Bank Coordination and Monetary Transmission: Evidence from India

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Abstract

We propose a new channel for the transmission of monetary policy shocks, the coordination channel. We develop a New Keynesian model in which bank lending is strategically complementary. Banks do not observe the distribution of loans but infer it using Gaussian signals. Under this paradigm, expectations of tighter credit conditions reduce banks' lending response to monetary shocks. As a result, lack of coordination and information about other banks' actions dampen monetary transmission. We test these predictions by constructing a dataset that links the evolution of interest rates to firms' bank credit relationships in India. Consistent with our model, we find that the cross-sectional mean and dispersion of lending rates, which capture the expected value and the precision of the signals of credit extended by other banks, are significant predictors of monetary transmission. Our quantitative results suggest that lending complementarities reduce monetary transmission to inflation and output by about a third.

Keywords: Monetary policy transmission, India, lending rates

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1 Introduction

Multiple banking and loan syndications are common features of corporate lending. In such arrangements, creditors face a coordination problem: fear of premature foreclosure by other banks may lead to pre-emptive action, undermining the project (Morris and Shin, 2004). Accounts of past financial crises emphasize coordination failure among lenders (Radelet and Sachs, 1998; Fischer, 1999; Bernanke, 2018). Despite the salience of this problem, it has received less attention from the literature on monetary policy.

In this paper, we argue that the lack of coordination in bank lending dampens monetary transmission. Theoretically, we show that a coordinated response of credit to a monetary policy shock is larger than the uncoordinated benchmark. Empirically, we document a muted response of lending rates to policy rate changes when banks expect credit conditions to be tighter, which dampens transmission to inflation and output. Quantitatively, we find that this coordination channel can have large and persistent macroeconomic effects.

Our model embeds banks linked through firms' credit relationships in a standard New Keynesian (NK) framework. Capital-intensive projects in the real sector are financed via bank debt. The probability that these projects are successful is increasing in the capital raised. Monetary policy shocks are transmitted to the real sector via changes in the policy rate, i.e., the interest rate at which commercial banks borrow from the central bank. Banks cannot observe interest rates offered by other members of the loan syndicate but instead observe a signal with Gaussian noise. Lastly, lending costs are convex in loans and multiplicatively increasing in loans and the policy rate.

Under this paradigm, we argue that bank coordination acts as a propagation mechanism for monetary transmission. We analytically show that the pass-through of policy rate changes to commercial bank lending is dependent on the cross-sectional mean and dispersion of lending rates. In our framework, the probability of successful project implementation is conditional on the total credit extended to the project. Thus, the marginal benefit of lending is additively increasing in individual loans and the expected lending by other banks. Moreover, the marginal cost of lending is multiplicatively increasing in individual loans and the policy rate. Together, these conditions imply that variations in the policy rate change individual lending in proportion to the expected credit extended by other banks. As a result, monetary transmission is higher when expected aggregate credit is higher, or, equivalently, when the cost of credit (i.e., the lending rate) is lower. Moreover, since signals of loans extended by other banks are Gaussian, monetary transmission is increasing (decreasing) in the precision (variance) of these signals.

We test these predictions using Indian linked bank-firm data merged with information on interest rates. In 2016, the monetary policy regime changed to a Marginal Cost of Funds based Lending Rate (MCLR) regime to increase transparency. The MCLR is a tenor-linked internal benchmark determined by the bank depending on the period left for the repayment of a loan, and serves as the minimum interest rate that a bank can lend at. Our focus on the MCLR is conducive to our identification strategy. The MCLR does not include the premium charged by banks on lending to risky borrowers. Thus, it circumvents concerns about credit rationing being a potential explanation for the rigidity of credit. Moreover, since lending complementarities influence outcomes via multiple banking, the network of such arrangements plays a crucial role in our analysis. To capture this aspect, we infer the multiple banking network using granular data on firms' credit relationships. Employing measures of the centrality of this network, we proxy the exposure of each bank to beliefs about lending by other connected banks.

Our empirical analysis in the cross-section of banks supports the hypothesis that bank coordination propagates the credit channel of monetary policy. In particular, we estimate the effect of the first two moments of the cross-sectional distribution of the MCLR on monetary transmission. Our static estimates from a fixed effects model suggest that the cross-sectional mean and dispersion of lending rates significantly reduce the pass-through of the Repo rate to the MCLR. Moreover, our dynamic estimates from a Panel VAR show that these effects persist for a few months.

We conduct an additional robustness test of our findings to address endogeneity concerns. A potential problem in our empirical strategy is the collinearity of lending rates and policy rates. To circumvent this issue, we exploit an institutional change that led to a substantial reduction in average lending rates to infer the effect of lending rates on monetary transmission. The surprise demonetization in India forcefully increased deposits in the banking system, which exerted downward pressure on lending rates. We show that this period was associated with increased monetary transmission.

The foregoing analysis is qualitative, and leaves open the question of how important is the coordination channel relative to the traditional channel of monetary transmission. We answer this question by structurally estimating our model. In the model, as in the data, the impact of an increase in the policy rate has a muted effect on output and inflation when bank lending exhibits strategic complementarities. Our baseline estimates suggest that lending complementarities reduce monetary transmission to inflation and output by about a third.

Related Literature: Our paper lies at the nexus of two disparate strands of research: (i) monetary transmission, and (ii) bank coordination.

Traditional monetary theory has ignored the role of bank coordination. Existing theories of monetary transmission via bank lending operate through three channels.[1] The first is the bank reserves channel, which focuses on the role of reserves in determining the volume of demand deposits and, thus, bank lending (Bernanke and Blinder, 1988; Kashyap and Stein, 1995). The second is the bank capital channel in which an increase in nominal interest rates can adversely affect maturity-mismatched bank balance sheets featuring long-duration nominal assets and short-duration nominal liabilities (Van den Heuvel et al., 2002; Bolton and Freixas, 2000; Brunnermeier and Sannikov, 2016; Di Tella and Kurlat, 2017). The third is the market power channel in which policy rate changes incentivize banks to change markups on deposits, thereby affecting loanable funds (Scharfstein and Sunderam, 2016; Drechsler et al., 2017).[2] We contribute to this literature by presenting a new mechanism for monetary transmission: banks' motives to coordinate lending.

There is a burgeoning body of work that empirically investigates the coordination problems associated with multiple banking. Brunner and Krahnen (2008) provide indirect evidence of coordination motives among creditors. Chen et al. (2010) identify the effect of strategic complementarities in outflows from mutual funds by showing that the sensitivity of outflows to bad performance is stronger in funds that exhibit stronger strategic complementarities. Hertzberg et al. (2011) use a natural experiment from Argentina to show that lenders reduce credit in anticipation of other lenders' reactions to the negative news about the firm. Our analysis adds to this literature by examining the impact of coordination motives among creditors on monetary transmission.

Our paper is also related to the literature on the of role of financial intermediaries in the propagation of monetary policy shocks, which started with Bernanke and Gertler (1995).[3] They argue that information asymmetries between borrowers and lenders and the resulting agency problems translate into a wedge between the cost of external and internal finance. In a similar vein, we argue that the lack of coordination amongst lenders can drive a wedge between the policy rate and lending rates. In Curdia and Woodford (2010), as in our model, banking matters for transmission, and there can be imperfect pass-through from the policy rate to lending rates. In their model, the wedge between borrowing and lending rates stems from the assumption that banks incur a resource cost when making loans, and that some loans will not be repaid. In our model, in contrast,

[1] See Christiano et al. (1999) for a survey on the literature on monetary policy transmission.

[2] The implication of passthrough frictions on credit provision in these models differs starkly from that in our framework. Imperfect competition improves credit provision by raising the net interest margin (Duffie and Krishnamurthy, 2016). In contrast, coordination failure hampers credit provision.

[3] See Beck et al. (2014) for a survey. Some recent examples in this growing literature include Christiano et al. (2014), Ireland (2014), Del Negro et al. (2017), Brunnermeier and Koby (2018), and Piazzesi et al. (2018).

credit spreads are a result of coordination failures. On a related note, Brown et al. (2009) show that information sharing is associated with improved availability and lower cost of credit to firms. We contribute to this literature by showing that information sharing across banks can increase monetary transmission when bank lending is uncoordinated.

There is strong evidence that the transmission of policy rate changes to these macroeconomic variables is weak in developing countries (Montiel et al., 2010; Davoodi et al., 2013). Moreover, Montiel et al. (2010) argue that the bank lending channel is likely to be the dominant channel for monetary transmission in developing countries and find this channel either weak or unreliable. Sengupta (2014) and Mishra et al. (2016) examine the strength of monetary transmission in India using a structural VAR methodology popularized in this literature. They find that the transmission of monetary policy shocks to lending rates is partial. Our explanation for weak monetary transmission rests on the bank lending channel, which has empirical relevance in India.

The remainder of the paper is structured as follows. Section 2 presents a simple model that provides intuition linking bank coordination and monetary transmission. Section 3 describes the institutional background. Sections 4 and 5 describe our data and empirical work. Section 6 quantitatively illustrates the implications of lending complementarities on the transmission of monetary policy shocks to inflation and output. Section 7 offers concluding remarks.

2 Model

In this section, we embed banks that feature lending complementarities in a NK model. In doing so, we adapt the conceptual framework of Hertzberg et al. (2011) to examine the effects of bank coordination and incomplete information on monetary transmission. Since our eventual goal is to determine the effect of lending complementarities and bank coordination in a standard monetary policy framework, the behaviors of households, firms, and the monetary authority in our model purposefully mimic that in the NK model. The novelty of our framework stems from commercial banks' behavior, and this building block will be the focus of much of our analysis. In our model, firms operate labor-intensive projects while banks finance capital-intensive projects.

2.1 Households

There are a continuum of households of unit measure. We assume preferences of the representative household are of the following form:

$$u(C_t, H_t) = \frac{C_t^{1-\gamma}}{1-\gamma} - \chi \frac{H_t^{1+\varphi}}{1+\varphi}.$$

Taking prices as given, households maximize the expected present discounted valued of utilities:

$$\max_{C_t, H_t, B_t} \mathbb{E}_t \sum_{\tau > 0} \beta^\tau u(C_{t+\tau}, H_{t+\tau}),$$

where $\beta \in (0,1)$ denotes the rate of time-preference and $C_t \equiv \left(\int_0^1 C_t(i)^{1-1/\epsilon} di \right)^{\frac{\epsilon}{\epsilon-1}}$. Here $C_t(i)$ represents the quantity of good i consumed by the household in period t. Households face the following budget constraint:

$$\int_0^1 P_t(i) C_t(i) di + B_t = R_{t-1} B_{t-1} + W_t H_t.$$

In addition to the consumption/savings and labor supply decisions, households allocate their consumption expenditures among the different goods. This requires that consumption expenditures $\int_0^1 P_t(i) C_t(i) di$ be minimized to achieve a given level of consumption index C_t. The solution to this cost minimization problem yields the following set of demand equations:

$$C_t(i) = \left(\frac{P_t(i)}{P_t} \right)^{-\epsilon} C_t \; \forall i \in [0,1],$$

where $P_t = [\int_0^1 P_t(i)^{1-\epsilon} di]^{\frac{1}{1-\epsilon}}]$.

2.2 Firms

There are a continuum of firms of unit measure. Each firm produces a differentiated good, but they all use an identical technology, represented by the production function:

$$Y_t(i) = N_t(i) \; \forall i \in [0,1].$$

Following Calvo (1983), all firms cannot optimally set prices. In particular, a fraction $\theta \in (0,1)$ of firms are not allowed to reset prices. For these firms, $P_t = P_{t-1}$. For the remaining firms, $P_t = P_t^\star$ where $P_t^\star$ denotes the optimal price set by the representative firm given the nominal rigidity. That is,

$$P_t = (\theta P_{t-1}^{1-\epsilon} + (1-\theta) P_t^{\star 1-\epsilon})^{\frac{1}{1-\epsilon}}.$$

Firms solve for this price using:

$$\max_{P_t^\star} \mathbb{E}_t \sum_{\tau > 0} Q_{t,t+\tau} [P_t^\star - MC_{t+\tau}] Y_{t+\tau|t}$$

subject to the sequence of demand constraints:

$$Y_{t+\tau|t} = \left(\frac{P_t^\star}{P_{t+\tau}}\right) C_{t+\tau} \;\forall \tau \geq 0,$$

where $Q_{t,t+\tau} \equiv \beta^\tau (C_{t+\tau}/C_t)^{-\gamma}(P_t/P_{t+\tau})$ is the stochastic discount factor for households, and MC_t denotes the nominal marginal cost of producing one unit of goods.

2.3 Banks

There are N banks where $1 < N < \infty$. We consider a setting in which all banks pool resources to finance a single capital-intensive project, an assumption we relax in Section 2.6.3. Let $L_{i,t}$ be the amount lent by bank i in period t, where $0 < \sum_i L_{i,t} < 1 \;\forall t$. The gross interest rate on each loan extended by bank i in period t is assumed to be $R_{i,t} \geq 1$. In contrast to Hertzberg et al. (2011), we allow the interest rate to respond to changes in the supply of loans. The loan either pays off $R_{i,t}L_{i,t}$ or, if the firm defaults on the loan, it pays zero. The probability that an individual loan is repaid is increasing and concave in aggregate credit. In particular, we assume that the probability that the project is successful is given by $\mathbb{P}(\sum_{j\neq i} L_{j,t} + L_{i,t}) = (\sum_{j\neq i} L_{j,t} + L_{i,t})^\mu$, $\mu \in (0,1]$, which is increasing and concave in aggregate credit. This captures each bank's incentive to coordinate: if one bank lowers the amount it is willing to lend, this can disrupt the operations of the firm and hence lower the firm's ability to pay its other loans.[4] Banks cannot observe loans offered by other members of the syndicate but instead observe only a noisy signal given by:

$$s_t = \sum_{j\neq i} L_{j,t} + \eta_t, \text{ where } \eta_t \sim \mathcal{N}(0, \sigma^2).$$

Further, suppose the bank's prior is given by $\mathcal{N}(0, \sigma_p^2)$.[5] This implies that the probability that bank i will receive its payoff is increasing in the amount of credit extended by bank j weighted by the precision of the estimate.

While Hertzberg et al. (2011) consider an exogenous cost function to get an interior solution, we consider a setting in which the cost of lending depends on the policy rate set by the central bank. We denote the cost function by $c(L, p) > 0$ where $c_L, c_{LL}, c_p > 0$.

Assumption 1. *$c(L, p)$ is multiplicatively increasing in L and p.*

A special case that we pay particular attention to is $c(L, p) = \frac{L^2 p}{2\alpha}$. This term can

[4]This formulation saturates the density of the multiple banking network. We relax this assumption in the empirical analysis.

[5]Here we assume that the prior mean equals zero to analytically obtain a sharp result. However, this assumption is not imperative for the main mechanisms of the model to be operational.

also capture intermediation costs for lending to informal enterprises that are relatively opaque. The existing literature treats these costs as increasing and convex function of the volume of loans intermediated. The convexity of these costs stems from the assumption that as banks seek to expand the volume of loans beyond well-capitalized enterprises, the marginal borrower is progressively in a weaker position to offer collateral and is progressively less transparent (Mishra et al., 2014).

