighten$. Panel B shows that a one standard deviation shock of $\Delta deli$ (0.0042) results in a cumulative change in $\Delta tighten$ of 1.8 times its standard deviation (0.2588) after ten quarters. In line with Hancock and Wilcox (1994, 1997), and Black et al. (2020), this suggests that banks reduce their lending in response to a shock in capital losses. Panel E shows that a one standard deviation shock of $\Delta tighten$ results in a cumulative increase in $\Delta deli$ of 1.4 times its standard deviation after ten quarters, which is consistent with previous research (An and Sanders 2010, Ghosh 2018). This positive effect can have several causes. Tighter funding liquidity may reflect the heightened concern about future credit risk, thus leading to higher expected delinquency rates. In addition, stricter financing requirements make restructuring the loans more difficult, potentially increasing delinquency rates. More lax lending standards may allow borrowers to refinance their existing higher-rate loan into a lower-rate obligation, contributing to lower delinquency rates. On the other hand, tighter funding liquidity could lead to fewer delinquencies as new loans become safer. These first two causes seem to outweigh the last one.

Panels G and J show that shocks to the change in funding liquidity $\Delta tighten$ and the change in market liquidity $\Delta mliq$ are mutually reinforcing, consistent with results from Brunnermeier and Pedersen (2009) for the stock market. A one standard deviation shock of $\Delta tighten$ (0.2588) leads to a cumulative decrease in $\Delta mliq$ of about 0.5 times its standard deviation (4.8020) after three quarters. This is consistent with the finding of Wiley (2017) that relaxing bank lending standards increases market liquidity in the private CRE market. In turn, a one standard deviation shock of $\Delta mliq$ leads to a cumulative decline in $\Delta tighten$ of about 0.2 times its standard deviation after ten quarters.

Panels L and O present the interactions between the change in market liquidity $\Delta mliq$ and real returns r. Panel L reveals that a shock of r does not result in a statistically significant change of $\Delta mliq$, as the confidence intervals include zero at all points in time. Panel O shows that a one standard deviation shock of r (0.0321) leads to a cumulative decrease in $\Delta mliq$ of about 0.55 times its standard deviation (4.8020) after ten quarters. Fisher et al. (2003), Ling et al. (2009), and Bokhari and Geltner (2011) suggest the procyclical behavior of prices and liquidity that is not visible in our model controlling for the delinquency rate and funding liquidity. A possible explanation is that the procyclical effect documented in the aforementioned papers is fully captured by the funding liquidity measure instead (see previous and next paragraphs).

Panels H and N present the interactions between the change in funding liquidity $\Delta tighten$ and the real return on the price index r. In Panel H, a one standard deviation shock of $\Delta tighten$ (0.2588) leads to a cumulative decrease in r of 0.7 times its standard deviation (0.0321) in the tenth quarter. Panel N shows that a one standard deviation shock of the real index return r leads to a cumulative increase in $\Delta tighten$ by one standard deviation in the twelfth quarter.

Panels C and I present the interactions between the change in delinquency rates $\Delta deli$ and the change in market liquidity $\Delta mliq$. Panel C shows that a one standard deviation shock of $\Delta deli$ (0.0042) leads to a cumulative decline in $\Delta mliq$ of 0.8 times its standard deviation (4.8020) after eight quarters. Panel I shows that a one standard deviation shock of $\Delta mliq$ leads to a slight cumulative decline in $\Delta deli$ of 0.55 times its standard deviation after ten quarters. An explanation could be that in a more liquid market, delinquent properties are more likely to be sold before they actually default and go into foreclosure. Similar results have been found for firm default risk in the equity market (Brogaard et al. 2017, Nadarajah et al. 2021) and bond market (He and Xiong 2012, Chaumont 2020).

