Dissecting The Risk-Taking Channel of Monetary Policy: A New Approach and Evidence from Peru*

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Abstract

We adopt a different perspective on the risk-taking behavior of banks, focusing on how banks allocate loans across risky markets following a monetary policy shock in Peru. Utilizing a novel time series of identified monetary policy shocks, we first present robust evidence, at the aggregate level, indicating that credit market equilibrium is predominantly driven by supply forces. Subsequently, employing micro-data at the branch level, and an econometric strategy centered on local credit markets, and the geographic distribution of risk, we further demonstrate that the risk-taking channel constitutes a significant credit supply-side mechanism in the transmission of monetary policy. We use a theoretical model to illustrate that an expansionary monetary policy shock activates the risk-taking channel by modifying a bank's risk appetite and prompting a rebalancing of its loan portfolio, resulting in increased lending to riskier markets. Empirically, a branch-level estimation confirms that the sensitivity of lending to monetary policy changes escalates with the riskiness of borrowers. At higher levels of aggregation, these results retain both their economic and statistical significance. Additional estimations reveal that the risk-taking channel of monetary policy exerts a substantial impact on the total lending issued by financial institutions, regardless of their size. A closer examination, however, indicates that a significant portion of the dynamic responses of credit to monetary policy shocks predominantly occurs in markets below the median of the risk distribution.

Keywords: Financial firms, risk-taking, portfolio, monetary policy.

JEL Classification: G21, E44, E5.

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1 Introduction

Since the Great International Financial Crisis, two changes have emerged: i) central banks have adopted expansionary monetary policy positions more frequently, setting rates at historically very low levels[1]; and ii) the role of the financial system and the credit markets as mechanisms for the transmission and amplification of shocks has been a focus of greater importance among policy makers and the macro literature. Together, these have called for the macro literature to investigate more on the transmission mechanisms of monetary policy operating via changes on banks' decisions. In particular, the effects of very low monetary policy rates on the risk-taking behavior of banks have been given great attention. The risk-taking behavior of banks is key to understand the role of the credit exuberance and business cycles (Adrian and Song Shin, 2010; Borio and Zhu, 2012; Jordà, Schularick and Taylor, 2013; Jiménez, Ongena, Peydró and Saurina, 2014; Maddaloni and Peydró, 2015; Acharya, Eisert, Eufinger and Hirsch, 2019).

In this paper, we seek to answer the following question: How does the risk exposure of financial-firms change with monetary policy movements? Relative to the existing literature we take a different view on the risk-taking behavior of banks, and rather than focusing on large versus small banks, we focus on how each bank can allocate loans differently across risky locations after a monetary policy (MP) shock. In this interpretation, we see the credit allocation by banks as a portfolio problem, which must be operative across all financial institutions, either highly or poorly capitalized. Thus, monetary policy shocks alter the opportunity cost and profitability of lending (Adrian and Song Shin, 2010), and have differential effects across pools of borrowers to which a bank lends, by altering a bank's preference for issuing loans to high-risk or low-risk borrowers. In general, this paper shows empirical estimates about the role of risk on the transmission of MP shocks: a bank's risk-taking mechanism.

We argue that Peru is a good setting to investigate the risk-taking behavior of financial firms and its interaction with monetary policy. Peru is an emerging market with limited developed capital markets, so credit markets are critical for monetary policy transmission. Credit-to-GDP ratio is of around 40 percent, which is very low relative to advanced economies[2]. During the last 20 years, credit in Peru has grown by around 11 percent per year, above the average growth rate of nominal GDP of 7 percent. Between 2000 and

[1]For example, after 2009 the number of countries at the Zero Lower Bound have increased overtime, and with the Covid-19 global shock, it not only include Advanced Economies but also Emerging market economies.

[2]Data from the Bank of International Settlements show that the credit-to-GDP ratios in Advanced Economies are above 100 percent.

2019 credit to GDP ratio almost doubled from 24.8 to 43.1 percent. Both the extensive and intensive margin contributed to the growth of credit (SBS, 2020). Thus, risk-taking channel is expected to be important and sizable.

However, for the risk-taking channel of monetary policy to be meaningful, one must demonstrate that credit supply factors are more important for determining equilibrium after a monetary policy shock. As a result, we divide the analysis of credit markets into two steps. First, at the aggregate level, we present strong evidence that supply factors are relatively more important for credit market equilibrium following a monetary policy shock. Once this is established, we demonstrate in a second step, using micro-data at the branch level, that the risk-taking channel is a meaningful and statistically significant supply side mechanism of monetary policy.

Monetary policy is endogenous to the business cycle and, by extension, to the credit markets that we study. To overcome monetary policy endogeneity and provide a causal relationship between monetary policy power and credit markets, we first construct novel time series of monetary policy shocks for Peru using the same approach as Romer and Romer (2004). We use annual forecasts for GDP growth and inflation released by the Central Bank of Peru, supplemented with forecasts from professional forecasters, as in Holm, Pascal and Tischbirek (2021), when Central Bank forecasts are not available. Provided the identified monetary policy shocks, we use Peruvian aggregate and micro-data on lending outcomes to show evidence that supply factors are important to explain the effect of MP changes on the credit markets. More importantly, these supply decisions are reflected in the overall risk of the banks' asset side.

First, we use the following intuition to interpret the empirical findings at the aggregate level: the response of lending rates to monetary policy shocks provides a signal about leading forces in equilibrium. Thus, for a supply side leading mechanism, one must observe that after a MP shock, the contraction in credit supply caused by banks is greater than a proportional fall in credit demand, resulting in a credit market adjustment that necessitates a rise in lending rates. This is precisely what the results show. At the aggregate level, using Local Projections, an empirical model that imposes few constraints in the data, we show that after a contractionary monetary policy shock there is a persistent and economically significant negative response of aggregate credit and an increment in lending rates after a monetary policy shock. Also, the results show, by using a market measure of overall risk, that a monetary policy impacts the risk-taking behavior of banks. Further analysis using a VAR for robustness confirms these findings. This robust fact, to several specifications, suggests that supply side changes and risk-taking behavior are relevant for the credit market equilibrium. With this in mind, further, we investigate the

significance of the risk-taking channel of monetary policy that arises from changes in the banks' preferences to extend credit to high-risk or low-risk borrowers using micro-data.

Second, using micro-data and an empirical strategy, we show that monetary policy shocks act as a supply side mechanism in the credit market via the risk-taking channel. In particular, we use branch-level and bank-province level data, as well as a within-bank comparison, to control for omitted variables like lending opportunities and credit demand conditions. We define local markets at the province level.

In particular, after an expansionary MP shock, banks can take advantage of a better outlook of the economy and lower funding costs, which, in turn, increase banks' appetite for risk and allocate more loans to riskier markets. This differential response is given by credit frictions on the credit supply side that create a bias in the way banks assess risk, and as a result value markets differently and take advantage of lending in risky but profitable markets. This intuition is consistent with the positive general equilibrium effects of low policy rates on bank's default probability, and expected profits with it, which drives bank's incentives to take excessive risk (Adrian and Song Shin, 2010; Agur and Demertzis, 2012; Altunbas, Gambacorta and Marques-Ibanez, 2014).

We provide a model to rationalize this risk-taking channel of the monetary policy studied empirically. The simple model aims to shed lights on banks' preferences on issuing high-risk loans or low-risk (i.e., on the composition of credit supply) after monetary policy changes. With the model in hand, we do not aim to quantitatively capture what is observed in the data, but rather to qualitatively capture the mechanism that might be observed in the data and that we latter describe as the (excessive) risk-taking channel. According to the model, after a monetary policy ease, banks' preferences on high-risk loans increases. This is because the low policy rate reduces the marginal cost of funding and as a consequence increases the volume of loans, which in turn increase bank default probability and hence increases bank preferences on taking excessive risk. This accentuates banks' incentives to hold a larger fraction of high-risk loans.

Empirically, we exploit two observations about credit markets. First, lending is an informational intensive activity, and banks need to screen among potential set of borrowers due to informational asymmetries. Geographic proximity reduces the costs of transmitting and processing that information. i.e., credit markets are still local (Nguyen, 2019). Second, risk varies across markets. In particular, as heterogeneous inherent characteristics across markets persist, risk varies geographically. Thus, we consider credit markets at the province level, and obtain measures of risk by computing non-performing loans (NPL) ratio at the province level.

A key idea in the identification strategy is that NPL signals banks to rebalance their

lending portfolio taking advantage of profitable but riskier local markets, capturing the risk-taking channel mechanism. For the identification strategy to work, it is important to have variation in riskiness that is independent of a bank's lending opportunities or demand factors influencing bank's decisions. We use a within-bank identification, and by comparing across branches of the same bank, we am able to control for a bank's lending opportunities and identify the effects of the risk-taking channel on the lending sensitivity to monetary policy shocks.

The branch-level estimation confirms that the sensitivity of lending to MP changes is increasing in the riskiness of borrowers, even within a financial firm. After 100 bps expansionary monetary policy shock, a branch operating in an average high NPL market increases lending growth by 228.8 bps relative to a branch operating in an average low NPL market.[3] This result shows statistical and economical significance of the main prediction of the model, that is robust to several sample definitions and sample periods. We show that the effects of monetary policy on lending are similar if we consider in the sample all financial firms and not only those financial firms serving more than two province markets. Also, the risk-taking channel at the branch level is similar for banks and non-banks. The results do not change if we exclude from the sample the metropolitan area, that accounts a lion's share of total credit. In fact, by focusing on riskier markets, estimates of the risk-taking channel are larger, and of similar magnitude for all types financial institutions: banks, non-banks and the 4 largest banks in the country. These findings contradict empirical evidence suggesting that undercapitalized banks are more likely to extend credit to risky borrowers (Jiménez, Ongena, Peydró and Saurina, 2014; Acharya, Eisert, Eufinger and Hirsch, 2019; Andrews and Petroulakis, 2019; Faria e Castro, Pascal and Sánchez, 2021).

Also, the results remain statistically significant if we control for sample selection or omitted variables such as bank concentration that may bias the estimates. The risk-taking channel estimate barely changes after we control for standard Herfindahl index, which shows the results do not pick up bank concentration effects.

The results at the branch level are partial equilibrium estimates, and the risk-taking channel at the branch level may not be economically significant at higher levels of aggregation. First, we demonstrate that micro-data at the branch level can generate credit dynamics that are similar to those observed with aggregate data. After estimating credit dynamics responses at the branch level across the risk distribution of credit local markets, we show that monetary policy has meaningful responses in local markets with risk distri-

[3]The average high (low) NPL corresponds to the average of markets with NPL above (below) the median.

butions below the percentile 80. We also observe that the risk-taking channel is led by the dynamics of branches operating in markets below the median of the risk distribution in the overall periods following the monetary policy shock.

In addition, to show that the risk-taking channel estimates at the branch level capture overall bank behavior we aggregate lending at the province level, and use a within-province estimator. The idea is that at the bank level, the average risk that a bank faces across all markets in which it operates must be more important. In other words, the impact of the risk-taking channel of MP must be determined by the average riskiness of the local markets in which a financial firm operates. To explore this argument, we compute a financial firm-level measure of borrower riskiness NPL-Bank, by averaging the local market riskiness of all financial firm's branches, NPL-Branch, weighted by each branch share of the financial firm's total lending. To reach identification we compare the lending growth rate of different banks in the same province. The results of this within-province estimator show that after an expansionary monetary policy shock, banks that operate in riskier markets increase lending much more, relative to those banks serving less risky markets. A one standard deviation increase in NPL-Bank raises lending by 233.1 bps per 100 bps expansionary monetary policy shock.

Further, We aggregate the data to the province level to examine the overall effects of the risk-taking channel on lending and employment. We find that provinces whose banks lend in risky markets after an expansionary MP shock see larger increases in lending relative to other provinces. We also find that the risk-taking channel has the predicted direction effects on province employment. The effects are meaningful and statistically significant.

Finally, we verify that the results hold at the bank level and, after an expansionary MP shock, financial firms operating in riskier markets generate larger profits and issue higher foreign currency loans.

The remainder of this paper is partitioned as follows. Section 2 presents the literature review. Section 3 constructs the time series of identified monetary policy shocks for the Peruvian economy. Section 4 examines the validity of the identified monetary policy shocks and presents aggregate empirical evidence pointing to a supply side mechanism of adjustment in credit markets following a monetary policy shock, as well as bank risk-taking behavior consistent with it. In section 5 we develop a theoretical model to understand the risk-taking channel and guide our empirical exploration. Section 6 presents the sources and summary statistics of the micro-data we use for the empirical estimations of the risk-taking channel of monetary policy at the branch level. Section 7 presents the main estimates of the risk-taking channel under the branch-level identification strategy. Section

8 shows estimates of the effects of the risk-taking channel under different levels of data aggregation. Finally, section 9 concludes.

2 Literature Review

There has been a large amount of research into the impact of domestic policy rates on the degree of bank risk-taking, known as the "risk-taking channel" (term coined by Borio and Zhu (2012)). The literature on risk-taking commonly suggests that a lower domestic interest rate increases bank risk-taking (see, e.g., Jiménez, Ongena, Peydró and Saurina (2014)). And we find the same results. In that sense, the contribution of this work is the approach used at both the aggregate and micro levels using loan information from Peruvian bank branches. Next, we examine the literature that is closely related to this paper.

