Bank Coordination and Monetary Transmission: Evidence from India*

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Abstract

We propose and test a new channel for monetary transmission, the bank coordination channel. A bank's lending to a distressed firm responds more to policy rate cuts when other banks follow suit as the influx of external financing increases the firm's creditworthiness. More connected banks in the multiple banking network are more exposed to coordination failures and exhibit weaker transmission. We test these predictions using a difference-in-differences design and unique data that abstracts out demand-side factors. Network effects due to lending complementarities account for 65 percent of interest rate pass-through and decrease transmission to inflation and output by a third.

Keywords: Monetary transmission, creditor coordination, multiple banking network

JEL Classification Numbers: E43, E52, G21

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1 Introduction

Multiple banking is a standard feature of corporate lending. In these credit arrangements, banks connected through their exposure to common projects 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 failures among banks. For example, Radelet and Sachs (1998), Fischer (1999), and Bernanke (2018) argue that lender miscoordination was a key driver of the 1997-98 Asian financial crisis and the Global Financial Crisis of 2008-09. Despite the salience of this problem, it has received less attention from the literature on monetary transmission. This is surprising given that a large portion of this literature focuses on the bank lending channel (Bernanke and Blinder, 1988; Kashyap and Stein, 1995; Jiménez et al., 2012). This paper attempts to fill this gap in the literature. We develop a theoretical model and utilize a clean empirical setup for identification to show that coordination problems in multiple banking arrangements can substantially reduce the potency of monetary policy.

India provides a good setting to test this coordination channel. There is substantial heterogeneity in the number of cross-bank links implied by joint lending arrangements in India. This variation allows us to identify the coordination channel by comparing monetary transmission in more connected banks to that in less connected ones. Though our difference-in-differences strategy can account for observed and unobserved changes in aggregate demand at the macro-level, changes in borrower risk at the micro-level may still bias our results. Thus, a key identification challenge is disentangling borrower risk from credit supply. A recent change in the monetary policy framework of the Reserve Bank of India (RBI) allows us to address this challenge. To foster transparency in bank lending, the RBI instituted the Marginal Cost of Funds based Lending Rate (MCLR) system in 2016, which compelled banks to disclose the minimum interest rate they can lend at. Since the MCLR does not include the premium charged by banks on lending to risky borrowers, by focusing on the pass-through of monetary policy shocks to the MCLR, we circumvent concerns about credit rationing being a potential explanation for the rigidity of credit.

Nevertheless, our analysis has implications beyond India. The coordination channel may be particularly relevant in advanced economies, where generous bank closure policies induce banks to herd ex-ante by betting on common risks to increase the likelihood of being bailed out (Acharya and Yorulmazer, 2007). Jain and Gupta (1987) provide evidence supporting such herding behavior among U.S. banks in their lending decisions. In a similar vein, Roncoroni et al. (2021) document a high degree of overlap in bank exposures among European banks. Our proposed mechanism can also explain a long-lasting puzzle in the evidence obtained from developing economies. Montiel et al. (2010) argue that the bank lending channel is likely to be the dominant channel for monetary transmission in developing countries but find this channel either weak or unreliable. India is no exception in this regard (Sengupta, 2014; Mishra et al., 2016).

We begin by laying out a New Keynesian (NK) model in which banks are linked through firms' credit relationships. In our model, capital-intensive projects are financed via bank debt. The probability that these projects are successful is increasing in the total capital raised from all banks. Banks cannot perfectly observe the lending decisions of other banks but can observe noisy signals about them. 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.

Our first set of results shows that bank coordination acts as a propagation mechanism for monetary transmission. We show that an uncoordinated response of credit to a monetary policy shock is smaller than the coordinated benchmark. This muted response of credit dampens transmission to inflation and output. Intuitively, banks have a larger incentive to pass cheap credit to capital-intensive projects if other banks follow suit as the influx of external financing increases the probability of project success. In other words, if banks could coordinate, thereby avoiding the difficulty in interpreting each other's lending decisions, and finance the capital-intensive project in unison, the default risk associated with the project would be lower, and lending would be more responsive to monetary shocks. Furthermore, interest rates on project loans and household borrowing are inextricably linked in equilibrium to nullify arbitrage opportunities. As a result, variations in the cost of project loans stemming from coordination failures are transmitted to the cost of household borrowing, which in turn affects consumption, output, and inflation.

Our second set of results shows that when credit is uncoordinated, informational frictions reduce monetary transmission further. In particular, when bank lending is strategically complementary and unobservable, the magnitude of the lending response to a monetary policy shock is increasing in expected external credit, which is determined not only by the total credit provided by other banks but also by the precision of these credit signals. Thus, dispersion in credit dampens transmission—an effect that is absent without informational frictions.

Our third set of results shows that the network of multiple banking arrangements is crucial in shaping monetary transmission. In the data, some banks are more connected than others. We ask if differences in connectedness have different implications for monetary transmission. We consider an extension of the baseline model in which banks are heterogenous in connectedness and show that monetary transmission is less pronounced in more connected banks. Intuitively, more connected banks are more exposed to coordination failures and, thus, transmission is weaker in such banks.

We test these predictions using data from India that links firms to their banks. We merge this data with information on interest rates. To identify the coordination channel of monetary policy, we exploit the cross-sectional implications of credit sensitivity to monetary conditions according to the connectedness of banks in the multiple banking network. 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.

We use this data to cleanly identify the hypothesized effects. Our unique data on MCLR enables us to identify this supply-side phenomenon by abstracting out all demand-side influences. As the MCLR data captures the base lending rate decided by a bank, it abstracts out all borrower-specific determinants such as demand for credit and borrower's credit risk. By including time and bank fixed effects in our tests, we also control for all macroeconomic factors and bank characteristics. We first estimate the effect of bank connectedness on interest rate pass-through. To this end, we exploit India's multiple banking network architecture that resembles a hub-and-spoke structure featuring a densely connected set of core banks and a sparsely connected set of periphery banks. We use a k-shell decomposition to identify the set of core and periphery banks in the multiple banking network. We then show that transmission is less pronounced in core banks than in periphery banks, consistent with our theory. We find that in response to a 100 basis point increase in the Repo rate, MCLRs in periphery banks increase by 25.5 basis points more than in core banks. We also show that our results are not driven by alternative mechanisms stemming from differences in the size and composition of bank balance sheets.

To provide further evidence on the mechanism, we estimate how the effect of external credit conditions on monetary transmission varies with bank connectedness. Our static estimates from a fixed-effects model suggest that tighter external credit conditions, corresponding to a higher mean and dispersion of the cross-sectional distribution of MCLRs of other banks, significantly reduce the pass-through of monetary policy shocks to the MCLRs of connected banks. Moreover, our dynamic estimates from a panel vector autoregression (PVAR) show that these effects persist for a few months.

Next, we document large network effects following monetary policy shocks that operate via the coordination channel. Our empirical strategy uses spatial econometrics methods to decompose the overall effect of monetary policy shocks on MCLRs into a direct effect and network effects. The direct effect of a policy rate hike is an increase in the cost of borrowing on the discount window, due to which banks cut back on project lending. In addition, changes in lending by other banks impact projects' default risk, due to which banks adjust their lending further. We find that 61 to 64 percent of the overall effect of monetary policy shocks can be attributed to such network effects.

In the final part of our empirical analysis, we show that the model's predictions are also borne out in loan-level data. We follow Khwaja and Mian (2008) to address the endogeneity bias that may arise from the matching of banks and firms. Specifically, we focus on firms borrowing from multiple banks and identify the effect of a monetary policy shock induced by external credit conditions by controlling for credit demand through firm-year fixed effects. We find that an increase in the policy rate by 100 basis points decreases lending to a firm by an additional INR 0.14 crores when external lending to that firm is INR 1 crore higher.

The foregoing analysis is qualitative and leaves open the question of how important is the coordination channel insofar as transmission to the macroeconomic targets of the central bank (i.e., inflation and output) is concerned. To answer this question, we structurally estimate our model. In our model, as in the data, monetary policy shocks have a muted effect on inflation and output relative to the standard model. Our baseline estimates suggest that lending complementarities reduce monetary transmission to inflation and output by about a third. Moreover, our counterfactual experiments reveal that the authorities need not resort to a fundamental reform of the financial architecture to address the dampening of transmission due to coordination failures. We show that regulators can considerably reduce the extent of dampening by more aggressive inflation and output targeting.

Related Literature. Our paper lies at the intersection 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 several 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 (Bolton and Freixas, 2000; Van den Heuvel et al., 2002; 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] In addition, banks' exposure to interest rate risk is a key determinant of transmission

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

[2]The implication of pass-through 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

to bank lending (Gomez et al., 2021). 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 lender coordination on monetary transmission.

Building on the analytical insights of Morris and Shin (2004), Bebchuk and Goldstein (2011) analyze a related question of using policy rates as a means of getting the economy out of a credit freeze. Our work differs from theirs in several dimensions. First, in their model, there is information asymmetry between borrowers and lenders in that the fundamentals of the project are not publicly known. In our model, the information asymmetry is amongst lenders. Second, Bebchuk and Goldstein (2011) are interested in how the fundamental threshold determining equilibrium selection depends on monetary policy. Our model, in contrast, features a unique equilibrium and focuses on transmission in that equilibrium. Third, if one were to interpret a reduction in the likelihood of a credit freeze due to a monetary policy shock as an increase in monetary transmission, then the results of Bebchuk and Goldstein (2011) imply that an increase (decrease) in policy rates decreases (increases) transmission. In our model, transmission remains muted in the presence of lending complementarities irrespective of the direction of policy rate changes.

Our paper is also related to the literature on the 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

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).

loans will not be repaid. In our model, in contrast, credit spreads are a result of coordination failures. In addition, our paper contributes to the literature that studies the role of financial linkages as a mechanism for shock propagation. Much of this literature examines network interdependencies generated by the commonality of exposures as we do. However, the existing literature focuses on the effect of multiple banking on the transmission of bank distress. For instance, Kiyotaki and Moore (1997), Cifuentes et al. (2005), Gai and Kapadia (2010), and Greenwood et al. (2015) study how the insolvency of one bank ignites a fire sale of its assets, deteriorating the balance sheet of other banks holding similar assets. Our work, in contrast, focuses on the role of multiple banking in the transmission of monetary shocks.

Outline. 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. Section 4 describes our data and empirical work. Section 5 quantitatively illustrates the implications of lending complementarities on the transmission of monetary policy shocks to inflation and output. Section 6 offers concluding remarks.

2 Model

In this section, we adapt the conceptual framework of Hertzberg et al. (2011) to examine the effects of bank coordination on monetary transmission. We show that lending complementarities can be embedded into the standard macroeconomic model in a relatively straightforward yet rigorous way. The basic structure of our model is as follows: There are three types of agents, called households, firms, and banks. In addition, our model includes a monetary authority, which sets the path of policy rates. Since our eventual goal is to determine the effect of lending complementarities on transmission in a standard 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 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. We separate the operations of labor-intensive projects and capital-intensive projects to incorporate inertia in the price setting in a tractable manner.

2.1 Households

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

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

where C_t is the consumption index, and H_t denotes hours of work or employment.

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:

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

where P_t is the price of the consumption good, W_t denotes the nominal wage, R_t^h denotes the nominal interest rate on household borrowing, and B_t represents the quantity of one-period risk-free nominal discount bonds purchased in period t and maturing in period $t+1$. 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 $P_t = [\int_0^1 P_t(i)^{1-\epsilon} di]^{\frac{1}{1-\epsilon}}$. We also assume that households are subject to a solvency constraint, $\lim_{T\to\infty} \mathbb{E}_t[B_T] \geq 0 \ \forall t$, that prevents them from engaging in Ponzi-schemes.

2.2 Firms

There is 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

A finite number of $\mathfrak{N}$ banks pool resources to finance a capital-intensive project. Let $L_{i,t}$ be the amount lent by bank i in period t, where $0 < \sum_{i=1}^{\mathfrak{N}} L_{i,t} < 1 \ \forall t$. The gross interest rate on each loan extended by bank i in period t is assumed to be $R_{i,t} \geq 1$.[4] 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 $\mathbb{P}(\sum_{i=1}^{\mathfrak{N}} L_{i,t}) = (\sum_{i=1}^{\mathfrak{N}} L_{i,t})^\mu$, $\mu \in (0,1]$. 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.[5] Hertzberg et al. (2011) model strategic complementarities in lending by assuming that the no-default is linearly increasing in aggregate credit. Indeed, this is a special case in our model where $\mu = 1$. However, Proposition 1 highlights that a log-linearized version of the economy cannot endogenously generate credit spreads when $\mu = 1$, which is why we allow for a more general function for the no-default probability.

We also assume that banks do not have complete information about loans provided by other members of the syndicate but instead observe only a noisy signal given by:

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

[4]Any profits accrued to entrepreneurs operating the capital-intensive project are rebated lump sum to households. We assume these profits to be zero without loss of generality.

[5]This formulation saturates the density of the multiple banking network. We relax this assumption in Section 2.7.2.

Further, we assume that the banks' prior is given by $\mathcal{N}(0, \sigma_p^2)$.[6] This implies that the probability that bank i will receive a strictly positive payoff is increasing in the expected credit extended by banks $j \neq i$ weighted by the precision of these signals.

Following Hertzberg et al. (2011), we consider a cost function that is convex in loan provision. The increasing marginal cost of lending reflects the costs of additional monitoring that are required for larger loans. This assumption can also capture intermediation costs for lending to informal enterprises that are relatively opaque. In particular, the convexity of these costs could stem 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). In addition, we assume that the cost of intermediating loans is increasing in the policy rate ($R^\star$), i.e., the interest rate at which commercial banks borrow from the central bank. This assumption reflects the dependence of banks' liquidity risk on monetary policy. The more loans extended by banks, the smaller is the precautionary buffer of reserves that can be used to address liquidity mismatches created by transfers of deposits across banks (Bianchi and Bigio, 2014; Drechsler et al., 2018; Piazzesi and Schneider, 2018). Such reserve deficits can be tapped by overnight borrowing from the central bank serviced at the policy rate. We model $c(L, R^\star)$ as multiplicative because if this function were additively separable in L and $R^\star$, then lending would be independent of monetary shocks; this would shut out the key channel that we are studying. A special case that we pay particular attention to is $c(L, R^\star) = \frac{L^2 R^\star}{2\alpha}$.

Assumption 1. *The cost of loan provision, $c(L, R^\star)$, is multiplicatively increasing in loans (L) and the policy rate ($R^\star$); and satisfies the following conditions: $c_L, c_{LL}, c_{R^\star} > 0$.*

Given prices, $\{R_t^\star, R_{i,t}\}$, and the signal of project loans provided by other banks, s_t, bank i solves the following problem in period t:

$$\max_{L_{i,t}} \ \mathbb{P}\big(\mathbb{E}^i[\sum_{j \neq i} L_{j,t} \mid s_t] + L_{i,t}\big) L_{i,t} R_{i,t} - c(L_{i,t}, R_t^\star). \tag{1}$$

In addition to financing capital-intensive projects, banks accept deposits from and make loans to households. We assume that lending decisions are made before deposits enter the banking system. Moreover, we assume that, within each bank, project financing and household lending are handled by separate divisions. This assumption is not only empirically relevant but also convenient for our analysis as it allows us to examine the project financing decision in isolation.

[6] 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.

2.4 Monetary Authority

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

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

where ϵ_t^p is an AR(1) monetary policy shock, and $\bar{R}^\star$, $\bar{\pi}$, and $\bar{Y}$ are steady state values of the policy rate, the inflation rate and GDP respectively. 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

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

If net liquidity injections by the central bank are zero, then equilibrium in the money market necessitates

$$L_t = B_t \quad \forall t \geq 0. \tag{2}$$

Market clearing in the labor market requires

$$H_t = \int_0^1 N_t(i) di \quad \forall t \geq 0.$$

Suppose the no-default probability is close to unity. In that case, the interest rate on household borrowings should equate with the rate of return from the project when successful. This stems from the no-arbitrage condition as banks can internally reallocate funds in search of the highest yield. As we argue below, this assumption does not qualitatively affect our main result but simplifies our characterization of general equilibrium in this economy.

We present a log-linearized version of a closed economy that can be characterized by four equations in four variables: output ($\hat{y}_t$), inflation ($\hat{\pi}_t$), policy rate ($\hat{r}_t^\star$), and nominal interest rate ($\hat{r}_t$). Here and throughout the paper, a hat over a variable denotes the percentage deviation from its steady-state value. 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 symmetric equilibria.

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:

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

In the above equation, $\epsilon^p_t = \rho^p \epsilon^p_{t-1} + \eta^p_t$, where $\eta^p_t \sim \mathcal{N}(0, \sigma^2_p)$.

2.5.1 Strategic Complementarities and the Credit Spread

In the standard NK model, policy rate changes are passed completely to the nominal interest rate, i.e., $\hat{r}^\star_t = \hat{r}_t \; \forall t$. In contrast, in our model, interest rate pass-through is imperfect.

Proposition 1. *If savings is a fixed fraction of output and information is complete, then changes in the equilibrium credit spread are given by:*

$$\hat{r}_t - \hat{r}^\star_t = (1-\mu)\hat{y}_t \quad \forall \mu \in (0, 1].$$

Proposition 1 reveals that there exists a wedge between changes in policy rates and changes in nominal interest rates in our model.[7] To see why, it is helpful to consider first a setting where there are no strategic complementarities in lending (i.e., $\mu = 0$), and lending costs are linear in loans (i.e., $c(L, R^\star) = LR^\star$). In such a scenario, the marginal cost of lending is simply given by the policy rate ($R^\star_t$) and the marginal benefit by the interest rate charged on project loans (R_t). As the optimal project financing decision equates the marginal benefit of lending with its marginal cost, the interest rate on project loans equals the policy rate. Thus, without strategic complementarities in lending, there would be perfect interest rate pass-through as in the standard NK model. However, in our setting, both the benefit and cost of project lending are increasing in loanable funds. The marginal benefit

[7]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.

of lending is increasing in loans as the project has a higher chance of succeeding when it secures more funding. The marginal cost of lending is increasing in loans due to the (convex) cost of financial intermediation. Moreover, as banks funnel household savings into project loans and savings are a function of output, loanable funds are also linked to output. As a result, changes in output influence the credit spread in our model. This wedge dampens monetary transmission to macroeconomic variables. To see this, note that increases in the policy rate induce households to save more and consume less, thereby reducing output. As an increase in the policy rate tends to be contractionary, Proposition 1 implies that, relative to their steady state values, a percent increase in the policy rate results in less than a percent increase in the lending rate. A similar logic can be used to see why a percent decrease in the policy rate results in less than a percent decrease in the lending rate.

In the above argument, we have assumed that the no-default probability is close to unity. This assumption implies that the interest rate on household borrowing equates with the return from the project when successful.[8] However, in general, lending complementarities introduce an additional wedge between these two variables. To see this, note that in equilibrium, the expected return on project financing should equate with its opportunity cost, i.e., the interest rate on household borrowing. In particular, $R_t \mathbb{P}(\sum_{i=1}^{\mathfrak{N}} L_{i,t}) = R_t^h$. If savings is a fixed fraction of output, then we can substitute the market-clearing condition for loanable funds into the no-arbitrage condition and log-linearize around steady states to get $\hat{r}_t + \mu \hat{y}_t = \hat{r}_t^h$. Combining this equation with the credit spread derived in Proposition 1, we find that $\hat{r}_t^h - \hat{r}_t^\star = \hat{y}_t$. Note that in this general setting, the dampening of monetary transmission due to lending complementaries will be even larger than that in our baseline model.[9]

2.5.2 Necessary and Sufficient Condition for Unique Equilibria

Strategic complementaries in lending can generate multiple equilibria, which poses an empirical challenge that we detail below. We provide a necessary and sufficient condition for determinacy in the following proposition. We focus on contemporaneous data interest rate rules where $\rho = 0$.

[8] The link between lending rates on household borrowing and project financing in our model implies that monetary policy shocks have a muted effect on consumption expenditure, a key feature of the data. Private final consumption expenditure is the largest component of GDP in India, and its share has been roughly constant post-deregulation. These facts suggest that the weak response of output to monetary shocks in India is primarily driven by the weak response of consumption to these shocks, as in our model.

[9] The difference between the credit spread in the two settings is given by $\mu \hat{y}_t$. Though this difference is endogenous and determined by economic conditions in equilibrium, the reduction in interest rate pass-through due to μ is of first-order importance and unlikely to be offset by second-order effects operating via differences in $\hat{y}_t$ between the two settings. A numerical characterization of the general model shows that this is indeed the case under the baseline parametrization detailed in Section 5.

Proposition 2. *Under contemporaneous data interest rate rules, a necessary and sufficient condition for an equilibrium to be unique is*

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

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

2.6 Partial Equilibrium

In this section, we consider a partial equilibrium setting to sharply characterize the credit response to monetary policy shocks. This allows us to disentangle the effect of coordination failures on monetary transmission. The log-linearized general equilibrium version of the economy also masks the effect of beliefs on monetary transmission, which we can address using our partial equilibrium analysis. We assume a downward-sloping demand for loans, $L^{D}_{i,t}/R^{\varkappa}_{i,t}$, where $L^{D}_{i,t} > 0 \ \forall i$ and $\varkappa > 0$. Equilibrium in the loanable funds market requires $L_{i,t}R^{\varkappa}_{i,t} = L^{D}_{i,t} \ \forall i \ \forall t$. 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 shocks from the response of loans to these shocks, which will also be helpful when interpreting our empirical results on interest rate pass-through.

