Worth the Risk? The Performance of Banks Reliant on CLO Funding

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Abstract

We study the effect of bank reliance on CLO funding on bank risk. We document that an exogenous increase in CLO funding significantly decreases bank expected default frequency, with a 1.6% reduction one quarter from the shock for the average bank in response to a standard funding shock. Changes in asset composition and income origination help explain this result. Upon an expansion in CLO funding, banks increase the origination of institutional business loans, fostering origination fees and net noninterest income. Banks also market a large share of the loans they participate in, decreasing the proportion of loans they hold on their balance sheets despite the rise in origination. The performance of the loans they retain on their balance sheets also improves, further strengthening bank conditions. Our results contribute to the literature on bank risk management and the increasing role the shadow banking system plays in funding banks and business lending, carrying relevant implications for the bank regulatory process.

Keywords: CLOs, institutional loans, institutional investors, bank risk, bank performance.

JEL Classification: G21, G23, G32.

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1 Introduction

By mid 2021, the roughly $800 billion of outstanding U.S. collateralized loan obligations (CLOs) represented close to one-third of all commercial and industrial (C&I) loans outstanding in the United States.[1] This was the result of a meteoric raise starting in the 1990s, only temporarily halted by the events of the 2007-2009 financial crisis, and arguably a reflection of the ever-growing shadow banking system and the originate-to-distribute (OTD) modern model of banking. This progressive raise of CLOs has spurred a nascent strand of the literature that studies how CLOs affect economic outcomes. We contribute to this literature by documenting the causal effect of CLO funding on bank performance, with a specific focus on bank riskiness.

The primary motivation for our study is the premise that reliance on CLOs may help banks improve their performance and reduce their riskiness by optimizing the use of resources to support credit origination and manage the related credit risks. Anecdotal evidence suggests that this is actually part of the reasons why banks rely on CLOs. For instance, JPMorgan Chase & Co.'s 2020 Form 10-K states: *"Management of the Firm's wholesale credit risk exposure is accomplished through a number of means, including: [l]oan underwriting and credit approval process, [l]oan syndications and participations, [l]oan sales and securitizations..."*

In light of current work on bank risk management studying the effects of securitization on bank performance, however, it is ex ante unclear whether CLO funding would ultimately alleviate or worsen bank riskiness. Firstly, there is the issue of incentives and lending standards, which suggests that banks face conflicting interests when they can sell loans they originate, and can as a result lower their efforts to screen and/or monitor their credits.

For example, the literature on mortgage backed securities clearly documents the detrimental effects that securitization had on lending standards before the financial crisis (e.g., Mian and Sufi, 2009; Keys, Mukherjee, Seru, and Vig, 2010; Nadauld and Sherlund, 2013).

[1] As calculated comparing estimates of outstanding CLOs reported by Bloomberg (for instance in two recent articles on May 28 and July 8, 2021) and data on total C&I loans provided by the Board of Governors of the Federal Reserve System.

Yet, at the same time, the literature on CLO funding and credit standards is far less definite. While evidence in Bord and Santos (2015) suggests that CLO funding can result in weakening lending standards, this message is generally at odds with that conveyed by Benmelech, Dlugosz, and Ivashina (2012).

Secondly, there is the advantage of risk transfer. Even if CLO funding does lead to worse loan performance, banks could still avoid facing the consequences of it if they successfully transfer the related credit risks. But again, the literature is not conclusive on this point either. On the one hand, the work by Drucker and Puri (2009) suggests that loans sales –the first step in the securitization process– can actually be a helpful risk management tool. On the other hand, the literature on other securitization vehicles casts some doubts about how generally applicable this result is (see, for instance, Acharya, Schnabl, and Suárez, 2013).

Thus, all things considered, the matter of whether and how CLO-funded lending ultimately affects bank riskiness remains an empirical question. In our analysis, we find that an exogenous increase in bank CLO funding indeed decreases bank riskiness, captured by a falling expected default frequency, for about half a year, with a peak effect after one quarter.

We also document three main mechanisms through which securitization can affect bank riskiness. First, in the wake of an increase in institutional investors' appetite for business loans, banks ramp up loan origination, fostering origination fees and net noninterest income. Second, banks also reduce the amount of C&I loans outstanding on their balance sheets, despite the boost in the origination of loans, thus reducing credit risk exposures. And, lastly, the performance of the remaining loans on their balance sheets temporarily improves as well. All elements combined contribute to develop a coherent explanation to the results obtained from the analysis of expected default frequencies.

1.1 Markets, Market Participants, and Identification Strategy

Our study relies on the intrinsic relation between the syndicated loan market and the CLO market to device a strategy for the identification of the effects of CLO funding on bank riskiness. A stylized representation of the interactions between these markets and their participants is illustrated in Figure 1.

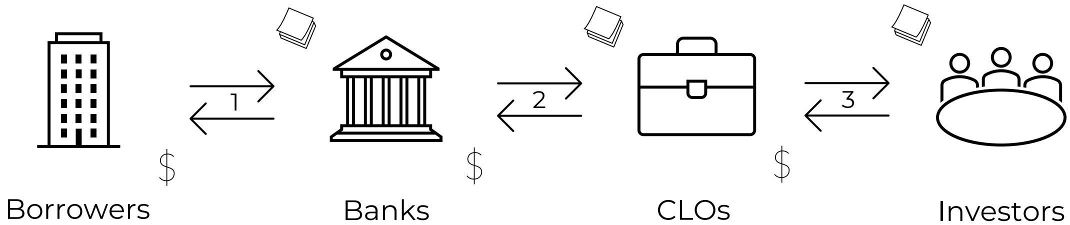


Figure 1: Origination and Securitization of Syndicated Loans: Loans originated by conventional banks for Corporations are securitized, transformed into CLOs, and sold to Institutional Investors.

In the OTD model of banking, CLOs funded by institutional investors ultimately fund syndicated institutional loans originated by banks.[2] In a representative case, a lead bank arranges a loan to a corporate borrower and distributes this loan on a pro rata basis among syndicate participants – Market 1 in Figure 1.[3] The loan can next be traded in a secondary market where a wide range of market participants can acquire it. CLOs constitute a prominent group among these participants. This step corresponds to Market 2.

Institutional loans are predominantly term loans with characteristics especially appealing to institutional investors, including bullet repayment and penalizations for early repayment. CLOs fund the acquisition of loans through the sale of CLO tranches to a large base of sophisticated investors, providing a securitization vehicle through which institutional investors can efficiently buy into the future cash flows of diversified portfolios of institutional loans. The institutional investors include insurance companies, mutual funds, pension funds, endowment funds, among others. This is Market 3 in the figure.

Institutional investors find in CLOs a convenient way to indirectly invest in corporate loans, as CLOs offer tranches taylored for different risk profiles and can be traded readily. As the institutional investors' appetite for risky assets changes over time, so does their demand for CLOs. An increase in appetite for these assets translates in more acquisitions of CLO tranches, which in turn provides CLO managers with the funding necessary to acquire more loans. Ultimately, lead arrangers find improved market conditions to originate and fund

[2]Our explanation here applies to cash and arbitrage CLOs which are unrelated to banks, as opposed to balance sheet CLOs sponsored by banks.

[3]Historically, banks have been the main participants of these syndications, although more recently the syndicate composition has been changing.

more new institutional loans.

To address the main research question of the paper, it would be sufficient to estimate a panel model of the form:

$$BankRisk_{i,t} = \alpha_i + \beta CLOFunding_{i,t} + \Phi Controls_{i,t} + \upsilon_{i,t}, \tag{1}$$

provided we had both a suitable measure of bank riskiness and an exogenous measure of CLO funding.

Several options to gauge bank riskiness can be found in the literature. We adopt a measure of expected default frequency that builds on Merton (1974)'s bond pricing model and has been extensively applied both in academic works and the industry. However, measures plausibly providing exogenous variations of CLO funding are not readily available. A main novel contribution of our paper is to propose an approach to tackle the identification of β in (1) by using an interacted time-series/cross-section variable in the spirit of shift-share empirical designs (Borusyak, Hull, and Jaravel, forthcoming; Bartik, 1991; Blanchard and Katz, 1992; Autor, Dorn, and Hanson, 2013; Nunn and Qian, 2014), in which the time series component is obtained exploiting the market structure previously discussed.

Our approach combines then two components. The first component captures variation on the time dimension. We employ a VAR model to jointly represent the structure of the institutional loan and CLO markets. The transmission mechanism of institutional investor demand shocks for CLOs to loan origination is identified by sign restrictions. Once we have identified this shock, the second component we use is a measure of bank reliance on the CLO market to fund the origination of loans, which embeds cross-sectional heterogeneity. The resulting interacted variable can be thought of as a measure of treatment intensity, conditional on time fixed effects, bank fixed effects, and a set of predetermined observable bank characteristics.

Finally, we use the local projections method of Jordà (2005) to estimate the causal effects of CLO funding on different measures of bank performance at quarterly frequency and up to a one-year horizon, starting with expected default frequency. Our main finding is that the expected default frequency of the average bank in our sample falls by 1.6% in response to a one-standard deviation shock to the institutional investor demand for CLOs one quarter from the shock.

1.2 Related Literature

Our work speaks to various strands of the literature in financial intermediation, credit markets, and securitization. It also relates to the modern empirical literature using mixed micro-macro data and methods to identify causal effects in a panel framework of analysis.

Our paper closely relates to the literature on the effects of the sale of business loans on bank behavior (which includes, among others, Gorton and Pennacchi, 1995; Boot, 2000; Parlour and Plantin, 2008; Drucker and Puri, 2009; Gande and Saunders, 2012; Li, Saunders, and Shao, 2015; Loutskina, 2011; Parlour and Winton, 2013; Shleifer and Vishny, 2010).

