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A High-Frequency Measure of Chinese Monetary Policy Shocks

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Keywords: monetary policy, inter-bank market, macroeconomic announcements, asset prices, China
JEL Classification: E52, G12, G14

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1. Introduction

Measuring unexpected changes to monetary policy (i.e., monetary policy shocks) helps to correctly identify the policy impacts on both asset prices and the real economy for causal inference (Cochrane and Piazzesi, 2002; Bernanke and Kuttner, 2005; Nakamura and Steinsson, 2018; Swanson, 2021). Measuring these changes is particularly challenging, however, given that monetary policy in emerging markets often times lacks a key proxy for measuring its policy stance and features multi-dimensional objectives as well as a complex toolkit (Gopinath, 2019),[1] and also that monetary policy regimes are constantly evolving (Unsal, Papageorgiou, and Garbers, 2022).[2]

Our paper introduces a parsimonious way for identifying monetary policy shocks up to daily frequency for emerging markets, as first tailored to the market setting of China. Most importantly, our paper not only provides a simple, higher-frequency, and sufficient statistic indicative of Chinese monetary policy shocks ready for use, but provides a framework of validation tests to evaluate the quality of our measured shock series against outstanding alternative measures.[3] After showing that our shock series outperforms others, we provide important causal evidence shedding light on Chinese monetary policy transmission. Our

[1] Many central banks in emerging markets have adopted explicit objectives for financial stability in addition to the objective of maintaining price stability as commonly adopted among advanced economies (Kim and Mehrotra, 2017, 2018). Many emerging markets also target exchange rates and monetary aggregates in addition to price inflation (IMF, 2015). For example, the central bank of China, the People's Bank of China (PBOC), carries on quite a few policy objectives, which include maintaining currency and price stability, so it may promote economic growth and employment, as well as ensure financial stability. Since 2013, PBOC has helped advance financial reform in China and promoted the development of domestic financial markets (Yi, 2023).

[2] Borio (2019) summarizes that emerging markets have been moving away from standard inflation-targeting monetary policy regimes. For example, with de jure exchange rate flexibility, central banks in emerging markets often identify exchange rate stability as the de facto primary anchor over any inflation objective (IMF, 2015). In addition, central banks in Brazil, Indonesia, and China, among others, have changed their policy targets to move from quantity-based (e.g., a broad money measure such as the M2 growth or total credit measure) to price-based (e.g., policy-anchored short-term interest rates).

[3] Though based on different data sources and assumptions, for example, Chen, Ren, and Zha (2018), Lu, Tang, and Zhang (2023), and Das and Song (2023) present their own measures of monetary policy shocks in China and examine the impacts of Chinese monetary policy on shadow banking, on corporate investments, and on interactions between monetary and fiscal policy in China, respectively. Little is known about their measurement qualities and about how to interpret the similarities and differences across different sets of results.

paper therefore is the first to jointly construct and validate Chinese monetary policy shocks, and study Chinese monetary policy transmission for causal inference. Our paper contributes to the literature addressing the first-order question for emerging markets on whether monetary policy shocks are poorly measured or whether monetary policy transmission is simply not operating.

We first highlight three major stylized facts related to monetary policy transmission shared between China and other emerging markets. These facts serve as key motivations for our methodology design. First, emerging markets typically lack a key reference policy measure that sufficiently reflects its monetary policy stance (e.g., the Target Federal Funds rate in the U.S.). In particular, their futures and derivatives markets are relatively less developed in terms of both limited product varieties and low trading volume (Upper and Valli, 2016). Second, under multiple objectives, central banks in emerging markets take multiple tools for monetary policy practice, which include both quantity-based monetary policy tools (e.g., money supply adjustment, quota-based liquidity and credit allocation policies, and large-scale asset purchase programs) and policy interest rate management (Arslan, Drehmann, and Hofmann, 2020; Basu, Boz, Gopinath, Roch, and Unsal, 2020).[4] Third, emerging markets like China heavily rely on bank financing for channeling credit, which means that the banking system operates as the main transmission channel through which monetary policy could affect financial markets and the real economy (Giannetti and Ongena, 2012; Ehlers and Villar, 2015; He and Wei, 2023).[5] Therefore, the inter-bank market is the key adjustment margin in the transmission of monetary policy in emerging markets that immediately

[4]As for other available policy tools other than policy interest rate adjustments, central banks in emerging markets for example frequently use lending facilities by which the central bank directly injects liquidity into the banking system. Impacted economies include India, Indonesia, Malaysia, Thailand, Brazil, Chile, China, Colombia, Mexico, Peru, Israel, Russia, Saudi Arabia, and South Africa (Van't Dack, 1999; Warjiyo and Juhro, 2019). Hardy and Zhu (2023) study the market impacts of large asset purchase programs implemented by central banks during Covid-19 years across a list of 24 emerging markets, including Argentina, Brazil, Bulgaria, Chile, China, Colombia, Czechia, Egypt, Hungary, India, Indonesia, South Korea, Malaysia, Mexico, Peru, Philippines, Poland, Romania, Russia, South Africa, Thailand, Turkey, Ukraine, and Uruguay.

[5]By the end of 2021, outstanding bank loans accounted for 61.68% of Aggregate Financing to the Real Economy (AFRE) (i.e., "Total Social Financing" in China), which measures the total scale of financial supports from the Chinese financial system to its real economy as calculated by the PBOC (He and Wei, 2023).

responds to monetary policy changes (Hachem and Song, 2021; Sifat, Zarei, Hosseini, and Bouri, 2022; Yi, 2018, 2023).[6]

In the context of the Chinese market, we base our approach for constructing monetary policy shocks by specifically addressing the measurement difficulties rooted in these institutional complexities of emerging markets. First, instead of directly taking any ad-hoc monetary policy-related instrument to proxy for policy changes, we rely on serious estimations to uncover a "latent factor" that serves as a sufficient statistic of Chinese monetary policy shocks. Second, without taking a prior on whether quantity-based or interest rate-based policy tools are more effective in shaping monetary policy transmission, we consider a comprehensive list of monetary policy changes concerning both quantity and interest rate changes in China. Third, we specifically focus on changes in the costs of inter-bank borrowing among Chinese commercial banks in the inter-bank market, as induced by Chinese monetary policy changes, in order to capture "shocks" to monetary policy as Chinese banks are immediately exposed to monetary policy transmission. Also, since China lacks the developed and liquid markets of interest rate swaps, futures, and derivatives, our shocks are estimated based on spot interest rate changes driven by monetary policy adjustments.

Importantly, to best isolate the *unexpected* shock component to policy-triggered inter-bank interest rates, we adopt the common approach of using high-frequency financial data to identify the abrupt changes in interest rates in short windows of announcement events of all relevant monetary policy instruments (Kuttner, 2001; Bernanke and Kuttner, 2005; Nakamura and Steinsson, 2018).[7] Our shocks are reflective of interest rate changes in the inter-bank market on the announcement day of monetary policy changes relative to the

[6]The inter-bank market has been explicitly discussed as the primary target market for the operations of Chinese monetary policy (Yi, 2018, 2023).

[7]Also see Gürkaynak, Sack, and Swanson (2005) and Swanson (2021) for extracting principle components of interest rate changes around the Federal Reserve's FOMC announcements, and Altavilla, Brugnolini, Gürkaynak, Motto, and Ragusa (2019) for changes in the ECB's announcements of Key ECB interest rates in the euro area. We note that a more classic approach of identifying monetary policy shocks relies on the estimations of an interest rate determination rule or of a dynamic equation system first and then obtain the residual series as monetary policy shocks (Taylor, 1993; Christiano, Eichenbaum, and Evans, 1999; Uhlig, 2005; Chen, Ren, and Zha, 2018). However, this approach is largely based on low-frequency macroeconomic data for causal inference.

previous day. Given that transaction-level inter-bank borrowing data up to even higher frequency of minutes or seconds is not publicly available, our shock series consists of daily frequency. Nonetheless, our approach can nicely adapt to other emerging markets, which are subject to similar constraints of the availability of higher data frequency. We finally present a single and parsimonious time series of interest rate-based Chinese monetary policy shocks of daily frequency, for which we achieve a significant amount of "dimension reduction" after filtering all these institutional background.

Specifically, our shocks are constructed based on a heteroscedasticity-based partial least squares (PLS) method (Rigobon, 2003; Rigobon and Sack, 2004), which involves two steps for shock identifications in the spirit of Fama and MacBeth (1973) and Bu, Rogers, and Wu (2021).[8] However, relative to Bu, Rogers, and Wu (2021) in the application of estimation for the U.S. monetary policy shocks, our identifications are much enriched in the following aspects, concerning the specific institutional details in China. First, instead of examining the changes in treasury yields or Federal Funds Rate futures prices as in the U.S. market, we examine the average market responses of issuance interest rates of Negotiable Certificate Deposits (NCD) of different maturities issued by different commercial banks. While the treasury yield curve in China is relatively stable and Chinese futures market is underdeveloped, The NCD market has quickly developed into one of the most important inter-bank markets in China, through which a large universe of heterogeneous Chinese commercial banks are actively borrowing among each other via NCD issuance.[9] Importantly, changes in NCD issuance rates are tightly related to the balance sheet management of banks, which immediately respond to monetary policy changes (Yi, 2023). Second, given a wide range of monetary

[8]The PLS method works the best for estimation given its ability to handle multicollinearity and high-dimensional data using a small sample effectively, which provides stable estimates and allows for easy interpretation of coefficient estimates (Bu, Rogers, and Wu, 2021). As we demonstrate, estimating for monetary policy shocks involves taking a small data sample (for a finite number of monetary policy events) of many interest rates (considering the term structure of related interest rates) with a considerable number of co-movements.

[9]NCDs are issued by a predominant share of deposit-taking banks in China. The issuing banks obtain the non-deposit source of borrowing at a cost in a market setting. By 2022, 2051 banks have been actively issuing NCDs and trading assets among each other, and the outstanding NCD balance has reached about 15 trillion yuan.

policy tools implemented in China, we consider inter-bank interest rate changes in windows of many different policy events for estimations of Chinese monetary policy shocks involving both changes in the quantity-based and interest rate-based policy tools. This is different from the routine U.S. applications of focusing on FOMC announcement event windows only (Bernanke and Kuttner, 2005; Lucca and Moench, 2015).

Specifically, in the first step of our two-step estimation procedure, we exploit the NCD interest rate dynamics in short windows of a wide coverage of different types of announcement events of the central bank of China, the People's Bank of China (PBOC). In particular, we consider PBOC's policy changes including quantity-based adjustments (e.g., open market operations in the form of reverse repurchase agreements, liquidity injections to banking systems via lending facilities, changes in reserve requirement ratios) along with interest-rate based adjustments such as changes in benchmark deposit rates and loan prime rates.[10] We then run time-series regressions to estimate the average sensitivity of our selected inter-bank interest rates of different maturities across different policy events and tools; these regressions measure the market interest rates' average risk exposure to monetary policy (i.e., the "beta"). Importantly, we consider the responses of the term structure of inter-bank interest rates, by which our constructed shocks reflect both shorter-run and longer-run impacts of monetary policy. This is highlighted as a prerequisite for best measuring monetary policy shocks (Nakamura and Steinsson, 2018). In the second stage, we run repeated cross-sectional regressions of response interest rates on the beta to isolate the common and unobservable component of abrupt interest rate variations for only those days of announced monetary policy changes. Importantly, our measured unexpected monetary policy changes in China are infrequent, since the PBOC does not aim to continuously surprise the market unless it

[10]The PBOC has continuously pushed forward efforts to introduce newer tools in addition to the traditional toolkit. Since 2013, the PBOC has regularly completed transactions with banks in the inter-bank market through repurchase agreement transactions (repo) and liquidity injections via short-term lending facilities (SLF) in order to target the 7-day repurchase rate pledged for interest rate bonds by deposit-taking institutions in China's inter-bank market (DR007). In addition, the PBOC regularly manages longer-term liquidity operation with banks via medium-term lending facilities (MLF) in order to target longer-term interest rates (i.e., the Loan Prime Rate (LPR) associated with bank lending).

must.

Our sample of estimation covers years from 2015 to 2021, over which our daily times series of Chinese monetary policy shocks is constructed.[11] We denote positive (negative) shocks to indicate unexpected inter-bank interest rate hikes (cuts) driven by exogenous monetary tightening (expansion) in China. Given our shock series, we find that our measured unexpected monetary policy changes are generally consistent with known monetary policy cycles in China. Importantly, before we use our measured monetary policy shocks for examining the Chinese monetary policy transmission, we provide systemic validations of shocks series using asset price data. We cast our validation tests based on a crucial assumption: if our constructed shocks are reflective of unexpected monetary policy changes, shock variations may operate as an aggregate risk that commands a risk premium in the cross-section of stock returns. Given that Chinese financial firms such as commercial banks, security firms, asset management firms, insurance companies, and real estate companies are all immediately exposed to monetary policy risk in the transmission chain of monetary policy changes, we examine whether our measured monetary policy shocks are priced in the cross-section. Hence, a good measure of monetary policy shocks should help identify the price of monetary policy risk.

Based on a portfolio analysis of financial stocks, we find that the return exposure to our measured monetary policy shocks negatively predicts excess returns, and our results are robust after we adjust for common risk factors associated with equity pricing in China (Liu, Stambaugh, and Yuan, 2019), suggesting that a negative risk premium is related to our measured monetary policy shocks. Specifically, a long-short portfolio of high monetary policy-beta stocks relative to low beta stocks generates an annualized excess return of -2%. As

[11] We note that detailed NCD data to be made public, which ensures that our measure of monetary policy shocks can be easily updated in real time. According to regulation on information releases of NCDs, the National Inter-bank Funding Center (NIFC) under the supervision of the PBOC publishes timely contract details of each NCD issuance associated with each bank issuer. See regulation details in "Rules for the Issuance and Trading of Inter-Bank Certificates of Deposit in the Inter-Bank Market" (NIFC, 2017). Therefore, the real-time data availability of NCD interest rates is guaranteed as long as the NCD market in China is operates legally.

investors demand higher returns for stocks with low and negative monetary policy-beta (i.e., stocks perform poorly when our measured monetary policy is unexpectedly contractionary), Chinese monetary policy shocks carry a negative price-of-risk that implies a slowdown of economic growth when monetary policy is tightening.[12] To hedge against monetary policy risk, investors are willing to pay a premium for stocks with high monetary policy-beta (i.e., do well when monetary policy is tightening). In addition, we do various asset pricing tests using alternative quantity-based and interest rate-based shock series as in Chen, Ren, and Zha (2018), Lu, Tang, and Zhang (2023), and Das and Song (2023), and we find that none of these measures exhibit similar impacts on stock returns as our measured shocks do.

Finally, we examine the effectiveness of Chinese monetary policy transmission by delving into how non-financial sectors are affected by our measured monetary policy shocks. Importantly, we show that monetary policy changes significantly shift the equity and credit risk in firms of non-financial sectors. In addition, these changes raise the real cost of borrowing across industries, resulting in non-trivial impacts on the real economy. Moreover, based on the results of our Vector Autoregression (VAR) estimations, we show that our measured Chinese monetary policy shocks have real and dynamic effects on macroeconomic aggregates. In our Internet Appendix, we include our results when we use the local projection method as in Jordà (2005). We confirm that our measured shocks consistently shift asset prices in a reasonable and dynamic way. All these results confirm our findings that tightening monetary policy in China is a contractionary risk.

The rest of our paper is structured as follows. In Section 2, we describe the essential institutional background of monetary policy practice in China and provide details of the monetary policy events we consider in our paper. In Section 3, we discuss the details of our

[12]Our results also suggest that monetary policy transmission in China to asset prices is little affected by the potential confounding "information effect" (Nakamura and Steinsson, 2018; Bauer and Swanson, 2023). That is, the U.S. Federal Reserve's announcements of federal funds rate cuts may be read as "bad" news suggesting an economic slow-down, which contaminates the direct effects of monetary policy changes. See also Romer and Romer, 2000; Campbell, Evans, Fisher, Justiniano, Calomiris, and Woodford, 2012; Miranda-Agrippino, 2016; Hansen, McMahon, and Tong, 2019; Cieslak and Schrimpf, 2019; Paul, 2019; Jarociński and Karadi, 2020; Lunsford, 2020.

empirical setting, including our various data sources and a comprehensive description of the NCD data. In Section 4, we discuss the methodology we use to construct daily shocks and examine the properties of our measured shock series. In Section 5, we provide a systemic validation of the quality of our shock measures, as compared to alternative measures in the literature. Finally, after we provide additional results in Section 6 regarding monetary policy transmission into the non-financial sector and the real economy, we conclude our paper with Section 7.