This paper is related to the literature that study the different channels through which monetary policy might affect bank risk-taking decisions (see, e.g., Adrian and Song Shin (2010); Agur and Demertzis (2012, 2015); Dell'Ariccia, Laeven and Marquez (2014); Dell'Ariccia, Laeven and Suarez (2016)). It mainly highlights two channels: the *profit* and the *leverage* channel. According to the *profit* channel, a lower rate reduces funding costs of banks and hence increases banks' profits at good times. This in turn increases banks' incentives to take risk. According to the *leverage* channel, the lower rate makes leverage less expensive. Then, banks have less of their own money (bank net worth) to fund risky loans. This means that the bank internalizes less risk and increases risk-taking incentives. Dell'Ariccia, Laeven and Marquez (2014) conclude that when leverage is endogenous, low interest rates lead to higher bank risk-taking.[4] Even though, in this paper we develop a different framework, we are able to find these two *leverage* and *profit* channels; and we also find that a lower policy rate increases bank risk-taking. In contrast to this literature, we develop a model with more than one type of risky investment so we explicitly model banks relative preferences regarding high-risk and low-risk loans after a contractionary or expansionary monetary policy. In contrast to Dell'Ariccia, Laeven and Marquez (2014), this work focuses on excessive bank risk-taking. To this end, it builds a simple model to quantitatively measure this excessive risk-taking. It proposes an optimal macroprudential policy and looks at the effects of domestic and foreign interest rates on excess risk-taking and on the optimal policy.

Also, this paper is related to the empirical literature that studies the risk-taking chan-

[4] Dell'Ariccia, Laeven and Marquez (2014) assumes banks' limited liability and asymmetric information, depositors cannot observe ex-ante the bank's risk-taking level.

nel of monetary policy. This typically finds excess bank risk-taking increases after a reduction in the policy rate. Altunbas, Gambacorta and Marques-Ibanez (2014) find that in the European Union the low interest rates over an extended period of time contributed to an increase of market perceptions of banks' risk. Maddaloni and Peydró (2015) show that lending standards deteriorate after a reduction in the short-term interest rate. Ioannidou, Peydró and Saurina (2015) by using Bolivian data show that when interest rates are low, banks take on higher risk and reduce the loan rates of risky borrowers. In addition, Chen, Wu, Nam-Jeon and Wang (2017), using a panel-data from more than 1000 banks in 29 emerging economies during 2000-2012, find that bank's riskiness increases when the monetary policy is eased. Paligorova and Santos (2019) find that banks require relative lower risk credit premium in periods of monetary policy easing relative to tightening. Angeloni, Faia and Lo Duca (2015) take a different approach, and by examining US aggregate data through a VAR model, shows that the leverage channel of bank risk-taking is more significant after a monetary policy shock.

This paper is also related to the literature of the practice of zombie lending. Andrews and Petroulakis (2019) and Faria e Castro, Pascal and Sánchez (2021) show empirical evidence that poorly capitalized banks are more likely to extend credit to risky and inefficient borrowers. Giannetti and Simonov (2013) observed a more relaxed lending behavior for capitalized banks during the Japanese banking crisis of the 1990s. Schivardi, Sette and Tabellini (2021) documented similar lending standards relaxation for Italy during the financial crisis, as did Acharya, Eisert, Eufinger and Hirsch (2019) during the aftermath of the European sovereign crisis following the ECB Outright Monetary Transactions program.

In particular, this paper is closely related to Jiménez, Ongena, Peydró and Saurina (2014) that using credit register data from Spain find robust evidence that a lower policy rate induces lowly capitalized banks to grant more loan applications to ex ante risky firms (than highly capitalized banks). As they state, this is the first paper to empirically study the impact of the monetary policy rate on the composition of the supply of credit, in particular on banks' risk-taking. In that sense this paper follows in spirit the same research question than Jiménez, Ongena, Peydró and Saurina (2014) facing several identification challenges as well. This paper aims to contribute to this literature by following a different econometric approach. By using a series of identified monetary policy shocks and micro-data at the branch level we aim to exploit the differences of risky investment opportunities across provinces. This is, while in Jiménez, Ongena, Peydró and Saurina (2014), they study the risk-taking channel across banks and see banks' risk-taking response conditional on banks' capital to asset ratio after a monetary policy change; in this paper we study

the risk-taking channel within banks and observe banks' decisions on the composition of low-risk and high-risk credit after a monetary policy change. We show evidence that the risk-taking channel behavior is equally likely across all financial firms, highly or poorly capitalized.

3 Monetary policy shocks identification

The key policy rate of the Central Bank of Peru is the Reference Interest Rate, i_t. Although it is the main variable to measure the conventional monetary policy stance, in this paper we do not consider changes in the policy rate, Δi_t, as monetary policy shocks. Monetary policy changes, Δi_t, are potentially endogenous to the business cycle and as a consequence to credit markets outcomes that we study in this chapter. To address this concern, and identify the causal effects of changes in the monetary policy stance we need to capture orthogonal movements to the systematic component of the monetary policy instrument.

To do so, we employ the Romer and Romer (2004) method to identify monetary policy shocks. The basic idea of this approach is to orthogonalize changes in the policy rate from the central bank's projections of the main target macroeconomic variables. Therefore, following Romer and Romer (2004) we regress the policy change between two meetings, Δi_m, on the central bank forecasts for GDP, $y^f_{m,t+k}$, and the inflation, $\pi^f_{m,t+k}$, for horizon $t+k$ and the corresponding forecast changes, denoted $\Delta\pi^f_{m,t+k}$ and $\Delta y^f_{m,t+k}$. Specifically, we estimate the following regression at a meeting-by-meeting frequency:

$$\begin{aligned}\Delta i_m =& \alpha_1 + \sum_{h=2}^{12} d_h + \alpha_2 i_{m,-1} + \sum_{k=0}^{1} \beta^{\pi}_k \pi^f_{m,t+k} + \sum_{k=0}^{1} \beta^{y}_k y^f_{m,t+k} \\ &+ \sum_{k=0}^{1} \beta^{\Delta\pi}_k \Delta\pi^f_{m,t+k} + \sum_{k=0}^{1} \beta^{\Delta y}_k \Delta y^f_{m,t+k} + \gamma_1 e_{m,-1} + \gamma_2 \mathbf{1}^{IT}_{m<2007m1} + \epsilon^{MP}_m \end{aligned} \quad (1)$$

where the dependent variable Δi_m is the change of the policy rate at meeting m and $i_{m,-1}$ is the level of the policy rate prior to meeting m. We estimate this regression for the period 2003m9 to 2019m12. Since 2003m9 the Central Bank of Peru sets the Reference Interest Rate, i_t as the benchmark rate for the interbank lending market each month, according to a previously announced schedule. Figure 9 in Appendix A.2 shows that the policy rate in Peru during the sample period is not constrained by the zero lower bound limit, and therefore we can measure shocks associated to conventional monetary policy.

For all policy meetings, we rely on Central Bank of Peru's historical forecasts, which

were created shortly before the meeting. When this is not the case, we follow Cloyne and Huertgen (2016); Holm, Pascal and Tischbirek (2021) by using market participants' forecasts as a proxy for the central bank's forecasts. Appendix A.1 describes in detail the sources and procedure we use to assign the different forecasts to policy meetings.

Differently than Romer and Romer (2004) we do not use quarterly forecasts for inflation and GDP, but annual forecasts as in Holm, Pascal and Tischbirek (2021). Thus, the index k in the specification (1) denotes the year of the forecast relative to the meeting date m that takes a year t. Annual forecasts are available and consistently published during the sample period. We also do not include contemporaneous variables since real-time data is not consistently available for the sample period. However, we control for recent economic conditions by including $i_{m,-1}$, the level of the policy rate prior to meeting m. We also control for the regime change in inflation targeting by including the dummy $\mathbf{1}^{IT}_{m<2007m1}$. The Central Bank of Peru officially committed to a lower range of inflation targeting regime beginning in February 2007.[5] Furthermore, because Peru is a partially dollarized economy, the benchmark interest rate is supplemented by other instruments such as sterilization operations to reduce excessive volatility in the exchange rate. As a result, we add the exchange rate on the day before the meeting as an additional explanatory variable, $e_{m,-1}$.[6] Finally, to account for differences in information sets across the year for a fixed event of forecasting,[7] we include monthly dummies $d_h;, h = 2, 3, ..., 12$.

3.1 Estimation Results

We estimate the empirical equation (1) via OLS for the sample period 2003m9-2019m12, and for a total of 188 monetary meetings.[8] Table 1 shows the results of the estimation. The signs of all coefficients are as expected. Over the sample period, Peruvian monetary policy was conducted countercyclically. Thus, if projected inflation or output growth is high or has been rising in comparison to the prior forecasts, monetary policy tightens to counteract the business cycle. However, only current year changes in inflation forecasts, and next year GDP forecast are statistically significant. The constant and the coefficient associated

[5] From February 2007, the inflation target was reduced from 2.5 to 2.0 percent, maintaining the tolerance of one percentage point up and down

[6] We must notice that the Central Bank of Peru does not have a commitment for a specific level of the exchange rate. However, by adding $e_{m,-1}$ we control for financial conditions that may impact on monetary policy decisions.

[7] The Expectation Survey is a type of survey conducted for "fixed events". For example, in each quarter panelists are asked to forecast output growth and inflation for the current calendar year and the next, implying that the forecast horizon changes with each survey round.

[8] Although for sample period there were 195 monetary policy meetings, we exclude 7 meetings on the basis of lack of information captured by released forecasts. Appendix A.1 describes in detail the meetings and forecasts we consider in the estimation

with the lag of interest rates are both negative, reflecting the secular trend decline and mean reversion in interest rates. The coefficient associated with the foreign exchange rate is positive and statistically significant, implying that monetary policy tightens when the domestic currency falls in value. The coefficient associated with the regime change in the inflation target is negative, indicating that monetary policy became tighter after 2007, consistent with a lower inflation target regime. The R^2 of the regression is 0.37 which is of similar magnitude as the ones reported by Romer and Romer (2004); Cloyne and Huertgen (2016); Holm, Pascal and Tischbirek (2021) for United States, United Kingdom and Norway, respectively.

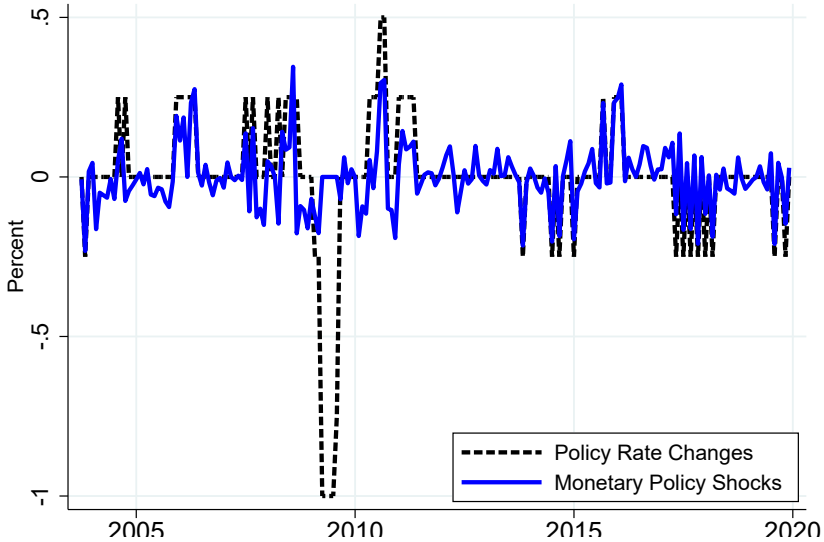
As in Romer and Romer (2004) we convert the series of residuals ϵ_m^{MP} from the estimated specification (1) from a meeting-by-meeting frequency into monthly and quarterly time series, by assigning each shock to the month or quarter in which it occurred. Because monetary policy meetings were held once a month for the sample period estimation, assigning meeting shocks to monthly series was simple. For the excluded monetary policy meeting we assign zero to the corresponding shock. Figure 1 shows the estimated monetary policy shocks and the corresponding monetary policy changes. Quarterly shocks are shown in figure 10 in Appendix A.3.

Table 1. *Determinants of the policy rate change*

	Coef.	**S.D**	**P-val**
Constant	-0.648	0.292	0.028
$i_{m,-1}$	-0.067	0.014	0.000
$\pi^f_{m,t}$	0.018	0.023	0.429
$\pi^f_{m,t+1}$	0.057	0.036	0.112
$\Delta\pi^f_{m,t}$	0.025	0.014	0.079
$\Delta\pi^f_{m,t+1}$	0.046	0.030	0.125
$y^f_{m,t}$	0.001	0.030	0.969
$y^f_{m,t+1}$	0.095	0.054	0.082
$\Delta y^f_{m,t}$	0.005	0.022	0.833
$\Delta y^f_{m,t+1}$	0.059	0.041	0.148
$e_{m,-1}$	0.125	0.066	0.059
$\mathbf{1}^{IT}_{m<2007m1}$	-0.024	0.031	0.446
N =188			
R-sqrt = 0.37			

Note: Estimation for the determinants of policy changes, as in specification (1). Sample period 2003m9-2019m12. See Appendix A.1.

Figure 1. *Peru: Monthly Monetary policy shocks*



Note: This figure shows the series of residuals ϵ_m^{MP} from the estimated specification (1), converted from a meeting-by-meeting frequency into monthly time series.

Some of the monetary policy shocks are large and reflect also large movements in policy rates. Contractionary shocks were particularly noticeable in 2008m8 and 2010m9, when current year inflation was above the target inflation range. It is also important to notice that although monetary policy shocks and policy rate changes commove they are significantly different. We can test the predictability of the monetary policy shocks. The F-statistic of a regression on 6 lags of inflation and an indicator of economic activity is 1.39 with a p-value of 0.17. When the number of lags is increased to 12, the F-statistic is 0.87, with a p-value of 0.71. As a result, there is no proof of predictability.

This series of shocks only reflect exogenous variation in monetary policy and not any endogenous feedback effects from the business cycle to policy. Thus, in the following sections we use them to study credit outcomes and mechanisms in response to monetary policy changes.