A common theme in this literature is whether loan sales affect bank incentives to perform their traditional screening and monitoring roles, potentially conditioning loan, borrower, and lender performance. Another strand of this literature focuses on the use of securitization in bank risk management. Loutskina (2011) and Shleifer and Vishny (2010) show that bank loan origination and bank balance sheets adjust in response to changes in market conditions, a result consistent with our findings. The procyclical response of loans exacerbates both the upside and downside of the economic cycle.

Our work also relates to the literature studying how the marketability of business loans can affect the supply of credit. In particular, Ivashina and Sun (2011) and Nadauld and Weisbach (2012) have shown that institutional investors and securitization can indeed shift the supply of credit – which is an element of relevance to develop our identification strategy. Moreover, our work also relates to the literature on CLO funding and lending standards (Benmelech, Dlugosz, and Ivashina, 2012; Bord and Santos, 2015), which has thus far yielded mixed evidence.

Similarly, our research is also related to extant works studying the role of securitization on bank performance, such as Casu, Clare, Sarkisyan, and Thomas (2013) which, using pre-crisis data and a broad definition of securitization, does not find a strong relationship. We depart from extant works by focusing solely on the securitization of business loans via CLOs in the post-financial crisis period, with a market operating under a new regulatory framework and encompassing new market participants and institutions. All of these differences make it plausible to expect also a different relation between securitization and bank performance.

On a more general level, our work contributes to the literature on shadow banking and the shift of banking towards an OTD model, a strand that has developed significantly in the last decade to include works like Gorton and Metrick (2012); Pozsar, Adrian, Ashcraft, and Boesky (2013); DeYoung (2014); Culp and Neves (2017); Adrian, Aschcraft, Breuer, and Cetorelli (2019); Boot and Thakor (2019), to name but a few.

Lastly, on the empirical grounds the methodology we propose draws principles from the applied econometric work both in micro and macroeconomics. Interacted variables have been extensively used, especially as instrumental variables, in different empirical microeconometric applications in labor economics (Bartik, 1991; Blanchard and Katz, 1992; Autor, Dorn, and Hanson, 2013; Acemoglu and Restrepo, Forthcoming) and development economics and international aid (Werker, Ahmed, and Cohen, 2009; Nunn and Qian, 2014; Nizalova and Murtazashvili, 2016). At the same time, mixed identification strategies have been used to identify the effects of monetary and fiscal policies in macro-econometric models (Blanchard and Perotti, 2002; Romer and Romer, 2004, 2017). Our empirical strategy shares the spirit of these papers, yet it provides a novel approach by taking the information obtained from a structurally identified VAR model to construct the interacted variable used as a regressor in the main panel model.

2 Empirical Methodology

In this section we describe the empirical methodology that leads to the estimation of model (1) and of the impulse response functions of the default risk probability to bank CLO funding by local projection (Jordà, 2005).

2.1 Measuring Default Risk

We start with the construction of the default risk probabilities that constitute the left hand side variable of model (1).

The measure we use is the expected default frequency, an application of Merton (1974)'s bond pricing model pioneered by KMV (later acquired by Moody's), designed to gauge a firm's distance-to-default. This application is has been extensively used both in the industry and the academic literature (see, for instance, Vassalou and Xing, 2004; Duffie, Saita, and Wang, 2007; Campbell, Hilscher, and Szilagyi, 2008; Bharath and Shumway, 2008).

The distance-to-default, DD_t, can be thought of as a firm's market net-worth standardized by its asset volatility:

$$DD_t = \frac{A_t - L_t}{A_t \sigma_A}, \tag{2}$$

where A_t is the market value of the assets of the firm at time t, L_t the value of its liabilities, and σ_A is the standard deviation of the annual percentage change of A_t.

The approach models the value of the equity of a firm as the price of a perpetual call option on A_t with strike price given by L_t. A firm is considered in default when the value of assets falls below that of liabilities, i.e. when $DD_t < 0$. Applying option pricing theory, knowledge of today's assets value A_t and of the return volatility σ_A allows us to calculate the probability that $DD_T < 0$ in period $T > t$, under some distributional assumptions about the underlying stochastic process of A_t.

The expected default frequency, EDF_t, is then defined as

$$EDF_t = Pr(DD_T < 0 | DD_t), \tag{3}$$

where T is usually taken to be $t + 12$ months.

Computing the probability in (3), it must be noted, entails some challenges. The most important one arises from the fact that data on A_t and σ_A are not directly observable. Hence, they must be inferred from other available data –noticeably, the value of equity, its volatility, the value of liabilities, and the risk-free rate– and their relations within an option pricing model.[4] A second challenge stems from the frequency of data available. While market data, such as the risk-free rate, can be available at daily frequency, other data, such as the book value of liabilities, can be available at quarterly frequency only. These elements

[4]See, for instance, section 2.1 in Bharath and Shumway (2008) for a detailed exposition.

can potentially cause EDF to be noisy. Nonetheless, as illustrated in Section 3, our EDF measure closely correlates in aggregate with well-established indicators of financial stress.

2.2 Measuring CLO Funding

The second piece necessary for the estimation of model (1) is the construction of the CLO funding variable on the right-hand side of the panel regression. We propose a methodology inspired by the Bartik (1991)'s shift-share interacted instrumental variable approach used in empirical econometrics.[5]

The key insight in our case is to form an exogenous regressor by combining a plausibly exogenous source of time variation with a source of cross-sectional variation that is not required to be exogenous. The interaction between these two elements yields an exogenous factor at the panel level and OLS estimates of this model are consistent under a set of relatively mild assumptions that we discuss in detail in Section 2.3 (Nizalova and Murtazashvili, 2016; Borusyak, Hull, and Jaravel, forthcoming).

Let $\overline{E}_i$ and S_t respectively indicate the cross-section and time-series components of the interacted term. We define the CLO funding measure as:

$$CLOFunding_{i,t} = \overline{E}_i \times S_t. \tag{4}$$

$\overline{E}_i$ represents the relevance of institutional loans in the mix of loans led by bank i throughout the entire sample period. As CLOs are key buyers of institutional loans, this provides a cross-sectionally heterogenous measure of bank reliance on CLO funding. Let $E_{i,t}$ be the proportion of institutional loans to all loans arranged by bank i in quarter t and T_n the time sample size, $\overline{E}_i$ is simply the sample average of $E_{i,t}$:

$$\overline{E}_i = \frac{1}{T_n} \sum_{t=1}^{T_n} E_{i,t}.$$

In order to identify S_t, the structural institutional investor demand shock for institu-

[5] See Borusyak, Hull, and Jaravel (forthcoming) and Goldsmith-Pinkham, Sorkin, and Swift (2020) for recent technical discussions on the use of these instruments.

tional loans taking place through the CLO market, we resort to a small-scale VAR model.[6] This VAR model provides a stylized representation of the institutional loan market previously described in Section 1.1 and Figure 1, and can be specified with the following vector of four endogenous variables, Y_t:

$$Y_t = \begin{bmatrix} CLOPrice_t \\ LoanVolume_t \\ LoanSpread_t \\ BankEDF_t \end{bmatrix}, \tag{5}$$

where $CLOPrice_t$ is the price level of investment opportunities in the market for corporate loan-backed securities, i.e. a price index for the CLO market; $LoanVolume_t$ is the aggregate volume of new institutional loans originated by the banking sector; $LoanSpread_t$ is the spread associated with those new institutional loans; and $BankEDF_t$ is the banking sector EDF as defined above. We leave for Section 3 a more detailed discussion of the sources and construction of these variables.

The order p reduced-form VAR model can be written as:

$$Y_t = \sum_{l=1}^{p} B_l Y_{t-l} + u_t$$

where B_l is a matrix of parameters and the reduced-form VAR residuals are collected in u_t. Let A_0 be the structural impact multiplier that linearly relates the structural shocks of the VAR model,w_t, to the reduced-form residuals, u_t:

$$u_t = A_0 w_t.$$

We estimate the reduced-form VAR using Bayesian techniques with Normal-Wishart priors and $p = 6$ lags, at monthly frequency, and we identify the structural shocks w_t by use of sign and zero restrictions on the elements of A_0.[7] Table 1 illustrates the identification

[6]The financial literature has previously resorted to VAR models to study the dynamics of the corporate loan market. See, for instance, Barraza, Civelli, and Zaniboni (2019).

[7]We perform the estimation procedure using the econometric package developed by Dieppe, Legrand, and

$$\begin{bmatrix} u_t^{clo} \\ u_t^{vol} \\ u_t^{spr} \\ u_t^{edf} \end{bmatrix} = \begin{bmatrix} + & - & - & - \\ + & + & + & - \\ - & - & + & + \\ 0 & * & * & + \end{bmatrix} \begin{bmatrix} w_t^{InstD} \\ w_t^{BankS} \\ w_t^{CorpD} \\ w_t^{FinRisk} \end{bmatrix}$$

Table 1: Identifying restrictions of the monthly structural shocks of the VAR model. The four shocks identified are an institutional investor demand shock for institutional loans w_t^{InstD}, a bank supply shock w_t^{BankS}, a corporate demand shock w_t^{CorpD}, and an aggregate financial sector risk shock $w_t^{FinRisk}$. The symbols $+/-$ indicate a positive/negative on-impact sign restriction, 0 indicates an on-impact zero restriction, and $*$ indicates unrestricted coefficients.

assumptions.

We adopt a supply/demand identification logic conceptually similar to the strategy implemented in Kilian and Murphy (2012) and Inoue and Kilian (2013) to identify supply and demand shocks in the oil market.[8] The motivation of the shocks in our model, however, relies on the dual nature of the institutional loan market discussed in Section 1.1. In this market, banks originate loans with the twofold goal of lending to the corporate sector as well as selling these loans to CLOs funded by institutional investors.

The core piece of our identification strategy is defined by the upper-left 3×3 sub-matrix of A_0. We use this block to characterize the bank supply of institutional loans, structurally identified by shock w_t^{BankS} in Table 1, pivoting between the corporate demand for institutional loans and the institutional investor demand for institutional loans taking place through the CLO market, identified by shocks w_t^{CorpD} and w_t^{InstD} respectively.