Related Literature. Our paper is related to three strands of literature. First, our paper is in parallel with the rich literature on monetary policy shocks in the U.S. economy. Earlier papers isolate orthogonalized innovations to the U.S. Federal Funds Rate by estimating a VAR system with assumptions on the shock structure, either using recursive ordering or sign restrictions with macroeconomic data (Christiano, Eichenbaum, and Evans, 1999; Uhlig, 2005). In addition, conditional on some measure of the central bank's internal information, a narrative approach based on textual analysis or machine learning techniques is also adopted to back out the "correct" nominal interest rate shocks (see Romer and Romer (2004) and more recently Drechsel and Aruoba (2022) and Handlan (2022)). Another approach is to take the higher frequency financial data of the Fed Funds futures in order to identify interest rate shocks on U.S. FOMC announcement days (Kuttner, 2001; Bernanke and Kuttner, 2005). More recently in this literature, the surprise component of monetary policy is measured by unexpected changes in interest rates across much narrower windows that center on the timing of FOMC statement releases (see, for example, Nakamura and Steinsson, 2018; Rogers, Scotti, and Wright, 2018). Also, rather than focus on unexpected target changes to the Federal Funds Rate, U.S. monetary policy variations are further spanned by extra risk factors including the Forward Guidance of future interest rate paths and Large Scale Asset Purchases (i.e., Quantitative Easing) (Gürkaynak, Sack, and Swanson, 2005; Gertler and Karadi, 2015; Swanson, 2021). In the spirit of Rigobon (2003) and Rigobon and Sack (2004), we use a two-stage heteroskedasticity-based partial least squares (PLS) approach to identify shocks to Chinese monetary policy. However, our paper relies on the augmentation of the baseline specification of this literature and examines the inter-bank interest rate changes around days of many different but relevant monetary policy events in China to obtain a sufficient statistic capturing Chinese monetary policy shocks. This results in a single time series respecting the institutional complexities and our approach can be easily adapted to measure monetary policy shocks in other emerging markets. Importantly, our paper not only presents a measure of Chinese monetary policy shocks, but is also the first paper to validate our measured shocks against alternatives and finally provides important evidence on Chinese monetary policy transmission for causal inference.

Second, our paper is related to the literature that examines impacts of central bank announcements on financial markets. Savor and Wilson (2013, 2014) find that the U.S. equity market exhibits larger excess returns on FOMC announcement days relative to non-announcement days. Also, Lucca and Moench (2015) document the pre-FOMC equity announcement premium. Ai and Bansal (2018) and Ai, Bansal, and Han (2021) theoretically show that the pre-announcement premium can be a result of investors with recursive preferences who require information in response to incoming central bank announcements. Hu, Pan, Wang, and Zhu (2022) meanwhile find that the heightening and subsequent reduction of market uncertainty is relevant for generating the pre-FOMC announcement premium. Brusa, Savor, and Wilson (2019) show that equity markets of many countries all exhibit strong reactions to U.S. FOMC announcements. Fleming and Remolona (1999) and Balduzzi and Moneta (2017) explore FOMC announcement effects on the treasury and bond market, respectively. Further, Muller, Tahbaz-Salehi, and Vedolin (2017) examine pricing impacts of FOMC announcements on exchange rate markets. In the market setting of China, Guo, Jia, and Sun (2023) and Han, Hu, and Jia (2023) document that stock returns in China are very responsive to macroeconomic announcements. Following these event-window studies, our paper identifies Chinese monetary policy shocks by uncovering the common component of variations behind inter-bank interest rates across maturities, as triggered by Chinese monetary policy announcements. Importantly, based on our daily shock measures, our paper is the first that reveals the negative price-of-risk based on asset pricing test in the cross-section of financial stocks, and also shows tightening monetary policy in China is a contractionary risk.

Third, our paper is closely related to the literature that evaluates the effects of monetary and fiscal policies on the Chinese economy. Ru (2018), Cong, Gao, Ponticelli, and Yang (2019) and Huang, Pagano, and Panizza (2020) show that state-owned enterprises (SOE) benefit from massive monetary and fiscal expansion in the amount of four trillion RMB during the years 2008-2010 by increasing their borrowing and investments with lowered costs, although doing so results in negative externalities on privately-owned enterprises. Chen, Ren, and Zha (2018), Chen, He, and Liu (2020), and Hachem and Song (2021) show how credit tightening in China can trigger expansion of shadow-banking business that accumulate excessive credit risk. Chen, Gao, Higgins, Waggoner, and Zha (2023) meanwhile find that fiscal expansion in China through increased government-backed infrastructure investment has weakened the monetary policy stimulus provided to private firms. Relying on low-frequency macroeconomic data, the existing papers mostly study the general implications of a joint credit and fiscal expansion window of 2008-2010 without being able to disentangle the unexpected changes to monetary or fiscal policy. Our paper is the first that explicitly constructs and verifies Chinese monetary policy shocks, addressing the measurement difficulties rooted in the complex institutional background, and systematically examines the transmission of Chinese monetary policy into both financial and non-financial sectors for causal inference. Importantly, we are the first that seriously proposes the methodology design for estimating the latent monetary policy risk factor up to daily frequency for emerging markets like China. Our cross-sectional asset pricing tests also suggest that Chinese monetary policy changes deliver direct and prompt effects on asset prices.

A few papers have proposed their own measures of monetary policy shocks in China

(See Chen, Ren, and Zha (2018), Lu, Tang, and Zhang (2023), and Das and Song (2023)). Chen, Ren, and Zha (2018) is one of the few pioneer studies to measure Chinese monetary policy shocks that respond to the institutional uniqueness of the Chinese economy. They first estimate the endogenous regime-dependent policy reaction function of the PBOC, taking the M2 growth rate as the policy instrument, and then derive the measure of monetary policy shocks based on residuals. Lu, Tang, and Zhang (2023) treat shocks to monetary policy as open-to-open log price differences of the dominant contract of China's 5-year treasury bond futures, both before and after PBOC's announcements of quarterly Chinese Monetary Policy Reports and its decisions on benchmark interest rates and reserve requirement ratio changes. They aggregate daily shocks within a month and study the impacts of monetary policy on firms' investments. Das and Song (2023) measure Chinese monetary policy shocks using daily close-to-close changes of 1-year interest rate swaps based on the 7-day repo rate around the PBOC's relevant monetary policy events. Based on their measured shocks, they find that monetary policy in China must be coupled with fiscal policy adjustments to deliver significant impacts on the macroeconomy.

Our paper draws similarities and differences relative to these papers in the following dimensions. First, instead of directly taking daily differences on observable asset prices around monetary policy event days, our paper differs from Lu, Tang, and Zhang (2023) and Das and Song (2023) by providing more serious estimations of the "unobserved and latent" component driven by monetary policy changes that could affect the whole term structure of inter-bank interest rates, which are immediately exposed to Chinese monetary policy transmission because of the dominant role of China's banking system. Our paper is similar to these in that we maintain that higher-frequency shock measures are crucial for identifying monetary policy transmission in China; thus, our paper also complements Chen, Ren, and Zha (2018) in that we use higher frequency financial data for identifications. Second, in addition to presenting a shock series, our paper is the first that validates our measured shocks along with these alternative measures; we also show that our measure outperforms. Third, we more carefully select monetary policy announcement events and maturity of interest rates based on which we extract from our monetary policy shocks. For example, as shown in Guo, Jia, and Sun (2023), the quarterly issues of Monetary Policy Reports in China do not contain many monetary policy surprises and offer simply a detailed summary of PBOC's monetary policy actions, which have already been priced in stock prices. Finally, with respect to our results, we find that our measured shock series is uniquely reflective of monetary policy risk in China, which commands a negative risk premium and shifts macroeconomic aggregates.

2. Institutional Background

In this section, we briefly review the development of Chinese monetary policy practice and discuss a number of important monetary policy tools of the PBOC. In particular, we highlight the importance of focusing on the inter-bank market to uncover Chinese monetary policy shocks at a higher frequency.

2.1. Monetary Policy in China

China's central bank, the People's Bank of China (PBOC), has consistently enacted initiatives to improve its monetary policy framework over time. The PBOC first assumed its role as China's central bank in 1984. From 1984 to 1997, the PBOC strictly regulated quotas on bank credit and cash supplies, which helped contain domestic inflation and promote economic growth. In 1996, the growth rate of the broad measure of monetary aggregates M2, which is the quantity-based measure of aggregate money supply, was officially set as an intermediate target for China's monetary policy practice. In 1998, PBOC abolished credit quotas for major national banks and then introduced standard monetary policy tools that included management of the Required Reserves Ratio (RRR), adjustments on benchmark loan interest rates (BLR), and routine open market operations in order to indirectly achieve money growth targets. Since 2013, the PBOC developed additional monetary policy tools to deal with shrinkage in foreign reserves and fluctuations in financial markets. As a result, Chinese monetary policy transmission is increasingly relying on a demand-based market system to allocate credit, and interest rate liberalization is one of the PBOC's top priorities for achieving this objective.

In particular, because of the predominant role that the Chinese banking system plays in channeling funds to the real sector, the effective transmission of monetary policy is mainly conducted through the Chinese banking sector (Yi, 2018; He and Wei, 2023). For example, the PBOC has regularly carried out both short-term lending facilities (SLF) and medium-term lending facilities (MLF), under which the PBOC makes discount loans directly to banks who require extra funding liquidity. Since 2019, all new bank loans in China have been required to be priced relative to the Loan Prime Rate (LPR), a key reference loan rate in China, as an replacement of its predecessor, the BLR. The PBOC's MLF operations then effectively affect the longer-term liability of banks and guide the formation of the LPR, which results in the transmission of monetary policy into businesses and households.

2.2. Inter-bank Borrowing in China

Since the mid-1990s until 2015, the PBOC extensively liberalized interest rates in China, starting with inter-bank lending rates, and then followed by the bank lending rates and deposit rates. Specifically, market-based repurchase agreements (repo) were introduced in 1997, through which banks could use government bonds as collateral in exchange for short-term funding among banks. This largely allowed banks to borrow and lend among each other with market-determined interest rates. Such a market-based pricing mechanism significantly contributes to the further expansion of the inter-bank market, as well as to the rapid development of the inter-bank bond market in China (Chen, He, and Liu, 2020).

An important feature of Chinese monetary policy practice is that the inter-bank market is immediately exposed to Chinese monetary transmission. That is, participating banks and non-bank financial institutions in the inter-bank market promptly respond to monetary policy changes through inter-bank borrowing and lending (Yi, 2018, 2023). For example, inter-bank borrowing costs as measured by inter-bank market interest rates like DR007 and R007 can be swiftly affected by the PBOC's 7-day reverse repo (RevRepo) transactions with inter-bank market participants.[13] This affects the cost of borrowing and the lending of excessive reserves in the banking system; in turn, the cost and quantity of borrowing among inter-bank financial institutions would be affected by such policy changes. The responsiveness of inter-bank borrowing, which is the closest step to monetary policy actions in the chain, thus matters critically if the capital market and credit allocation are to function well in China.

To capture borrowing and lending activities among banks in the inter-bank market that are driven by monetary policy changes in China, we focus on changes in inter-bank market rates as proxied by yields of returns associated with inter-bank NCDs within day windows of monetary policy changes for two primary reasons. First, the NCD market covers a much wider range of bank participants in the inter-bank market as compared to a smaller set of market-making banks that are actively involved with the PBOC for repo transactions and SLF operations. Second, compared to offered rates and very short maturities of market rates in the inter-bank market like Shibor (Shanghai Interbank Offered Rate), FR007 (Fixing Repo Rate), DR007 and R007, the NCD market has a nice spectrum of varied maturities covering real inter-bank borrowing and lending transactions among banks. Since its onset in 2013, the NCD market has quickly developed into one of the most important components of the inter-bank bond market in China.

[13] R007 and DR007 are both market inter-bank interest rates in China. R007 refers to the 7-day weighted average interest rate of repurchase agreements, while DR007 refers to the 7-day weighted average interest rate of pledged repo transactions. One key difference between the two is the type of participating institution associated with each: the market determining R007 covers non-financial institutions (R007) whereas that of DR007 includes mostly commercial banks with higher quality securities as pledges.

2.3. *Relevant Monetary Policy Events*

In this paper, we measure the responsiveness of inter-bank interest rates to announced monetary policy changes, so we may uncover latent Chinese monetary policy shocks. Since interest rates can be affected by different policy tools, we next discuss further our selection of the PBOC's monetary policy events for our shock identification.

We require that our considered monetary policy events should be identifiable by the date and time of a PBOC's monetary policy public announcement, which discusses real-time policy decisions and triggers immediate market reactions. We therefore focus on those relevant monetary policy events other than those events when the PBOC released macro and financial data. For example, statistics of monetary aggregates in China, including M0/M1/M2 measures and the outstanding balance of the Total Social Financing in China, are routinely published by PBOC each month. Because these data releases come with delays (e.g., data of the previous month are released in the next month), these announcement events are not related to immediate policy actions of the PBOC that could have real-time market impacts.[14] Thus, we do not consider the PBOC's data-release macro announcements for our analysis.

Our sample then consists of 146 events that involve PBOC's real-time monetary policy decisions over the sample period from January 2015 to December 2021. A long list of PBOC's monetary policy actions are covered in out study, which includes the PBOC's announced changes to the RRR and the PBOC's announced repo transactions that affect 7-day RevRepo interest rates. We also consider the PBOC's policy events with announced changes to the BLR and LPR. In addition, we consider all events of MLF operations covering both quantity and MLF rate changes, which are announced in real-time in the middle of each month.[15] In

[14] The quarterly issues of Chinese Monetary Policy Reports contain data summaries and PBOC's assessment of monetary policy appropriateness. These reports are not the key channels through which PBOC's updated decisions on monetary policy tools are announced to the public (Guo et al., 2023).

[15] Details regarding interest rates and quantities of PBOC's SLF operations conducted in a month are not released in real-time along with operations, but rather announced at the beginning of the next month with delays. Since we do not consider dates of beginning-of-month announcements of SLF operations to be relevant for pinpointing the dates of monetary policy decisions, we do not include these events for shock identifications.

summary, we consider both quantity-based (MLF, RevRepo, RRR) and the interest rate-based policy change events (MLF, LPR, BLR), allowing for the fact that inter-bank market interest rates can be well affected by both types of policy changes.[16] For further details, we use Section A of the Internet Appendix to discuss exact definitions, as well as the scope and associated announcement events of Chinese monetary policy practices.

3. Data

Our data is drawn from a diverse array of sources. We obtain precise timestamps for each of our monetary policy announcement events directly from the PBOC's official website. We focus primarily on detailed issuance-level data of the Nonnegotiable Certificate of Deposit (NCD) as obtained from Wind, which is posted on the website of National Inter-bank Funding Center (NIFC) every weekday. The daily stock returns and firm characteristics are also from Wind, and daily yield curves data are provided by ChinaBond. Other financial data include inter-bank market interest rates other than NCD rates, corporate and enterprise bond yields, and stock market indexes, all of which are sourced from the Choice Database. For shock validation using asset pricing tests, we use the China equity market factors as highlighted in Liu, Stambaugh, and Yuan (2019) from Robert F. Stambaugh's home page.

In the next section, we discuss how we identify a monetary policy event window based on the timing of PBOC's announcements. We then provide a detailed discussion of our NCD data followed by our data summary.

3.1. Event Window

Macroeconomic announcements in China may or may not be scheduled ahead of time, and public agencies often release macro news when financial markets are closed for trading

[16] For example, these MLF operation events are included in our sample regardless of whether the MLF rate associated with the MLF operation is changed, because inter-bank interest rates can be affected both by quantity and rate changes of MLF operations as well.

(Guo, Jia, and Sun, 2023; Han, Hu, and Jia, 2023). In Table 1, we therefore first summarize the date and time of announced monetary policy events in our sample. According to Panel (a), changes to LPR and BLR and changes to reverse repo rates can occur as early as the beginning of a month or as late as the end of a month. On the other hand, although we expect that the PBOC's announcements of monthly MLF operations occur around the middle of a month, we still see that the exact dates of MLF announcements exhibit variations within a month. Our considered policy change events of LPR announcements fall exactly on the 20$^{\text{th}}$ for every month as a prescheduled LPR announcement date. Panel (b) shows the within-week day distribution of these policy events. We see that all policy events occur evenly across weekdays and weekends, suggesting that the day of a policy announcement is largely unexpected within a week.

Panel (c) displays the average timestamps of each category of policy events conditional on whether the policy events arrive in non-trading hours. We separate the non-trading hours from trading hours of the money, bond, and inter-bank markets as governed by the China Foreign Exchange Trade System (CFETS) and the NIFC, which operates from 9:00 a.m. to 12:00 p.m. and 1:30 p.m. to 5:00 p.m. on a regular trading day. Our results suggest that policy events associated with changes to the LPR and reverse repo rates are consistently announced during trading hours. Other relevant monetary policy events may arrive to the market when the inter-bank market is closed. In Panel (d), we show how frequent these policy events overlap each other. The off-diagonal entries all suggest that only a very small number of days see co-released monetary policy announcement events. Our results are therefore not driven by some extremely important days on which many policy changes arrive.