2.6.1 Symmetric Equilibria with Complete Information

In this section, we restrict attention to a complete information setting in which banks can observe each other's lending decisions. We focus on symmetric equilibria in which banks independently finance the project. Given interest rates, $\{R_{i,t}, R^{\star}_{t}\}$, the collection $\{L_{i,t}\}$ of loans to capital-intensive projects is a symmetric uncoordinated equilibrium of the financial network if it solves (1), and $L_{i,t} = L_{j,t} \ \forall i \ \forall j \ \forall t$. We compare these outcomes against a coordinated benchmark in which banks finance the project collectively and equally share the return ex-post. Let L^{C}_{t} and L^{U}_{t} denote the period-t loans provided in the coordinated benchmark and uncoordinated symmetric equilibria, respectively.

Proposition 3. *If information is complete, then*

(i) The credit response to a monetary policy shock in the coordinated benchmark is larger than that in symmetric uncoordinated equilibria, i.e., $\mathfrak{D}_t \equiv \left|\frac{\partial L^{\mathrm{C}}_{t}}{\partial R^{\star}}\right| - \left|\frac{\partial L^{\mathrm{U}}_{t}}{\partial R^{\star}}\right| > 0,$

(ii) The dampening of the credit response to a monetary policy shock due to coordination failures is strictly increasing in the number of banks in the financial system, i.e., $\frac{\partial \mathfrak{D}_t}{\partial \mathfrak{N}} > 0.$

The first part of Proposition 3 shows that the pass-through of a monetary policy shock to aggregate credit is higher when banks coordinate lending. This is because individual banks do not account for strategic complementaries in lending when responding to monetary shocks in a symmetric uncoordinated equilibrium. Banks would have a larger incentive to pass cheap credit, for instance, to capital-intensive projects if other banks were doing the same because the influx of external financing would increase the probability of project success. When banks coordinate their lending responses to monetary shocks, the default risk of the capital-intensive project is lower and transmission more pronounced.

The second part of the proposition shows that the difference between the credit response to a monetary policy shock in the coordinated benchmark and uncoordinated equilibrium is increasing in the number of banks in the financial system. The intuition behind the second result is that as the number of 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

This section shows that when banks lack complete information about the lending decisions of other banks, expectations of tighter credit provision by other connected banks reduce monetary transmission. For tractability, we assume $\mathfrak{N} = 2$ and consider the case in which the no-default probability is linearly increasing in aggregate credit. We focus on uncoordinated equilibria and investigate the effect of external project financing on monetary transmission when banks update their beliefs using Bayes' Rule. We denote by $L_{i,t}(L, \sigma)$ the period-t best-response function of bank i given that project loans provided by other banks are normally distributed with a mean of L and a standard deviation of σ.

Assumption 2. $\alpha < \frac{R_t^\star}{2R_{i,t}}$ $\forall i$ $\forall t$.

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

Proposition 4. *Suppose $\mu = 1$, information is incomplete, and banks do not coordinate their lending decisions. Then optimal loan provision has the following properties:*

(i) Banks reduce lending in response to an increase in the policy rate, i.e.,

$$\frac{\partial L_{i,t}(L,\sigma)}{\partial R^\star} \; < \; 0 \; \forall (L,\sigma) \gg \mathbf{0} \; \forall i \; \forall t,$$

(ii) The impact of a policy rate change on loans granted by a bank is increasing in the

expected level of credit extended by other banks, i.e.,

$$\left|\frac{\partial L_{i,t}(L,.)}{\partial R^{\star}}\right| > \left|\frac{\partial L_{i,t}(\tilde{L},.)}{\partial R^{\star}}\right| \forall L > \tilde{L}\ \forall i\ \forall t,$$

(iii) *The impact of a policy rate change on loans granted by a bank is decreasing in the dispersion in credit extended by other banks, i.e.,*

$$\left|\frac{\partial L_{i,t}(.,\sigma)}{\partial R^{\star}}\right| < \left|\frac{\partial L_{i,t}(.,\tilde{\sigma})}{\partial R^{\star}}\right| \forall \sigma > \tilde{\sigma}\ \forall i\ \forall t.$$

The first result in Proposition 4 shows that bank lending is strictly decreasing in the policy rate. Intuitively, a lower policy rate implies that it is cheaper for banks to borrow on the discount window to meet any liquidity shortfalls, which stimulates project lending ex-ante.

The second result in Proposition 4 shows that the impact of a policy rate change on loans granted by a bank and, thus, on its lending rate, is increasing in the expected level of credit extended by other banks. That is, the higher the loans offered by bank $j \neq i$, the larger the transmission of policy rates to the loans offered by bank i. Note that in partial equilibrium, this also implies that the lower the interest rates offered by bank $j \neq i$, the higher is interest rate pass-through in bank i. This is because more external credit lowers the probability of the project defaulting, which effectively increases the expected return from the project. To see this more clearly, it is helpful to consider the extreme case in which no individual bank can finance the entire project, but both banks together can meet the funding requirement. If the funding requirement is met, the project succeeds; else, it fails. Suppose that banks do not find it profitable to lend to the project at the prevailing policy rate. However, if the policy rate is lowered sufficiently, banks can make strictly positive profits from lending to the project if it succeeds. Note that in this stylized setting, changes in the policy rate will only impact lending if both banks expect that the project will secure funding from the other bank. This example serves to illustrate how monetary transmission depends on external credit conditions.

The third result in Proposition 4 shows that a higher dispersion in external project financing also dampens monetary transmission. In particular, the impact of a policy rate change on the loans granted by a bank is decreasing in the dispersion in credit provided by other banks. This effect emerges as a larger variance in external credit reduces the precision of its signal, which effectively dampens complementarity in lending. In fact, one can show that there is no monetary transmission in the extreme case when signals of external credit are completely uninformative, i.e., when $\sigma = \infty$.

Figure 1 graphically illustrates the proof of these results. Suppressing the time notation, the marginal benefit of project loans intermediated by bank i is given by $R_i(\mathbb{E}[L_j] + 2L_i)$, which is additively increasing in the expected quantum of credit provided by other banks to the project ($\mathbb{E}[L_j]$) and the loans extended by bank i (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 $c_L(L_i, R^\star)$, which, by assumption, is multiplicatively increasing in its arguments. Thus, an increase in the policy rate ($R^\star$) 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.

Figure 2(b) summarizes the main results of this section. It 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) the coordinated benchmark. There are three main takeaways. First, monetary transmission is highest in the coordinated equilibrium. Second, incomplete information in the uncoordinated equilibrium dampens monetary transmission. Third, the weak lending response to a policy rate change persists for a few periods but eventually converges to the outcome obtained in the uncoordinated equilibrium under complete information. This is because, as shown in Figure 2(a), beliefs about credit provided by other banks become more precise as banks receive more signals of aggregate credit over time.

2.6.3 Discussion of the Convex Cost Assumption

Our partial equilibrium results are derived under the assumption that the no-default probability is linear (i.e., $\mu = 1$), which is the case examined by Hertzberg et al. (2011). Under this linearity assumption, for coordination failures to have bite, we require that the second partial derivative of the cost of loan provision with respect to lending is non-zero, which is satisfied by the convex cost assumption we impose in our framework. Figure 1 graphically illustrates how our results hinge on the assumption that the cost of providing loans is convex in the level of loans. If the cost function were linear instead, as in panel (b) of the figure, monetary transmission would not depend on aggregate credit conditions. Formally, one can show that if the cost function is linear in loan provision and given by $c(L, R^\star) = LR^\star/\alpha$, then $\partial L_i/\partial R^\star = 1/2\alpha R_i$, which is independent of $\{L_j\}_{j\neq i}$ in partial equilibrium. However, if we allow the no-default probability to be concave (i.e., $\mu < 1$), then even under a linear cost function, lack of coordination can affect monetary transmission. To see this, note that in partial equilibrium, banks' lending decisions depend on two variables:

the policy rate and external project financing. When the no-default probability is linear, these two effects do not interact with each other. This is because the no-default probability can be additively decomposed when it is linear, i.e., $\mathbb{P}(\mathbb{E}^i[\sum_{j\neq i} L_j] + L_i) = \mathbb{P}(\mathbb{E}^i[\sum_{j\neq i} L_j]) + \mathbb{P}(L_i)$ when $\mu = 1$, which implies that marginal gains in expected revenues of bank i from an increase in external project financing are constant and do not depend on bank i's lending decision. As a result, bank i's lending response to a monetary policy shock is independent of external credit conditions. In contrast, when $\mu < 1$, then the no-default probability cannot be additively decomposed and, thus, the effect of the policy rate on lending cannot be disentangled from external credit conditions.

2.7 Network Effects

In this section, we present two static extensions of our baseline model to study the network effects of monetary policy shocks on bank lending. The role of networks in the propagation of shocks is part of a growing literature. Gai et al. (2011), Acemoglu et al. (2015), and Donaldson et al. (2022) examine how the density of the network of interbank liabilities contributes to financial instability. 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. We contribute to this literature by studying how the network of multiple banking linkages affects the transmission of monetary shocks. First, we provide a decomposition of the lending response of banks to a monetary policy shock into direct and network effects. Second, we consider a setting where banks are heterogeneous in connectedness and show that monetary transmission is less pronounced in more connected banks.

2.7.1 Decomposition

We first consider an environment in which $\mathfrak{N}$ banks finance $\mathfrak{M}$ projects. 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 decompose the lending response to a monetary policy shock into direct and network effects.

We denote bank i's loan for project j by L_{ji}, and the fixed return of bank i from project j by R_{ji}. Let $\tilde{R}_{ji} \equiv R_{ji}/R^{\star}\ \forall i\ \forall j$.

Proposition 5. *Suppose $\mu = 1$. Then the credit response to a monetary policy shock can be* *decomposed as:*

$$\frac{dL_{ji}}{dR^{\star}} = \underbrace{\frac{\alpha \sum_{k \neq i} \frac{dL_{jk}}{dR^{\star}}}{\tilde{R}_{ji}^{-1} - 2\alpha}}_{\text{Network Effects}} \quad \underbrace{- \frac{\left\{ \sum_{l=1}^{\mathfrak{M}} L_{li} + \tilde{R}_{ji}^{-1} \sum_{l \neq j} \frac{dL_{li}}{dR^{\star}} \right\}}{\tilde{R}_{ji}^{-1} - 2\alpha}}_{\text{Direct Effects}} \; \forall i \; \forall j.$$

This expression shows how changes in policy rates translate into changes in credit through the network of multiple banking arrangements. In particular, $-\left\{ \sum_{l=1}^{\mathfrak{M}} L_{li} + \tilde{R}_{ji}^{-1} \sum_{l \neq j} \frac{dL_{li}}{dR^{\star}} \right\} / (\tilde{R}_{ji}^{-1} - 2\alpha)$ is the direct response to a monetary policy shock of lending of bank i to project j. This captures the idea that an increase in the policy rate makes it more costly for banks to borrow on the discount window, due to which they cut back on project lending. In addition, changes in lending by other banks impact projects' default risk, due to which banks adjust their lending further. These network effects are captured by $\alpha \sum_{k \neq i} \frac{dL_{jk}}{dR^{\star}} / (\tilde{R}_{ji}^{-1} - 2\alpha)$. This term links monetary transmission in one bank to monetary transmission in other banks. Below, we quantify the relative contributions of these direct and network effects using spatial econometrics methods.

2.7.2 Transmission in Core vs. Periphery Banks

Our baseline model features a homogenous set of banks, all interconnected via multiple banking arrangements. In the data, however, some banks are more connected than others. Presumably, differences in connectedness can have different implications for monetary transmission. This section argues that the lending response to monetary policy shocks is more muted in more connected banks. To show this, we extend our baseline framework by considering a network of $\mathfrak{m}$ core banks connected to each other via a loan syndication agreement, where $\mathfrak{m} > 1$. In addition, each core bank also serves as the lead bank in a separate loan syndication that it shares with a unique set of $\mathfrak{n}$ periphery banks, where $\mathfrak{n} > 1$. Figure 3(b) provides an illustration of the network topology. We are interested in comparing monetary transmission in core banks to that in periphery banks in an uncoordinated equilibrium.

Core banks solve a two-dimensional optimization problem to jointly determine their lending decisions in the core and periphery consortiums. We denote the loans provided by an individual core bank (indexed by i) in the core and periphery consortiums as $L_{i,c}$ and $L_{i,p}$ respectively, and the loans provided by the periphery bank (indexed by j) in the periphery consortium led by bank i as $L_{j,i,pp}$. Given interest rates $\{R^{\star}, R_i\}$ and the loans extended by other connected banks, $\{\{L_{j,i,pp}\}_j, \{L_{j,c}\}_{j \neq i}\}$, core bank i solves the following problem:

$$\max_{L_{i,c}, L_{i,p}} (\mathfrak{m} L_{.,i,pp} + L_{i,p})^{\mu} L_{i,p} R_i + ((\mathfrak{n} - 1) L_{-i,c} + L_{i,c})^{\mu} L_{i,c} R_i - \frac{(L_{i,c} + L_{i,p})^2 R^{\star}}{2\alpha},$$

where we invoke the symmetry of allocations within the set of core and periphery banks respectively.

Periphery banks solve a problem akin to that presented in the baseline analysis barring one crucial difference. We assume that periphery banks bear a lower cost of loan provision than do core banks. We pursue this approach because one can show that the solution to the model without differential costs is indeterminate, precluding comparative statics. Moreover, this assumption is also empirically relevant since lead banks often bear a disproportionate burden of the costs associated with project monitoring in loan syndications. Specifically, periphery bank j that belongs to the lending consortium led by core bank i solves:

$$\max_{L_{j,i,pp}} ((\mathfrak{m}-1)L_{-j,i,pp} + L_{j,i,pp} + L_{i,p})^{\mu} L_{j,i,pp} R_i - \frac{(L_{j,i,pp} - \omega)^2 R^{\star}}{2\alpha},$$

where $\omega > 0$ captures the differential cost of loan provision between core and periphery banks.

Lemma 1 characterizes the optimal lending decisions of core and periphery banks in closed-form. We then use this characterization to show that the lending response of periphery banks to a monetary policy shock is larger than that of core banks when the cost of loan provision is high enough (Proposition 6). We restrict attention to symmetric equilibria in which $\forall j, j' \; \forall i, i' \; L_{j,i,pp} = L_{j',i',pp} \equiv L_{pp}$, $L_{i,p} = L_{i',p} \equiv L_p$, and $L_{i,c} = L_{i',c} \equiv L_c$.

Lemma 1. *If $\mu = 1$, then optimal allocations in a symmetric uncoordinated equilibrium are given by:*

$$L_{pp} = \omega \left\{ 1 - \frac{R\alpha}{R^{\star}} \left[1 + \mathfrak{m} \left(\frac{R^{\star}/R\alpha - 1}{R^{\star}/R\alpha - 2} \right) \right] \right\}^{-1}, \tag{3}$$

$$L_c = L_{pp} \frac{\mathfrak{m}}{1 + \mathfrak{n} - 2\chi}, \tag{4}$$

$$L_p = \chi L_c, \tag{5}$$

$$\textit{where } \chi \equiv \frac{R\alpha[1+\mathfrak{n}]}{R^{\star}} - 1.$$

Proposition 6. *Suppose $\mu = 1$ and α is small enough. Then in all symmetric uncoordinated equilibria, the decrease in credit due to a monetary policy shock is larger in periphery banks than in core banks:*

$$\min \left\{ \frac{\partial (L_c + L_p)}{\partial R^{\star}}, 0 \right\} > \frac{\partial L_{pp}}{\partial R^{\star}}.$$

To gain some intuition for the above result, note that core banks are more connected in the multiple banking network than periphery banks. More interconnections open the door to more coordination failures, which decreases the credit response to a monetary policy shock.

3 Institutional Background

3.1 The Dominance of Multiple Banking

In October 1996, the RBI lifted various regulations regarding the conduct of multiple banking arrangements. Notably, the central bank withdrew instructions relating to maximum permissible bank finance, and banks were free to participate in consortium agreements irrespective of the quantum of credit involved. Moreover, all restrictions relating to project loans by commercial banks were lifted. Traditionally, project finance was the domain of term-lending institutions.

Unsurprisingly, loan syndications in India have increased post-deregulation substantially.[10] This can be vividly seen in panel (a) of Figure C.1, which plots the evolution of the number of loan syndications in India. Since deregulation, the number of loan syndications has grown more than three times—rising from 49 in 1996 to 193 in 2021. We see a similar trend in the value of loan syndications, which grew from USD 3 billion in 1996 to USD 204 billion at its peak in 2010, but have since plateaued; see panel (b) of Figure C.1.

Moreover, loan syndications do not seem to be related to lender characteristics, such as residence or ownership. Panel (c) of Figure C.1 plots the composition of participants in loan syndications and shows that foreign banks predominantly participated in such arrangements. However, after financial deregulation, the share of domestic bank participation in loan syndications has increased considerably. Moreover, we see that both private sector and public sector banks alike participate in such agreements. From the borrowers' side, interbank loans comprise only a small fraction of loan syndications. This can be seen clearly in panel (d) of Figure C.1, which disaggregates loan syndications by industry. The majority of loan syndications are to non-financial firms, which is the margin that we focus on in this paper.

However, lack of coordination and information sharing have been significant obstacles in the smooth functioning of multiple banking arrangements. In the wake of financial deregulation, the Standing Coordination Committee (SCC) was set up in October 1999 by the RBI Governor, which assembled representatives of select financial institutions and banks to deliberate on issues of common interest. One of the key issues flagged by the SCC is the inordinate delays in the sanctioning of credit facilities, particularly under project financing, which the committee attributes to coordination failures among the members of the consortium:

"*The delay arises generally on account of lack of coordination and consensus among lenders on financing the amount of cost overrun or restructuring or rehabilitation.*" RBI (2001)

[10]Here we focus on loan syndications as they are a subset of multiple banking arrangements for which time series data are readily available.

Other regulatory bodies like the Central Vigilance Commission and the Indian Banks Association have raised similar concerns (RBI, 2009).

In addition, despite recent advances, the credit information system in India has many gaps that exacerbate coordination failures among lenders. The RBI's Central Repository of Information on Large Credits (CRILC) was established in 2014 to close the information gap between creditors. CRILC provides a timely window on any degradation of credit of a borrower at a bank to the central bank and to other banks having the same entity as a borrower. However, the purview of CRILC is limited to large corporate borrowers, i.e., those having aggregate exposure of INR 50 million and above. Moreover, despite the plethora of credit information repositories in India, a recent RBI report highlights that credit information is spread over multiple systems in bits and pieces, making it costly to process (RBI, 2018).

3.2 Monetary Policy Framework

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, 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.[11]

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 abandoned in 2003 in favor of 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 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 Marginal Cost of Funds based Lending Rate (MCLR) system in 2016. The BPLR, the base rate, and the MCLR were internal benchmarks set by each bank for the pricing of credit. However,

[11] In our analysis, we restrict attention to the Repo rate. An alternate specification in which the outcome variable is the spread between the bank base 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.

unlike the BPLR and the base rate, the formula for computing the MCLR is determined by the RBI and 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. The ultimate interest 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. 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 RBI constituted an Internal Study Group to review the working of the MCLR system in 2017. The Study Group pointed out several instances where banks arbitrarily adjusted the MCLR, which impeded the transmission of policy rate cuts to borrowers.

4 Empirical Evidence

In this section, we empirically examine the effect of lending complementarities on monetary transmission. Propositions 1, 4, and 6 lead to the following testable hypotheses:

Hypothesis 1: *Monetary transmission is less pronounced in more connected banks. In particular, interest rate pass-through is weaker in core banks than in periphery banks.*

Hypothesis 2: *When banks are connected through common exposures, tighter external credit conditions reduce monetary transmission. Specifically, interest rate pass-through is lower when the mean and dispersion of the price of external credit are higher.*

Hypothesis 3: *A bank's lending to a project responds more to monetary policy shocks when other banks lend more to that project.*

Next, we test these hypotheses by constructing a dataset that links the evolution of interest rates to firms' bank credit relationships in India.

4.1 Data

We now describe the data. Our data covers the universe of scheduled commercial banks in India, which includes public sector banks, (domestic) private banks, and foreign banks.

Interest Rates: The interest rate data is collected from individual data releases by the RBI and the Database of the Indian Economy (DBIE). The data is at a monthly frequency and ranges from June 2016 to February 2020. As the MCLR system became effective in April 2016, we start our sample in June 2016. To avoid the influence of Covid induced monetary policy changes, we end our sample in February 2020. Figure 4 depicts the MCLRs and the central bank policy rate over our sample period. 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 bank MCLRs are considerably higher than the policy rate, alluding to the weakness of monetary transmission. Second, there is substantial variation in the response of bank MCLRs to changes in the policy rate, alluding to the heterogeneity in monetary transmission.

Loans: To test the model's predictions at the loan level, we use data from a credit registry maintained by the Ministry of Corporate Affairs (MCA), Government of India. The registry tracks all secured lending to all MCA-registered firms in India by scheduled commercial banks, documenting the size of each loan and the date they were sanctioned. We aggregate all loans extended by a creditor to a firm over a month. The loan-level data also allows us to test the model's predictions over a longer time horizon than the interest rate data. Our sample starts from November 2004, which is when the RBI began using the LAF to address liquidity mismatches, and ends at the onset of the Covid pandemic (i.e., February 2020).