The identification scheme of w_t^{InstD} is defined by the first column of the sub-block of A_0. A positive institutional investor demand shock raises on impact the price of CLOs, increases the origination of institutional loans, and decreases the loan spreads at issuance. These effects of institutional investors and CLOs on the conditions in the corporate loan market are empirically supported by findings in Ivashina and Sun (2011) and Nadauld and Weisbach (2012). We interpret this as a liquidity shock in the CLO market, whereby investors make more funds available to CLO managers and in so doing stimulate the origination of institutional loans to be acquired by CLOs.

van Roye (2016).

[8]See Canova (2007) and Kilian and Lütkepohl (2017) for details on identification using sign restrictions.

Similarly, the second and third columns of the matrix identify w_t^{BankS} and w_t^{CorpD}. A positive bank loan supply shock is assumed to have a negative impact on the price index of CLOs (as more loans and CLOs are available), a positive effect on the origination of new institutional loans, and a negative impact on the spreads corporations pay to borrow these loans from the banking sector. On the other hand, a positive corporate demand for institutional loans is assumed to make the CLO index fall (again, as more loans and CLOs are available) and increase the origination of institutional loans and the loan spreads.

The specification of the VAR model also includes aggregate bank EDF, the same left hand side variable of the panel analysis, which justifies the use of shock w_t^{InstD} as a plausibly exogenous time series component in the interacted variable (4). The presence of this variable in the VAR also allows us to further refine the identification of this shock by adding a fourth structural shock to the model: an aggregate financial sector risk shock, $w_t^{FinRisk}$.

We explicitly identify this latter shock as it can directly affect bank choices, including that of credit supply (Ivashina and Scharfstein, 2010), and default risk at the same time. This source of variation could otherwise confound the estimates of the effects of CLO funding on bank riskiness and, given our specific focus on CLO funding, should be kept separate from w_t^{InstD}.

The fourth column of A_0 illustrates the restrictions that identify $w_t^{FinRisk}$. Higher financial risk is assumed to have a detrimental impact on the CLO price index and institutional loan origination, while increasing loan spreads and default probabilities. As we can see from Table 1, w_t^{InstD} and $w_t^{FinRisk}$ are in principle very similar shocks as they would share the same identifying restrictions on the first three variables of the model. We distinguish between the two of them based on their effect on EDF.

The assumption is that the aggregate financial sector risk shock must affect bank sector EDF more rapidly and to a greater extent than a liquidity shock in the CLO market. The impact of $w_t^{FinRisk}$ on EDF is positive, as riskier aggregate financial conditions increase bank default risk, while we set the effect of w_t^{InstD} on EDF to zero ($A_0(4,1) = 0$). This assumption boils down to imposing that banks' EDF takes longer than a month to respond to this specific liquidity shock – for instance, because banks need some time to manage their balance sheets in response to the shock.[9]

Since the response of EDF to the liquidity shock is intrinsically related to our research question and we do not have a clear prior knowledge to inform the sign of this restriction, the choice of a zero restriction for $A_0(4,1)$ can also be interpreted as taking a conservative stance. In a robustness check presented in the Appendix, however, we relax this restriction and modify the identification scheme by leaving both the sign of $A_0(4,1)$ and the last column of A_0 unrestricted. In this form, the interpretation of the fourth shock changes and it is treated as a residual, catch-all shock that absorbs all other confounding factors. Ultimately, our results are not sensitive to this choice.

As above, we leave the sign of the effect of w_t^{BankS} and w_t^{CorpD} on EDF unrestricted, as we do not have specific prior information on these effects either. Interestingly, as illustrated in Figure A4 in the Appendix, the response of EDF to w_t^{CorpD} is close to zero. Given the parallel between corporate demand and institutional investor demand in the CLO-institutional loan market structure we portray, this feature of the EDF response to the corporate demand shock indirectly provides some empirical support to the zero restriction we adopt for $A_0(4,1)$.

2.3 Panel Model and Local Projections

The final step of the empirical methodology is the estimation of the impulse response function by using the local projections method. This approach constructs a response function by simply tracking the estimates of β in the panel model at different lags of the interaction term (see Jordà, 2005).

More precisely, we consider the following specification of model (1):

$$EDF_{i,t+j} = \alpha_i^j + \gamma_t^j + \beta^j(\overline{E}_i \times S_t) + \sum_{k=1}^{K} \phi_k^j(\overline{E}_i \times S_{t-k}) + \sum_{k=1}^{K} \theta_k^j EDF_{i,t-k} + X_{i,t-1}\Gamma + \varepsilon_{i,t}^j, \quad (6)$$

where the i and t subscripts denote banks and time period; α_i and γ_t respectively indicate bank and time fixed effects; $\overline{E}_i$ is our measure of bank reliance on the CLO market; S_t is

[9] An alternative plausible identification assumption would be to impose a response of aggregate EDF to the institutional investor demand shock smaller than that to the aggregate financial risk and set, for example, $A_0(4,1) < A_0(4,4)$. Our zero restriction follows the same spirit, yet it is simpler to implement and focuses on the timing of the effect rather than its size and direction.

provided by the structural institutional investor demand shock, w_t^{InstD}; $X_{i,t-1}$ is a vector of bank-specific controls and $\varepsilon_{i,t}$ is the error term. Finally, script j with $j = 1, 2, ..., J$ tracks the coefficient β^j for the estimation of the local projections up to horizon J. In our benchmark application, we take $K = 1$ quarter and $J = 4$ quarters. The model is estimated by least squares.[10]

The vector of bank-specific controls, $X_{i,t-1}$, includes a set of variables found by Casu, Clare, Sarkisyan, and Thomas (2013) to be relevant determinants of the bank decision to securitize, namely: real estate loans to total loans; commercial & industrial loans to total loans; deposits to total assets; noninterest income to net operating revenue; the log of total assets; and the growth rate of total loans. It also includes a measure of balance sheet liquidity, as Loutskina (2011) has shown this is related to securitization. The measure is inspired by Kashyap and Stein (2000) and is computed as the sum of securities available for sale, federal funds sold in domestic offices and securities purchased under agreements to resell, scaled by total assets. The last variable in this vector is the ratio of equity to total assets, as this can naturally affect both lending and risk. In all cases, these controls are lagged one quarter.

Nizalova and Murtazashvili (2016) show that the OLS estimates of β^j in Equation (6) are consistent as long as the source of heterogeneity among individuals – the banks' propensity to arrange institutional loans, $\overline{E}_i$, in this case – and the residual $\varepsilon_{i,t}^j$ of equation (6) are jointly independent of the treatment – in this case, the institutional investors demand shock S_t.

In our empirical strategy, meeting this condition primarily builds on the exogeneity of S_t, recovered as a structural shock from a VAR model that includes the aggregate bank EDF. This variable is independent of $\overline{E}_i$ by design. Moreover, the inclusion of the vector of control variables, $X_{i,t-1}$, controlling for pre-determined, time-varying observable bank characteristics that might affect the decision to originate institutional loans, and the use of both bank fixed effects, α_i, controlling for time-invariant unobservable characteristics at the bank level and of the time fixed-effects, γ_t, controlling for any omitted source of common time variation complement the aggregate exogeneity of S_t strengthening the assumption of

[10]Equation (6) is a dynamic panel with large T with respect to N, which renders least squares a suitable estimation method (see, for instance, chapter 8 in Baltagi, 2013). Romer and Romer (2017), for instance, also estimate a model equivalent to that in equation (6) by OLS.

independence of $\varepsilon^j_{i,t}$.

Intuitively, the use of the interaction term $\overline{E}_i \times S_t$ is similar to a *difference-in-differences* estimation strategy, where the estimates compare the default risk of banks that rely more heavily on institutional investors to banks that rely less on institutional investors to fund loans, in periods following high institutional demand pressure relative to periods following low institutional demand pressure for loans, as Nunn and Qian (2014) notice in their application.[11]

3 Data Sources and Elaboration

Bank Data. To construct the bank-level EDF measure for the panel model, we use market data from the Center for Research in Security Prices (CSPR) and balance sheet data from Standard & Poor's COMPUSTAT and we follow the input definitions and estimation procedure described in Bharath and Shumway (2008).[12]

The aggregate time series $BankEDF_t$ for the VAR model is constructed as the average EDF for all U.S.-based financial companies – Standard Industrial Classification (SIC) codes between 6000 and 6999. Figure 2 illustrates this monthly series. This series suitably reflects the market conditions in the financial sector. As a reference, Figure 2 also displays the Kansas City Fed Financial Stress Index: the correlation between the two series is 0.80 during this period.

We also use bank-level data from the FR Y-9C reports provided the Board of Governors of the Federal Reserve System. This data set accounts for the majority of the control variables we use in the panel analysis and, also, a number of dependent variables we discuss below. For the sake of brevity here, we refer the reader to Section A in the Appendix for a thorough description of the sources and construction of these variables.

[11] The interaction term in equation (6) also resembles the approach introduced by Kashyap and Stein (2000), and employed by Loutskina (2011), where a measure of exposure with cross-sectional heterogeneity is interacted with a time series.

[12] As the authors note, this approach is the same employed by Vassalu and Xing (2004); Duffie, Saita, and Wang (2007); Campbell, Hilscher, and Szilagyi (2008), and others. Bohn and Crosbie (2003) provide an intuitive description of the main elements of this application of option pricing theory, although their estimation differs from academic works, fundamentally, in that in their case the mapping between the distance to default and the expected default frequency is implemented based on (proprietary) historical data.