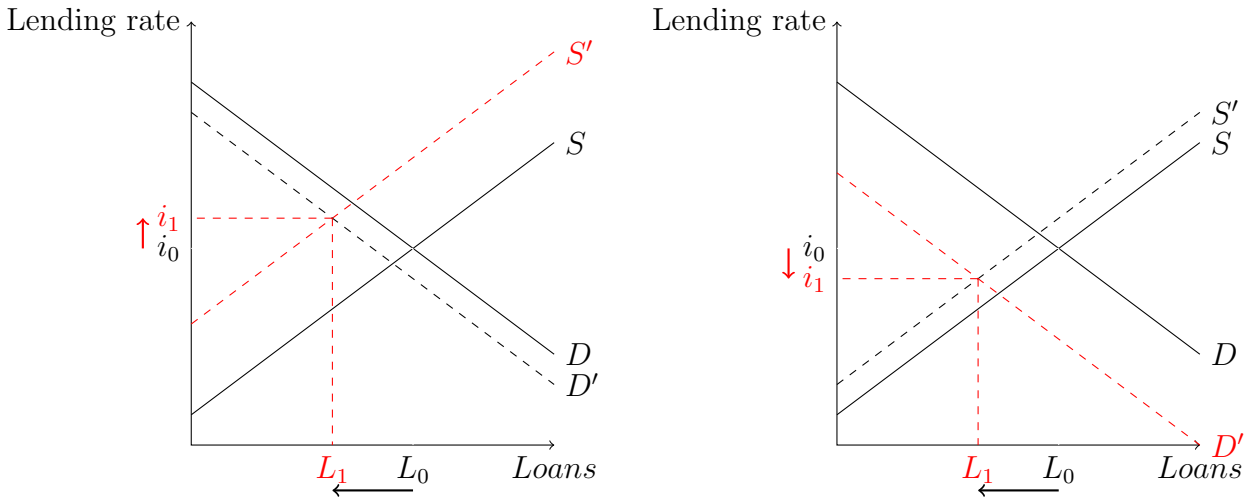
4 How does the credit market adjust to a MP shock? An aggregate time series view

First, the risk-taking mechanism of the monetary policy requires a market equilibrium determination led primarily by the supply side of the market made by banks, such that the quantity movements in banking lending are also accompanied by that risk-taking behavior. Although, the process of adjustment after a MP shock may be convoluted due

to the different supply and demand forces contending at the same time, the equilibrium response of the credit market, in terms of total lending quantity and lending rates, still gives us a clear signal to disentangle which underlying force is driving the credit market adjustment after a MP shock.

Figure 2. *Credit market adjustment to a contracionary MP shock*

Panel A: Supply credit side leading channel Panel B: Demand credit side leading channel



Note: The figures show the adjustment of the credit market after a MP shock. Panel Panel A: the credit supply side responds more aggressively, and credit spreads rise. Panel B: the credit demand side responds more aggressively, and credit spreads fall.

Figure 2 shows the intuition about the adjustment forces leading to a credit market equilibrium after a contracionary MP shock. On one side, the Panel A pictures a situation where the supply side response is higher relatively to demand side response. After a MP shock, the contraction in the credit supply by banks is bigger than a proportional fall in credit demand and it leads to an adjustment in the credit market that requires a raise in lending rates. On the other side, Panel B illustrates the scenario where the credit demand side responds much more relatively the supply response, in which case, a fall in lending rates is needed to guarantee a new equilibrium. Notice, that the response of lending interest rates to a MP shock provides us a clear indication about which side of credit markets is determining a new equilibrium. One interpretation is that the risk-taking behavior of banks determines a supply side determination of credit market equilibrium. Thus, for a given fall in credit demand, banks take a lower risk and extend significantly less loans, so the credit supply curve shifts to the left, and the lending rate rises.

In this part, we use this intuition and document some facts about the equilibrium responses of credit markets (quantities and lending rate) after a monetary policy shock.

We focus on a fully dynamic model based on credit aggregate quantities and in the later sections we explore the heterogeneous effects of monetary policy shocks under the risk-taking mechanism.

To begin, we use a flexible model that imposes few constraints on the data to establish causal effects on aggregate variables. Specifically, we use the identified monetary policy shocks and run local projections to model the dynamic equilibrium response of economic activity and credit market variables after monetary policy shock. This section of the analysis also serves as a test of the monetary policy identification and its ability to capture what one knows about the responses of macroeconomic variables to monetary policy actions. Let y_t be the outcome variable at time t. Following Jordà (2005) we estimate the series of the following regressions:

$$y_{t+h} - y_{t-1} = \alpha_h + \beta_h \, \epsilon_m^{MP} + \sum_{k=1}^{K} \gamma_k^h X_{t-k} + u_t^h \,, \tag{2}$$

where $h = 1, 2, ..16$. The coefficients β_h give the percentage change at horizon h in response to a 100-basis-point monetary policy shock. X_t denotes a vector of controls. Following the same specification as in Romer and Romer (2004), it includes three years of lagged values of the monetary policy shock and two years of lagged values of the dependent variable. Also, it adds a dummy variable for the period after 2009Q1. After the Global Financial Crisis the main macroeconomics variables started to show lower growth rates and more volatility. Importantly, the specification (2) leaves the contemporaneous response unrestricted, and it differs from a typical Cholesky identification usually used in VAR specifications. Later we compare these estimates with a VAR model that imposes more constraints on the aggregate data.[9]

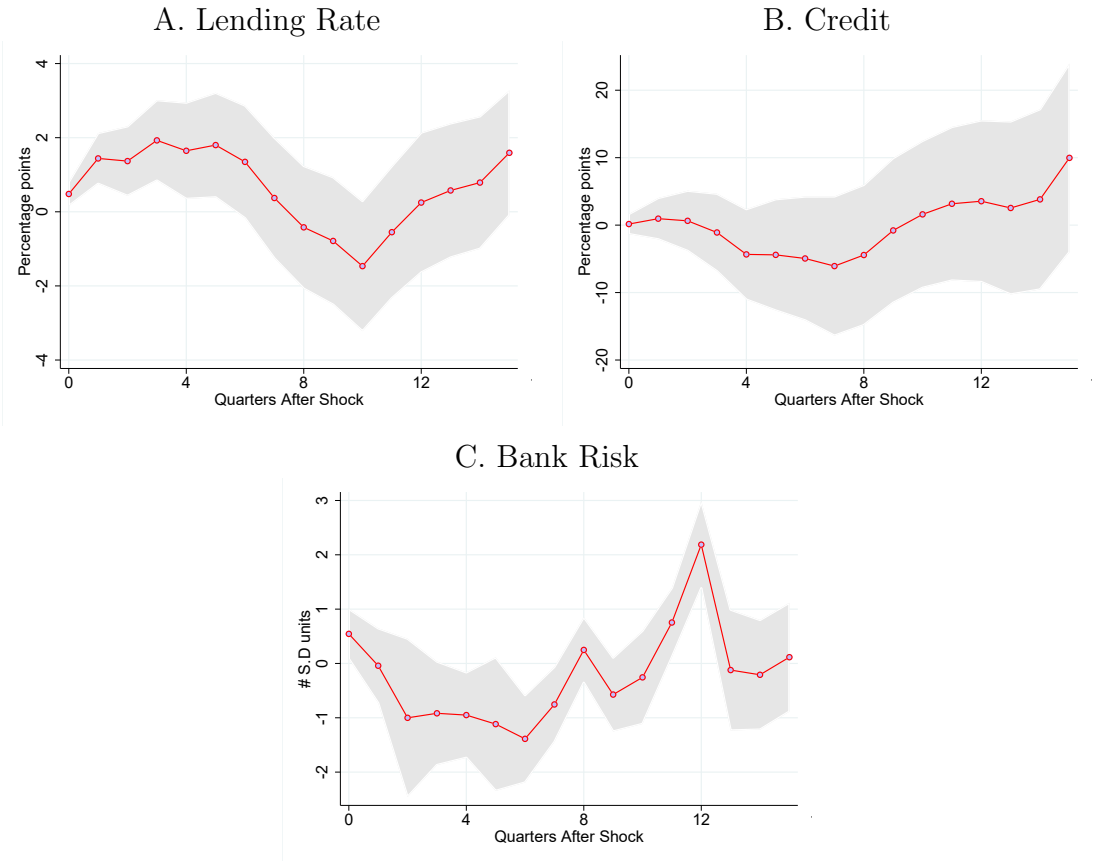
4.1 Estimation Results of Local Projections on Macro variables

The local projections, in specification (2), are estimated on a quarterly frequency for the sample period 2003Q4-2019Q4. We use the quarterly monetary policy shocks, as shown in figure 10 in Appendix A.3. First, we consider the impact of a contractionary shock of 100 basis points on credit market outcome variables at the aggregate level: credit, average lending rate and a measure of overall bank risk-taking. Following a similar strategy as in Angeloni, Faia and Lo Duca (2015), we measure total bank risk-taking as the quarterly realized volatility of the S&P/BVL Financials Index (PEN), calculated as the standard

[9]More specifically, In Appendix D we estimate a VAR for the Peruvian aggregate data, under a Cholesky identification, to study monetary policy shocks.

deviation of the index's daily returns over each quarter. The basic idea is that financial markets react to any information of bank default that is ultimately triggered by bad news on bank's investment returns. Due to data availability we estimate the specification (2) for bank risk for the shorter sample period 2011Q4-2019Q4 and with only 1 lag for the dependent variable.[10] A detailed description of the other aggregate variables is provided in the appendix C.

Figure 3. *Local projections Results: Monetary Policy Shock, Credit Market and risk-taking*



Note: This figure shows the impulse response functions to a 100 basis points contractionary monetary policy shock under the specification (2). 68 percent confidence bands are shown, using Newey and West (1987) standard errors. Sample period 2003q4 - 2019q4. Due to data availability we estimate the local projection for bank risk for the sample period 2011q4 - 2019q4.

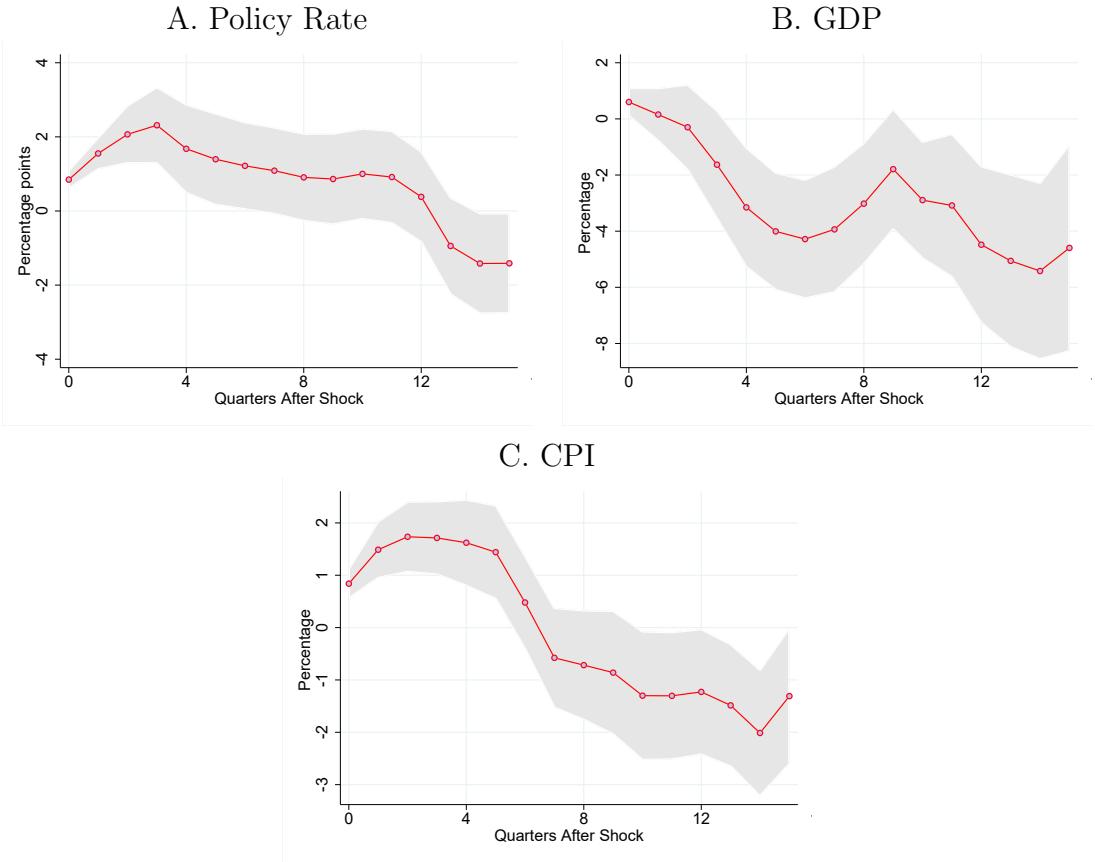
The impulse responses of credit market outcomes after the contractionary monetary policy shock are shown in Figure 3. The panel A of Figure 3 shows an increment in lending rates after a 100 basis point rise in the monetary policy rate: when the impact

[10]Daily data on S&P/BVL Financials Index (PEN) in only available from 01/01/2011 onward. However, we also get a similar pattern for impulse response if we include 6 lags for the dependent variable, but the estimates are very imprecise after 8 quarters.

occurs the lending rate rises and reaches a maximum increment of 2% after two quarters and it is still up at around this level one year later. The panel B of Figure 3 displays the persistent and economically significant negative response of aggregate credit after a monetary policy shock: credit declines by around 3% four quarters after the shock, and reaches a decline of around 5% in the subsequent year. More importantly, Panel C shows that after the MP shock the measure of overall risk of banks, perceived by investors, falls by around 1 standard deviation after 3 quarters. In Appendix B we check and confirm that the results are robust to various baseline regression modifications.

Furthermore, in the Appendix D we demonstrate that the equilibrium response of credit markets is qualitatively consistent with estimates from a model that imposes more constraints on the data: a VAR with a Cholesky identification for monetary policy shocks. Figure 14 shows that after a monetary policy shock one observes an increment of lending rates and a decline in credit. These findings are robust to several specifications, ordering of variables, detrending or scheme identification (see Figure 16 in Appendix D.2).

