Shadow Banking, Money Supply, and Liquidity Transformation: Evidence from China[1]

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ABSTRACT

We empirically test the theoretical predictions of Moreira and Savov (The Journal of Finance, 72:2381-2432, 2017) and corroborate the relationship between shadow banking and monetary policy. Applying a vector error correction model to aggregate monthly data in China, we find an inverse relationship between bank credit and shadow banking credit, which weakens the transmission effect of the credit channel; and a positive relationship between financial assets' liquidity and shadow banking activities, which hampers growth. In short, shadow banking affects money supply and liquidity, effectively participating in credit transmission and liquidity transformation, thereby influencing monetary policy goals of CPI and GDP.

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The outbreak of the global financial crisis (GFC) in 2008 revealed the risk of shadow banking, which drew global attention. Shadow banking refers to "credit intermediation involving entities and activities outside the regular banking system" (FSB (2014)). Shadow banking has grown outside of regulatory oversight for more than 30 years, but it expanded rapidly before the GFC. The total assets of nonbank financial institutions, known as other financial intermediaries (OFIs), increased from $26 trillion in 2002 to $62 trillion in 2007 (FSB (2011)). The large, unregulated credit boom was heavily concentrated among riskier borrowers (Mian and Sufi (2009)), eventually collapsing and contributing to the GFC (Gorton (2010); Gorton and Metrick (2012)).

Shadow banking institutions are market based with the main funding sources (i.e., securities lending transactions) lacking back-up lines of credit, rendering them particularly vulnerable to a liquidity crisis. During the GFC, major central banks adopted unconventional monetary policies (i.e., quantitative easing (QE)) to provide liquidity to stimulate economic recovery. To avoid systemic collapse, central banks not only supported individual financial institutions in the banking sector but also forcefully accommodated liquidity demand from the dysfunctional financial markets covering shadow banking institutions[2]. Unconventional policies released liquidity on an unprecedented scale, flooding massive credit into the economy. For instance, the Federal Reserve's balance sheet rapidly more than doubled from September to December in 2008.

Since the financial turmoil, the worldwide financial environment has shifted, with a number of authorities tightening regulations and subsequently implementing a contractionary monetary policy. Nevertheless, the shadow banking sector experienced further expansion globally after the GFC – OFIs' assets reached $92 trillion in 2015, and the growth rate of OFIs' assets was 9% over the period of 2011-2015, nearly three times the bank assets growth rate of 3.1% (FSB (2017)). This rapid increase poses substantial challenges for central banks. Investors prefer high-yield shadow banking products over low-yield investment in the banking sector (i.e., bank deposits), while shadow banking lending diverts funds from the banking sector into the shadow banking sector. These activities are likely to change the relationship between monetary aggregates and economic growth, alter monetary transmission channels, and blur monetary authorities' judgments about liquidity in the economy. Monetary authorities require sufficient and accurate information to make optimal monetary policy choices to attain desired macroeconomic outcomes. It is therefore important to understand the changing landscape of financial markets and to gain in-depth knowledge of the complicated working channels and potential consequences of the less-known shadow banking sector.

This study is inspired by the latest theoretical contribution to this emerging field of research by Moreira and Savov (2017), and it makes an important contribution to the

[2] Whether and to what extent central banks should support unregulated shadow banking institutions in a time of crisis is still open to debate among scholars and policy makers. It is, however, outside the scope of this study and we omit discussions of this issue.

knowledge about shadow banking by providing empirical evidence. Moreira and Savov (2017) proposed a macrofinance model characterizing shadow banking as fragile liquidity transformation – turning risky loans into short-term money-like instruments. The model predicts a trade-off between stability and economic growth: shadow banking provides credit and liquidity to the economy and boosts growth, while shadow banking also induces uncertainties and slows growth. This paper tests these theoretical predictions by addressing the following questions. How does the shadow banking sector affect the money supply and the monetary transmission of the credit channel, thereby influencing monetary policy goals? How does the shadow banking sector contribute to liquidity transformation, thereby influencing monetary policy goals?

As such, this paper relates to a strand of literature on the macroeconomic relationships and extends our understanding of the impact of shadow banking on monetary policy from the perspectives of money supply and liquidity transformation. The banking sector was traditionally the dominant supplier of credit in the economy, but it has been partly supplanted by the shadow banking sector. As it becomes more difficult to obtain loans from the banking sector under a contractionary monetary policy, borrowers turn to shadow banking institutions. As shown in Table I, shadow banking credit (entrusted and trust loans) increases in China when bank loans decrease, partially offsetting the effect of the contractionary monetary policy implemented in 2009. On the other hand, liquidity is an important leading indicator of economic cycles. However, the monetary economics literature has exclusively emphasized the role of the money supply, and the role of liquidity as an indicator of monetary policy stances has been completely ignored (Buera and Nicolini (2017)).

[Table I near here]

This paper is also motivated by the rapidly rising shadow banking sector in China and the growing importance of the Chinese financial sector in the global financial system. The recent growth in global shadow banking assets has been largely driven by emerging economies, especially China. In 2016, OFIs' loans increased by 18% in emerging economies, in sharp contrast to a decline of 0.5% in advanced economies (FSB (2017)). In China, as of the end of 2016, the estimated outstanding shadow savings instruments and shadow banking credit were approximately 77% and 55% of GDP, respectively (Ehlers, Kong and Zhu (2018)). To gain a better understanding of these dynamics, this study provides a detailed description of the evolution of the shadow banking sector in China. China is now the second largest economy in the world and home to the world's largest banking system, with four of the world's top ten largest banks by total assets; hence, its macroeconomic performance and stability are likely to have significant consequences for the rest of the world.

We apply the standard method for estimating the effects of monetary policy – the vector autoregression (VAR) model, which addresses a simultaneity problem that monetary policy affects the economy and meanwhile responds endogenously to changing macroeconomic conditions. Recent applications of this approach in studying macroeconomic relationships include Benati (2015) and Tsangarides (2010). In particular, applying a vector error correction model (VECM) to aggregate monthly data

over the period of 2012Q1-2018Q1,[3] we find an inverse relationship between bank credit and shadow banking credit, which weakens the monetary transmission effect of the traditional bank credit channel; and a positive relationship between financial assets' liquidity and shadow banking activities, which hampers growth. Overall, shadow banking has a significant effect on broad money (M2) growth, liquidity, consumer price index (CPI), and GDP, effectively participating in credit transmission and liquidity transformation. Our results corroborate the theoretical prediction of Moreira and Savov (2017). The findings shed light on the role of shadow banking in the attainment of monetary policy goals and provide useful information for policy makers in formulating and implementing monetary policies.

The remainder of this paper proceeds as follows. Section I reviews the literature on shadow banking, and section II provides a detailed account of the shadow banking sector in China. Section III describes the data and section IV outlines the VECM framework. Section V analyzes the empirical results. Section VI summarizes the findings, discusses policy implications, and provides policy recommendations. Section VII concludes the study.

I. Literature Review

Shadow banking dates back to the 1960s, when western countries eased restrictions and encouraged the development of a nonbank financial system to promote economic growth. It broadly refers to the proliferation of leveraged nonbank investment methods, such as asset-backed securities and credit derivatives, in the US financial market. However, the term "shadow banking" was not coined until the recent GFC in 2007 by a PIMCO analyst – McCulley. "Banking" implies that shadow banking institutions perform functions similar to those of traditional banks, while "shadow" indicates their co-existence as banks' shadow under no or light regulations. Important components of shadow banking businesses include asset securitization, asset-backed commercial paper conduits, money market funds, repo markets, investment banks and mortgage companies.

Despite a relatively short (surfaced) history since 2007, the literature on shadow banking has mushroomed in the past few years due to its proven profound consequences. Early research mainly focused on developed countries (i.e., the US and Europe) and explored the forces driving shadow banking, such as regulatory arbitrage (Acharya, Schnabl and Suarez (2013)), financial innovation and technological advancement (Boz and Mendoza (2010); Turner (2012)), and demand-side drivers (Claessens, Kose and Terrones (2012); IMF (2014)). Duca (2016) found that shadow banking activities adapt to changing information, reserve requirements, and regulation in the long term, but they are more affected by interest rate ceilings on bank deposits, risk, and the economic

[3]Since China's central bank adjusted the definition of broad money (M2) in October 2011, our sample starts from 2012 to avoid potential bias due to the inconsistent measurement of M2. There is no obvious answer regarding the sample size for cointegration relations, and a sample of 40-100 observations has been common in published work, e.g., Juselius (2006).

prospects in the short term.

Both shadow banking institutions and banks provide credit to the economy, and the interaction between them can influence the monetary transmission of the credit channel and economic performance. Allen et al. (2019) argued that the rapid development of shadow banking is essentially a market reaction to credit shortages. Benmelech, Meisenzahl and Ramcharan (2017) found evidence that reduced consumer financing from the shadow banking sector has a negative effect on the real economy (e.g., the automobile industry). Similarly, Ivashina, Scharfstein and Stein (2015) demonstrated that contractions in shadow banking activities sharply reduce the credit supply, which has a cross-border effect on other economies. Eurozone banks cut dollar-denominated lending due to the sovereign debt crisis, and these overseas shocks are transmitted to the US economy.

The financial system typically holds long-term illiquid assets financed by short-term liabilities, especially for the highly leveraged shadow banking sector. The shadow banking system is stable and improves welfare under rational expectations, but it becomes vulnerable to liquidity shortages and crises when investors are too optimistic to overlook tail risks (Gennaioli, Shleifer and Vishny (2014)). When uncertainties dried up the wholesale market lending channel, the sub-prime mortgage crisis amplified into the severe GFC of 2008 (Brunnermeier (2009)). Moreira and Savov (2017) characterize shadow banking as fragile liquidity transformation that turns risky loans into short-term money-like instruments. These instruments are highly liquid and attractive to investors (i.e., households, firms, and institutional investors) in good (quiet) times, but when the market environment becomes more uncertain, such liquidity rapidly evaporates and causes sharp contractions in liquidity. Their model predicts a trade-off between stability and economic growth: shadow banking boosts liquidity, asset prices and growth, while increased uncertainties induce financial and economic fragility and slow growth.

As China has become one of the main contributors to the post-crisis growth in global shadow banking assets, research enthusiasm has tended to follow the trend. Allen et al. (2019) provided a comprehensive analysis of the reasons, risks, pricing, and regulation of entrusted loans using transaction-level data. Acharya, Qian and Yang (2017) focused on another major component of the shadow banking sector – wealth management products (WMPs) -- and found that the swift rise of shadow banking in China was triggered by the stimulus plan during the GFC. Chen, Ren and Zha (2018) found evidence that the contractionary monetary policy after the GFC caused shadow banking loans to rise rapidly. Hachem and Song (2015) argued that asymmetric competition between banks is both a short-term stabilizer and a long-term risk. These studies address different research issues. There have also been extensive studies of monetary policy in China, but none of them has examined the influence of shadow banking. An exception is Chen, Ren and Zha (2018), who focused on the banking sector and examined how monetary policy affects banks' balance sheets, reporting that shadow banking undermines the effectiveness of monetary policy. Our study builds on Chen, Ren and Zha (2018) by examining the impact of shadow banking on monetary policy in terms of both money supply and liquidity transformation, based on the principle of monetary policy transmission mechanisms. Unlike Chen, Ren and Zha (2018), which

was based on a micro-dataset of listed banks and listed firms, our paper is based on a sample that includes comprehensive data on entrusted loans, trust loans, and WMPs involving both listed and non-listed banks and firms.

II. Shadow Banking in China

In this section, we provide a comprehensive overview of the evolution of the shadow banking sector in China in terms of size, business channels and products, driving forces, regulation, and its potential effects on macroeconomic policies and growth.