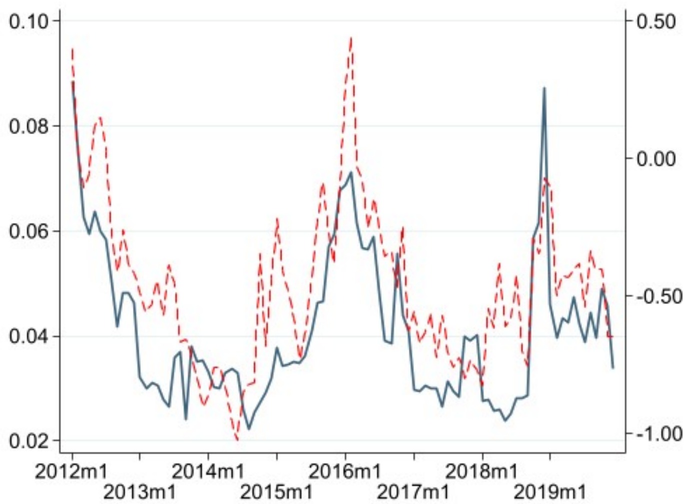


Figure 2: Monthly Average Expected Default Frequency of U.S.-based Financial Firms (solid blue line, left axis) and Kansas City Financial Stress Index (dash-dotted red line, right axis), 2012-2019 period.

Loan Data. Our data on business loans include all facilities syndicated in the U.S., issued by U.S. firms, and in U.S. dollars between January 2012 and December 2019 from the Thomson Reuters LPC DealScan data set. When we refer to institutional loans, we refer to all term loan B through term loan K facilities from this set. Institutional loans represent 33% of all term loans in the sample and account for 55% of their dollar amount. Term loans B, we shall add, represent 98% of the institutional loans.

In forming the panel data set used for the local projection analysis, we must first take into account the fact that large banks often arrange deals through multiple subsidiaries. Hence, we start by consolidating at the top Bank Holding Company (BHC) or Financial Holding Company (FHC) level all lead arrangers belonging to a same organization.[13] Given that riskiness is intrinsically related to the regulation framework banks are subject to and that *domestic* and *foreign* banks have been subject to different regulations over time, we focus on *domestic* BHCs and FHCs only for comparability. The process of loan and bank aggregation thus yields a first sample of 28 top banks originating at least 50 loans during the sample period, which earned in aggregate 10,531 lead arranger credits in institutional loans.

As we intend to study the effect of CLO funding on bank performance, we define a

[13] Appendix B details the aggregation procedure.

minimum level of reliance on this market to deem a bank relevant to our study. Thus, we retain then in our panel only top lenders for which institutional loans constitute at least 5% of the loans they lead during the sample period. This leaves us with 16 top banks taking 10,106 lead arranger credits in institutional loans.[14] Table A2 in the Appendix lists these lead arrangers together with their corresponding measure of reliance on CLO funding.

CLO Market Data. To gauge the conditions in the CLO market we use CLODI, the Palmer Square CLO Debt Index maintained by Bloomberg. This is a total return index of original rated A, BBB, and BB CLO debt issued after January 1, 2009 in the United States. The index includes only cash and arbitrage CLOs backed by broadly syndicated leveraged loans.[15] As of October 31, 2021 A, BBB, and BB CLO tranches accounted for 37.5, 36.3, and 26.3% of this index, respectively.[16]

4 Main Results

4.1 Bank Riskiness: Evidence from the VAR Structural Analysis

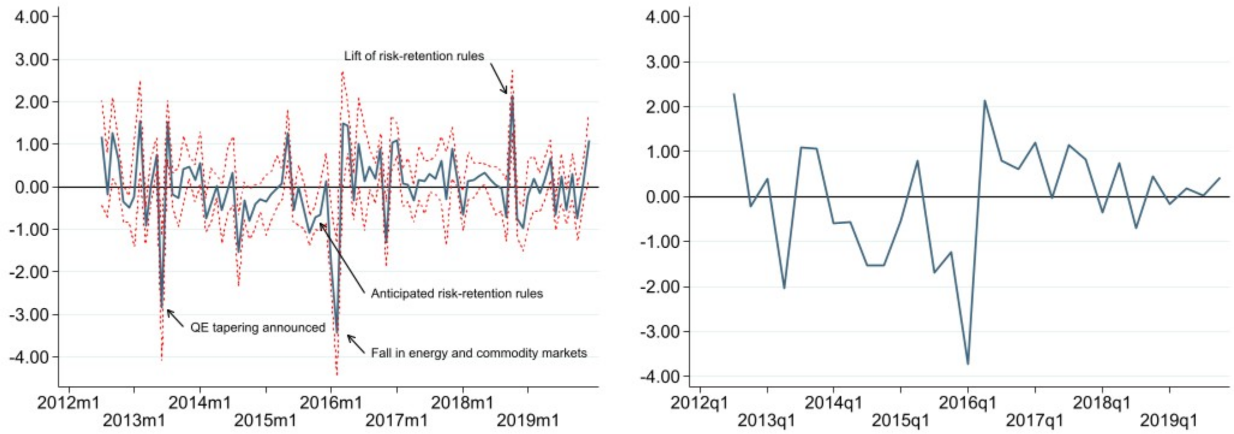
Before delving into the main results from the local projections, we introduce a set of outcomes that help visualize the results from the VAR model – namely, the identified structural institutional investor demand shock and the response function of aggregate EDF to this shock.

We start with the structural institutional investor demand shock at monthly frequency identified with the sign restrictions presented in Table 1. This is introduced in Panel (a) of Figure 3. The series is distributed around zero, with a standard deviation of one, and it captures the main events in the CLO market arguably well.

[14] This step is meant to prevent noise arising from banks that only seldom issue loans that could be bought by CLOs. For instance, the group of 28 top banks includes a holding company that in our loans data only received one institutional loan lead arranger credit during the 2012-2019 period, which makes evident that the bank's business is not reliant on CLO funding.

[15] This excludes Balance Sheet CLOs and other types like Middle-Market CLOs, ABS CDOs, and Emerging Market CLOs.

[16] For further details on the index construction, see Palmer-Square-Capital-Management (2021b) and Palmer-Square-Capital-Management (2021a)



(a) Monthly Shocks

(b) Quarterly Shocks

Figure 3: Structural Institutional Investor Demand Shock in the CLO Market. Panel (a) presents the monthly structural shock identified in the VAR model. The solid blue line represents the median of the posterior distribution of the shock. The dashed red lines represent the $14th/86th$ percentile of the posterior distribution. The observations corresponding to four significant market events are indicated by the arrows. Panel (b) displays the quarterly version of the shock, which results from summing the monthly median posterior by quarter.

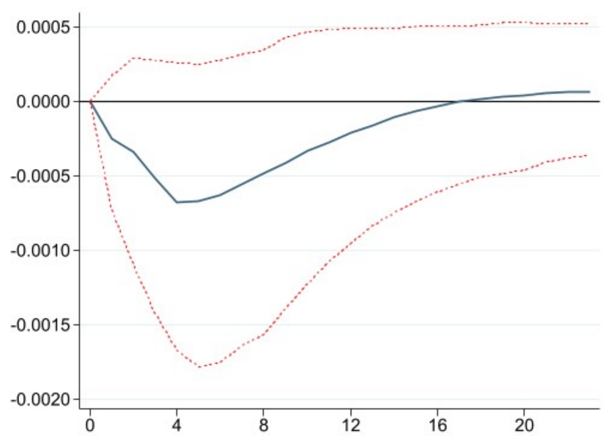


Figure 4: Response of Aggregate EDF to a one-standard deviation Institutional Investors Demand shock. The solid blue line represents the median response of EDF to the shock. The dashed red lines represent the $14th/86th$ percentile bands of the posterior distribution of the response. The unit of time on the horizontal axis is months.

For instance, the large negative shock observed in June 2013 matches the announcement of the Quantitative Easing tapering by the Fed, which increased uncertainty in financial markets and severely disrupted the high-yield investment segment by causing outflows of available funds into other asset classes. The negative shocks throughout the second half of 2015 that culminated in the large negative shock in February 2016 reflect consolidations of CLO managers in anticipation of changes in risk-retention rules that took place in 2016 and concerns over loans in the energy, metals and mining sectors being downgraded.[17] In contrast, the large positive shock in October 2018 corresponds to the effects of the large wave of reset and refinance transactions caused by the repeal of the risk-retention rules in early 2018.[18]

The monthly frequency of the VAR model is very convenient for at least two reasons. First, it provides us with a suitable sample to reliably estimate a VAR model within a relatively short time span of eight years. Second, it also gives us the necessary flexibility to model the dynamics of the institutional loan and CLO markets, particularly regarding the lag structure of the model and the structural identification restrictions.

Yet, the bank-level data used in the panel analysis for the vector of control variables is only available at a quarterly frequency, provided this is the highest available frequency for accounting data from which the controls are obtained. To harmonize the frequency of both data sets, we follow Holm, Paul, and Tischbirek (2021) and aggregate the monthly institutional investors demand shock at quarterly frequency by summing the shocks over each quarter. The result is still a zero-mean series with a slightly higher standard deviation of about 1.2, as illustrated in Panel (b) of Figure 3. A visual inspection makes already apparent that the quarterly series preserves the key events observable at monthly frequency.[19]

[17] As part of the Dodd-Frank Act, new risk-retention rules were imposed to the CLO market, which required managers to hold 5% of their CLOs starting from 2016. Loans in the energy, metals and mining sectors usually constitute around 5-7% of CLOs pools. The weak energy and commodity market of 2015, which reached its bottom in February 2016 with a large fall of global energy prices, triggered multiple downgrades of companies in these industries.

[18] The 2016 deals were done under the risk-retention rules at significantly higher spreads than 2018 and were subject to a 2-year non-call period. The majority of these deals reached their refinancing and reset eligibility during 2018, providing CLO managers and equity holders with the right incentives to lower the deal's liability costs. October 15th was the last date for renegotiation before year-end, since transactions can only occur on deal payment dates.