Our day distribution analysis suggests that monetary policy events may occur on any day and time of a month, even when the inter-bank market is closed for trading. Importantly, we seek to pin down the market reactions of NCD interest rates to these policy events on the first trading day right after announcements when the inter-bank market is reopened for trading. To do so, we define *a monetary policy announcement day* as the one-day trading window in which NCD interest rates first react to announced monetary policy changes. Specifically, if a monetary policy event arrives before 5:00 p.m. on a trading day t, then day t is the announcement day. However, if the announced event arrives to the market after 5:00 p.m. on a trading day, on weekends, or over the holidays, then the announcement day is associated with the next following trading day.[17] Our final sample consists of 138 distinct monetary policy announcement days.

3.2. NCD Data

Our shock identifications are largely based on issuance-level NCD data that are regularly published by NIFC, which regulates the inter-bank market under the authorization of the PBOC, and provides detailed financial infrastructure services related to issuance, trading, and information concerning these inter-bank NCDs. The NIFC releases all NCD market-related information in real-time up to daily frequency. Our NCD data then include comprehensive details of every book-entry NCD that was issued by deposit-taking financial institutions (i.e., mostly commercial banks) in order to obtain extra funding in the inter-bank market. Each data entry captures a newly issued NCD product and encompasses the following details:

i) NCD Issuance-related: abbreviated NCD name, yield of return (i.e., the NCD rate), announcement date, planned NCD issuance date, planned issuance amount, actual issuance amount, maturity, price, coupon payment type, accrual date, due date, and issuing method;

ii) Issuer-related: issuer's name, registration province, credit rating, issuer type.

In accordance with NIFC stipulations, we note that each NCD announcement concerning an NCD issuance must be publicly disclosed to all investors at least one trading day prior

[17] We confirm that our empirical results are robust if the market-close threshold is arbitrarily set at 4:50 p.m. or 3:00p.m as stock markets on the Shenzhen Stock Exchange and the Shanghai Stock Exchange both close for trading at 3:00 p.m. on a regular trading day.

to the actual issuance day. Similarly, the reference yield of return must be pre-specified one day before its actual issuance. We then associate the announcement dates for all our NCD issuance, rather than the dates of actual issuance, with our pre-defined monetary policy announcement days. Finally, we calculate average changes in these NCD yields of return on monetary policy announcement days relative to that of the previous day without the monetary policy events, so we may isolate the NCD rate responses to unexpected monetary policy changes.

3.3. Descriptive Statistics

In this section, we summarize and discuss our NCD data further. Over our sample years, almost all issued NCDs are one of the following five maturities: one month, three months, six months, nine months, or one year. Only a trivial share of 0.07% of NCDs have a maturity of two years and 0.09% have a maturity of three years. By focusing on the most popular five maturities of NCDs and their total sum as a measure of market capitalization, we plot the values of issuance across maturities over time in Figure 1. As the yellow solid line in the figure shows, the NCD market cap surged from 5 trillion RMB yuan in 2015 to 13 trillion yuan in 2016, and this trajectory was sustained in the ensuing period. Given the high trading volume of NCDs in the secondary market, NCDs organically emerged as a cornerstone financial instrument of inter-bank borrowing in China. In addition, as captured by the red solid line, the NCDs of a 3-month maturity were dominant in earlier years, although banks more recently are more likely to issue 1-year NCDs, as indicated by the grey solid line.

We then provide summary statistics regarding NCD issuance by issuer type across maturities in Table 2. We make the following observations. First, as the second column shows, about 850 banks in China have issued at least one NCD, and all state-owned commercial banks (SOCB) and joint-stock commercial banks (JSCB), which are the largest banks in China, actively participate in the NCD market. Second, based on statistics regarding the amount of issuance and the number of issued NCDs, we find that urban commercial banks

(UCB) are the most active issuers in the NCD market, as they contribute the largest share of NCD issuance, followed next by rural commercial banks (RCB). Urban commercial banks issue twice as many NCDs as rural commercial bank issuers, even though more rural bank issuers exist. Third, joint-stock commercial banks issue as many NCDs as rural commercial banks; that said, state banks issue much fewer NCDs than both urban and rural banks do. Importantly, the average amount of NCD borrowing for join-stock and state banks is significantly larger than that of urban and rural banks. In terms of relative issuance shares, we observe that foreign-invested banks, private banks, and other bank types play a minor role in the NCD market. Finally, while average NCD rates in our sample are close to 3.2%, issuing rates among state-owned banks are slightly lower than those of other issuing bank types.

4. Methodology and Estimation of Shocks

In this section, we introduce our methodology for constructing China's monetary policy shocks up to daily frequency. In particular, we uncover a latent factor that moves inter-bank NCD interest rates across maturities on monetary policy event days only. Our method assumes that unexpected monetary policy surprises occur entirely on the PBOC's announcement days for monetary policy changes. We estimate our shock series by using a two-step Fama-MacBeth procedure that includes a Partial Least Square (PLS) approach (Fama and MacBeth, 1973; Bu, Rogers, and Wu, 2021). For an initial check, we show that our constructed monetary policy shocks are qualitatively consistent with different episodes of monetary policy adjustments. That said, we note that our measured unexpected interest rate hikes (cuts) in the episode of monetary expansion (contraction) indicate that the market expects even more interest rate cuts (hikes) than the actual interest rate realizations.

4.1. Estimation Procedures

We demonstrate that latent monetary policy shocks as denoted by e_t can be uncovered through estimations. Given that the inter-bank market is immediately exposed to monetary policy transmission in China, these unobserved monetary policy shocks should induce unexpected and prompt variations in inter-bank NCD interest rates once monetary policy changes are announced.

Following our method, we then extract monetary policy shocks from shared variations across NCD rates of different maturities driven by the PBOC's announced policy changes within an one-day event window. In line with subsection 3.3, we examine market reactions of 20 portfolio-level NCD rates, which are issuance amount-weighted NCD rates aggregated up to the level of 4 issuer-types (UCBs, RCBs, JSCBs, and SOCBs) and 5 major maturities (1-month, 3-month, 6-month, 9-month, and 1-year).

For better interpretations of the scale of our constructed shocks, we normalize the unit of the unobserved shock series aligned with the 1-year NCD issuance rate of urban commercial banks, denoted as UCB(1Y); we do so since urban commercial banks are the most active NCD issuers and their most popular maturity of NCD issuance is one year. It can be easily shown that our estimation results are insensitive to the choice of normalizing the scale of shocks.

Specifically, our estimation procedures involve two steps. In the first step, for each issuer type $j \in \{UCB, RCB, JSCB, SOCB\}$ of NCD issuance of maturity $i \in$ {1-mon, 3-mon, 6-mon, 9-mon, 1-year}, we estimate the factor loading β_i^j of the portfolio-level inter-bank NCD rate to monetary policy changes by using the following specification:

$$\Delta r_{i,t}^j = \alpha_i^j + \beta_i^j e_t + \varepsilon_{i,t}^j \tag{1}$$

in which $\Delta r_{i,t}^j = r_{i,t}^j - r_{i,t-1}^j$ captures changes in NCD rates at the portfolio level as of the monetary policy announcement day t relative to the day before monetary policy changes

$t-1$. Since residuals $\varepsilon^j_{i,t}$ are unrelated to monetary policy shocks on announcement days, β^j_i therefore reflects the sensitivity of inter-bank interest rates to latent monetary policy shocks. Performing estimations at the portfolio level not only makes our estimates of factor loading more precise but also includes the heterogeneity of monetary policy shocks on different types of bank issuers and on various maturities.

Given our normalization of the monetary shock series e_t to UCB(1Y), we effectively normalize $\beta^{UCB}_{\text{1-year}} = 1$. Hence, our effective specification for estimating the factor loading for each portfolio is:

$$\Delta r^j_{i,t} = \theta^j_i + \beta^j_i \Delta r^{\text{UCB}}_{\text{1-year},t} + \xi^j_{i,t} \tag{2}$$

in which β^j_i maintains the interpretation of a loading to Chinese monetary policy shocks but the reduced-form residuals follow as $\xi^j_{i,t} = -\beta^j_i \varepsilon^{\text{UCB}}_{\text{1-year},t} + \varepsilon^j_{i,t}$. Importantly, we see a challenge from this estimation given that the regressor $\Delta r^{\text{UCB}}_{\text{1-year},t}$ and the error term $\xi^j_{i,t}$ are correlated, stemming from the $-\beta^j_i \varepsilon^{\text{UCB}}_{\text{1-year},t}$ component. In order to address this "error-in-variable" challenge, we employ the heteroskedasticity-based estimator method proposed by Rigobon (2003), Rigobon and Sack (2004), and more recently by Bu, Rogers, and Wu (2021); this method enables us to consistently estimate the factor loading β^j_i using instrumental variables (IV).

In the second step, we undertake the cross-sectional regressions of $\Delta r^j_{i,t}$ on the estimated factor loading $\hat{\beta}^j_i$ for each monetary policy event day t to uncover latent monetary policy shocks e_t according to the following specification:

$$\Delta r^j_{i,t} = \alpha^j_i + e_t \hat{\beta}^j_i + u^j_{i,t} \tag{3}$$

in which e_t is the coefficient of interest for each regression. More importantly, this coefficient estimate identifies precisely the sign and size of monetary policy shocks on a policy change event day t. By collecting all coefficient estimates for monetary policy event days of a total number of T days, we take the time series $\{e_t\}^{t=T}_{t=1}$ as our baseline monetary policy shock series, which is parsimonious enough and is of daily frequency.

4.2. The Shock Series

Next, we plot our constructed baseline monetary policy shock series for simple visual inference. First, Panel (a) of Figure 2 directly plots daily shocks in units of basis points of annualized returns. Positive (negative) shocks indicate abrupt and unexpected interest rate hikes (cuts) on monetary policy event days. Panel (b) of Figure 2 plots the monthly shock series, which aggregates daily shocks through simple summation within a month.

Across these two panels, we observe substantial interest rate cuts throughout the year 2015, when China's GDP growth rate slowed to 6.9%, which was the slowest since 1990 and also, down from an average annual growth rate of around 10% over the previous 30 years.[18] In addition, at the onset of the COVID-19 pandemic in early 2020, we observe sharp decreases in policy-induced interest rates. Since the last quarter of 2016 until 2019, China is was significantly deleveraged to contain the burgeoning systemic risk in the financial market. These episodes were well captured by our interest rate hikes over these years. In addition to these observations, we note an interesting intra-year seasonality of interest rate shocks in that rate cuts are more prevalent towards the end of each year. In summary, our shocks are well aligned with cyclical patterns in Chinese economy (at least qualitatively) for an initial quality check.

Importantly, we highlight that unexpected interest rate hikes (cuts) given our shock measure simply reflect that the market is expecting even more interest rate cuts (hikes) than the actual interest rate realizations. This also means that directly taking interest rate differences without disentangling latent shocks, as the literature often does without justification, suffers from serious endogeneity issues.

We conduct additional comparisons between our baseline shock series and effective changes in underlying monetary policies for additional visual validation. In Figure 3, we

[18] The Chinese stock market also had a major crash in 2015, starting from June until 2016.

plot comparisons that show that our identified monetary policy shocks and underlying interest rate instruments generally line up in terms of directions of movement. However, we note that the magnitudes of our estimated shocks are smaller compared to the original rate changes. This again suggests that our shock series is more related to the smaller but unexpected component of interest rate changes. As a result, it is inadequate to use the PBOC's monetary policy instrument changes to denote monetary policy surprises.

5. Validations and Comparisons

In this section, we provide systemic validation tests on our constructed shock series before we conduct our additional analysis on Chinese monetary policy tranmission. We show that our daily shock series indeed captures the variation of monetary policy risk. Though our shocks are constructed from inter-bank interest rates data, we demonstrate the external validity of our shocks by showing that Chinese stock market returns react negatively only to our measured interest rate hikes when we control for a number of alternative measures in the literature. Given that Chinese financial firms are closely connected to the inter-bank market, we document that our measured Chinese monetary policy shocks command a negative risk premium among financial stocks, which are similarly exposed to monetary policy transmission. However, none of the alternative existing measures of daily monetary policy shocks deliver similar results.

5.1. Characteristics of Existing Shock Measures

In this subsection, we show that in terms of the shock distribution, our PLS-based Chinese monetary policy shocks are symmetrical and have both positive and negative shocks with close-to-zero means and medians as well as a sizeable spread of shocks. We also document significant differences across the outstanding alternative shock measures. We then proceed to fill a gap in the literature by providing a criterion by which we can assess the properties of a shock measure.

We first summarize and compare key data moments of our baseline Chinese monetary policy shocks based on our PLS two-stage estimation, labeled as PLS^0, and alternative measures of monetary policy shocks. In particular, to ensure that our shock measure is not driven by any issuer-type of NCD issuance, we present alternative shock series based on estimations of a sample that excludes NCD issuance rates of state-owned banks (SOCBs), labeled as PLS^1, as well as a shock series based on estimations of a sample that only considers NCD issuances of urban (UCBs) and rural banks (RCBs), labeled as PLS^2. We make comparisons among these series to ensure the internal consistency of our methodology.

In addition, we compare our shock series with some important measures in the literature: (1) quarterly shocks to Chinese M2 growth rates, which is a quantity-based monetary policy measure (CRZ) as in Chen, Ren, and Zha (2018), (2) daily interest rate-based measure on differences in the rates of interest rate swaps (DS) as in Das and Song (2023), and (3) monthly interest rate-based measure aggregated over daily differences of rates in 5-year government treasury futures (LTZ) as in Lu, Tang, and Zhang (2023). Except for the LTZ shock series that we directly obtain from the authors,[19] we closely follow methods of estimation and obtain the CRZ and DS shock series on our end. First, we update and extend the quarterly CRZ shock series using quarterly macroeconomic data that we sourced from the Atlanta Fed (Chang, Chen, Waggoner, and Zha, 2015), resulting in a series covering 2000Q1 to 2021Q4. We reverse the sign of the shock series such that positive values indicate contractionary shocks. Second, we replicate and extend the DS(1y) and DS(5y) shock series to December 2021 using the daily close-to-close change in the rate on 1-year and 5-year interest rate swaps based on the inter-bank 7-day repo rate, FR007(1Y) and FR007(5Y), around the date of monetary policy announcements as in Das and Song (2023).[20]

For fair comparisons across the shock series, we aggregate our PLS shock series and the

[19]We thank Lu, Tang, and Zhang (2023) for providing their monthly shock series to us.

[20]We do not reconstruct and reexamine the monetary-fiscal joint coordination shocks in our paper as Das and Song (2023) highlight that monetary policy transmission in China would be much stronger if monetary and fiscal policies were coordinated.

DS shock series to monthly in line with the data frequency of the LTZ shock series, also drawing closer to the data frequency of CRZ shocks. Without imposing the interpolation scheme, we use the original quarterly frequency of CRZ shocks. In Table 3, fixing the same sample periods, we tabulate the data moments of all monthly and quarterly shock series in the upper section of Panel (a). We also report data statistics in the lower section of the panel regarding monthly changes in the 1-year treasury yield, DR007, 3-month Shibor rates, and 1-year FR007, as well as the M2 Year-over-year growth rate. Across rows in Panel A, we see that PLS and DS shocks all suggest that monetary policy is lax on average while the mean LTZ and CRZ shocks appear to be contractionary. However, the average size of PLS shocks is closer to zero compared to that of DS shocks. Similarly, except for LTZ and CRZ shocks, the median of our PLS-based shocks and DS shocks is close to zero, and the standard deviation of PLS and DS shocks is much larger. That said, based on the results from the last two columns, the only shocks that exhibit statistically significant serial correlations are the CRZ shocks. Drawing references to Panel B, we see that interest rates associated with treasury market, inter-bank market, and interest rate swaps are all negative on average in our sample years. These are roughly consistent with implications from PLS and DS shock measures that suggest monetary policy expansion. In addition, perhaps because monthly M2 growth rates are negative in these years, the estimated CRZ shocks still suggests that monetary policy is tightening.

Panel (b) of Table 3 presents our pair-wise correlations of the shock series, with the quarterly CRZ shock values mapped to months in each quarter. We first see that the correlation coefficients among our baseline measure, PLS^0, and the two alternative shock series, PLS^1 and PLS^2, are all large, positive and statistically significant, with a correlation coefficient around 0.99 and 0.92, respectively. This suggests that our approach of measuring monetary policy shocks is robust to varied choices of reference rates. Given that we estimate our measure of Chinese monetary policy shocks based on inter-bank NCD interest rates (whereas the DS shock series are derived from the direct differences of interest rate swaps), it is reasonable to see their correlations are much smaller and remain close to 0.4, although the considered announced monetary policy events across these measures are quite similar.[21] Moving down the rows, we see that LTZ shocks are negatively correlated with PLS shocks and that DS shocks up to a coefficient of 0.2 to 0.3. However, quantity-based CRZ shocks exhibit non-significant correlations with all other interest rate-based shocks, which reflect the differences in underlying monetary policy instruments for shock estimations.