Panels D and M present the interactions between the change in delinquency rates $\Delta deli$ and the real return on the price index r. In Panel D, a one standard deviation shock of $\Delta deli$ (0.0042) leads to a cumulative decrease in r of 0.7 times its standard deviation (0.0321) in the thirteenth quarter. Increases in delinquency rates could lead to foreclosures and fire sales, depressing transaction prices (Calomiris et al. 2013). Panel M shows that a one standard deviation shock of the real index return r (0.0321) leads to a cumulative increase in $\Delta deli$ by 1.2 times its standard deviation (0.0042) in the twelfth quarter. One explanation could be that in booming markets, banks' expectations of high payouts and high property prices result in lax lending standards with more risky loans with a corresponding future risk of default (Mian and Sufi 2009), and a price shock of commercial real estate can be followed by a turning point (Zhou and Sornette 2006) with subsequent high delinquency rates and a severe tightening of funding liquidity (see also Panel N).

In conclusion, first, shocks in the change in delinquency rates and tighter funding liquidity negatively affect the change in market liquidity and asset price index returns (Panels C, D, G, and H). Our findings contribute to the evidence that funding liquidity is an important determinant of CRE asset prices (Brown 2000, Ling et al. 2016, Wiley 2017). Second, we find that an increase in delinquency rates leads to a tightening of funding liquidity (Panel B). Third, we find evidence that changes in funding liquidity and market liquidity are mutually reinforcing, in line with Brunnermeier and Pedersen (2009) for the financial market (Panels G and J). Fourth, shocks in price index real returns lead to an increase in the change of delinquency rate and a tightening of funding liquidity (Panels M and N).

5.2 Forecast Error Variance Decomposition

We perform a forecast error variance decomposition (FEVD) to describe the dynamics of the endogenous variables. The FEVD is based on the orthogonalized impulse response functions (OIRFs). We use the following Cholesky ordering: $\Delta deli, \Delta tighten, \Delta mliq, r$. Further on, we discuss the results from an alternative ordering. Table 4 presents the FEVD for various forecast horizons, for 1–4, 8, and 12 quarters.

As expected, for shorter forecast horizons, most of the variation in a variable comes from shocks to the variable itself. For longer horizons, the weights of other variables increase gradually. Note that the impact of shocks to the market liquidity $\Delta mliq$ on the variation of other variables is negligible for all forecast horizons.

Panel (a) shows the FEVD for the response of delinquency rates $\Delta deli$. For forecast horizons from 4 quarters onward, about 8% of the variation in $\Delta deli$ stems from shocks to the change in funding liquidity $\Delta tighten$. The impact of shocks to the real return on the price index r on the variation in $\Delta deli$ increases with the length of the forecast horizon, to 14% for a 12-quarter horizon.

Panel (b) shows the FEVD for the change in funding liquidity $\Delta tighten$. For a 1-quarter forecast horizon, 20% of the variation in $\Delta tighten$ is from shocks to the change in delinquency

Table 4. FEVD for $y_{i,t} = (\Delta deli_t, \Delta tighten_t, \Delta mliq_{i,t}, r_{i,t})'$

Response quarter	$\Delta deli$	$\Delta tighten$	$\Delta mliq$	r
(a) $\Delta deli$				
1	1	0	0	0
2	0.9901	0.0014	0.0008	0.0077
3	0.9140	0.0548	0.0013	0.0299
4	0.8677	0.0823	0.0011	0.0489
8	0.8053	0.0744	0.0009	0.1195
12	0.7799	0.0788	0.0023	0.1390
(b) $\Delta tighten$				
1	0.2026	0.7974	0	0
2	0.2545	0.7402	0.0044	0.0009
3	0.3456	0.6350	0.0139	0.0055
4	0.4275	0.5442	0.0140	0.0143
8	0.5380	0.3501	0.0140	0.0978
12	0.5279	0.3337	0.0149	0.1235
(c) $\Delta mliq$				
1	0.0649	0.0081	0.9269	0
2	0.0921	0.0429	0.8557	0.0093
3	0.1052	0.0887	0.7946	0.0115
4	0.1085	0.0858	0.7870	0.0187
8	0.1241	0.0843	0.7579	0.0338
12	0.1237	0.0887	0.7527	0.0350
(d) r				
1	0.0087	0.0052	0.0021	0.9840
2	0.0154	0.0068	0.0025	0.9753
3	0.0309	0.0156	0.0033	0.9502
4	0.0333	0.0155	0.0054	0.9457
8	0.0495	0.0334	0.0075	0.9095
12	0.0662	0.0342	0.0079	0.8917