Multiple Banking Network: To measure exposure to external credit conditions, we exploit granular data on Indian bank-firm links 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 C.2 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 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 5 depicts the multiple banking 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. Our empirical analysis uses a row-normalized version of the adjacency matrix to disentangle the direct effects of monetary policy shocks from the network effects. We also 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. We employ these centrality measures to proxy exposure to beliefs about lending by other connected banks.

Bank Characteristics: The literature suggests that monetary transmission depends on the size and composition of bank balance sheets. To account for this, we obtain data on the following variables from the DBIE. First, we obtain data on total assets to control for bank size. Second, we obtain data on the capital to assets ratio to absorb any differential transmission of monetary policy that may be present due to bank capitalization in our regressions. Our measure of bank capital is paid-up capital plus reserves and surplus as per the RBI classification. Third, we obtain data on bank deposits to account for changes in lending due to differential borrowing conditions. Another key factor impeding quick and adequate transmission to banks' lending rates has been the 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 proxy deposit maturity using the ratio of time deposits to demand deposits.

Monetary Policy Targets: We collect data on output growth and inflation to account for the potential endogeneity of the monetary policy shock (Ramey, 2016). In particular, we obtain data on the Consumer Price Index (CPI) and the Index of Industrial Production (IIP) from the DBIE. The IIP tracks the growth of various sectors in the economy, such as manufacturing, mining, and power, and has been traditionally used in the empirical literature as a high-frequency proxy for output variations (see, for instance, Barth and Ramey, 2001). The volatilities of these variables also serve as key targets in our quantitative analysis.

Alternative Monetary Policy Tools: We obtain data on several instruments used by the RBI to regulate money supply in the economy. The RBI mandates that a certain fraction of bank deposits be held as reserves, which is determined by the Cash Reserve Ratio (CRR). The lower the CRR, the higher the liquidity with banks, which goes toward lending. 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. 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. To capture the 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.[12] We control for changes in these alternative monetary policy tools in our regressions.

4.2 Identification Strategy

To identify the coordination channel of monetary policy, we exploit the unique data we have on the MCLR for each bank over time. Since the MCLR corresponds to the base lending rate, borrower-specific risk and aggregate demand for credit are completely abstracted out. As the coordination channel that we test is purely a supply-side phenomenon, abstracting out these demand-side confounders removes a key identification concern from our empirical design. By including time fixed effects and bank fixed effects, we control for all macro-level and bank-specific factors as well. Our difference-in-differences analyses then utilize purely the cross-sectional variation in the connectedness of banks to test our hypothesis. In particular, we interact the change in the Repo rate with measures of network centrality, which is in the spirit of Kashyap and Stein (2000), Jiménez et al. (2012), Dell'Ariccia et al. (2017), and Drechsler et al. (2017). An identification strategy that compares loan syndications across branches but within the same bank is not conducive to our setting. This is because large loan syndications are typically done at bank headquarters and not in smaller branches.

As highlighted by Bernanke and Lown (1991), inferring loan supply using the cost of a bank loan to the borrower is challenging for at least two reasons. First, the cost of a bank loan is multidimensional, involving, for example, collateral and compensating balance requirements. Second, it is difficult to control for systematic changes in the quality of the

[12] 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.

borrower receiving the loan. Banerjee and Duflo (2001), Banerjee et al. (2004), and De and Singh (2011) document that formal and informal credit providers in India decline to extend credit beyond a certain point regardless of the credit terms to limit moral hazard on the part of the borrowers. Such credit rationing could also be a reasonable explanation for the weak response of credit to monetary policy shocks. Our focus on the MCLR allows us to disentangle credit terms and borrower risk from credit supply. Previous studies on monetary transmission have instead focused on the weighted average lending rate that accounts for the distribution of risk across borrowers. The MCLR allows us to better identify variations in bank loan supply as it does not include the premium charged by banks on lending to risky borrowers. In addition, we control for time fixed effects in our models, which allows us to disentangle any observed and unobserved changes in aggregate demand from loan supply.

Moreover, disparities in lender characteristics can lead to substantial bias in estimates of the interaction coefficients. To convincingly identify the effect of coordination motives on loan supply, we focus on models that include bank fixed effects and time-varying bank characteristics. This allows us to control for cross-sectional differences in the way that banks with varying characteristics respond to monetary policy shocks. Bank ownership, for instance, may 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. Differences in the credit spread across public, private, and foreign banks can be clearly seen in Figure C.3. 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 C.1 for more details. Our empirical strategy allows us to absorb such differential impacts of monetary policy.

To further investigate the mechanism, we study how interest rate pass-through across differentially connected banks is affected by external credit conditions. Under our assumptions on signal structure, the mean and dispersion of the cross-sectional distribution of MCLRs of other banks serve as sufficient statistics for external credit conditions in a complete financial network. To control for differential exposure to external credit conditions, we interact these variables with the centrality of banks in the multiple banking network. We then examine the effect of external credit conditions on two measures of monetary transmission that have been emphasized in the existing literature. Our first measure is the coefficient on the first difference of the policy rate in a regression in which the first difference of the MCLR is the outcome variable, which is similar to Das (2015). Following Acharya et al. (2020), our second measure is the spread between the MCLR and the policy rate.

The interest rate regressions, however, do not provide an insight into the dependence of transmission on external credit conditions on the intensive margin as banks may refuse to sanction loans for a variety of reasons that are not reflected in the MCLR. To identify these intensive margin responses, we use loan-level regressions. As we have data on loan applications, bank characteristics, and firm identities, we can still disentangle demand from the supply of loans and account for time-dependent confounders by including firm-by-month fixed effects in our model. In addition, we can control for any observed and unobserved heterogeneity in relationship lending using bank-by-firm fixed effects.

Another concern is that 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). In particular, the presence of multiple equilibria precludes causal statements about the effect of external credit conditions on transmission as variations in bank credit could alternatively be explained by self-fulfilling expectations. To circumvent these concerns, in Proposition 2 we isolated the conditions under which the model delivers a unique equilibrium. In Section 5, we estimate the model using Indian data and validate that the necessary and sufficient condition for uniqueness holds.

4.3 Results

4.3.1 Tests for Hypothesis 1

Hypothesis 1 states that monetary transmission is less pronounced in more connected banks. A notable feature of the multiple banking network in India is that it exhibits a core-periphery (CP) architecture. Such networks have received considerable attention in the literature on financial networks. Galeotti and Goyal (2010), Lux (2015), Van der Leij et al. (2016), Babus and Hu (2017), and Farboodi (2021) 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. In particular, our theory suggests that transmission is weaker in the densely connected core relative to the sparsely connected periphery. To test this, we first partition banks into core and periphery groups and then test for differential interest rate pass-through across these groups.

To capture differences in connectedness across banks, we use measures of centrality of the multiple banking network. Basu et al. (2019) argue that centrality measures are better indicators of connectedness than extant measures in the literature that focus on pairwise relationships between institutions. We employ two centrality measures well known in the network literature: degree and eigenvector. Degree centrality assigns a score based simply on the number of links held by each node in the network. In our context, degree centrality counts the number of banks connected to each bank via common exposures. Eigenvector centrality captures the idea that a bank may be more influential if it is connected to other influential banks. In particular, eigenvector centrality takes into account how well connected a bank is, how many links their connections have, and so on through the multiple banking network. Note that eigenvector centrality differs from degree centrality as a bank that has many links does not necessarily have a high eigenvector centrality as it might be that all linkers are not very connected in the multiple banking network.

We then use a k-shell decomposition to identify the set of core banks in the multiple banking network (Carmi et al., 2007; Garas et al., 2012). 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.

To test for differential interest rate pass-through according to connectedness, we use a difference-in-differences strategy that compares interest rate pass-through in more connected banks to that in less connected ones. Specifically, we run the following regression:

$$MCLR_{i,t} = \beta_1 REPO_t \times \mathcal{C}_i + \boldsymbol{\beta_2} \boldsymbol{B}_{i,t} + \xi_i + \Xi_t + \epsilon_{i,t}. \tag{6}$$

The dependent variable, $MCLR_{i,t}$, is the MCLR of bank i in month t. The explanatory variable is an interaction term between the policy rate in month t, $REPO_t$, and the connectedness of bank i in the multiple banking network, $\mathcal{C}_i$. In addition to employing degree and eigenvector centrality to measure connectedness, we also use an indicator that equals one for core banks and zero for periphery banks. Bank-level characteristics are captured by $\boldsymbol{B}_{i,t}$. Bank fixed effects and time fixed effects are denoted by ξ_i and Ξ_t, respectively. The equation is estimated with standard errors clustered at the bank level. We do not explicitly control for $REPO_t$ and $\mathcal{C}_i$ in this specification as these terms are absorbed by time and bank fixed effects, respectively. Applying arguments from Angrist and Pischke (2008), hypothesis 1 is

$$\beta_1 = \left.\frac{\partial MCLR_{i,t}}{\partial REPO_t}\right|_{\text{High } \mathcal{C}_i} - \left.\frac{\partial MCLR_{i,t}}{\partial REPO_t}\right|_{\text{Low } \mathcal{C}_i} < 0.$$

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

For robustness, we also consider the following specification that investigates how changes in the policy rate translate into changes in MCLRs according to the connectedness of banks in the multiple banking network:

$$\Delta MCLR_{i,t} = \beta_1 \Delta REPO_t \times \mathcal{C}_i + \boldsymbol{\beta}_2 \boldsymbol{B}_{i,t} + \xi_i + \Xi_t + \epsilon_{i,t}. \tag{7}$$

In this model, the dependent variable, $\Delta MCLR_{i,t}$, is the first difference in the MCLR of bank i in month t. The explanatory variable is an interaction term between the first difference in the policy rate in month t, $\Delta REPO_t$, and the centrality of bank i, $\mathcal{C}_i$. This empirical strategy compares $\frac{\partial \Delta MCLR_{i,t}}{\partial \Delta REPO_t}$ in more connected banks to that in less connected ones and removes any potential bias originating from non-stationarity in MCLRs.

Table 1 provides support for hypothesis 1. In panel A, we report results for specification (6), where we estimate how the effect of the policy rate on MCLRs varies according to bank connectedness. Columns 1 and 2, which report the results for the test where degree centrality is used to measure connectedness, show that higher connectedness significantly reduces interest rate pass-through. This result is confirmed when we use eigenvector centrality to measure bank connectedness (columns 3 and 4), and when we compare transmission across core and periphery banks (columns 5 and 6). Even the magnitude of the coordination channel seems sizable. We find that MCLRs in periphery banks increase by 25.5 basis points more than in core banks in response to a 100 basis point increase in the policy rate. These results are statistically indistinguishable from the results for specification (7) where we focus on variations in first differences of interest rates instead of levels (panel B).

4.3.2 Tests for Hypothesis 2

Hypothesis 2 states that in a connected financial network, interest rate pass-through is lower when the mean and dispersion of the price of external credit are higher. To test this hypothesis, we estimate the following model:

$$\begin{aligned} MCLR_{i,t} = {} & \beta_1 REPO_t \times \mathcal{C}_i \times \bar{R}_{j \neq i,t} + \beta_2 REPO_t \times \mathcal{C}_i \times \sigma(R)_{j \neq i,t} + \boldsymbol{\beta}_3 \boldsymbol{B}_{i,t} \\ & + \xi_i + \Xi_t + \epsilon_{i,t}. \end{aligned} \tag{8}$$

The main explanatory variables are triple interaction terms between the policy rate, network centrality, and the first two moments of the distribution of MCLRs of other banks. Specifically, $\bar{R}_{j \neq i,t}$ and $\sigma(R)_{j \neq i,t}$ in the above specification respectively denote the cross-sectional mean and dispersion of MCLRs of all banks barring bank i in period t, which we interact with the policy rate in period t, $REPO_t$, and the connectedness measure of bank i, $\mathcal{C}_i$. We also control for time-varying bank-level characteristics ($\boldsymbol{B}_{i,t}$), bank fixed effects (ξ_i), and time fixed effects (Ξ_t). Note that this specification captures the idea that external credit conditions do not matter for transmission to MCLRs of disconnected banks, as predicted by our theory. In the above empirical model, hypothesis 2 is $(\beta_1, \beta_2) < \mathbf{0}$. $\beta_1 < 0$ implies that an increase in the mean of the external cost of credit dampens interest rate pass-through, while $\beta_2 < 0$ implies that an increase in the dispersion in the external cost of credit dampens interest rate pass-through. In addition, as in Section 4.3.1, we also consider a specification that focuses on first differences instead of levels:

$$\Delta MCLR_{i,t} = \beta_1 \Delta REPO_t \times \mathcal{C}_i \times \bar{R}_{j\neq i,t} + \beta_2 \Delta REPO_t \times \mathcal{C}_i \times \sigma(R)_{j\neq i,t} + \boldsymbol{\beta}_3 \boldsymbol{B}_{i,t} + \xi_i + \Xi_t + \epsilon_{i,t}. \tag{9}$$

Table 2 provides partial support for hypothesis 2. Irrespective of the measure of bank connectedness we employ, we find that the coefficient on the interaction term featuring the cross-sectional mean of MCLRs of other banks (i.e., β_1 in specification (8)) is negative and statistically significant at conventional levels (see panel A). We find that when the cross-sectional mean of MCLRs of other banks is 100 basis points higher, then interest rate pass-through is two basis points lower in core banks vis-à-vis periphery banks. These results are robust to employing the full set of control variables. The point estimate for β_1 remains negative but looses precision when we consider specification (9) that features first differences in interest rates instead of levels (see panel B). These results are consistent with our hypothesis that an increase in the cross-sectional mean of MCLRs of other banks dampens monetary transmission. However, the positive coefficient on the interaction term featuring the dispersion in MCLRs of other banks does not support our hypothesis.

As explained in Section 2.5.1, interest rate pass-through is perfect in the absence of lending complementarities, which implies a constant credit spread. In the presence of lending complementarities, however, changes in external credit conditions alter interest rate pass-through and generate fluctuations in the credit spread. Hence, an alternative test for hypothesis 2 is:

$$MCLR_{i,t} - REPO_t = \alpha + \beta_1 \mathcal{C}_i \times \bar{R}_{j\neq i,t} + \beta_2 \mathcal{C}_i \times \sigma(R)_{j\neq i,t} + \boldsymbol{\beta}_3 \boldsymbol{X}_t + \boldsymbol{\beta}_4 \boldsymbol{B}_{i,t} + \xi_i + \xi_i t + \epsilon_{i,t}. \tag{10}$$

In this model, the dependent variable captures the bank-specific credit spread, i.e., the difference between the MCLR of bank i in period t and the central bank policy rate in period t. The main explanatory variables are interaction terms between measures of bank connectedness and the cross-sectional mean and dispersion of MCLRs of other banks. As before, $\bar{R}_{j\neq i,t}$ and $\sigma(R)_{j\neq i,t}$ respectively denote the cross-sectional mean and dispersion of MCLRs of all banks barring bank i in period t; and $\mathcal{C}_i$ is the connectedness of bank i in the multiple banking network. Bank-level characteristics are captured by $\boldsymbol{B}_{i,t}$. Bank fixed effects and bank-specific time trends are denoted by ξ_i and $\xi_i t$, respectively. We also include a vector of time-specific controls, which we denote by $\boldsymbol{X}_t$. In the above empirical model, hypothesis 2 is $(\beta_1, \beta_2) > \mathbf{0}$, which implies that the mean and dispersion of the external cost of credit are positively associated with the credit spread.

Table 3 reports the panel estimates using specification (10). In odd-numbered columns, we report the results for the test with bank fixed effects and bank-specific time trends, while in even-numbered columns we add aggregate and bank-level controls. In columns 1-2 of the table, we measure connectedness on the extensive margin by setting $\mathcal{C}_i = 1$ if bank i is connected to at least one other bank via common lending arrangements, and zero otherwise. Note that this corresponds to assuming that the density of the multiple banking network is a 100 percent since no bank in our sample is disconnected. In both specifications, we find that $\beta_i \; \forall i \in \{1, 2\}$ are positive and statistically significant. That is, the credit spread is positively associated with the mean and dispersion of the cost of credit intermediated by other banks, providing support for hypothesis 2. We find that the credit spread increases by 26 basis points when the cross-sectional mean of MCLRs of other banks is 100 basis points higher and by 193 basis points when the dispersion in MCLRs of other banks is 100 basis points higher.[14,15] These results are robust to employing continuous measures of bank connectedness that allow us to control for differences in connectedness across banks (see columns 3-6).

We also re-run specification (10) using subsamples of core and periphery banks. Figure 6 compares the estimated effects on the credit spread of a 100 basis point increase in the mean and dispersion of the external price of credit across the core and periphery groups. The mean effect for core banks is about 2.5 times as large as that for periphery banks, while the dispersion effect is about five times as large. These results suggest that external credit conditions play a larger role in shaping monetary transmission in more connected banking networks.

[14] In a Taylor-rule setting, inflation and GDP growth determine the path of policy rates. To account for this, we considered augmented specifications that featured first-order lagged measures of month-on-month growth in the CPI and the IIP. Our main results are not sensitive to the inclusion of these terms. Moreover, the differences between the baseline estimates for our key interaction terms and the corresponding point estimates from the specification that controls for inflation and output variations are not statistically significant.

[15] As a robustness check, we also considered specifications where we use first-order lagged values of the mean and dispersion of MCLRs of other banks instead of contemporaneous values. The results were qualitatively unchanged.

4.3.3 Test for Hypothesis 3

Hypothesis 3 states that a bank's lending to a project responds more to monetary policy shocks when other banks lend more to that project. We use loan-level data to test this hypothesis. Specifically, we run the following regression:

$$Loans_{i,k,t} = \beta_1 REPO_t \times \sum_{j \neq i} Loans_{j,k,t} + \boldsymbol{\beta}_2 \boldsymbol{B}_{i,t} + \xi_i + \xi_i t + f_{k,t} + g_{i,k} + \epsilon_{i,k,t}, \quad (11)$$

where $Loans_{i,k,t}$ denotes total loans provided by bank i to firm k in month t. As in our interest rate pass-through regressions, we control for time-varying bank characteristics ($\boldsymbol{B}_{i,t}$), bank fixed effects (ξ_i), and bank-specific time trends ($\xi_i t$). Following Khwaja and Mian (2008), we also control for firm-by-month fixed effects ($f_{k,t}$) to absorb variations in borrower risk and time-dependent confounders. Note that changes in the Repo rate are absorbed by firm-by-month fixed effects as well. In addition, we control for bank-by-firm fixed effects ($g_{i,k}$) to absorb cross-sectional variations in credit relationships. In the presence of these fixed effects, β_1 is identified by comparing how loan supply responds to changes in the Repo rate for two banks with different levels of (external) credit to the same firm. Our theory predicts that $\beta_1 < 0$, i.e., the response of bank lending to a monetary policy shock is more pronounced when external credit to common projects is higher.

Table 4 reports estimates of β_1 in equation (11), which provide support for hypothesis 3. Columns 1 and 2, which report the results for the tests with and without bank-level controls, show that an increase in the policy rate by 100 basis points decreases lending to a firm by INR 0.14 crores more when external lending to that firm is INR 1 crore higher. A concern is that the MCA data is plagued with singleton groups (i.e., groups with only one observation). Maintaining singleton groups in linear regressions where fixed effects are nested within clusters can overstate statistical significance and lead to incorrect inference (Correia, 2015). To address this issue, we show that our main results are robust to the exclusion of singletons from our dataset (columns 3 and 4 of Table 4).

4.3.4 Dynamic Effects

Another prediction of our model is that when credit is uncoordinated, informational frictions can lead to a persistent dampening of monetary policy shocks. To evaluate this prediction, we use panel vector autoregressions (VARs). 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 run the following regression:

$$\boldsymbol{Y}_{i,t} = \boldsymbol{Y}_{i,t-1}\boldsymbol{\beta}_1 + \boldsymbol{X}_{i,t}\boldsymbol{\beta}_2 + \boldsymbol{\xi}_i + \boldsymbol{e}_{i,t}, \text{ where}$$

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

In the above empirical model, $\boldsymbol{X}_{i,t}$ is a vector of endogenous covariates, and $\boldsymbol{\xi}_i$ is a vector of bank fixed effects. We assume that the innovations have the following characteristics: $\mathbb{E}(\boldsymbol{e}_{i,t}) = \boldsymbol{0}$, $\mathbb{E}(\boldsymbol{e}'_{i,t}\boldsymbol{e}_{i,t}) = \Sigma$, and $\mathbb{E}(\boldsymbol{e}'_{i,t}\boldsymbol{e}_{i,s}) = \boldsymbol{0}\ \forall t > s$.

Figure 7 depicts the impulse response function of changes in MCLRs to a monetary policy shock in the PVAR specification with ordering $[\Delta MCLR \quad \Delta REPO]$, i.e., our baseline PVAR specification without any interaction terms or exogenous controls. In Figure 8, we decompose these effects by explicitly including the interaction terms.[16,17] The estimated effects of policy rate changes and the interaction terms have signs that are consistent with hypothesis 2. In particular, the pass-through of changes in the Repo rate to changes in MCLRs is positive. However, interest rate pass-though is tempered by tighter external credit conditions, which manifests in the negative impulse responses corresponding to the interaction terms. Moreover, the effects of Repo rate changes and the interaction term featuring the cross-sectional mean of other banks' MCLRs are significant, both with and without the exogenous controls. However, the effect of the interaction term featuring the cross-sectional dispersion in MCLRs of other banks is imprecise. In addition, these effects persist for about 2-3 months post the shocks. These results are consistent with our theory, which shows that when credit is uncoordinated, informational frictions can lead to a persistent dampening of monetary policy shocks.