Shadow banking has expanded rapidly in China since the GFC, and banks and OFIs have developed a broad range of shadow banking channels and products. Three major components of shadow banking are trust loans, entrusted loans, and WMPs. Trust loans are made by trust companies, which are the main nonbank intermediation channels. Entrusted loans – a unique form of intermediation in China – are loans made between two non-financial firms using a bank as a service agent. WMPs, issued by banks or OFIs, are a key funding source for the shadow banking sector. Due to variations in the definition and classification criteria, as well as the lack of regulation (i.e., insufficient disclosure requirements), detailed data on shadow banking in China are unavailable. According to central bank statistics, shadow banking credit (entrusted and trust loans) accounted for 11-25% of new financing over the period of 2012-2017. According to the banking regulator's annual reports – China Banking Wealth Management Market Report – the outstanding balance of WMPs issued by banking institutions has been constantly increasing from 7.1 trillion RMB in 2012 to 29.54 trillion RMB in 2017. Estimates by Ehlers, Kong and Zhu (2018) indicated that two major forms of shadow banking credit are of similar size: trust and entrusted loans account for 26% of GDP, and WMP-financed bonds account for 23% of GDP.

The rapid expansion of the shadow banking sector in China has been facilitated by financial innovations (i.e., securitization), technological advancement, and market adaptations. Shadow banking intermediaries have emerged in different forms, including: (1) commercial banks' off-balance sheet businesses, such as WMPs, entrusted loans, trust loans, and undiscounted bankers' acceptance; (2) non-deposit financial institutions and products, such as trust companies and securitization; and (3) informal finance, such as private/informal lending, pawnshops, microcredit companies, and P2P online lending platforms (IMF (2014)). In a typical business model, entities with resources (normally commercial banks) siphon funds from channels or capital pools (such as WMPs) to provide funding for the real economy while acting as links in the middle of transaction chains. One distinct feature in China is that the shadow banking sector intertwines with the banking sector through direct connections (i.e., participating in banking intermediation and securitization business chains) and indirect linkages (i.e., sharing common counterparties) (Jiang and Yao (2017)). These connections or linkages are formed through a variety of channels, including: (1) bridging channels, such as financing trusts, securities companies, insurance companies, fund managers, leasing companies or futures companies; (2) nonbank investment channels, such as non-government loans, entrusted loans, private equity funds and trusts; and (3) market

channels using the cooperative products of nonbank trust institutions, trust rights, securities firms or fund-specific asset management (FSB (2013)).

Shadow banking in China is driven by both supply- and demand-side factors. On the supply side, commercial banks face tight regulations, including caps on banks' total lending, interest rate limits on deposits, loan-to-deposit requirements (no more than 75%), reserve requirements, and government interventions (Jiang and Yao (2017)). Since the GFC, banking competition has become increasingly fiercer, and many banks have undertaken shadow banking activities to benefit from regulatory arbitrage. Commercial banks have become a central player in the shadow banking sector. For instance, there were only 81 banking institutions issuing WMPs in 2010, which increased to 562 in 2017. Banks cooperate with OFIs through innovative products and channels and act as intermediaries beyond the reach of regulation. The complex shadow banking business practice is supported by implicit guarantees or public backstops (Claessens and Ratnovski (2014); Kane (2014)), as well as investors' (false) perceptions of credit guarantees by banks (Dang, Wang and Yao (2015)). On the demand side, the investor base has increased significantly with China's remarkable economic growth. Individual and institutional investors have strong demand for high-yield investment products (i.e., WMPs) as an alternative to low-yield bank deposits. On the other hand, the state-controlled banking sector prefers to extend loans to large firms, especially state-owned enterprises (SOEs). Because of market impediments and/or tight regulations, certain borrowers have restricted access to bank loans. These less-favored borrowers seek alternative financing sources and create strong demand for shadow banking loans. Allen, Qian and Qian (2005) found that small and medium-sized enterprises (SMEs) in the private sector rely in particular on informal financing channels.

The stimulus package of 4 trillion RMB (USD585 billion) in 2008, and the subsequent contractionary monetary policy in 2009 fueled the rise of the shadow banking sector. The package was implemented via the banking system, mainly through the four largest state-controlled banks. Vast credit at low costs provided great opportunities and incentives for these state-controlled banks and privileged firms (i.e., large firms and SOEs) to engage in shadow banking activities. Some privileged firms take advantage of their access to cheaper bank loans and extend entrusted loans to less-privileged firms (Allen, et al. (2018)). Small and medium-sized banks that face differential market competition pressure significantly increased shadow banking activities after the stimulus package (Acharya, Qian and Yang (2017)). When monetary authorities tightened credit control in 2009, the credit shortage had the greatest effects on the less-favored borrowers (i.e., SMEs), which were already suffering deeply from the recession. The credit demand in the shadow banking sector thus became much stronger than before.

Because shadow banking has developed largely outside regulatory oversight, and it is difficult to regulate a sector that involves innovative channels, businesses and products with large chains, regulators are unclear, ambiguous, and even ambivalent regarding how and to what extent to regulate this sector (Wei and Davis (2014)). It is unclear what businesses (products or parts of transaction chains) should fall under

which regulatory body's (or bodies') supervision. In China, the segregation regulatory model presets the scope of regulation and regulatory authorities, which do not cover shadow banking activities. The legislation and legal framework has also lagged; hence, the shadow banking sector has been practically left in a "regulatory vacuum".

Shadow banking has significant implications for macroeconomic policies and real sectors. Under China's dual taxation system, taxation income is shared between the central and local governments. Local governments bear the majority of fiscal costs, and the large expenditure gap was previously financed by aggressively raising debt via local governmental financing vehicles. When the central government restricted this practice, local governments turned to shadow banking borrowing. Shadow banking lending cumulates massive debts among local governments, with significant risk implications for the financial sector. This practice alleviates local governments' financing constraints, but undermining the central government's ability to control fiscal policies and maintain financial stability.

Shadow banking can exert more direct influences on quantity-based monetary policy in China relative to price-based monetary policy in developed countries (i.e., the US). In China, the monetary transmission is dominated by the credit channel. Authorities largely rely on a 75% ceiling on the loan-to-deposit ratio (set for commercial banks) to affect bank credit, in turn affecting aggregate demand and output through credit markets. Because interest rates are not fully liberalized, the quantity-based monetary policy sets broad money supply (M2) growth as the intermediate target to serve the ultimate goals of economic development (aggregate output) and price stability. The central bank's decisions on monetary policy are strongly influenced by the State Council to achieve the central government's goals. A range of monetary instruments is employed to regulate the money supply and to influence interest rates and liquidity. These instruments include: (1) rate-based instruments, such as central bank base interest rates and the reserve requirement ratio; (2) quantity-based instruments, such as open market operations (OMOs), central bank lending facility, and rediscounting; and (3) other tools specified by the State Council.

III. Data

A. Variables and Preliminary Data Analysis

Monetary authorities employ different money supply measures, and the exact definitions depend on the country. In general, narrow money M1 is a more liquid component consisting of cash and cash equivalents, while broad money M2 (equivalent of credit) consists of cash, savings and deposits flowing through the economy. Since the Chinese central bank explicitly targets monetary aggregates, researchers have frequently employed quantity-based policy indicators, such as the growth rate of narrow money (M1) or broad money (M2) (Burdekin and Siklos (2008); Xie (2004)). Other scholars have preferred an index-based approach to measuring monetary stances (Xiong (2012)). In this study, we employ the standard method for estimating the effects of monetary policy – the VAR framework pioneered by Sims (1980). In particular, we employ the VECM, which addresses the simultaneity between monetary policies and macroeconomic developments while accounting for the cointegration properties of

variables in the system.

We specify two models – the money supply model and the liquidity transformation model. The money supply model focuses on the credit provision to the real economy and is used to investigate how shadow banking interacts with the banking sector and how these two sources of credit jointly affect economic growth. A standard VAR system for analysing the monetary transmission mechanism contains a vector of macroeconomics non-policy variables, such as GDP and price levels, and a vector of policy variables, such as interest rates and bank reserves. Following the literature, we include two non-policy variables – *GDP* as a measure of output and *CPI* as a measure of price stability. Taking into account that China's monetary authorities adopt a quantity-based monetary policy framework and explicitly target monetary aggregates, we employ quantity-based policy indicators, namely *BankCredit* defined as the increase in bank loans and *M2Growth* defined as the year-on-year growth rate of broad money (M2). The variable of our main research interest is *ShadowCredit*, defined as the sum of trust loans, entrusted loans, and listed firms' investments in long-term WMPs. Entrusted loans are the most frequently employed measure of shadow banking lending in China (i.e., Allen, et al. (2018); Chen, Ren and Zha (2018)). Unlike studies focusing on listed firms, we use the central bank's comprehensive data on entrusted loans and trust loans involving both listed firms and unlisted firms. Our measure of shadow banking credit also includes listed firms' investment in long-term WMPs (with a maturity of more than 6 months or rolled over without a maturity date), which represents a channel of shadow banking lending.

The liquidity transformation model focuses on the liquidity provision to the economy and is used to investigate how shadow banking interacts with the banking sector and how they jointly influence the structure of liquidity and economic growth. The literature on the role of liquidity in monetary policy analysis is scarce, providing little guidance. We include the same non-policy variables as in the money supply model – *GDP* and *CPI*. We include two policy variables – *BankCredit* as a measure of liquidity from the banking sector and *LiquidityRatio* as a measure of the structure of liquidity in the economy, defined as the ratio of the narrow money (M1) growth rate to the broad money (M2) growth rate. This ratio is frequently used as an important indicator of economic momentum and monetary policy stance in the quarterly *China Monetary Policy Report*. A higher ratio indicates more highly liquid assets in the economy since narrow money (M1) grows faster than broad money (M2). Liquidity from the shadow banking sector is proxied by *ShadowBanking*, defined as the sum of trust loans, entrusted loans and listed firms' total investment in WMPs. The key difference between *ShadowCredit* in the money supply model and *ShadowBanking* in the liquidity transformation model is that the latter includes listed firms' investments not only in long-term WMPs, but also in short-term WMPs. Investments in short-term WMPs more than double that in long-term WMPs (see sample statistics in Table 2) and they exhibit different trend, as shown in Figure I. Compared with other types of investors (i.e., individual and institutional investors), listed firms have more opportunities to invest in real sectors. Their investment preferences in short-term money-like WMPs or long-term WMPs (as a lending channel) enable us to examine how the shadow banking sector

influences both the quantity and the structure of the liquidity in the economy.

[Figure 1 near here]

The sample period of 2012Q1 to 2018Q1 falls into a single contractionary monetary policy regime starting in 2009, for which VAR-type models provide parameter stability and reliable descriptions of the monetary transmission mechanisms (Bagliano and Favero (1998)). Data on trust loans, entrusted loans, bank loans, and macroeconomic variables are collected and checked across multiple sources, including the China Statistics Network, the central bank statistics, and the National Bureau of Statistics. Transaction-level data on listed firms' investments in WMPs are collected from listed banks' annual reports and are cross-checked with data from the CSMAR database and Wind economic database. We have 104,309 observations on WMPs, which are totaled into monthly aggregate time-series data. Table II reports summary statistics in which the quarterly series of GDP is converted into a monthly series using the proportional Denton method of interpolation. As shown in the table, the amount of shadow banking intermediation activity is substantial, accounting for more than 30% of bank loans over the period of 2012Q1-2018Q1.

[Table II near here]

For time-series analysis, nonstationary time series often lead to false regression results. The evolution of endogenous variables (in logarithmic form) in Figure 2 raises concerns about variable stationarity. *GDP, BankCredit,* and *ShadowCredit* tend to be stationary, while *CPI, M2Growth,* and *LiquidityRatio* tend to be nonstationary.[4] We perform the augmented Dickey-Fuller test (Dickey and Fuller, 1979)) and the Kwiatkowski–Phillips–Schmidt–Shin test (KPSS) (Kwiatkowski, et al., (1992)) to examine whether these variables are stationary or they follow a unit root, and the results are reported in Table III. The maximum lag order (bandwidth) for KPSS is derived from an automatic bandwidth selection routine. The results confirm that *GDP, BankCredit, ShadowCredit,* and *ShadowBanking* are stationary; *CPI, M2Growth,* and *LiquidityRatio* are nonstationary (or marginally stationary) in levels, but their first-order difference is stationary at the 1% significance level.