The objective of bank i is

$$\mathbb{P}\big(\mathbb{E}_i[\sum_{j\neq i} L_{j,t} \mid s_t] + L_{i,t}\big) L_{i,t} R_{i,t} - c(L_{i,t}, p_t).$$

2.4 Monetary Authority

To close the model the monetary policy authority sets its interest rate according to a standard Taylor Rule:

$$\frac{p_t}{\bar{p}} = \left(\frac{p_{t-1}}{\bar{p}}\right)^{\rho} \left\{ \left(\frac{\pi_t}{\bar{\pi}}\right)^{\phi^{\pi}} \left(\frac{Y_t}{\bar{Y}}\right)^{\phi^{y}} \right\}^{1-\rho} e^{\epsilon_t^p}$$

where ϵ_t^p is an AR(1) monetary policy shock, and $\bar{p}$, $\bar{\pi}$, and $\bar{Y}$ are steady state values the policy rate, the inflation rate and GDP. The central bank reacts to the deviation of the inflation rate and the GDP from their steady state values in a proportion of ϕ^{π} and ϕ^{y}, and smoothes its rate of doing so in a proportion of degree ρ.

2.5 General Equilibrium

Market clearing in the goods market requires $Y_t(i) = C_t(i)$, $\forall i \in [0,1]$ $\forall t \geq 0$. Thus, it follows that

$$Y_t = C_t \quad \forall t \geq 0.$$

Equilibrium in the money market necessitates

$$L_t = B_t \quad \forall t \geq 0. \tag{1}$$

Market clearing in the labor market requires

$$H_t = \int_0^1 N_t(i) di.$$

We present a log-linearized version of a closed economy that can be characterized by four equations in four variables, the output gap ($\hat{y}_t$), the inflation rate ($\hat{\pi}_t$), the policy rate ($\hat{p}_t$), and the nominal interest rate ($\hat{r}_t$). We omit standard derivations for the first three equations; see Galí (2008) for details. We focus our attention on the fourth equation, which is novel and emerges in our framework due to the presence of lending complementarities. This equation determines the wedge between lending rates and the policy rate in a symmetric uncoordinated lending equilibrium.

The first equation is the NK Phillips' Curve, which can be derived by the aggregation of the supply decision of firms. This equation links current inflation to future expected inflation and the output gap:

$$\hat{\pi}_t = \beta \mathbb{E}_t[\hat{\pi}_{t+1}] + \kappa \hat{y}_t$$

where

$$\kappa = \frac{(1-\theta)(1-\theta\beta)}{\theta}(\gamma + \varphi).$$

The second equation is the dynamic IS Curve, which can be derived from the Euler equation and the resource constraint. This equation describes the intertemporal allocation of consumption:

$$\hat{y}_t = \mathbb{E}_t[\hat{y}_{t+1}] - \frac{1}{\gamma}(\hat{r}_t - \mathbb{E}_t[\hat{\pi}_{t+1}]),$$

The third equation is the monetary policy rule, which links the policy rate to the inflation rate and to the output gap:

$$\hat{p}_t = \rho \hat{p}_{t-1} + (1-\rho)[\phi^{\pi}\hat{\pi}_t + \phi^{y}\hat{y}_t] + \epsilon^p_t.$$

Here $\epsilon^p_t = \rho^p \epsilon^p_{t-1} + \eta^p_t$, where $\eta^p_t \sim \mathcal{N}(0, \sigma^2_p)$. In the standard NK model, policy rate changes are passed completely to the nominal interest rate, i.e., $\hat{p}_t = \hat{r}_t \; \forall t$. Strategic complementarities in lending drive a wedge between this relationship.

Proposition 1. *Suppose savings is a fixed fraction of output and information is complete. Then in all symmetric uncoordinated lending equilibria:*

$$\hat{r}_t = \hat{p}_t + (1-\mu)\hat{y}_t.$$

Proposition 1 reveals that lending complementarities introduce a wedge between changes in policy rates and changes in nominal interest rates.[6] This wedge dampens monetary transmission to macroeconomic variables. This effect emerges because an increase in the policy rate tends to be contractionary, while a decrease tends to be expansionary. Thus, Proposition 1 implies that, relative to their steady state values, a unit deviation in

[6]The assumption of savings being a fixed fraction of output keeps the model tractable. It helps maintain a system of equations in output, inflation, and interest rate deviations from steady states.

the policy rate results in less than a unit deviation in the lending rate. The log-linearized version of the economy, however, masks the effect of beliefs on monetary transmission. We address this using a partial equilibrium analysis in the following sections.

2.6 Partial Equilibrium

We assume a downward-sloping demand for loans, $L^D_{i,t}/R^{\omega}_i$, where $L^D_{i,t} > 0\,\forall i$ and $\omega > 0$. Equilibrium in the loanable funds market requires $L_{i,t}R^{\omega}_{i,t} = L^D_{i,t}$. This implies a negative relationship between the supply of loans and lending rates. Under this assumption, we can infer the relationship between bank lending rates and monetary policy shocks from the response of loans to these shocks, which will be useful for our empirical analysis.

2.6.1 Symmetric Equilibria with Complete Information

In this section, we study the effect of bank coordination on monetary transmission. We restrict attention to symmetric equilibria with complete information as it allows us to get a stark result: monetary transmission is more pronounced when banks act in a coordinated fashion.

Proposition 2. *In all symmetric equilibria with complete information:*

(i) The pass-through of a monetary policy shock to aggregate credit is higher when banks coordinate lending.

(ii) The difference between the credit response of a monetary policy shock in the coordinated and uncoordinated equilibrium is increasing in N.

The intuition behind the second result in Proposition 2 is that as the number of the banks increases in a complete financial network, the exposure of banks to uncoordinated actions increases, which reduces the transmission of monetary policy shocks.

2.6.2 Incomplete Information

For tractability, we assume $N = 2$ and consider the case in which the probability of successful project implementation is linearly increasing in aggregate credit, i.e., $\mathbb{P}\big(E_i[L_{j,t} \mid s_t] + L_{i,t}\big) = E_i[L_{j,t} \mid s_t] + L_{i,t}$. We focus on non-coordinated equilibria, and investigate the effect of bank coordination on monetary transmission when banks update their beliefs using Bayes' Rule.

Assumption 2. $\alpha < \frac{p_t}{2R_{i,t}}\ \forall i\ \forall t$.

Assumption 2 ensures that the solution to the bank's problem is interior and well defined.

Proposition 3. *Suppose $\mu = 1$ and information is incomplete. Then*

$$(i) \quad \partial L_{i,t}(L,\sigma)/\partial p \; < \; 0 \, \forall (L,\sigma) \gg \mathbf{0} \, \forall t, \tag{2}$$

$$(ii) \quad | \, \partial L_{i,t}(L,.)/\partial p \, | > | \, \partial L_{i,t}(\tilde{L},.)/\partial p \, | \;\; \forall L > \tilde{L} \, \forall t, \tag{3}$$

$$(iii) \quad | \, \partial L_{i,t}(.,\sigma)/\partial p \, | < | \, \partial L_{i,t}(.,\tilde{\sigma})/\partial p \, | \;\; \forall \sigma > \tilde{\sigma} \, \forall t. \tag{4}$$

The first result in Proposition 3 shows that banks reduce lending in response to an increase in the policy rate. The second result in Proposition 3 shows that lower costs of financing amplify monetary transmission. The impact of a policy rate change on loans granted by a particular bank and, thus, on its lending rate, is increasing in the expected level of credit extended by other banks. That is, the higher (lower) the loans (interest rates) offered by bank $j \neq i$, the larger the transmission of policy rates to the loans (interest rates) offered by bank i. The third result in Proposition 3 shows that a higher dispersion in lending rates also dampens monetary transmission. The impact of a policy rate change on the loans granted by a particular bank is decreasing in the dispersion of credit extended by other banks. There is no effect in the extreme case when other bank lending rates are completely uninformative, i.e., when $\sigma = \infty$. This effect emerges as a larger variance in lending rates reduces the precision of the signal of other banks' lending practices, which effectively dampens complementarity in lending.

Figure 1 illustrates these results. Suppressing the time notation, the marginal benefit of loans by bank i is given by $R_i(\mathbb{E}[L_j] + 2L_i)$, which is additively increasing in $\mathbb{E}[L_j]$ and L_i. Thus, increasing the expected credit extended by other banks only increases the intercept of the marginal benefit curve, shifting it upwards. The marginal cost of loans is given by $c_L(L_i, p)$, which, by assumption, is multiplicatively increasing in its arguments. Thus, an increase in p increases the slope of the marginal cost curve. This implies that policy rate changes have a larger effect on lending when the expected credit extended by other banks is higher, or equivalently, when the mean and precision of these signals are higher. Notice that both our results hinge on the assumption that the cost of loans, $c(.)$, is convex in the level of loans. If the cost was linear instead, then monetary transmission would not be dependent on lending moments.

Figure 2(b) depicts monetary transmission, as measured by the change in lending in response to a change in the policy rate, in (i) an uncoordinated equilibrium under incomplete information, (ii) an uncoordinated equilibrium under full information, and (iii) a coordinated equilibrium. There are three takeaways from this exercise. First, monetary transmission is highest in the coordinated equilibrium. Second, incomplete information in the uncoordinated equilibrium dampens monetary transmission. Third, the anemic response of lending to a policy rate change persists for a few periods but recovers as banks learn more about aggregate credit; see Figure 2(a).

2.6.3 Network Effects

It is useful to consider a static environment in which N banks finance M projects to further illustrate the role of multiple banking linkages in shaping monetary transmission. Our setting is similar to Anand et al. (2012) and Acemoglu et al. (2020). They show how the structure of financial networks shapes outcomes in a coordination game in which banks exposed to liquidity shocks decide whether to rollover short-term credit when facing the risk of the borrower defaulting. In this section, we apply insights from their work to study the network effects of monetary policy shocks on bank lending.[7]

For tractability, we assume the curvature of lending complementary is fixed to unity. Let L_{ji} denote bank i's loan for project j. We denote the fixed return of bank i from project j by R_{ji}. Let $\hat{R}_{ji} \equiv R_{ji}/p \ \forall i \ \forall j$.

Proposition 4. *Suppose $\mu = 1$. Then*

$$\frac{dL_{ji}}{dp} = \underbrace{\frac{\alpha \sum_{k \neq i} \frac{dL_{jk}}{dp}}{\hat{R}_{ji}^{-1} - 2\alpha}}_{\text{Network Effect}} \underbrace{- \frac{\left\{\sum_{l=1}^{M} L_{li} + \hat{R}_{ji}^{-1} \sum_{l \neq j} \frac{dL_{li}}{dp}\right\}}{\hat{R}_{ji}^{-1} - 2\alpha}}_{\text{Direct Effect}} \ \forall i \ \forall j.$$

This expression shows how changes in policy rates translate to changes in credit through the network of multiple banking arrangements. In particular, $-\left\{\sum_{l=1}^{M} L_{li} + \hat{R}_{ji}^{-1} \sum_{l \neq j} \frac{dL_{li}}{dp}\right\} / (\hat{R}_{ji}^{-1} - 2\alpha)$ captures the direct response to a monetary policy shock of lending of bank i to project j. The network effect is captured by $\alpha \sum_{k \neq i} \frac{dL_{jk}}{dp} / (\hat{R}_{ji}^{-1} - 2\alpha)$. This term links monetary transmission in one bank to monetary transmission in other banks.

3 Monetary Policy Framework in India

The Liquidity Adjustment Facility (LAF) is a critical element of the monetary policy framework of the RBI. Since November 2004, The RBI has used the LAF to aid banks in adjusting any mismatches in liquidity. Under the LAF, the Reserve Bank sets its Repo and Reverse Repo rates. The RBI's standing facilities supplement the LAF. In principle,

[7] The role of networks in the propagation of monetary policy shocks is part of a growing literature. Gai et al. (2011) and Acemoglu et al. (2015) examine how the density of the network of interbank liabilities contributes to financial instability and shock propagation. Elliott et al. (2014) and Cabrales et al. (2017) study how cross-holdings of different organizations' assets can amplify external shocks. Ozdagli and Weber (2017) argue that production networks shape the stock market response to monetary shocks.

the reverse repo rate is a fixed distance under the repo rate, and the marginal standing facility (MSF) rate is a fixed distance above the repo rate. In our analysis, we restrict attention to the Repo rate.[8]

Since the deregulation of interest rates in 1994, the issue of transmission from the policy rate to banks' lending rates has been a matter of concern (RBI, 2017). Upon deregulation, banks were required to declare their prime lending rates (PLR) - the interest rate charged for the most creditworthy borrowers. The PLRs of banks were inflexible, however, and the regime was eventually abandoned in favor fo the Benchmark PLR (BPLR), which accounted for the bank-specific cost of funds, operational costs, regulatory requirements, and profit margins. This regime was also deemed unsatisfactory as it was not an appropriate reflection of median lending rates.

In 2010, the base rate system (BRS) came into effect, wherein the base rate was the minimum rate for most loans with the actual lending rate charged to the borrowers being the base rate plus borrower-specific charge or spread. The BRS was opaque, however, and clouded an accurate assessment of the speed and strength of the transmission (Acharya, 2017). To foster transparency and flexibility in bank lending, the RBI instituted the MCLR system in 2016. The BPLR, the base rate and the MCLR were internal benchmarks set by each bank for pricing of credit. However, unlike the BPLR and the base rate, the formula for computing the MCLR is determined by the RBI. Despite these changes, transmission remains incomplete under the MCLR system (RBI, 2017). This concern was recently reiterated by the RBI Deputy Governor:

> "*Data suggests that the pass-through from policy rate changes to bank lending rates has been slow and muted. This lack of adequate monetary transmission remains a key policy concern for the Reserve Bank as it blunts the impact of its policy changes on economic activity and inflation.*" – Viral Acharya, Inaugural Aveek Guha Memorial Lecture (November 16, 2017).

The MCLR is based on the cost structure of banks. In addition to operating costs, the MCLR is determined by the cost of raising new deposits at different tenors. We view the effects of coordination being transmitted via these borrowing costs. That is, if aggregate credit is higher, then more projects will succeed in the real sector, leading to higher deposits, and lower deposit rates. The ultimate floating rate on loans imposes a premium over the MCLR, which depends on the interest rate reset frequency of the loan and a spread based on the borrower's credit profile.

[8] An alternate specification in which the outcome variable reflects the spread between the commercial bank lending rates and the Reverse Repo rate or the MSF rate would deliver similar results as the constant term in our regression would simply absorb the fixed distance.

4 Data

We construct a novel dataset that links the evolution of interest rates to firms' bank credit relationships in India. The sample covers the universe of banks in India. Our data is at a monthly frequency and ranges from 2016M6-2020M2. The MCLR system only became effective in April 2016; this institutional change restricts our sample size.

The interest rate data is extracted from individual data releases by the Reserve Bank of India (RBI) and the Database of the Indian Economy. Figure 3 depicts the commercial bank lending rates and the central bank policy rate over our sample period. Commercial bank lending rates refer to the MCLR at end of month. The central bank policy rate is the Repo Rate, which is the rate at which the RBI lends money to commercial banks in the event of any shortfall of funds, at end of month. Two salient patterns emerge. First, most commercial bank lending rates are considerably higher than the central policy rate, alluding to the weakness of monetary transmission. Second, there is substantial variation in the response of commercial bank lending rates to changes in the policy rate, alluding to the heterogeneity in monetary transmission.