[19] An alternative approach would be to form a monthly panel and estimate local projections with versions of model (6) without bank-level controls, but enriching the lag structure of the remaining terms in the

Lastly, we introduce in Figure 4 the response function of aggregate EDF to the institutional investors demand shock from the benchmark VAR model. The response is negative, but quite small and not significant at the conventional confidence levels used in Bayesian estimation. Although modest in economic terms (the response at its trough is $-.07\%$, just about $1/60th$ of the average aggregate EDF of 0.041 for U.S.-based financial institutions), the response hints at a fall in the aggregate riskiness of the financial sector in the wake of an increase in the institutional investor demand for institutional loans. The flip side of this result is, of course, that a contraction in the supply of liquidity in the CLO market can increase the riskiness of banks, a point deserving policy makers' attention.[20]

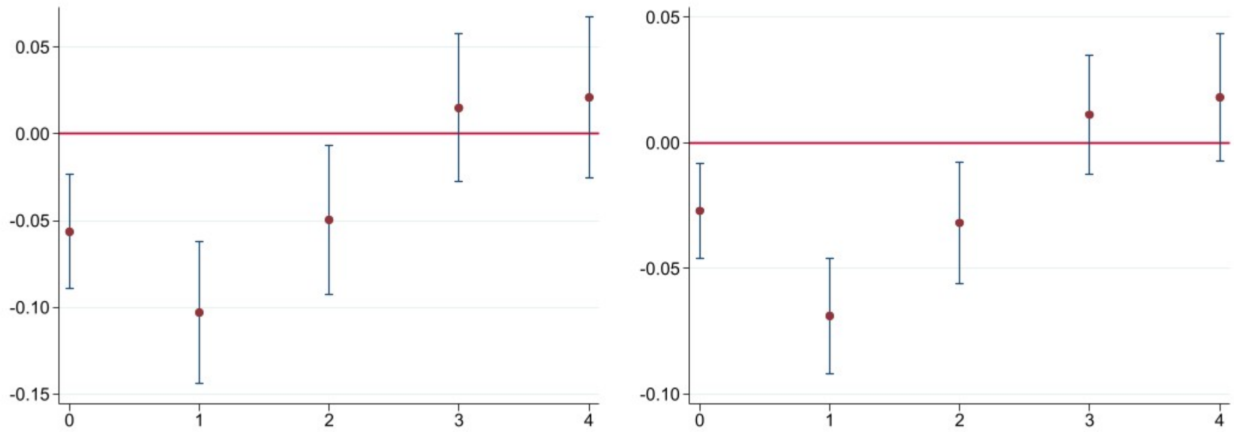
4.2 Bank Riskiness: Evidence from the Panel Analysis

We report now the results for the impulse response functions based on the local projections from model (6). Figure 5 Panel (a) documents the average response function of EDF for the banks in our sample to a one unit increase in our measure of CLO funding, gauged by the interaction term $\overline{E}_i \times S_t$. The red dots are point estimates of the response β^j at different horizons, while the vertical blue lines represent 90% confidence intervals. The model includes bank fixed effects, time fixed effects, lagged values of the dependent variable and interaction term (with $K = 1$), and the set of lagged bank-level controls described in Section 2.3. The estimation is carried out by OLS and the standard errors are clustered at the bank level.

The results show that EDF decreases by almost 6% immediately upon the shock to reach a maximum fall of 10.3% one quarter from the change. After two quarters the decrease in EDF is about 5% and still significant, after which the effect disappears. A simple economic interpretation of these effects can be obtained by considering the impact of a one-standard deviation S_t shock on the hypothetical bank with average exposure to the CLO market. The EDF of the average bank in our sample responds to a typical institutional

model. This alternative specification would resemble those employed, for instance, in Romer and Romer (2017). Using a monthly panel, our main results on bank riskiness remain consistent with those we obtain using the quarterly panel. The monthly panel, however, does not allow us to examine other outcomes of interest and it is primarily for this reason that we resort to the quarterly panel.

[20]For completeness, we report the full set of impulse response functions for the benchmark VAR model in Figure A4. The figure clearly illustrates the identification assumptions outlined in Section 2.2.



(a) Benchmark: Including Time F.E.

(b) Alternative: Including S&P 500 Index

Figure 5: CLO Funding and Expected Default Frequency. The figure presents the local projection of bank EDF to a one unit increase in CLO funding reliance, $\overline{E}_i \times S_t$, estimated in the panel model. Panel (a): Benchmark EDF result, which includes time fixed effects. Panel (b): Alternative model, which includes the S&P 500 in lieu of time fixed effects. Red dots are point estimates. Blue vertical lines correspond to 90% confidence intervals.

investor demand shock by falling about 1.6% one quarter after the shock.[21]

This result is broadly consistent with the response of EDF in the VAR model, as it shows that increases in CLO funding can sooth riskiness among financial institutions. Yet, it also indicates that the magnitude of the response for banks that rely more on CLO funding is much larger than for the average financial institution in the market.

Robustness Checks. A natural concern that arises in interpreting the previous result is that lower bank EDF could mechanically be the result of a general improvement in market conditions that increases both banks' market value of equity and institutional investors funding at the same time. In other words, there might be a concern that the institutional demand shock identified in the previous stage still embeds broader liquidity effects not specifically confined to the CLO market, and that these components are not fully controlled for in the baseline specification of the panel model with time fixed effects. We address this concern by directly controlling for the stock market conditions in the LP model, substituting the log of average monthly S&P 500 index for the time fixed effects in the benchmark model. Panel

[21] The shocks S_t are standardized by design, with a unit standard deviation. The average exposure measure in the sample is $\overline{E} = .157$.

(b) of Figure 5 shows that implementing this alternative specification does not affect the shape or significance of the response function, although the effects are about 30% smaller.

We run several additional robustness checks and obtain similar results, as reported in Appendix C. For instance, we recover the institutional investors demand shock from an alternative VAR model where the Kansas City Financial Stress Index, a more general definition of financial stress, replaces the average EDF of U.S.-based financial firms as a proxy for financial conditions. Figure A1 in the Appendix presents the LP results when we use this alternative shock to build the interacted variable $\overline{E}_i \times S_t$. Bank EDF falls up to 16% one quarter after the unit increase in CLO funding.

Another possible concern comes from the demand shock S_t used to form the interaction term being a synthetic variable estimated in the VAR. We check how the uncertainty around this estimate affects the local projection of EDF in Figure A2 of Appendix C. We take $1,000$ draws from the posterior distribution of S_t and recalculate $\overline{E}_i \times S_t$ for each draw. We then re-estimate the coefficients of panel model (6) and collect them in a vector for each horizon j. The figure illustrates the median of these coefficient vectors, along with confidence bands given by their $14th/86th$ percentiles. Incorporating this step also preserves our benchmark result. The shape and significance pattern of the LP is the same, while the response magnitude is only slightly smaller.

In the last robustness check we discuss here, we estimate a VAR model where a more generic residual shock replaces the aggregate risk shock used in the benchmark model. This residual shock captures the effect on the system dynamics of other aggregate shocks not explicitly identified by the remaining three structural shocks in the model.[22] Table A1 in Appendix C formalizes the identification restrictions of this case in which, notably, the restriction $A(4,1) = 0$ is not longer used. Figure A3 in the Appendix C reports the response of EDF under this alternative model. As before, EDF also falls in this case, with a response at the trough of 17% one quarter after the change in CLO funding.

[22]See Kilian and Murphy (2014) for a similar application.

5 Mechanism Analysis

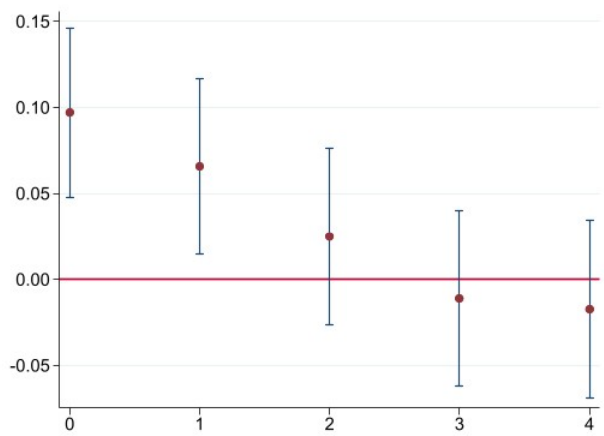
We now examine plausible mechanisms by which CLO funding can affect bank risk. Our analysis points to three main channels of transmission. First, upon a shock banks undergo a change in the structure of their balance sheets, reducing the amount of resources they pledge to finance loans. Second, this adjustment entails a shift from interest-based to fee-based income origination. Lastly, the CLO funding shock also results in a temporary improvement of loan performance. Overall, banks take higher CLO funding as an opportunity to strengthen their ODT business practices, use their resources more efficiently, and lower their riskiness.

5.1 Balance Sheet Changes

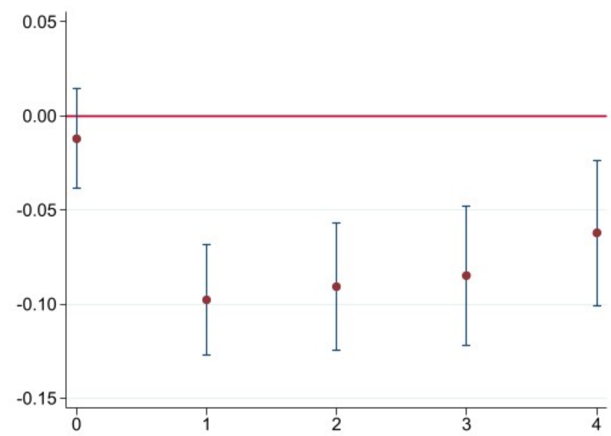
The first part of the hypothesized transmission mechanism is that increasing CLO funding provides banks with incentives to switch from conventional originate-to-hold loans to originate-to-distribute transactions. Moreover, banks could also off-load outstanding business loans from their balance sheets, seeking a more efficient use of their capital. This substitution between loan types would also generate higher noninterest income from growing origination fees, helping banks improve income from lending activities relative to the size of their balance sheets.