[Figure 2 near here]

[Table III near here]

When time-series variables contain a unit root in levels but are stationary in first-order differences, there can be one or more long-term equilibrium relationships among the variables. If such relationships exist, conventional VAR models could become spurious (Granger and Newbold (1974)), and the VECM is more appropriate because it adjusts for both short-term changes in variables and deviations from long-term equilibrium. The VECM considers the cointegration properties of variables and better predicts their evolution. The cointegration relations also provide identification restrictions and differentiate shocks that have permanent or transitory effects (Phillips (1998)).

We perform a Johansen cointegration test to determine the existence of long-term relationships among the variables. First, the lag length for the VECM is

[4] *ShadowBanking* exhibits a similar trend to *ShadowCredit* and is not plotted.

determined based on selection criterion statistics for Akaike's information criterion (AIC), the Hannan and Quinn information criterion (HQIC), and Schwarz's Bayesian information criterion (SBIC). We apply the principle that the VECM model should choose the lag length that minimizes these statistics for a series of vector autoregressions of order 1 through a maximum lag of 6. Table IV reports the results, and a lag number of 2 is selected based on the AIC, HQIC, and SBIC statistics in Panel A. In Panel B, we choose a larger lag number of 2, although the results suggest a lag for one period.

[Table IV near here]

The Johansen cointegration test is used to determine the number of cointegration equations (r) that minimize an information criterion in a VECM, and Table V reports the results. Based on Johansen's "trace" statistic and "maximum eigenvalue" statistic, we can, at the 5% significance level, reject the null hypothesis of no cointegration vector since the trace statistics are greater than their corresponding critical values. We cannot reject the null hypothesis of 2 cointegration vectors, thus, there are at least two cointegration relationships in both Panel A and Panel B.

[Table V near here]

IV. The VECM

The VECM is an extension of the VAR framework when there are one or more cointegration relationships. The VECM treats all selected variables as endogenous and regresses one against the others simultaneously. The VECM estimates the first differences in the nonstationary variables and the lagged error correction terms. Unlike conventional VAR models, in which the effect of a shock of any variable dissipates over time, the VECM differentiates between transitory shocks (the effect dissipates over time) and permanent shocks (the effect does not dissipate over time). The results from the VECM offer more useful information for policy making.

A general specification of the VECM is shown in Eq. (1).

$$\Delta y_t = \alpha(\beta y_{t-1} + \mu + \rho t) + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \gamma + \tau t + \varepsilon_t \qquad (1)$$

where y_t is a K×1 vector of endogenous variables, α and β are the K×r matrices of parameters, $\Gamma_1, \ldots, \Gamma_{p-1}$ are the K×K matrices of parameters, γ is a K×1 vector of parameters, τ is a K×1 vector of trend coefficients, and t is a linear time trend.

Depending on restrictions on the trend parameters, the VECM has five different specifications (Johansen (1995)), and our data better fit the specification with a restricted constant. In particular, there is no linear or quadratic trend in the un-differenced data, while a nonzero μ allows the cointegration equations to be stationary around nonzero means, thereby providing the intercepts for differenced data. The parameters of the VECM are estimated based on the concentrated maximum likelihood framework proposed by Johansen (1988). The empirical specification is shown in Eq. (2).

$$\Delta y_t = \alpha(\beta y_{t-1} + \mu) + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \qquad (2)$$

where y_t is a K×1 vector of endogenous variables (*lBankCredit, lM2Growth,*

lShadowCredit, lCPI, and *lGDP* in the money supply model and *lBankCredit, lLiquidityRatio, lShadowBanking, lCPI, and lGDP* in the liquidity transformation model); α and β are the K×r matrices of parameters; and $\Gamma_1,\ldots, \Gamma_{p-1}$ are the K×K matrices of parameters.

The coefficients on the lagged differenced terms capture the short-term effect. The coefficients of the lagged error correction terms measure the adjustment speed of endogenous variables to the equilibrium level, capturing the long-term effect. The size and statistical significance of these coefficients indicate the adjustment tendency to equilibrium. A significant coefficient suggests that the current outcomes are affected by previous equilibrium errors. To identify the cointegration vectors, we follow the Johansen normalization method (1995). This approach is widely used when theory provides insufficient guidance on a priori restrictions for the integration vectors and is thus suitable for our analysis because there lacks theoretical guidance on how shadow bank credit can interact with other macroeconomic variables in the system.

After the VECM is estimated, we employ orthogonalized impulse response functions (OIRFs) to identify the responsiveness of the dependent variables to a one standard deviation shock (also known as innovations) to other variables in the system. An OIRF measures the effect of an orthogonalized shock to an endogenous variable on itself or on other variables. When the OIRF from the shocks of one variable to another gradually decreases to zero over time, the shocks to the first variable is said to have a transitory effect on the second variable. When the OIRF from the shocks of a nonstationary variable does not decrease to zero, the effect is said to be permanent. Since some of the OIRFs do not disappear over time, the cumulative OIRFs will diverge over time.

Forecast error variance decompositions (FEVDs) measure the fraction of forecast error variance in an endogenous variable that can be attributed to the orthogonalized shocks to itself or to another endogenous variable (Lütkepohl (2005)). FEVD shows how much of the future uncertainty of one variable is caused by future shocks on the other variables in the system. FEVD evolves over time, and the shocks on a variable might be not important in the short term but can be very important in the long term. We adopt Cholesky decomposition, which places endogenous variables in a specific order: the orthogonalized shocks to the first variable are not contemporaneously affected by the shocks of any of other variables, the second variable is assumed not to be affected by others, and so on.

Because the order of variables matters, we organize variables by relative exogeneity in a decreasing order. We place non-policy variables after policy variables and shadow banking measures between policy variables and non-policy variables. As such, we have the following order: *BankCredit, M2Growth, ShadowCredit, CPI* and *GDP* in the money supply model, and *BankCredit*, *LiquidityRatio*, *ShadowBanking*, *CPI* and *GDP* in the liquidity transformation model. We also estimate the models in a different order by placing shadow banking measures right after bank credit and results are generally consistent with our main results. Stata program is used to estimate the VECM based on the Johansen method to estimate the parameters of cointegration relationships, and it generates the full model estimates jointly, along with relevant test

statistics.

V. Empirical Results from the VECM

A. Cointegration Relationships

In the VECM, causality is dynamic as variables adjust to deviations from the long-run equilibrium, and variables that are statistically significant bear the main task of the adjustments. The coefficients of cointegration equations describe long-term equilibrium, which can be considered as long-term elasticities when all variables are in logarithms (Johansen (2005)). Two cointegration relationships are identified in the money supply model, as shown in Panel A of Table VI. The first cointegration equation, shown in Eq. (3), suggests the following long-term relationships in the system. First, shadow banking credit and bank credit are inversely related, indicating an offsetting effect. When bank credit decreases by 1%, shadow banking credit increases by 2.7% (=1/0.37). The result is consistent with the finding of Allen et al., (2019) that shadow banking (entrusted) loans are more likely to occur when credit from the banking sector is tight. Second, bank credit promotes economic growth, consistent the foundation of monetary policy that monetary stimulus boosts output. When bank credit increases by 1%, GDP will increase by 1.07% (=1/0.93). Third, shadow banking credit also promotes economic growth, consistent with the theoretical prediction of Moreira and Savov (2017) that a boom in shadow bank credit induces an economic boom. When shadow banking credit increases by 1%, GDP increases by 0.40% (=0.37/0.93). Finally, CPI is not a significant factor in this co-integration relationship.

[Table VI near here]

$$lBankCredit + 0.37lShadowCredit - 0.16lCPI - 0.93lGDP - 0.68 = Error \quad (3)$$

The second cointegration equation, shown in Eq. (4), indicates the follow long-term relationships in the system. First, there is a positive relationship between broad money (M2) growth and shadow banking credit. When the M2 growth rate increases by 1%, shadow banking credit increases by 1.54% (=1/0.65). Second, shadow banking credit has a positive impact on the CPI. When shadow banking credit increases by 1%, the CPI increases by 0.98% (=0.65/0.66). The coefficient on *CPI* is insignificant in Eq. (3) but significant in Eq. (4), implying that shadow banking credit influences the CPI more than bank credit does (this is confirmed by the impulse response analysis in the sub-section D). This outcome is likely because extending shadow credit enables financial intermediaries to supply more money (Moreira and Savov (2017)) and hence has a stronger effect on the CPI. Third, as identified in the first cointegration relationship in Eq. (3), shadow banking credit promotes growth. When shadow banking credit increases by 1%, GDP increases by 0.44% (=0.65/1.47).

$$lM2Growth - 0.65lShadowCredit + 0.66lCPI + 1.47lGDP - 12.01 = Error \quad (4)$$

Fourth, the intermediate monetary target of M2 growth is negatively related to CPI and GDP. Moreover, when considering the two cointegration equations in Eq. (3) and Eq. (4) jointly (i.e., plugging one into the other), there appears a negative relationship between bank credit and the M2 growth. These results are in contradiction to the literature that an increase in bank credit is expected to increase M2 growth, in turn increasing CPI and boosting economic growth. We attribute these unexpected

results to the rising shadow banking credit, which is stimulated by the dual-track interest rate system and distortions in the Chinese financial sector. China operates a dual-track interest rate system, under which interest rates are largely regulated in the banking sector but marketized in the interbank and wholesale markets. As a monetary transmission mechanism works, an increase in bank credit lowers interest rates in the banking sector. Investors search for higher returns and invest in high-yield shadow banking investment vehicles (such as WMPs). As a result, the prevailing market rates are likely to be high due to shadow banking activities, discouraging consumption and lowering CPI. Shadow banking investment products effectively crowd out money-like investment instruments in the traditional banking sector (Moreira and Savov (2017)). When uncertainty is low, investors are willing to invest in shadow banking products, and intermediaries have strong incentives to supply shadow banking products for higher returns. Meanwhile, low lending rates in the banking sector provide privileged firms with opportunities to obtain cheaper loans and repackage them as shadow banking credit (entrusted loans) for higher returns. It is argued that up to two-thirds of shadow banking lending is effectively "bank loans in disguise" (Elliott, Kroeber and Qiao (2015)). Moreover, M2, as defined by China's authorities, includes deposits, social housing funds, and a small proportion of WMPs that guarantee both principal and returns. A large proportion of shadow banking activities, such as entrusted loans and up to 90% of WMPs, are not included in M2. Hence, following an increase in bank credit, M2 growth decreases in the long run because funds are channeled to the shadow banking sector and are largely excluded by the broad money measure of M2.