4.3.5 Network Effects

In this section, we exploit methods from spatial econometrics to decompose the response of MCLRs to a monetary policy shock into a direct effect and network effects. Ozdagli and Weber (2017) use a similar strategy to decompose the response of stock returns to monetary policy shocks. To apply the spatial regression, we first convert the data into a balanced panel with $\mathfrak{N}(= 71)$ banks and $T(= 43)$ periods. We then run the following regression:

$$\Delta \boldsymbol{MCLR}_t = \zeta \boldsymbol{\mathcal{A}}\, \Delta \boldsymbol{MCLR}_t + \boldsymbol{\beta}\Delta \boldsymbol{REPO}_t + \boldsymbol{\mu} + \boldsymbol{\epsilon}_t, \tag{12}$$

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

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

where $\boldsymbol{MCLR}_t$ and $\boldsymbol{REPO}_t$ respectively denote the $\mathfrak{N} \times 1$ vectors of MCLRs and policy rates, and $\boldsymbol{\mathcal{A}}$ is the $\mathfrak{N} \times \mathfrak{N}$ row-normalized adjacency matrix. This formulation encapsulates both random- and fixed-effects models. We assume that $\boldsymbol{\mu} \sim \mathcal{N}(0, \sigma_\mu^2)$ in the random effects model, and that $\boldsymbol{\mu}$ captures bank fixed effects in the fixed effects model. The coefficient of interest, ζ, captures the network spillover effects on MCLRs across banks. This specification can be partially justified using Proposition 5, which analytically shows that the direct effects are additively separable from the network effects. Table 5 presents the estimated results of the SAR models. The network effect is estimated to be positive and significant, suggesting that lending rates offered in banks connected to a particular bank also affect the lending rates in that bank. The magnitude and standard errors of the estimates are similar in the random- and fixed-effects SAR models.

We are also interested in measuring the extent to which changes in the policy rate impact lending rates in bank i directly versus indirectly via changes in the lending rates in bank $j \neq i$. We follow Pace and LeSage (2006) to disentangle these effects. For illustrative purposes, we omit time subscripts and re-write the SAR model as:

$$\Delta \boldsymbol{MCLR} = S(\boldsymbol{\mathcal{A}})\boldsymbol{\beta}\Delta \boldsymbol{REPO} + S(\boldsymbol{\mathcal{A}})(\boldsymbol{\mu} + \epsilon),$$

where $S(\boldsymbol{\mathcal{A}}) = (\boldsymbol{I}_{\mathfrak{N}} - \zeta\boldsymbol{\mathcal{A}})^{-1}$. The diagonal elements of $S(\boldsymbol{\mathcal{A}})$ capture the direct effect of monetary policy shocks on MCLRs, and the off-diagonal elements capture the network effects. The average direct effect is $\frac{1}{\mathfrak{N}}\sum_{i=1}^{\mathfrak{N}} S(\boldsymbol{\mathcal{A}})_{i,i}\boldsymbol{\beta}_i$, and the average total effect is $\frac{1}{\mathfrak{N}}\sum_{i=1}^{\mathfrak{N}} \boldsymbol{I}'_{\mathfrak{N}} S(\boldsymbol{\mathcal{A}})\boldsymbol{\beta}$. The average network effect is the difference between the average total effect and the average direct effect. In our preferred specification, we find that the average network effect is approximately twice as large as the average direct effect. We also consider a specification that includes the full set of covariates and obtain similar results.

4.3.6 Alternative Mechanisms

This section shows that our baseline results are not driven by alternative mechanisms that stem from differences in the size and composition of bank balance sheets and have been emphasized in the literature on monetary policy transmission.

First, we consider the bank assets channel. Kashyap and Stein (1995) find that large and small banks respond differently to a monetary policy contraction. Second, we consider the bank capital channel. The existing literature shows that the impact of monetary policy on lending behavior is more pronounced for banks with less liquid balance sheets (Kashyap and Stein, 2000). 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. In addition, Dell'Ariccia et al. (2017) find that risk-taking by banks is negatively associated with increases in the policy rate, and that this relationship is less pronounced for banks with relatively low capital. Third, we consider the deposit channel. Using U.S. data, Drechsler et al. (2017) show that market power affects deposit spreads, and, thus, total deposits and loanable funds. To account for these alternative bank lending channels, we consider a specification featuring interactions between relevant bank characteristics and the policy rate. That is, we run the regression:

$$\begin{aligned} MCLR_{i,t} = {} & REPO_t \times [\beta_1 \mathcal{C}_i + \beta_2 A_{i,t} + \beta_3 CA_{i,t} + \beta_4 D_{i,t}] + \boldsymbol{\beta}_5 \boldsymbol{B}_{i,t} \\ & + \xi_i + \Xi_t + \epsilon_{i,t}, \end{aligned} \tag{13}$$

where $A_{i,t}$, $CA_{i,t}$, and $D_{i,t}$ denote total assets, the capital to asset ratio, and total deposits of bank i in period t respectively. In the above empirical model, we use the core indicator variable to measure bank connectedness, $\mathcal{C}_i$. Figure 9 depicts the results. The coefficients on the interaction terms capturing the asset, capital, and deposit channels are not significantly different from zero at the 0.05 level. More importantly, the point estimates and standard errors on the interaction term between the Repo rate and bank connectedness are consistent with our baseline results.

4.3.7 Is Connectedness a Proxy for Bank Size or Market Power?

Another concern is that our baseline results may be driven by bank size, which may be positively associated with connectedness. If this is the case, we should expect the effect of external credit conditions on monetary transmission to be more pronounced for larger banks. We do not find any evidence supporting this claim in the data. Specifically, we take the cross-section of banks and assign them into non-overlapping quintiles of the mean of total assets from lowest to highest, and then run our baseline regression over subsamples of banks belonging to each quintile. Panels (a) and (b) of Figure 10 plot the estimates for the coefficients of the lending rate moments across quintiles of bank size. The point estimates suggest that the effects of the mean and dispersion of lending rates on transmission are most pronounced for medium-size banks and small banks, respectively. Moreover, we do not detect any systematic patterns or differences across bins by size. In a similar vein, we also validate that our results are not driven by differences in market power across banks (Panels (c) and (d) of Figure 10). We use the Lerner index to measure market power, which has several advantages over alternative potential measures of competition (Claessens and Laeven, 2004; Beck et al., 2013). One property of the Lerner index that is particularly useful for our analysis is that it is available at the bank level, unlike most other competition measures.

We assign banks into quintiles of the mean of Lerner indices and run our baseline regression over subsamples of banks belonging to each quintile. Again, we do not detect any significant differences in the coefficients of the lending rate moments across quintiles. These facts are prima facie evidence that differences in size or market power do not drive our baseline results.

5 Quantitative Results

In this section, we structurally estimate our model to assess the quantitative importance of the coordination channel relative to the traditional interest rate channel of monetary policy. Our estimates suggest that coordination failures amongst banks can substantially dampen monetary transmission to the macroeconomic targets of the central bank. We also show that our model does a better job in matching the volatilities of inflation and output growth in the data than the standard model.

5.1 Parametrization

We follow a three-step strategy to estimate the parameters of the model. First, we fix a subset of parameters independently of equilibrium conditions. We set the discount factor (β) to 0.99, which implies a steady-state annualized real interest rate of 7 percent. The parameter controlling the persistence of the monetary shock process (ρ^p) is set to 0.4, which generates estimates of σ_p consistent with the data.

Second, 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 (ρ) is set to 0. The observations for inflation and output respectively correspond to HP-filtered log deviations from mean values of the CPI and the IIP. 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 NK literature (Galí, 2008).

Third, 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. We then use the Metropolis-Hastings algorithm to obtain the posterior distribution. 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 C.2 for details. This procedure yields the following set of estimates. The coefficient of relative risk aversion (γ) is set to 1.06. This implies an elasticity of intertemporal substitution of 0.94, which falls within the range of cross-country estimates in the literature

(Havranek et al., 2015). The elasticity of the marginal disutility with respect to labor (φ) is set to 0.65. This implies a Frisch elasticity of labor supply of 1.5, which is broadly consistent with existing macro estimates (Chetty et al., 2011). The price rigidity parameter (θ) is set to 0.81. Thus, on average, a firm reoptimizes prices every $(1-0.81)^{-1} \approx 5$ months. This estimate is consistent with the empirical literature that studies the frequency at which prices change. Using 1988-2004 microdata collected by the US Bureau of Labor Statistics, Klenow and Kryvtsov (2008) find that firms change prices every 4-7 months. The curvature of lending complementarity (μ) is set to 0.44. Since μ is absent from the NK model, we use the NK-LC estimate for this parameter. The standard error of the monetary policy shock (σ_p) is set to 0.08.

Table 6 summarizes our baseline parameterization. It is straightforward to check that the necessary and sufficient conditions for the uniqueness of equilibria (see Proposition 2) are satisfied in both the NK and NK-LC models under this parametrization.

5.2 Model Fit

This section shows that our model fits the data better than the standard NK model in terms of matching inflation and output volatilities. Table 7 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 much higher at 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. We also simulate the distributions of inflation and output in the NK and NK-LC models by feeding in the observed log deviations of the Repo rate from mean values over our sample period. Figure 11 shows that the NK model over-predicts the observed variance of inflation and output, while the NK-LC model closely tracks the data.

5.3 Dampening of Monetary Transmission

The effect of lending complementarities on monetary transmission can be vividly seen in Figure 12, which compares the impulse response functions of inflation and output to a (one standard deviation) monetary policy shock in the standard NK model with those in the NK-LC model. When bank lending exhibits strategic complementarities, an increase in the policy rate has a muted effect on inflation and output relative to that in the NK model. Our model differs from the NK model in its static predictions but features similar dynamics. Thus, the dampening of transmission in the immediate period following the monetary policy shock is identical to that in future periods. It turns out that lending complementarities reduce monetary transmission to inflation and output by 32 percent under the baseline calibration. This estimate, however, is sensitive to model primitives.

5.3.1 Sensitivity Analysis

Table 8 reports the impact of the coordination channel on monetary transmission for various parameterizations. In particular, keeping all else constant, we perturb one parameter at a time and compute 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. We discuss these results below.

Price Inertia: The coordination channel is highly elastic to the degree of price rigidity. In particular, increasing the fraction of firms that can alter prices substantially reduces the effect of lending complementarities on monetary transmission. Holding other parameters fixed, increasing the fraction of firms that can alter prices to 0.5 reduces the dampening of transmission to 18 percent. To see this, note that when prices are less sticky, the Phillips curve is steeper, and output tends to be less responsive to monetary policy shocks. Proposition 1 shows that when banks have incentives to coordinate lending, the pass-through of changes in the policy rate to lending rates is more pronounced when such output deviations are smaller. Thus, relative to the standard model in which there is complete interest rate pass-through, the dampening of transmission due to coordination failures is less when more firms can reset their prices every period.

Preferences: A moderate level of risk aversion also plays a crucial role in amplifying the coordination channel. To see this, note that the dynamic IS curve implies that output deviations tend to be more responsive to monetary shocks when agents' relative risk aversion is lower, which reduces interest rate pass-through. Increasing the coefficient of relative risk aversion to 2 reduces the dampening of transmission to 23 percent. In contrast, the Frisch elasticity of labor supply has a modest impact on the coordination channel.

Monetary Policy Rule: The parameters that govern the Taylor rule have significant implications for the coordination channel. Increasing the weight on output deviations in the Taylor Rule reduces the dampening of monetary transmission due to lending complementarities. To see this, consider a temporary unexpected shock that raises output. Proposition 1 suggests that such a shock tends to reduce interest rate pass-through. Moreover, note that a positive weight on output deviations in the Taylor Rule implies that the monetary authority will increase the policy rate in response to increased output. This counteracts the initial unexpected output shock, and, thus, output does not rise as much as it would in the absence of the policy response. Therefore, endogenous policy responses tend to cushion the dampening of monetary transmission due to lending complementarities. The larger the weight on output deviations in the Taylor Rule, the larger the counteracting effect due to endogenous policy responses, and the smaller is the dampening of monetary transmission. Since the Phillips curve determines that inflation and output deviations are positively associated, one can use a similar logic to see why increasing the weight on inflation deviations in the Taylor Rule also reduces the dampening of transmission.

These results have important policy implications. They highlight that a fundamental reform of the financial architecture is not required to address the dampening of transmission due to coordination failures. The authorities can reduce the extent of dampening considerably by more aggressive inflation and output targeting. We find that raising ϕ^y to 1 reduces the dampening of transmission to 24 percent while raising ϕ^π to 3 reduces the dampening to 29 percent. Since both of these weights are approximately twice as large as our baseline estimates, this counterfactual exercise suggests that the RBI should be more aggressive in targeting output than inflation to address the adverse effects of coordination failures on monetary transmission.

5.4 Additional Considerations

5.4.1 Interactions with Demand and Supply Shocks

In this section, 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. 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.[18]

Table 9 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.

[18] In this augmented setting, the modified 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 $\hat{y}_t = \mathbb{E}_t[\hat{y}_{t+1}] - \frac{1}{\gamma}(\hat{r}_t - \mathbb{E}_t[\hat{\pi}_{t+1}]) + \epsilon_t^D$.

5.4.2 Impact on Production

Our baseline model incorporates lending complementarities in the standard three equation NK model. In this setting, bank lending only affects output through changes in consumption expenditure. This simplifies the analysis and permits us to get better intuition. The fact that there is no explicit role for investment in the baseline framework is typical of standard textbook treatments (Galí, 2008). Nevertheless, even in these models, there is an inverse relationship between the demand for current spending and the interest rate, a key channel of monetary policy transmission.

In Appendix D, we consider the model presented in Christiano et al. (2001) (henceforth CEE), which features a more prominent role for investment. In their model, banks lend directly to intermediate good producers. These funds are used to finance the wage bill since workers must be paid in advance of production. To incorporate lending complementarities into their model, we assume that multiple banks provide such working capital loans and that the default probability of these loans depends on the aggregate credit extended by all banks. In this richer setting, coordination failures can impact output not only through the expenditure side of the economy but also through the production side, which reduces transmission even further.

6 Conclusion

In this paper, we presented a tractable model in which banks' incentives to coordinate lending and its interaction with monetary policy shocks generate several predictions for monetary transmission that are consistent with Indian data.

In our model, strategic complementarities in bank lending create a wedge between changes in the policy rate and changes in the lending rate. This wedge leads to imperfect interest rate pass-through, which is a salient feature of the data. This fact, however, can be rationalized by a large class of monetary models. The following predictions distinguish our work from the existing literature. In our model, as in the data, the effect of policy rate changes on bank lending to a firm is higher when other banks lend more to that firm. Moreover, this coordination channel of monetary policy transmission is more pronounced in banks that are more connected via joint lending arrangements. Our results show that the lack of coordination in multiple banking arrangements can substantially blunt the impact of monetary policy shocks.

Our model highlights several possible avenues for policy interventions. Although our results suggest that regulators can increase monetary transmission by limiting banks' exposures to common assets, doing so may make the financial system less stable. It is well known that 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). Our work, in contrast, focuses on the macroeconomic cost of multiple banking in that it hampers the ability of policymakers to stabilize inflation and employment. Any restructuring of the multiple banking architecture should thus balance the tradeoff between macroeconomic stability and financial stability.

While constraints on the commonality of bank exposures can be an important tool for managing the dampening of transmission that arises through interconnectedness, they are not the only tool. Our results suggest that the extent of dampening can be reduced considerably by more aggressive inflation and output targeting. This prescription aligns with Yellen (2013), who argues that reforms that limit interconnectedness should be viewed with caution and advises regulators to pursue policies that preserve the financial stability benefits of interconnectedness while managing its harmful side effects.

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Appendix

A Figures and Tables

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

Notes: These figures illustrate how the lending response to a monetary policy shock depends on external credit conditions. Here we assume that the curvature of lending complementary (μ) equals one. Panel (a) shows that bank i's lending response to a monetary policy shock is higher when bank $j \neq i$ lends more to the project. We focus on the credit response to an expansionary monetary policy. The blue and red lines correspond to the marginal benefit and marginal cost of lending for bank i, respectively. The marginal benefit curve is increasing in loans when the interest rate on project loans (R_i) is positive since an increase in project lending increases the creditworthiness of the project. The marginal cost curve is increasing in loans as the cost of financial intermediation is convex in loans. The point at which the marginal benefit and marginal cost curves intersect gives us the optimal lending decision. Consider a reduction in the policy rate from $R_1^\star$ to $R_2^\star$. This reduces the slope of the marginal cost curve as banks can now borrow funds on the discount window at a lower interest rate. The difference, $\Delta L_i(E[L_{j1}])/\Delta R^\star$, depicts the increase in lending under the expansionary monetary policy. Contrast this lending response to that in a setting in which bank j lends less to the project. In this case, a reduction in lending by bank j increases the probability of the project defaulting, which reduces bank i's marginal benefit of lending to the project. This is captured by a downward shift of the marginal benefit curve to the dashed blue line. Hence, the optimal lending decision in this setting is $L_i(L_{j2}, R_1^\star)$. Moreover, under the expansionary monetary policy discussed above, the lending decision would be $L_i(L_{j2}, R_2^\star)$. Notice that the lending response to a monetary policy shock is much smaller in this case, i.e., $\Delta L_i(E[L_{j1}])/\Delta R^\star > \Delta L_i(E[L_{j2}])/\Delta R^\star$. Panel (b) highlights how this result hinges on the shape of the cost of loan provision. It shows that monetary transmission is independent of external credit conditions when the cost of loan provision is linear. In particular, $\Delta L_i(E[L_{j1}])/\Delta R^\star = \Delta L_i(E[L_{j2}])/\Delta R^\star$ when the cost function is linear.

(a) Convex Cost Function

(b) Linear Cost Function

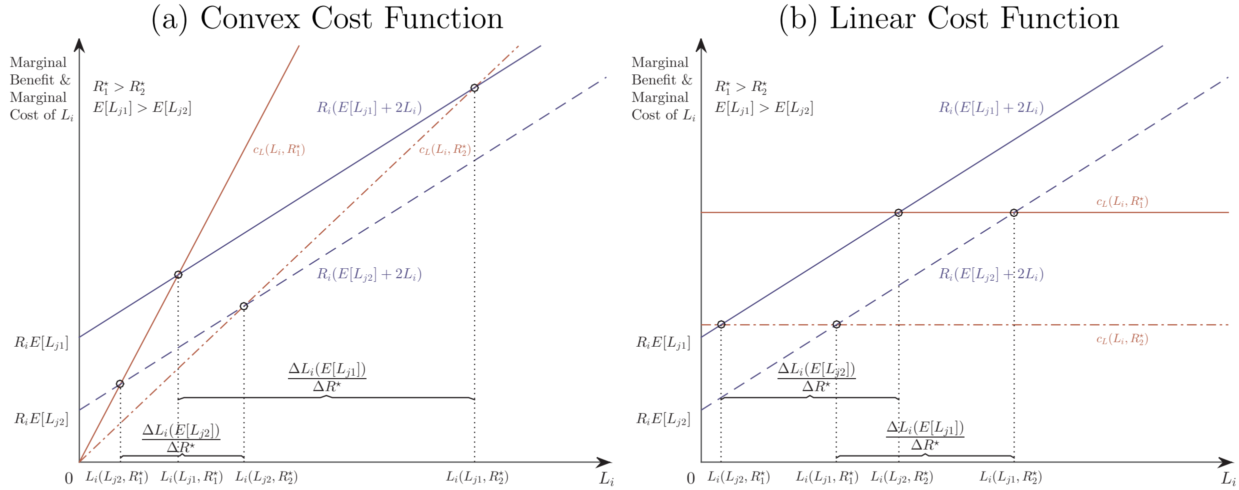
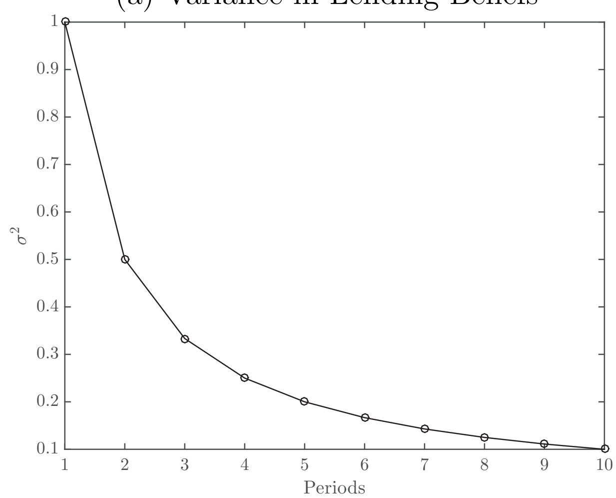


Figure 2: The Effect of Coordination and Information on Monetary Transmission

Notes: These figures show that informational frictions dampen monetary transmission when credit is uncoordinated. 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.