5.2. Shock Validations: Stock Return Responses to Monetary Policy Shocks

In line with the classic framework that examines stock return reactions to monetary policy surprises (Bernanke and Kuttner, 2005; Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018; Ozdagli and Velikov, 2020), we first draw the external validity of our measured Chinese monetary policy shock series relative to alternative measures. In particular, as shown in Bauer and Swanson (2023), stock returns are less affected by confounding effects that the "central bank is also learning from the news". Our identifications based on our stock return data deliver statistical power for differentiating the measures.

Again, to make fair comparisons, we use monthly data frequency. Specifically, by using standard filtering on firm size, listing duration, and trading volume following Liu, Stambaugh, and Yuan (2019), we obtain monthly stock returns for individual firms listed on the Shanghai and Shenzhen Stock Exchanges.[22] We run regressions at the stock level by using the following specification:

$$r_{i,m}^{ex} = \alpha + \beta_1 \mathrm{MP}_{m-1} + \beta_2 \mathrm{Cred}_{m-1} + \beta_3 \mathrm{MP}_{m-1} \times \mathrm{Cred}_{m-1} + \Gamma \mathrm{Controls}_{i,m} + \epsilon_{i,m} \tag{4}$$

[21] Das and Song (2023) consider a smaller set of announcement windows for its narrow measure of monetary policy shocks including policy changes to the RRR, BLR, MLF rates, and the RevRepo rate. They ignore the fact that changes in the MLF quantities also affect the interest rates and do not include these MLF events. In addition, they are short of 6 LPR policy change events we consider for our baseline measure.

[22] Precisely, at the end of each month, we exclude firms that are public for fewer than 6 months, stocks with fewer than 120 days of trading records during the past 12 months, stocks with fewer than 15 days of trading records in the recent month, and the bottom 30% of stocks ranked by the previous month end's market capitalization. Notably, our sample does not exclude financial firms. As we will show in Subsection 5.3, financial firms are needed for our shock validation exercises.

in which $r^{ex}_{i,m}$ is the month m return of stock i in percent in excess of the risk-free rate measured by the one-year deposit rate. MP_{m-1} denotes the monthly monetary policy shock series of the previous month $m-1$. We include the lag term to avoid the look-ahead bias caused by the fact that monetary policy events might occur well after the large return variations within a month. We consider our baseline monetary policy shocks, PLS^0 along with the three alternative shocks in the literature with the CRZ quarterly shocks aligned with the three months in a quarter. In addition, so we may easily compare the magnitude of estimates, we normalize the monthly shocks MP_{m-1} for all measures using their respective standard deviations. The coefficient estimate of β_1, which is our key focus of interest, measures the size of return responses to a one standard deviation of contractionary monetary policy shocks.

In addition, the outstanding balance of Aggregate Financing to the Real Economy (AFRE), or Total Social Financing in China, is the key measure of the magnitude of the real sector being financed (He and Wei, 2023), which may also affect stock returns. We include additional controls of the credit quantity measure and its interaction with the measure of monetary policy shocks. We take the difference between the outstanding balance of Total Social Financing, and the Wind-surveyed analysts' consensus forecasts, then normalized by its sample standard deviation, as denoted by Cred_{m-1} with a one-month lag.[23] For additional controls, we include those co-variates of a firm's fundamentals, including total assets, Book-to-Market ratio (B/M), and operating leverage, all as of $m-1$, along with the time-invariant firm fixed-effects.

We report our estimation results in Table 4. We first run regressions by focusing on stock market impacts of five competing monetary policy shock measures without considering the effects of total credit supplies. In columns (1) to (5) of Panel (a) of Table 4, the negative coefficient estimates of β_1 suggest that a one standard deviation monetary policy tightening across all interest rate-based or M2-based shock measures leads to drops in stock returns in China, consistent with standard theory predictions (e.g., Bernanke and Kuttner (2005)).

[23]For regressions involving additional controls of Cred_{m-1}, our sample covers years from January 2016 to December 2021, as limited by the first introduction of AFRE forecast data in Wind since January 2016.

However, our baseline measure, the PLS-based estimated monetary policy shocks in China, exhibit the largest negative effects, which also are the most significant both statistically and economically ($\hat{\beta}_1 = -1.33, t - \text{stat} = -3.21$). Similarly, the impacts of DS shocks based on 1-year interest rate swaps, DS(1y) shocks, are also significant, though with a much smaller magnitude and a larger confidence band around the estimate ($\hat{\beta}_1 = -0.92, t - \text{stat} = -2.22$). Therefore, a one standard deviation increase in policy-induced interest rate hikes as measured by PLS^0 shocks (3.68bp) cause stock excess returns drop by 1.33% in a month, while returns drop by 0.92% in response to a one standard deviation increase in DS(1y) shocks (6.20bp). On the other hand, the effects of DS(5y) shocks, CRZ shocks, and LTZ shocks are all insignificant.

Most importantly, we conduct a placebo test by drawing 200 "hypothetical" monetary policy shock series using our PLS 2-stage method with the exception that we randomly pick 138 announcement days from our sample years for each shock series generation. We then report differences in the coefficient estimate β_1 that we report in the last row of Table 4. We show that estimations using our "true" PLS^0 shock series deliver a significantly negative coefficient relative to that which take any one of the all 200 shock series with bootstrap-based t-statistic of -24.24. This shows that our monetary policy shock measures contain the information that negatively affects stock returns.

Moving to column (6), we consider both the effects of our measured monetary policy shocks, along with direct and interaction effects of unexpected changes in total credit supply with interest rate shocks. Our estimation results show that the Chinese monetary policy tightening as measured by positive PLS shocks again significantly reduces stock returns when there is no change to the unexpected total social financing ($\hat{\beta}_1 = -2.51, t - \text{stat} = 5.97$). In addition, though the direct effects of credit supplies seem to be insignificant given an insignificant estimate of $\hat{\beta}_2$, the coefficient estimate of the interaction term between our measured interest rate shocks and our quantity changes measure is statistically significant ($\hat{\beta}_3 = 1.19, t - \text{stat} = 3.82$). This suggests that additional policy firming via the shrinkage in credit quantities reinforces the negative impacts of heightened interest rates in China. It also implies that changes in total credit supplies are needed to better understand the transmission of monetary policy, which helps improve the goodness of fit.

Moving to columns (7) to (10), we report our results based on estimations when we iteratively add one more additional measure of the alternative monetary policy shocks relative to the specification as in column (6). Using these exercises, we examine if effects of our PLS-based monetary policy shocks on stock returns are subsumed by effects associated with other policy shock measures. Nonetheless, across columns, we find that our baseline monetary policy shocks consistently and negatively shift stock returns, regardless of whether we consider additional effects driven by DS(1y), DS(5y), CRZ and LTZ shocks separately. In column (11), we show that our proposed measure of Chinese monetary policy shocks is still uniquely hammering the stock returns even we control for all DS, CRZ, and LTZ shocks separately. In Panel (b) of Table 4, we display all these results using our alternative PLS-base estimated monetary policy shocks. Our results suggest that contractionary monetary policy shocks, identified by either PLS^1 or PLS^2 shocks, result in similar reductions of stock returns. However, none of the three alternative measures of monetary policy shocks have distinctive effects with any statistical significance.

5.3. Shock Validations: Cross-sectional Returns Among Financial Firms

We next provide additional validation tests of our measured monetary policy shocks in China when we exploit our higher frequency data structure up to daily. Our tests are based on the key assumption that non-bank financial institutions, which also participate in the inter-bank market so they may borrow and lend among themselves, should be very responsive to our measured monetary policy changes.

We therefore examine stock returns to different shock measures by focusing on Chinese financial firms only. When we include both banks and non-bank financial intuitions, all firms should be promptly exposed to monetary policy transmission. We obtain the set of financial stocks according to the Wind's primary industrial classification for financial industry companies. Specifically, over our sample years, we compute the stock returns of 38 commercial banks, 75 diversified financial services (covering multi-sector holding corporations, asset management firms, and investment banking and brokerage firms), 7 insurance companies, and 152 real estate firms that include real estate investment trust companies, all of which are respectively listed under the four subcategories of financial firms by Wind.

5.3.1. Financial Firms' Exposure to Chinese Monetary Policy

We examine Chinese financial firms' exposure to our measured monetary policy changes and study firm characteristics related to the exposure. We first estimate the rolling monetary policy factor loading $\beta_{i,m}^{MP}$ for each financial firm as of each month according to the following specification:

$$R_{i,t}^{ex} = \alpha + \beta_{i,m}^{MP} \mathrm{PLS}_t^0 + \epsilon_{i,t} \tag{5}$$

in which $R_{i,t}^{ex}$ denotes the excess returns of firm i of a trading day t in the past three months relative to the end day of a month m. We obtain the $\beta_{i,m}^{MP}$ estimate of each month by regressing the excess returns on our measured policy shocks PLS_t^0 again normalized by the sample standard deviation.[24] The factor loading measure $\beta_{i,t}^{MP}$ thus gauges the return sensitivity to one standard deviation increases of our daily monetary policy shocks (i.e., the monetary policy beta).

Financial firms are then assigned into quintile portfolios sorted by their $\beta_{i,m}^{MP}$, and the five portfolios are re-balanced every month. Table 5 reports the Chinese monetary policy beta of the five portfolios ranked from smallest to largest exposure with respect to our measured monetary policy shocks. In addition, we present the time-series averages of the cross-sectional median of firm fundamentals for each quintile portfolio, including the logged market capitalization (ME), book-to-market (B/M), earnings-to-price (E/P) ratios, and leverage ratios.

[24] For the estimate of $\beta_{i,m}^{MP}$, we align excess returns of a non-announcement trading day with no shocks for $\mathrm{PLS}_t^0 = 0$.

The entries in the first row of Table 5 suggest that firms that are most positively exposed to our measured monetary policy shocks exhibit an average beta of 2.19, in contrast to -1.76 for firms in the lowest monetary policy beta group that are negatively exposed to monetary policy changes. In sum, stocks exhibiting positive and high betas perform well when monetary policy is tightening whereas stocks exhibiting negative and low betas perform poorly given contractionary monetary policy shocks. With respect to other firm characteristics in Table 5, we note that the largest and smallest beta groups are associated with firms with smaller B/M ratio, E/P ratio, and lower leverage ratios as compared to those of the three portfolios with medium-sized monetary policy betas.

5.3.2. Monetary Policy Risk and the Cross-section of Stock Returns

Since Chinese financial firms are risk-sensitive to monetary policy changes, we examine the relationship between a financial firm's monetary policy exposure and the cross-section of stock returns more rigorously. We specifically check if the Chinese monetary policy "risk" is priced in the cross-section of these financial stocks, which would also imply that our identified monetary policy shocks are largely unexpected market surprises.

Specifically, we calculate the value-weighted monthly returns of the quintile portfolios sorted by their monetary policy betas, along with returns on a portfolio that takes the long position on the largest monetary policy beta firms and the short position on the smallest monetary policy beta firms; we label this the H-L portfolio. We report our portfolio returns in Table 6. Panel A of Table 6 shows monthly average stock returns in excess of the risk-free rate, $E[R_t] - R_f$, in percentages as well as t-statistics for the six portfolios. Stocks with the smallest and negative monetary policy betas deliver positive excess returns of 0.91% while the stocks with the largest and positive betas exhibit negative excess returns of -0.78%. The long-short portfolio (H-L) yields a monthly excess return of -1.70% with a t-statistic of -2.08, which is both economically and statistically significant. That is, the monetary policy beta is negatively related to excess returns, and stocks that do well when there is monetary policy tightening earn negative excess returns whereas stocks that do poorly generate positive excess returns on average.

Next, we adopt standard procedures to access how much the excess return differentials across monetary policy beta-sorted portfolios can be explained by the existing risk factors documented for Chinese equity market. Based on the four factors of market (MKT), size (SMB), value (VMG), and turnover (PMO) that are proposed in Liu et al. (2019), we report risk-adjusted returns (αs) for portfolios derived from fitting a single market factor model (CAPM), the CH-3 model, as well as the CH-4 model in Panel B, Panel C, and Panel D, respectively. In addition, we augment CH-3 factors with additional factors constructed on profitability (RMW) and investment (CMA) characteristics following Fama and French (2015), so we may obtain αs based on a five-factor model,[25] as shown in Panel E. Across Panels B to E, our results suggest that none of these risk factors is sufficient to account for the pronounced return spread of portfolios sorted on monetary policy betas. The risk-adjusted returns for the long-short portfolio are economically large and statistically significant regardless of the factors that we consider ($\alpha_{\text{CAPM}} = -1.89\%, t_{\text{CAPM}} = -1.98; \alpha_{\text{CH-3}} = -2.32\%, t_{\text{CH-3}} = -2.19; \alpha_{\text{CH-4}} = -2.12\%, t_{\text{CH-4}} = -2.07; \alpha_{\text{CH-3 + RMW + CMA}} = -2.12\%, t_{\text{CH-3 + RMW + CMA}} = -1.90$). That is, stocks more positively exposed to monetary policy shocks require lower excess returns even with common risk factors adjusted. Hence, in terms of our measure of Chinese monetary policy shocks, Chinese monetary policy serves as an important extra risk factor that commands a negative risk-premium in the cross-section of financial stocks. Most importantly, this demonstrates that our measured variations of monetary policy shocks indeed detect a risk factor that is driven by announced Chinese monetary policy changes.

We further run Fama-MacBeth regressions to examine the relationship between monetary policy betas and excess returns. Our regression specification at the stock level is as follows:

$$R^{ex}_{i,m+1} = \zeta + \psi\beta^{MP}_{i,m} + \Gamma\text{Controls}_{i,m} + \epsilon_{i,m+1} \tag{6}$$

[25] A firm's profitability is measured by its ROE, the ratio of its earnings over book equity. A firm's investment rate is measured by its annual asset growth rate.

in which $R^{ex}_{i,m+1}$ is the next month $m+1$ excess return of stock i. $\beta^{MP}_{i,m}$ is the firm-specific monetary policy exposure as of month m that we estimate following Equation (5). ψ indicates whether future returns are related to monetary policy beta measures. We add additional controls of firm characteristics, which are highlighted in Table 5.

As we report in Table 7, regardless of our using these firm characteristics, our regression results suggest that firms' exposure to measured monetary policy shocks negatively predicts next month excess returns of financial stocks with statistical significance. This result is consistent with portfolio analyses thus far and suggests the existence of a negative premium related to Chinese monetary policy risk.

In sum, we demonstrate that monetary policy exposure commands a negative premium in the cross-section of stock returns among financial firms in China, and these firms are directly exposed to Chinese monetary policy transmission. Our asset-pricing tests suggest that our measured monetary policy shocks indeed capture the variation of monetary policy risk in China.

5.3.3. Price-of-Risk of Chinese Monetary Policy Shocks

Lastly, we provide an additional GMM-based test to show that our monetary policy shocks, as a risk factor, are negatively priced in the cross section of test assets' returns. We take a simple two-factor model approach in which the market-wise excess returns, MktRF_t, represent the first factor, and our baseline measure of Chinese monetary policy shocks, PLS^0 serves as the second factor. To estimate the price-of-risk of these two factors, we follow the procedure detailed in Cochrane (2005) and specify the Stochastic Discount Factor (SDF) as:

$$\text{SDF}_t = 1 - \lambda \text{MktRF}_t - \lambda_{\text{MP}} \text{PLS}^0_t. \tag{7}$$

The specification suggests that investors' marginal utility is driven by two aggregate risks: aggregate market shocks and monetary policy shocks. We then consider the a range of testing assets, including our six monetary policy beta-sorted portfolios and six size-E/P portfolios. We then conduct a GMM estimation of the following unconditional moment:

$$E[R_i^{ex}] = -cov(\text{SDF}, R_i^{ex}). \tag{8}$$

In addition, we estimate two statistics for cross-sectional fit, the sum of squared errors (SSQE) and mean absolute percent errors (MAPE), as well as the J-statistic of over-identifying model restrictions. An insignificant J-statistic suggests that the null hypothesis of an SDF model's pricing errors being equal to zero is not rejected.

Table 8 presents the results of our estimations of a single factor model and the two-factor model. We first report the price of risk for monetary policy risk and market risk separately in columns (1) and (2) and then display their estimates jointly in column (3). Our results in columns (1) and (2) suggest that the price of monetary policy risk λ_{MP} is negative and that the price of market risk λ is positive, though both are insignificant if estimated as a single factor model. In column (3), beyond the classic findings that the market factor is not well priced on average, we find that our estimated price of monetary policy risk is significantly negative ($\lambda_{\text{MP}} = -1.236, t - \text{stat} = -2.167$). In terms of asset pricing errors, the SSQE and MAPE of CAPM are 0.119% and 0.880%, respectively. Although the J-test is statistically insignificant across columns, we show that considering additional monetary policy risk helps improve the model's goodness of fit by reducing pricing errors.