Within our panel setting, we are able to test directly the significance of this shift in the type of loans banks originate. In particular, we would expect larger effects on the institutional loan origination among banks that rely more heavily on CLO funding. Panel (a) of Figure 6 provides support to this conjecture as it shows that an increase in CLO funding causes a raise in the relative share of institutional loans origination with respect to all loans arranged by a bank for two quarters, with a peak response on impact. Previous literature suggests that increasing CLO funding could also increase the origination of institutional loans (e.g. Ivashina and Sun, 2011). Our empirical evidence is consistent with this mechanism.

We also find that the expansion in institutional lending is accompanied by a persistent fall in C&I loans held to maturity on the bank balance sheet starting from the first quarter after the shock, as Panel (b) of Figure 6 shows. This is consistent with banks not only



(a) Institutional Loans



(b) C&I Loans

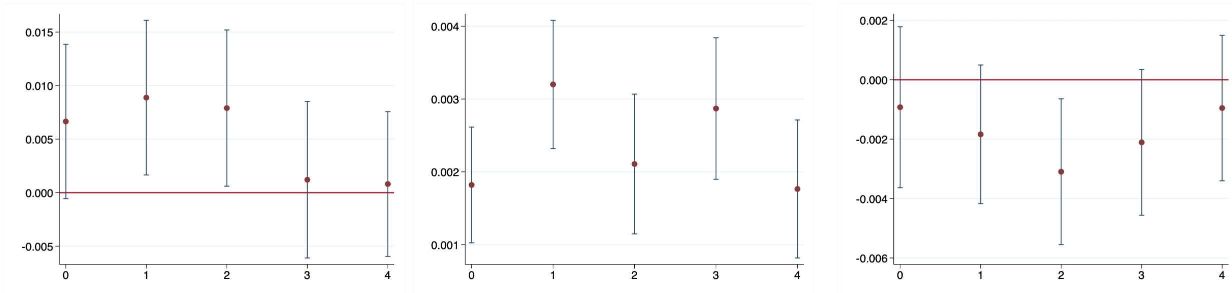
Figure 6: CLO Funding, Institutional Loan Origination and On- and Off-Balance Sheet Changes. This figure presents the local projections of different outcomes of interest in response to a one unit increase in the CLO funding reliance, $\overline{E}_i \times S_t$, estimated in the panel model. Panel (a): Ratio of institutional loans arranged to all loans arranged. Panel (b): Log of C&I loans on bank balance sheet. Red dots represent point estimates. Blue vertical lines represent 90% confidence intervals.

marketing a larger share of the new loans they originate, but also with them likely selling a portion of their existing loans. The possibility of generating higher income from origination fees while employing fewer assets suggests an improvement of bank's efficiency that would lower bank risk.[23]

5.2 Income Generation

The second part of the transmission mechanism takes place through a change in the income generation process which accompanies the change in loan structure of the bank balance sheets. A key feature of the OTD model of banking is the shift from interest-based to fee-based income generation. In this section, we document this shift occurs when a bank reliant on CLO funding experiences an exogenous increase of institutional investors demand for institutional loans.

[23]We also find some evidence, reported in Figure A5 of the Appendix, pointing to a temporary increase of C&I loans held for trading purposes, plausibly as banks hold in this account part of the newly originated loans for distribution. Alternatively, banks might (also) shed some of the C&I loans previously meant to be held to maturity off their balance sheets, temporarily reclassifying them as trading C&I loans while seeking to take advantage of the higher institutional investor demand. These effects would be consistent with the fall in C&I loans previously documented in Panel (b) of Figure 6.



(a) Net Noninterest Income (b) Underwriting Fees (c) Net Interest Income

Figure 7: CLO Funding and Income Generation. This figure presents the local projections of income outcomes in response to a one unit increase in CLO funding reliance, $\overline{E}_i \times S_t$, estimated in the panel model. Panel (a): Ratio of net noninterest income to lagged equity. Panel (b): Ratio of investment banking, advisory, and underwriting fees and commissions to lagged equity. Panel (c): Net interest income to lagged equity. Red dots represent point estimates. Blue vertical lines represent 90% confidence intervals.

Panel (a) in Figure 7 illustrates that increases in CLO funding cause a long-lasting, positive response of the portion of return on equity represented by noninterest income. The response is hump-shaped, with the largest effects observed within the first two quarters since the shock. Support to this finding is also provided by the response of underwriting fees, a key component of noninterest income and encompassing origination fees, reported in Panel (b) of the figure.

Goel, Lewrick, and Tarashev (2020) suggest that, in response to changes in external factors, banks rebalance their activities in order to optimize their performance. Brunnermeier, Dong, and Palia (2020) additionally point out to a negative relationship between the evolution of interest and noninterest income. For these reasons, we could expect a concurrent decrease in the origination of interest income as banks shift towards fee origination activities in response to a CLO funding shock. Panel (c) in Figure 7 illustrates this is indeed what occurs to the interest component of returns on equity.

Interestingly, though, the decrease in the net interest income is smaller than the increase in net noninterest income, especially in the first portion of the response after the shock. For instance, one quarter after the shock the magnitude of the response of noninterest income is roughly four times as large as that of interest income. It is still twice as large in the second quarter. Thus, overall, the response to the CLO funding shock leads to a net improvement in the income generation process, which helps explain the decreasing bank riskiness.

5.3 Loan Performance

As a last piece of the mechanism analysis, and motivated by previous literature studying the performance of loans sold or otherwise securitized, we explore the role of loan performance in the transmission mechanism.

On the one hand, excess institutional investor demand could cause banks to relax their loan screening and monitoring practices. This effect would lead to poorer loan performance and could increase bank riskiness if banks fail to manage loan credit risks effectively. On the other hand, increasing CLO demand for institutional loans could give banks an opportunity to restructure their nonperforming loan portfolios, reducing bank riskiness.

We empirically address this point by studying the response of C&I loan delinquency to the CLO funding shock. Figure 8, which centers on nonaccrual delinquent C&I loans, suggests that the CLO funding shock temporarily reduces the weight of delinquent loans on the bank balance sheets, although this effect is reversed over the four-quarter horizon.[24] We can suggest two alternative, not mutually exclusive, mechanisms to explain this result.

The first is that increasing availability of CLO funding gives banks the opportunity to originate new loans used to refinance nonperforming credits, along the lines of the zombie lending or ever-greening effects documented in the literature (see, for instance, Hu and Varas, 2021; Bonfim, Cerqueiro, Degryse, and Ongena, 2020). The second explanation is that increasing availability of CLO funding simply gives banks the opportunity to offload nonperforming loans to the market.

This opportunistic bank behavior would share some insights with the literature showing that banks sell different types of loans depending on specific circumstances. For instance, Irani, Iyer, Meisenzahl, and Peydró (2021) document that undercapitalized banks are more likely to sell nonperforming loans, provided their higher risk weights for capital requirements.

[24] We find very similar results for all C&I loan deliquency illustrated in Figure A6 of the Appendix. In contrast, Figure A7, also in the Appendix, shows that past due loans still accruing do not respond to the shock, which suggests that the loans banks dispose of or refinance are actually those in more dire conditions. Additionally, we note that in our sample nonaccrual loans average 1.32 per cent with respect to commercial loans, while past due loans still accruing represent only 0.34 per cent, which helps explain the response when all past due loans are combined in Figure A6.

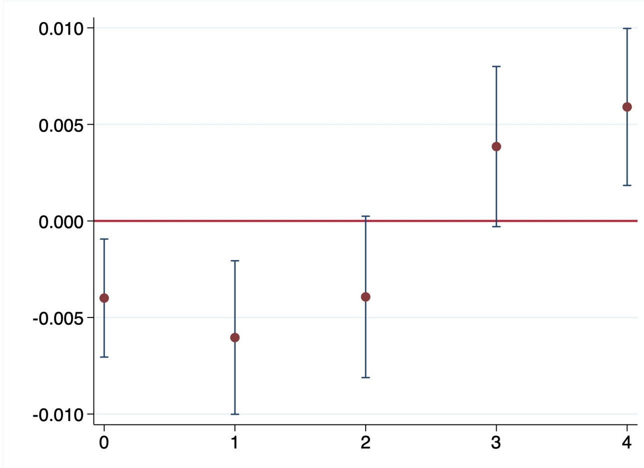


Figure 8: CLO Funding and Loan Performance. This figure presents the local projections of Delinquent nonaccrual C&I loans, scaled by C&I loans, in response to a one unit increase in CLO funding reliance, $\overline{E}_i \times S_t$, estimated in the panel model. Red dots represent point estimates. Blue vertical lines represent 90% confidence intervals.

Still, while both of the preceding arguments seem plausible ex ante, further investigation is required to more clearly depict this mechanism.

6 Conclusion

We study the causal effect of CLO funding on bank riskiness. Our main contribution is to show that positive CLO funding shocks can reduce bank probability of default for half a year.

We also explore plausible mechanisms that can help explain the main result, and we conclude that three aspects play a prominent role. The first one is the increase in the origination of institutional loans, which fosters origination fees and strengthens net noninterest income. The second one is a more efficient use of resources. Given a more robust demand to buy their loans, banks can retain on their balance sheets lower amounts of loans despite the increase in origination. The third one is the temporary improvement in the performance of those loans that banks choose to retain, which can further strengthen their financial positions.

Our results contribute to the literature on bank risk management, primarily providing the identification of a causal link between CLO funding and bank riskiness. They also contribute to the literature studying the shadow banking system and how it affects the performance of banks. Ultimately, our paper informs the policy-making process, providing relevant insights to bank regulators and supervisors.

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Appendix

A Variable Definitions and Sources

Dependent Variables for Local Projections Analysis

The following dependent variables come from own elaboration using the data sources cited below.