In the liquidity transformation model, two cointegration equations are identified as shown in Panel B of Table VI. In the first cointegration equation in Eq. (5), only the coefficient on *GDP* is significant. The result suggests a positive relationship between bank credit and GDP, and the sign and magnitude of the coefficient are consistent with those in the money supply model. In the long run, the liquidity from the banking sector has no significant relationship with the liquidity provided by the shadow banking sector. The second cointegration equation in Eq. (6) reveals the following results. First, there is a positive relationship between the liquidity ratio and GDP. When authorities inject liquid, especially highly liquid assets, to the economy, GDP grows as expected. A 1% increase in the liquidity ratio can lead to 0.23% (=1/4.35) increase in GDP. Hence, policy variables – *BankCredit* and *LiquidityRatio* – consistently indicate that liquidity from the traditional banking sector boosts GDP. Second, there is a positive relationship between the liquidity ratio and shadow banking activities. With relatively more cash and cash equivalent in the economy, shadow banking lending and investment increase. A 1% increase in the liquidity ratio, the shadow banking sector transforms and provides 0.54% more liquidity. Third, liquidity provided by shadow banking activities nevertheless lowers GDP. For a 1% increase in liquidity from the shadow banking sector, GDP falls by 0.43% (=1.86/4.35). The results are in line with the view of Moreira and Savov (2017) that a shadow banking boom supplies more liquidity but increases fragility, subsequently lowering growth. Shadow baking credit is found to be heavily concentrated among riskier borrowers (Mian and Sufi (2009)), which is likely to have a negative impact on growth. Moreover, large SOEs and list firms are the mainstay of the economy and have more investment opportunities in the real sector. As these firms engage in shadow banking activities, few resources enter into real economy and these resources are also likely to be allocated to inefficient firms and projects.

$$lBankCredit - 0.03lShadowBanking + 0.15lCPI - 0.73lGDP - 0.34 = Error \quad (5)$$
$$lM1/M2Ratio - 1.86lShadowBanking - 0.26lCPI - 4.35lGDP + 48.76 = Error \quad (6)$$

It is important to test that the above cointegration equations are correctly specified to proceed with the analysis. Figure 2 plots the predicted cointegration equations over time, indicating no concerns regarding the stationarity of the cointegration equations. We also test the stability of the models and examine whether we have correctly specified the number of cointegration equations. The companion matrix of a VECM with K endogenous variables and r number of cointegration equations has $K-r$ unit eigenvalues. If the process is stable, the moduli of the remaining r eigenvalues are strictly less than one. As shown in Figure 3, other than the imposed unit moduli, none of the eigenvalues is close to the unit circle, suggesting no misspecification. The results justify the use of the VECM, and the models are stable and well specified.

[Figure 3 near here]

[Figure 4 near here]

B. Long-Term and Short-Term Adjustments

Table VII reports the estimated long-term adjustment parameters (alpha) – the coefficients on the lagged error correction terms that measure the adjustment speed toward equilibrium and capture the interactive effects among endogenous variables. These coefficients (alpha) are statistically significant in most equations, further confirming that a conventional VAR model would be misspecified. Overall, the VECM is well estimated, and the signs of these coefficients are consistent with the expected economic relationships among these variables. For instance, for the money supply model shown in Panel A, in the bank credit equation, the coefficient on the lagged error term of the first cointegration equation (ce1) is negative and significant (-1.16), indicating that a positive error term in Eq. (3) lowers bank credit in the subsequent period. This result indicates negative feedback to bank credit to bring back equilibrium. A positive error term in Eq. (3) can be viewed as bank credit above the equilibrium, and it should decline in the subsequent period toward equilibrium. Although bank credit does not appear in Eq. (4), this cointegration relationship can still have a significant effect on bank credit. A positive error term in Eq. (4) can be considered to indicate GDP above the equilibrium and should decline in the subsequent period. Falling GDP will result in a positive error term in Eq. (3), and bank credit should decrease to restore equilibrium, consistent with the negative and significant coefficient (-0.77) on the lagged error term of the second cointegration equation (ce2). For the liquidity transformation model shown in Panel B, in the shadow banking equation, the coefficient on the lagged error term of the second cointegration equation (ce2) is positive and significant (0.46), indicating that a positive error term in Eq. (6) increases liquidity from the shadow banking sector in the subsequent period. This is consistent with the adjustment process – a positive error term in Eq. (6) can be considered to indicate liquidity from the shadow banking sector below equilibrium, and it should increase in the subsequent period to reach equilibrium. A positive error term in Eq. (6) can be alternatively interpreted as GDP below the equilibrium and should increase in the subsequent period. An increase in GDP will lead to a negative error term in Eq. (5), and liquidity from the shadow banking sector should fall to return equilibrium, consistent with the negative and significant coefficient (-1.01) on the lagged error term of the first cointegration equation (ce1).

[Table VII near here]

Only a few of the estimated coefficients on the lagged differenced endogenous variables (short-term adjustment parameters) are significant.[5] In the money supply model, bank credit is negatively affected by changes in GDP, while M2 growth is positively affected by changes in bank credit (at the 10% significance level). CPI is positively driven by changes in bank credit and M2 growth, while GDP is mainly driven by its own lagged changes. These results are in line with expectations. Evidence shows that shadow banking credit also plays an important role in short-term adjustments. An increase in shadow banking credit leads to a fall in CPI in the subsequent period, and this short-term effect becomes positive in the long run as identified in the cointegration relationships (Eq. 4). Shadow banking credit is not a policy variable and is mainly driven by market demand, tending to encourage investment instead of consumption, and CPI falls in the short run, but in the long run, more money supply from the shadow banking sector pushes up CPI. Shadow banking credit has a negative impact on GDP, which is statistically significant but economically insignificant. In the liquidity transformation model, bank credit adjusts negatively to changes in GDP, consistent with the results from the money supply model. Changes in bank credit have a positive impact on liquidity from the shadow banking sector. The more liquidity the banking sector provides, the more intermediation activities (lending and investing) that are conducted in the shadow banking sector to supply liquidity. In sort terms, liquidity changes have limited impact on the monetary policy goals.

C. Impulse Response Analysis

When the VECM is used to study monetary policy, the OIRFs and FEVDs are at the center of the analysis. These residual analyses are more informative for understanding the interdependence between variables in the dynamic context of innovative shocks. The impulse response analysis is used to identify the short-term and long-term responses of one variable following an involuntary economic shock to another variable. As shown in Figure 5(a) and (b), the majority of impulse response effects become stable and permanent after five to seven periods.

[Figure 5a near here]

[Figure 5b near here]

Figure 5(a) plots impulse response effects for the money supply model. The results show that policy variables are responsive to changes in macroeconomic conditions, generally consistent with the central tenet of quantity-based monetary policy. After positive shocks to GDP, both bank credit and M2 growth immediately adjust downward to regulate the economy against potential overheating. But only the response of bank credit is significant up to two periods and subsequently disappears over the longer term. We also observe the following impulse responses, while none of them is statistically significant. First, positive shocks to CPI indicate a faster increase in money supply than the growth of real output, and as expected, bank credit and M2 growth responds negatively to maintain price stability. Second, M2 growth responds negatively to shocks to bank credit, and this unexpected result is consistent with the cointegration relationship identified and discussed in section 4.1. Third, GDP responds positively to shocks from bank credit and M2 growth, while CPI responds negatively to shocks to bank credit.

[5] Results are not reported to save space, available from authors on request.

Regarding our main research interest of this study, the results show that shadow banking credit is responsive to shocks to key macroeconomic variables. Shadow banking credit responds negatively to shocks to bank credit, while the effect is significant for one period and then tends to dissipate in the long term. Shadow banking credit responds positively to shocks to M2 growth, CPI, and GDP, indicating that a greater money supply, higher inflation, and economic boom stimulate shadow banking credit. These response effects are statistically significant (as shown in Figure A1a in Appendix). On the other hand, following positive shocks to shadow banking credit, M2 growth decreases, while CPI and GDP increase, for which only the response of CPI is significant and permanent.

Figure 5(b) plots the results from the impulse response functions for the liquidity transformation model. Positive shocks to GDP cause immediate liquidity contraction in the banking sector, but in the long run, bank credit adjust upward to sever the economic boom. After positive shocks to bank credit, GDP increases as more liquidity boosts the economy. The OIRF results also show that liquidity from the shadow banking sector is an important factor in the system. We find that it responds negatively to shocks to bank credit in the short terms (up to two periods) but positively to shocks to liquidity ratio in the long term. On the other hand, positive shocks to the liquidity from the shadow banking sector leads a negative response from CPI and GDP, respectively. These impulse response effects are statistically significant (as shown in Figure A1b in appendix). We also observe a number of response effects among these endogenous variables, while these effects are statistically insignificant. For instance, following positive shocks to CPI, the banking sector responds negatively by reducing liquidity supply to control inflation, but the liquidity ratio increases, likely because of rational market reactions that investors tend to hold more liquid assets under higher inflation.

D. Forecast Error Variance Decompositions (FEVD) Analysis

The decomposition of the variance helps us to understand how much of the forecast error variance of each of the variables can be explained by exogenous shocks to itself and other variables or to identify the variables that have more influences on other variables. Table VIII reports the results from Cholesky FEVD analysis, showing that the forecast error variance of each endogenous variable mainly comes from its own shocks. For instance, in Panel A, the self-explained forecast error variance is 88% for bank credit, 97% for M2 growth, 75% for shadow bank credit, 94% for CPI, and 82% for GDP by the second period, and the corresponding figures are 71%, 96%, 24%, 82% and 88% by the twentieth period, respectively. The remainder of this subsection focuses on how the remaining forecast error variance of each variable is explained by other variables and how these effects evolve over time.

[Table VIII near here]

Panel A focuses on the FEVD for the money supply model. The error variance of bank credit is explained by shocks to M2 growth by 6%, CPI by 1%, and GDP by 4% in the second periods, which increase to 15%, 8%, and 4% in the twentieth period, respectively. M2 growth is mainly self-explained with little influence from other

variables in the model. In the short term, shadow banking credit is mainly influenced by bank credit with whose shocks explaining 20% of the forecast error variance of shadow banking credit in the first period. Over a longer term, shadow banking credit is largely determined by other variables in the system – shocks to M2 growth, CPI and GDP explain 19%, 24% and 27% of the error variance of the shadow banking credit by the twentieth period, respectively. In the long term, shadow banking credit is the most influential factor for CPI, while bank credit is the dominant factor explaining the error variance of GDP.

Panel B reports the FEVD results for the liquidity transformation model. The error variance of the liquidity from the banking sector is mainly attributable to shocks to GDP by 11% in the long term. The error variance of the liquidity ratio is mainly self-explained, with contributions from shocks to shadow banking activities at 3% in the twentieth period. Liquidity provided by the shadow banking sector is more sensitive to shocks to other variables in the system, and in the long term, its forecast error variance is attributable to shocks to the liquidity ratio by 32%, banking credit by 11%, GPD by 7%, and CPI by 3% (by the twentieth period). In the longer term, the liquidity transformation by the shadow banking sector is the most influential factor for CPI and exerts more influence on GDP than the banking sector. Shocks to the liquidity from the shadow banking sector explain 45% of the error variance of GDP, which is more than double that of banking credit at 18%.

VI. Findings, Policy Implications, and Policy Recommendations

We have identified cointegration relationships of endogenous variables to characterize long-term equilibrium and performed impulse responses analysis and FEVD analysis. We find that the shadow banking sector plays an important role in credit provision and liquidity transformation, and the main findings are summarized as follows. From the money supply model, we find that: (1) shadow banking credit is inversely related to bank credit in the long run, and shocks to bank credit explain 20% of the forecast error variance of shadow banking credit in the short term (decreasing in the long run); (2) bank credit boosts GDP as expected, while shadow banking credit has a more pervasive monetary transmission effects on CPI and GDP based on the cointegration analysis and impulse response analysis; and (3) unexpectedly, bank credit is negatively related to M2 growth, which in turn is negatively related to CPI and GDP. These unexpected results can be explained by the rising shadow banking sector and resultant inaccurate measurement of monetary aggregates (e.g., M1 and M2). From the liquidity transformation model, we find that in the long term: (1) liquidity from the banking sector promotes GDP, and the shocks to banking liquidity explain 18% of the forecast error variance of GDP; (2) highly liquid assets in the financial sector induce liquidity provision and transformation in the shadow banking sector, and shocks to the liquidity ratio explain one-third of the forecast error variance of liquidity from the shadow banking sector; (3) more highly liquid assets tend to boost GDP; and (4) liquidity from the shadow banking sector lowers GDP, and its shocks explain nearly half of the forecast error variance in GDP.