5.3.4. Validations: Alternative Shock Measures

For DS shocks of daily frequency,[26] we perform the same set of portfolio analyses after we estimate the 3-month rolling window monetary policy beta, given their shock series. In Table 9, we report return spreads across portfolios sorted by differently estimated beta measures. In Panel A of Table 9, we find that the long-short portfolio does not command

[26]For lower frequency shocks like the LTZ shocks of the monthly series and the CRZ shocks of the quarterly series, accurate monetary policy beta cannot be obtained given a limited sample size. We therefore do not provide portfolio tests that take these shocks.

statistically significant returns regardless of whether returns are risk-adjusted or not; however, return spreads are consistently positive. In addition, we take the daily DS(5y) shocks for our portfolio analyses and our results in Panel B suggest that monetary policy exposure to DS(5y) shocks are again not priced in the cross-section of stock returns among these financial firms when we control for the important market risk. Still, the return spreads, if any, are positive. Therefore, when financial firms are immediately exposed to Chinese monetary policy transmission, our PLS-based measure of Chinese monetary policy shocks outperforms alternative measures in terms of its variation, which is reflective of an important monetary policy risk factor that is additionally priced in the cross-section of stock returns among these firms.

6. Transmission into the Real Economy

In this section, with our validated daily measure of Chinese monetary policy shocks, we finally examine the causal impacts of unexpected changes of monetary policy in China on firms of non-financial sectors and on major macroeconomic variables. In Section B of the Internet Appendix, we show additional results highlighting the significant dynamic effects of monetary policy shocks in China on asset prices when we use a local projection method as in Jordà (2005).

6.1. Impacts on Non-financial Sectors

We first shift our focus to the effects of monetary policy changes on real economic activities beyond the financial sector. In particular, we show both firms' equity risk and bond risk are elevated by contractionary monetary policy shocks across non-financial industries. In addition, unexpected monetary policy changes captured by our measured policy shocks have large and real impacts on non-financial firms, suggesting effective monetary policy transmission in China.

We first examine the Chinese monetary policy's average impacts on the returns of the sector-specific value-weighted portfolio. In addition to the financial sector, we consider returns to sectors that include Consumers, Cyclical, Technology, Media, Telecom (TMT), and Utilities as categorized by Wind.[27] We again use our baseline specification following Equation (4) in subsection 5.2:

$$R^{ex,j}_{m,m+h} = \alpha + \beta_{1,h}\text{PLS}^0_{m-1} + \beta_{2,h}\text{Cred}_{m-1} + \beta_{3,h}\text{PLS}_{m-1} \times \text{Cred}_{m-1} + \varepsilon^j_{m,m+h}, \tag{9}$$

in which $R^{ex,j}_{m,m+h}$ is the holding period excess return from month t to month $t+h$ (including month t) for each sector j's value-weighted portfolio formed at the end of month $m-1$. We consider the impacts of horizons of $h = 0, 1, 2$ corresponding to the three months immediately after the monetary policy shocks. We control for the effects associated with interest rate-based monetary policy shocks that affect returns conditional on unexpected total credit supplies as measured by Cred_{m-1}.

We report our estimation results in Table 10. Our results suggest that all the sectors we consider, including both financial and non-financial real sectors, respond to monetary policy tightening negatively. By increasing interbank borrowing costs immediately, monetary policy shocks reduce firm valuations across sectors within months after the shocks. In particular, we again find that eased aggregate credit supplies significantly alleviate impacts of policy-induced interest rate changes on the cyclical, financial, and utilities sectors. Taking the cyclical sector as an example, a one standard deviation of positive PLS^0_{t-1} that coincides with a friendly credit condition in the preceding month will result in an annualized drop of 12.42%.

Next, we examine the effects of monetary policy on credit risk for Chinese firms across sectors. To do so, we examine the impacts of monetary policy shocks in China on yield curves of industrial AAA-rated bonds in excess of the risk-free rate. Largely driven by the

[27]Following the Wind's primary industry classification, the Consumers sector include firms producing non-durable and durable consumer products, the Cyclical sector comprises the energy and materials industries, and the TMT sector consists of information technology and telecommunication services provisions.

availability of yield curves data across industries from ChinaBond Pricing Data, we consider the following sectors: Coal, Construction and Engineering, Electric Utilities, Real Estate, Highways, and Steel; we include this final industry even though only AAA−-rated bond yields are available for it. We provide regressions of monetary policy shocks on bond excess yields and present our results in Table 11.

Across panels concerning the credit risk of different maturities, we find in column "0m" that there is an increase in spot spreads of all industrial bonds following an unexpected monetary tightening, with an average $\hat{\beta}_1$ of approximately 0.135, which is statistically significant at the 90% level. For 3-month maturities of industrial bonds, the impacts of contractionary monetary policy shocks on excess bond yields are the most pronounced. Similarly, when coupled with eased credit supplies, tightening monetary policy shocks again have attenuated effects on bond yields.

6.2. VAR Estimation: Dynamic Effects

Based on our Vector Auto-regression Analysis, we next examine the duration of effects of monetary policy shocks in China on real macroeconomic variables.

By first using Cholesky ordering to position our cumulative monetary policy series, we estimate a typical monthly VAR system. We then consider up to four variables including the monthly year-of-year producer price index (PPI) inflation, the monthly year-of-year growth rate in industrial value added (IVA), and the credit spread that captures the difference between the yields of 1-year AAA-rated enterprise bonds and 1-year treasury yields. We use a Bayesian method with conjugate Minnesota priors to obtain our estimation, and show our impulse responses that we derive from the VAR estimation in Figure 4.

In Panel (a), we first show our impulse responses of a 3-variable VAR system without credit spreads. We observe an immediate drop in inflation following monetary policy tightening shocks while industrial growth decreases after two months, albeit without statistical significance. Notably, the drops of inflation reach the maximum in about 5 months and 10 months after the shocks. In Panel (b), we present our results when credit spread is added to the VAR system. Our results find that credit spread surges and peaks around 6 months after monetary policy tightening. The responses of inflation and output remain robust to the inclusion of credit spread; that is, both inflation and output growths exhibit immediate declines after a contractionary monetary policy shock, with inflation experiencing a significant drop. Our VAR results are very consistent with standard predictions of monetary policy transmission regarding macroeconomic dynamics (e.g., Gertler and Karadi (2015) and Jarociński and Karadi (2020)).

7. Conclusion

This paper fills an important gap in the literature by presenting an easy-to-implement estimation procedure that identifies Chinese monetary policy shocks. This procedure is potentially applicable to other emerging markets using higher-frequency financial data up to daily. Our approach results in a sufficient statistic indicative of unexpected Chinese monetary policy shocks that accommodates both quantity-based and interest rate-based monetary policy changes in China. Our method exactly addresses the key measurement difficulties rooted in the complex institution of emerging markets for lack of a key reference variable that measures the monetary policy stance and for having too many monetary policy tools under multiple policy objectives. Our measure therefore obtains the dimension reduction by filtering the complex institutional background and frequent changes in the policy toolkit.

Most importantly, our paper is the first to construct and simultaneously validate empirically our measured monetary policy shock series, as compared to a range of alternative shock measures outstanding. We show that based on asset pricing tests, the stock exposure to our measured monetary policy tightening shocks negatively predicts excess returns. Our measured Chinese monetary policy shocks effectively capture unexpected monetary policy changes in China, delivering a negative risk premium among financial stocks that are immediately exposed to monetary policy transmission. However, we show that none of the alternative measures, either quantity-based or interest rate-based, are neither uniquely able to shift average stock returns nor priced in the cross-section.

Finally, shedding light on monetary policy transmission in China, we show that our identified monetary policy shocks significantly shift equity and credit risk across firms of non-financial sectors. Monetary policy shocks also have significant impacts on the dynamics of inter-bank interest rates, treasury rates, corporate bond yields, equity prices, inflation, and output growth, suggesting strong and effective transmission of Chinese monetary policy in this largest emerging market.

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Tables and Figures

Table 1. Summaries of Announcement Timing

(a) Day of Month Distribution of Announcements

	Min	P25	Median	P75	Max	Mode	No. Events
MLF	3	13	15	17	30	15	104
LPR	20	20	20	20	20	20	6
RRR	1	4	8	23	29	4 & 6	14
BLR	1	11	23	25	28		5
RevRepo	3	14	18	25	30	3	17

Note: This table summarizes the distribution of announcements based on their percentile cut-off day within a month, spanning from January 2015 to December 2021. The numerical value i within each cell corresponds to the i-th day of the month. Min: the earliest day of the month identified as an announcement day. Max: the latest day of the month for an announcement event. Percentiles: percentile values of the day of month distribution. Mode: the day of the month with the highest frequency of announcements. MLF refers to monthly medium-term lending facilities operations. LPR denote events of policy changes to loan prime rate. BLR denote events of policy changes to the benchmark lending rate. RRR denote events of policy changes to the required reserve ratio. RevRepo denote events of policy changes to the 7-day reverse repo rate.

(b) Day of Week Distribution of Announcements

	Mon	Tue	Wed	Thurs	Fri	Sat	Sun
MLF	23.08	19.23	20.19	14.42	20.19	2.88	
LPR	33.33	16.67	16.67	16.67	16.67		
RRR	14.29	14.29	14.29		35.71		21.43
BLR	20.00	20.00			20.00		40.00
RevRepo	17.65	41.18		35.29	5.88		

Note: This table presents the count of announcement events categorized by timing groups, along with the average time in a day for announcement releases. The three defined groups include: (1) announcements released during trading hours; (2) announcements released after trading hours from Monday to Thursday; and (3) announcements released between market closure on Friday until midnight on Sunday. Trading hours are 9:00 - 12:00pm and 1:30 - 5:00pm (i.e., the trading hours for money, bond, and inter-bank markets on CFETS under T + 1 settlement).

(c) Timing Distribution of Announcements

	Weekday within Trading Hours		Mon-Thur after Trading hours		On Weekends	
	No. Anns.	Avg. Time	No. Anns.	Avg. Time	No. Anns.	Avg. Time
MLF	82	10:48:59	17	17:56:46	5	17:02:59
LPR	6	9:30:00				
RRR	3	16:21:49	4	18:15:50	7	16:43:36
BLR			3	18:17:12	4	16:53:45
RevRepo	17	9:47:56				

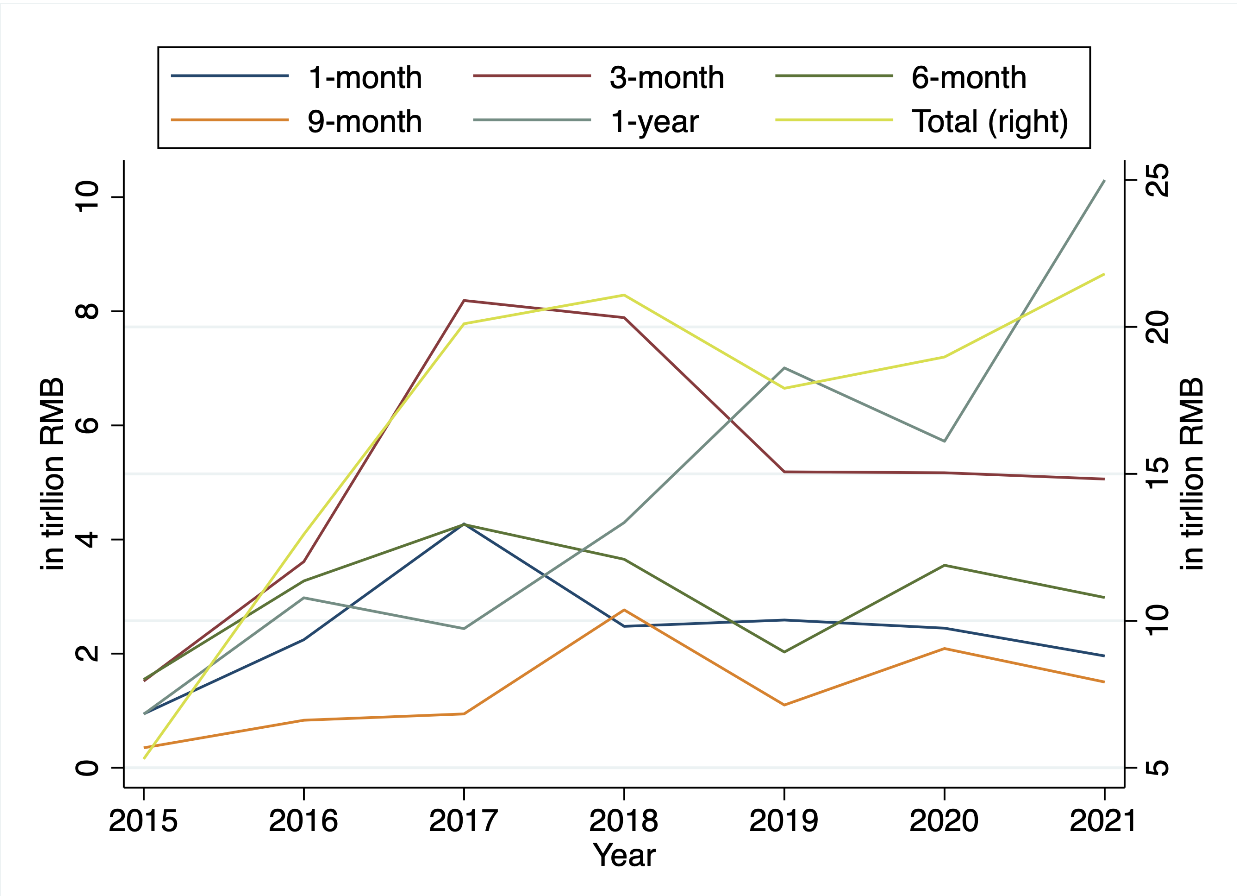
Note: This table reports the distribution of announcements as percentages on each day of the week for each type of announced monetary policy event. Due to rounding, column totals might not sum up exactly to one.

(d) Co-released Announcements

	MLF	LPR	RRR	BLR	RevRepo
MLF	104				
LPR	0	6			
RRR	1	0	14		
BLR	0	0	2	5	
RevRepo	3	0	0	0	17

Note: The table presents the number counts of row-labeled announcement events that coincide with the column-labeled announcement events. An overlap is considered if two announcement events arrive to the market on the same announcement day. The sum of row or column values may not necessarily match the total number of announcement events for a specific announcement label.

Fig. 1. The Amount of NCD Issuance by Maturities



Note: The figure plots the aggregated annual issuances of NCDs (in trillion RMB) across five different maturities. The sample period is from January 2015 to December 2021. The issuance amount corresponding to each maturity is indicated by the scale on the left y-axis, while the total sum of issuance amounts is indicated by the scale on the right y-axis.