(a) Variance in Lending Beliefs



(b) Monetary Transmission

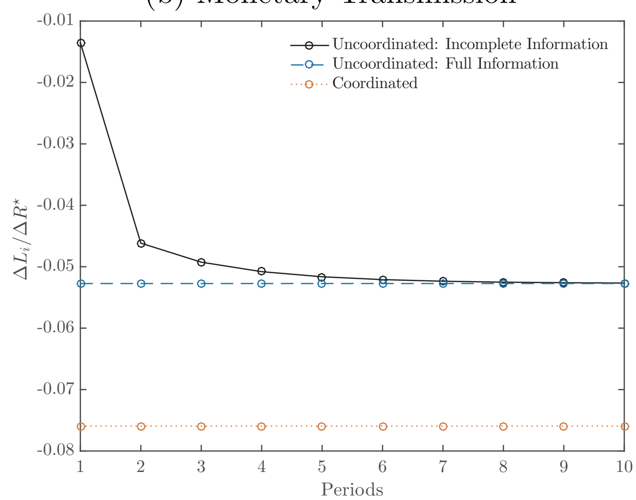
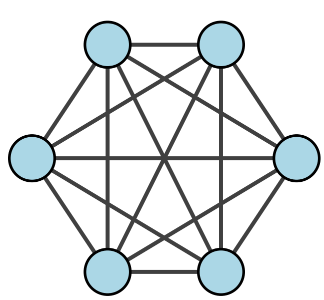


Figure 3: Multiple Banking Network Topology in Baseline Model and Extension

Notes: These graphs illustrate differences in the network topology in our baseline model and extension. Our baseline model considers a mesh network in which all banks are connected through their exposure to a single project. Panel (a) depicts this case when the number of banks in the network equals six. Our extension considers a core-periphery network in which core banks are more connected than periphery banks. In particular, we assume that there are $\mathfrak{m}$ core banks that are all connected to each other via a common loan syndication. In addition, each core bank is connected to a unique set of $\mathfrak{n}$ periphery banks. Panel (b) depicts this case with three core banks and two periphery banks.

(a) Mesh Network with $\mathfrak{N} = 6$



(b) Core-periphery Network with $\mathfrak{m} = 3$ and $\mathfrak{n} = 2$

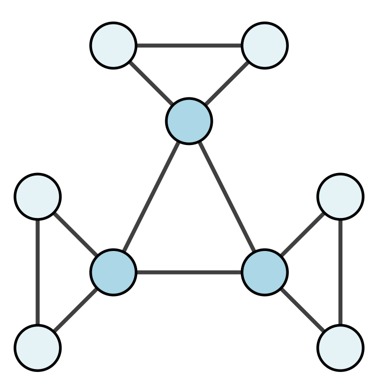


Figure 4: Bank Lending Rates and Policy Rate

Notes: This figure depicts the evolution of key interest rates. Lending rates (displayed in grey) reflect bank-specific MCLRs.

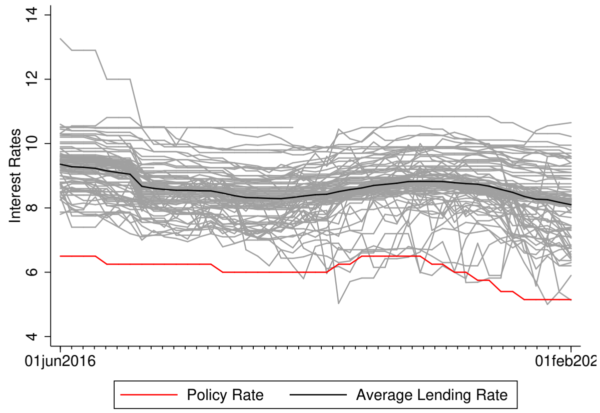


Figure 5: Multiple Banking Network in India

Notes: This graph depicts the multiple banking network in India, which is highly dense and heterogenous. In the graph, 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.

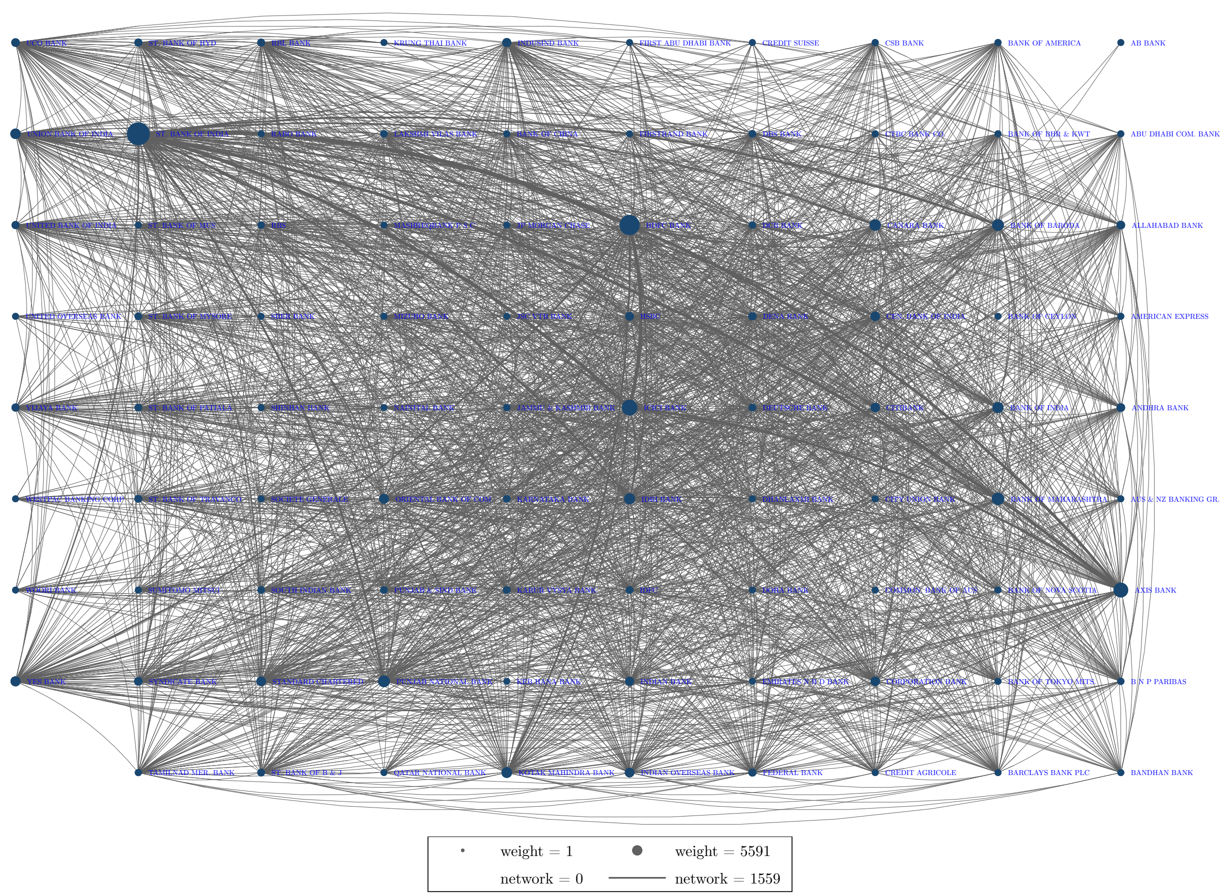


Figure 6: Effect of Lending Rate Moments on Transmission: Core vs. Periphery Banks

Notes: These figures show that the coordination channel is more pronounced in the subgraph of core banks than in the subgraph of periphery banks. Specifically, we report OLS estimates and associated 95% confidence intervals of key coefficients in the following set of regressions:

$$MCLR_{i,t}^{k} - REPO_t = \alpha^k + \beta_1^k \bar{R}_{j\neq i,t}^{k} + \beta_2^k \sigma(R)_{j\neq i,t}^{k} + \boldsymbol{\beta}_3^k \boldsymbol{X}_t + \boldsymbol{\beta}_4^k \boldsymbol{B}_{i,t} + \xi_i + \xi_i t + \epsilon_{i,t}^k \ \forall k \in \{\text{Core, Periphery}\}.$$

The dependent variable is the spread between the MCLR of bank i and the Repo rate in month t. The explanatory variables are moments of the cross-sectional distribution of MCLRs of all banks barring bank i in period t. The variables capturing the mean and dispersion of external MCLRs for bank i in period t are denoted by $\bar{R}_{j\neq i,t}$ and $\sigma(R)_{j\neq i,t}$, respectively; these variables are computed using 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. Time-varying aggregate controls and bank-level controls are captured by $\boldsymbol{X}_t$ and $\boldsymbol{B}_{i,t}$, respectively. Bank fixed effects, time fixed effects, and bank-specific time trends are captured by ξ_i, Ξ_t, and $\xi_i t$, respectively. The sample period is 2016M6-2020M2. The mean and dispersion effects in subsample $k \in \{\text{Core, Periphery}\}$ presented in the figures are captured by β_1^k and β_2^k, respectively.

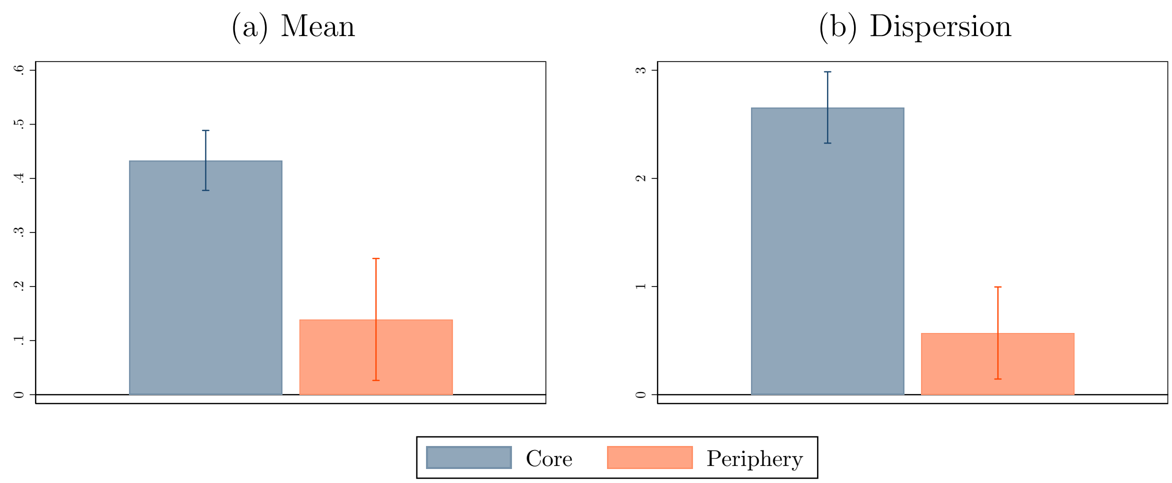


Figure 7: PVAR Impulse Response Function: Response of MCLRs to a Monetary Policy Shock w/o Lending Rate Moment Interactions

Notes: This plot depicts the orthogonalized impulse response function of $\Delta MCLR$ to a $\Delta REPO$ shock in the PVAR specification with ordering $[\Delta MCLR \quad \Delta REPO]$. The sample period is 2016M6-2020M2. The results suggest that interest rate pass-through is positive and significant, but imperfect.

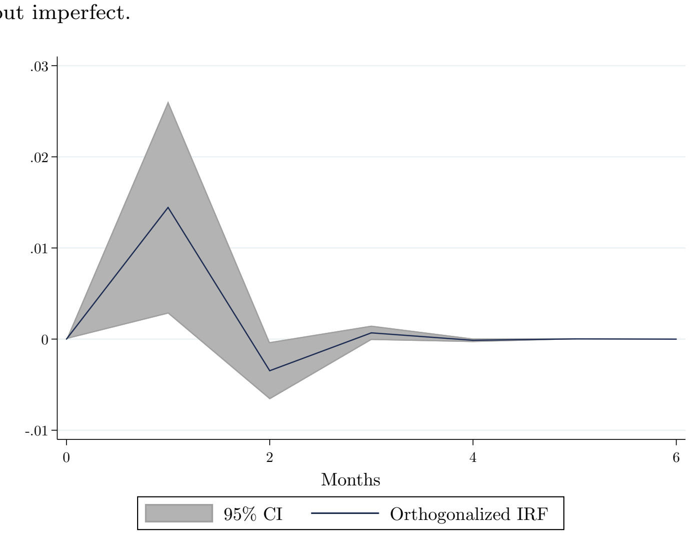


Figure 8: PVAR Impulse Response Function: Responses of $\Delta MCLR$ w/ Lending Rate Moment Interactions

Notes: This plot depicts the orthogonalized impulse response functions (OIRF) of $\Delta MCLR$ in the PVAR specification with ordering $[\Delta MCLR \quad \Delta REPO \quad \Delta REPO \times \bar{R}_{i\neq j} \quad \Delta REPO \times \sigma(R)_{i\neq j}]$. In the first column, we present OIRFs to changes in $\Delta REPO$; in the second column, we present OIRFs to changes in $\Delta REPO \times \bar{R}_{i\neq j}$; and in the third column, we present OIRFs to changes in $\Delta REPO \times \sigma(R)_{i\neq j}$. In the first and second rows, we report the results excluding and including exogenous controls, respectively. The set of exogenous controls include the time deposits share, the consistency of the monetary policy stance, and the SLR. The sample period is 2016M6-2020M2. The results suggest that tighter external credit conditions, captured by a higher cross-sectional mean of other banks' MCLRs ($\bar{R}_{i\neq j}$) and a higher cross-sectional standard deviation of other banks' MCLRs ($\sigma(R)_{i\neq j}$) reduce interest rate pass-through.

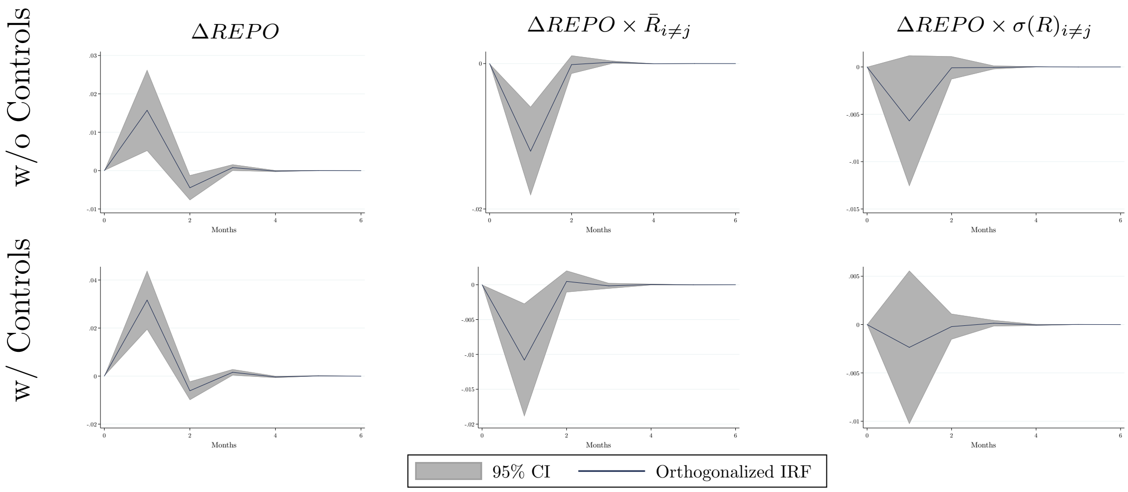


Figure 9: Alternative (Bank Lending) Channels of Monetary Transmission

Notes: This figure shows that our estimates for the coordination channel are robust to the inclusion of alternative bank lending channels of monetary transmission. We report OLS estimates and associated 95% confidence intervals from the regression:

$$MCLR_{i,t} = REPO_t \times [\beta_1 \mathcal{C}_i + \beta_2 A_{i,t} + \beta_3 CA_{i,t} + \beta_4 D_{i,t}] + \boldsymbol{\beta_5 B}_{i,t} + \xi_i + \Xi_t + \epsilon_{i,t}.$$

The dependent variable, $MCLR_{i,t}$, is the MCLR of bank i in month t. The explanatory variables are interaction terms between the Repo rate in period t, $REPO_t$, and (i) connectedness of bank i in the multiple banking network, $\mathcal{C}_i$; (ii) assets of bank i in month t, $A_{i,t}$; (iii) capital to asset ratio of bank i in month t, $CA_{i,t}$; and (iv) total deposits of bank i in month t, $D_{i,t}$. Time-varying bank-level controls are captured by $\boldsymbol{B}_{i,t}$. Bank fixed effects and time fixed effects are captured by ξ_i and Ξ_t, respectively. The sample period is 2016M6-2020M2. In the above empirical model, the strengths of the coordination, asset, capital, and deposits channels in transmitting monetary policy shocks to bank base lending rates (i.e., MCLRs) are captured by β_1, β_2, β_3, and β_4, respectively. Asset and deposit positions are denominated in INR lakhs. We measure connectedness, $\mathcal{C}_i$, using an indicator that equals one for banks that belong to the core and zero otherwise.

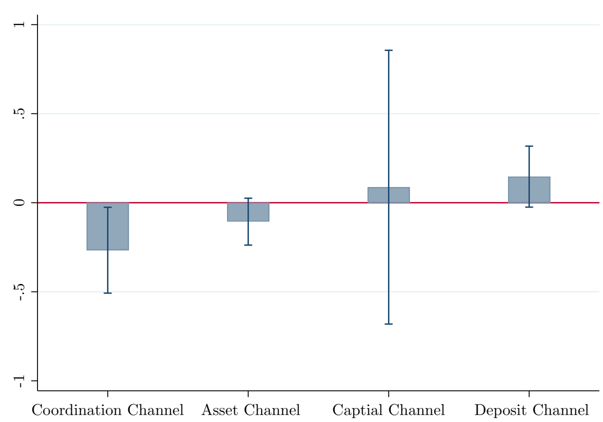


Figure 10: Effect of Lending Rate Moments on Monetary Transmission by Asset and Market Power Quintiles

Notes: These figures illustrate the cross-sectional heterogeneity in the effect of lending rate moments on the credit spread. To generate the plot, we take the cross-section of banks and assign them into non-overlapping quintiles of (mean) total assets and (mean) market power from lowest (1st quintile) to highest (5th quintile). We then run regression:

$$MCLR^q_{i,t} - REPO_t = \alpha^q + \beta^q_1 \mathcal{C}_i \times \bar{R}_{j\neq i,t} + \beta^q_2 \mathcal{C}_i \times \sigma(R)_{j\neq i,t} + \boldsymbol{\beta}^q_3 \boldsymbol{X}_t + \boldsymbol{\beta}^q_4 \boldsymbol{B}_{i,t} + \xi_i + \xi_i t + \epsilon^q_{i,t},$$

using subsamples of banks in each quintile q. The dependent variable is the spread between the MCLR of bank i and the Repo rate in month t. The explanatory variable is an interaction term between the connectedness of bank i in the multiple banking network, $\mathcal{C}_i$, and moments of the cross-sectional distribution of MCLRs of all banks barring bank i in period t. The variables capturing the mean and dispersion of external MCLRs for bank i in period t are denoted by $\bar{R}_{j\neq i,t}$ and $\sigma(R)_{j\neq i,t}$, respectively. Time-varying aggregate controls and bank-level controls are captured by $\boldsymbol{X}_t$ and $\boldsymbol{B}_{i,t}$, respectively. Bank fixed effects, time fixed effects, and bank-specific time trends are captured by ξ_i, Ξ_t, and $\xi_i t$, respectively. The sample period is 2016M6-2020M2. Panels (a)-(b) and panels (c)-(d) report the results when we split our sample in asset quintiles and market power quintiles, respectively. Vertical bands represent 95% confidence intervals for the point estimates in each quintile. We use the Lerner index (LI) to measure market power. To calculate the LI for each bank, we follow Demirgüç-Kunt and Martínez Pería (2010) and Anginer et al. (2014). In particular, we first estimate the following log cost function:

$$\begin{aligned}\log(TC_{i,t}) \quad = \quad & \alpha + \beta_1 \log(Q_{i,t}) + \beta_2 \log(Q_{i,t})^2 + \beta_3 \log(W_{1,i,t}) + \beta_4 \log(W_{2,i,t}) + \beta_5 \log(W_{3,i,t}) \\ & + \beta_6 \log(Q_{i,t}) \times \log(W_{1,i,t}) + \beta_7 \log(Q_{i,t}) \times \log(W_{2,i,t}) + \beta_8 \log(Q_{i,t}) \times \log(W_{3,i,t}) + \beta_9 \log(W_{1,i,t})^2 \\ & + \beta_{10} \log(W_{2,i,t})^2 + \beta_{11} \log(W_{3,i,t})^2 + \beta_{12} \log(W_{1,i,t}) \times \log(W_{2,i,t}) + \beta_{13} \log(W_{1,i,t}) \times \log(W_{3,i,t}) \\ & + \beta_{14} \log(W_{2,i,t}) \times \log(W_{3,i,t}) + \xi_i + \tau_t + \epsilon_{i,t}.\end{aligned}$$

Here $TC_{i,t}$ is total costs in INR crores; $Q_{i,t}$ is the quantity of output and is measured as total assets in INR crores; $W_{1,i,t}$ is the ratio of interest expenses to total deposits; $W_{2,i,t}$ is payments to and provisions for employees as a share of total assets; $W_{3,i,t}$ is the ratio of other operating expenses to total assets. The subscripts i and t denote bank and year identifiers. We take the natural logarithm of all variables, and include bank and year fixed effects. We further impose the following restrictions on regression coefficients to ensure homogeneity of degree one in input prices:

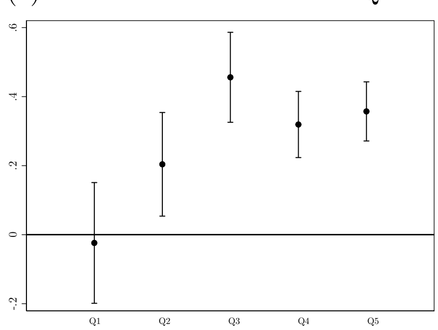
$$\beta_3 + \beta_4 + \beta_5 = 1; \beta_6 + \beta_7 + \beta_8 = 0; \beta_9 + \beta_{12} + \beta_{13} = 0; \beta_{10} + \beta_{12} + \beta_{14} = 0; \beta_{11} + \beta_{13} + \beta_{14} = 0.$$

We then use the coefficient estimates from the previous regression to estimate marginal cost for each bank i in year t:

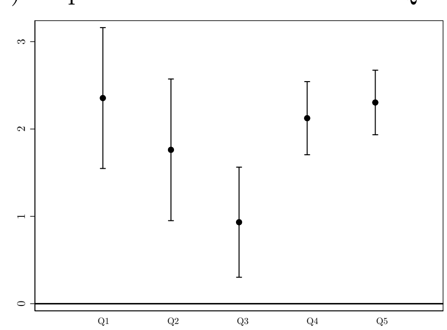
$$MC_{i,t} \quad = \quad \partial TC_{i,t} / \partial Q_{i,t} = TC_{i,t}/Q_{i,t} \times [\beta_1 + \beta_2 \log(Q_{i,t}) + \beta_6 \log(W_{1,i,t}) + \beta_7 \log(W_{2,i,t}) + \beta_8 \log(W_{3,i,t})].$$

The LI is then computed as $(P_{i,t} - MC_{i,t})/P_{i,t}$, where $P_{i,t}$ is the price of assets and equal to the ratio of total income to total assets. We restrict attention to the period 2006-2020 when computing the LI.