Figure 4. *Local projections Results: Monetary Policy Shock & The Business cycle*



Note: This figure shows the impulse response functions to a 100 basis points contractionary monetary policy shock under the specification (2). 68 percent confidence bands are shown, using Newey and West (1987) standard errors. Sample period 2003q4 - 2019q4.

All these aggregate empirical evidence points out a supply side mechanism of adjustment in credit markets and it is consistent with the existence of a risk-taking channel after a MP shock[11]. Motivated by this robust aggregate evidence in next sections I discuss the risk-taking channel as credit supply side of mechanism of monetary policy shocks. And in particular, how banks allocate loans and how risks are reflected in their asset side of the balance.

Finally, we also show the validity of the identified monetary policy shocks by testing its power to explain the main macroeconomic variables. we estimate local projection for GDP and the consumer price index. Figure 4 shows the estimated impulse responses to a contractionary shock of 100 basis points. Panel A shows that the policy rate increases consistently and subsequently reverses. Panel B shows that economic activity contracts persistently after 2 quarters and one year after GDP is around 4% below its initial level. Consumer prices also decline after 6 quarters, it persistently stays around 2% below its initial level after 2 years. These results are consistent with standard textbook responses of GDP and CPI to monetary policy tightening.

In Appendix D.1 we also show that these results are consistent with impulse responses obtained from a standard VAR with a Cholesky identification for monetary policy shocks. The local projections method produces larger and more persistent impulse responses than the VAR method. Different sample periods do not explain these differences[12]. But, as shown by Cloyne and Huertgen (2016) these differences may mainly be explained by the different implied shock paths in the two methods[13]. The magnitude and persistence of the impulse responses obtained from the local projections, reported in 4, are consistent with those shown by Romer and Romer (2004); Holm, Pascal and Tischbirek (2021).

5 A Model of the Risk-Taking Channel

In this section, we develop a two-period model with a continuum of measure one of identical banks, identical households, and non-identical firms[14]. Banks operate in competitive

[11] Quispe (2001) and Carrera (2011) also analyses the effects of monetary policy on credit markets in Peru, by using aggregate data. However, their analysis is limited to look the total impact on lending, independently of any distinction between credit demand or supply side mechanisms or lending rates or risk-taking measures.

[12] **?** estimate a VAR for a larger sample, 2003Q1-2009Q4, but which does not feature bank risk, and the impulse responses for credit, lending rates, CPI and GDP show similar magnitudes and persistence than those from VAR we estimate here.

[13] The local projections are specified in differences, thus a shock to the level of the policy rate is permanent. However, the VAR is specified in levels and a shock to the level of the policy rate is temporary.

[14] This theoretical framework is an extension of the closed-economy version model developed in Pozo (2019).

markets. For simplicity, we assume that in this economy there are only two provinces and that each bank has two branches, one in each province.[15] These two provinces are different because of type of firms that exist within each province. There is an infinite number of firms in each province. All firms in a province are identical. In one province there are firms with high uncertainty on their production function; while in the other province there are firms with low uncertainty on their production function. The uncertainty level is measured with the size of the standard deviation of the productivity level of the production function.

Bank lending decisions are about how much to lend to each of these two provinces, or, equivalently, to each type of firm. While loans are issued by each branch, lending decisions are taken at the bank level. Since we assume the loan lending rate is state-contingent, loans to the province with high-uncertainty firms (named high-risk loans) represent the investment opportunity with high-risk from bank's perspective; while loans to the province with low-uncertainty firms (named low-risk loans) represent the investment opportunity with low-risk from bank's perspective. We assume firms cannot borrow from other firms.

There are risk-neutral households in each province. For simplicity, we assume they are identical within provinces and across provinces. They own banks and firms. Also, they supply inelastically one unit of labor, and make bank deposits at the bank branches located at provinces where they live. We assume labor cannot freely move across provinces. Banks use an exogenous initial equity and households' deposits to fund their risky loans.[16] There are two key assumptions, limited liability faced by banks and deposit insurance. The interaction of these allows us to model the excessive risk-taking behavior of banks.[17] For simplicity, we assume banks are not able to issue equity. Besides, the deposit insurance is funded by the government through lump-sum taxes on households. Firms demand bank loans to purchase capital that combined with labor are used to produce.

Note that the simplicity of the model helps us to clearly understand its implications. Furthermore, since we do not model heterogeneity on the credit demand side of loans at the province level nor heterogeneity on the credit supply side at its bank level, in order to test the qualitative results with the data in the empirical model need to do our best effort in order to control by credit demand shocks at the province level and to control by credit supply bank shocks at bank level.

The timing of the model is as follows: at t=0 households make bank deposits, banks

[15]This framework can be easily extended to more than two provinces and hence more than two bank branches; however, there are no gains in terms of intuition or qualitative results by doing so.

[16]We assume the initial equity is exogenous without abstracting too much from reality since it is well known that to raise new equity is a long-term process.

[17]The risk-taking involves the volume and not the type of credit.

decide how much to lend to high-risk firms and low risk-firms, and firms purchase capital. At the beginning of t=1 productivity level is realized, and capital and labor are combined for production. Also, the (state-contingent) bank loan interest rate is realized. Finally, bank loans and workers are repaid.

Since banks have limited liability, the only resources available to pay bank obligations are banks' gross returns of their investment activities. As a result, in this two-period model, at t=1 bank dividends are identical to final bank equity and hence banks transfer non-negative dividends to domestic households. Each time that banks are not able to fully repay depositors they default. Due to the deposit insurance, if banks default, the government collects lump-sum taxes from households and complements banks' payments so that depositors are fully repaid.

Output of i firms at t=1 is given by the following production function:[18]

$$y_i = z_i k_i^{\alpha_i},$$

where $i \in \{h, l\}$, h stands for high-risk firms and l for low-risk firms, k_i is capital, $0<\alpha_i< 1$ so we assume diminishing marginal returns to capital, and z_i is the multiplicative aggregate shock to productivity. While k_i is chosen at t=0, z_i is known at t=1. We assume z_i has a lognormal distribution, $ln(z_i) \sim N(\mu_i, \sigma_i^2)$, F^i is the cumulative density function and f^i is the probability density function of z_i. For convenience, we assume $\mu_i = \sigma_i^2/2$ so that the unconditional mean of z_i is one and hence independent of σ_i^2. For simplicity, we assume z_h and z_l are independent. We assume that $\sigma_h > \sigma_l$ so that h firms exhibit a higher volatility on their productivity shock. Hence, in this setup we characterize the different level of risk of bank lending opportunities with different values of the volatility of the productivity shock.

Firms demand bank loans in order to purchase capital. We assume firms do not hold equity and all bank loans are used to purchase capital, i.e., $l_i = k_i$, where l_i are bank loans to i firms. Firms' profits are therefore,

$$\pi_i = (1 - \delta_i)k_i + z_i k_i^{\alpha_i} - r_i^l l_i - w_i,$$

where δ_i is the capital depreciation, $(1-\delta_i)k_i$ is the leftover capital, r_i^l is the lending rate, and w_i is the wage of the unit of labor supplied. Since we assume that the lending rate is state-contingent, the first order condition of i loans is,

$$(1 - \delta_i) + \alpha_i z_i k_i^{\alpha_i} = r_i^l, \tag{3}$$

[18]For simplicity, since supply of labor force is inelastic, we can omit the labor factor.

which represents the demand curve of bank loans of i firms.

The problem of the household is straightforward. Let say that $\bar{r}$ is the required gross return on deposits d from $t = 0$ to $t = 1$ and agreed at $t = 0$. Since the deposits are fully protected by deposit insurance, it holds that $\bar{r}$=r, where r denotes the risk-free interest rate. Since households are risk-neutral, the equilibrium condition that avoids a corner solution yields r=$\frac{1}{\beta}$, where β is the household's exogenous discount factor. Hence, households are indifferent to the amount they deposit in banks. It follows that the deposit supply faced by banks is perfectly elastic at the interest rate of r.

An individual bank can only fund its loans with households' deposits, d, and the exogenous initial equity, n. The bank balance sheet is,

$$l_h + l_l = d + n. \tag{4}$$

Since banks have limited liability, banks' resources available to pay back deposits are only the risky gross returns of their loans. This means that if these returns are not enough to fully repay depositors, bank defaults and repays only partially to depositors and deposit insurance is activated. As a result, final bank equity (or bank profits) or equity at the beginning of period $t = 1$, cannot take negative values, i.e.,

$$\pi^b = max\{0, r_h^l l_h + r_l^l l_l - rd\}.$$

Banks default at $t = 1$ if $(r_h^l, r_l^l) \in \Omega_{r^l}$ where,

$$\Omega_{r^l} = \left\{(r_h^l, r_l^l) | r_h^l l_h + r_l^l l_l < rd\right\},$$

and hence $\pi^b = 0$. It follows that the endogenous probability that bank defaults at $t = 1$ is given by,[19]

$$p = \int_0^\infty \int_0^{r_h^{l*}} dF^{r,h}(r_h^l) dF^{r,l}(r_l^l) = \int_0^\infty F^{r,h}(r_h^{l*}) dF^{r,l}(r_l^l).$$

where $F^{r,i}$ is the cdf of r_i^l and inherits the distributional properties of z_i, and

$$r_h^{l*} = max\left\{0, \frac{rd - r_l^l l_l}{l_h}\right\} \tag{5}$$

[19]We calibrate the model so the limited liability binds and hence bank default probability is positive.

The expected present value of future bank profits under limited liability is,

$$\mathbb{E}\{\beta\left(max\{0, r_h^l l_h + r_l^l l_l - rd\}\right)\}. \tag{6}$$

Hence, when a bank has limited liability, it cares only about the states of nature where its revenues are higher than all its obligations. Since bank deposit return is risk-insensitive (i.e., $\bar{r} = r$) due to the deposit insurance, the bank cannot internalize the negative effects on profits of its risk-taking decision through a higher required return of deposits. In other words, a higher loan level, which increases the bank's default probability, is not going to increase the deposit return required by households and hence it does not reduce the bank's profits when the bank does not default.

The individual bank seeks to maximize (6) subject to the bank balance sheet, (4). Recall bank internalizes that its the lending decision might affect r_h^{l*} and hence its default probability. The first order conditions for l_h and l_l yield, respectively,[20]

$$\int_0^{+\infty}\int_{r_h^{l*}}^{+\infty} \beta(r_h^l - r)dF^{r,h}(r_h^l)dF^{r,l}(r_l^l) = 0,$$

$$\int_0^{+\infty}\int_{r_h^{l*}}^{+\infty} \beta(r_l^l - r)dF^{r,h}(r_h^l)dF^{r,l}(r_l^l) = 0,$$

which can be rewritten, respectively, as[21]

$$r = \mathbb{E}\{r_h^l | (r_h^l, r_l^l) \in \Omega'_{r^l}\}, \qquad r = \mathbb{E}\{r_l^l | (r_h^l, r_l^l) \in \Omega'_{r^l}\}.$$

In the general equilibrium, using (3), these yield,

$$r = (1-\delta_h) + \alpha_h \mathbb{E}\{z_h | (z_h, z_l) \in \Omega'_z\} l_h^{\alpha_h - 1}, \qquad r = (1-\delta_l) + \alpha_l \mathbb{E}\{z_l | (z_h, z_l) \in \Omega'_z\} l_l^{\alpha_l - 1}, \tag{7}$$

where Ω'_z is the complement set of

$$\Omega_z = \{(z_h, z_l) | (1-\delta_h) l_h + (1-\delta_l) l_l + \alpha_h z_h l_h^{\alpha_h} + \alpha_l z_l l_l^{\alpha_l} < rd\},$$

and hence bank defaults at $t = 1$ if $(z_h, z_l) \in \Omega_z$. And it is easy to verify that when there is unlimited liability the first order conditions for l_h and l_l yield, respectively,

$$r = (1-\delta_h) + \alpha_h \mathbb{E}\{z_h\} l_h^{\alpha_h - 1}, \qquad r = (1-\delta_l) + \alpha_l \mathbb{E}\{z_l\} l_l^{\alpha_l - 1}. \tag{8}$$

[20] Proof in Appendix G.1.

[21] Ω' is the complement of Ω.

Comparing (7) and (8), we find that when there is limited liability and deposit insurance, (7), bank decision is no longer socially optimal. In particular, marginal benefits of capital are overestimated from bank's perspective since she only cares on those situations when her profits are positive. As a result, bank cares on the expected return of capital conditional on non-defaulting. In contrast, under unlimited liability, banks internalize negative profits and hence care on the unconditional expected returns or, equivalently, bank likelihood of having negative profits does not affect lending decisions. This in turn leads to an inefficiently high level of both high-risk and low-risk loans under limited liability and insured deposits. Ceteris paribus, the higher the bank default probability, the higher bank's incentives to supply excessive loans and hence to take excessive risk.

More technically, since bank profits are positively associated with z_h and z_l, bank defaulting events are associated with higher values of z_h and/or z_l. Then, the conditional expectations of the productivity levels in (7) are clearly higher than the unconditional expectations in (8). This results in both loans higher under limited liability. Later, we see the results when z_h and z_l are positively and negatively correlated.

Indeed, in the absence of deposit insurance, deposit returns are risk-sensitive and hence bank profits look like the unlimited liability scenario. As a result, the optimality condition under limited liability and non-insured deposits is going to be the same as under unlimited liability, i.e., the limited liability itself does not create any inefficiency in this two-period model.[22]

Furthermore, under unlimited liability, equation (7), we see that there is only a direct impact of the policy rate r on credit, while under limited liability, in addition to the direct effect, there is an indirect effect that is given by the general equilibrium effects on bank default probability, which affects bank incentives to issue excessive loans. Hence, this indirect effect of the policy rate is named the *excessive* bank risk-taking channel.