Notes: The forecast error variance decomposition corresponds to the estimates given in Table A.2.

rate $\Delta deli$. This percentage increases to 53% for a 12-quarter horizon. The change in delinquency rates $\Delta deli$ is thus essential for forecasting the change in funding liquidity $\Delta tighten$. The impact of shocks to the real return on the price index r on the variation in $\Delta deli$ increases with the length of the forecast horizon, from 0.1% for a 1-quarter to 12% for a 12-quarter forecast horizon.

Panel (c) shows the FEVD for the change in market liquidity $\Delta mliq$. Shocks in the change in delinquency rate $\Delta deli$ and the change in funding liquidity $\Delta tighten$ contribute to 12% and 9% of the variation in $\Delta mliq$ for a 12-quarter forecast horizon, respectively. The impact of shocks to the real return on the price index r on the variation in $\Delta mliq$ for the same horizon is rather small, 4%.

Panel (d) shows the FEVD for the real return on the price index r. Shocks to the change in delinquency rate $\Delta deli$ and the change in funding liquidity $\Delta tighten$ contribute marginally to the variation in r for a 12-quarter forecast horizon, 7% and 3%, respectively.

The FEVD results change when the endogenous variables are ordered as $\Delta tighten$, $\Delta deli$, $\Delta mliq$, and r, see Appendix Table A.3. The main difference can be observed in the contribution of shocks to the change in delinquency rate $\Delta deli$ to the FEVD of the change in funding liquidity $\Delta tighten$ in Panel (b). While the contribution is still significant at 35% for a 12-quarter forecast horizon, it is significantly smaller compared to the main results (53%). This suggests that $\Delta deli$ is reasonably ordered before $\Delta tighten$, as delinquency rates have a more significant impact on funding liquidity than vice versa.

6 Conclusions

To our knowledge, this study is the first to analyze the dynamic interactions among delinquency rates, funding and market liquidity, and asset price index returns in regional CRE markets in the U.S. We find that an increase in banks' delinquency rates on CRE loans leads to a tightening of bank lending standards, consistent with previous findings (Hancock and Wilcox 1994, 1997, Black et al. 2020). In turn, a tightening of bank lending standards leads to an increase in delinquency rates, consistent with earlier literature (e.g., Seslen and Wheaton (2010), An and Sanders (2010), Ghosh (2015), Gaudêncio et al. (2019)) that uses lending standards-related metrics. This result underscores the importance of funding conditions for financial stability and the performance of CRE markets. Our findings also confirm that a tightening of bank lending standards contributes to a decrease in price index returns and market liquidity. This finding is consistent with Ling et al. (2016), Wiley (2017) that the prices of illiquid private CRE properties respond positively to looser lending standards. Moreover, we find that rising prices lead to higher delinquency rates, tighter funding liquidity and a decline in market liquidity. In addition, our paper is also the first to show that a sustained decline in market liquidity can lead to an increase in delinquency rates in private CRE markets.

We add empirical evidence from the CRE market to the conclusion from Brunnermeier and Pedersen (2009) that funding and market liquidity are mutually reinforcing. Our findings suggest that looser financing conditions can increase market liquidity, facilitating transactions. Conversely, increased market liquidity can encourage a loosening of credit conditions.