All in all, our results indicate that shadow banking plays an important role in

money supply and liquidity transformation with significant policy implications. First, the counteractive effect between bank credit and shadow banking credit undermines the effectiveness of monetary policy. Bank credit has a stronger effect on GDP than shadow banking credit because of inefficient credit allocation by the shadow banking sector. A reduction in bank credit will induce more shadow banking credit and lowers GDP growth. Hence, a policy of reducing bank credit should be implemented in conjunction with proper control over shadow banking credit. Second, the shadow banking sector has effectively become part of the credit transmission channel and is involved in liquidity transformation. Shadow banking activities have changed the relationship between key macroeconomic variables with significant influences on the attainment of monetary policy goals. Policy makers should consider these changes when designing and implementing policy. Third, when deposit-taking banks are the main financial intermediaries, traditional monetary aggregates (e.g., M2) are good indicators of aggregate credit. With the rising shadow banking sector, the official measures of money supply (e.g., M2 growth) and liquidity structure (e.g., the ratio of M1 growth to M2 growth) are no longer appropriate indicators of the monetary policy stance. The poor aggregate measure of M2 can cloud monetary authorities' judgment and undermine policy reactions.

Shadow banking activities can pose a major threat to financial stability. Shadow banking institutions perform similar functions to banks, but they adopt riskier business practices (i.e., more serious maturity mismatch) without support from public backstops in case of market failures. These off-balance sheet risky investment vehicles in the shadow banking sector are mainly funded through WMPs without regulatory requirements on capital and liquidity buffers. Shadow banking relies on wholesale market funding and the banking sector, increasing the liquidity risk of the financial sector. More importantly, shadow banking can synchronize different markets through interconnections with the banking sector, which can magnify systemic risk and even threaten macroeconomic stability.

Shadow banking renders lending channels and liquidity transformation more opaque and makes it difficult for central banks to manage the money supply and liquidity in the economy. The potentially severe consequences of the shadow banking sector require the attention and actions of the authorities. Currently, the Chinese authorities focus on immediate threats to systemic risk and address the issues that surface. For example, to curb the rapidly expanding shadow banking activities, the authorities launched a series of regulatory actions in the second half of 2016. Actions included tightening the rules on WMPs and the asset management plans of nonbank financial institutions, deleveraging campaigns to slow bank credit growth, institutional reforms by merging banking and insurance regulators into a single authority, and the strengthening of regulatory coordination. Such efforts have slowed shadow banking activities since 2017. However, IMF is still skeptical of the real effect of these efforts and believes that the shadow banking sector continues to pose a threat to systemic risk in China. Moreira and Savov (2017) argued that shadow banking presents a trade-off between stability and economic growth. Shadow banking activities provide abundant liquidity and induce economic booms, while as shadow banking builds up uncertainties

and starts to decline, growth suffers. Hence, the real impact of these regulatory actions remains to be seen.

The development of shadow banking is a double-edged sword. Shadow banking deepens financial development, enriches financial markets, mobilizes funds, and promotes economic growth. In the long term, the shadow banking sector should become an important complement to the financial sector. Authorities should provide a competitive and well-informed environment for the healthy development of the shadow banking sector. To this end, we propose the following policy recommendations. First, we suggest adopting price-based monetary policy indicators to enhance the central bank's ability to effectively implement monetary policy. Evidence has overwhelmingly indicated that the rise of shadow banking renders quantity-based monetary aggregates (e.g., broad money M2) poor indicators of monetary policy. Major advanced economies have been using price-based indicators since the early 1990s to target inflation by adjusting short-term interest rates (e.g., the federal funds rate in the US, the bank rate in the UK, and the repo rate in Europe). Relative to aggregate monetary growth, a price-based indicator is more informative with respect to future real economic variables, such as GDP, consumption and employment (Bernanke and Blinder (1992); Christiano and Eichenbaum (1992)). Second, we suggest expanding banking reforms that alleviate distortions in the banking system. The Chinese banking sector has undergone market-oriented reforms over the past three decades. Despite remarkable achievements, the banking sector remains controlled by the five largest state-controlled banks, and preferential lending and government intervention still prevail. Reform measures to address these distortions will benefit the sound development of the banking (financial) sector, as well as the shadow banking sector. Third, we recommend liberalizing the (dual-track) interest rate system, which is the critical condition for the success of the aforementioned reforms. The elimination of interest rate differentials helps to rationalize shadow banking activities and promotes more efficient allocation of credit. Finally, we suggest enhancing regulatory coordination and cooperation, which can better address the complexity and integrated nature of shadow banking businesses. Implicit guarantees for investment vehicles should be gradually phased out, and shadow banking institutions should be required to hold an appropriate level of capital and a liquidity buffer against their risk taking. In addition, efforts are needed to educate investors to ensure that they understand the risks that they take when investing in risk-fraught shadow banking investment products.

VII. Conclusion

Applying the VECM to monthly time-series data over the period of 2012Q1-2018Q1, we find a significant impact of the shadow banking sector on monetary policy, corroborating the theoretical predictions of Moreira and Savov (2017). Shadow banking changes the relationships between key macroeconomic variables, impairs the ability of the authorities to implement monetary policy, and potentially poses a major threat to financial stability. The effective implementation of monetary policy is crucial, and we provide a set of policy recommendations to address these challenges caused by shadow banking activities, such as adopting price-based monetary policy indicators, expanding

banking reform, liberalizing interest rates, and strengthening regulatory coordination and cooperation. The shadow banking sector is an important complement to the financial sector, and more research is needed to better understand its impacts and the role of regulators in shaping the future of the shadow banking sector.

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Tables

Table I: Total social financing, bank loans, and shadow banking credit in China

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Total social financing	7.0	13.9	14.0	12.8	15.8	17.3	16.4	15.3	17.8	19.4
Bank loans	4.9	9.6	7.9	7.5	8.2	8.9	9.8	11.3	12.4	13.8
Entrusted and trust loans	0.7	1.1	1.3	1.5	2.6	4.4	3.0	1.6	3.0	3.0

Note: All variables are flow values in trillion RMB. Source: China's central bank.

Table II: Sample statistics (2012Q1-2018Q1)

Variables	No. Obs.	Mean	Std. Dev.	Min	Max
GDP	75	5650.84	972.37	3749.62	7961.51
CPI (%)	75	2.13	0.73	0.80	4.50
M2Growth (%)	75	12.41	1.97	8.20	16.10
M1/M2Ratio (%)	75	94.88	63.59	9.09	249.02
BankCredit	75	923.65	416.80	385.20	2685.03
ShadowCredit	75	276.83	211.98	-220.69	1387.98
ShadowBanking	75	343.48	225.34	-220.65	1402.53

Note: All monetary variables are in billion RMB. CPI: consumer price index. M2Growth: year-on-year growth rate of broad money M2. M1/M2Ratio: the ratio of the narrow money (M1) growth rate to the broad money (M2) growth rate. ShadowCredit: the sum of entrusted loans, trust loans, and listed firms' investments in long term (or rolled over) wealth management products (WMPs). ShadowBanking: shadow banking activities, including shadow banking credit and listed firms' investments in short-term WMPs.

Table III: Unit root tests

	ADF			KPSS		
Variables	Lags	t- stat	p-value	Bandwidth	stat	Result (5%)
lGDP	1	-5.78	0.00***	5	0.04	Stationary I(0)
lGDP	0	-5.61	0.00***	3	0.04	Stationary I(0)
lCPI	1	-2.79	0.06*	6	0.17**	Nonstationary I(1)
lCPI	0	-11.03	0.00***	4	0.04	Stationary I(0)
lM2Growth	1	-2.27	0.45	6	0.16**	Nonstationary I(1)
lM2Growth	0	-7.18	0.00***	5	0.05	Stationary I(0)
lM1/M2Ratio	1	-2.46	0.35	6	0.112	Nonstationary I(1)
lM1/M2Ratio	0	-12.62	0.00***	5	0.09	Stationary I(0)
lBandCredit	1	-10.50	0.00***	3	0.04	Stationary I(0)
lBandCredit	0	-17.95	0.00***	2	0.02	Stationary I(0)
lShadowCredit	0	-6.49	0.0***	5	0.10	Stationary I(0)
lShadowCredit	0	-13.45	0.00***	5	0.06	Stationary I(0)
lShadowBanking	0	-7.00	0.00***	5	0.07	Stationary I(0)
lShadowBanking	0	-13.65	0.00***	5	0.05	Stationary I(0)

Note: (1) Δ denotes the first difference. All variables are in logarithms; (2) ADF is the augmented Dickey-Fuller test with the null hypothesis of non-stationarity; (3) KPSS is the Kwiatkowski–Phillips–Schmidt–Shin (1992) test with the null hypothesis of stationarity. The critical values (with linear trends) are 0.119 for 10%, 0.146 for 5%, and 0.216 for 1%. (4) CPI: consumer price index. M2Growth: year-on-year growth rate of broad money M2. LiquidityRatio: the ratio of the narrow money (M1) growth to the broad money (M2) growth. ShadowCredit: the sum of entrusted loans, trust loans, and listed firms' investment in long-term (or rolled over) wealth management products (WMPs). ShadowBanking: the sum of shadow banking credit and listed firms' investment in short-term WMPs. (5)*, **, *** denote a rejection of the null hypothesis at the 10, 5, and 1% critical values, respectively.

Table IV: Selection-order criteria for lag length (Obs:66 2012m9-2018m2)

lag	LL	LR	df	p	AIC	HQIC	SBIC
Panel A: The money supply model							
0	14.7789				-0.29633	-0.23078	-0.13045
1	167.845	306.13	25	0	-4.17711	-3.78382*	-3.18181*
2	198.91	62.132	25	0	-4.36092*	-3.63989	-2.53621
3	218.528	39.235	25	0.035	-4.19782	-3.14905	-1.54369
6	285.87	55.417*	25	0	-3.96576	-1.93376	1.17661
Panel B: The liquidity transformation model							
0	-77.1837				2.49042	2.55596	2.6563
1	116.678	387.72	25	0	-2.62662*	-2.23333*	-1.63132*
2	138.167	42.977	25	0.014	-2.5202	-1.79917	-0.69549
3	156.911	37.488	25	0.052	-2.33063	-1.28185	0.323502
6	232.747	75.575*	25	0	-2.35597	-0.32397	2.7864

Note: (1) LL=log likelihood, LR=likelihood ratio test, AIC=Akaike's information criterion, HQIC=the Hannan and Quinn information criterion, SBIC=Schwarz's Bayesian information criterion. (2) The lag with the smallest value is the order selected by the criterion, and "*" indicates the optimal lag length. (3) Endogenous variables include *lBankCredit, lM2Growth, lShadowCredit, lCPI,* and *lGDP* in Panel A and *lBankCredit, lM1/M2Ratio, lShadowBanking, lCPI,* and *lGDP* in Panel B. (4) CPI: consumer price index. M2Growth: year-on-year growth rate of broad money M2. M1/M2Ratio: the ratio of the narrow money (M1) growth rate to the broad money (M2) growth rate. ShadowCredit: the sum of entrusted loans, trust loans, and listed firms' investment in long-term (or rolled over) wealth management products (WMPs). ShadowBanking: shadow banking activities including shadow banking credit and listed firms' investment in short-term WMPs.