In addition, from (6) the *profit* channel consists that a lower r increases bank profits and hence reduces bank incentives to take risk so bank can benefit the most from the positive profits. And from (5) we observe that ceteris paribus a higher bank leverage (i.e., lower l_h/d and/or lower l_l/d) increase r_h^{l*} and hence bank default probability. This in turn increases banks' incentives to take excessive risk or equivalently to issue excessive loans. This is known as the *leverage* channel.

Also, notice that from equation (8) while under unlimited liability credit response to monetary policy is independent of the bank equity to asset ratio, i.e. independent of bank leverage, under limited liability this is not the case. In particular, this simple

[22]Proof in Appendix G.2.

model supports the empirical findings of Jiménez et al. (2014). This is, as suggested in figure 21 in Appendix G.3 lowly capitalized banks (i.e., banks with low bank equity to asset ratio) grant more high-risk loans than highly capitalized banks (i.e., banks with high bank equity to asset ratio) after a monetary policy ease.

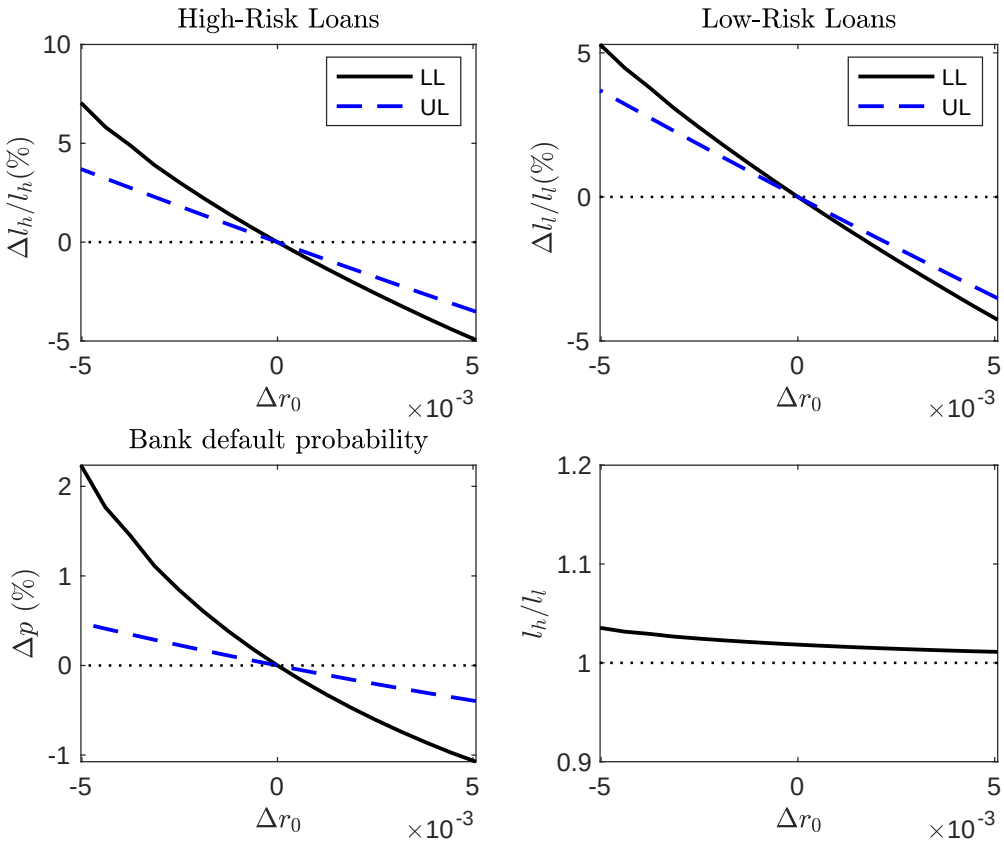
Next, we see how high-risk and low-risk loans responds to the monetary policy position, i.e., the risk-free interest rate. To do so, instead of solving for the partial derivative of loans with respect to r, which is not straightforward and we might not be able to conclude easily about the sign, we parametrize the model with standard parameter values, whenever feasible, and simulate changes on r.[23] In addition, we set $\alpha_h = \alpha_l$ and $\delta_h = \delta_l$, so the only difference (if there is) of the response of high-risk and low-risk loans to a monetary policy change is explained by the difference of the uncertainty sizes of the productivity shocks. In particular, in the baseline calibration, we set $\rho = 0$, $\beta = 0.99$, $\delta_h = \delta_l = 0.20$, $\alpha_h = \alpha_l = 0.33$. The other parameters n and σ_h and σ_l are set so that bank default probability and bank leverage $((l_h + l_l)/n)$ equate 3%, and 7.0, respectively, and $\sigma_l = 0.25\sigma_h$. It yields $n = 0.59$, $\sigma_h = 1.48$ and $\sigma_l = 0.37$.

In equilibrium, high-risk loans are 4.3% inefficiently high and low-risk loans are 2.5% inefficiently high. This implies that there is a stronger preference for high-risk loans. Since banks might default with a positive probability, they do not internalize the losses when the return on the loans is very low, but internalize the benefits when return is very high. Hence, they have a stronger preference for loans with returns that exhibit a higher uncertainty.

According to figure 5 after a monetary policy easy (i.e., $\Delta r_0 < 0$), both types of loans increase under limited liability (black solid line) and unlimited liability (blue dashed line). Notice that under limited liability the increment is higher. This latter is due to the indirect effect of policy rate on loans due to the excessive risk-taking channel. This is, in equilibrium the cost of deposits (policy rate) is smaller, which pushes down bank default probability, while bank loans are higher, which pushes up bank default probability. In equilibrium the latter dominates and hence bank default probability increases, as shown in Figure 5. This, as explained before, increases bank incentives to take more excessive risk and hence to excessively supply more low-risk and high-risk loans to firms.

[23] In order to have a positive default probability of banks, we need to set δ_h and δ_l with a parameter value higher than what is used in the literature.

Figure 5. *Monetary Policy Impact*



Note: Figure shows the responses of some variables to changes of the monetary policy rate under LL and UL. LL: Limited Liability, UL: Unlimited Liability. In the baseline calibration, we set $\rho = 0$, $\beta = 0.99$, $\delta_h = \delta_l = 0.20$, $\alpha_h = \alpha_l = 0.33$. The other parameters n and σ_h and σ_l are set so that bank default probability and bank leverage $((l_h + l_l)/n)$ equate 3%, and 7.0, respectively, and $\sigma_l = 0.25\sigma_h$. It yields $n = 0.59$, $\sigma_h = 1.48$ and $\sigma_l = 0.37$.

More importantly, for the purpose of this paper, Figure 5 reports that a monetary policy ease produces a stronger increase of high-risk loans. Hence, this model provides evidence that after a monetary policy ease, banks raise their preferences of holding a larger share of high-risk loans on their loan portfolio.[24] This is because the higher bank default probability, the larger expected profits, and the higher bank incentives to take excessive risk and hence this accentuates the already stronger preferences on high-risk loans.

Finally, these results are qualitatively robust when productivity shocks of high-risk firms and low-risk firms are positively and negatively correlated as reported in figures 20 and 21 in Appendix G.3, respectively.

In the micro empirical section of this paper we use this result to test the risk-taking

[24] In fact, figure 5 shows that the ratio of high-risk to low-risk loans is always higher than one.

channel mechanism underpinning our model. Ideally, we would like to observe risk directly, but we consider non-performing loans ratio in a local market as one degree of variation in riskiness.

6 Micro Data

At the micro level, the analysis is based on Peruvian financial firm branch-level data and bank-province data. The Peruvian credit market is segmented locally, as there is heterogeneity in the number of institutions serving a given province. But also, there are large financial institutions with an extended geographical lending network that can overpass geographical market segmentation and serve more than one local market. The Peruvian financial system is composed by five main financial groups: banks, CAMCs, CRACs, EDPYMES and *empresas financieras*.[25] Banks engage in a wide range of financial activities and operate on a national scale. The latter four groups, non-bank financial institutions, provide limited financial services, intermediate small amounts of loans, and they are primarily focused on credit to small businesses and consumers, and reaching unbanked individuals.[26] The empirical analysis focuses on all financial institutions, bank and non-banks.

6.1 Data Sources

Province Lending: The dataset comprises Peruvian branch-level data information from 2002m1 to 2018m12 about loans and deposits extended by banks across districts. The data on lending and number of financial institutions or branches operating in province is provided by the Peruvian financial regulator, *Superintendencia de Banca, Seguros y Administradoras de Fondos de Pensiones* (SBS).

Financial firms data: The financial firms data comes from balances reported to the Peruvian financial regulator. We access to data available from 2002m1 to 2017m09.

Non-Performing loans: The key variable for riskiness is Non-Performing Loans (NPL) at the province level. It was computed as the time average of yearly NPL ratios for each of

[25]The Peruvian financial regulator, *Superintendencia de Banca, Seguros y Administradoras de Fondos de Pensiones*, classifies the financial institutions into these five groups: i) Banking companies, ii) CAMCs, which are Municipal Savings Associations, iii) CRACs, which are Rural Savings and Loan entities, iv) EDPYME, that is an Entity for Small and Micro Business, and v) *empresas financieras*, that are financial or specialized companies

[26]CAMCs are mainly owned by regional governments; CRACs, privately-owned financial firms, originally focused on lending to the agriculture sector and rural areas, now offer commercial lending and personal loans in urban areas. EDPYMES are focused in lending to medium and small firms and *empresas financieras* mainly focused in consumer lending

189 provinces in the country. To compute this NPL measures we make use of granular on credit data from the Credit Registry Data (RCC). This is a loan-level data that contains debt classification at client-level and at loan-level originated in the financial system.[27] The data is available at a quarterly frequency for the 2003Q1-2010Q3 period and at a monthly frequency for the 2010M10-2018M12 period. Debtors are identified by an SBS code, tax ID (RUC) and national ID (DNI). Thus, we compute NPL ratios at the province level or bank-province level at a quarterly basis from 2003Q1 to 2008Q4.

Thus, we first match the credit registry data with geographic location, in a province. Then, we use the geographic location of a debtor provided by the Peruvian tax administration (SUNAT) and finally we match this information to Location codes (UBIGEO).[28] The goal is to obtain a panel-data on credit and non-performing loans ratio at bank-province-time level. In this process, we identify a sample of all formal loans from the financial institutions.

Specifically, for the construction of any bank-province-time level variable, we proceed as follows:

1. Identify a sample of clients with RUC(Tax ID) in RCC.
2. Match clients with RUC in RCC with Locational data from SUNAT.
3. Select loans provided to private non-financial firms $\rightarrow$ Loans by RUC and Location
4. Construct credit information, risk-taking measures at bank-province-time level.

Note that we make two strong assumptions. First, we assume that loans go to the registered location of a borrower. It could be that the registered location is different to the one where the debtors' activities are performed. However, we assume this is an odd case. Second, we also assume that loans located in a certain region are issued by an agency from the same region. Appendix E shows the results of this matching process. In general, the sample to compute NPL captures very well the dynamics of aggregate credit market in Peru.

In the analysis the risk-taking measure is captured by the non-performing loans ratio, which we calculate using the Peruvian financial regulator (SBS) criterion,

$$\frac{\text{loan arrears (Big firms(15d), small firms(30d) mortgage(30d), personal(90d))}}{\text{Total credits}}.$$

[27] This information is restricted. We thank to the Central Bank of Peru, BCRP, for giving us access to use the datasets.

[28] Once we have a UBIGEO, we use the Peruvian Bureau of statistics' information on location of a UBIGEO in a region.

Employment: we collect data on employment from administrative data provided by SUNAT.[29] The data cover all formal employment at monthly frequency from 2011m1 to 2018m12. we compute quarterly growth rate employment at the province level by matching the available firm's location information to Location codes (UBIGEO).

6.2 Summary Statistics

Table 2 presents the descriptive statistics for the main variables in the analysis. It shows the cross-section and time averages. The empirical analysis uses variation on lending at branch-level. There are 3682 branches located in 451 districts and 189 provinces. The

Table 2. *Data: Statistics*

	All		Low NPL		High NPL	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Panel A. Province Characteristics						
Population (Thousand)	169.6	689.8	256.7	969.3	83.5	84.1
Area (sq. km.)	6,703.1	12,518	7,762	15,292	5,655.0	8,932.6
Formal Employment (share)	2.2	3.5	2.9	4.3	1.5	2.1
NPL-Branch (%)	15	18	6.1	3.1	24.7	21.0
Obs.(Provinces)	189		94		95	
Panel B. Branch Characteristics						
Loans (Thousand S/)	121.6	978.6	199.3	1,352.4	37.9	73.2
Loan growth (%)	4.5	19	4.9	22	3.9	15.9
Obs.(branch × Quarter))	68,969		35,773		33,196	
Panel C. financial firms Characteristics						
Assets (Mill. S/)	4,321.6	14,111.5	7,721.9	19,189.9	926.6	2,713.2
Loans (Mill. S/)	2,789.7	8,961.6	4,957.7	12,201.3	625.2	1,593.9
NPL-Bank (%)	5.1	5.3	2.3	.68	7.8	6.5
Obs.(Bank × Quarter))	2,490		1,245		1,245	

Note: This table provides summary statistics at the province, branch, bank level. All panels provide a breakdown by high and low non-performing loan (NPL), using below and above the median NPL for each respective sample. Panel A presents characteristics for all provinces with at least one financial firm branch. The underlying data are from the 2017 census. Data on employment comes from SUNAT. Panel B presents data on total credit and loan growth at the branch level. Panel C presents data about financial firms. Data from SBS. The underlying data are for NPL is based on RCC data, matched with locational data.