Our baseline measure of monetary transmission focuses on the wedge between the MCLR and the Repo rate:

$$MT_{i,t} = MCLR_{i,t} - REPO_t,$$

where i denotes the bank and t denotes the month. In our analysis, we also employ another measure of monetary transmission: the coefficient on the first difference in $REPO_t$ in a regression in which the first difference of the $MCLR_{i,t}$ is the outcome variable.

Figure 4 plots key interest rates aggregated by bank ownership. The MCLR decreased from 9.4 percent in June 2016 to 8.3 percent in January 2018. It reverted to 8.8 percent in January 2019, and decreased thereafter. These trends are less vivid but appear to be present in the MCLR-Repo Spread. We argue that the evolution of this spread is not only influenced by the cross-sectional mean of lending rates, but also its dispersion. The cross-sectional dispersion of the MCLR for private sector banks was larger than that for public sector banks and foreign banks at the beginning of our sample. Since then, the dispersion in lending rates for public sector banks and foreign banks has risen substantially and outpaced that of private sector banks. Our empirical strategy addresses these differences using bank-specific fixed effects. Our empirical strategy also exploits the exposure of lending rates to policy rates. We proxy this exposure using changes in the number of bids received under the LAF. Figure 5 plots the time-series for LAF bids.

To measure exposure to lending beliefs, we exploit the granularity of Indian linked bank-firm data from the Centre for Monitoring Indian Economy (CMIE). We restrict attention to non-financial firms' relationships with the list of commercial banks in the RBI sample and use the latest available estimates for each firm. There are 17,761 non-financial firms in the pruned sample. The three largest lenders to these firms are SBI, HDFC, and ICICI, which lend to 5591, 4645, and 3060 firms, respectively. Figure 6 depicts the distribution of the number of banking relationships of non-financial firms. A typical firm in our sample has credit relationships with about three banks on average.

We also use the data to construct the underlying network for multiple banking relationships in India. The ideal dataset for our analysis would contain information on each firm's loan portfolio, which would permit an examination of multiple banking connections on the intensive margin. However, the CMIE data only allows us to identify which banks lend to the same firms. We use this data to proxy the undirected multiple banking network. In particular, we construct the following weighted adjacency matrix

$$\boldsymbol{\mathcal{A}} = \begin{bmatrix} \mathcal{A}_{1,1} & \mathcal{A}_{1,2} & \cdots \\ \vdots & \ddots & \\ \mathcal{A}_{89,1} & & \mathcal{A}_{89,89} \end{bmatrix}, \text{ where } \quad \mathcal{A}_{i,j} = \begin{cases} \sum_{l=1}^{17,761} \mathbb{1}_{L_{li}>0, L_{lj}>0} & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases}.$$

Figure 7 depicts the multiple baking network in India. There are 89 banks in the multiple banking network, with a total of 4818 connections. The density of this network is 61.5 percent, which suggests that multiple banking is pervasive in India. We use degree and eigenvector centrality ($\mathcal{C}$) to measure how pivotal each bank is in the network (Bavelas, 1948; Sabidussi, 1966; Freeman, 1978). Network centrality can be interpreted in terms of the immediate risk of a bank being affected by the lending decision of other banks in the network. In the empirical analysis, we use these measures to proxy exposure to beliefs about lending by other banks.

5 Empirical Estimates

5.1 Identification

5.1.1 Determinacy

Models featuring strategic complementaries can lead to multiple equilibria, which complicates identification. Ignoring multiplicity may result in misspecification and result in inconsistent estimates (Jovanovic, 1989; Tamer, 2003). To circumvent these concerns, we isolate the conditions under which the model delivers a unique equilibrium.

Proposition 5. *Under contemporaneous data interest rate rules, a necessary and sufficient con-*

dition for uniqueness is

$$\kappa(\phi^{\pi} - 1) + (1 - \beta)(\phi^{y} + 1 - \mu) > 0.$$

Perhaps surprisingly, the above condition for determinacy is weaker than that in the standard NK model; see Bullard and Mitra (2002).

5.1.2 Fixed Effects

Our specification allows us to control for cross-sectional differences in the way that banks with varying characteristics respond to monetary policy shocks. Kashyap and Stein (2000) show that the impact of monetary policy on lending behavior is more pronounced for banks with less liquid balance sheets. There is also strong empirical evidence that suggests that banks with lower capital ratios grant fewer loans and take less credit risk in response to tighter monetary conditions (Jiménez et al., 2012; Ioannidou et al., 2015). Moreover, Acharya et al. (2020) find that well capitalized banks respond more to expansionary monetary policy. Bank fixed also help to absorb any differential transmission of monetary policy that may be present due to the risk-taking channel. Dell'Ariccia et al. (2017) find that risk-taking by banks is negatively associated with increases in the policy rate, and that this relationship less pronounced for banks with relatively low capital.

Bank ownership may also interact with monetary policy transmission. Bhaumik et al. (2011) document considerable differences in the reactions of different types of banks to monetary policy in India. Moreover, Cetorelli and Goldberg (2012) show that global operations insulate U.S. banks from changes in monetary policy. This is because global banks can use cross-border internal funding in response to local shocks. A similar argument applies to foreign banks operating in India. Indeed, the correlation between the Repo rate and the MCLR for foreign banks is 0.42, compared to 0.47 for domestic banks; see Table 1 for more details. Bank fixed effects serve to absorb these differential impacts of monetary policy.

In addition, we control for differential changes in banks' lending opportunities. In particular, we include bank-month fixed effects to absorb all time-varying differences between banks. This allows us to control for changes in the demand for loans across banks.

5.1.3 The MCLR and Borrower-specific Risk

One explanation for the sluggishness of bank lending could be credit rationing.[9] To limit moral hazard on the part of the borrowers, credit providers may decline to extend

[9] Voluminous evidence exists on formal and informal credit rationing in India, especially for smaller firms (Banerjee and Duflo, 2001; Banerjee et al., 2004; De and Singh, 2011).

credit beyond a certain point regardless of the credit terms. This approach focuses on the relationships between lenders and borrowers to explain the inflexibility of lending. We instead focus on the relationships amongst lenders to explain the rigidity in credit. We identify this effect empirically by focusing on the MCLR instead of the weighted average lending rate (which has received more attention in previous studies on monetary transmission in India). In particular, the MCLR does not include the premium charged by banks on lending to risky borrowers. Thus, the distribution of risk across borrowers is unlikely to bias our results.

5.2 Interest Rate Pass-through

5.2.1 Time-series Estimates

We first test if our predictions at the aggregate level using the following linear model:

$$MT_t^k = \alpha^k + \beta_1^k \bar{R}_t^k + \beta_2^k \sigma(R)_t^k + \boldsymbol{\beta}_3^k \boldsymbol{X}_t + \epsilon_t^k. \tag{5}$$

Here $k \in \{\text{Public, Private, Foreign}\}$ denotes bank ownership. The dependent variable, MT, is our measure of monetary transmission. We compute this using the difference between average lending rates of scheduled commercial banks and the central bank policy rate. The main explanatory variables are average lending rates ($\bar{R}$) and the cross-section dispersion in lending rates ($\sigma(R)$). We also include a vector of time-specific controls, which we denote as $\boldsymbol{X}_t$.

5.2.2 (Static) Panel Estimates

Specification (5) does not consider bank-wise monetary transmission, but rather looks at aggregate level trends. Though we show that our results hold even in the aggregate level regression, aggregation masks bank-specific trends and can lead to spurious results. To address this concern, we construct a disaggregated panel that tracks for each bank i in month t, the idiosyncratic wedge between the MCLR of bank i and the policy rate, as well as the cross-sectional mean and dispersion of all other banks $j \neq i$. We then estimate the following model:

$$MT_{i,t} = \alpha + \beta_1 \mathcal{C}_i \times \bar{R}_{j \neq i,t} + \beta_2 \mathcal{C}_i \times \sigma(R)_{j \neq i,t} + \boldsymbol{\beta}_3 \boldsymbol{X}_t + \xi_i + \Xi_{i,t} + \epsilon_{i,t}. \tag{6}$$

Here $\bar{R}_{j \neq i,t}$ and $\sigma(R)_{j \neq i,t}$ respectively denote the cross-sectional mean and dispersion of lending rates of all banks barring bank i. Bank fixed effects and bank-month fixed effects are denoted by ξ_i and $\Xi_{i,t}$ respectively.

We also consider the following model:

$$\Delta MCLR_{i,t} = \alpha + \beta_1 \Delta REPO_t \times LAF_t + \beta_2 \Delta REPO_t \times LAF_t \times \mathcal{C}_i \times \bar{R}_{j\neq i,t} + \beta_3 \Delta REPO_t \times LAF_t \times \mathcal{C}_i \times \sigma(R)_{j\neq i,t} + \boldsymbol{\beta}_4 \boldsymbol{X}_t + \xi_i + \Xi_{i,t} + \epsilon_{i,t}. \quad (7)$$

This specification modifies the model used in previous studies that examine the pass-through of policy rate cuts to lending rates (Das, 2015) to incorporate interactions of the policy rate with the moments of lending rates. We also control for the exposure of Repo transactions. Due to the lack of data on bank-specific Repo bids, we use the aggregate levels to measure exposure. In particular, we weight changes in the Repo rate by the total bids received in each month (normalized by the sample mean).

5.2.3 Panel VAR

Panel VARs are a good fit for our analysis in that they are unique in their ability to model dynamic interdependencies across interest rates, cross-sectional heterogeneity across banks, and the evolving pattern of monetary transmission. Panel VARs have been previously used in the literature to study the impact of monetary and fiscal shocks across units and time; see Canova and Ciccarelli (2013) for a survey. Following Holtz-Eakin et al. (1988), we use a panel vector autoregression (PVAR):

$$\boldsymbol{Y}_{it} = \boldsymbol{Y}_{it-1}\boldsymbol{A}_1 + \boldsymbol{X}_{it}\boldsymbol{B} + \boldsymbol{\xi}_i + \boldsymbol{e}_{it}, \text{ where}$$

$$\boldsymbol{Y}_{it} = [\Delta MCLR_{it}, \Delta REPO_t \times LAF_t, \Delta REPO_t \times LAF_i \times \bar{R}_{i\neq j,t}, \Delta REPO_t \times LAF_t \times \sigma(R)_{i\neq j,t}]'.$$

We assume that the innovations have the following characteristics: $\mathbb{E}(\boldsymbol{e}_{it}) = \boldsymbol{0}$, $\mathbb{E}(\boldsymbol{e}_{it}'\boldsymbol{e}_{it}) = \Sigma$, and $\mathbb{E}(\boldsymbol{e}_{it}'\boldsymbol{e}_{is}) = \boldsymbol{0}\ \forall t > s$.

5.2.4 Potential Covariates

Maturity of Deposits: A key factor impeding quick and adequate transmission to banks' lending rates has been long maturity profile of bank deposits at fixed interest rates. Since retail deposits comprise the bulk of the funds of banks, transmission to banks' MCLR is inextricably linked to movements in the cost of such deposits (Patel et al., 2014; Acharya, 2017). In particular, a longer maturity renders lending rates more inflexible. To account for this constraint on monetary transmission, we control for maturity of deposits using the ratio of time deposits to demand deposits.[10]

[10] To address this issue, an external benchmark system was introduced effective October 1, 2019 for select categories of loans under which transmission to banks' lending rates will no longer be contingent upon adjustment in deposit interest rates. Under the new regime, the RBI mandates all scheduled commercial

Consistency of Monetary Policy Stance: Another confounding variable in the analysis could be the monetary policy stance of the RBI. In particular, banks may be more willing to pass policy rate cuts to lending rates if they believe that the policy rate cut is unlikely to be reversed in the near future. As such, the consistency of announcements regarding the future path of interest rates can have contemporaneous effects. During our sample period, the monetary policy stance was changed four times: from accommodative to neutral in February 2017; then to calibrated tightening in October 2018; then back to neutral in February 2019; and to accommodative in June 2019. To capture inconsistency of the monetary policy stance, we construct a dummy variable that equals one if the monetary policy stance was changed in the last quarter.

Financial Repression: The transmission of monetary policy shocks may also be reduced by legal restrictions on the interest rates (Montiel et al., 2010). The Patel Committee Report (Patel et al., 2014) suggests that credit frictions are a major impediment to monetary transmission in India. The RBI itself determines a key credit market friction. Banks in India are subject to a statutory liquidity ratio (SLR)—a particular share of net liabilities that banks must invest in gold and/or government approved securities. Lahiri and Patel (2016) argue that a binding SLR may invert the monetary transmission mechanism in the sense that a reduction in the policy rate ends up raising lending spreads. To address this concern, we explicitly control for first differences in the SLR in our regressions but find no evidence that the SLR affects monetary transmission.

Reserve Requirement: Monetary transmission may also be dependent on the Cash Reserve Ratio (CRR). The RBI mandates that a certain fraction of bank deposits be held as reserves. The lower the CRR, the higher the liquidity with banks, which goes toward lending. The CRR has remained steady at 4 percent over our sample period, which allows for cleaner identification.

Regulatory Environment: Mishra et al. (2014) argue that institutional arrangements, such as weak contract enforcement and poorly defined property rights, impede the bank lending channel. According to the World Bank Doing Business Indicators, the number of days to enforce contracts in India has remained steady at 1445 days over the sample period. Thus, the effect of contract enforcement on monetary transmission is absorbed by the constant terms in our regressions. Though we concede that institutional arrangements would play a more prominent role in a cross-country analysis.

banks (excluding regional rural banks) to link all new floating rate personal or retail loans and floating rate loans to micro and small enterprises (MSEs) to the policy repo rate or any other benchmark market interest rate published by Financial Benchmarks India Private Ltd. (FBIL).

5.2.5 Results

Static Estimates: Table 2 reports the OLS estimates for the aggregate level regression. When we consider the full sample, the estimates suggest that the mean and dispersion of lending rates significantly reduce the wedge between lending rates and the policy rate. When we split the sample into private and non-private banks, we find that the effect of mean lending rates is not statistically away from zero. However, the effect of dispersion in lending rates (which measures the lack of precision of the signal of the aggregate cost of credit) remains positive and statistically significant. Figure 8 graphically depicts the positive relationship between the first two moments of the distribution of lending rates and monetary transmission.

Table 3 reports the panel estimates in bank-month units using our first measure of monetary transmission, that is, the spread between the MCLR and the Repo rate. These results are consistent with the findings from the aggregate level regressions. Table 4 reports the panel estimates using the alternate specification. The coefficient on the interaction term featuring the cross-sectional mean of other bank lending rates is negative and statistically significant. This supports our baseline estimates and is consistent with the hypothesis that higher lending rates offered by other banks dampen monetary transmission. However, the coefficient on the interaction term featuring the cross-sectional dispersion of other bank lending rates do not support our baseline results.