- *EDF*. Own elaboration, following the procedure described in Bharath and Shumway (2008), using data from CPST, CRSP, FRED.
- Institutional loan origination, used in Panel 6a. The quarterly ratio of institutional loans led to all loans led by a bank, on a proportional basis. For each loan arranged, a portion is asigned to a bank, which is the inverse of the number of banks arranging the loan. Suppose, for instance, that bank A arranges two loans during quarter t: institutional loan I and non-institutional loan N. Loan I is co-arranged with another bank B, so A is asigned 1/2 institutional loan. Loan N is arranged solely by A instead, so A is asigned 1/1 non-institutional loan. Then, this institutional loan origination measure for bank A in quarter t is $0.5/(0.5 + 1) = 1/3$. Elaborated with data from DealScan.

The following dependant variables come from the FR Y-9C Report.

- Log of C&I loans: LN(BHDM1766).
- Net noninterest income to lagged equity: (quarterly change of BHCK4079 - quarterly change of BHCK4093) / LAG1.BHCK3210.
- Investment banking, advisory, and underwriting fees and commissions to lagged equity: quarterly change of BHCKC888 / LAG1.BHCK3210.
- Net interest income to lagged equity: quarterly change of BHCK4074 / LAG1.BHCK3210.
- Delinquent nonaccrual C&I loans to C&I loans: BHCK1608 / BHDM1766.

- Trading C&I loans to C&I loans: BHCKF614 / BHDM1766.
- All C&I past due to C&I loans: (BHCK1606 + BHCK1607 + BHCK1608) / BHDM1766.
- Past due C&I loans still accruing to C&I loans: (BHCK1606 + BHCK1607) / BHDM1766.

Control Variables for Local Projections Analysis

The following control variables come from the FR Y-9C Report.

- Real estate loans to total loans: BHCK1410 / BHCK2122.
- Commercial & industrial loans to total loans: BHDM1766 / BHCK2122.
- Deposits to total assets: (BHDM6631+BHDM6636+BHFN6631+BHFN6636) / BHCK2170.
- Noninterest income to net operating revenue: quarterly change of BHCK4079 / (quarterly change of BHCK4079 + quarterly change of BHCK4074).
- Log of total assets: LN(BHCK2170).
- Growth rate of total loans: LN(BHCK2122) - LN(LAG1.BHCK2122).
- Balance sheet liquidity: securities available for sale plus federal funds sold in domestic offices and securities purchased under agreements to resell, all scaled by total assets. (BHCK1773+ BHDMB987+BHCKB989) / BHCK2170.
- Equity to total assets: BHCK3210 / BHCK2170.

The following is market data used in a robustness check.

- S&P 500 index. Log of quarterly average of S&P 500.

Time Series Variables for VAR Analysis

- CLODI, Palmer Square CLO Debt Index. Palmer Square produces two related indices: the Palmer Square CLO Senior Debt Index (CLOSE) and Palmer Square CLO Debt Index (CLODI). According to the firm, these indices *"seek to reflect the investable universe for U.S. dollar denominated collateralized loan obligations... CLODI is comprised of original rated A, BBB, and BB debt issued after January 1, 2009 subject to certain inclusion criteria... Both indices are comprised solely of cash and arbitrage CLOs backed by broadly syndicated leveraged loans."* (Palmer-Square-Capital-Management, 2018) Used in logs. Source: Bloomberg.

- Financial system *EDF*. Own elaboration, as described in the text, using data from CPST, CRSP, FRED. This time series is the monthly average of the *EDF* for all U.S.-based financial companies – Standard Industrial Classification (SIC) codes between 6000 and 6999.

- Kansas City Financial Stress Index. Source: FRED.

- Institutional loans volume. The monthly sum of the amount of all institutional loans (term loan B through term loan K) originated to U.S. firms, in U.S. dollars, syndicated in the U.S. Seasonally adjusted and used in logs. Source: DealScan.

- Institutional loans all-in-spread drawn. The monthly average of All-In Drawn spread on all institutional loans (term loan B through term loan K) originated to U.S. firms, in U.S. dollars, syndicated in the U.S. Source: DealScan.

B Identifying Lead Arrangers and Aggregating them at the Top Bank Holding Company (BHC) or Financial Holding Company (FHC)

Estimating bank reliance on CLO funding starts with defining those banks that lead institutional loans, defined as facilities named Term Loan B through Term Loan K, and likely to be part of the group of loans referred to as Broadly Syndicated Loans (BLS). A bank is defined as a transaction lead lender if it receives Lead Arranger Credit in DealScan.

A financial institution can act as lead arrenger through different subsidiaries. For instance, DealScan records loans led by several arms belonging to the Domestic Financial Holding Company *"Goldman Sachs Group, Inc., The,"* including *"Goldman Sachs & Co."* (since Apr/2017 legally called *"Goldman Sachs & Co. LLC."*) and *"Goldman Sachs Bank USA."*

The process of estimating bank reliance on CLO funding requires that we aggregate all loan originations from a same top domestic financial institution. We start by identifying all lead arrangers leading at least 50 transactions during the 2012-2019 sample period and then consolidate all the related lead arrangers partaining to the same top institution. Our focus is on those cases where the top financial institution is either a Domestic Bank Holding Company (BHC) or a Domestic Financial Holding Company (FHC).

In order to consolidate transactions at the BHC/FHC level, we rely on a number of sources of information. The first source is DealScan itself, which records parent and ultimate parent company information for a given bank. While this is often a good starting point in the aggregation process, it is not necessarily entirely accurate in all cases. A key reason being that this mapping only reflects the latest bank-parent-ultimate parent relationship recorded by DealScan – i.e. it does not keep track of historical relationships. For instance, a given bank could be sold from one BHC/FHC to another one at some point in time, and the record in DealScan would only reflect the latest relationship established. To address this and other possible information gaps, we resort to the National Information Center to identify the lead arranger and link it to the relevant top BHC/FHC over time, which requires studying the financial institution history and the hierarchical organization. Often, this process also requires searching for information that helps us depict the evolution of the different bank relationships, particularly in what regards consolidations. Thus, we complement the previous sources with news, SEC filings available from EDGAR, corporate announcements, general information available on the *Investor Relations* sections of the banks' websites, and other sources of information that can help us obtain a clear picture of the BHC/FHC structure over time. It is also during this step that we consolidate at the BHC/FHC also smaller subsidiaries which might have led fewer than 50 transactions. Lastly, when possible, we cross-validate our matchings with other matchings previously established in the literature (specifically, those made by Barraza, Lee, and Yeager, 2015; Schwert, 2018).

We emphasize lastly that our choice to work with *Domestic* BHC and FCH stems from the need to work with comparable banking organizations, particularly in what regards financial regulation. Riskiness and the different measures of it we can think of are intrinsically related to the regulatory requirements banks are subject to, and Domestic and Foreign institutions operating in the United States have been subject to (sometimes significantly) different requirements over time, which renders infeasible a meaningful comparison between these two types of institutions.

C Robustness Checks for the Benchmark Result

C.1 Alternative Aggregate Risk Variable in the VAR Model

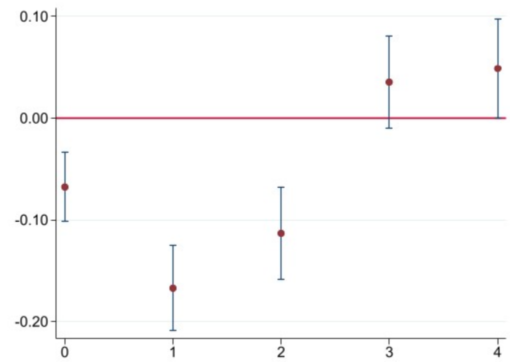

Figure A1: Response of EDF. The institutional investor demand shock is estimated in a VAR model where the Kansas City Financial Stress Index replaces the average EDF of U.S.-based financial firms used in the benchmark model. Linear projection estimates from panel model. Red dots represent point estimates. Blue vertical lines represent 90% confidence intervals.

C.2 Accounting for Variability in the Estimation of Shock S_t

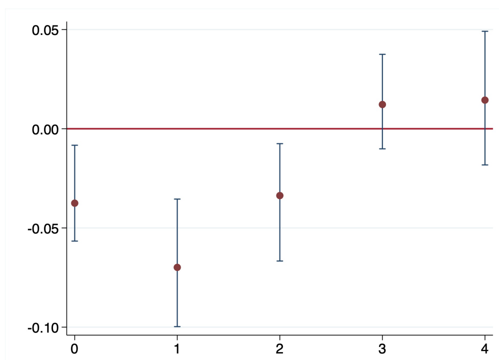

Figure A2: Response of EDF – benchmark model. The confidence bands are constructed by Monte Carlo simulation taking $1,000$ draws from the posterior distribution of S_t, recalculating $\overline{E}_i \times S_t$, and re-estimating the coefficients β^j in panel model (6). For each horizon j, the red dots represent the median of the vector of the $1,000$ estimated coefficients, while the blue vertical lines correspond to the $14/86th$ percentiles of the vectors.

C.3 Alternative Identification of Institutional Investors Demand Shock

In an alternative strategy to identify the institutional investors demand shock, a residual shock substitutes the aggregate risk shock employed in the benchmark strategy. This means that the fourth column of matrix A_0 is left entirely unrestricted. Moreover, in this case we also leave unrestricted the response of aggregate EDF to the institutional investors demand shock for CLOs. The following table represents this strategy:

$$\begin{bmatrix} u_t^{clo} \\ u_t^{vol} \\ u_t^{spr} \\ u_t^{edf} \end{bmatrix} = \begin{bmatrix} + & - & - & * \\ + & + & + & * \\ - & - & + & * \\ * & * & * & * \end{bmatrix} \begin{bmatrix} w_t^{InstD} \\ w_t^{BankS} \\ w_t^{CorpD} \\ w_t^{Resid} \end{bmatrix}$$

Table A1: Alternative sign restrictions for the identification of the structural shocks of the VAR model. The four shocks identified are an institutional investor demand shock for institutional loans, a bank supply shock, a corporate demand shock, and a residual shock. The symbols $+/-$ indicate a positive/negative on-impact restriction, respectively, while $*$ indicates unrestricted coefficients.