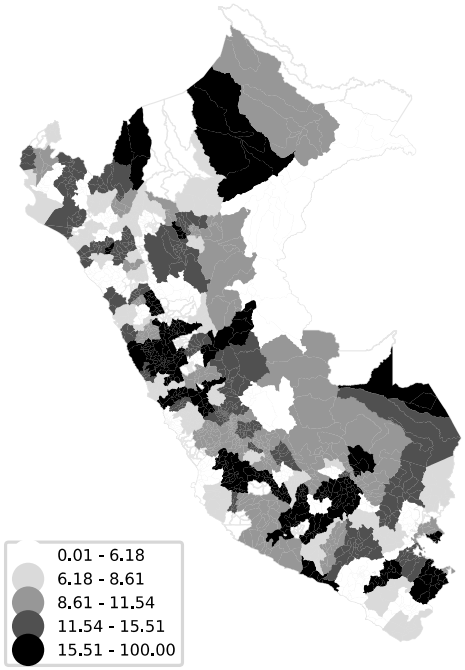
identification strategy uses variation in riskiness of local credit markets, which we measure

[29]This information is restricted. we thank to the Central Bank of Peru, for giving us access to use this dataset.

using the Non-Performing Loans (NPL) at the given province, NPL-Branch. The NPL-Branch is calculated by adding all non-performing loans in a given province in a given year and then averaging the results over all years. we then assign to each financial firm branch in the data the NPL of the province in which it is located.

Figure 6 shows the map NPL-branch across Peru. A lower value indicates lower level of riskiness. There is heterogeneity across provinces, from a minimum NPL-Branch of 0.07 to a maximum of 1.

Figure 6. *Province risk heterogeneity : $NPL - Branch$*



Note: Given data on non-performing loans ratio at a province p and month t, it shows for each province p a time average computed as $\frac{\sum_t NPLf_{p,t}}{T}$, where T is the number periods in the sample. Sample: 2003m1-2017m12.

All panels in Table 2, for presentation purposes, provide a breakdown by high and low non-performing loan (NPL) using the median NPL as a threshold value to divide the respective samples. Panel A of Table 2 shows statistics of the data for all provinces with at least one financial firm branch. It is noticeable that low-risk local provinces (Low NPL-Branch) are larger and have higher formal employment than high-risk provinces. The average population in low-risk provinces is 256.7 thousand versus 83.5 in high-risk provinces. Formal employment share is almost double in low-risk markets: 2.9 versus 1.5.

Branch-level summary statistics is shown in Panel B of Table 2. Branches in low-risk provinces are larger (199.3 thousand Pen Soles versus 37.9 thousand Pen Soles). The average branch holds loans worth 121.6 thousand Pen Soles. However, branches in low-

risk provinces show a higher credit growth rate on average relative to branches in high-risk provinces.

Panel C of Table 2 presents statistics at the financial level. For the financial firm-level analysis we compute a financial firm level measure of risk, NPL-bank, which is defined as the weighted average of NPL-Branch across all of the financial firm's branches, using branch lending shares as weights. Financial firms with low NPL-bank are larger, with assets worth 7721.9 million PEN soles versus 926.6 million PEN soles for high NPL-bank financial firms.

One key assumption of the empirical strategy is that the underlying riskiness of credit local markets is heterogeneous. Furthermore, differences in the underlying riskiness of local credit markets induce geographic variation in Non-Performing Loans (NPL). We regress the measure of NPL on some regional structural characteristics that affect borrowers' riskiness to provide some evidence that this measure of NPL captures some fundamental riskiness. We collect annual data on a measure of capital stock available per worker as a proxy for firm investment, the share of the population with elementary education as a proxy for overall education, the average number of social conflicts as a proxy for business environment, and the number of mining operations in a region as a proxy for exposure to foreign shocks.[30].

[30]Information of number of mining operations in each region was obtained from the Ministry of Mining and Oil Production. The rest of indicators were gathered from the Index of Regional Competitivity published by the Peruvian Institute of Economics

Table 3. *NPL and Regional Indicators*

	Dependent variable: NPL				
	(1)	(2)	(3)	(4)	(5)
Capital per worker	0.214**				0.164
	(0.101)				(0.139)
Share Basic Education		0.831			0.142
		(0.536)			(0.705)
Social Conflicts			4.359*		3.428*
			(2.154)		(1.947)
Mining Operations				0.170	0.0720
				(0.265)	(0.296)
R^2	0.176	0.128	0.126	0.00831	0.260
Observations	24	24	24	24	24

Note: This table estimates the relationship of regional indicators, as proxies for underlying province risk, and NPL, the measure of riskiness. NPL is aggregated to a regional level by taking averages across its provinces. Consistently, the regressors are also time averages over the annual sample 2010-2018. Capital per worker is a measure of the amount of capital available per worker. Share Basic Education is the percentage of the population who has received elementary education. Social Conflict is the average number of social conflicts in the regions. All these regional indicators were obtained from the Index of Regional Competitivity published by the Peruvian Institute of Economics. Mining Operations denotes the average number of mining operations in a region, reported by the Ministry of Mining and Oil Production. Robust Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

NPL ratios are positively correlated with all previous measures of underlying riskiness, as shown in Table 3. In regions with higher levels of firm investment, NPL ratios are higher. Furthermore, regions with low educational levels and greater exposure to commodity prices fluctuations, due to the presence of mining operations in the region, have higher NPL ratios. Although these variables are not statistically significant. Finally, and most importantly, higher business environment volatility is associated to a higher NPL. Higher NPL ratios are found in regions with a higher number of social conflicts.

7 Monetary policy transmission at the bank-branch level: The Risk-Taking Channel

In this section, we attempt to establish direct causal effects of monetary policy on lending through the risk-taking channel mechanism. we investigate a causal link between credit market riskiness, as measured by the NPL ratio, and the power of monetary policy trans-

mission, by exploiting the monetary policy shocks, we constructed in Section 3, and the bank-branch level Peruvian data, described in Section 6. This section first shows estimates of the aggregate effects of monetary policy implied by the bank-branch level data. To put it in another way, it displays macro estimates derived from micro-data.

Second, the results are then disaggregated to investigate the risk-taking channel of monetary policy by utilizing geographic variation in Non-Performing Loans (NPL). We follow a similar strategy as in Drechsler, Savov and Schnabl (2017) to show a direct causal effect. In particular, we use bank branch-level and bank-province level data so we can control for omitted variables such as lending opportunities and credit demand conditions. Basically, through this identification we shed light on the risk-taking channel as a credit supply side mechanism of monetary policy. Under this approach, we conduct a cross-sectional analysis showing that the risk-taking channel is greater in exactly those pool of borrowers where theory would predict that banks' incentives to take risk are likely to be stronger.

7.1 Micro-Macro Responses of Credit to Monetary Policy Shocks

The validity of the branch-level data to capture the conditional response of credit to monetary policy shocks is a first step in the micro analysis. Thus, we first look for micro-macro impulse responses based on micro bank-branch level data on credit. Following similar strategy as Holm, Pascal and Tischbirek (2021), we estimate a series of the following local projection regressions as follows:

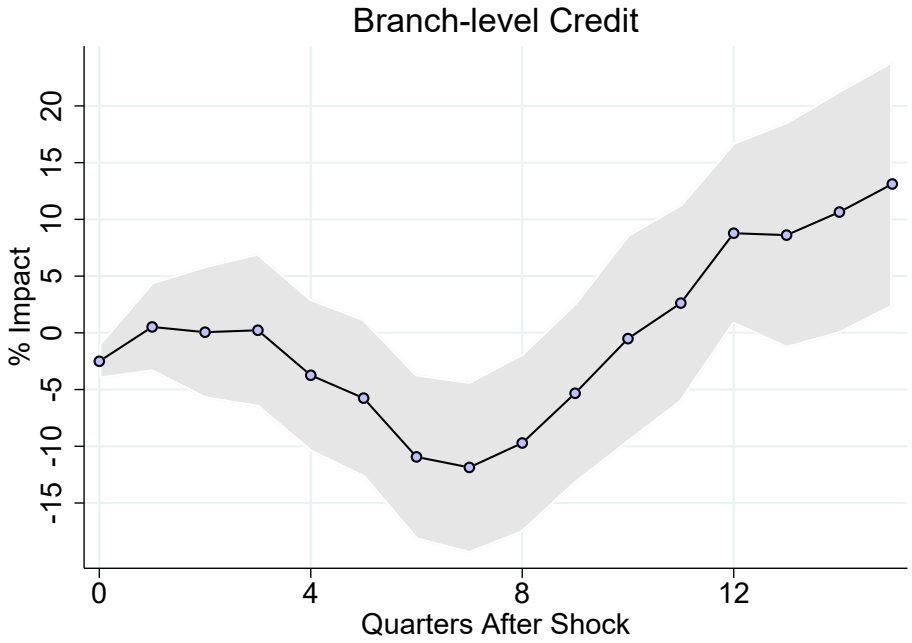
$$\frac{y_{j,t+h} - y_{j,t-1}}{\bar{y}_{t-1}} = \alpha_{j,h} + \beta_h \, \epsilon_t^{MP} + \sum_{k=1}^{K} \gamma_k^h X_{j,t-k} + u_{j,t}^h \,, \tag{9}$$

where $y_{j,t}$ is the amount of credit supplied by bank-branch j at time t. The dependent variable is the change in y_j from period $t-1$ to $t+h$, $h = 0, 1, ..16$. The key normalization variable is $\bar{y}_{t-1}$ which is the average value of credit across all branches in period $t-1$. Thus, under this normalization the β_h is comparable to the corresponding coefficient estimate on the aggregate data in specification (2) in Section 4.1. The coefficient β_h gives the percentage change of the average branch credit at horizon h in response to a 100-basis-point monetary policy shock. $\alpha_{j,h}$ is a branch specific fixed effect at horizon h. $X_{j,t}$ denotes a vector of controls. Following the specification (2), it includes three years of lagged values of the monetary policy shock and 2 years lagged values of the dependent variable.

The estimated impulse response for bank-branch credit is shown Figure 7. This result

is comparable with the macro impulse response of aggregate credit shown in Figure 3. Surprisingly, both the micro-macro response of credit at the branch level and the macro response of aggregate credit, shown in Figure 3, to monetary policy shocks exhibit similar dynamics overtime. However, the micro-macro response is more severe, and credit falls by around 13 percent seven quarters after the shock, which is significantly higher than the aggregate macro response fall of around 8 percent.

Figure 7. *Micro-Macro Impulse Response of Credit to a contractionary monetary Policy Shock*



Note: This figure shows the Micro-Macro impulse response function of credit to a 100 basis points contractionary monetary policy shock under the local projection specification (9). 68 percent confidence bands are shown, using Driscoll and Kraay (1998) standard errors. Sample period 2003q4 - 2019q4.

Overall, this response demonstrates that monetary policy influences credit at the branch level, and it follows the expected direction, it is comparable to the aggregate level response and it is statistically significant. With this in hand, we examine the risk-taking channel as a credit supply side mechanism of monetary policy at the branch level in the following section.

7.2 The risk-taking channel mechanism: Micro evidence

7.2.1 Identification Strategy

This section investigates the connection between risk and the power of monetary policy transmission. We use the Non-Performing Loans (NPL) as a measure of the riskiness of a local credit market. As developed in Section 6.2, we assume that the geographic variation in Non-Performing Loans (NPL) is induced by differences in structural riskiness of local credit markets. This closely reproduce the idea of local credit markets (Nguyen, 2019). Geographic proximity reduces the costs of transmitting and processing that information of borrowers. Thus, branches specialize in asses the riskiness of pool of borrowers they face in local market.

A key idea in the identification strategy is that NPL, capturing the risk-taking channel mechanism, signals financial firms to rebalance their lending portfolio and take advantage of profitable but riskier local markets. Financial firms internally can allocate funds across branches, but there are some administrative costs to reallocate resources across markets due to geographic segmentation. An expansionary monetary policy shock introduces additional incentives for financial firms to pay cost for portfolio rebalancing. In particular, additional cheaper funding leads to rebalance lending in such a way that a bank-branch facing a risky market expand lending much more relative to a bank-branch facing a less risky market, since excess of deposits is not costly but profitable. Under the risk-taking channel, lending supply should be more sensitive in riskier local lending markets.

For the identification strategy to work, it is important to have variation in riskiness that is independent of a financial firm's lending opportunities or demand factors influencing financial firm's decisions. To obtain such variation we compare lending across branches of the same financial firm located in different provinces at the same time. This is a within-financial firm identification, and we refer to it as branch-bank estimation. By comparing across branches of the same financial firm, one can control for the financial firm's lending opportunities and identify the effects of the risk-taking channel on the sensitivity of lending to monetary policy.

7.2.2 Branch-Bank estimation

Equation 10 implements the identification strategy and it is the main specification at the branch-level in a given province. The dependent variable, $\Delta y_{b(j)pt}$, is the growth rate of all loans granted by a branch j of a financial firm b in the province p at time t. NPL-Branch$_p$ is the indicator of riskiness of the local credit market in province p. ϵ_t^{MP} is the monetary

policy shock constructed in Section 3. We include bank-time fixed effects, α_{bt}, for bank b that owns a branch j; and α_j , $\alpha_{p(j)}$, $\alpha_{r(j)t}$ are branch , province and region-time fixed effects, respectively.

$$\begin{aligned}\Delta y_{b(j)pt} = \alpha_j + \alpha_{p(j)} + \alpha_{r(j)t} + \alpha_{bt} + \beta\, \text{NPL-Branch}_p \times \epsilon_t^{MP} \\ + \gamma_X X_{b(j)p,t} + \epsilon_{b(j)pt}\end{aligned} \tag{10}$$

The key set of fixed effects are the bank-time fixed effects, α_{bt}, which absorbs all time differences across banks, to control for a bank's lending opportunities. So, we compare across branches of the same bank. NPL-Branch$_p \times \epsilon_t^{MP}$ captures the MP risk-taking channel. Basically, with $\beta < 0$, after a expansionary MP shock, branches operating in riskier provinces extend more loans relative to its branches in less risky locations.

Branch, province and region-time fixed effects are additional controls. Branch fixed effects control for branch-specific characteristics such as invariant managerial quality. Province fixed effects control for province specific differences, and region-time fixed effects control for economic or financial trends at a specific region level. If we omit bank-time fixed effects, we add time fixed effect to control for country level trends.