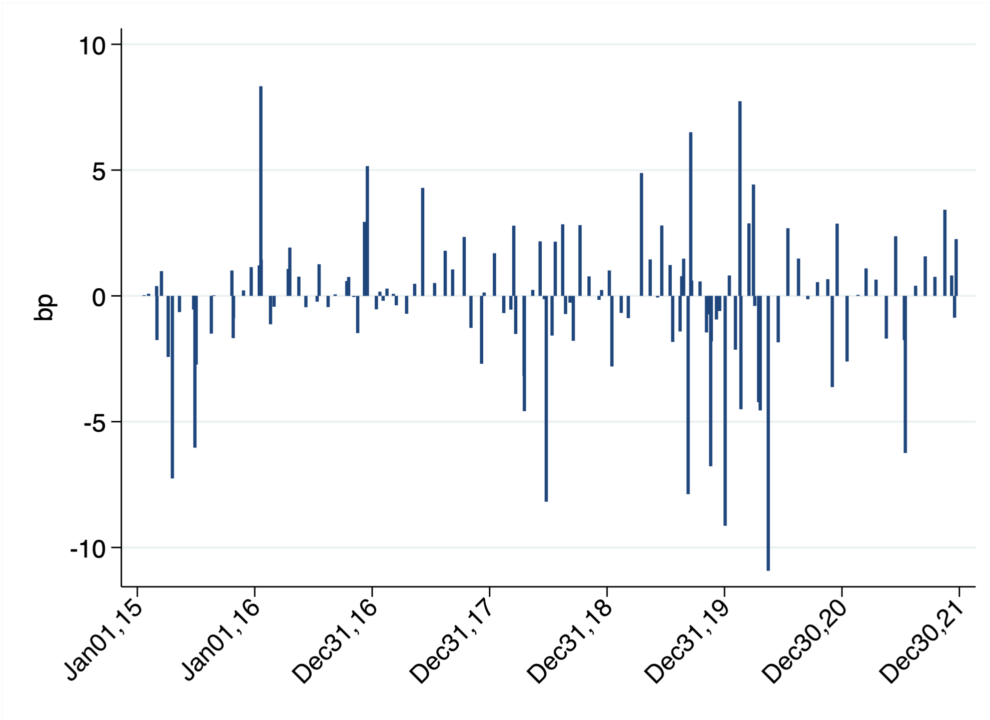
Table 2. Summary Statistics of NCD Issuance

Issuer Type	Num of Issuers	Stat	Tenor (months) 1	3	6	9	12	Total
Urban Commercial Bank	121	Avg Amt (in 100mln RMB)	6.65	5.86	4.96	3.97	4.96	5.32
		Avg Rate (%)	3.00	3.26	3.43	3.46	3.44	3.33
		Num of Issuance	13,188	19,321	17,610	9,271	24,413	83,803
Rural Commercial Bank	596	Avg Amt (in 100mln RMB)	2.90	3.50	3.73	2.99	3.80	3.39
		Avg Rate (%)	3.28	3.34	3.35	3.32	3.44	3.34
		Num of Issuance	10,721	11,053	7,932	2,482	5,599	37,787
Joint-Stock Commercial Bank	12	Avg Amt (in 100mln RMB)	11.69	19.49	14.28	12.60	18.97	16.64
		Avg Rate (%)	3.10	3.31	3.46	3.27	3.08	3.25
		Num of Issuance	3,368	9,028	5,392	3,258	7,237	28,283
State-Owned Commercial Bank	6	Avg Amt (in 100mln RMB)	14.14	25.48	25.46	20.15	38.86	28.37
		Avg Rate (%)	3.37	3.17	3.24	3.08	2.84	3.06
		Num of Issuance	336	1,250	560	471	1,324	3,941
Foreign-Invested Bank	29	Avg Amt (in 100mln RMB)	6.10	4.16	3.37	2.44	3.70	4.10
		Avg Rate (%)	2.61	2.86	3.01	3.03	3.01	2.89
		Num of Issuance	293	667	438	118	261	1,777
Private Bank	15	Avg Amt (in 100mln RMB)	3.13	1.49	1.19	0.96	1.27	1.67
		Avg Rate (%)	2.73	3.06	3.32	3.35	3.61	3.22
		Num of Issuance	310	414	278	85	461	1,548
Others	67	Avg Amt (in 100mln RMB)	1.28	2.36	1.73	1.23	0.92	1.72
		Avg Rate (%)	3.45	3.95	3.81	3.58	4.11	3.77
		Num of Issuance	173	209	118	34	47	581
Total	846	Avg Amt (in 100mln RMB)	5.85	8.67	6.50	6.06	8.46	7.40
		Avg Rate (%)	3.11	3.28	3.41	3.38	3.35	3.31
		Num of Issuance	28,389	41,942	32,328	15,719	39,342	157,720

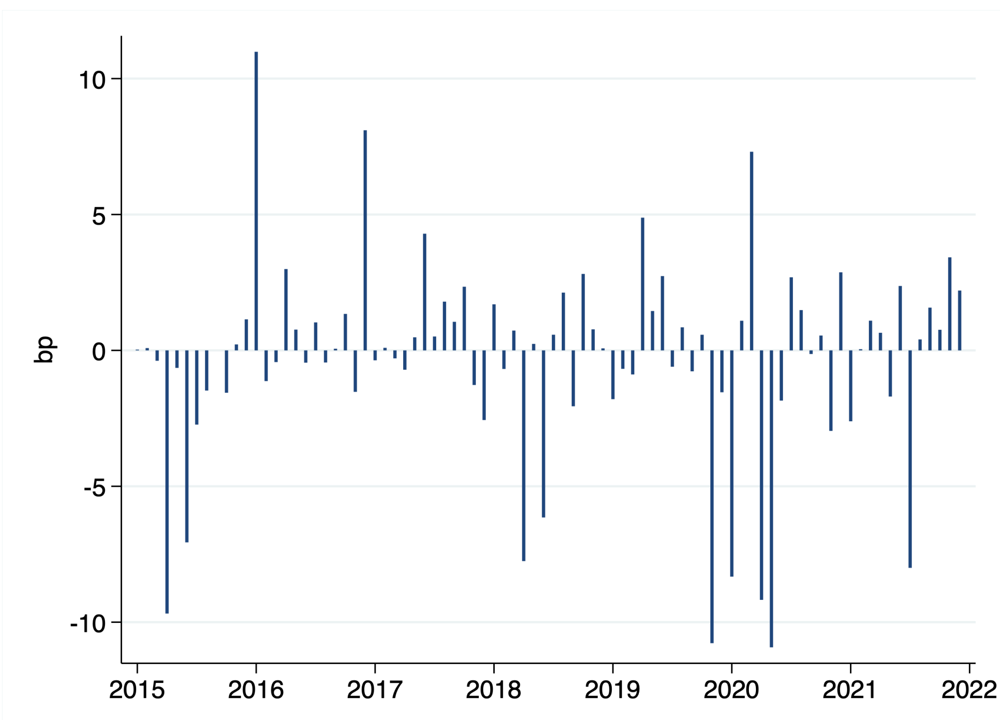
Note: This table reports the average actual issuance amount (in 100 million RMB) and the average issuance rate (in annualized percentage points) for each NCD issuance across issuer types and maturities. Row "Num of Issuance" reports the total number of NCD issuance for each type of issuer across maturities. The last column reports the same statistics for each issuer type without distinguishing the maturities of NCDs issued. The sample period spans from January 2015 to December 2021.

Fig. 2. Chinese Monetary Policy Shock Series

(a) Daily

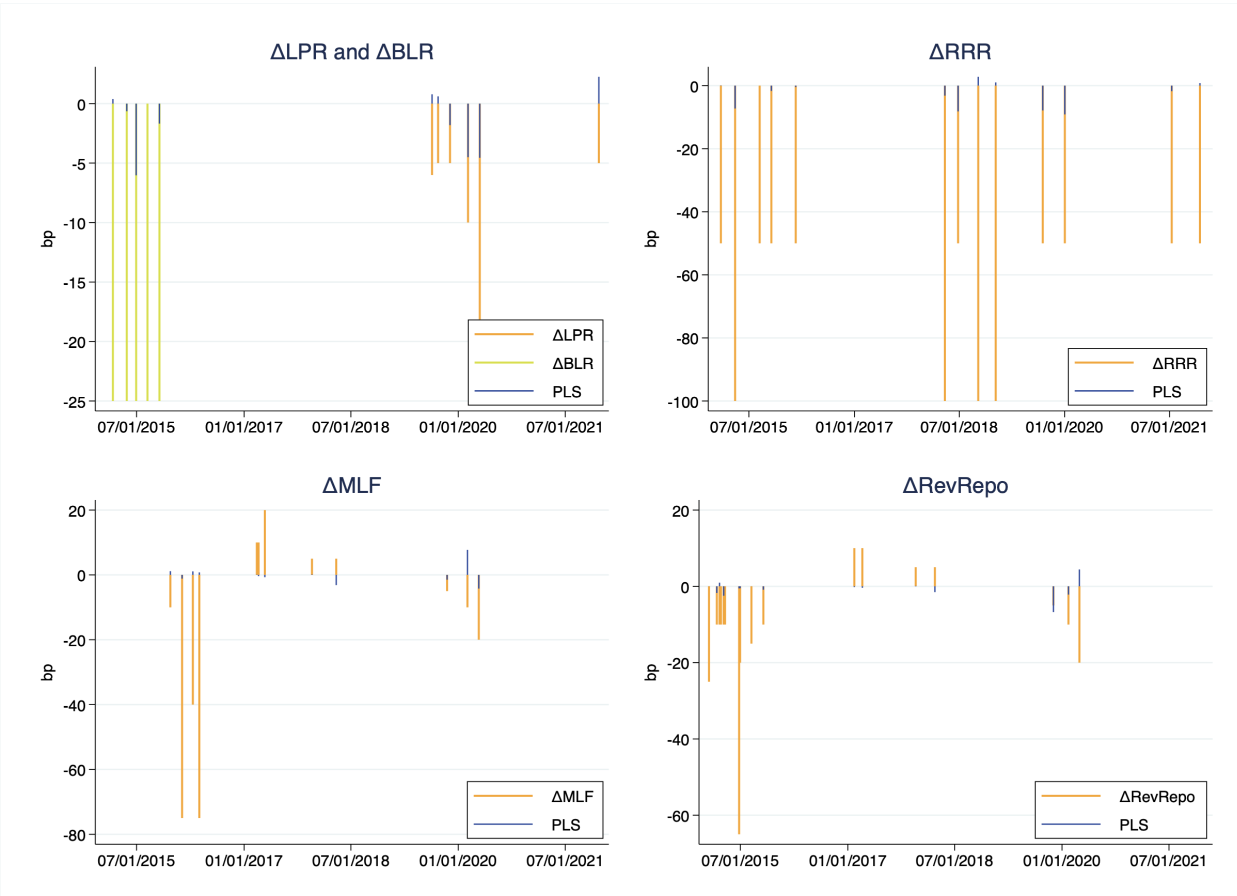


(b) Monthly



Note: Panel (a) plots the daily time series of our Chinese monetary policy shocks in basis points, estimated through heteroskedasticity-based partial least squared (PLS) regressions with instrumental variables (IV). Panel (b) plots the monthly time series of the shock series, which does simple summations of daily shocks within each month. The sample period is from January 2015 to December 2021.

Fig. 3. Monetary Policy Shock Series v.s. Changes in Monetary Policy Instruments



Note: Our daily shocks denoted as "PLS" is juxtaposed against changes in each underlying monetary instrument expressed in basis points. "LPR" denotes changes to the loan prime rate, "BLR" denotes changes to the benchmark lending rate, "RRR" denotes changes to the required reserve ratio, "MLF" denotes changes to the medium-term lending facility rate, "RevRepo" denotes changes to the 7-day reverse repo rate. The sample period is from January 2015 to December 2021.

Table 3. Chinese Monetary Policy Shock Series: Data Summary

(a) Summary Statistics

	Obs	Avg	Std	Min	Med	Max	AR(1)	p-value
				Monetary Policy Shock Series				
PLS^0	84	-0.32	3.68	-10.93	0.08	10.99	0.04	0.72
PLS^1	84	-0.26	3.13	-9.97	0.08	8.70	-0.00	1.00
PLS^2	84	-0.15	2.61	-8.18	0.08	7.29	0.03	0.78
DS(1y)	84	-1.98	6.20	-35.65	0.00	11.31	0.03	0.76
DS(5y)	84	-1.58	4.91	-26.27	0.00	13.00	-0.08	0.45
LTZ (%)	84	0.24	0.96	-1.44	0.24	4.33	0.06	0.58
CRZ (%)	28	0.30	0.61	-1.72	0.30	1.33	0.16	0.37
				Monthly Statistics				
ΔTreasury(1y)	84	-1.16	5.40	-34.35	-0.27	10.65	-0.04	0.70
ΔDR007	84	-0.28	12.79	-34.23	0.32	31.88	-0.01	0.95
ΔShibor3M	84	-0.52	3.05	-13.24	0.00	7.15	0.25	0.02
ΔFR007(1y)	84	-2.29	6.83	-35.65	-0.59	15.53	0.03	0.79
ΔM2(YoY) (%)	84	-0.61	1.82	-3.30	-0.70	3.20	0.85	0.00

(b) Correlations

	PLS^0	PLS^1	PLS^2	DS(1y)	DS(5y)	LTZ	CRZ
PLS^0	1						
PLS^1	0.99***	1					
PLS^2	0.92***	0.95***	1				
DS(1y)	0.43***	0.42***	0.42***	1			
DS(5y)	0.43***	0.43***	0.43***	0.93***	1		
LTZ	-0.27**	-0.23**	-0.18**	-0.25**	-0.29***	1	
CRZ	0.11	0.14	0.17	0.12	0.13	0.06	1

Note: This table reports summary statistics and correlation coefficients among our baseline and alternative PLS-based shock series, as well as other existing shocks in the literature. Monthly changes to market interest rates and M2 YoY growth rates are also reported. All are expressed in units of basis points except otherwise stated in the table. PLS^0: refers to our baseline shock series aggregated up to monthly frequency. PLS^1: refers to the shock series estimated based on a sample of NCD issuance rates of UCBs, RCBs and JSCBs after being aggregated up to monthly. PLS^2: refers to the shock series estimated based on a sample of NCD issuance rates of UCBs and RCBs only after being aggregated up to monthly. *DS(1y)* and *DS(5y)* shocks are the monthly aggregation of daily shocks based on our estimation following Das and Song (2023) by using interest rate swaps of 7-day repo rate with 1-year and 5-year maturity. CRZ shocks follow from the replication of Chen et al. (2018) by using quarterly macroeconomic time-series data. LTZ shocks are the monthly shock series of Lu et al. (2023), directly provided by the authors. The sample period is from January 2015 to December 2021. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 4. Stock Market's Reactions to Monetary Policy Shock Series and Credit Condition

(a) Baseline

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
PLS^0_{t-1}	-1.3256**					-2.5116***	-2.3828***	-2.6353***	-2.4895***	-2.4418***	-2.3744***
	(0.4131)					(0.4207)	(0.4580)	(0.4543)	(0.4261)	(0.3905)	(0.4971)
$DS(1y)_{t-1}$		-0.9236*					-0.4761				-0.2155
		(0.4159)					(1.4805)				(1.4550)
$DS(5y)_{t-1}$			-0.8796					0.4784			
			(0.4975)					(0.8706)			
CRZ_{t-3}				-1.1015					0.1211		0.3158
				(0.8748)					(0.5462)		(0.7513)
LTZ_{t-1}					-0.2808					0.7990	0.7978
					(0.8718)					(0.7273)	(0.6622)
$Cred_{t-1}$						-0.8868	-0.9000	-0.8776	-0.8671	-1.1842	-1.1626
						(0.8616)	(0.8644)	(0.8448)	(0.8725)	(0.8667)	(0.8895)
$PLS^0_{t-1} \times Cred_{t-1}$						1.1864**	1.1665**	1.1962**	1.1710**	1.3284***	1.3106***
						(0.3102)	(0.3165)	(0.3118)	(0.3146)	(0.2887)	(0.3168)
Constant	78.8377*	68.7362*	73.0913*	57.6180**	79.4194*	54.2871***	54.5296***	54.1411***	53.8862**	51.7460***	50.5226***
	(34.6861)	(34.0228)	(33.4298)	(23.5279)	(38.7272)	(13.0007)	(13.1269)	(13.0534)	(13.8239)	(10.5928)	(10.5870)
Observations	124,730	124,730	124,730	119,528	124,730	110,060	110,060	110,060	107,163	110,060	107,163
Adjusted R^2	0.02	0.02	0.01	0.02	0.01	0.03	0.03	0.03	0.03	0.03	0.04
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE by Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
True Difference	-1.1790***										
	(-24.24)										

Note: This table presents outcomes of panel regressions on the current month's stock returns taking into account different monetary policy shock series and credit conditions of the preceding month. PLS^0_t is our baseline shock series at the monthly level, while PLS^1_t and PLS^2_t are our two alternative shock series. CRZ_t is the quarterly replication of Chen et al. (2018) shock series. $DS(1y)_t$ and $DS(5y)_t$ are the monthly replicated shock series of Das and Song (2023). LTZ_{t-1} is the monthly shock series of Lu et al. (2023), provided by the authors. $Cred_t$ is the difference between realized outstanding stock level of Aggregate Financing to the Real Economy (AFRE) and analysts' consensus forecast, normalized by the time-series average. The control firm characteristics are log of total assets, log of book-to-market ratio, and book leverage ratio. All independent variables are normalized to unit standard deviation. "True Difference": the mean coefficient difference between 200 shock series with 138 randomly assigned monetary policy announcement days and that of estimation using our baseline shock series PLS^0, with p-values calculated based on Fisher's permutation test and t-statistic reported in parentheses below using 1000 times bootstrapping. The sample period is January 2015 to December 2021. Standard errors clustered at the firm and industry level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 4. (Continued)