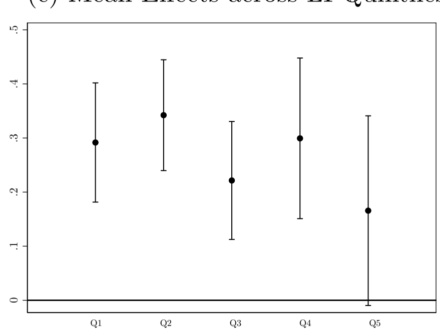
(a) Mean Effects across Asset Quintiles



(b) Dispersion Effects across Asset Quintiles



(c) Mean Effects across LI Quintiles



(d) Dispersion Effects across LI Quintiles

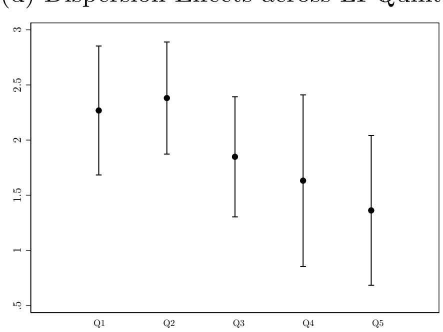


Figure 11: Simulated Distributions of Inflation and Output: Model(s) vs. Data

Notes: This figure compares the distributions of inflation and output deviations from their steady states in the model to the corresponding distributions in the data. It shows that our model fits the data better than the standard NK model in terms of matching the observed volatiles of inflation and output. The data series correspond to log deviations from mean values; the sample period is 2016M6-2020M2. 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 models by feeding in the observed log deviations of the Repo rate from mean values.

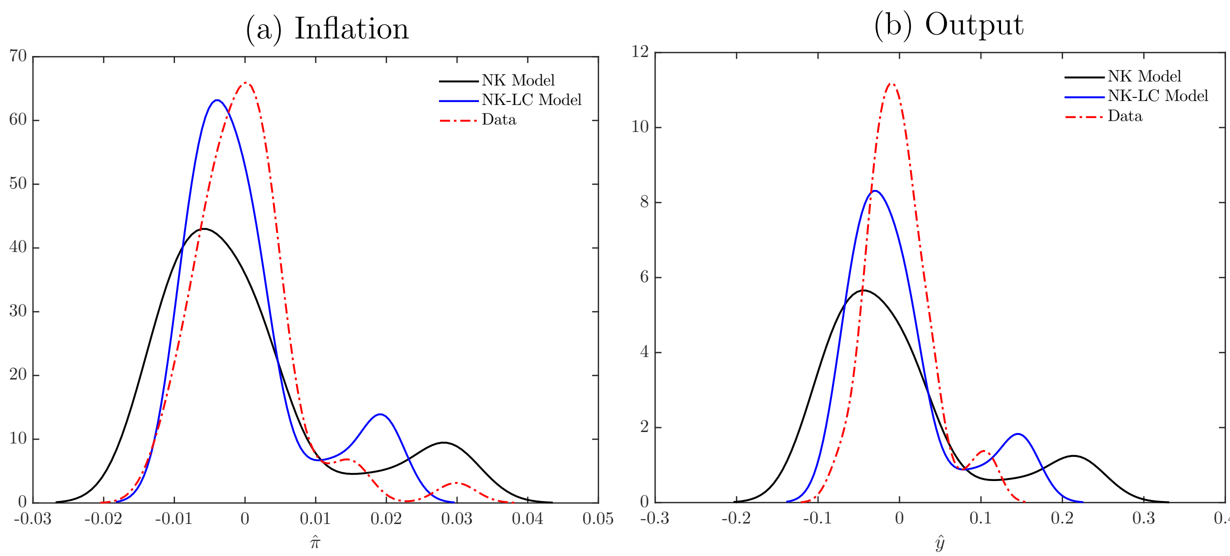


Figure 12: Simulated Impulse Responses to Monetary Policy Shock

Notes: These figures depict simulated impulse response functions of inflation and output to a (one standard deviation) monetary policy shock in the NK model with those in the NK-LC model. Time horizon in months. The scale on the y-axis in panel (a) is 10^{-3}. The figures show that lending complementarities reduce transmission to inflation and output by 31.95 percent.

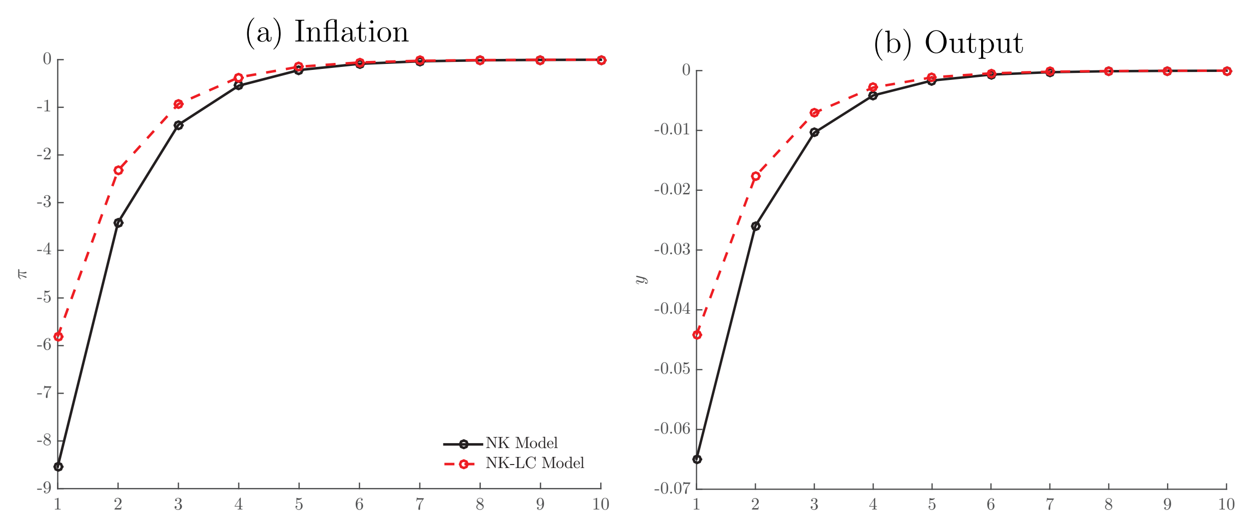


Table 1: Effect of Connectedness on Monetary Transmission

Notes: This table shows how interest rate pass-through varies with bank connectedness. In the panels below, we run the following regression models:

$$\text{Panel A:} \quad MCLR_{i,t} = \beta_1 REPO_t \times \mathcal{C}_i + \boldsymbol{\beta_2} \boldsymbol{B}_{i,t} + \xi_i + \Xi_t + \epsilon_{i,t},$$

$$\text{Panel B:} \quad \Delta MCLR_{i,t} = \beta_1 \Delta REPO_t \times \mathcal{C}_i + \boldsymbol{\beta_2} \boldsymbol{B}_{i,t} + \xi_i + \Xi_t + \epsilon_{i,t}.$$

The dependent variable, $MCLR_{i,t}$, is the MCLR of bank i in month t. The explanatory variable is an interaction term between the Repo rate in period t, $REPO_t$, and the connectedness of bank i in the multiple banking network, $\mathcal{C}_i$. Time-varying bank-level controls are captured by $\boldsymbol{B}_{i,t}$. Bank fixed effects and time fixed effects are captured by ξ_i and Ξ_t, respectively. The sample period is 2016M6-2020M2. We report estimates for the coefficient β_1 for the above specifications. Our theory predicts $\beta_1 < 0$, i.e., interest rate pass-through is lower in more connected banks. In columns (1)–(2) and (3)–(4), we respectively use the observed degree and eigenvector centrality (normalized by the sample maxima) of the multiple banking network to measure bank connectedness. In columns (5)–(6), we construct an indicator that equals one for banks that belong to the core and zero otherwise to measure connectedness. 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. Standard errors are clustered at the bank level and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
Connectedness Measure ($\mathcal{C}_i$)	Degree Centrality		Eigen. Centrality		Core Indicator	
Panel A: Levels						
$REPO \times \mathcal{C}$	-0.306*	-0.285*	-0.297*	-0.278*	-0.249***	-0.255***
	(0.155)	(0.161)	(0.160)	(0.166)	(0.0765)	(0.0787)
Observations	3664	3558	3664	3558	3664	3558
R^2	0.840	0.838	0.840	0.838	0.842	0.840
Panel B: First Differences						
$\Delta REPO \times \mathcal{C}$	-0.232*	-0.242*	-0.239*	-0.245*	-0.160**	-0.178**
	(0.136)	(0.138)	(0.137)	(0.139)	(0.0759)	(0.0784)
Observations	3575	3473	3575	3473	3575	3473
R^2	0.132	0.134	0.132	0.134	0.132	0.135
Bank FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Bank Level Controls	N	Y	N	Y	N	Y

Table 2: Effect of External Credit Conditions on Monetary Transmission

Notes: This table shows how external credit conditions impact interest rate pass-through in connected banks. In the panels below, we run the following regression models:

$$\text{Panel A:}\quad MCLR_{i,t} = \beta_1 REPO_t \times \mathcal{C}_i \times \bar{R}_{j\neq i,t} + \beta_2 REPO_t \times \mathcal{C}_i \times \sigma(R)_{j\neq i,t} + \boldsymbol{\beta_3} \boldsymbol{B}_{i,t} + \xi_i + \Xi_t + \epsilon_{i,t},$$

$$\text{Panel B:}\quad \Delta MCLR_{i,t} = \beta_1 \Delta REPO_t \times \mathcal{C}_i \times \bar{R}_{j\neq i,t} + \beta_2 \Delta REPO_t \times \mathcal{C}_i \times \sigma(R)_{j\neq i,t} + \boldsymbol{\beta_3} \boldsymbol{B}_{i,t} + \xi_i + \Xi_t + \epsilon_{i,t}.$$

The dependent variable, $MCLR_{i,t}$, is the MCLR of bank i in month t. The explanatory variable is a triple interaction term between the Repo rate in period t, $REPO_t$, the connectedness of bank i in the multiple banking network, $\mathcal{C}_i$, and moments of the cross-sectional distribution of MCLRs of all banks barring bank i in period t. The variables capturing the mean and dispersion of external MCLRs for bank i in period t are denoted by $\bar{R}_{j\neq i,t}$ and $\sigma(R)_{j\neq i,t}$, respectively. Time-varying bank-level controls are captured by $\boldsymbol{B}_{i,t}$. Bank fixed effects and time fixed effects are captured by ξ_i and Ξ_t, respectively. The sample period is 2016M6-2020M2. We report estimates for β_1 and β_2 for the above specifications. Our theory predicts that $(\beta_1, \beta_2) < \mathbf{0}$, i.e., interest rate pass-through is lower when external credit conditions are tighter. In columns (1)–(2) and (3)–(4), we respectively use the observed degree and eigenvector centrality (normalized by the sample maxima) of the multiple banking network to measure bank connectedness. In columns (5)–(6), we construct an indicator that equals one for banks that belong to the core and zero otherwise to measure connectedness. 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. Standard errors are clustered at the bank level and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
Connectedness Measure ($\mathcal{C}_i$)	Degree Centrality		Eigen. Centrality		Core Indicator	
Panel A: Levels						
$REPO \times \mathcal{C} \times$ LR Mean	-0.0307**	-0.0288**	-0.0307**	-0.0288**	-0.0201***	-0.0204***
	(0.0135)	(0.0139)	(0.0139)	(0.0144)	(0.00664)	(0.00681)
$REPO \times \mathcal{C} \times$ LR SD	0.496**	0.478**	0.512**	0.497**	0.203***	0.196***
	(0.207)	(0.209)	(0.223)	(0.224)	(0.0690)	(0.0712)
Observations	3664	3558	3664	3558	3664	3558
R^2	0.842	0.840	0.843	0.840	0.842	0.840
Panel B: First Differences						
$\Delta REPO \times \mathcal{C} \times$ LR Mean	-0.145	-0.154	-0.134	-0.142	-0.0599	-0.0690
	(0.436)	(0.444)	(0.464)	(0.471)	(0.133)	(0.141)
$\Delta REPO \times \mathcal{C} \times$ LR SD	1.322	1.421	1.197	1.281	0.467	0.547
	(4.970)	(5.068)	(5.282)	(5.367)	(1.548)	(1.633)
Observations	3575	3473	3575	3473	3575	3473
R^2	0.132	0.134	0.132	0.134	0.133	0.135
Bank FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Bank Level Controls	N	Y	N	Y	N	Y

Table 3: Effect of External Credit Conditions on the Credit Spread

Notes: This table shows that bank credit spreads are positively associated with the mean and dispersion of the cross-sectional distribution of other banks' lending rates. We run the regression model:

$$MCLR_{i,t} - REPO_t = \alpha + \beta_1 \mathcal{C}_i \times \bar{R}_{j\neq i,t} + \beta_2 \mathcal{C}_i \times \sigma(R)_{j\neq i,t} + \boldsymbol{\beta}_3 \boldsymbol{X}_t + \boldsymbol{\beta}_4 \boldsymbol{B}_{i,t} + \xi_i + \xi_i t + \epsilon_{i,t},$$

The dependent variable is the spread between the MCLR of bank i and the Repo rate in month t. The explanatory variable is an interaction term between the connectedness of bank i in the multiple banking network, $\mathcal{C}_i$, and moments of the cross-sectional distribution of MCLRs of all banks barring bank i in period t. The variables capturing the mean and dispersion of external MCLRs for bank i in period t are denoted by $\bar{R}_{j\neq i,t}$ and $\sigma(R)_{j\neq i,t}$, respectively. Time-varying aggregate controls and bank-level controls are captured by $\boldsymbol{X}_t$ and $\boldsymbol{B}_{i,t}$, respectively. Bank fixed effects, time fixed effects, and bank-specific time trends are captured by ξ_i, Ξ_t, and $\xi_i t$, respectively. The sample period is 2016M6-2020M2. We present the coefficients β_1 and β_2 in the table below. In columns 1–2, we use an indicator that equals one if a bank is connected, and zero otherwise, to measure bank connectedness; since all banks are connected in our restricted sample, the density of the network is 100 percent. In columns 3–4 and 5–6, we respectively use the observed degree and eigenvector centrality (normalized by the sample maxima) of banks in the multiple banking network to measure bank connectedness. 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. Standard errors are clustered at the bank level and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
Connectedness Measure ($\mathcal{C}_i$)	Extensive Margin		Degree Centrality		Eigen. Centrality	
$\mathcal{C}\times$ LR Mean	0.345***	0.255***	0.456***	0.304***	0.433***	0.287***
	(0.0558)	(0.0691)	(0.0612)	(0.0756)	(0.0573)	(0.0720)
$\mathcal{C}\times$ LR SD	2.285***	1.927***	2.990***	2.715***	2.745***	2.510***
	(0.203)	(0.234)	(0.225)	(0.251)	(0.213)	(0.240)
Observations	3901	3705	3664	3476	3664	3476
R^2	0.758	0.762	0.763	0.772	0.763	0.772
Bank FE	Y	Y	Y	Y	Y	Y
Bank-specific Time Trends	Y	Y	Y	Y	Y	Y
Aggregate Controls	N	Y	N	Y	N	Y
Bank Level Controls	N	Y	N	Y	N	Y

Table 4: Effect of External Firm Credit on Monetary Transmission to Internal Firm Credit

Notes: This table provides evidence on the coordination channel of monetary policy using loan-level data. We run the regression:

$$Loans_{i,k,t} = \beta_1 REPO_t \times \sum_{j\neq i} Loans_{j,k,t} + \boldsymbol{\beta}_2 \boldsymbol{B}_{i,t} + \xi_i + \xi_i t + f_{k,t} + g_{i,k} + \epsilon_{i,k,t}.$$

The dependent variable is total loans provided by bank i to firm j in month t. The explanatory variable is an interaction term between the connectedness of bank i in the multiple banking network, $\mathcal{C}_i$, and moments of the cross-sectional distribution of MCLRs of all banks barring bank i in period t. Bank-level controls are captured by $\boldsymbol{B}_{i,t}$. Bank fixed effects, bank-specific time trends, firm-time fixed effects, and bank-firm fixed effects are captured by ξ_i, $\xi_i t$, $f_{k,t}$, and $g_{i,k}$, respectively. We present estimates for β_1 in the table below. Our theory predicts that $\beta_1 < 0$, i.e., an increase in the Repo rate decreases lending to a firm by more when external lending to that firm is higher. The data is at the bank $\times$ firm $\times$ month level and the sample period is 2004M11-2020M2. Loan amounts are denominated in INR crores. Columns (1)-(2) report estimates using the entire sample. Columns (3)-(4) discard singleton groups from the sample. Standard errors are clustered at the bank level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
REPO $\times$ Total Loans to Firm by Other Banks	-0.139***	-0.139***	-0.139***	-0.139***
	(0.0158)	(0.0158)	(0.00471)	(0.00469)
Bank FE	Y	Y	Y	Y
Bank-specific Time Trends	Y	Y	Y	Y
Firm x Bank FE	Y	Y	Y	Y
Firm x Month FE	Y	Y	Y	Y
Bank Level Controls	N	Y	N	Y
Observations	150143	148969	13295	13183
R^2	1.000	1.000	0.991	0.992

Table 5: Decomposition of Direct and Network Effects

Notes: This table decomposes the impact of monetary policy shocks on MCLRs into direct and network effects. We report quasi–maximum likelihood (QML) estimators for variants of the following regression model:

$$\Delta \boldsymbol{MCLR}_t = \zeta \boldsymbol{\mathcal{A}}\, \Delta \boldsymbol{MCLR}_t + \boldsymbol{\beta}\, \Delta \boldsymbol{REPO}_t + \boldsymbol{\mu} + \boldsymbol{\epsilon}_t,$$

where $\boldsymbol{MCLR}_t$ and $\boldsymbol{REPO}_t$ respectively denote the $\mathfrak{N} \times 1$ vectors of MCLRs and policy rates, and $\boldsymbol{\mathcal{A}}$ is the $\mathfrak{N} \times \mathfrak{N}$ row-normalized adjacency matrix. $\boldsymbol{\mu} \sim \mathcal{N}(0, \sigma_\mu^2)$ in the random effects model; $\boldsymbol{\mu}$ captures bank fixed effects in the fixed effects model. The sample period is 2016M6-2020M2. In columns 1–2, we report the results without including control variables. In columns 3–4, we include the full set of aggregate and bank-level controls. The outcome variable in all columns is $\Delta MCLR$. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
$\Delta REPO$	0.102***	0.101***	0.0804**	0.0808**
	(0.0301)	(0.0300)	(0.0323)	(0.0322)
ζ	0.648***	0.650***	0.622***	0.623***
	(0.0329)	(0.0328)	(0.0346)	(0.0346)
Direct Effect	0.105***	0.105***	0.0829**	0.0833**
	(0.0314)	(0.0313)	(0.0337)	(0.0336)
Network Effect	0.187***	0.185***	0.133**	0.131**
	(0.0566)	(0.0557)	(0.0560)	(0.0537)
Total Effect	0.292***	0.290***	0.216**	0.215**
	(0.0857)	(0.0848)	(0.0882)	(0.0857)
Estimator	RE	FE	RE	FE
Deposit Maturity Controls	N	N	Y	Y
Monetary Stance Controls	N	N	Y	Y
SLR Controls	N	N	Y	Y
Bank Level Controls	N	N	Y	Y
Observations	3053	3053	3053	3053

Table 6: Baseline Parameterization

Notes: This table summarizes our baseline parameterization in the NK and NK-LC models. We calibrate β independently to match the steady-state annualized real interest rate of 7 percent. The Taylor rule coefficients, $\{\phi^\pi, \phi^y\}$, are independently estimated using OLS using HP-filtered log deviations from mean values of the CPI and the IIP. We set the persistence of policy rate, ρ, to zero to ensure determinacy, and set the persistence of monetary policy shock to be consistent with the data. $\{\gamma, \varphi, \theta, \mu, \sigma_p\}$ are estimated using the Metropolis-Hastings algorithm to match log deviations of the policy rate from mean values. We estimate this set of parameters separately in the NK and NK-LC models, and then use averages across the two models. More details on estimating this block of parameters are provided in the supplementary appendix.