Table V: Johansen tests for cointegration

Maximum rank	parms	LL	Eigenvalue	Trace statistic	5% critical value
Panel A: The money supply model				Trend: constant, Obs70, lag2	
0	30	151.3946	.	96.1851	68.52
1	39	169.4995	0.40386	59.9753	47.21
2	46	186.2415	0.38019	26.4913*	29.68
3	51	194.7931	0.21677	9.388	15.41
Panel B: The liquidity transformation model				Trend: constant, Obs70, lag2	
0	5	29.77483	.	160.0751	68.52
1	14	71.94377	0.69513	75.7372	47.21
2	21	96.91681	0.50513	25.7911*	29.68
3	26	106.2791	0.23182	7.0665	15.41

Note: (1) The "*" for the trace statistic at maximum rank 2 indicates r=2 selected by Johansen's multiple-trace test procedure. (2) Endogenous variables include *lBankCredit, lM2Growth, lShadowCredit, lCPI,* and *lGDP* in Panel A and *lBankCredit, lM1/M2Ratio, lShadowBanking, lCPI,* and *lGDP* in Panel B. (3) parms: number of parameters. (4) CPI: consumer price index. M2Growth: year-on-year growth rate of broad money M2. M1/M2Ratio: the ratio of the narrow money (M1) growth rate to the broad money (M2) growth rate. ShadowCredit: the sum of

entrusted loans, trust loans, and listed firms' investment in long-term (or rolled over) wealth management products (WMPs). ShadowBanking: shadow banking activities including shadow banking credit and listed firms' investment in short-term WMPs.

Table VI: Cointegration equations

	Panel A: The money supply model			Panel B: The liquidity transformation model			
	Coef.	SE	z-stat		Coef.	SE	z-stat
Cointegration equation 1	p>chi2: 0.000				p>chi2: 0.000		
lBankCredit	1	.	.	lBankCredit	1	.	.
lM2Growth	0	(omitted)		lM1/M2Ratio	0	(omitted)	
lShadowCredit	0.37	0.12	2.97***	lShadowBanking	-0.03	0.11	-0.3
lCPI	-0.16	0.19	-0.84	lCPI	0.15	0.14	1.1
lGDP	-0.93	0.39	-2.36**	lGDP	-0.73	0.3	-2.46**
Constant	-0.68	3.55	-0.19	Constant	-0.34	2.69	-0.13
Cointegration equation 2	p>chi2: 0.000				*p*>chi2: 0.000		
lBankCredit	0	(omitted)		lBankCredit	0	(omitted)	
lM2Growth	1	.	.	lM1/M2Ratio	1	.	.
lShadowCredit	-0.65	0.11	-5.74***	lShadowBanking	-1.86	0.24	-7.73***
lCPI	0.66	0.17	3.83***	lCPI	-0.26	0.3	-0.87
lGDP	1.47	0.36	4.09***	lGDP	-4.35	0.64	-6.84***
Constant	-12.01	3.25	-3.70***	Constant	48.76	5.76	8.47***

Note: (1) This table reports estimation results for cointegration relationships of the vector error correction model ($\Delta y_t = \alpha(\beta y_{t-1} + \mu) + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t$). (2) CPI: consumer price index. M2Growth: year-on-year growth rate of broad money M2. M1/M2Ratio: the ratio of the narrow money (M1) growth rate to the broad money (M2) growth rate. ShadowCredit: the sum of entrusted loans, trust loans, and listed firms' investment in long-term (or rolled over) wealth management products (WMPs). ShadowBanking: shadow banking activities including shadow banking credit and listed firms' investment in short-term WMPs. (3) *, **, *** denote a rejection of the null hypothesis at the 10, 5, 1 significance level, respectively.

Table VII: Long-term adjustment parameters of the vector error correction model

Panel A: The money supply model				Panel B: The liquidity transformation model		
	Coef.	S.E.	z-stat	Coef.	S.E.	z-stat
ΔlBankCredit				*ΔlBankCredit*		
$\_ce1_{t-1}$	-1.16	0.21	-5.47***	-0.96	0.18	-5.51***
$\_ce2_{t-1}$	-0.77	0.23	-3.33***	0.06	0.07	0.83
ΔlM2Growth:				*ΔlM1/M2Ratio*		
$\_ce1_{t-1}$	-0.07	0.04	-1.70*	0.15	0.21	0.71
$\_ce2_{t-1}$	-0.04	0.04	-0.93	-0.08	0.09	-0.98
ΔlShadowCredit:				*ΔlShadowBanking*		
$\_ce1_{t-1}$	-0.41	0.36	-1.15	-1.01	0.25	-4.07***
$\_ce2_{t-1}$	0.98	0.39	2.51***	0.46	0.10	4.54***
ΔlCPI:				*ΔlCPI:*		
$\_ce1_{t-1}$	-0.18	0.13	-1.36	-0.07	0.11	-0.65
$\_ce2_{t-1}$	-0.26	0.15	-1.76*	0.11	0.04	2.49***
ΔlGDP:				*ΔlGDP:*		
$\_ce1_{t-1}$	0.07	0.03	2.30**	0.08	0.02	3.36***
$\_ce2_{t-1}$	0.02	0.03	0.64	0.03	0.01	3.15***
No. Obs /Log Likelihood			70/184.58			70/64.15

Note: (1) This table reports estimated coefficients on lagged error correction terms (alpha) for the vector error correction model ($\Delta y_t = \alpha(\beta y_{t-1} + \mu) + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t$). (2) ce: cointegration equation. CPI: consumer price index. M2Growth: year-on-year growth rate of broad money M2. M1/M2Ratio: the ratio of the narrow money (M1) growth rate to the broad money (M2) growth rate. ShadowCredit: the sum of entrusted loans, trust loans, and listed firms' investment in long-term (or rolled over) wealth management products (WMPs). ShadowBanking: shadow banking activities including shadow banking credit and listed firms' investment in short-term WMPs. (3)*, **, *** denote a rejection of the null hypothesis at the 10, 5, and 1% significance levels, respectively.

Table VIII: Cholesky forecast error variance decomposition (FEVD)

Step	Panel A: The money supply model					Panel B: The liquidity transformation model				
	lBank Credit	*lM2 Growth*	*lShado w Credit*	*lCPI*	*lGDP*	*lBank Credit*	*lM1/M2 Ratio*	*lShado w Banking*	*lCPI*	*lGDP*
Impulse: lBankCredit						*Impulse: lBankCredit*				
1	1.000	0.024	0.203	0.003	0.113	1.000	0.003	0.077	0.005	0.109
2	0.881	0.015	0.196	0.010	0.048	0.952	0.004	0.126	0.010	0.039
5	0.842	0.026	0.140	0.026	0.046	0.923	0.003	0.151	0.012	0.113
10	0.791	0.026	0.090	0.032	0.061	0.869	0.002	0.123	0.009	0.161
15	0.748	0.025	0.066	0.034	0.062	0.828	0.001	0.112	0.008	0.171
20	0.709	0.025	0.053	0.035	0.063	0.792	0.001	0.106	0.007	0.177
Impulse: lM2Growth						*Impulse: lM1/M2Ratio*				
1	0.000	0.976	0.008	0.002	0.065	0.000	0.997	0.014	0.106	0.015
2	0.056	0.971	0.050	0.030	0.058	0.004	0.978	0.095	0.069	0.030
5	0.069	0.954	0.119	0.026	0.031	0.008	0.970	0.188	0.047	0.030
10	0.098	0.957	0.161	0.026	0.024	0.018	0.968	0.262	0.040	0.031
15	0.125	0.958	0.181	0.026	0.022	0.027	0.968	0.299	0.037	0.031
20	0.148	0.959	0.193	0.025	0.021	0.034	0.967	0.321	0.036	0.031
Impulse: lShadowCredit						*Impulse: lShadowBanking*				
1	0.000	0.000	0.788	0.017	0.002	0.000	0.000	0.909	0.012	0.072
2	0.007	0.001	0.752	0.014	0.020	0.002	0.018	0.740	0.080	0.296
5	0.016	0.003	0.478	0.079	0.017	0.006	0.027	0.608	0.132	0.415
10	0.019	0.004	0.339	0.102	0.025	0.014	0.030	0.533	0.140	0.433
15	0.020	0.004	0.274	0.111	0.026	0.019	0.031	0.494	0.144	0.442
20	0.021	0.005	0.237	0.116	0.026	0.023	0.032	0.470	0.145	0.447
Impulse: lCPI						*Impulse: lCPI*				
1	0.000	0.000	0.000	0.978	0.101	0.000	0.000	0.000	0.876	0.084
2	0.013	0.007	0.001	0.940	0.056	0.004	0.000	0.010	0.834	0.036
5	0.029	0.009	0.153	0.860	0.023	0.011	0.000	0.020	0.789	0.023
10	0.048	0.008	0.200	0.832	0.013	0.024	0.000	0.027	0.782	0.025
15	0.066	0.008	0.226	0.821	0.009	0.035	0.000	0.031	0.779	0.026
20	0.082	0.007	0.241	0.815	0.007	0.044	0.000	0.033	0.778	0.026
Impulse: lGDP						*Impulse: lGDP*				
1	0.000	0.000	0.000	0.000	0.719	0.000	0.000	0.000	0.000	0.721
2	0.042	0.006	0.000	0.006	0.818	0.038	0.000	0.029	0.008	0.599
5	0.044	0.009	0.109	0.008	0.883	0.051	0.000	0.033	0.020	0.419
10	0.043	0.005	0.211	0.008	0.878	0.075	0.000	0.055	0.030	0.350
15	0.041	0.004	0.252	0.008	0.881	0.091	0.000	0.064	0.032	0.329
20	0.039	0.004	0.277	0.008	0.883	0.106	0.000	0.070	0.034	0.319

Note: CPI: consumer price index. M2Growth: year-on-year growth rate of broad money M2. M1/M2Ratio: the ratio of the narrow money (M1) growth rate to the broad money (M2) growth rate. ShadowCredit: the sum of entrusted loans, trust loans, and listed firms' investment in long-term (or

rolled over) wealth management products (WMPs). ShadowBanking: shadow banking activities including shadow banking credit and listed firms' investment in short-term WMPs.

Figures

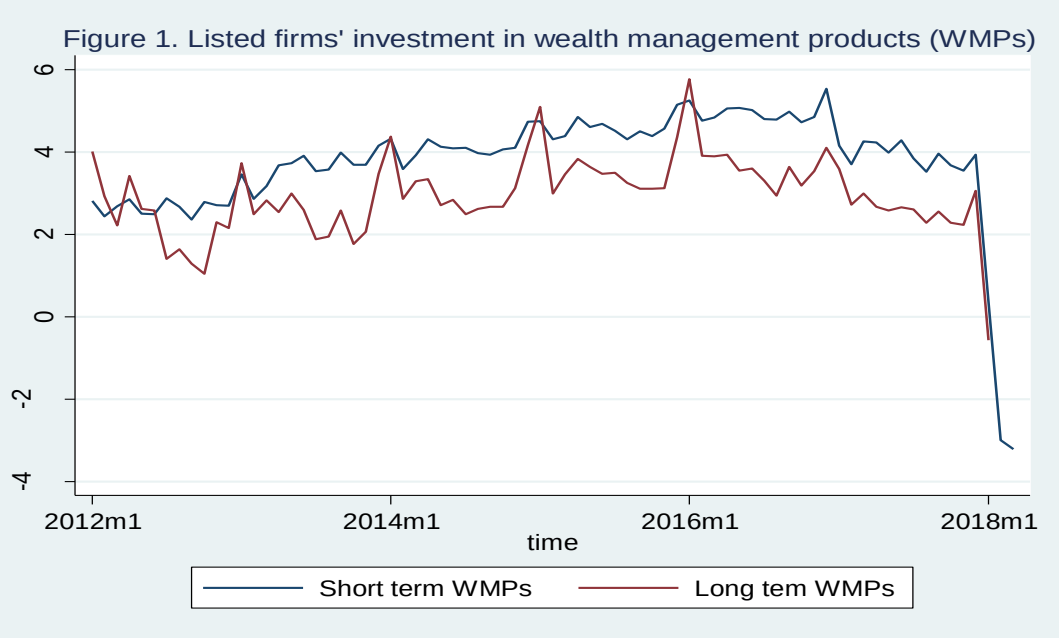


Figure 1. Listed firms' investment in wealth management products (WMPs)
6
4
2
0
-2
-4
2012m1
2014m1
2016m1
2018m1
time
Short term WMPs
Long tem WMPs