Dynamic Estimates: Figure 9 depicts the impulse response function of changes in the MCLR to a monetary policy shock in the PVAR specification with ordering $[\Delta MCLR \quad \Delta REPO \times LAF]$, i.e., our baseline PVAR specification without any interaction terms or exogenous controls.

Figure 10 decomposes these effects.[11,12] The estimated effects of policy rate changes and the interaction terms have signs that are consistent with our baseline static estimates. The estimated effects of Repo rate changes and the interaction term featuring the cross-sectional average of other banks' lending rates are significant, both with and without the exogenous controls. The estimated effect of the interaction term featuring the cross-sectional dispersion of other banks' lending rates is significant without controls, but becomes imprecise when we control for the time deposits share, the consistency of the monetary policy stance, and the SLR. Moreover, these effects persist for about 2-3 months post the shocks.

[11] We find evidence that all past values are useful in prediction using a VAR-Granger causality Wald test (Granger, 1969).

[12] The model is stable as all moduli of the companion matrix based on the estimated parameters are smaller than one. Using levels instead of percent first differences, in contrast, fails the unit root test and yields explosive dynamics.

5.2.6 Inferring Network Effects

The graph of multiple banking relationships in India features a core-periphery (CP) architecture. Such networks have received considerable attention in the literature on financial networks. Galeotti and Goyal (2010), Lux (2015), and Van der Leij et al. (2016) provide a rationale for the emergence of such a structure using network formation theory. Craig and Von Peter (2014) provide evidence on the existence of CP networks in interbank markets. Our findings reveal that the network of multiple banking relationships also exhibits a similar structure. We use this structure to investigate the key mechanism of the model. Specifically, we ask if the coordination channel is more pronounced in the densely connected core relative to the sparsely connected periphery.

Following Carmi et al. (2007) and Garas et al. (2012), we use a k-shell decomposition to identify the set of core banks in the multiple baking network. We begin by eliminating all unconnected banks. Then, in each iteration, we discard the least connected bank.[13] That is, we eliminate the bank with the lowest eigenvector centrality in the connected network. We repeat the process until we arrive at the smallest non-empty subgraph of connected banks. After this iterative pruning process is completed, all remaining nodes in the subgraph have an eigenvector centrality of 0.15. The core group of the multiple banking network comprises of 47 banks. We refer to the set of banks that exclude the core as the periphery.

We re-run specification (6) using sub-samples of core and periphery banks. Figure 11 reports the estimated effect on monetary transmission (as measured by credit spreads) of the mean and dispersion of lending rates of other banks in the respective sub-sample. The results suggest that coordination plays a larger role in shaping monetary transmission in more connected banking networks. The mean effects for core banks are about 2.5 times as large as for periphery banks, while the dispersion effects are about five times as large.

5.2.7 Robustness: Endogeneity Concerns

One potential problem in our baseline empirical strategy is the collinearity of lending rates and policy rates. To circumvent this issue, we exploit an institutional change that led to a substantial reduction in average lending rates to infer the effect of lending rates on monetary transmission.

Demonetization led to a sweeping decrease in bank lending rates. The average MCLR decreased by 4 percent m-o-m in January 2017, from 9.1 percent to 8.7 percent. The reduction in lending rates was consistent across private, public, and foreign banks; see Figure 4. The reason for this decrease in lending rates was that the regulation forcefully increased

[13]If the set of least connected banks is a non-singleton, we discard in alphabetical order.

deposits in the banking system. This exerted downward pressure on deposit rates, aiding balance sheet positions of banks, and allowed banks to lower their lending rates. Chanda and Cook (2019) find that deposit growth during demonetization was accompanied by subsequent increases in lending by the banking system, and higher economic activity. We argue that part of this expansionary effect could have been driven by an increase in monetary transmission.

To estimate the impact of demonetization on lending rates and monetary transmission, we use a Regression Discontinuity in Time (RDiT) design to exploit temporal variation. The fact that demonetization was an unexpected shock to the banking system is critical to this identification strategy. We restrict attention to levels instead of first differences here as the Repo rate remained steady at 6.25 percent during demonetization, leaving no variation to exploit when measuring the change in monetary transmission during this period. In particular, we consider the following specification:

$$MCLR_{i,t} = \alpha + \beta_1 REPO_t \times LAF_t + \beta_2 \mathbb{1}(D)_t \times REPO_t \times LAF_t + \beta_3 \mathbb{1}(D)_t + \boldsymbol{\beta_4 X}_t + \xi_i + \epsilon_{i,t}. \tag{8}$$

Here $\mathbb{1}(D)$ denotes an indicator variable for observations after December 2016, which was the deadline to deposit old currency notes, and before April 2017, which is when the transfer limits on cash withdrawals that were imposed during demonetization were lifted, and deposits could be taken out of the banking system.[14]

Table 5 reports the estimation results. Consistent with our hypothesis, the estimate for β_3 is negative and significant, suggesting that demonetization significantly decreased lending rates. Moreover, the estimate for β_2 is positive and significant, which indicates that this period witnessed increased monetary transmission.

5.3 Implications for Inflation and Output

In this section, we estimate the effect of bank coordination on monetary transmission to inflation and output. In particular, we use the following model:

$$\begin{aligned} Y_t^Y &= \alpha^Y + \beta_1^Y \hat{Y}_t + \beta_2^Y \dot{e}_t + \beta_3^Y \Delta REPO_t \times LAF_t + \beta_4^Y \Delta REPO_t \times LAF_t \times \bar{R}_{j\neq i,t} \\ &\quad + \beta_5^Y \Delta REPO_t \times LAF_t \times \sigma(R)_{j\neq i,t} + \boldsymbol{\beta_6^Y X}_t + \xi_i + \Xi_{i,t} + \epsilon_{i,t},\ \forall (Y, \hat{Y}) \in (\dot{y}, \pi) : Y \neq \hat{Y}. \end{aligned} \tag{9}$$

Here $\dot{y}$ denotes month-on-month output growth, which is proxied by the growth rate of the Index of Industrial Production. The inflation rate, π, is calculated using month-on-month CPI growth.

[14] We also consider a specification in which the indicator variable is active after the announcement of Demonetization, and obtain similar conclusions.

In addition to the standard set of controls, we also control for the growth in the monthly average INR-USD exchange rate, which we denote as $\dot{e}$. The exchange rate could potentially affect both independent as well as dependent variables in our baseline specification. Concerning the outcome variables, there exists an extensive literature that documents the incidence of changes in the exchange rate on growth, which operates via the current account. The underlying mechanism is simple: changes in the exchange rate affects the terms of trade and, thus, the export-import mix, which in turn affects output and inflation. Concerning the explanatory variables, the Uncovered Interest Parity (UIP) suggests that expected future changes in the nominal exchange rate are related to the difference between domestic and foreign interest rates. Barring episodes in which the Indian Rupee was sterilized, we suspect that the link between interest rates and the exchange rate has been tight. In this case, the correlation between exchange rates (a potential component of the error term) and interest rates (explanatory variable) could bias the point estimates.

The results in Table 6 show the effects of lending rate moments on the transmission of monetary policy shocks to inflation and output. The estimated effects of an increase in the policy rate on inflation and output are negative and significant. Our empirical results also suggest bank coordination dampens monetary transmission to inflation and output. In particular, the coefficients on the interaction terms featuring the mean and dispersion of lending rates are positive and significant.

6 Quantitative Results

In this section, we use the NK model to show how bank coordination affects monetary transmission to the key macroeconomic targets of the central bank, i.e., inflation and output. In the model, as in the data, lending complementarities dampen monetary transmission to inflation and output.

6.1 Parameterization

We follow a two-step strategy to estimate the parameters of the model. First, we externally estimate the Taylor rule coefficients, $\{\phi^{\pi}, \phi^{y}\}$, using OLS. We consider a contemporaneous data interest rate rule. Specifically, the parameter controlling the persistence of the policy rate is set to $\rho = 0$. The observations for inflation and output respectively correspond to HP-filtered log deviations from mean values of the CPI and the Index of Industrial Production. The observations for the policy rate correspond to log deviations of the Repo rate from mean values. This procedure yields $\phi^{\pi} = 1.4$ and $\phi^{y} = 0.43$. These estimates are broadly consistent with the New Keynesian literature (Galí, 2008).

Second, we internally estimate the deep parameters of the model, $\{\gamma, \varphi, \theta, \mu, \epsilon^p\}$, using Bayesian estimation to match log deviations of the policy rate from mean values. Barring the curvature of lending complementarity, which is a novel addition to the NK model, we set the prior mean of these parameters to values commonly found in the business cycle literature. To remain agnostic about the underlying data generating process, we use the average of the estimated parameters in the NK model and the model featuring lending complementarities (NK-LC); see Table 7. This procedure yields the following set of estimates. The coefficient of relative risk aversion is set to 1.06. The elasticity of the marginal disutility with respect to labor, which determines the Frisch elasticity of labor supply, is set to 0.65. The price rigidity parameter is set to $\theta = 0.81$. The curvature of lending complementarity is set to $\mu = 0.44$.[15] The standard error of the monetary policy shock is set to $\epsilon^p = 0.08$.

Lastly, the parameter controlling the persistence of the monetary shock process is set to $\rho^p = 0.4$. The savings rate is set to $\Lambda = 1/3$, which is consistent with Indian data. The rate of time-preference is set to $\beta = 0.99$. Table 8 summarizes our baseline parameterization.[16]

6.2 Model Fit

Here we show that the model with lending complementarities fits the data better in terms of implied volatilities of inflation and output. Table 9 compares the volatilities of inflation and output in the data with those simulated in the NK and NK-LC models. The data moments correspond to standard deviations of HP-filtered log deviations from mean values over the sample period. The model moments correspond to standard deviations of log deviations from steady states. We compute these using a simulation of 100 economies over 5000 periods. The standard deviation of inflation deviations is 0.006 in the model with lending complementarities, which is relatively close to its data counterpart of 0.007. In contrast, the volatility of inflation in the NK model is 0.009. The model with lending complementarities outperforms the NK model in the output dimension as well. The standard deviation of output deviations is 0.04 in the data, 0.05 in the NK-LC model, and 0.07 in the standard NK model. Figure 12 shows that the NK model over-predicts the observed variance of inflation and output, while the NK-LC model closely tracks the data.

6.3 Dampening of Monetary Transmission

The effect of lending complementarities on monetary transmission can be vividly seen Figure 13, which compares the impulse response functions of inflation and output to a

[15] Since μ is absent from the NK model, we use the NK-LC estimate for this parameter.

[16] Notice that the necessary and sufficient conditions for the uniqueness of equilibria are satisfied in both the NK and NK-LC models under this parametrization.

monetary policy shock in the standard NK model with those in the NK-LC model. When bank lending exhibits strategic complementarities, the impact of an increase in the policy rate has a muted effect on output and inflation relative to that in the NK model. Lending complementarities reduce monetary transmission to inflation and output by about a third under the baseline calibration.

This estimate is sensitive to model primitives. Table 10 measures the impact of the coordination channel on monetary transmission for various parameterizations by computing the percent reduction in the impulse of inflation/output to a monetary policy shock in the NK-LC model relative to that in the standard NK model. The coordination channel is highly elastic to the degree of price rigidity. Increasing the fraction of firms that can alter prices substantially reduces the effect of lending complementarities on monetary transmission. A moderate level of risk aversion also plays a crucial role in amplifying the coordination channel. In contrast, the parameters that govern the Taylor rule and the Frisch elasticity of labor supply have a modest impact on the coordination channel.

6.4 Interactions with Demand and Supply Shocks

Here we study how lending complementarities affect the relative contribution of demand and supply shocks in the determination of macroeconomic variables. As in Smets and Wouters (2007), we introduce demand and mark-up shock processes, which we denote by ϵ_t^D and ϵ_t^S respectively.[17] These shock processes are determined by $\epsilon_t^i = \rho^i \epsilon_{t-1}^i + \eta_t^i \quad \forall i \in \{D, S\}$. We set the persistence of demand and supply shocks (ρ^D and ρ^S) to 0.9.

Table 11 reports the variance decomposition of inflation, output, the policy rate, and the lending rate under the benchmark calibration. Lending complementarities have a marginal effect on shock contributions to output. In both the NK and NK-LC models, supply shocks explain about 94 percent of output variation. In contrast, the contribution of supply shocks to inflation increases by about 2 percent when we introduce lending complementarities. The effect of supply shocks on interest rates is also substantially larger in the NK-LC model relative to that in the NK model.

7 Conclusion

In this paper, we argue that the lack of coordination in multiple banking relationships dampens monetary transmission. When credit is uncoordinated, informational frictions reduce monetary transmission further. We test these predictions using bank-level data

[17] The modified NK Phillips' Curve is given by $\hat{\pi}_t = \beta \mathbb{E}_t[\hat{\pi}_{t+1}] + \kappa \hat{y}_t + \epsilon_t^S$, and the modified IS Curve is given by $\hat{y}_t = \mathbb{E}_t[\hat{y}_{t+1}] - \frac{1}{\gamma}(\hat{r}_t - \mathbb{E}_t[\hat{\pi}_{t+1}]) + \epsilon_t^D$.

from India. We show that the impact of policy rate changes on lending rates reduces significantly when the expected cost of credit extended by other banks is higher, and when this signal is less precise. In the model, as in the data, lack of coordination and information sharing across banks have persistent effects on monetary transmission.

There are several aspects of multiple banking that make it beneficial for financial stability. Multiple banking relationships help insure against bank distress (Detragiache et al., 2000) and alleviate a soft-budget constraint problem (Kornai, 1980; Dewatripont and Maskin, 1995). These are relevant concerns for policymakers, as evidenced by the recent release of a prudential framework by the RBI, which warned lenders with intent to evergreen stressed accounts.[18] Our work, in contrast, focuses on an under-appreciated cost of multiple banking. We show that such relationships can blunt the impact of monetary policy. In doing so, our analysis highlights a tradeoff between financial stability and macroeconomic stability.