Our findings could provide guidance to policymakers and CRE loan lenders in the context of persistent booms associated with high prices in the CRE market, which could be due to lax lending standards in the past with risky loans. Banks could be aware of the results of changing lending standards under different market conditions. On one hand, if the market is overheated, tighter funding liquidity can help lenders filter out low-quality investments, further reducing delinquency rates in the future. On the other hand, more lax lending standards in a down market can help restructure and refinance financially distressed loans of borrowers, which can prevent a further decline in delinquency rates. Our suggestion is that bank or policymaker decisions on lending standards should depend largely on the prevailing market status, as reflected in transaction price levels. Loan standards should ideally be counter-cyclical, meaning that they should be stricter during boom periods to prevent excessive risk-taking and more lenient during downturns to support the market and prevent a credit crunch.

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A Additional Tables

Table A.1. Panel unit root test results

	$\Delta deli$	$\Delta tighten$	$\Delta mliq$	r	ts	ds	$r^m - r^f$
ADF	−1.89	−2.53			−4.21***	−3.30*	−3.50**
MW	0.09	73.52**	686.45***	371.70***	1264***	263.67***	771.76***
IPS	12.22	−3.53***	−20.3***	−13.89***	−34.62***	−11.65***	−25.22***

Notes: This table presents unit root results where the null hypothesis is non-stationarity. The Augmented Dickey-Fuller test (ADF) is used for individual time-series ($\Delta deli$, $\Delta tighten$, ts, ds, and $r_t^m - r_t^f$). Maddala-Wu (MW) and Im-Pesaran-Shin (IPS) statistics are used to test the panel data ($\Delta deli$, $\Delta tighten$, $\Delta mliq$, r, ts, ds, and $r^m - r^f$). *p<0.1; **p<0.05; ***p<0.01.

Table A.2. PVAR estimation results for $y_{i,t} = (\Delta deli_t, \Delta tighten_t, \Delta mliq_{i,t}, r_{i,t})'$

	$\Delta deli_t$	$\Delta tighten_t$	$\Delta mliq_t$	r_t
$\Delta deli_{t-1}$	0.8113***	0.1182***	−0.3351***	−0.2120***
	(0.0111)	(0.0090)	(0.0609)	(0.0496)
$\Delta tighten_{t-1}$	0.0960***	1.1066***	−0.6030***	−0.1053
	(0.0133)	(0.0109)	(0.0850)	(0.0886)
$\Delta mliq_{t-1}$	−0.0163	0.0382***	−0.2602***	0.0471*
	(0.0120)	(0.0103)	(0.0238)	(0.0276)
r_{t-1}	0.0524***	0.0144**	−0.0944***	0.3116***
	(0.0080)	(0.0069)	(0.0248)	(0.0820)
$\Delta deli_{t-2}$	−0.2332***	0.1305***	0.1544*	0.0609
	(0.0104)	(0.0073)	(0.0835)	(0.0587)
$\Delta tighten_{t-2}$	0.4104***	−0.4060***	−0.2608**	−0.1551
	(0.0162)	(0.0145)	(0.1262)	(0.1181)
$\Delta mliq_{t-2}$	−0.0127	0.0434***	−0.0971***	−0.0388
	(0.0151)	(0.0100)	(0.0309)	(0.0325)
r_{t-2}	0.0458***	0.0196***	−0.0239	−0.0931**
	(0.0119)	(0.0062)	(0.0220)	(0.0432)
$\Delta deli_{t-3}$	0.2492***	−0.0140	−0.0861	−0.0217
	(0.0125)	(0.0092)	(0.0977)	(0.0816)
$\Delta tighten_{t-3}$	−0.4163***	0.2768***	0.6875***	0.5332***
	(0.0166)	(0.0112)	(0.1282)	(0.1391)
$\Delta mliq_{t-3}$	−0.0049	0.0052	−0.1524***	−0.0451*
	(0.0129)	(0.0060)	(0.0303)	(0.0260)
r_{t-3}	0.0241***	0.0116*	−0.0495**	−0.0781***
	(0.0086)	(0.0067)	(0.0205)	(0.0257)
$\Delta deli_{t-4}$	−0.1021***	0.0212***	0.1414*	0.0803
	(0.0077)	(0.0058)	(0.0832)	(0.0528)
$\Delta tighten_{t-4}$	0.0362**	−0.2832***	−0.1634**	−0.5528***
	(0.0164)	(0.0088)	(0.0784)	(0.0696)
$\Delta mliq_{t-4}$	−0.0279**	0.0392***	0.2134***	−0.0347
	(0.0113)	(0.0080)	(0.0307)	(0.0298)
r_{t-4}	0.0394***	0.0390***	−0.0468*	0.0518
	(0.0111)	(0.0095)	(0.0274)	(0.0366)
ts_t	0.0004	0.0820***	−0.0571**	0.0440
	(0.0041)	(0.0039)	(0.0262)	(0.0347)
ds_t	0.1308***	0.0876***	−0.2989***	−0.0992***
	(0.0060)	(0.0049)	(0.0268)	(0.0377)
$r_t^m - r_t^f$	−0.0121***	0.0394***	−0.1028***	−0.0291
	(0.0040)	(0.0042)	(0.0328)	(0.0466)
Constant	−0.0130***	0.0097***	0.0165	−0.0121
	(0.0032)	(0.0019)	(0.0115)	(0.0196)