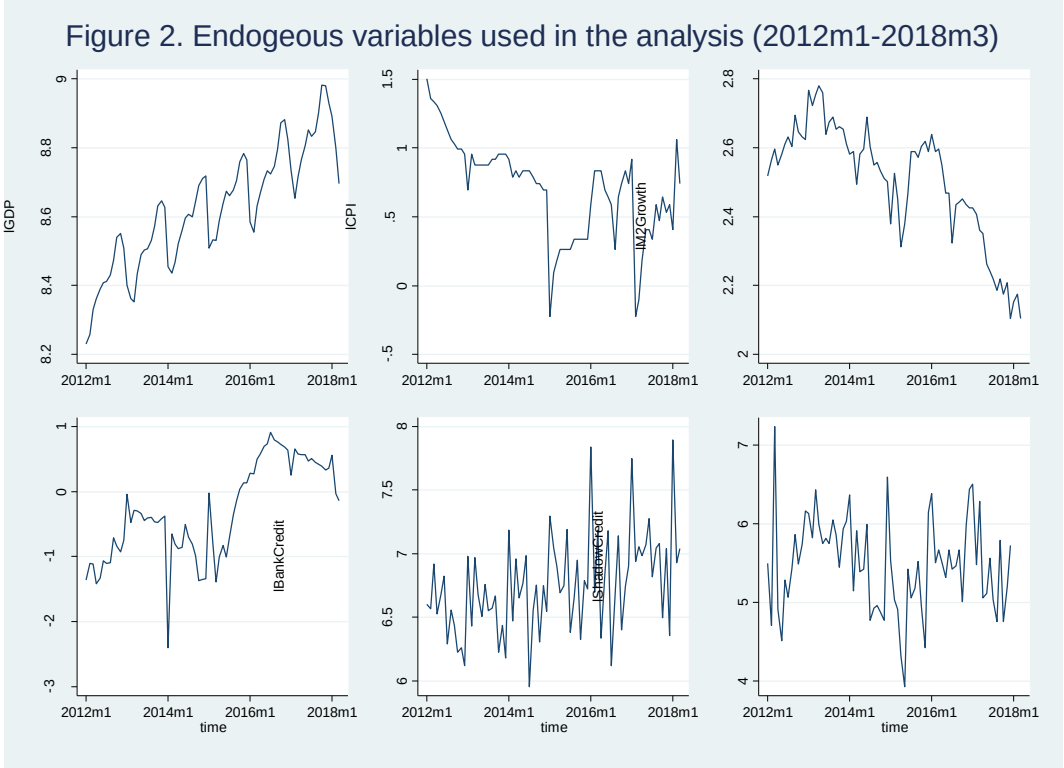
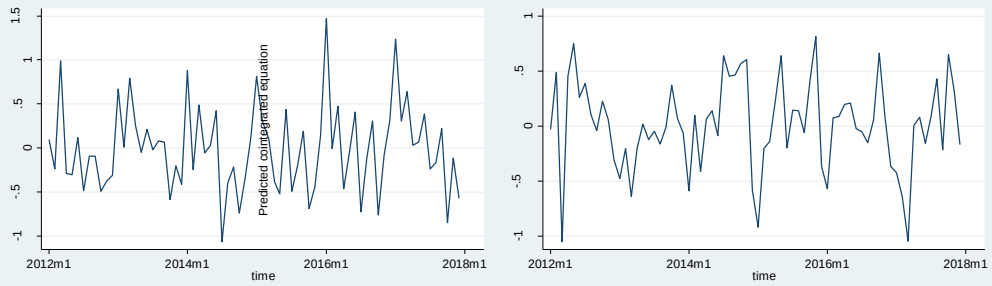


Figure 2. Endogeous variables used in the analysis (2012m1-2018m3)
lGDP
lCPI
lM2Growth
lBankCredit
lShadowCredit
2012m1
2014m1
2016m1
2018m1
time

Figure 3. In-sample VECM forecasts

(a)Shadow banking and money supply



(b)Shadow banking and liquidity transformation

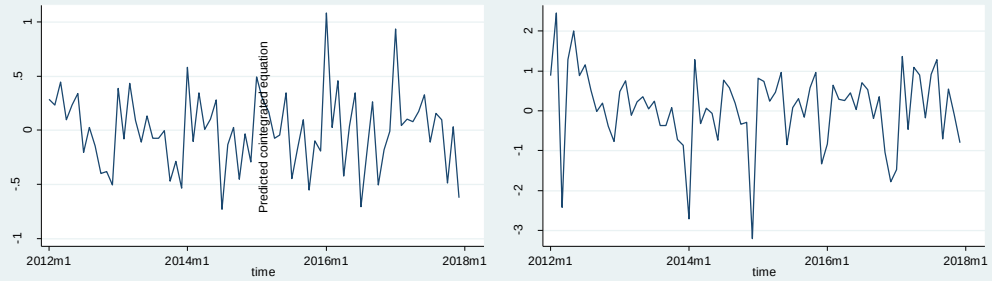


Figure 4. Eigenvalue stability condition

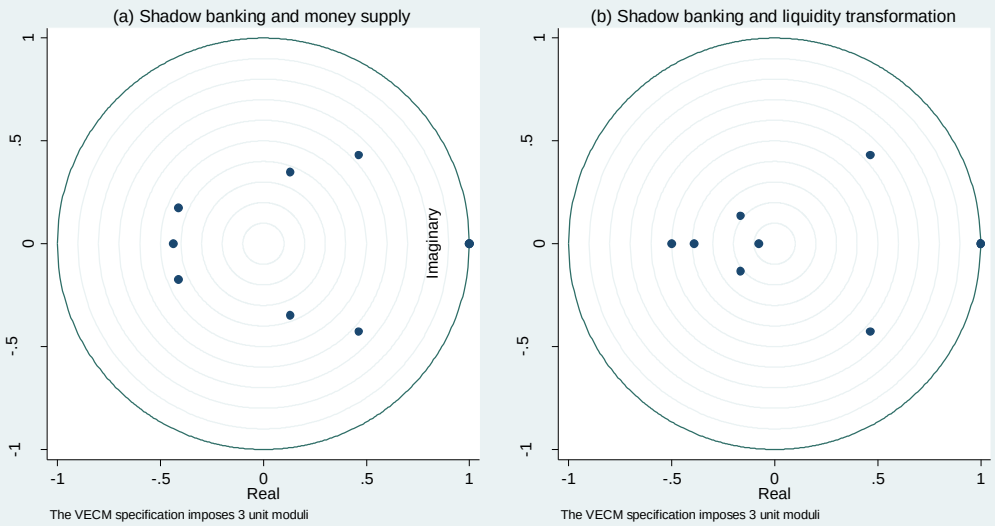


Figure 5(a). Impulse responses for shadow banking and money supply

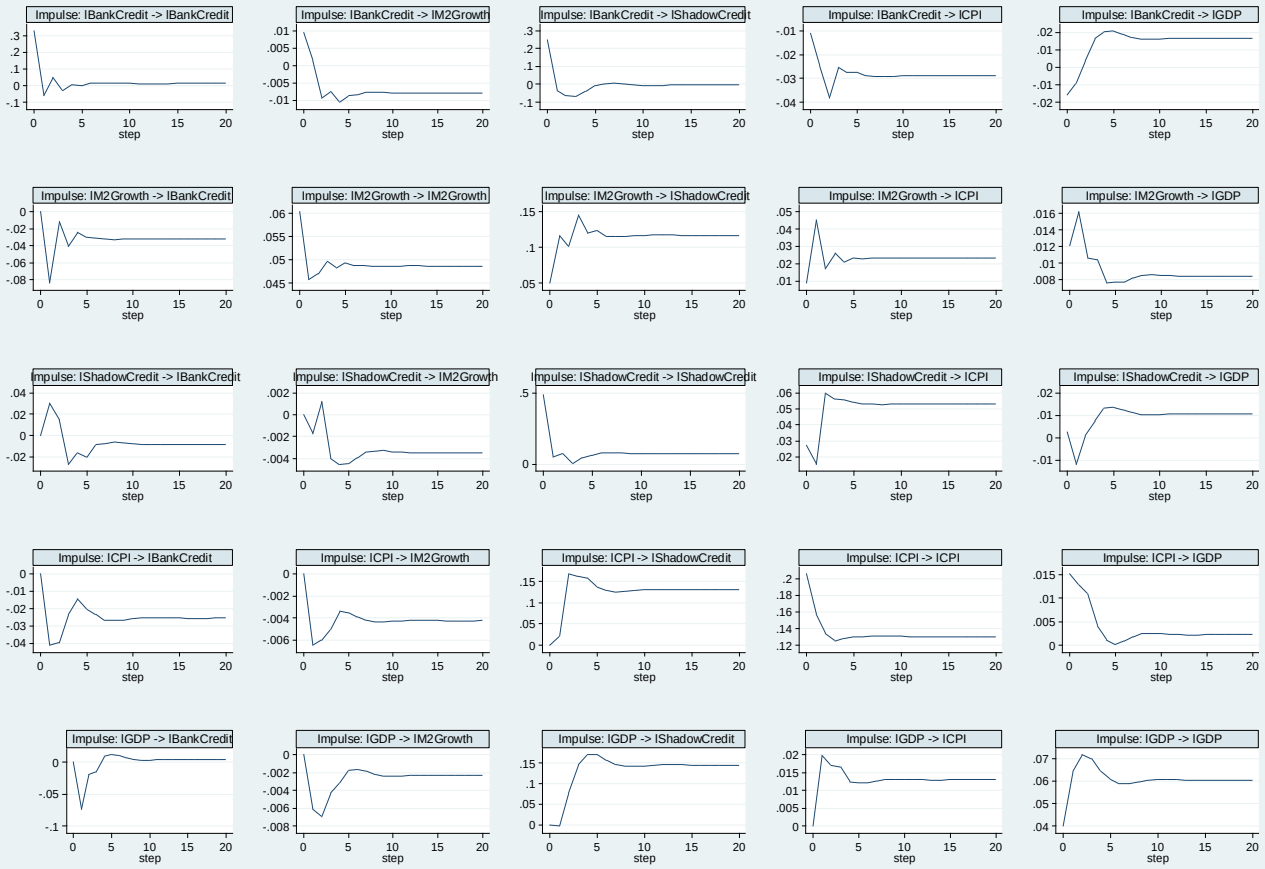
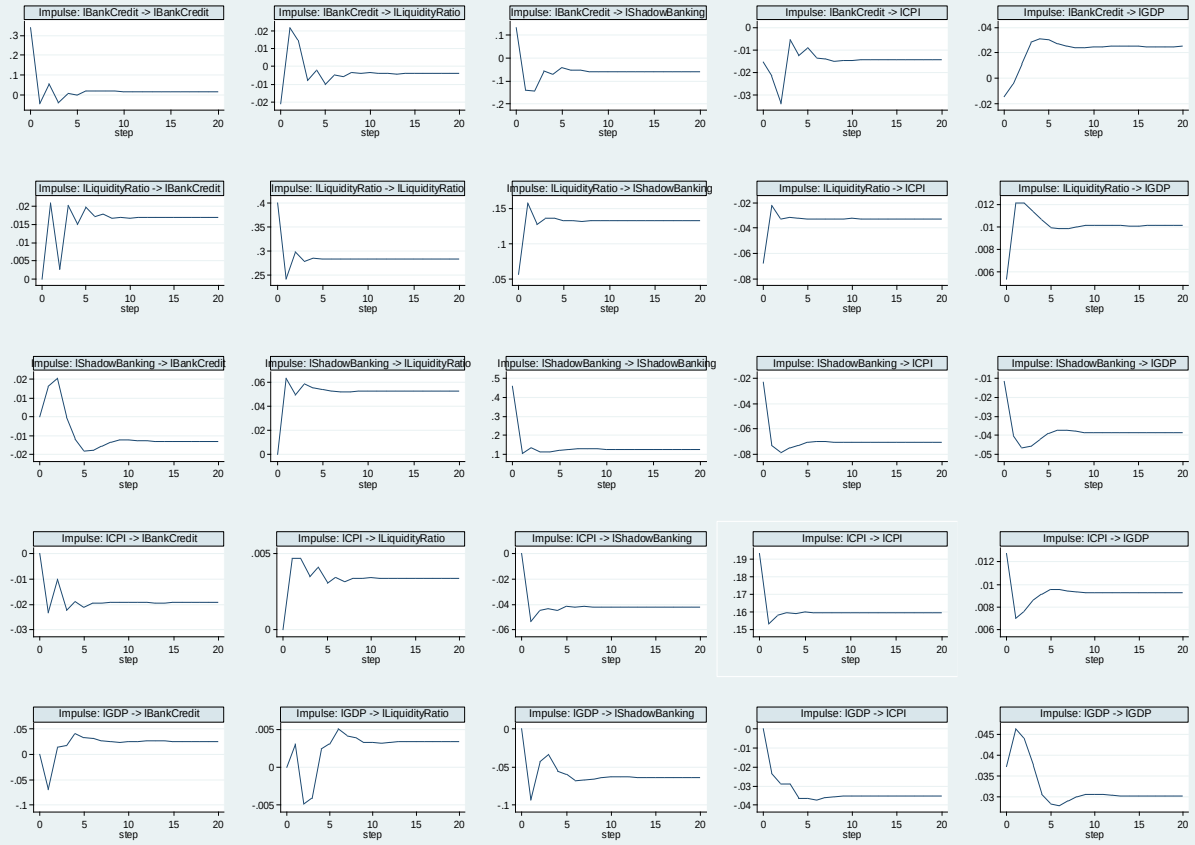