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Appendix

A Proofs

Proof of Proposition 1: As derived in the proof of Proposition 2, in a symmetric uncoordinated lending equilibrium:

$$p_t L_t^{1-\mu} = \frac{R_t \alpha(\mu + N)}{N^{1-\mu}}. \tag{10}$$

Furthermore, suppose that savings is a fixed fraction of output,

$$B_t = \Lambda Y_t, \text{where } \Lambda > 0. \tag{11}$$

Substituting (11) and (1) in (10), we arrive at:

$$R_t = \frac{p_t (Y_t)^{1-\mu} (\Lambda N)^{1-\mu}}{\alpha(\mu + N)}$$

Log-linearizing around steady states:

$$\hat{r}_t = \hat{p}_t + (1-\mu)\hat{y}_t. \square$$

Proof of Proposition 2: As banks solve a static problem, we suppress the time notation. If banks are uncoordinated, then each bank i maximizes the following objective:

$$(\sum_{j \neq i} L_j + L_i)^{\mu} L_i R_i - \frac{L_i^2 p}{2\alpha}$$

The first order condition of this problem can be rearranged to yield:

$$R_i \left[\mu (\sum_{j \neq i} L_j + L_i)^{\mu - 1} L_i + (\sum_{j \neq i} L_j + L_i)^{\mu} \right] = \frac{L_i p}{\alpha}$$

In symmetric equilibria, $L_j = L_i \equiv L$. Thus,

$$L = \left[\frac{R\alpha(\mu + N)}{N^{1-\mu} p} \right]^{\frac{1}{1-\mu}}$$

$$\implies \frac{\partial L_{\text{Uncoordinated}}}{\partial p} = -\left[\frac{R\alpha(\mu + N)}{N^{1-\mu}} \right]^{\frac{1}{1-\mu}} \left(\frac{1}{1-\mu} \right) p^{\frac{\mu}{\mu - 1}}$$

We now consider the case when banks coordinate lending. In this case, banks choose L to maximize:

$$N^{\mu}L^{\mu+1}R - \frac{L^2 p}{2\alpha}$$

The first order condition of this problem can be rearranged to yield:

$$L = \left[\frac{R\alpha N^{\mu}(\mu+1)}{p}\right]^{\frac{1}{1-\mu}}$$

$$\implies \frac{\partial L_{\text{Coordinated}}}{\partial p} = -\left[R\alpha N^{\mu}(\mu+1)\right]^{\frac{1}{1-\mu}}\left(\frac{1}{1-\mu}\right)p^{\frac{\mu}{\mu-1}}$$

As $\mu > 0$ and $N > 1$, $\mid \frac{\partial L}{\partial p} \mid$ is larger when banks coordinate, which completes the proof for part (i). To see part (ii), let $\mathcal{D} \equiv \mid \partial L_{\text{Coordinated}}/\partial p \mid - \mid \partial L_{\text{Uncoordinated}}/\partial p \mid$. Partially differentiating this expression w.r.t. N:

$$\frac{\partial \mathcal{D}}{\partial N} = \left(\frac{1}{1-\mu}\right)^2 p^{\frac{\mu}{\mu-1}}\left[R\alpha\mu\right]^{\frac{1}{1-\mu}}(N^{\mu} - N^{\mu-1})^{\frac{\mu}{1-\mu}}N^{\mu-2}(\mu(N-1)+1) > 0. \square$$

Proof of Proposition 3: Under incomplete information, the optimal choice of lending satisfies the first order condition:

$$R_i\left(\frac{L_j\sigma_p^2}{\sigma^2+\sigma_p^2} + 2L_i\right) = c_L(L_i, p).$$

Since banks are atomistic, they treat the interest rate as fixed when making their lending decision. In this case, an increase in the policy rate (p) reduces lending (assuming R is small). Therefore, a necessary condition for the optimality of bank i's lending decision under the special case for the cost function is:

$$L_i = \frac{L_j\sigma_p^2}{(\sigma^2+\sigma_p^2)(p/(R_i\alpha)-2)}$$

Differentiating the above expression with respect to the policy rate yields the following result:

$$\frac{\partial L_i}{\partial p} = -\frac{L_j\sigma_p^2}{R_i(\sigma^2+\sigma_p^2)(p/(R_i\alpha)-2)^2}.$$

All parts of the proposition immediately follow from this result. $\square$

Proof of Proposition 4: Bank i solves the following problem:

$$\sum_{j=1}^{M} R_{ji} \sum_{k=1}^{N} L_{jk} L_{ji} - \frac{(\sum_{j=1}^{M} L_{ji})^2 p}{2\alpha}$$

Thus, a necessary condition for optimality of loan by bank i to firm j is:

$$F_{ji} \equiv \sum_{k=1}^{N} L_{jk} + L_{ji} - \sum_{l=1}^{M} L_{li} p/(R_{ji}\alpha) = 0 \quad \forall i\, \forall j$$

Totally differentiating this expression

$$0 = \frac{\partial F_{ji}}{\partial p} dp + \sum_{l=1}^{M} \sum_{k=1}^{N} \frac{\partial F_{ji}}{\partial L_{lk}} dL_{lk} \implies \frac{dL_{ji}}{dp} = \frac{1}{\hat{R}_{ji}^{-1} - 2\alpha_i} \left\{ \alpha \sum_{k \neq i} \frac{dL_{jk}}{dp} - \hat{R}_{ji}^{-1} \sum_{l \neq j} \frac{dL_{li}}{dp} - \sum_{l=1}^{M} L_{li} \right\} \quad \forall i\, \forall j. \quad \square$$

Proof of Proposition 5: The dynamic system featuring lending complementarities can be written as

$$\begin{bmatrix} \hat{y}_t \\ \hat{\pi}_t \end{bmatrix} = \Omega \begin{bmatrix} \gamma & 1 - \beta\phi^{\pi} \\ \kappa\gamma & \kappa + \beta(\gamma + \phi^y + 1 - \mu) \end{bmatrix} \begin{bmatrix} \mathbb{E}_t[\hat{y}_{t+1}] \\ \mathbb{E}_t[\hat{\pi}_{t+1}] \end{bmatrix} + \Omega \begin{bmatrix} 1 \\ \kappa \end{bmatrix} \epsilon_t^p$$

where

$$\Omega \equiv \frac{1}{\gamma + \phi^y + \kappa\phi^{\pi} + 1 - \mu}.$$

Since both $\hat{y}_t$ and $\hat{\pi}_t$ are free, determinacy of the system hinges on both the eigenvalues of

$$\Omega \begin{bmatrix} \gamma & 1 - \beta\phi^{\pi} \\ \kappa\gamma & \kappa + \beta(\gamma + \phi^y + 1 - \mu) \end{bmatrix}$$

being less than unity. The associated characteristic polynomial is given by

$$\lambda^2 - \lambda\Omega[\gamma + \kappa + \beta(\gamma + \phi^y + 1 - \mu)] + \Omega\gamma\beta = 0,$$

where λ denotes the eigenvalues. Thus, both eigenvalues are less than unity if

$$\Omega\gamma\beta < 1 \tag{12}$$

and

$$\Omega[\gamma + \kappa + \beta(\gamma + \phi^y + 1 - \mu)] < 1 + \Omega\gamma\beta. \tag{13}$$

Equation (12) holds as $\beta \in (0, 1)$. Equation (13) holds if $\kappa(\phi^{\pi} - 1) + (1 - \beta)(\phi^y + 1 - \mu) > 0$. $\square$

B Figures and Tables

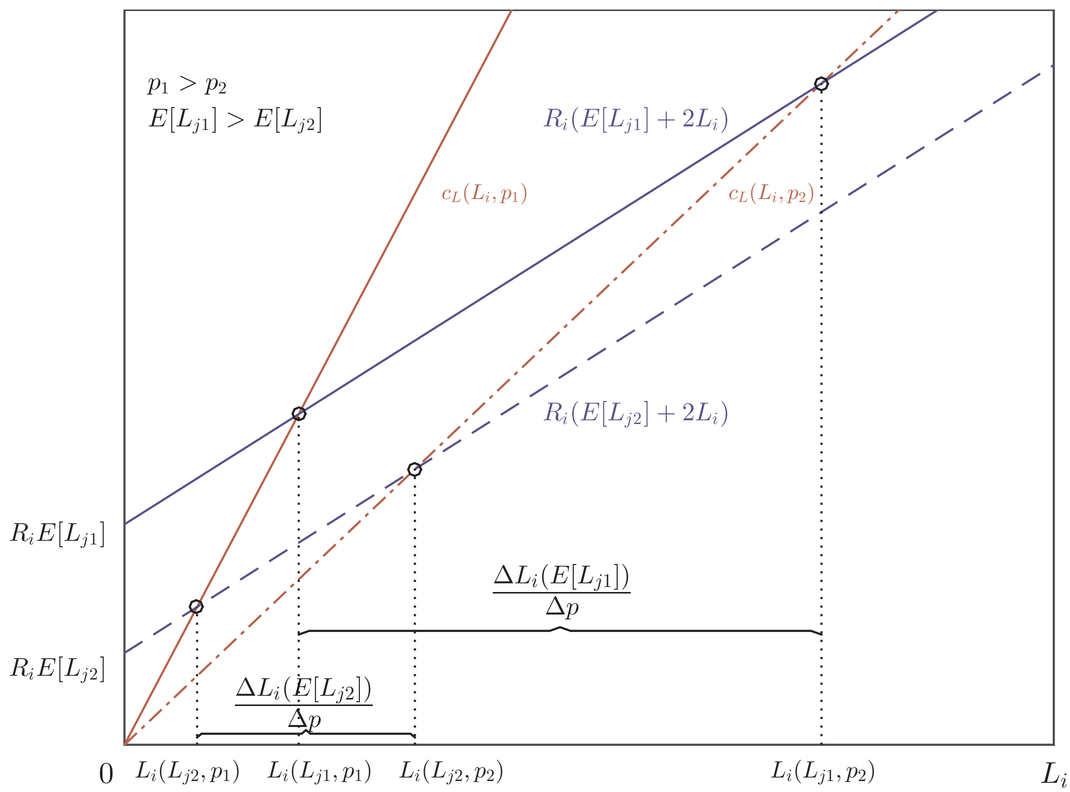
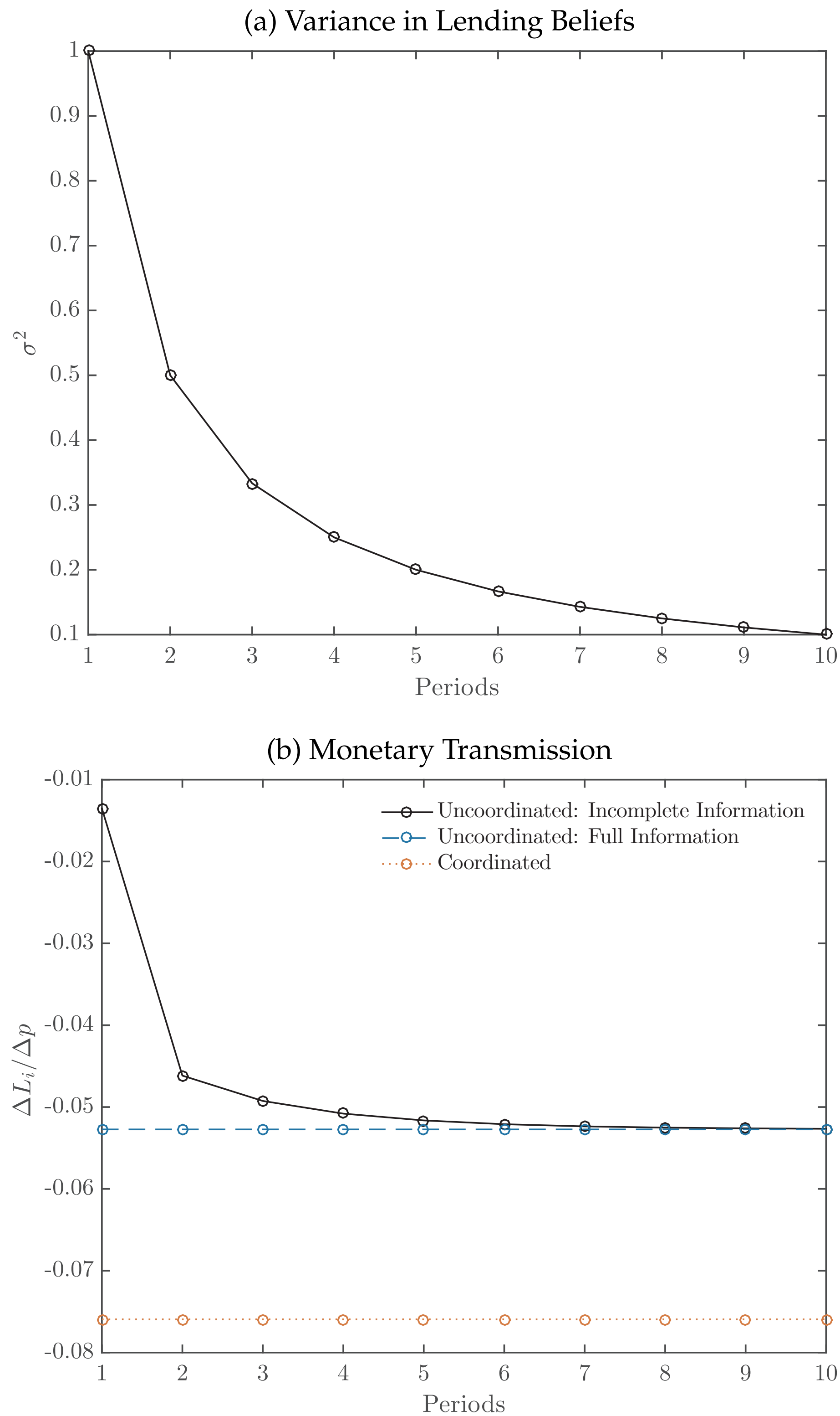


Figure 1: Illustration of Dependence of Monetary Transmission on Lending Moments



Notes: The prior mean of lending of other banks in the incomplete information case is set to the full information level in the uncoordinated equilibrium. We assume unit variance in the noise. We compute the change in lending in response to a change in the policy rate from 1 percent to 2 percent. The lending rate is fixed at one for this exercise. α is set to 0.15 for this exercise which satisfies Assumption 2.