We also include $X_{b(j)p,t-k}$, a vector of controls. To control for initial credit conditions or specific variance of observation we add one lag of all loans granted by a branch j, $logy_{b(j)p,t-1}$. We also try different sets of controls, such as lags of dependent variables and lags of monetary policy shock interacted with the average NPL, to control for the mean reversion property of endogenous variable at the branch level and shock diffusion, respectively. Adding these controls is consistent with previous Local Projections specifications, in equations (2) and (9). We cluster errors at time and bank-level.

Results

Table 4 shows the results of the estimation of equation (10). The sample include all branches from all financial firms, banks and non-banks. The quarterly sample covers the period from 2004Q1 to 2018Q12. Lending data was winsorized at the 2% to control bias results due to outliers. From columns (1) to (4), we add or take out regressors. The preferred specification is in Column (2). Overall, we intend to control for variables that might influence the lender decision and that may be also correlated with a financial firm ownership, firm size, regional economic conditions, managerial decisions or initial branch trends.

Table 4. *Branch-level estimation: Results*

	Dependent variable: Δy_{bdt}			
	(1)	(2)	(3)	(4)
NPL-Branch $\times \epsilon_t^{MP}$	-0.0714***	-0.123***	-0.0908	-0.177*
	(0.0252)	(0.0431)	(0.0825)	(0.100)
y_{t-1}	-0.115***	-0.120***	-0.120***	-0.109***
	(0.0134)	(0.0160)	(0.0154)	(0.0179)
Controls Lag Dep.		✓	✓	✓
Bank-Time FE	✓	✓	✓	
Region-Time FE	✓	✓		
Branch FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Time FE				✓
R^2	0.346	0.348	0.329	0.179
Observations	68969	65321	65321	65724

Note: This table estimates the effect of the Peruvian monetary policy shocks on lending growth, $\Delta y_{b(j)pt}$. Quarterly Sample: 2004Q1 to 2018Q12 at the branch-level. The sample includes only banks with branches in two or more provinces. Lending growth is the log change in credit at the branch level. NPL-Branch measures market riskiness in the province where a branch is located. ϵ_t^{MP} is the monetary policy shock. Fixed effects are described at the bottom of the table. Standard errors clustered at time and bank-level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

Columns (1) and (2) show that allowing for lags of branch lending growth rates makes no very significant difference in the risk-taking channel. Column (2) shows the operative and statistically significant risk-taking MP channel. It confirms that the sensitivity of lending to MP changes is increasing in riskiness of borrowers, even within a financial firm. After 100 bps expansionary monetary policy shock, financial firms raise lending growth rates by 12.3 bps more at their branches in a high risky locations relative to their branches operating in low risky locations, per unit of NPL change. In particular, after 100 bps expansionary monetary policy shock, a branch operating in an average high NPL market (24.7) raises lending growth by 228.8 bps relative to a branch operating in an average low NPL market (6.1).[31] This result presents evidence of the main prediction of the model: higher lending inflows into riskier regions relative to less risky regions after an expansionary monetary policy shock.

Column (3) omits region-time fixed effects while column (4) also omits bank-time fixed effects. The risk-taking channel coefficients is similar as the one in column (2). All of

[31]The average high (low) NPL corrresponds to the average of markets with NPL above (below) the median.

these results confirms that the sensitivity of lending to monetary policy rate changes is increasing in the riskiness of the pool of borrowers, even within financial firms.

Robustness

Results from robustness tests are shown in Appendix F. First, Table 10 in the Appendix F.1 shows that the effects of monetary policy on lending are bit larger in the sample that includes all financial firms and not only those financial firms serving more than two province markets. i.e a specification without bank-time fixed effects. Table 11 in the Appendix F.2 shows additional robustness to the main specification. It shows that even after controlling for sample selection and omitted variables such as bank concentration, the risk-taking channel of monetary policy at the branch level remains statistically significant. First, excluding observations from the initial years, 2002-2004, with some measurement issues and low representation of aggregate credit, has no effect on the significance and only slightly changes the magnitude of the main estimate. Second, restricting the sample before and after the Great Financial Crisis (GFC) to control for monetary stance, international liquidity availability, and international rate levels does not change the direction of the risk-taking channel, and they are very similar in magnitude between periods. Third, controlling for a measure of bank competition has little effect on the risk-taking channel estimate, demonstrating the robustness of the results and that it is not picking up the bank concentration effects.[32] Risky but profitable markets would also be those in which large banks or banks with greater market power prefer to operate. These type of banks obtain funding more easily, weakening the risk-taking channel of monetary policy. This robustness test, however, demonstrates that the risk-taking channel is independent of the degree of bank concentration in local markets.

Further, Table 5 shows robustness to the main specification in equation (10) for different samples of financial institutions and geographic areas. These robustness tests also show some evidence of risk-taking channel heterogeneity across different types of financial institutions and local credit markets. Column (1) considers all branches for all financial institutions, column (2) restricts the sample to branches of banks, column (3) considers branches of Peru's four largest banks, and column (4) considers branches of non-bank financial institutions. Panel A considers the entire sample of branches from all Peruvian local markets. Panel B, on the other hand, show results from a sample that excludes branches operating in the metropolitan area, which accounts for the lion's share of credit

[32]It includes HH-Branch as measure of bank competition. It is computed by summing up the squared credit-market shares of all banks participating in a given province in a given year, and then averaging over all years.

in the country.[33]

Table 5 shows that the direction of the risk-taking channel of monetary policy on branch lending is consistent across all samples.

Panel A in Table 5 shows that the direction of the risk-taking channel of monetary policy on branch lending is consistent across banks, non-banks, and they are identical in magnitude for these two groups. However, for the sample of large banks this sensitivity on lending is in the opposite direction, although smaller and not statistically significant.[34]

[33] Pozo and Rojas (2023) show that branches in the metropolitan area (regions of Lima and Callao) account for around 75 percent of total credit, and it is mainly concentrated in the credit to corporate and large firms.

[34] The four largest banks in Peru have more branches and are present in almost all of the country's provinces. They are more cautious, and their decision not to take excessive risks may work against them. Furthermore, because they have more alternative funding options, large banks are less sensitive to monetary policy shocks.

Table 5. *Branch-level estimation: Robustness I*

	Dependent variable: Δy_{bdt}			
	(1) All	(2) Banks	(3) Large Banks	(4) Non-Banks
Panel A: Full Sample				
NPL-Branch $\times \epsilon_t^{MP}$	-0.0714***	-0.110	0.0419	-0.110*
	(0.025)	(0.19)	(0.15)	(0.056)
y_{t-1}	-0.115***	-0.136***	-0.144***	-0.0833***
	(0.013)	(0.016)	(0.012)	(0.011)
Observations	68969	30965	17703	34244
R^2	0.346	0.342	0.311	0.427
Panel B: No Metropolitan Area Sample				
NPL-Branch $\times \epsilon_t^{MP}$	-0.152**	-0.184*	-0.175*	-0.190**
	(0.064)	(0.092)	(0.057)	(0.092)
y_{t-1}	-0.112***	-0.117***	-0.116***	-0.0724***
	(0.014)	(0.0099)	(0.0080)	(0.010)
Observations	44056	19849	11649	32703
R^2	0.416	0.392	0.345	0.427
Controls Lag Dep.	✓	✓	✓	✓
Bank-Time FE	✓	✓	✓	✓
Region-Time FE	✓	✓	✓	✓
Branch FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓

Note: This table estimates the effect of the Peruvian monetary policy shocks on lending growth. Lending growth is the log change in credit at the branch level, $\Delta y_{b(j)pt}$. Quarterly Sample: 2004Q1 to 2018Q12. The sample includes only banks with branches in two or more provinces. NPL-Branch measures market riskiness in the province where a branch is located. ϵ_t^{MP} is the monetary policy shock. Fixed effects are described at the bottom of the table. Large Banks sample considers only the large four banks in Peru. Non-Banks includes CAMCs, CRACs, EDPYMES and *empresas financieras*. Non Metropolitan Area sample: excludes Lima and Callao, which form the largest metropolitan area in the Peru. Standard errors clustered at time and bank-level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Panel B takes a closer look, and examine the geographic area that does not include the metropolitan area, where the risk-taking channel may be weaker. The metropolitan area accounts for roughly 75 percent of credit in the sample, and it is primarily concentrated in credit for safer borrowers, such as corporations and large businesses (Pozo and Rojas,

2023). First, estimates of the risk-taking channel are larger and statistically significant across different financial institution samples. Second, the risk-taking channel is quantitatively greater in the non-bank sample than in the bank sample. Third, the risk-taking channel is quantitatively similar in both the sample of the largest banks and the sample of non-banks.

These findings support the robustness of the risk-taking channel and demonstrate that it operates across all types of financial institutions. It demonstrates that the effects of monetary policy are precisely stronger and more significant in markets with a riskier pool of borrowers. Furthermore, it demonstrates that both banks and non-banks have an incentive to take on more risk following an expansionary policy shock. During an expansionary monetary policy stance, even highly capitalized banks, such as Peru's four largest banks, are equally likely to engage in this risk-taking behavior. The findings contradict empirical evidence suggesting that undercapitalized banks are more likely to extend credit to risky borrowers Jiménez, Ongena, Peydró and Saurina (2014); Acharya, Eisert, Eufinger and Hirsch (2019); Andrews and Petroulakis (2019); Faria e Castro, Pascal and Sánchez (2021).

All these results show that the risk-taking channel is economically and statistically significant, and it operates as a credit supply side mechanism of monetary policy and it is present at the branch level.

7.2.3 Impulse Responses along the risk distribution

This part investigates further the role of the risk-taking channel in monetary policy transmission, by exploring the dynamic responses of branch credit across the risk distribution of local credit markets. We divide bank branches into groups of equal size indexed by g = 1,2,...,5 and estimate separate impulse responses for each group. A branch j is allocated to group g in period t if it operates in region with a NPL $t-1$ that fell between the $(g-1)$-th and $g-$th quantile of the distribution. Ordering branches according to lagged NPL values guarantees that the group allocation is not influenced by the shock occurring in period t. For each group g we run the local projections as follows:

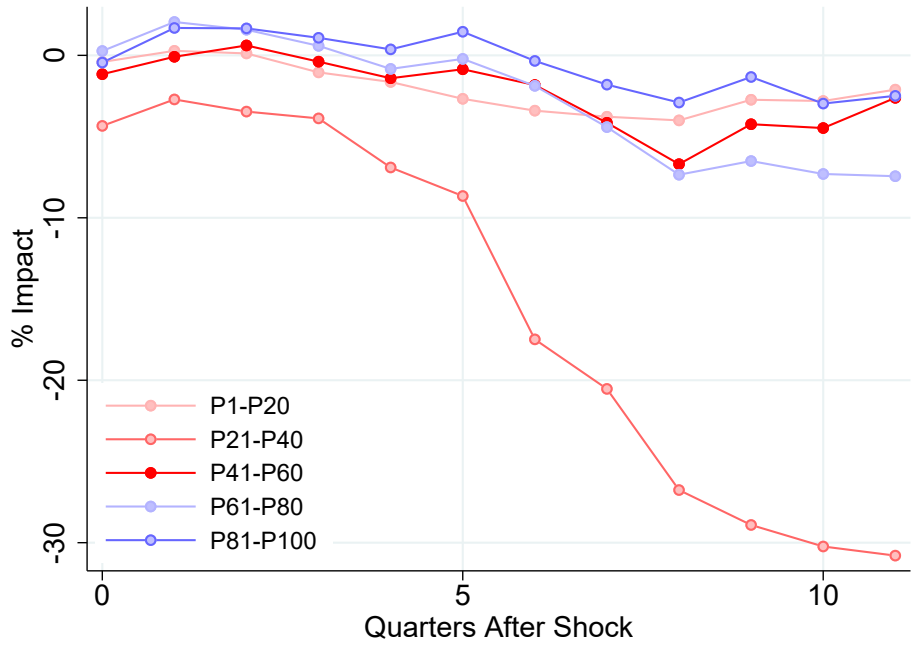
$$\frac{y_{j,t+h} - y_{j,t-1}}{\bar{y}^g_{j,t-1}} = \alpha_{j,h} + \beta^g_h \, \epsilon^{MP}_t + \sum_{k=1}^{K} \gamma^{g,h}_k X_{j,t-k} + u^h_{j,t} \,, \tag{11}$$

with similar notation as in specification (9), with $h = 0, 1.., 11$. Changes of y_j from $t-1$ to $t+h$ are expressed in $t-1$ units of average of group g at time $t-1$. In this

specification the key normalization variable is $\bar{y}^{g}_{j,t-1}$ which is the average value of credit across all branches in period $t-1$ in group g. Thus, under this normalization the β_h gives the percentage change of the average branch credit of group g at horizon h in response to a 100-basis-point monetary policy shock. $X_{j,t}$ includes three years of lagged values of the monetary policy shock and two years of lagged growth rates of the dependent variable, as in $X_{j,t}$ includes three years of lagged values of the monetary policy shock and two years of lagged growth rates of the dependent variable specifications (2) and (9).

Figure 8 shows micro impulse response of credit to a 100 basis points contractionary monetary policy shock across the five groups of the distribution of lagged NPL. To allow for a clear presentation, the figure only shows the point estimates, not the corresponding confidence intervals, because they display the impulse responses across the entire distribution.

Figure 8. *Impulse Responses of branch credit: Across the distribution of risk*



Note: This figure shows the micro impulse response function of branch credit to a 100 basis points contractionary monetary policy shock under the local projection specification (11) across 5 groups of the distribution of lagged NPL. 68 percent confidence bands are shown, using Driscoll and Kraay (1998) standard errors. Sample period 2003q4 - 2018q4.