Notes: Estimation results from Eq. (2) are based on 1,250 observations in $N = 25$ MSAs for $T = 50$ quarters from 2005Q2 to 2018Q4. The raw data contains 56 quarters. We lose 6 quarters because of the calculation of returns, the FOD transformation, and 4 lags of the dependent variable. The model is estimated by a one-step system GMM with collapsed instruments. The model satisfies the PVAR stability condition. Moreover, the Hansen J-statistic indicates exact identification ($\chi^2 = 734.0$ with p-value = 0.955). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.3. FEVD for $y_{i,t} = (\Delta tighten_t, \Delta deli_t, \Delta mliq_{i,t}, r_{i,t})'$

Response quarter	$\Delta tighten$	$\Delta deli$	$\Delta mliq$	r
(a) $\Delta tighten$				
1	1	0	0	0
2	0.9882	0.0065	0.0044	0.0009
3	0.9345	0.0461	0.0139	0.0055
4	0.8784	0.0933	0.0140	0.0143
8	0.6676	0.2205	0.0140	0.0978
12	0.6190	0.2425	0.0149	0.1235
(b) $\Delta deli$				
1	0.2026	0.7974	0	0
2	0.2209	0.7705	0.0008	0.0077
3	0.3220	0.6468	0.0013	0.0299
4	0.3765	0.5735	0.0011	0.0489
8	0.3640	0.5157	0.0009	0.1195
12	0.3456	0.5131	0.0023	0.1390
(c) $\Delta mliq$				
1	0.0012	0.0719	0.9269	0
2	0.0657	0.0693	0.8557	0.0093
3	0.1290	0.0649	0.7946	0.0115
4	0.1261	0.0683	0.7870	0.0187
8	0.1254	0.0829	0.7579	0.0338
12	0.1288	0.0836	0.7527	0.0350
(d) r				
1	0.0005	0.0134	0.0021	0.9840
2	0.0068	0.0153	0.0025	0.9753
3	0.0267	0.0198	0.0033	0.9502
4	0.0263	0.0226	0.0054	0.9457
8	0.0570	0.0260	0.0075	0.9095
12	0.0639	0.0366	0.0079	0.8917

Notes: Each panel reports the decomposition of the variance of the forecast error of the series in the panel heading. Figures within the panel are the fractions of the variance at each column attributable to the variable in each panel. Estimation results of Eq. (2), based on 1,250 observations in $N = 25$ MSAs for $T = 50$ quarters from 2005Q2 to 2018Q4. The model includes 4 lags of the dependent variable.

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