Figure 2: The Effect of Coordination and Information on Monetary Transmission

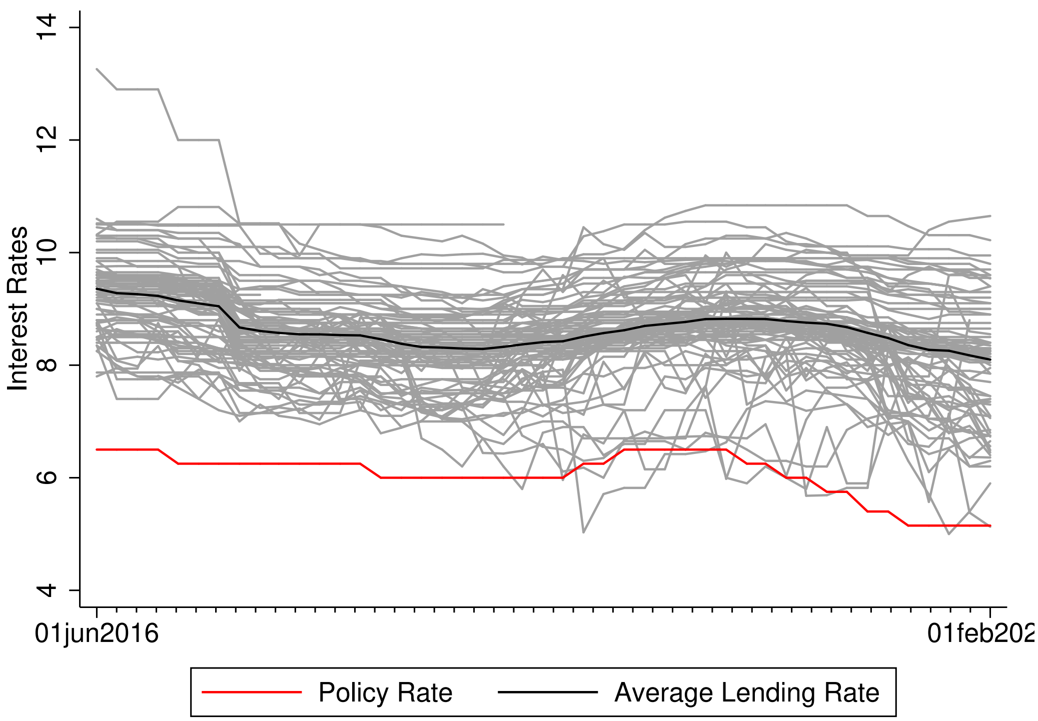
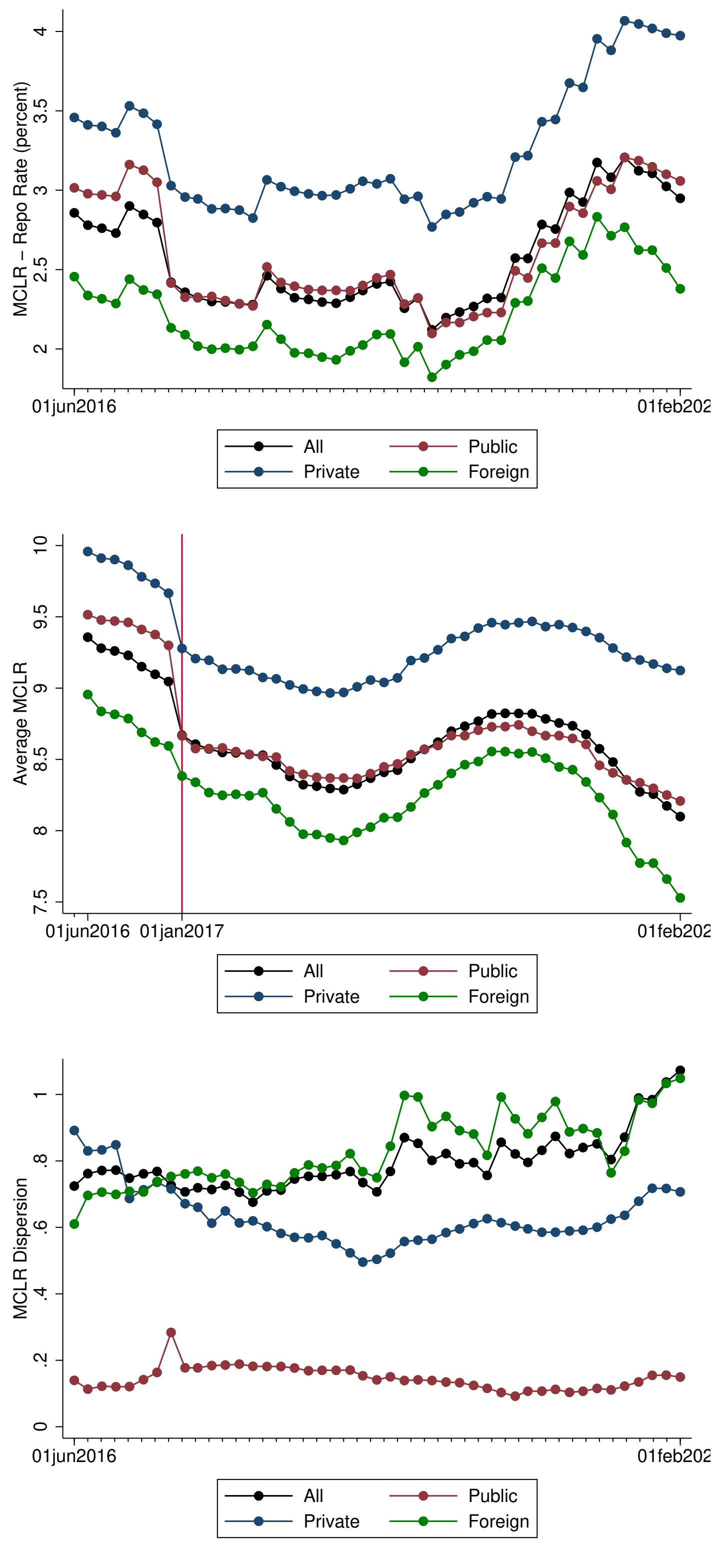


Figure 3: Bank Lending Rates and Policy Rate



Notes: The first plot depicts the wedge between commercial bank lending rates (i.e., MCLR) and the central bank policy rate (i.e., Repo rate). The second and third plots depict the cross-sectional mean and dispersion of commercial bank lending rates.

Figure 4: Aggregate Time Series

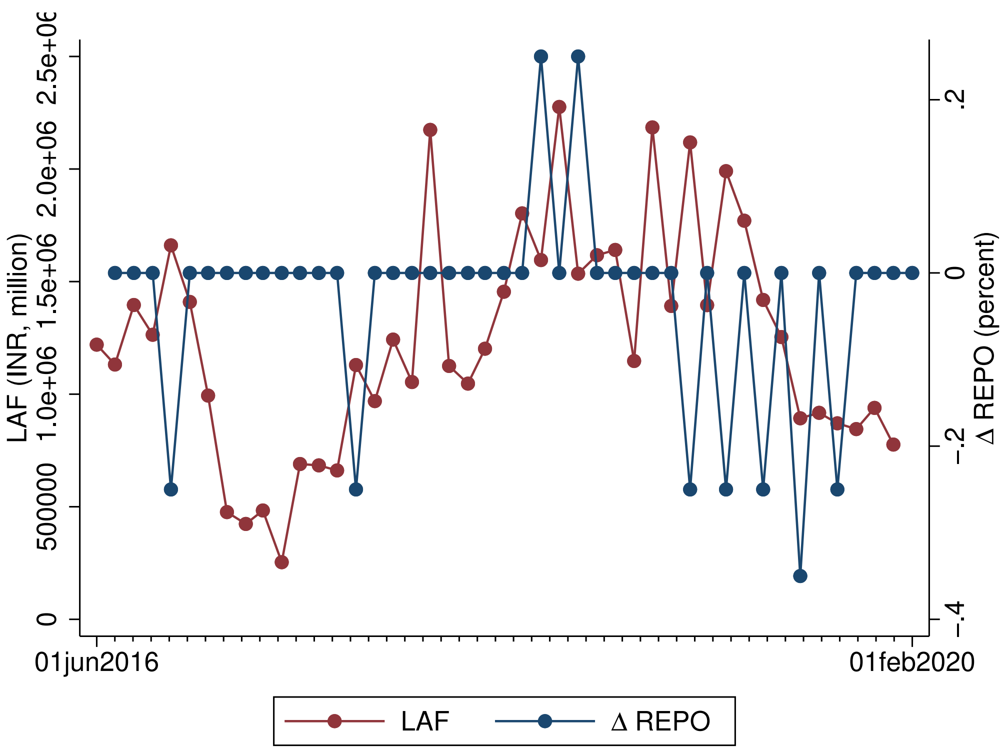
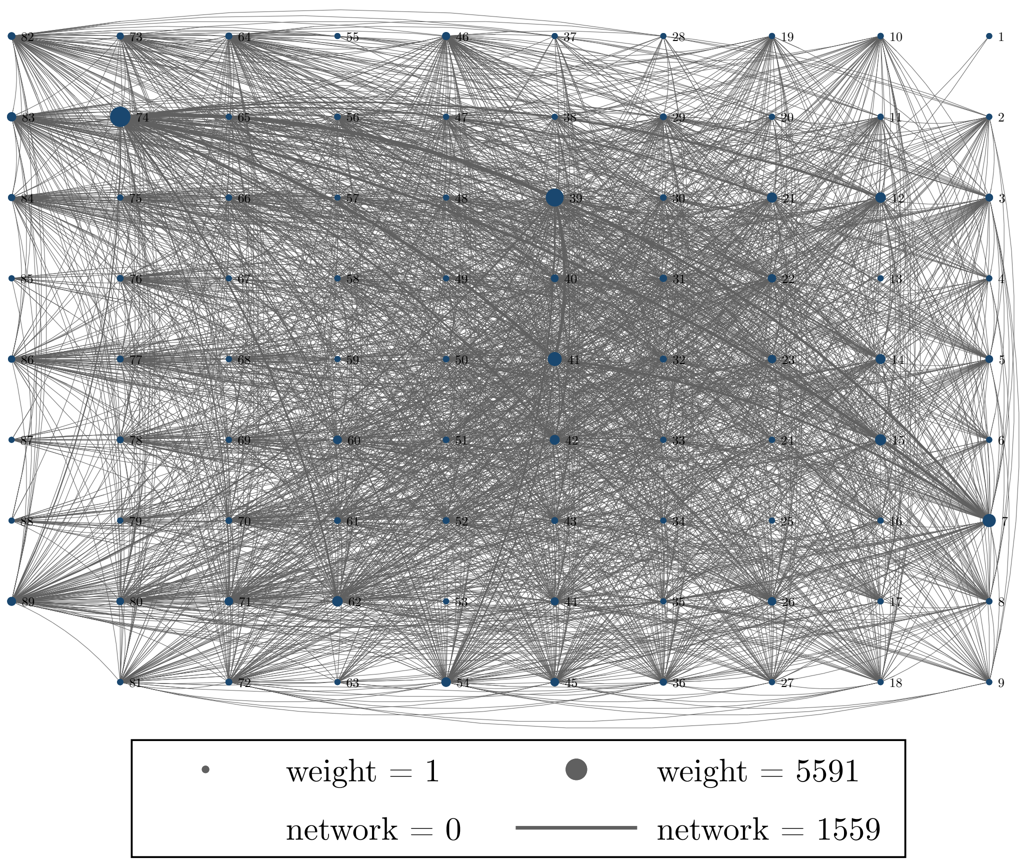


Figure 5: LAF Bids Received

Figure 6: Distribution of Number of (Bank) Credit Relationships of Firms



Notes: Each node represents a bank. The weight of each node represents the number of firm relationships of the respective bank. An edge between two nodes represents that there exists at least one firm that the two respective banks lend to. The width of the edge represents the number of such firms. The numbers associated with each node correspond to bank identifiers (see Table 1).

Figure 7: Multiple Banking Network in India

Table 1: Summary Statistics

Public Sector Banks	Bank ID	No. of Firm Credit Rel.	Degree Centrality	Eigenvector Centrality	Mean MCLR	S.D. MCLR	Corr(MCLR, REPO)
Allahabad Bank*	3	642	74	0.13	8.63	0.41	0.50
Andhra Bank*	5	649	68	0.12	8.70	0.39	0.60
Bank of Baroda*	12	1681	79	0.14	8.57	0.36	0.50
Bank of India*	14	1474	78	0.13	8.60	0.36	0.58
Bank of Maharashtra*	15	1944	68	0.12	8.80	0.37	0.65
Bhartiya Mahila Bank					9.02	0.42	0.58
Canara Bank*	21	1569	76	0.13	8.60	0.34	0.51
Central Bank of India*	22	900	80	0.13	8.57	0.38	0.61
Corporation Bank*	26	912	79	0.14	8.88	0.30	0.62
Dena Bank*	31	466	69	0.12	8.70	0.43	0.61
IDBI Bank*	42	1453	83	0.14	8.85	0.30	0.68
Indian Bank*	44	735	69	0.13	8.64	0.36	0.54
Indian Overseas Bank*	45	958	73	0.13	8.73	0.37	0.49
Oriental Bank of Commerce*	60	1012	75	0.13	8.68	0.39	0.59
Punjab and Sind Bank*	61	226	62	0.12	8.78	0.38	0.56
Punjab National Bank*	62	1700	79	0.14	8.49	0.38	0.56
State Bank of Bikaner and Jaipur*	72	283	59	0.11	9.27	0.39	0.62
State Bank of Hyderabad*	73	397	61	0.12	9.30	0.39	0.67
State Bank of India*	74	5591	83	0.14	8.31	0.39	0.52
State Bank of Mysore*	76	243	58	0.11	9.26	0.34	0.60
State Bank of Patiala*	77	271	59	0.11	9.04	0.54	0.73
State Bank of Travancore*	78	307	59	0.11	9.36	0.46	0.57
Syndicate Bank*	80	595	73	0.13	8.71	0.39	0.66
UCO Bank*	82	595	73	0.13	8.68	0.36	0.55
Union Bank of India*	83	1245	78	0.13	8.57	0.39	0.57
United Bank of India*	84	395	68	0.12	8.81	0.31	0.71
Vijaya Bank*	86	439	67	0.12	8.78	0.36	0.53

Private Sector Banks	Bank ID	No. of Firm Credit Rel.	Degree Centrality	Eigenvector Centrality	Mean MCLR	S.D. MCLR	Corr(MCLR, REPO)
Axis Bank Ltd.*	7	2753	79	0.14	8.58	0.36	0.54
Bandhan Bank Ltd.	9	24	36	0.07	10.61	0.90	0.51
Catholic Syrian Bank Ltd.	19	64	50	0.10	9.93	0.12	0.40
City Union Bank Ltd.	24	95	45	0.09	9.33	0.29	0.62
Development Credit Bank Ltd.*	30	148	65	0.12	10.28	0.41	0.03
Dhanalaxmi Bank Ltd.	33	69	58	0.11	9.90	0.23	0.33
Federal Bank Ltd.*	36	399	71	0.13	9.09	0.21	0.54
HDFC Bank Ltd.*	39	4645	82	0.14	8.47	0.33	0.40
ICICI Bank Ltd.*	41	3060	80	0.14	8.51	0.32	0.38
IDBI Bank*	42	1453	83	0.14	8.85	0.17	0.91
IDFC Bank Ltd*	43	237	72	0.13	9.04	0.35	-0.18
Indusind Bank*	46	754	77	0.13	9.44	0.34	0.22
Jammu and Kashmir Bank Ltd.*	50	158	71	0.13	8.88	0.27	0.65
Karnataka Bank Ltd.*	51	183	54	0.10	9.06	0.21	-0.26
Karur Vysya Bank Ltd.*	52	270	64	0.12	9.48	0.31	0.36
Kotak Mahindra Bank*	54	1354	77	0.13	8.88	0.33	0.69
Laxmi Vilas Bank Ltd.*	56	147	58	0.11	9.85	0.39	-0.25
Nainital Bank	59	10	25	0.05	8.52	0.27	0.53
RBL Bank*	64	331	72	0.13	9.83	0.36	0.33
South Indian Bank Ltd.*	70	207	63	0.12	9.29	0.30	0.42
Tamilnad Mercantile Bank Ltd.*	81	91	54	0.10	9.33	0.39	0.42
Yes Bank Ltd.*	89	1130	78	0.13	9.35	0.39	-0.21