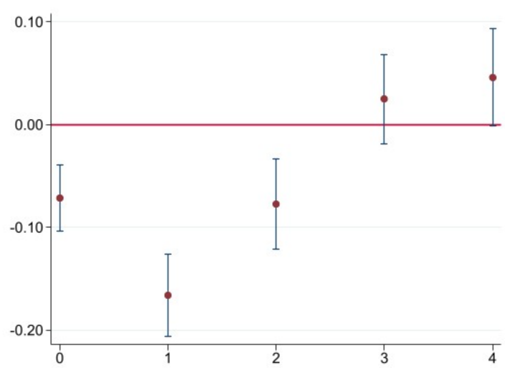

Figure A3: Response of EDF. The institutional investor demand shock is estimated in a VAR model where a residual shock replaces the aggregate risk shock. Linear projection estimates from panel model. Red dots represent point estimates. Blue vertical lines represent 90% confidence intervals.

D Additional Tables and Results

Lead Arrangers and their Reliance on CLOs

Financial Institution	$\overline{E}_i$
Ally Financial Inc.	17.6
Bank Of America Corporation	13.8
Capital One Financial Corporation	7.8
CIT Group Inc.	9.4
Citigroup Inc.	19.6
Citizens Financial Group, Inc.	13.0
Fifth Third Bancorp	11.1
Goldman Sachs Group, Inc., The	40.7
JPMorgan Chase & Co.	13.6
Keycorp	9.9
M&T Bank Corporation	6.8
Morgan Stanley	41.6
Suntrust Banks, Inc.	16.3
SVB Financial Group	8.6
Webster Financial Corporation	13.6
Wells Fargo & Company	8.3
Average	15.7
S.D.	10.6

Table A2: Reliance on CLO funding $\overline{E_i}$ ($\times 100$) for domestic BHC and FHC with at least fifty transactions led during the sample period 2012-2019. Reliance on CLO funding is constructed as described in the main text.

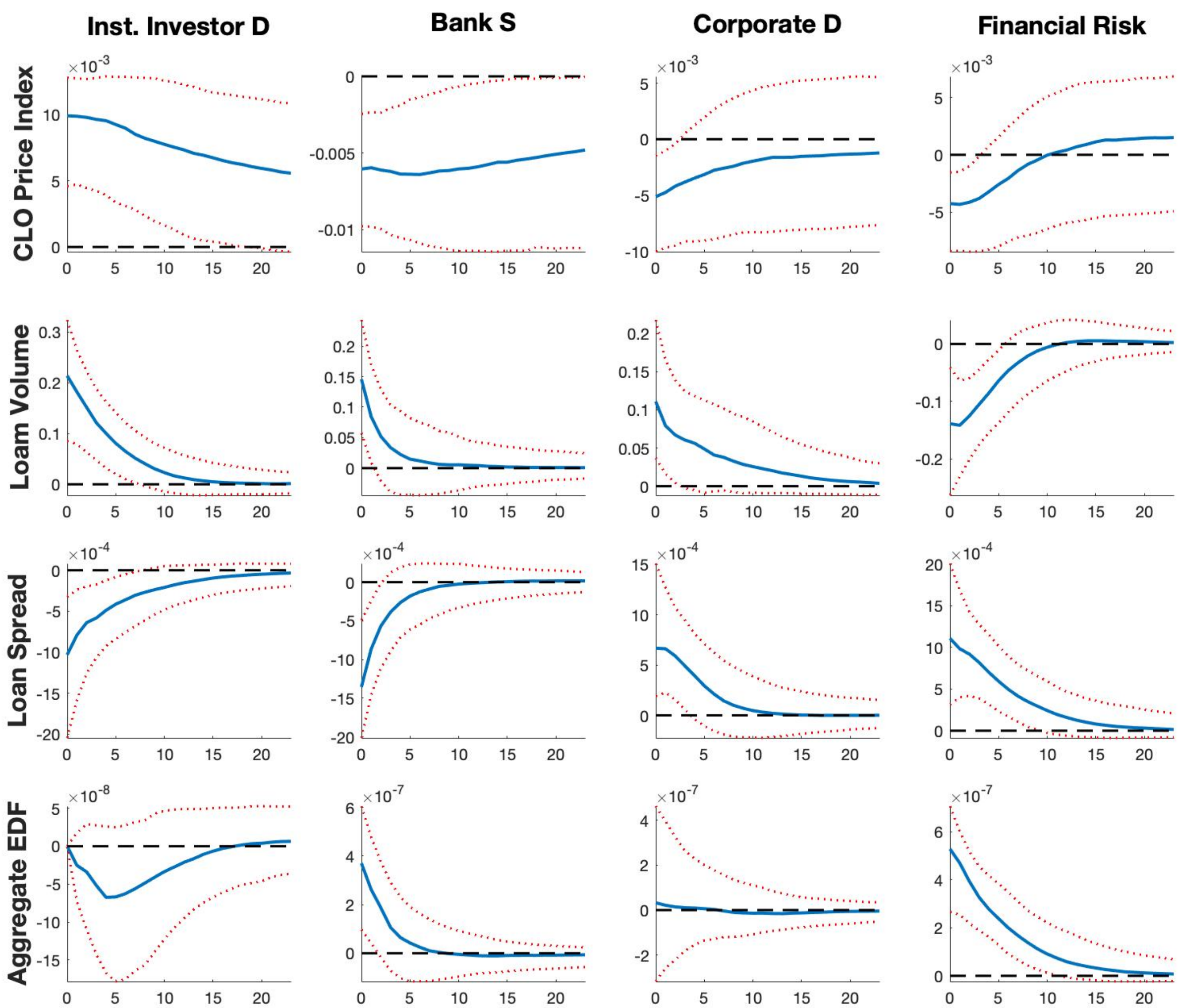

Figure A4: Response Functions of the Baseline VAR model. Responding variables are reported by row. Shocks are reported by column. The structural shocks are identified by the assumptions in Table 1. One-standard deviation shocks are considered. The blue line is the median posterior response to the shock. The dashed-red lines are the $14th/86th$ posterior bands. The unit of time on the horizontal axis is months.

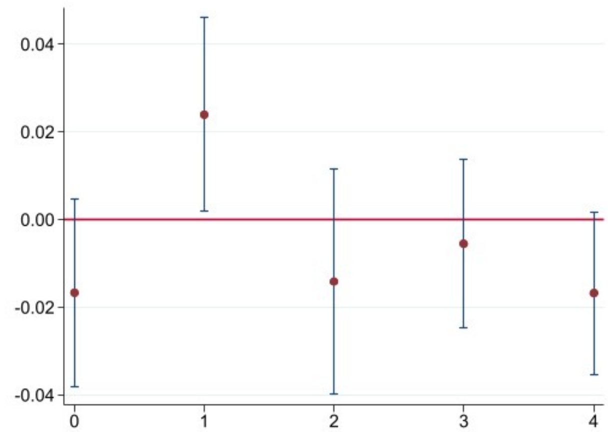

Figure A5: Local projections of the ratio of C&I loans available for trading to C&I loans on balance sheet in response to a one unit increase in the CLO funding reliance, $\overline{E}_i \times S_t$, estimated in the panel model. Red dots represent point estimates. Blue vertical lines represent 90% confidence intervals.

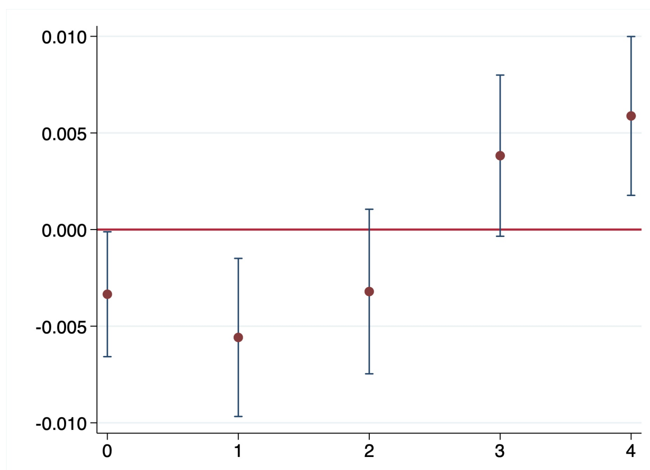

Figure A6: CLO Funding and Loan Performance. This figure presents the local projections of All C&I loans past due, scaled by C&I loans, in response to a one unit increase in CLO funding reliance, $\overline{E}_i \times S_t$, estimated in the panel model. Red dots represent point estimates. Blue vertical lines represent 90% confidence intervals.

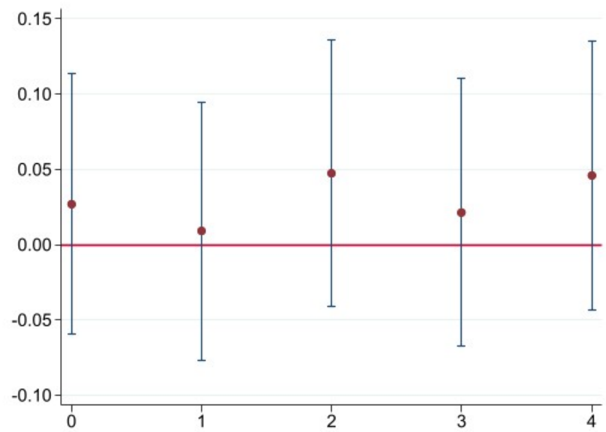

Figure A7: CLO Funding and Loan Performance. This figure presents the local projections of Past due C&I loans still accruing, scaled by C&I loans, in response to a one unit increase in CLO funding reliance, $\overline{E}_i \times S_t$, estimated in the panel model. Red dots represent point estimates. Blue vertical lines represent 90% confidence intervals.