(b) Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
PLS^1_{t-1}	-1.3938**	-2.1350***	-2.0399***	-2.3869***	-2.1267***	-2.0872***	-2.1076***							
	(0.4359)	(0.4021)	(0.2812)	(0.3872)	(0.4453)	(0.3655)	(0.3450)							
PLS^2_{t-1}								-0.9843*	-1.5770**	-1.4320***	-1.8753***	-1.5860*	-1.5610**	-1.6268***
								(0.4647)	(0.5730)	(0.2106)	(0.2854)	(0.6230)	(0.5690)	(0.1528)
$Cred_{t-1}$		-0.6916	-0.6967	-0.6878	-0.6709	-0.9777	-0.9697		-0.5996	-0.6042	-0.6040	-0.5774	-0.9102	-0.9061
		(0.9051)	(0.9153)	(0.8693)	(0.9143)	(0.9469)	(0.9495)		(0.9410)	(0.9562)	(0.9043)	(0.9485)	(1.0055)	(0.9879)
$PLS^1_{t-1} \times Cred_{t-1}$		0.8300**	0.8029**	0.8957**	0.8228**	0.9747**	0.9911**							
		(0.3134)	(0.3096)	(0.2802)	(0.3163)	(0.3402)	(0.3047)							
$PLS^2_{t-1} \times Cred_{t-1}$									0.5188	0.4718	0.6189**	0.5199	0.6917	0.7292**
									(0.3476)	(0.2884)	(0.2073)	(0.3583)	(0.4254)	(0.2561)
$DS(1y)_{t-1}$			-0.2756				0.0422			-0.3665				0.0826
			(1.6202)				(1.6050)			(1.6775)				(1.5876)
$DS(5y)_{t-1}$				0.7147							0.7235			
				(0.9886)							(0.9798)			
CRZ_{t-3}					0.1715		0.3437					0.2043		0.3908
					(0.5840)		(0.7485)					(0.6608)		(0.8047)
LTZ_{t-1}						0.7679	0.8191						0.8331	0.9006
						(0.7638)	(0.6629)						(0.8210)	(0.6624)
Constant	79.2927*	54.8776**	55.0257**	54.6313**	54.1662**	52.5990***	50.9023***	79.4678*	54.3761**	54.5237**	54.1892**	53.4305**	52.1666**	50.1768**
	(34.8834)	(14.6571)	(14.9065)	(14.6695)	(15.5071)	(12.2050)	(12.1030)	(35.7589)	(15.6023)	(15.7226)	(15.7936)	(16.5612)	(13.0973)	(13.3848)
Observations	124,730	110,060	110,060	110,060	107,163	110,060	107,163	124,730	110,060	110,060	110,060	107,163	110,060	107,163
Adjusted R^2	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.03
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE by Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents outcomes of panel regressions on the current month's stock returns taking into account different monetary policy shock series and credit conditions of the preceding month. PLS^0_t is our baseline shock series at the monthly level, while PLS^1_t and PLS^2_t are our two alternative shock series. CRZ_t is the quarterly replication of Chen et al. (2018) shock series. $DS(1y)_t$ and $DS(5y)_t$ are the monthly replicated shock series of Das and Song (2023). LTZ_{t-1} is the monthly shock series of Lu et al. (2023), provided by the authors. $Cred_t$ is the difference between realized outstanding stock level of Aggregate Financing to the Real Economy (AFRE) and analysts' consensus forecast, normalized by the time-series average. The control firm characteristics are log of total assets, log of book-to-market ratio, and book leverage ratio. All independent variables are normalized to unit standard deviation. The sample period is January 2015 to December 2021. Standard errors clustered at the firm and industry level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 5. Chinese Monetary Policy Exposure and Financial Firm Characteristics

	L	2	3	4	H
β^{MP}	-1.76	-0.55	0.18	0.86	2.19
Log ME	4.33	4.47	4.51	4.43	4.18
B/M	18.33	24.85	27.30	28.45	17.45
E/P	0.66	0.86	0.98	1.04	0.61
Lev	76.61	78.80	78.51	78.13	75.19
Num of firms	37	36	36	36	36

Note: This table presents the time-series average of cross-sectional medians of firm characteristics across five portfolios, sorted by their monetary beta (β^{MP}). The monetary beta β^{MP}s are estimated at the end of each month for each financial firm by regressing the past three months daily returns on the normalized PLS^0 shock. Market capitalization (ME) is computed by multiplying the closing price of the previous month by the total number of A shares outstanding, inclusive of non-tradable shares. The book-to-market ratio (B/M) is total shareholders' equity, excluding minority interests, divided by market capitalization. The earnings-to-price ratio (E/P) is the most recently reported net profit, excluding non-recurring gains or losses, divided by market capitalization. Book leverage (Lev) is calculated as the difference between total assets and total shareholders' equity, excluding minority interests, normalized by total assets. All ratios, including B/M, E/P, and Lev, are expressed as percentages. The sample period is January 2015 to December 2021 with the first portfolios formed at the beginning of April 2015.

Table 6. Quintile Portfolios of Financial Firms and Asset Pricing Factor Tests

	L	2	3	4	H	H - L
			Panel A: Excess Return			
$E[R_t] - R_f(\%)$	0.91	-1.12	1.01	-0.31	-0.78	-1.70
	[1.05]	[-2.07]	[1.23]	[-0.49]	[-1.07]	[-2.08]
			Panel B: CAPM			
α_{CAPM}	0.61	-1.37	0.77	-0.54	-1.13	-1.74
	[0.89]	[-2.97]	[1.04]	[-1.21]	[-2.12]	[-2.11]
MKT	1.01	0.85	0.82	0.79	1.15	0.14
	[5.32]	[19.50]	[8.44]	[7.59]	[11.24]	[0.99]
			Panel C: CH-3			
$\alpha_{\text{CH-3}}$	0.74	-2.01	-0.02	-0.95	-1.65	-2.39
	[0.92]	[-4.10]	[-0.03]	[-2.02]	[-2.18]	[-2.65]
MKT	1.01	0.85	0.82	0.79	1.15	0.14
	[5.32]	[19.50]	[8.44]	[7.59]	[11.24]	[0.99]
SMB	-0.27	0.12	-0.13	0.04	0.06	0.33
	[-2.45]	[1.24]	[-0.63]	[0.32]	[0.24]	[1.18]
VMG	-0.11	0.57	0.70	0.35	0.46	0.57
	[-0.60]	[3.61]	[3.87]	[2.39]	[1.30]	[1.67]
			Panel D: CH-4			
$\alpha_{\text{CH-4}}$	0.55	-2.01	0.05	-0.94	-1.55	-2.10
	[0.71]	[-3.87]	[0.11]	[-2.19]	[-1.93]	[-2.56]
MKT	1.13	0.96	0.98	0.86	1.20	0.07
	[6.35]	[10.81]	[9.20]	[7.24]	[8.20]	[0.38]
SMB	-0.38	0.12	-0.09	0.04	0.12	0.50
	[-3.14]	[1.31]	[-0.46]	[0.34]	[0.50]	[1.84]
VMG	-0.19	0.57	0.73	0.36	0.51	0.70
	[-1.02]	[4.07]	[4.38]	[2.26]	[1.54]	[2.36]
PMO	0.46	-0.01	-0.18	-0.01	-0.25	-0.70
	[2.49]	[-0.05]	[-1.34]	[-0.06]	[-1.20]	[-3.83]

Note: This table reports the monthly average excess returns for five portfolios of financial firms sorted on the monetary beta β^{MP} in Panel A. The monetary beta β^{MP}s are estimated at the end of each month for each financial firm by regressing the past three months daily returns on the normalized PLS^0 shock. To adjust for risk exposure, we perform time-series regressions of monetary beta-sorted financial portfolios' excess returns on the market factor (MKT) as the CAPM model in Panel B, on the CH-3 factors (Liu et al., 2019) (MKT, the size factor-SMB, and the value factor-VMG) in Panel C, on the CH-4 factors (MKT, SMB, VMG, and the turnover factor-PMO) in Panel D, as well as on the CH-3 factors and two additional factors constructed following Fama and French (2015) (MKT, SMB, VMG, the profitability factor-RMW, and the investment factor-CMA) in Panel E. The four factors data are sourced from Professor Robert F. Stambaugh's home page. The results reflect monthly data. t-statistics based on Newey-West standard errors with six lags are reported in brackets. The sample period is January 2015 to December 2021 with the first portfolios formed at the beginning of April 2015.

Table 6. (Continued)

	L	2	3	4	H	H - L
	Panel E: CH-3 + RMW + CMA					
$\alpha_{\text{CH-3 + RMW + CMA}}$	1.18	-1.64	-0.11	-1.06	-0.93	-2.12
	[1.42]	[-3.58]	[-0.18]	[-1.87]	[-0.94]	[-1.90]
MKT	1.09	0.95	0.95	0.83	1.28	0.20
	[5.42]	[12.81]	[6.72]	[6.85]	[9.21]	[1.10]
SMB	-0.43	0.00	-0.08	0.09	-0.19	0.25
	[-2.90]	[0.01]	[-0.27]	[0.67]	[-0.93]	[1.09]
VMG	-0.00	0.55	0.55	0.27	0.53	0.54
	[-0.01]	[3.54]	[4.46]	[1.53]	[1.71]	[1.52]
RMW	-0.40	-0.11	0.36	0.24	-0.42	-0.02
	[-1.85]	[-0.86]	[0.93]	[0.93]	[-1.84]	[-0.08]
CMA	-0.11	0.18	0.36	0.20	0.09	0.20
	[-0.90]	[1.51]	[1.18]	[1.54]	[0.48]	[0.96]

Note: This table reports the monthly average excess returns for five portfolios of financial firms sorted on the monetary beta β^{MP} in Panel A. The monetary beta β^{MP}s are estimated at the end of each month for each financial firm by regressing the past three months daily returns on the normalized PLS^0 shock. To adjust for risk exposure, we perform time-series regressions of monetary beta-sorted financial portfolios' excess returns on the market factor (MKT) as the CAPM model in Panel B, on the CH-3 factors (Liu et al., 2019) (MKT, the size factor-SMB, and the value factor-VMG) in Panel C, on the CH-4 factors (MKT, SMB, VMG, and the turnover factor-PMO) in Panel D, as well as on the CH-3 factors and two additional factors constructed following Fama and French (2015) (MKT, SMB, VMG, the profitability factor-RMW, and the investment factor-CMA) in Panel E. The four factors data are sourced from Professor Robert F. Stambaugh's home page. The results reflect monthly data. t-statistics based on the Newey-West standard errors with six lags are reported in brackets. The sample period is January 2015 to December 2021 with the first portfolios formed at the beginning of April 2015.

Table 7. Fama-MacBeth Regressions

	(1)	(2)	(3)
β^{MP}	-0.77	-0.77	-0.63
	[-1.85]	[-2.03]	[-1.65]
Log ME	0.30	0.34	0.25
	[1.26]	[1.65]	[1.17]
Log B/M	-0.46		-0.48
	[-1.63]		[-2.13]
Log E/P		-0.27	0.16
		[-1.06]	[0.57]
Lev			-0.12
			[-1.05]
Observations	14,615	12,625	12,625
R^2	0.07	0.09	0.11

Note: This table reports average slope coefficients from month-by-month Fama-MacBeth regressions for financial firms. Individual stocks' excess returns are regressed cross-sectionally on their monetary beta β^{MP} and other firm characteristics as of the previous month. The monetary beta β^{MP}s are estimated at the end of each month for each financial firm by regressing the past three months daily returns on the normalized PLS^0 shock. The columns correspond to different regression specifications, with nonempty rows indicating the included control variables. Control variables include the natural logarithm of market capitalization (Log ME), the natural logarithm of book-to-market ratio (Log B/M), the natural logarithm of earnings-to-price ratio (Log E/P), and book leverage (Lev). All independent variables are normalized to zero mean and unit standard deviation. t-statistics based on Newey-West standard errors with six lags are reported in brackets.

Table 8. Estimating the Price-of-Risk of Chinese Monetary Policy Shocks

	(1)	(2)	(3)
MktRF		0.061	-0.139
		[0.825]	[-1.018]
PLS^0	-0.646		-1.236
	[-1.544]		[-2.167]
SSQE(%)	0.111	0.127	0.119
MAPE(%)	0.785	0.931	0.880
J-statistic	9.606	10.285	8.081
p	0.476	0.416	0.526

Note: This table presents GMM estimates of parameters of the stochastic discount factor, $SDF = 1 - \lambda \times \text{MktRF} - \lambda_{\text{MP}} \times \text{PLS}^0$, using quintile portfolios sorted on monetary beta, β^{MP}. The monetary beta β^{MP}s are estimated at the end of each month for each financial firm by regressing the past three months daily returns on the normalized PLS^0 shock. We normalize the factors such that $E[m] = 1$ (see Cochrane (2005)). As a measure of fit, we report the sum of squared errors (SSQE), mean absolute pricing errors (MAPE), and the J-statistic of over-identifying model restrictions. Given the Euler equation $E[SDF \times R_i^e] = 0$, SSQE and MAPE are based on each testing asset i's monent error $u_i : u_i = \frac{1}{T}\sum_{i=1}^{T}[\widehat{SDF} \times R_{i,t}^e]$. SSQE and MAPE are defined as $\sum_{i=1}^{N} u_i^2$ and $\frac{1}{N}\sum_{i=1}^{N}|u_i|$, in which N is the number of testing assets and T is the number of months. t-statistics based on Newey-West standard errors with six lags are reported in brackets.

Table 9. Quintile Portfolios of Financial Firms - Das and Song (2023)

	Panel A: DS(1y)						Panel B: DS(5y)					
	L	2	3	4	H	H - L	L	2	3	4	H	H - L
						Excess Returns						
$E[R_t] - R_f(\%)$	-2.09	-0.99	-0.05	-0.06	0.12	2.21	-1.40	-0.83	-0.46	-0.79	1.34	2.74
	[-2.13]	[-1.33]	[-0.05]	[-0.03]	[0.06]	[1.39]	[-1.57]	[-0.91]	[-0.59]	[-0.55]	[0.81]	[2.12]
α_{CAPM}	-2.31	-1.18	-0.26	-0.27	-0.19	2.12	-1.63	-1.02	-0.65	-1.03	1.08	2.71
	[-3.15]	[-2.10]	[-0.38]	[-0.13]	[-0.20]	[1.56]	[-3.50]	[-1.32]	[-1.20]	[-0.66]	[1.22]	[2.21]
$\alpha_{\text{CH-3}}$	-1.84	-1.10	-1.73	-2.76	0.47	2.31	-2.00	-0.62	-1.15	-3.75	1.54	3.53
	[-3.13]	[-1.30]	[-2.38]	[-2.64]	[0.31]	[1.27]	[-3.76]	[-1.13]	[-2.24]	[-2.44]	[1.05]	[1.99]
$\alpha_{\text{CH-4}}$	-1.87	-1.16	-1.75	-3.20	0.55	2.42	-1.73	-0.89	-1.16	-3.97	1.49	3.23
	[-3.01]	[-1.65]	[-2.22]	[-3.40]	[0.31]	[1.14]	[-3.08]	[-1.40]	[-2.13]	[-2.66]	[1.00]	[1.74]
$\alpha_{\text{CH-3 + RMW + CMA}}$	-2.04	-0.64	-1.76	-3.22	-0.02	2.02	-1.73	-0.56	-0.81	-4.06	0.85	2.57
	[-2.42]	[-0.78]	[-2.53]	[-3.73]	[-0.01]	[0.93]	[-2.35]	[-0.61]	[-1.44]	[-3.84]	[0.64]	[1.38]
						Firm Characteristics						
β^{MP}	-1.82	0.25	1.42	2.66	4.54		-2.03	-0.44	0.58	1.55	3.20	
Log ME	4.85	4.60	4.72	4.42	4.18		4.79	4.61	4.66	4.47	4.18	
B/M	16.32	17.40	16.54	14.61	9.50		16.18	17.60	16.60	13.67	10.50	
E/P	0.69	0.51	0.52	0.32	0.18		0.64	0.54	0.48	0.31	0.20	
Lev	79.53	79.24	77.93	76.30	71.56		79.33	78.14	78.54	75.87	71.54	
Num of firms	35	35	35	35	33		35	35	35	35	33	

Note: Panel A (B) reports the monthly average excess returns and risk-adjusted excess returns for five portfolios of financial firms sorted on the monetary beta β^{MP}, which are estimated at the end of each month for each financial firm by regressing the past three months daily returns on the normalized DS(1y) (DS(5y)) shock (Das and Song, 2023). Due to the sparsity of DS(1y) and DS(5y) over the sample period from January 2015 to December 2021, there are only 31 out of 81 months with available β^{MP} and thus quintile portfolios formation are not consecutive (i.e., no portfolios were formed in 2019 and 2021). This table also reports the time-series average of the cross-sectional median of firm characteristics across the five portfolios in Panel A (B). t-statistics based on Newey-West standard errors with six lags are reported in brackets. The sample period is January 2015 to December 2021 with the first portfolios formed at the beginning of April 2015.