Foreign Banks	Bank ID	No. of Firm Credit Rel.	Degree Centrality	Eigenvector Centrality	Mean MCLR	S.D. MCLR	Corr(MCLR, REPO)
AB Bank Ltd.	1	1	2	0.00	7.14	0.66	0.18
Abu Dhabi Commercial Bank Ltd.	2	15	44	0.09	9.15	0.50	-0.21
American Express Banking Corporation	4	41	40	0.08	6.96	0.77	0.22
Australia and NZ Banking Group Ltd.	6	3	34	0.07	7.94	0.63	0.74
Bank International Indonesia					9.37	0.31	0.34
Bank of Bahrain and Kuwait	11	46	58	0.11	8.60	0.41	0.42
Bank of America	10	99	57	0.11	7.95	0.50	0.45
Bank of Ceylon	13	4	5	0.01	10.02	0.33	0.50
Bank of Nova Scotia	16	48	50	0.09	8.14	0.55	0.50
Bank of Tokyo Mits UFJ Ltd.	17	34	54	0.10	7.31	0.39	0.69
Barclays Bank	18	40	63	0.12	8.19	0.51	0.48
BNP Paribas	8	133	67	0.12	8.57	0.57	0.79
Citi Bank*	23	899	78	0.13	8.29	0.29	0.25
Commonwealth Bank of Australia	25	1	3	0.01	9.27	0.09	0.22
Credit Agricole Corp. & Investment Bank	27	35	50	0.10	7.86	0.53	0.82
Credit Suisse AG Bank	28	1	12	0.02	7.66	0.45	0.37
CTBC Bank Co.Ltd	20	13	36	0.07	7.91	0.54	0.68
Deutsche Bank*	32	311	72	0.13	9.56	0.48	0.34
Development Bank of Singapore*	29	246	76	0.13	8.51	0.30	0.63
Doha Bank QSC	34	6	37	0.07	8.60	0.35	0.30
Emirates NBD Bank (P.J.S.C)	35	6	36	0.07	8.31	0.36	0.73
First Abu Dhabi Bank PJSC	37	1	15	0.03	7.46	0.86	0.48
Firstrand Bank Ltd	38	6	34	0.07	8.71	0.41	0.47
Hongkong & Shanghai Bkg. Corpn*	40	629	77	0.13	8.43	0.37	0.15
Industrial and Commercial Bank of China	47	10	51	0.10	8.60	0.69	0.85
Industrial Bank of Korea					7.00	1.03	0.58
JP Morgan Chase Bank	48	38	52	0.10	8.49	0.67	0.75
JSC VTB Bank	49	2	35	0.07	10.50	0.00	
KEB Hana Bank	53	1	0		8.39	0.12	0.40
Kookmin Bank					6.37	0.01	
Krung Thai Bank PCL	55	1	1	0.00	8.23	0.24	0.32
Mashreq Bank	57	9	43	0.09	8.01	0.59	0.26
Mizuho Corporate Bank	58	55	49	0.09	7.92	0.48	0.64
National Australia Bank					8.23	0.68	0.01
Qatar National Bank S.A.Q	63	3	18	0.04	7.83	0.40	0.38
Rabobank International	65	15	35	0.07	8.16	0.48	0.45
Sber Bank	67	2	8	0.02	8.69	0.58	0.68
Shinhan Bank	68	24	38	0.08	8.31	0.22	0.11
Societe Generale	69	27	44	0.08	8.16	0.41	0.63
Sonali Bank Ltd.					7.22	0.82	0.12
Standard Chartered Bank*	71	959	79	0.14	9.07	0.33	-0.05
State Bank of Mauritius	75	22	54	0.10	9.28	0.66	0.36
Sumitomo Mitsui Banking Corporation	79	31	30	0.06	7.58	0.63	0.80
The Royal Bank of Scotland	66	147	53	0.10	7.52	0.95	0.07
United Overseas Bank	85	1	11	0.02	8.52	0.71	0.83
Westpac Banking Corporation	87	1	14	0.03	8.73	0.18	0.13
Woori Bank	88	3	22	0.04	8.24	0.42	0.03

Notes: * indicates the set of core banks; the details of arriving at this set are provided in Section 5.2.6. The CMIE sample does not report any bank-firm lending relationships for Bhartiya Mahila Bank, Bank International Indonesia, Industrial Bank of Korea, Kookmin Bank, National Australia Bank, and Sonali Bank Ltd. The RBI started to categorize IDBI Bank as a 'Private Sector Bank' for regulatory purposes with effect from January 21, 2019; IDBI Bank was categorized as a 'Public Sector Bank' in prior periods.

Table 2: Aggregate Estimates: Effect of Lending Rate Moments on Monetary Transmission

	All Banks$^{\diamond}$	All Banks*	Private Banks	Other Banks
Average Lending Rate	0.693***	0.221*	-0.0410	0.0970
	(0.132)	(0.120)	(0.322)	(0.165)
Lending Rate Dispersion	2.497***	2.446***	2.276*	1.247**
	(0.410)	(0.324)	(1.133)	(0.520)
Time Deposit Share	-0.272	7.124	-5.916	9.181*
	(5.783)	(4.632)	(8.069)	(5.204)
Consistency in Monetary Stance	-0.118	0.0360	0.0257	0.0347
	(0.113)	(0.0993)	(0.130)	(0.109)
SLR (first diff.)	-0.206	-0.208	-0.144	-0.233
	(0.286)	(0.232)	(0.467)	(0.273)
Observations	44	44	44	44
Adjusted R^2	0.330	0.372	0.070	0.058

Notes: This table reports OLS estimates from specification (5). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $\diamond$ and $\star$ denote weighted and unweighted estimates respectively. Other banks include public banks and foreign banks.

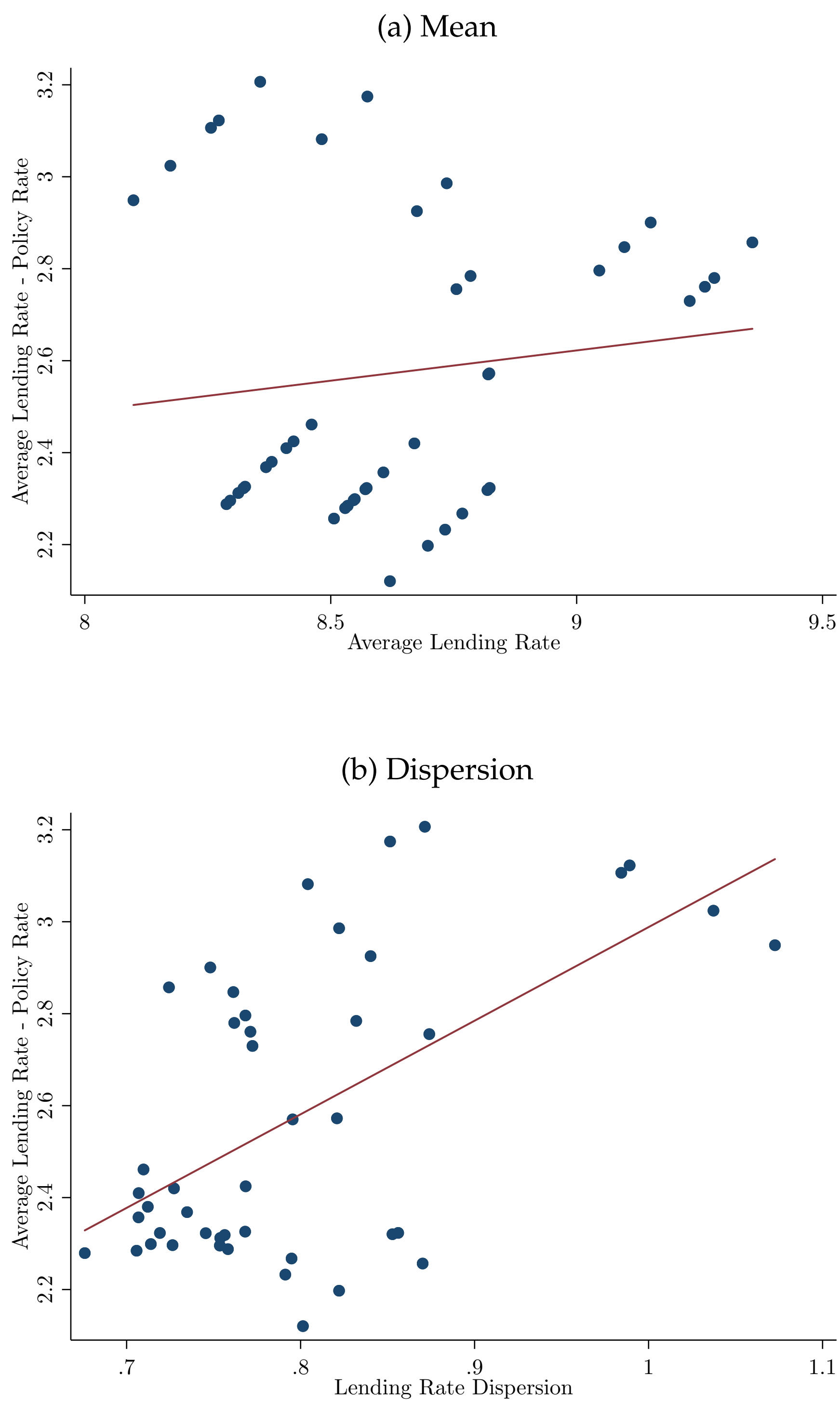


Figure 8: Relationship between Lending Rate Moments and Monetary Transmission at Aggregate Level

Table 3: Effect of Lending Moments on Monetary Transmission

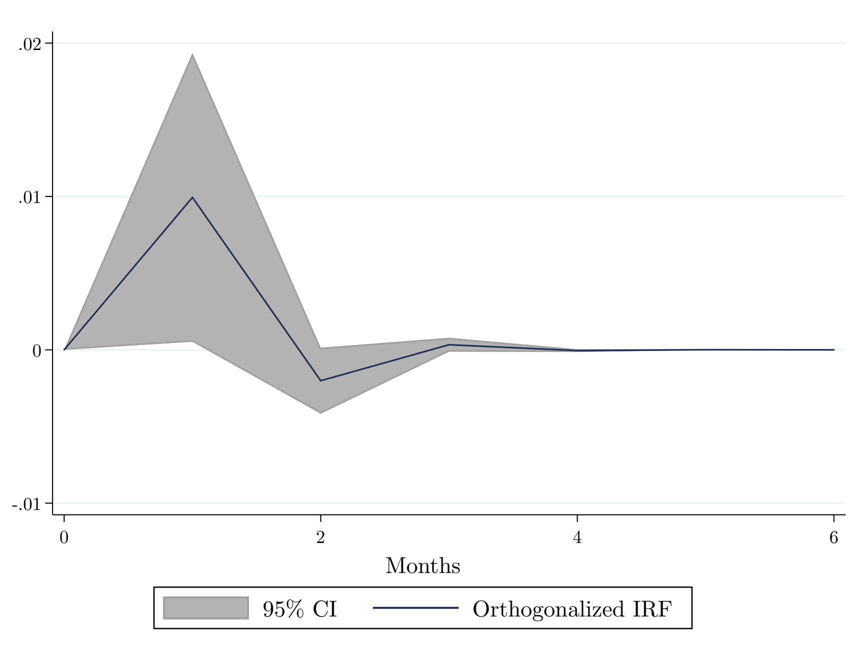
	MT	*MT*	*MT*	*MT*
Panel A: 100% Network Density				
Average Lending Rate	0.285***	0.307***	0.345***	0.274***
	(0.0418)	(0.0211)	(0.0249)	(0.0308)
Lending Rate Dispersion	2.373***	2.575***	2.285***	1.979***
	(0.175)	(0.0848)	(0.132)	(0.148)
Observations	3901	3901	3901	3811
Panel B: Degree Centrality				
$\mathcal{C}\times$ Average Lending Rate	-0.00162***	0.00448***	0.00550***	0.00383***
	(0.000220)	(0.000299)	(0.000321)	(0.000393)
$\mathcal{C}\times$ Lending Rate Dispersion	0.0288***	0.0449***	0.0360***	0.0341***
	(0.00242)	(0.00140)	(0.00161)	(0.00170)
Observations	3664	3664	3664	3580
Panel C: Eigenvector Centrality				
$\mathcal{C}\times$ Average Lending Rate	-0.838***	2.524***	3.166***	2.206***
	(0.127)	(0.170)	(0.183)	(0.225)
$\mathcal{C}\times$ Lending Rate Dispersion	16.23***	25.13***	20.08***	19.10***
	(1.395)	(0.799)	(0.924)	(0.984)
Observations	3664	3664	3664	3580
Bank FE	N	Y	Y	Y
Bank-Month FE	N	N	Y	Y
Deposit Maturity Controls	N	N	N	Y
Monetary Stance Controls	N	N	N	Y
SLR Controls	N	N	N	Y

Notes: This table reports OLS estimates from specification (6). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The variables capturing the mean and dispersion of lending rates for bank i are over the subsample of all banks $j \neq i$. In panel A, we assume that all banks are connected and the density of the network is 100 percent. In panels B and C, we respectively use the observed degree and eigenvector centrality of the multiple banking network to measure exposure to lending beliefs. Banks that do have any recorded lending history to non-financial firms in the CMIE data, and banks with zero network degree centrality are excluded from the sample in panels B and C.

Table 4: Alternate Specification: Effect of Lending Moments on Monetary Transmission

	$\Delta MCLR$	$\Delta MCLR$	$\Delta MCLR$	$\Delta MCLR$
Panel A: 100% Network Density				
$\Delta REPO \times LAF$	3.283***	3.394***	3.037**	4.109***
	(1.228)	(1.231)	(1.247)	(1.284)
$\Delta REPO \times LAF \times$ Average Lending Rate	-0.368***	-0.385***	-0.405***	-0.527***
	(0.118)	(0.118)	(0.121)	(0.126)
$\Delta REPO \times LAF \times$ Lending Rate Dispersion	0.0814	0.119	0.797	0.711
	(0.465)	(0.469)	(0.487)	(0.518)
Observations	3722	3722	3722	3722
Panel B: Degree Centrality				
$\Delta REPO \times LAF$	0.275***	0.275**	0.282**	0.235**
	(0.106)	(0.107)	(0.113)	(0.115)
$\Delta REPO \times LAF \times \mathcal{C} \times$ Average Lending Rate	-0.00331***	-0.00331***	-0.00349***	-0.00298***
	(0.000484)	(0.000493)	(0.000510)	(0.000508)
$\Delta REPO \times LAF \times \mathcal{C} \times$ Lending Rate Dispersion	0.0346***	0.0347***	0.0368***	0.0309***
	(0.00538)	(0.00544)	(0.00559)	(0.00564)
Observations	3498	3498	3498	3498
Panel C: Eigenvector Centrality				
$\Delta REPO \times LAF$	0.289**	0.290**	0.296**	0.250**
	(0.115)	(0.115)	(0.121)	(0.124)
$\Delta REPO \times LAF \times \mathcal{C} \times$ Average Lending Rate	-1.848***	-1.856***	-1.954***	-1.666***
	(0.282)	(0.287)	(0.297)	(0.296)
$\Delta REPO \times LAF \times \mathcal{C} \times$ Lending Rate Dispersion	19.20***	19.27***	20.47***	17.12***
	(3.148)	(3.181)	(3.271)	(3.297)
Observations	3498	3498	3498	3498
Bank FE	N	Y	Y	Y
Bank-Month FE	N	N	Y	Y
Deposit Maturity Controls	N	N	N	Y
Monetary Stance Controls	N	N	N	Y
SLR Controls	N	N	N	Y

Notes: This table reports OLS estimates from specification (7). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The variables capturing the mean and dispersion of lending rates for bank i are over the subsample of all banks $j \neq i$. In panel A, we assume that all banks are connected and the density of the network is 100 percent. In panels B and C, we respectively use the observed degree and eigenvector centrality of the multiple banking network to measure exposure to lending beliefs. Banks that do have any recorded lending history to non-financial firms in the CMIE data, and banks with zero network degree centrality are excluded from the sample in panels B and C.