Parameter	Value	Description
β	0.99	Discount rate
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
σ_p	0.08	Standard error of monetary policy shock

Table 7: Standard Deviation of Simulated Variables vs. Data

Notes: This table shows that the NK-LC model fits the data better than the standard NK model in terms of matching volatilities of inflation and output. The data moments correspond to HP-filtered log deviations from mean values; the sample period is 2016M6-2020M2. The simulated moments correspond to log deviations from steady states. Both the NK and the NK-LC models are simulated over 5000 periods with 100 replicas.

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

Table 8: Sensitivity Analysis

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. In the first column, we report our estimate for the dampening of transmission due to lending complementarities under our baseline parameterization. In subsequent columns, we perturb one parameter at a time and recompute our estimates. The results reveal that the dampening of transmission due to lending complementarities is highly sensitive to the coefficient of relative risk aversion, price inertia, and the coefficients on inflation and output in the Taylor rule.

Baseline	$\varphi = 2$	$\sigma = 2$	$\theta = 1/2$	$\phi^y = 1$	$\phi^\pi = 3$
0.3195	0.3147	0.2344	0.1836	0.2406	0.2853

Table 9: Variance Decomposition (in percent)

Notes: This table assesses how lending complementarities impact the quantitative importance of demand, supply, and monetary shocks in our simulations. We report the variance decomposition of inflation, output, the policy rate, and the lending rate in the NK and NK-LC models under our benchmark calibration.

	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

B Proofs

Proof of Proposition 1: As derived in the proof of Proposition 3, in a symmetric uncoordinated equilibrium:

$$R_t^\star L_t^{1-\mu} = \frac{R_t \alpha(\mu + \mathfrak{N})}{\mathfrak{N}^{1-\mu}}. \tag{14}$$

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

$$B_t = \Lambda Y_t, \text{where } \Lambda > 0. \tag{15}$$

Substituting (15) and (2) in (14), we arrive at:

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

Log-linearizing around steady states:

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

Proof of Proposition 2: 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

$$\Omega\gamma\beta < 1 \tag{16}$$

and

$$\Omega[\gamma+\kappa+\beta(\gamma+\phi^{y}+1-\mu)] < 1+\Omega\gamma\beta. \tag{17}$$

Equation (16) holds as $\beta\in(0,1)$. Equation (17) holds if $\kappa(\phi^{\pi}-1)+(1-\beta)(\phi^{y}+1-\mu)>0$. $\square$

Proof of Proposition 3: As banks solve a static problem, we suppress the time notation. If banks are uncoordinated, then each bank i maximizes the following objective:

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

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

$$R_i\Big[\mu(\sum_{j\neq i} L_j + L_i)^{\mu-1} L_i + (\sum_{j\neq i} L_j + L_i)^{\mu}\Big] = \frac{L_i R^{\star}}{\alpha}.$$

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

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

$$\implies \frac{\partial L^{\mathrm{U}}}{\partial R^{\star}} = -\left[\frac{R\alpha(\mu+\mathfrak{N})}{\mathfrak{N}^{1-\mu}}\right]^{\frac{1}{1-\mu}}\left(\frac{1}{1-\mu}\right)(R^{\star})^{\frac{\mu}{\mu-1}}.$$

We now consider the case when banks coordinate lending. In this case, banks choose L to maximize $\mathfrak{N}^{\mu}L^{\mu+1}R - \frac{L^2R^{\star}}{2\alpha}$. The first-order condition of this problem can be rearranged to yield:

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

$$\implies \frac{\partial L^{\mathrm{C}}}{\partial R^{\star}} = -\Big[R\alpha\mathfrak{N}^{\mu}(\mu+1)\Big]^{\frac{1}{1-\mu}}\left(\frac{1}{1-\mu}\right)(R^{\star})^{\frac{\mu}{\mu-1}}.$$

As $\mu>0$ and $\mathfrak{N}>1$, $\mid \frac{\partial L}{\partial R^{\star}} \mid$ is larger when banks coordinate, which completes the proof for part (i). To see part (ii), let $\mathfrak{D} \equiv \mid \partial L^{\mathrm{C}}/\partial R^{\star} \mid - \mid \partial L^{\mathrm{U}}/\partial R^{\star} \mid$. Partially differentiating this expression w.r.t. $\mathfrak{N}$:

$$\frac{\partial \delta}{\partial \mathfrak{N}} = \left(\frac{1}{1-\mu}\right)^2 (R^{\star})^{\frac{\mu}{\mu-1}}\big[R\alpha\mu\big]^{\frac{1}{1-\mu}}(\mathfrak{N}^{\mu}-\mathfrak{N}^{\mu-1})^{\frac{\mu}{1-\mu}}\mathfrak{N}^{\mu-2}(\mu(\mathfrak{N}-1)+1)>0. \square$$

Proof of Proposition 4: Under incomplete information, the optimal choice of lending satisfies the first-order condition:

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

Since loan officers are atomistic, they treat the interest rate as fixed when making their lending decision. In this case, an increase in the policy rate ($R^\star$) 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:

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

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

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

All parts of the proposition immediately follow from this result. □

Proof of Proposition 5: Bank i maximizes the following objective:

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

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

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

Totally differentiating this expression

$$0=\frac{\partial F_{ji}}{\partial p}dR^\star+\sum_{l=1}^{\mathfrak{M}}\sum_{k=1}^{\mathfrak{N}}\frac{\partial F_{ji}}{\partial L_{lk}}dL_{lk}$$

$$\implies\frac{dL_{ji}}{dR^\star}=\frac{1}{\tilde{R}_{ji}^{-1}-2\alpha_i}\left\{\alpha\sum_{k\neq i}\frac{dL_{jk}}{dR^\star}-\tilde{R}_{ji}^{-1}\sum_{l\neq j}\frac{dL_{li}}{dR^\star}-\sum_{l=1}^{\mathfrak{M}}L_{li}\right\}\quad\forall i\ \forall j.\quad\square$$

Proof of Lemma 1: We first characterize optimal loan provision by core banks in the core consortium. The first-order condition with respect to $L_{i,c}$ is given by:

$$R_i[\mu((\mathfrak{n}-1)L_{-i,c}+L_{i,c})^{\mu-1}L_{i,c}+((\mathfrak{n}-1)L_{-i,c}+L_{i,c})^{\mu}]=\frac{(L_{i,c}+L_{i,p})R^\star}{\alpha}.$$

In symmetric equilibria, $L_{i,c} = L_{i',c} \equiv L_c \ \forall i, i'$. Thus, the above condition can written as:

$$L_p = \frac{R\alpha(\mathfrak{n}L_c)^{\mu}[\mu/\mathfrak{n} + 1]}{R^{\star}} - L_c. \tag{18}$$

We now consider the optimal allocation of loans provided by the core bank in the periphery consortium. The first-order condition with respect to $L_{i,p}$ is given by:

$$R_i[\mu(\mathfrak{m}L_{.,i,pp} + L_{i,p})^{\mu-1}L_{i,p} + (\mathfrak{m}L_{.,i,pp} + L_{i,p})^{\mu}] = \frac{(L_{i,c} + L_{i,p})R^{\star}}{\alpha}.$$

In symmetric equilibria,

$$R[\mu(\mathfrak{m}L_{pp} + L_p)^{\mu-1}L_p + (\mathfrak{m}L_{pp} + L_p)^{\mu}] = \frac{(L_c + L_p)R^{\star}}{\alpha}.$$

Substituting (18):

$$\begin{aligned}\mu\left(\mathfrak{m}L_{pp} + \frac{R\alpha(\mathfrak{n}L_c)^{\mu}[\mu/\mathfrak{n} + 1]}{R^{\star}} - L_c\right)^{\mu-1}\left(\frac{R\alpha(\mathfrak{n}L_c)^{\mu}[\mu/\mathfrak{n} + 1]}{R^{\star}} - L_c\right) \\ +\left(\mathfrak{m}L_{pp} + \frac{R\alpha(\mathfrak{n}L_c)^{\mu}[\mu/\mathfrak{n} + 1]}{R^{\star}} - L_c\right)^{\mu} = (\mathfrak{n}L_c)^{\mu}[\mu/\mathfrak{n} + 1].\end{aligned} \tag{19}$$

When $\mu = 1$, then equation (18) reduces to

$$L_p = L_c\left(\frac{R\alpha[1 + \mathfrak{n}]}{R^{\star}} - 1\right) \tag{20}$$

while (19) can be written as

$$\frac{L_c}{L_{pp}} = \frac{\mathfrak{m}}{1 + \mathfrak{n} - 2\chi}. \tag{21}$$

To obtain a closed-form solution, next we characterize the optimal lending decision of periphery banks. A necessary condition for the optimality of $L_{j,i,pp}$ is given by:

$$R_i[\mu((\mathfrak{m}-1)L_{-j,i,pp}+L_{j,i,pp}+L_{i,p})^{\mu-1}L_{j,i,pp}+((\mathfrak{m}-1)L_{-j,i,pp}+L_{j,i,pp}+L_{i,p})^{\mu}] = \frac{(L_{j,i,pp} - \omega)R^{\star}}{\alpha}.$$

In symmetric equilibria, $L_{j,i,pp} + L_{j',i,pp} \equiv L_{pp} \ \forall j, j'$, and, thus, the above condition can be written as

$$R(\mathfrak{m}L_{pp} + L_p)^{\mu-1}[(\mu + \mathfrak{m})L_{pp} + L_p] = \frac{(L_{pp} - \omega)R^{\star}}{\alpha}.$$

Substituting (18), we obtain:

$$R\left[\mathfrak{m}L_{pp}+\left(\frac{R\alpha(\mathfrak{n}L_c)^{\mu}[\mu/\mathfrak{n}+1]}{R^{\star}}-L_c\right)\right]^{\mu-1}\left[(\mu+\mathfrak{m})L_{pp}+\left(\frac{R\alpha(\mathfrak{n}L_c)^{\mu}[\mu/\mathfrak{n}+1]}{R^{\star}}-L_c\right)\right]=\frac{(L_{pp}-\omega)R^{\star}}{\alpha}.$$

When $\mu = 1$, the above condition reduces to:

$$R[(1+\mathfrak{m})L_{pp}+L_c\chi]=\frac{(L_{pp}-\omega)R^{\star}}{\alpha}.$$

Dividing by RL_{pp} on both sides:

$$(1+\mathfrak{m})+\chi\frac{L_c}{L_{pp}}=\frac{(1-\omega/L_{pp})R^{\star}}{R\alpha}.$$

Using (21), we can characterize the ratio $\frac{L_c}{L_{pp}}$ in terms of model primitives, and, thus, the above condition can be written as:

$$1+\mathfrak{m}+\frac{\chi\mathfrak{m}}{1+\mathfrak{n}-2\chi}=\frac{(1-\omega/L_{pp})R^{\star}}{R\alpha}\implies L_{pp}=\frac{\omega}{1-\frac{R\alpha}{R^{\star}}\left[1+\mathfrak{m}\left(\frac{R^{\star}/R\alpha-1}{R^{\star}/R\alpha-2}\right)\right]}.\quad\square$$

Proof of Proposition 6: Notice that $\lim_{\alpha\downarrow 0}\frac{R^{\star}/R\alpha-1}{R^{\star}/R\alpha-2}=1$. Thus, using Lemma 1,

$$\lim_{\alpha\downarrow 0}L_{pp}=\frac{\omega}{1-\frac{R\alpha}{R^{\star}}\left[1+\mathfrak{m}\right]}.$$

Moreover, notice that for α small enough, the denominator of the above expression is positive, and, thus, L_{pp} is positive. Partially differentiating this expression w.r.t. $R^{\star}$ shows that $\partial L_{pp}/\partial R^{\star}<0$. Next, using Lemma 1, we can express the total lending response of core banks as

$$L_c+L_p=L_c(1+\chi)=\frac{L_{pp}\mathfrak{m}(1+\chi)}{1+\mathfrak{n}-2\chi}.$$

Thus,

$$\frac{\partial(L_c+L_p)}{\partial R^{\star}}=\frac{\mathfrak{m}(1+\chi)}{1+\mathfrak{n}-2\chi}\times\frac{\partial L_{pp}}{\partial R^{\star}}.$$

So, periphery banks will be more sensitive to a monetary policy shock than core banks if $\frac{\mathfrak{m}(1+\chi)}{1+\mathfrak{n}-2\chi}<1$ or, equivalently, when

$$\mathfrak{m}+\chi(\mathfrak{m}+2)<1+\mathfrak{n}.$$

Notice that χ is bounded below by -1, which is met when $\alpha=0$. At this lower bound the above condition reduces to $-2<1+\mathfrak{n}$ which is satisfied since $\mathfrak{n}>0$. As χ is continuous in α, there exists a positive α small enough such that the above condition is met. $\square$

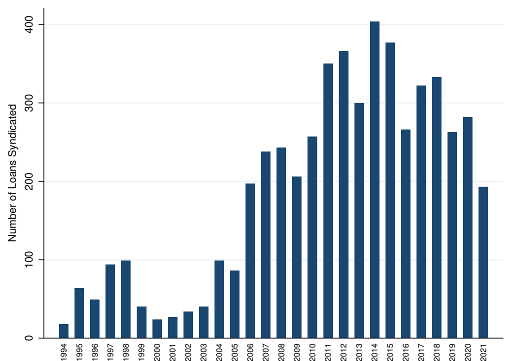
Supplementary Appendix

C Supplemental Figures and Tables

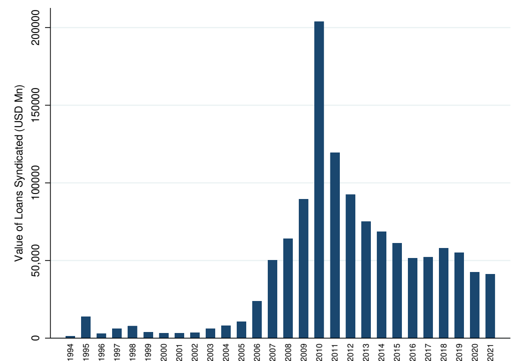
Figure C.1: Evolution and Composition of Loan Syndications in India

Notes: These figures depict the evolution and composition of a strict subset of multiple banking arrangements–loans syndications–in India over 1994-2021. It shows that the prevalence of loan syndications has increased considerably over this period, both in terms of the number of loans syndicated (see panel (a)) and the value of these loans (see panel (b)). Panel (c) presents a decomposition of the number of loans syndicated by type of lender and shows that loan syndications are not associated with bank ownership status. Panel (d) presents a decomposition of the number of loans syndicated by type of borrower and highlights that interbank loans comprise a small fraction of the total number of loans syndicated; this motivates our investigation of banks' common exposures to non-financial firms.
Source: SDC Platinum

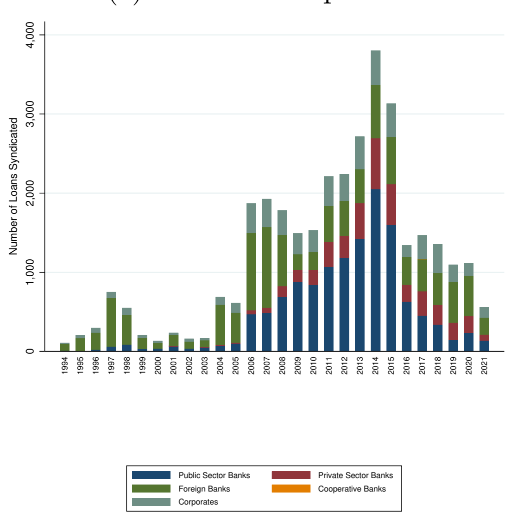
(a) Number of Syndications



(b) Value of Syndications



(c) Lender Composition



(d) Borrower Composition

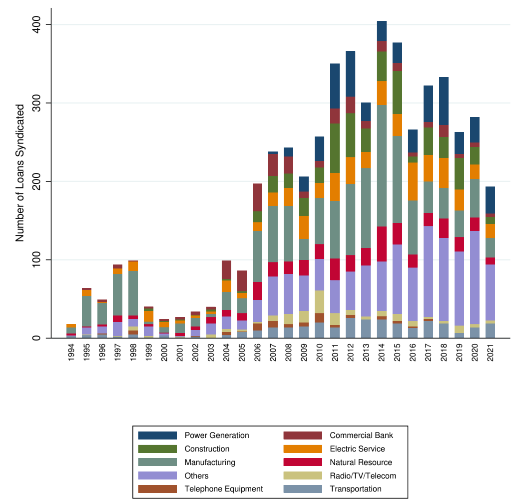


Figure C.2: Distribution of Number of (Bank) Credit Relationships of Firms

Notes: This figure plots the density of the number of banking relationships of non-financial firms in our CMIE sample.

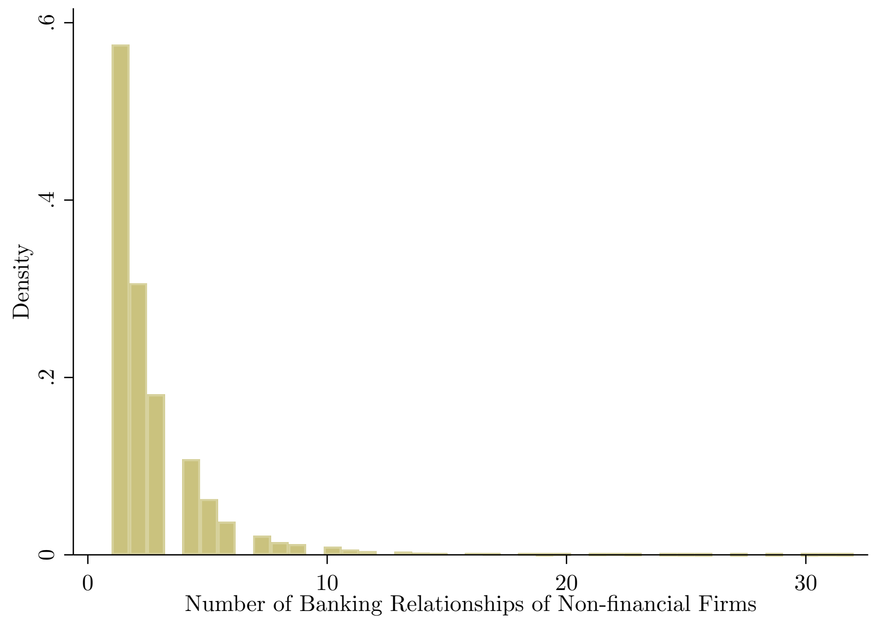


Figure C.3: Evolution of Credit Spread and Cross-sectional Moments of Lending Rates

Notes: The first plot depicts the wedge between bank base lending rates (i.e., MCLR) and the central bank policy rate (i.e., Repo rate), and provides visual evidence of a time-varying credit spread. The second and third plots depict the cross-sectional mean and dispersion of bank base lending rates.

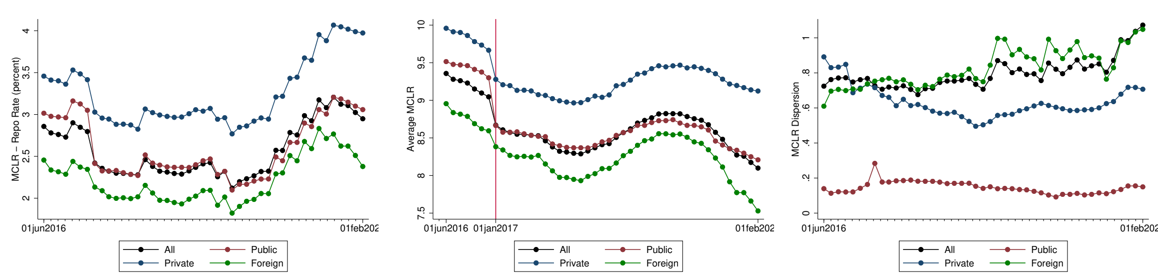


Table C.1: Descriptive Statistics by Financial Institution

Notes: This table reports statistics of bank-specific connectedness and cost of credit used in the empirical analysis. * indicates the set of core banks; the details of arriving at this set are provided in Section 4.3.1. 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.

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

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

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

Table C.2: Prior and Posterior Distribution of Estimated Parameters

Notes: This table reports estimates of the set of parameters that we obtain using Bayesian methods in the NK and NK-LC models, i.e., $\{\gamma, \varphi, \theta, \mu, \sigma_p\}$, as well as the assumptions we impose on the prior distributions of these parameters. The posterior distribution is obtained using the Metropolis-Hastings algorithm. The range reported below the posterior mean refers to the 90% HPD interval.

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)		
σ_p	0.05	0.0836	0.0711	Inverse Gamma	0.1
		(0.0425, 0.1311)	(0.0495, 0.0945)		

D Coordination Failures in the CEE Model

Final Good Firms. At time t, a final consumption good, Y_t, is produced by a perfectly competitive firm by combining a continuum of intermediate goods, indexed by $i \in [0, 1]$, using the technology

$$Y_t = \left[\int_0^1 (Y_t(i))^{\frac{1}{\lambda_f}} \right]^{\lambda_f}$$

where $1 \leq \lambda_f < \infty$, and $Y_t(i)$ denote the time t input of intermediate good i. Let P_t and $P_t(i)$ denote the time t price of the consumption good and intermediate good i, respectively.