Table 10. Different Sectors' Stock Response

	Consumer			Cyclical			Financial			TMT			Utilities		
h =	0	1	2	0	1	2	0	1	2	0	1	2	0	1	2
PLS^0_{t-1}	-1.6486*	-1.5482	-1.3692	-2.6339***	-2.8937	-3.4052	-1.3591*	-0.9495	-1.2779	-2.8720*	-3.7406	-4.9996*	-1.4941**	-4.7714*	-2.5520
	(0.8726)	(1.3454)	(1.7971)	(0.5874)	(1.8934)	(2.1962)	(0.7628)	(1.0957)	(1.3433)	(1.6854)	(2.4744)	(2.5651)	(0.6138)	(2.3955)	(1.8521)
$Cred_{t-1}$	-0.2987	0.4233	1.7621	-0.7016	-0.8134	-0.1589	-0.2344	0.7590	1.8617*	-0.4829	-0.5347	0.7813	-1.0518*	-2.0203*	-0.8658
	(0.8303)	(1.0112)	(1.3338)	(0.7730)	(1.3004)	(1.5980)	(0.7030)	(0.9384)	(1.0377)	(1.2770)	(1.5447)	(1.7029)	(0.5924)	(1.0665)	(0.8315)
$PLS^0_{t-1} \times Cred_{t-1}$	0.5092	1.1232	0.2866	1.5992***	2.2459**	1.9477*	1.0149**	0.9030	0.8691	1.0844	1.6810	2.0436	0.9746**	3.2915**	1.3990
	(0.6173)	(0.6943)	(0.7419)	(0.4216)	(0.9171)	(1.0291)	(0.4324)	(0.6293)	(0.6175)	(1.1904)	(1.3854)	(1.5423)	(0.3750)	(1.5994)	(1.0789)
Constant	0.1689	-0.3062	-1.2335	1.2408	2.2342	2.6536	0.3887	0.0208	-0.4673	-0.2307	-0.6778	-2.2621	1.0332	1.6794	1.2006
	(0.8068)	(1.2175)	(1.8625)	(0.7677)	(1.3908)	(2.0137)	(0.7810)	(1.1324)	(1.6503)	(1.1060)	(1.2976)	(1.8207)	(0.7390)	(1.0577)	(1.3860)
Observations	71	70	69	71	70	69	71	70	69	71	70	69	71	70	69
Adjusted R^2	0.00	-0.01	-0.00	0.06	0.02	-0.00	-0.01	-0.01	0.02	0.03	0.02	0.05	0.00	0.18	0.01

Note: This table reports the impact of monetary policy and credit condition on different sectors' stock performance. Every three columns correspond to the monthly value-weighted excess returns of each sector's portfolios, accumulated over 1 month, 2 months, and 3 months, respectively. PLS^0_t is our baseline shock series at the monthly level, representing the monetary condition. The credit condition, $Cred_t$, is measured by the difference between realized outstanding stock level of Aggregate Financing to the Real Economy (AFRE) and analysts' consensus forecast, normalized by its time-series average. All independent variables are normalized to unit standard deviation. Newey-West standard errors are reported. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 11. Different Industries' Bond Yields Response

	0m	1m	3m	6m	9m	1y	2y	3y	4y	5y
					Panel A: Coal					
PLS^0_{t-1}	0.1338*	0.2324**	0.2502**	0.2495**	0.2412**	0.2409**	0.2269**	0.2120**	0.1866**	0.1602*
	(0.0729)	(0.1072)	(0.1073)	(0.1133)	(0.1104)	(0.1085)	(0.1029)	(0.0988)	(0.0854)	(0.0804)
$Cred_{t-1}$		0.1797	0.1992*	0.2144**	0.2236**	0.2235**	0.2293**	0.2314***	0.2247***	0.2205***
		(0.1123)	(0.1045)	(0.1019)	(0.1023)	(0.1022)	(0.0937)	(0.0866)	(0.0766)	(0.0738)
$PLS^0_{t-1} \times Cred_{t-1}$		-0.1638**	-0.1830**	-0.1849**	-0.1860**	-0.1885**	-0.1866***	-0.1792***	-0.1655***	-0.1517***
		(0.0763)	(0.0715)	(0.0765)	(0.0761)	(0.0743)	(0.0689)	(0.0660)	(0.0561)	(0.0546)
Constant	2.5504***	2.8478***	2.9482***	3.0538***	3.1301***	3.1857***	3.3794***	3.5025***	3.6684***	3.7402***
	(0.0956)	(0.1208)	(0.1220)	(0.1177)	(0.1171)	(0.1189)	(0.1114)	(0.1087)	(0.1015)	(0.0991)
					Panel B: Construction & Engineering					
PLS^0_{t-1}	0.1355*	0.2398**	0.2570**	0.2564**	0.2479**	0.2478**	0.2339**	0.2192**	0.1946**	0.1683**
	(0.0738)	(0.1088)	(0.1093)	(0.1156)	(0.1128)	(0.1110)	(0.1057)	(0.1017)	(0.0886)	(0.0836)
$Cred_{t-1}$		0.1862	0.2056*	0.2211**	0.2305**	0.2303**	0.2363**	0.2387***	0.2319***	0.2278***
		(0.1133)	(0.1057)	(0.1032)	(0.1037)	(0.1036)	(0.0953)	(0.0883)	(0.0783)	(0.0756)
$PLS^0_{t-1} \times Cred_{t-1}$		-0.1701**	-0.1886**	-0.1906**	-0.1917**	-0.1942**	-0.1925***	-0.1852***	-0.1720***	-0.1583***
		(0.0769)	(0.0724)	(0.0775)	(0.0772)	(0.0754)	(0.0701)	(0.0673)	(0.0575)	(0.0560)
Constant	2.5668***	2.8652***	2.9655***	3.0719***	3.1490***	3.2055***	3.4007***	3.5244***	3.6920***	3.7642***
	(0.0970)	(0.1222)	(0.1237)	(0.1196)	(0.1193)	(0.1212)	(0.1140)	(0.1114)	(0.1045)	(0.1021)
					Panel C: Electric Utilities					
PLS^0_{t-1}	0.1341*	0.2328**	0.2499**	0.2491**	0.2407**	0.2404**	0.2263**	0.2114**	0.1858**	0.1595*
	(0.0732)	(0.1070)	(0.1072)	(0.1132)	(0.1103)	(0.1084)	(0.1028)	(0.0987)	(0.0853)	(0.0802)
$Cred_{t-1}$		0.1786	0.1976*	0.2127**	0.2219**	0.2218**	0.2274**	0.2294***	0.2226***	0.2184***
		(0.1119)	(0.1043)	(0.1016)	(0.1020)	(0.1019)	(0.0934)	(0.0864)	(0.0763)	(0.0736)
$PLS^0_{t-1} \times Cred_{t-1}$		-0.1649**	-0.1832**	-0.1850**	-0.1861**	-0.1885**	-0.1867***	-0.1792***	-0.1655***	-0.1517***
		(0.0759)	(0.0712)	(0.0762)	(0.0758)	(0.0740)	(0.0686)	(0.0657)	(0.0558)	(0.0542)
Constant	2.5529***	2.8524***	2.9522***	3.0581***	3.1345***	3.1902***	3.3844***	3.5078***	3.6740***	3.7459***
	(0.0957)	(0.1204)	(0.1216)	(0.1174)	(0.1168)	(0.1186)	(0.1112)	(0.1087)	(0.1014)	(0.0990)
Observations	83	71	71	71	71	71	71	71	71	71

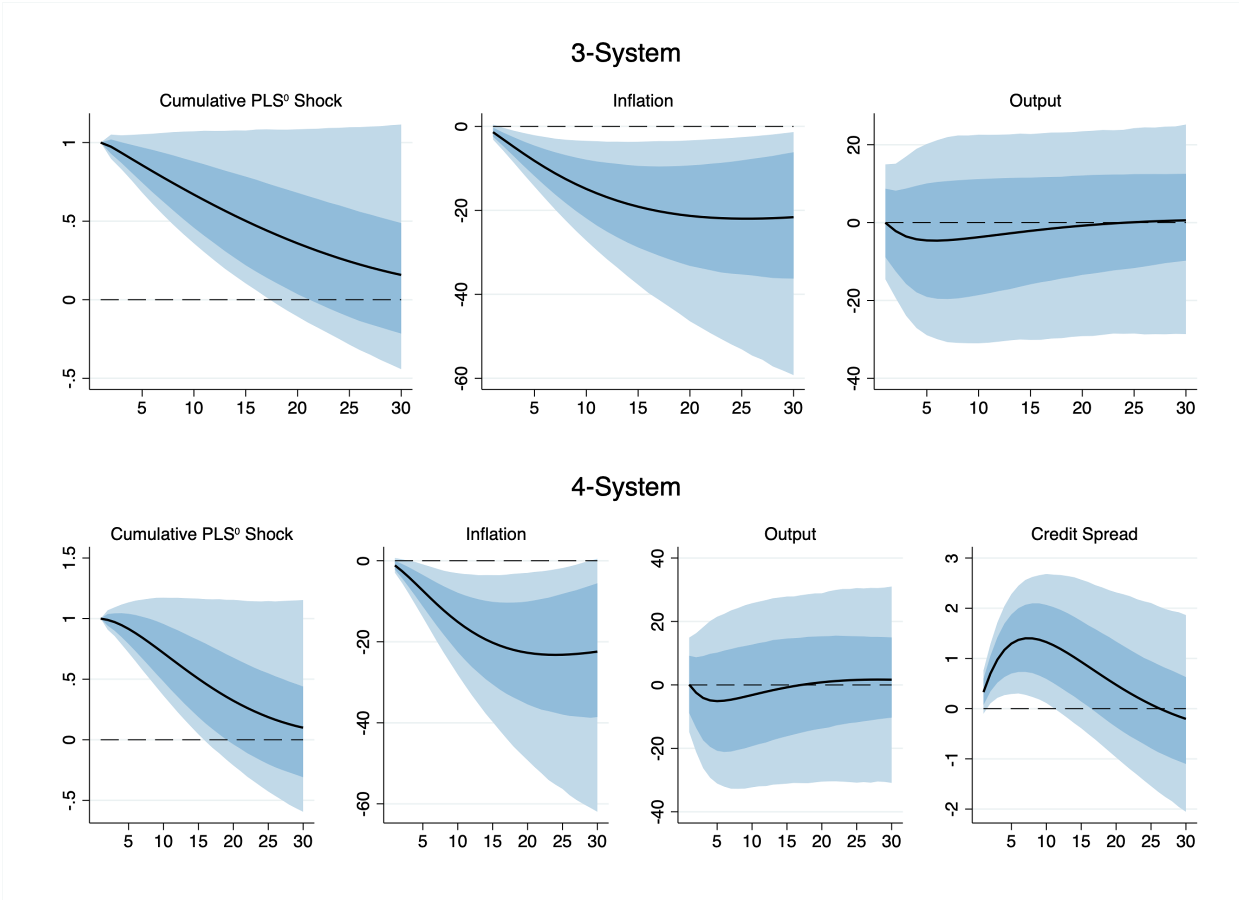
Note: This table reports the impact of monetary policy and credit condition on different industries' bond performance. Every panel reports the results for the month-end AAA-rated bond yields in excess of one-year deposit rate for each industry, except for that of steel, which has a highest bond rating of AAA−. Every column corresponds to a yield curve's maturity (i.e., 0m meaning spot rate). PLS^0_t is our baseline shock series at monthly level, representing the monetary condition. The credit condition, $Cred_t$, is measured by the difference between realized outstanding stock level of Aggregate Financing to the Real Economy (AFRE) and analysts' consensus forecast, normalized by its time-series average. All independent variables are normalized to unit standard deviation. The sample period is January 2015 to December 2021. Newey-West standard errors with two lags are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 11. (Continued)

	0m	1m	3m	6m	9m	1y	2y	3y	4y	5y
					Panel D: Real Estate					
PLS^0_{t-1}	0.1389*	0.2421**	0.2604**	0.2581**	0.2501**	0.2483**	0.2321**	0.2137**	0.1888**	0.1623*
	(0.0735)	(0.1058)	(0.1066)	(0.1135)	(0.1110)	(0.1093)	(0.1046)	(0.1012)	(0.0879)	(0.0834)
Cred_{t-1}		0.1706	0.1899*	0.2050**	0.2145**	0.2153**	0.2210**	0.2230**	0.2166***	0.2121***
		(0.1085)	(0.1009)	(0.0989)	(0.0999)	(0.1003)	(0.0925)	(0.0859)	(0.0760)	(0.0735)
$\text{PLS}^0_{t-1} \times \text{Cred}_{t-1}$		-0.1689**	-0.1884***	-0.1895**	-0.1906**	-0.1922**	-0.1891***	-0.1797***	-0.1661***	-0.1522***
		(0.0753)	(0.0709)	(0.0764)	(0.0763)	(0.0747)	(0.0698)	(0.0674)	(0.0577)	(0.0565)
Constant	2.5720***	2.8797***	2.9812***	3.0874***	3.1640***	3.2175***	3.4114***	3.5328***	3.7007***	3.7732***
	(0.0912)	(0.1141)	(0.1155)	(0.1115)	(0.1122)	(0.1148)	(0.1082)	(0.1064)	(0.0992)	(0.0970)
					Panel E: Highways					
PLS^0_{t-1}	0.1400*	0.2465**	0.2642**	0.2648**	0.2560**	0.2563**	0.2418**	0.2237**	0.2017**	0.1760**
	(0.0738)	(0.1104)	(0.1109)	(0.1168)	(0.1144)	(0.1128)	(0.1073)	(0.1025)	(0.0901)	(0.0850)
Cred_{t-1}		0.1879	0.2073*	0.2223**	0.2329**	0.2335**	0.2382**	0.2369**	0.2345***	0.2303***
		(0.1158)	(0.1081)	(0.1053)	(0.1058)	(0.1057)	(0.0971)	(0.0896)	(0.0798)	(0.0770)
$\text{PLS}^0_{t-1} \times \text{Cred}_{t-1}$		-0.1711**	-0.1897**	-0.1917**	-0.1931**	-0.1959**	-0.1935***	-0.1842***	-0.1729***	-0.1593***
		(0.0786)	(0.0739)	(0.0789)	(0.0786)	(0.0769)	(0.0714)	(0.0679)	(0.0584)	(0.0567)
Constant	2.5952***	2.8940***	2.9949***	3.1005***	3.1776***	3.2316***	3.4281***	3.5494***	3.7216***	3.7947***
	(0.0989)	(0.1258)	(0.1268)	(0.1221)	(0.1219)	(0.1238)	(0.1162)	(0.1131)	(0.1059)	(0.1033)
					Panel F: Steel					
PLS^0_{t-1}	0.1401*	0.2488**	0.2684**	0.2674**	0.2561**	0.2581**	0.2429**	0.2223**	0.1949**	0.1656**
	(0.0745)	(0.1122)	(0.1134)	(0.1197)	(0.1156)	(0.1141)	(0.1100)	(0.1043)	(0.0880)	(0.0822)
Cred_{t-1}		0.1989*	0.2205*	0.2348**	0.2423**	0.2415**	0.2448**	0.2467***	0.2486***	0.2448***
		(0.1183)	(0.1106)	(0.1084)	(0.1078)	(0.1077)	(0.0986)	(0.0908)	(0.0783)	(0.0751)
$\text{PLS}^0_{t-1} \times \text{Cred}_{t-1}$		-0.1745**	-0.1948**	-0.1964**	-0.1956**	-0.1988**	-0.1963***	-0.1869***	-0.1756***	-0.1593***
		(0.0796)	(0.0752)	(0.0800)	(0.0788)	(0.0771)	(0.0719)	(0.0675)	(0.0559)	(0.0535)
Constant	2.6783***	2.9708***	3.0711***	3.1815***	3.2573***	3.3142***	3.5144***	3.6426***	3.8208***	3.9007***
	(0.1024)	(0.1296)	(0.1309)	(0.1265)	(0.1260)	(0.1278)	(0.1198)	(0.1164)	(0.1081)	(0.1053)
Observations	83	71	71	71	71	71	71	71	71	71

Note: This table reports the impact of monetary policy and credit condition on different industries' bond performance. Every panel reports the results for the month-end AAA-rated bond yields in excess of one-year deposit rate for each industry, except for that of steel, which has a highest bond rating is AAA−. Every column corresponds to yield curve's maturity (i.e., 0m meaning spot rate). PLS^0_t is our baseline shock series at the monthly level, representing the monetary condition. The credit condition, Cred_t, is measured by the difference between realized outstanding stock level of Aggregate Financing to the Real Economy (AFRE) and analysts' consensus forecast, normalized by its time-series average. All independent variables are normalized to unit standard deviation. The sample period is January 2015 to December 2021. Newey-West standard errors with two lags are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Fig. 4. Impulse Responses - VAR Analysis



Note: This figure plots VAR impulse response functions from Bayesian identification with monthly data using 2 lags. Variables are ordered: cumulative PLS^0 shock series, monthly year-of-year producer price index (PPI) as inflation, the monthly year-of-year growth rate in industrial value added (IVA) as output, and the difference between the yields of 1-year AAA-rated enterprise bonds and 1-year treasury yields as credit spread. Impulse responses to a 1 percentage point increase in the cumulative PLS^0 shock series. Deep and shallow blue-shaded areas are 68% and 90% confidence intervals produced by 3000 times, respectively.