Notes: This plot depicts the impulse response function $\Delta MCLR$ to $\Delta REPO \times LAF$ shock in the PVAR specification with ordering $[\Delta MCLR \quad \Delta REPO \times LAF]$.

Figure 9: PVAR Impulse Response Function: Response of $\Delta MCLR$ to $\Delta REPO$ Impulse w/o Lending Rate Moment Interactions

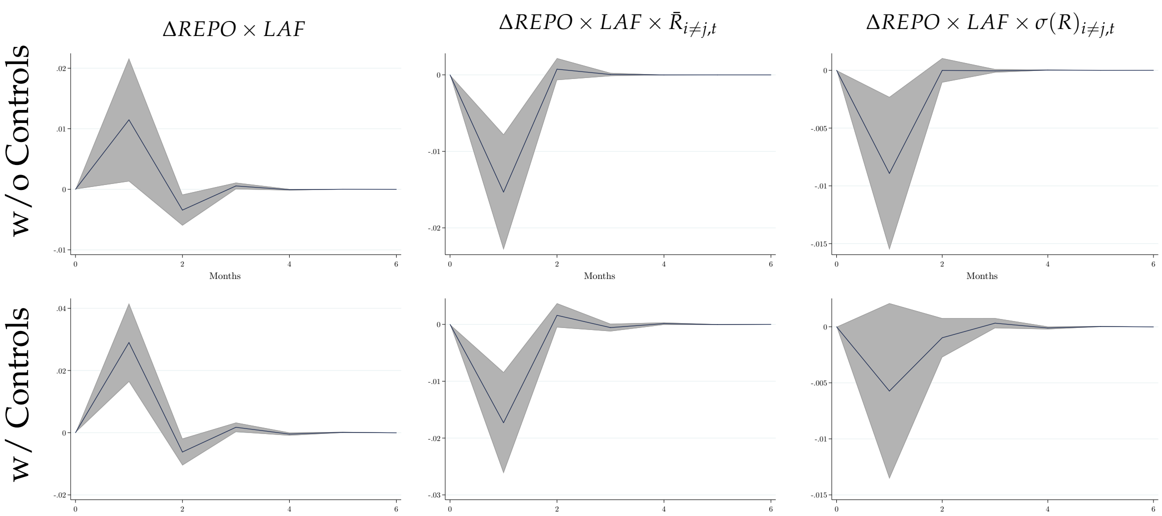
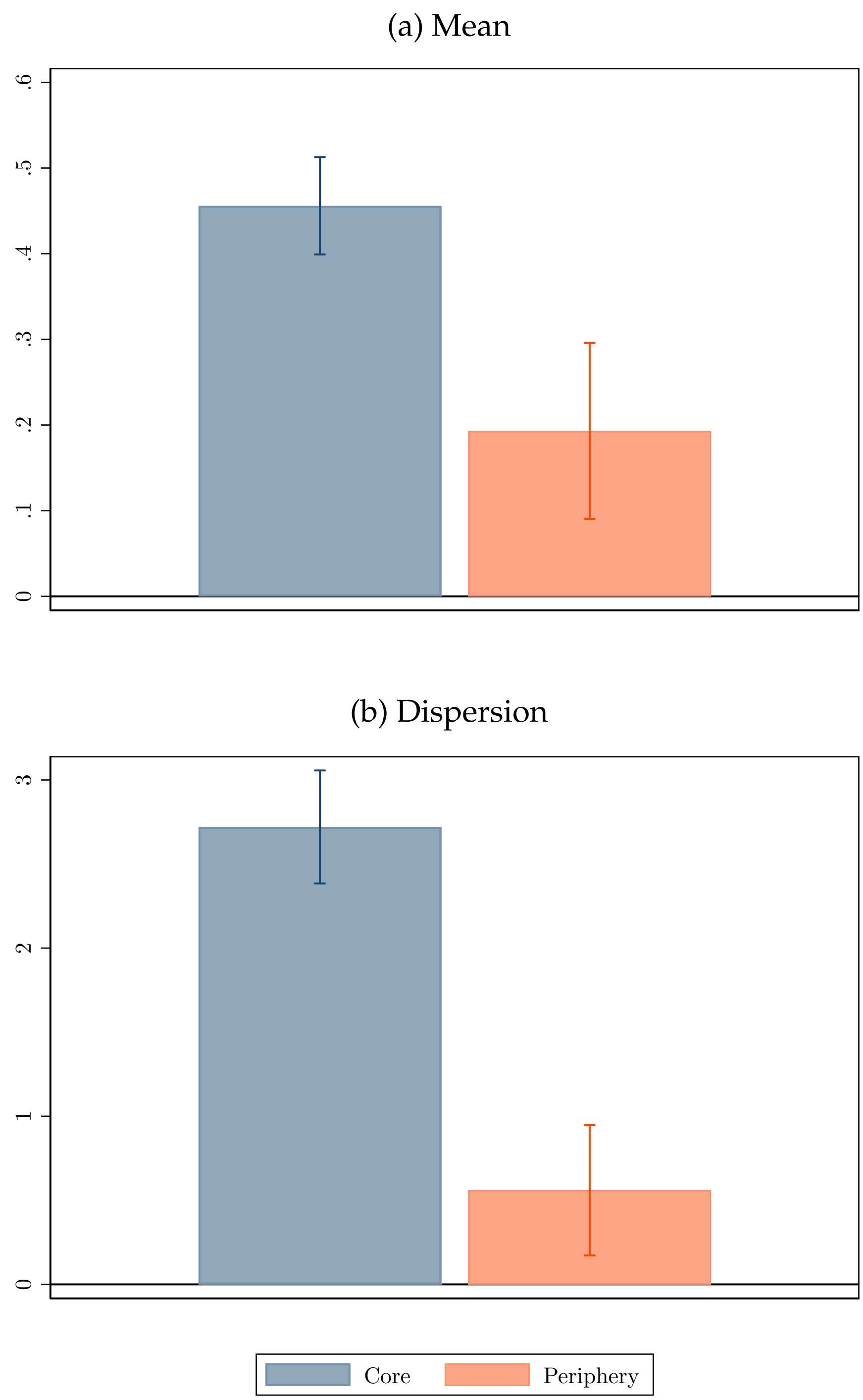


Figure 10: PVAR Impulse Response Function: Responses of $\Delta MCLR$ w/ Lending Rate Moment Interactions



Notes: These plots report OLS estimates and associated 95% confidence intervals from specification (6). The variables capturing the mean and dispersion of lending rates for bank i are over the subsample of all banks $j \neq i$ in the respective subgraphs of core and periphery banks, which we identify using a k-shell decomposition.

Figure 11: Effect between Lending Rate Moments and Monetary Transmission: Core vs. Periphery Banks

Table 5: Effect of Demonetization on Monetary Transmission

	$MCLR$	$MCLR$	$MCLR$
$REPO \times LAF$	0.0409***	0.0423***	0.0380***
	(0.00587)	(0.00297)	(0.00280)
$REPO \times LAF \times \mathbb{1}(D)$	-0.0217	-0.0102	0.852***
	(0.317)	(0.155)	(0.160)
$\mathbb{1}(D)$	0.184	0.109	-1.936***
	(0.739)	(0.361)	(0.374)
Bank FE	N	Y	Y
Deposit Maturity Controls	N	N	Y
Monetary Stance Controls	N	N	Y
SLR Controls	N	N	Y
Observations	3818	3818	3728

Notes: This table reports OLS estimates for specification (8). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effect of Lending Moments on Transmission to Inflation and Output

	π	π	$\dot{y}$	$\dot{y}$
$\Delta REPO \times LAF$	-0.0435***	-0.133***	-3.819***	-3.319***
	(0.00506)	(0.00377)	(0.0681)	(0.0769)
$\Delta REPO \times LAF \times$ Average Lending Rate	-0.000519	0.00738***	0.256***	0.208***
	(0.000529)	(0.000380)	(0.00653)	(0.00747)
$\Delta REPO \times LAF \times$ Lending Rate Dispersion	0.0634***	0.0925***	2.076***	1.948***
	(0.00190)	(0.00189)	(0.0343)	(0.0370)
Bank FE	Y	Y	Y	Y
Bank-Month FE	Y	Y	Y	Y
Deposit Maturity Controls	N	Y	N	Y
Monetary Stance Controls	N	Y	N	Y
SLR Controls	N	Y	N	Y
Exchange Rate Controls	N	Y	N	Y
Observations	3728	3728	3728	3728

Notes: This table reports OLS estimates for specification (9). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Prior and Posterior Distribution of Estimated Parameters

Parameter	Prior Mean	Post. Mean (NK)	Post. Mean (NK-LC)	Prior Dist.	Prior S.D.
γ	1	0.7962	1.3257	Normal	1
		(-1.2768, 3.0963)	(-0.1525,2.5421)		
φ	1	0.5029	0.8013	Normal	1
		(-1.4652, 2.4272)	(-0.9908,2.2513)		
θ	0.75	0.7132	0.8959	Normal	0.25
		(0.2712, 1.1195)	(0.6551,1.1674)		
μ	0.5		0.4386	Normal	0.25
			(0.0389, 0.8134)		
ϵ^p	0.05	0.0836	0.0711	Inverse Gamma	0.1
		(0.0425, 0.1311)	(0.0495, 0.0945)		

Notes: The range reported below the posterior mean refers to the 90% HPD interval.

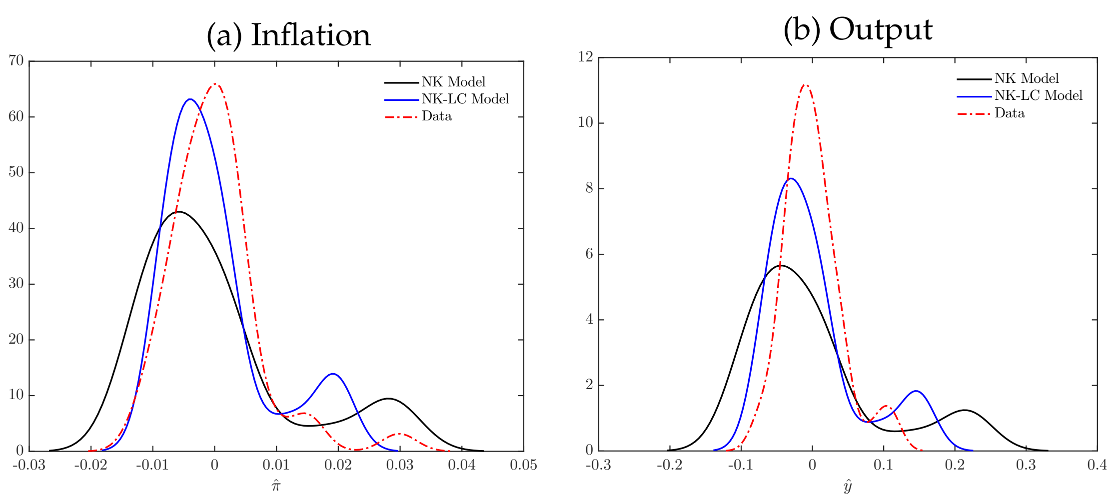
Table 8: Baseline Parameterization

Parameter	Value	Description
β	0.99	Rate of Time-preference
ϕ^π	1.4	Coefficient on Inflation in Taylor Rule
ϕ^y	0.43	Coefficient on Output in Taylor Rule
γ	1.06	Relative Risk Aversion
φ	0.65	Elasticity of Marginal Disutility w.r.t. Labor
θ	0.81	Probability of Retaining Old Price
μ	0.44	Curvature of Lending Complementarity
ρ	0	Persistence of Policy Rate
ρ^p	0.4	Persistence of Monetary Policy Shock
ϵ^p	0.08	Standard Error of Monetary Shock
Λ	1/3	Savings Rate

Table 9: Standard Deviation of Simulated Variables vs. Data

	Data	NK Model	NK-LC Model
Inflation ($\hat{\pi}$)	0.007	0.009	0.006
Output ($\hat{y}$)	0.04	0.07	0.05

Notes: The data moments correspond to HP-filtered log deviations from mean values. The simulated moments correspond to log deviations from steady states. Both the standard NK model as well as the model with lending complementarities (NK-LC) are simulated over 5000 periods with 100 replicas.

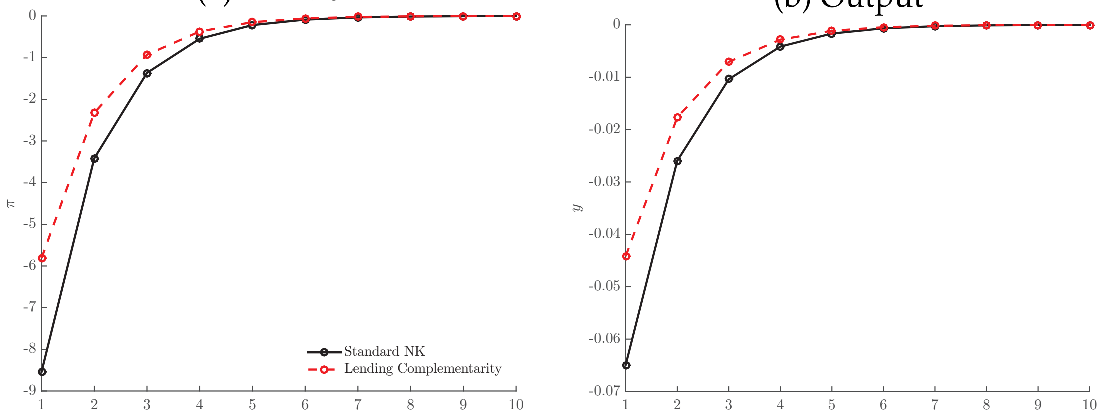


Notes: The data series correspond to log deviations from mean values. The cyclical components of inflation and output are extracted using an HP-filter. The simulated series correspond to log deviations from steady states. We simulate inflation and output in the NK and NK-LC model by feeding in the observed log deviations of the Repo rate from mean values.

Figure 12: Distributions of Inflation and Output: Model(s) vs. Data

(a) Inflation

(b) Output



Notes: The scale on the y-axis in plot (a) is 10^{-3}.

Figure 13: Impulse Responses to Monetary Policy Shock

Table 10: Sensitivity Analysis

Baseline	$\varphi = 2$	$\sigma = 2$	$\theta = 1/2$	$\phi^y = 1/4$	$\phi^\pi = 3$
0.3195	0.3147	0.2344	0.1836	0.3550	0.2853

Notes: This table reports the dampening of monetary transmission due to lending complementarities for various parameterizations as measured by the percent reduction in the impulse of inflation/output to a monetary policy shock in the NK-LC model relative to that in the standard NK model.

Table 11: Variance Decomposition (in percent)

	NK Model			NK-LC Model		
	Demand Shock	Supply Shock	Monetary Shock	Demand Shock	Supply Shock	Monetary Shock
Output	5.04	94.39	0.57	5.03	94.27	0.70
Inflation	2.45	97.54	0.01	0.59	99.40	0.00
Policy Rate	8.99	90.84	0.17	1.59	98.28	0.14
Lending Rate	8.99	90.84	0.17	4.77	95.17	0.06