Figure 5(b). Impulse responses for shadow banking and liquidity transformation



Note: Figure 5(a)-(b) from Stata estimation does not show confidence interval. We use the JMulTi program and all significant impulse responses are reported in appendix.

Appendix

Figure A1a: Significant impulse response in the money supply model

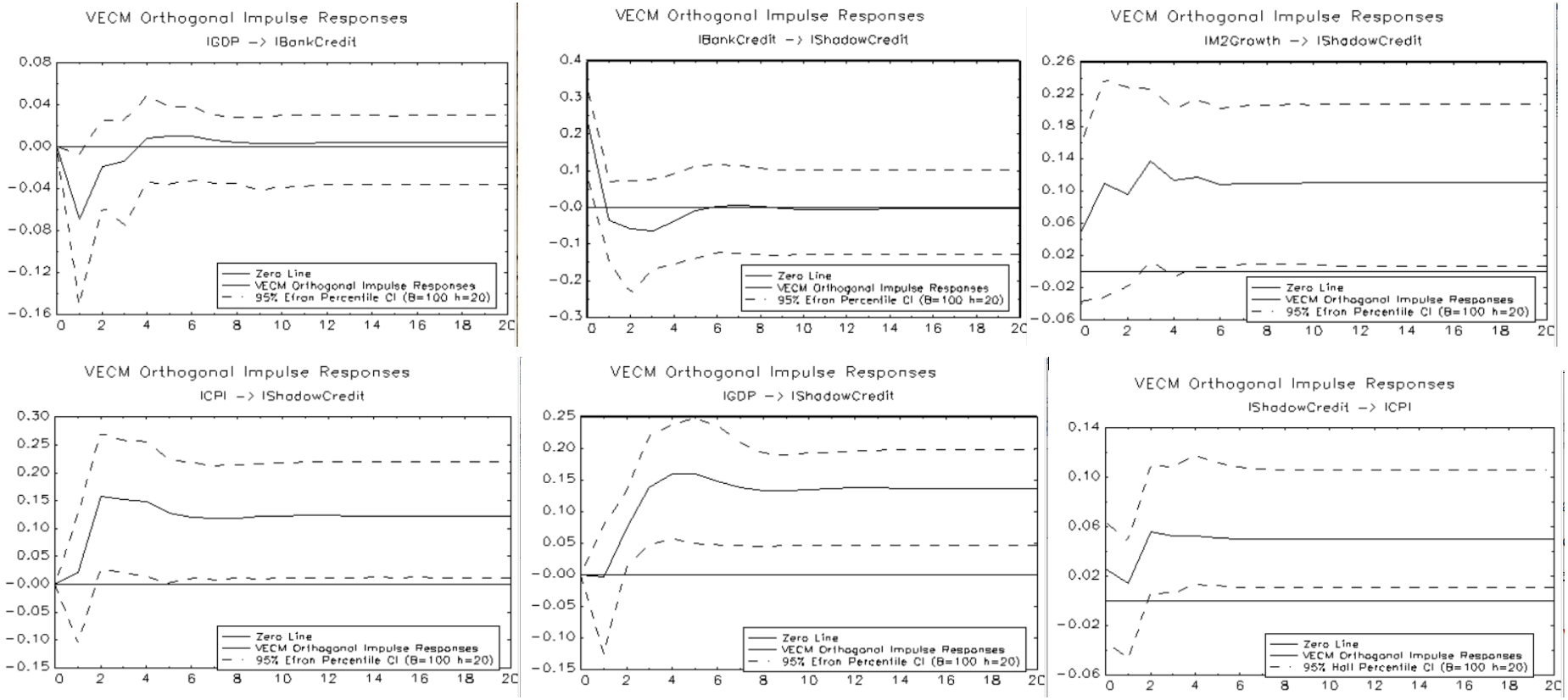
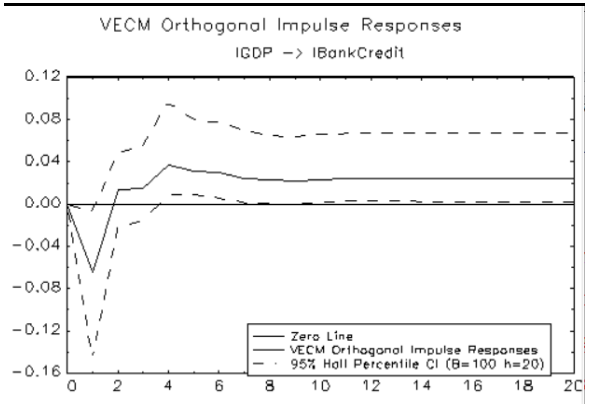
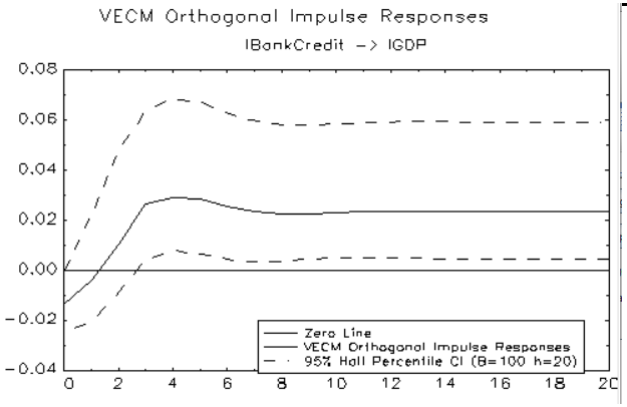
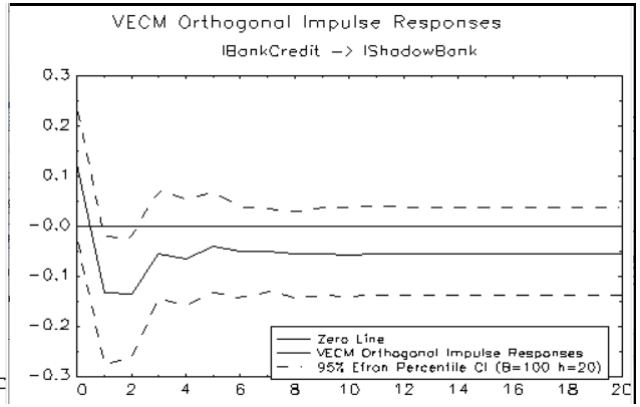
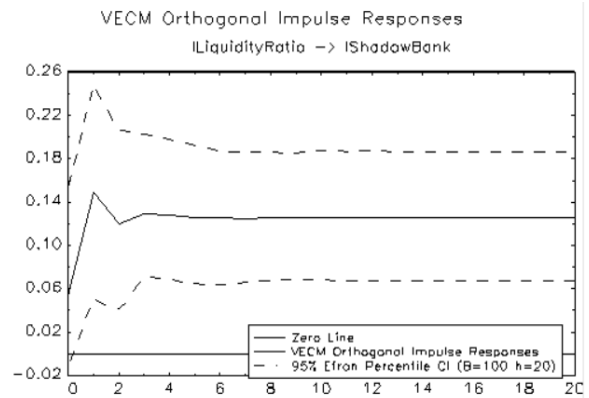


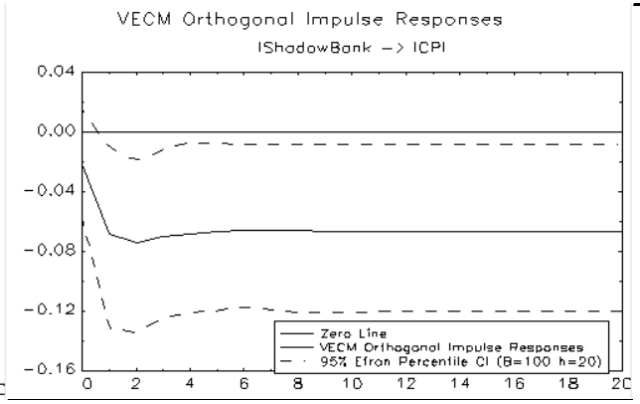
Figure A1b: Significant impulse responses in the liquidity transformation model

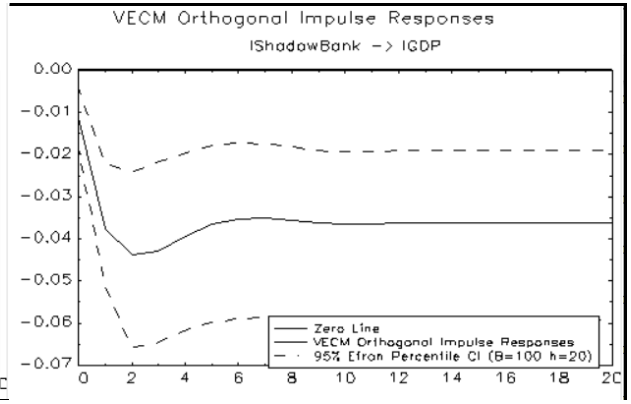

VECM Orthogonal Impulse Responses
lGDP -> lBankCredit
Zero Line
VECM Orthogonal Impulse Responses
95% Hall Percentile CI (B=100 h=20)


VECM Orthogonal Impulse Responses
lBankCredit -> lGDP
Zero Line
VECM Orthogonal Impulse Responses
95% Hall Percentile CI (B=100 h=20)


VECM Orthogonal Impulse Responses
lBankCredit -> lShadowBank
Zero Line
VECM Orthogonal Impulse Responses
95% Efron Percentile CI (B=100 h=20)


VECM Orthogonal Impulse Responses
lLiquidityRatio -> lShadowBank
Zero Line
VECM Orthogonal Impulse Responses
95% Efron Percentile CI (B=100 h=20)


VECM Orthogonal Impulse Responses
lShadowBank -> lCPI
Zero Line
VECM Orthogonal Impulse Responses
95% Efron Percentile CI (B=100 h=20)


VECM Orthogonal Impulse Responses
lShadowBank -> lGDP
Zero Line
VECM Orthogonal Impulse Responses
95% Efron Percentile CI (B=100 h=20)