Intermediate Good Firms. Intermediate good i is produced by a monopolist who can access the following technology:

$$Y_t(i) = \begin{cases} (k_t(i))^{\varsigma}(N_t(i))^{1-\varsigma} - \mathcal{F} & \text{if } (k_t(i))^{\varsigma}(N_t(i))^{1-\varsigma} \geq \mathcal{F} \\ 0, & \text{otherwise} \end{cases}$$

where $0 < \varsigma < 1$. Here, $N_t(i)$ and $k_t(i)$ denote the time t labor and capital services used to produce good i, and $\mathcal{F}$ denotes the fixed cost of production. Intermediate firms rent capital and labor in competitive factor markets. Profits are distributed to households at the end of each time period. Let R_t^k and W_t denote the nominal rental rate on capital services and the wage rate, respectively. We also assume that workers must be paid in advance of production. As a result, the firm must borrow its wage bill from a bank at the beginning of each period. Repayment occurs at the end of the period at the gross interest rate, R_t. The firm's real marginal cost is given by:

$$\mathcal{S}_t = \left(\frac{1}{1-\varsigma}\right)^{1-\varsigma} \left(\frac{1}{\varsigma}\right)^{\varsigma} (r_t^k)^{\varsigma}(w_t R_t)^{1-\varsigma}$$

where $r_t^k = R_t^k/P_t$ and $w_t = W_t/P_t$. The firm's time t profits are:

$$\left[\frac{P_t(i)}{P_t} - \mathcal{S}_t\right] P_t Y_t(i).$$

In each period, a firm faces a constant probability, $(1-\theta)$, of being able to reoptimize its nominal price. Let $P_t^\star$ denote the price set by a firm that can reoptimize at time t. The firm chooses $P_t^\star$ to maximize:

$$\mathbb{E}_{t-1} \sum_{\tau \geq 0} (\beta\theta)^\tau v_{t+\tau} [P_t^\star X_{t\tau} - s_{t+\tau} P_{t+\tau}] Y_{t+\tau}(i)$$

subject to

$$\left(\frac{P_t}{P_t(i)}\right)^{\frac{\lambda_f}{\lambda_f-1}} = \frac{Y_t(i)}{Y_t}.$$

Here

$$X_{t\tau} = \begin{cases} \pi_t \times \pi_{t+1} \times \ldots \times \pi_{t+\tau-1} & \text{if } \tau \geq 1 \\ 1 & \text{if } \tau = 0 \end{cases},$$

and v_t is the marginal value of a dollar to the household.

Households. There is a continuum of households, indexed by $i \in (0,1)$. The preferences of household i are given by:

$$\mathbb{E}_{t-1}^i \sum_{\tau \geq 0} \beta^{\tau-t}[u(c_{t+\tau} - bc_{t+\tau-1}) - z(h_{t+\tau}(i)) + v(q_{t+\tau})],$$

where $\mathbb{E}_{t-1}^i$ is the expectation operator, conditional on aggregate and household i idiosyncratic information up to, and including, time $t-1$; c_t denotes time t consumption; $h_t(i)$ denotes time t hours worked; $q_t \equiv Q_t/P_t$ denotes real cash balances; and Q_t denotes nominal cash balances. Here $b > 0$ allows for habit formation in consumption preferences. The household's asset evolution equation is given by:

$$M_{t+1} = R_t^h[M_t - Q_t + (g_t - 1)M_t^a] + A_t(i) + Q_t + W_t(i)h_t(i) + R_t^k u_t \bar{k}_t + D_t - P_t(i_t + c_t + a(u_t)\bar{k}_t).$$

Here, M_t is the household's beginning of period t stock of money, $W_t(i)h_t(i)$ is time t labor income. In addition, $\bar{k}_t$, D_t, and $A_t(i)$ denote, respectively, the physical stock of capital, firm profits and the net cash inflow from participating in state-contingent securities at time t. The variable g_t represents the gross growth rate of the economy-wide per capita stock of money, M_t^a. The quantity, $(g_t - 1)M_t^a$ is a lump-sum payment made to households by the monetary authority. The quantity, $M_t - P_t q_t + (g_t - 1)M_t^a$, is deposited by the household with a bank, where it earns the gross interest rate, R_t^h. The remaining terms, aside from consumption expenditures $P_t c_t$, pertain to the stock of installed capital, which we assume is owned by the household. The household's stock of capital evolves according to:

$$\bar{k}_{t+1} = (1 - \delta)\bar{k}_t + F(i_t, i_{t-1}).$$

Here, δ denotes the physical rate of depreciation and i_t denotes time t purchases of investment goods. The function, F, summarizes the technology which transforms current and past investment into installed capital for use in the following period. Capital services, k_t, are related to the physical stock of capital by

$$k_t = u_t \bar{k}_t.$$

Here, u_t denotes the utilization rate of capital, which we assume is set by the household. In the household's asset evolution equation, $R_t^k u_t \bar{k}_t$ represent the household's earnings from supplying capital services. The increasing, convex, function, $a(u_t)\bar{k}_t$, denotes the cost, in units of consumption good, of setting the utilization rate to u_t.

The Wage Decision. The household is a monopoly supplier of a differentiated labor service, $h_t(i)$. It sells this service to a representative, competitive firm which transfers it into an aggregate labor input, N_t, using the following technology:

$$N_t = \left[\int_0^1 (h_t(i))^{\frac{1}{\lambda_w}} \right]^{\lambda_w}.$$

The demand curve for $h_t(i)$ is given by:

$$h_t(i) = \left(\frac{W_t}{W_t(i)} \right)^{\frac{\lambda_w}{\lambda_w - 1}} N_t, \; 1 \leq \lambda_w \leq \infty,$$

where W_t is the aggregate wage rate, which is related to individual wages via the relationship:

$$W_t = \left[\int_0^1 (W_t(i))^{\frac{1}{1-\lambda_w}} \right]^{1-\lambda_w}.$$

The households set their wage rate according to a variant of the mechanism used to model price setting by firms. In each period, a household faces a constant probability, $1 - \theta_w$, of being able to reoptimize their nominal wage.

Banks. There are a finite number of banks, indexed by i. Banks accept deposits from households and lend to intermediate good firms. Given the policy rate, $R_t^\star$, nominal lending rate, R_t, and the signal of project loans provided by other banks, $s_t = \sum_{j \neq i} L_{j,t} + \eta_t$, bank i makes its lending decision, $L_{i,t}$, to maximize period t profits:

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

Monetary and Fiscal Policy. Monetary policy is set using a standard Taylor rule, as described in our baseline model. We also assume that the government has access to lump sum taxes and pursues a Ricardian fiscal policy.

Loan Market Clearing and the Resource Constraint. Banks receive $M_t - Q_t$ from households and a transfer, $(g_t - 1)M_t$ from the monetary authority, which they lend to intermediate good firms. Thus, loan market clearing requires

$$W_t N_t = L_t = g_t M_t - Q_t,$$

where $L_t = \sum_i L_{i,t}$.

The aggregate resource constraint is

$$c_t + i_t + a(u_t) \leq Y_t.$$

Functional Forms. We employ the same functional forms for preferences and investment adjustment costs as in Christiano et al. (2001). That is,

$$\begin{aligned} u(.) &= \log(.), \\ z(.) &= \psi_0 (.)^2, \\ v(.) &= \psi_q \frac{(.)^{1-\sigma_q}}{1-\sigma_q}. \end{aligned}$$

In addition, investment adjustment costs are given by:

$$F(i_t, i_{t-1}) = \left(1 - \tilde{F}\left(\frac{i_t}{i_{t-1}}\right)\right) i_t.$$

The function $\tilde{F}$ is restricted to satisfy $\tilde{F}(1) = \tilde{F}'(1) = 0$, and $X = \tilde{F}''(1) > 0$. The capital utilization function, $a(u_t)$, is assumed to satisfy $u_t = 1$, which implies $a' = r^k$. We also assume $a(1) = 0$. We denote $\bar{a}''/\bar{a}'$ by σ_a, where $\bar{a}''$ and $\bar{a}'$ denote the first and second derivative of a, evaluated in steady state. Lastly, loan provision costs are given by

$$c(L_{i,t}, R_t^\star) = L_{i,t}^2 R_t^\star.$$

Equilibrium. If the no-default probability associated with bank loans is close to unity and the wage bill is a fixed share of output,[19] then equilibrium in a log-linearized version of

[19] The assumption that the wage share is a constant share of output is not imperative for our results. If we were to dispose of this assumption, the credit spread would be determined by $\hat{r}_t - \hat{r}_t^\star = (1-\mu)(\hat{w}_t + \hat{l}_t)$. This change makes the model harder to solve quantitatively. Nevertheless, for the range of μ for which the Blanchard-Kahn conditions are satisfied, we find that our estimates for the dampening of transmission are not very sensitive to this change.

the model can be approximated by the following system of equations:

$$
\begin{aligned}
&\hat{\pi}_t = (1/(1+\beta))\hat{\pi}_{t-1} + (\beta/(1+\beta))\hat{\pi}_{t+1} + ((1-\beta\theta)(1-\theta)/((1+\beta)\theta))\hat{\mathcal{S}}_t,\\
&\hat{q}_t = (-1/\sigma_q)(\bar{r}\hat{r}_t/(\bar{r}-1) + \hat{\psi}_t),\\
&0 = \hat{w}_{t-1} - ((b_w(1+\beta\theta_w^2) - \lambda_w)/(b_w\theta_w))\hat{w}_t + \beta\hat{w}_{t+1} + (\beta(\hat{\pi}_{t+1} - \hat{\pi}_t)\\
&\qquad\qquad -(\hat{\pi}_t - \hat{\pi}_{t-1})) + ((1-\lambda_w)/(b_w\theta_w))(\hat{\psi}_t - \hat{n}_t),\\
&\hat{\psi}_{t+1} + \hat{r}_{t+1} - \hat{\pi}_{t+1} - \hat{\psi}_t = 0,\\
&\hat{u}_t = \hat{k}_t - \hat{\bar{k}}_t,\\
&\hat{r}_t^k = \hat{w}_t + \hat{r}_t + \hat{n}_t - \hat{k}_t,\\
&0 = -\hat{P}_{k',t} - \hat{\psi}_t + \hat{\psi}_{t+1} + (1-\beta(1-\delta))(\hat{r}_{t+1}^k) + \beta(1-\delta)\hat{P}_{k',t+1},\\
&(1/\beta - (1-\delta))(K_Y/C_Y)\hat{u}_t + \hat{c}_t + \delta(K_Y/C_Y)\hat{i}_t = (\varsigma/C_Y)\hat{k}_t + ((1-\varsigma)/C_Y)\hat{n}_t,\\
&\bar{g}\bar{m}(\hat{g}_t + \hat{m}_t) - \bar{q}\hat{q}_t - \bar{w}\bar{n}(\hat{w}_t + \hat{n}_t) = 0,\\
&\hat{m}_t - \hat{m}_{t-1} - \hat{g}_{t-1} + \hat{\pi}_t = 0,\\
&\hat{h}_t - \hat{c}_{t-1} = 0,\\
&\sigma_c(\hat{c}_t - \hat{h}_t b) - b\beta\sigma_c(\hat{c}_{t+1} - \hat{h}_{t+1}b) + \hat{\psi}_t = 0,\\
&\hat{P}_{k',t} = X(\hat{i}_t - \hat{i}_{t-1} - \beta(\hat{i}_{t+1} - \hat{i}_t)),\\
&\hat{\bar{k}}_{t+1} = (1-\delta)\hat{\bar{k}}_t + \delta\hat{i}_t,\\
&\hat{u}_t - (1/\sigma_a)\hat{r}_t^k = 0,\\
&\hat{r}_t^\star = \rho\hat{r}_{t-1}^\star + (1-\rho)[\phi^\pi\hat{\pi}_t + \phi^y\hat{y}_t] + \epsilon_t^p,\\
&\hat{r}_t - \hat{r}_t^\star = (1-\mu)\hat{y}_t,\\
&\hat{\mathcal{S}}_t = \varsigma\hat{r}_t^k + (1-\varsigma)(\hat{w}_t + \hat{r}_t),\\
&\hat{y}_t = \varsigma\hat{k}_t + (1-\varsigma)\hat{n}_t,
\end{aligned}
$$

where

$$
\begin{aligned}
&\bar{r} = 1/\beta,\\
&\bar{w} = MC^{1/(1-\varsigma)}(1-\varsigma)\varsigma^{\varsigma/(1-\varsigma)}\bar{r}_k^{\varsigma/(\varsigma-1)}/\bar{r},\\
&\bar{r}_k = (1/\beta - 1 + \delta),\\
&K_H = MC^{1/(\varsigma(1-\varsigma))}(\bar{r}_k/\varsigma)^{1/(\varsigma-1)},\\
&Y_H = (K_H)^\varsigma,\\
&K_Y = K_H/Y_H,\\
&C_Y = 1 - \delta K_Y,\\
&I_Y = \delta K_Y,\\
&b_w = (2\lambda_w - 1)/((1-\theta_w)(1-\beta\theta_w)),\\
&\sigma_c = \frac{1}{1-b}\frac{1}{1-\beta b}.
\end{aligned}
$$

Here, ψ_t is the marginal utility of P_t units of currency. That is, $\psi_t = v_t P_t$, where v_t is the Lagrange multiplier on the household's budget constraint.

Estimation. We briefly discuss the methodology we use to estimate our model. In our estimation, one period corresponds to a quarter. We set $\beta = 0.98$, which implies a steady state annualized real interest rate of 7 percent. We use the estimates of CEE for a subset of parameters, $\{\varsigma, \delta, \lambda_w, \sigma_a, \rho\}$. That is, we set the share of capital income to $\varsigma = 0.36$; this estimate is roughly consistent with the share of capital income in India post-liberalization. We set $\delta = 0.025$, which implies an annual depreciation rate equal to 10 percent. We set $\lambda_w = 1.05$; as observed by CEE, impulse response functions are insensitive to changes in this parameter. We set $\sigma_a = 0.01$, which corresponds to the assumption that the adjustment cost function for capital utilization is almost linear. We set the persistence of the policy rate to $\rho = 0.8$. To be consistent with Indian data, we set the coefficients on inflation and output deviations in the Taylor rule to $\phi_\pi = 1.5$ and $\phi_y = 0.5$, respectively. As in CEE, the parameter ψ_0 is chosen to imply a steady state value of N equal to unity. The parameter ψ_q is set to ensure $Q/M = 0.975$ in steady state. This is equal to the ratio of M1 and M2 at the beginning of our sample period. The parameter $\bar{g}$ is set to 1.025, which equals the quarterly average gross growth rate of M2 over our sample period. The remaining parameters, $\{\mu, \theta, \theta_w, b, X, \sigma_q\}$, are estimated using Bayesian estimation to match log deviations of the policy rate from mean values. We set the prior mean of these parameters to the benchmark estimates in CEE, and estimate the posterior distribution using the Metropolis-Hastings algorithm. As in our baseline analysis, we use the average of the estimated parameters in the CEE model and the model featuring lending complementarities (CEE-LC) barring the curvature of lending complementarity; see Table D.1. First, our point estimate of $\theta = 0.4$ implies that price contracts last on average 1.7 quarters. Second, our estimate of $\theta_w = 0.73$ implies that wage contracts last on average 3.8 quarters. Third, our estimate for the habit parameter is $b = 0.62$. Fourth, the elasticity of investment with respect to the price of installed capital is $1/X = 0.28$. Fifth, the parameter relating cash holding to the interest rate, σ_q, is estimated to be 9.7. Note that our estimates for $\{\theta, \theta_w, b, X, \sigma_q\}$ are very similar to corresponding values in Christiano et al. (2001). Lastly, our estimate for the curvature of lending complementarity, μ, is 0.53. The standard error of the monetary policy shock, σ_p, is set to 0.04. Table D.2 provides a summary.

Next, we estimate the impact of lending complementarities on the dampening of monetary transmission in this augmented system. Panels (a) and (b) of Figure D.1 compare the impulse response functions of inflation and output to a (one standard deviation) monetary policy shock in the CEE model with those in the CEE-LC model. There are two noteworthy

Table D.1: Prior and Posterior Distribution of Estimated Parameters

Notes: This table reports estimates of the set of parameters that we obtain using Bayesian methods in the CEE and CEE-LC models. The posterior distribution is obtained using the Metropolis-Hastings algorithm. The range reported below the posterior mean refers to the 90% HPD interval.

Parameter	Prior Mean	Post. Mean (CEE)	Post. Mean (CEE-LC)	Prior Dist.	Prior S.D.
θ	0.5	0.4100	0.3904	Normal	0.25
		(0.0212,0.8045)	(0.0113,0.7630)		
θ_w	0.7	0.7155	0.7514	Normal	0.25
		(0.6859,0.7401)	(0.7011,0.7815)		
b	0.63	0.6147	0.6225	Normal	0.25
		(0.2420,1.0351)	(0.2263,1.0003)		
X	3.571	3.5751	3.5899	Normal	0.5
		(2.8075,4.3970)	(2.7724,4.4918)		
σ_q	9.660	9.6545	9.6775	Normal	0.5
		(8.8971,10.4969)	(8.8383,10.4201)		
μ	0.5		0.5273	Normal	0.25
			(0.1323,0.9340)		
σ_p	0.05	0.0392	0.0395	Inverse Gamma	0.1
		(0.0265,0.0528)	(0.0261,0.0509)		

differences from our baseline results. First, the dampening of transmission to output and inflation are not identical here. Second, the dampening is time-varying, partially due to the policy rate's persistence. We focus on the dampening of transmission one year post the monetary policy shock. We find that the dampening of transmission to inflation and output at this juncture are 77 percent and 44 percent, respectively.

Figure D.1: Impulse Responses to Monetary Policy Shock

Notes: These figures depict simulated impulse response functions of inflation and output to a (one standard deviation) monetary policy shock in the CEE model with those in the CEE-LC model. Time horizon in quarters.

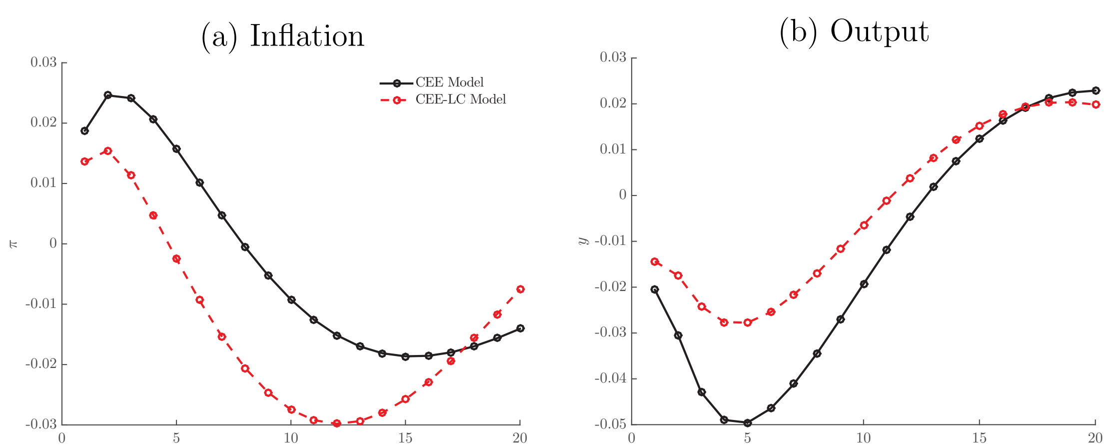


Table D.2: Variables and Parameters in CEE-LC Model

Notes: This table describes key variables in the CEE and CEE-LC models and summarizes our baseline parameterization.

Variable		Description
π		Inflation
y		Output
$\mathcal{S}$		Real marginal cost
q		Real transaction money
r		Nominal interest rate
m		Total money supply / M2
g		Money growth rate
ψ		Marginal utility of consumption
c		Consumption
w		Real wage
$P_{k'}$		Marginal product of capital in marginal utility terms
n		Aggregate labor allocation
h		Hours worked
$\bar{k}$		Capital stock
k		Capital services
i		Capital investment
u		Capacity utilization
r^k		Return to capital
$r^\star$		Policy rate
Parameter	**Value**	**Description**
β	0.98	Discount rate
ς	0.36	Capital share of production
δ	0.025	Capital depreciation rate
θ	0.40	Price stickiness
θ_w	0.73	Wage stickiness
λ_w	1.05	Household labor market power
$\bar{g}$	1.025	Steady state money growth rate
$\bar{q}$	0.44	Steady state M1
$\bar{m}$	0.45	Steady state M2
$\bar{n}$	1	Steady state labor supply
b	0.62	Habit parameter
σ_a	0.01	Parameter relating capacity utilization to return on capital
σ_q	9.66	Parameter relating cash holding to the interest rate
MC	0.83	Steady state marginal cost (1/markup)
ρ	0.8	Interest rate smoothing policy parameter
ϕ^π	1.5	Taylor rule coefficient on inflation deviations
ϕ^y	0.5	Taylor rule coefficient on output deviations
X	3.58	Reciprocal of elasticity of investment w.r.t. price of installed capital
μ	0.53	Curvature on lending complementarity