Consistent with the results shown in Section 7.2.2, the responses to a monetary policy shock vary systematically depending on the level of local credit market risk that the bank-branch is exposed to. From the previous results, one should expect a higher lending contraction of credit in riskier regions relative to less risky regions after an expansionary

monetary policy shock. Figure 8 shows that branches operating in credit markets below the median of the risk distribution determine a large portion of the credit dynamics response in the overall periods following the monetary policy shock. In particular, credit is contracted more frequently by branches operating at quantile 40 when compared to quantile 20. After two years, all branches operating in markets below the percentile 80 contract credit more than those operating in markets below the percentile 20. Another significant finding is that the response of those branches operating in markets at the top of the risk distribution shows very slight credit contraction across all time periods following the shock.

8 Aggregation of the Risk-Taking Channel

To identify the impact of the risk-taking channel on real activity one needs to revisit the estimates at higher levels of aggregation.

Previous results are at the branch-level, and they are partial equilibrium estimates. In general, the risk-taking channel at the branch level may not be economically significant at higher levels of aggregation, as financial firms can allocate lending across branches. At the bank level, the average risk that a bank faces across all markets in which it operates must be more important. In other words, the impact of the risk-taking channel of MP must be determined by the average riskiness of the local markets in which a financial firm operates. To explore this argument, we compute, a financial firm-level measure of borrower riskiness NPL-Bank, by averaging the local market riskiness of a financial firm's branches, NPL-Branch, weighted by each branch share of the financial firm's total lending.

An implication of the previous results at a more aggregate level must be that after an expansionary monetary policy shock, banks operating in risky markets (high NPL-Bank) expand lending much more relative to banks operating in less risky markets. However, testing this prediction is not easy, because one needs to control for differences in lending opportunities and credit demand conditions.

8.1 Within-province estimation

To overcome this challenge and ensure that financial firms face similar local lending opportunities we compare the lending growth rate of different banks in the same province.

Thus, we estimate the following OLS regression:

$$\Delta y_{bpt} = \alpha_{bp} + \delta_{pt} + \gamma\,\text{NPL} - \text{Bank}_{bt-1} + \beta\text{NPL} - \text{Bank}_{bt-1} \times \epsilon_t^{MP} \\ \gamma_X X_{bpt} + \epsilon_{bpt}\,, \tag{12}$$

where the dependent variable, Δy_{bpt}, is the change in log of all loans granted by a financial firm b in the province p at time t. NPL-Bank$_{b,t}$ is the indicator of riskiness of markets that a bank faces from $t-4$ to t. ϵ_t^{MP} is the monetary policy shock. We include bank-province fixed effects, α_{bp}, to control for specific constant bank-branch specializations or bank regional interaction characteristics. The key set of controls are province-time fixed effects, δ_{pt}, which absorb changes in local lending opportunities or local market demand conditions. Thus, identification of β, the effect of monetary policy shocks in bank lending supply, comes from comparing loans extended by banks located in the same province p at quartet t.

X_{bpt} is a vector of controls. Similar to the specification (10), it includes the initial level of credit, $logy_{bp,t-1}$, two years of lags of the dependent variables and three years of lags of the monetary policy shock interacted with lag of NPL conditions. Standard errors clustered at time and bank-level.

Table 6 shows the results. Column (1) includes all the set of fixed effects and controls. It shows that after an expansionary monetary policy banks that operate in riskier markets increase lending more aggressively relative to banks serving less risky markets. After 100 bps expansionary monetary policy shock, a one standard deviation increment in NPL-Bank (5.1) increases the positive effect on lending growth by 233.1 bps. In other words, financial firms operating in a market with an NPL-Bank that is one standard deviation above the mean raise lending by 233.1 basis points more than the average financial firm per 100 pbs expansionary monetary policy shock. This risk-taking channel estimate at the province level is quantitatively similar to the one estimated at the branch level, in Section 7.2.2. It adds to the evidence that monetary policy rates affect lending in a given province via changes in lending incentives of financial firms that take more risk. i.e the risk-taking channel as a credit supply mechanisms of monetary policy transmission.

Table 6. *Bank-Province estimation: Results*

	Dependent variable: Δy_{bdt}		
	(1)	(2)	(3)
NPL-Bank $\times \epsilon_t^{MP}$	-0.457**	-0.560*	-0.509*
	(0.211)	(0.286)	(0.305)
NPL-Branch $\times \epsilon_t^{MP}$		-0.0858	-0.0546
		(0.0740)	(0.0696)
NPL-Bank	-0.276***	-0.254	-0.0967
	(0.0880)	(0.156)	(0.127)
y_{t-1}	-0.0600***	-0.0622***	-0.00993***
	(0.00159)	(0.00941)	(0.00146)
Controls	✓	✓	✓
Province-Time FE	✓		
Bank FE	✓	✓	✓
Bank-Province FE	✓	✓	
Province FE	✓	✓	✓
Time FE	✓	✓	✓
R^2	0.296	0.193	0.0942
Observations	32010	33138	33164

Note: This table show estimates of the effect of the risk-taking channel on lending. The data are at the financial firm-province-quarter level from 2004Q1 to 2018Q4. Δy_{bpt} is the log change of the total amount of lending by a given financial firm in a given province and quarter. NPL-Bank is the last four quarters average of NPL-Bank measures from a given financial firm in a given quarter. NPL-Bank is the average NPL-branch using lending shares across branches as weights. Fixed effects are denoted at the bottom. Standard errors clustered at time and bank-level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

In column (2) includes the measure of local riskiness (NPL-Branch) interacting with the monetary policy shock.[35] Local riskiness has similar magnitude as those obtained in branch-level estimation, but is no longer statically significant. In contrast, the bank-level measure of risk-taking (NPL-bank) is similar to the one from column (1) and remains statistically significant. This result validate the assumption in Section 7.2.2 because it implies that portfolio lending decisions are made at the bank level, and banks allocate lending across branches.

Column (3) omits both the province-time and the bank-province fixed effects, and the main result remains similar in magnitude and statistically significant.

These findings suggest that the impact of financial firm risk-taking on the sensitivity of local lending to monetary policy is robust and substantial. Further, the Table 12 in

[35]To accomplish this, the province-time fixed effect is removed.

Appendix F.3 shows that the financial-firm level risk-taking channel operates through banks and non-banks. For the sample of large banks and banks, this sensitivity is even larger.

8.2 Province-level estimation

In this section we aggregate data and look for effects of the risk-taking channel on lending and employment at the province level. One implication of the previous findings is that after an expansionary monetary policy, provinces, or local markets, served by banks that lend in riskier markets should experience larger lending expansions relative to provinces served banks operating in less risky markets.

To test this implication, we develop NPL-Province, a measure of province exposure to banks that take more risk at the provincial level. It is calculated by taking the weighted average of NPL-Bank across all financial firms operating in a given province and multiplying it by their lending shares one year earlier, $t-4$. we estimate the following OLS regression:

$$\Delta y_{pt} = \alpha_p + \delta_t + \beta \text{ NPL-Province}_{p,t-1} + \gamma \text{ NPL-Province}_{p,t-1} \times \epsilon_t^{MP} + \gamma_X X_{pt} \,, + \varepsilon_{pt} \quad (13)$$

where Δy_{pt} is quarterly rate change of lending or year-over-year rate change of employment in province p at time t[36]. ϵ_t^{MP} is the monetary policy shock. NPL-Province is the weighted average of NPL-Bank for all financial institutions in province p weighted by their lending shares. α_p are province fixed effects and δ_t are time fixed effects. Similar to previous specifications, X_{pt} is a vector of controls. It includes the initial log level of endogenous variable, $y_{p,t-1}$, two years of lags of the dependent variable and three years of lags of the monetary policy shock interacted with lag of NPL conditions. Standard errors are clustered at time level.

Column (1) in Table 7 shows the results of the benchmark specification using total lending growth as the dependent variable. It shows that provinces whose banks lend in risky markets after an expansionary MP shock see a larger increase in lending relative to other provinces. After 100 bps fall in the monetary policy shock, a one standard deviation increment in NPL-Province (4.57) increases the positive effect on total lending growth by 356.5 bps. This result is statistically significant and its magnitude is high. Column (2) adds local riskiness as a control (NPL-Branch) and the main estimate remains very similar and statistically significant. These results support the proposition that the

[36]Data on employment shows seasonality. Thus, to control for it, the analysis is done on the year-over-year rate change of employment.

risk-taking channel affects bank lending. Columns (3) and (4) in Table 7 present the results for the year-over-year employment growth. Columns (3) shows that the risk-taking channel has the predicted direction effects on province employment. Monetary policy is more expansionary in riskier provinces. A one standard deviation increase in NPL-Province (4.57) annual employment growth by 877 bps per expansionary monetary policy shock of 100 bps. The result is statistically significant. Column (4) adds local riskiness as a control (NPL-Branch) and results does not change. All of these findings provide compelling evidence that the risk-taking channel boosts credit and real activity following an expansionary monetary policy shock.

Table 7. *Province-Level estimation: Results*

	$\Delta Loans$		$\Delta Employment$	
	(1)	(2)	(3)	(4)
NPL-Province $\times \epsilon_t^{MP}$	-0.780*	-0.800*	-1.918*	-1.915*
	(0.458)	(0.469)	(0.981)	(1.036)
NPL-Branch $\times \epsilon_t^{MP}$		-0.108		-0.432
		(0.111)		(0.252)
NPL-Province	-0.348	-0.337	-0.0416	-0.176
	(0.214)	(0.213)	(0.392)	(0.417)
$Loans_{t-1}$	-0.0589***	-0.0586***		
	(0.00847)	(0.00844)		
$Employment_{t-1}$			-0.438***	-0.439***
			(0.0346)	(0.0349)
Province FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
R^2	0.314	0.315	0.674	0.676
Observations	4878	4878	2164	2164

Note: This table show estimates of the risk-taking channel effect on Δy_{pt}: quarterly rate change of lending or year-over-year rate change of employment in province p at time t. The data are at the province-quarter level, and it corresponds to period 2004Q1-2018Q4 for lending and 2011Q1-2018Q4 for employment. NPL-Province is the last four quarters average of NPL-Province measures from a given province in a given quarter. NPL-Province is the average NPL-Bank using $t-4$ lending shares across provinces as weights. Fixed effects are denoted at the bottom. Standard errors clustered at time level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

8.3 Bank-level estimation

This section shows how banks change total lending after monetary policy shocks, and seek for evidence of the risk-taking channel effects reflected on loans and profits at the financial firm-level. The unit of observation is a financial firm-quarter.

In particular, an implication of the previous results are that after an expansionary monetary policy shock, banks operating in riskier markets increase lending more aggressively and obtain more profits relative to banks operating in less risky markets. We test this implication by running the following OLS regression:

$$\Delta y_{bt} = \alpha_b + \delta_t + \gamma \text{ NPL-bank }_{b,t-1} + \beta_1 \text{ NPL-bank }_{b,t-1} \times \epsilon_t^{MP} + \gamma_X X_{bt} + \varepsilon_{bt} \qquad (14)$$

where Δy_{bt} is the change in log of total loans, log of domestic currency loans or log of foreign currency loans or the financial margin to asset ratio. The financial margin is a profitability measure that reflects the percentage of profit that a financial firm earns from lending operations. It is defined as the ratio of the financial income net of financial expenses to total assets. ϵ_t^{MP} is the monetary policy shock. NPL-Bank is the weighted average of NPL-Branch for all financial institution's branches weighted by their lending shares. As a result, it captures the average risk that a bank faces across lending markets. α_b are financial firm fixed effects and δ_t are time fixed effects. X_{bt} is a vector of controls and previous specifications, it includes lags of the dependent variable, the log level of the dependent variable lagged one period, and lags of the MP shocks interacted with NPL-Bank.

Column (1) in Table 8 shows that in response to an expansionary monetary policy shock, financial firms that operate in riskier markets increase lending. The magnitude of the estimated coefficient is comparable to the previous estimates using bank-province data, show in Table 7. Column (2) and Column (3) show that the risk-taking channel operates mainly through foreign currency lending, which is statistically significant and larger in magnitude that domestic currency lending. These result may not be surprising, as lending in foreign currency tend to be riskier than domestic currency lending[37].

Finally, column (4) in Table 8 shows that after an expansionary monetary policy shock, financial firms operating in riskier markets tend to have more than proportionally profits, measured by the financial margin, relative to financial firms operating in more less risky markets. Following a 100 bps expansionary monetary policy shock, a one standard deviation increase in NPL-Bank (5.1) increases the positive effect on profits by 863.4 bps. This implies that changes in monetary policy introduce additional incentives, via higher

[37]For example, loans in foreign currency involve exchange rate risk.

profits, for banks to rebalance their lending portfolio by expanding more credit into riskier markets.

Table 8. *Bank-Level estimation: Results*

	Total loans	Domestic currency loans	Foreign currency loans	Financial margin
NPL-Bank $\times \epsilon_t^{MP}$	-1.047**	-0.1241	-3.888**	-1.693**
	(0.541)	(1.140)	(2.102)	(0.809)
Bank FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
R^2	0.477	0.461	0.404	0.96
Observations	1666	1666	1525	1673

Note: This table shows estimates of the risk-taking channel effects on bank-level lending and profits. The data are at the bank-quarter level and cover all financial firms from 2004Q1 to 2018Q12. It considers the change of log on total lending, log on domestic currency lending, log on foreign currency lending. The profit variable is the financial margin to assets ratio. Fixed effects are denoted at the bottom. Standard errors clustered by time in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

9 Conclusions

This paper, using Peruvian data, shows that monetary policy shocks operate in the credit markets as a supply side mechanism via the risk-taking channel. To obtain causal effects of monetary policy, we analyze data on credit market outcomes at the aggregate level and at the bank-branch level, together with a novel time series of identified monetary policy shocks for Peru. First, at the aggregate level, monetary policy shocks operate as a supply factor leading force for credit market equilibrium, and introduce incentives for financial firms to rebalance their lending portfolio across different local markets that varies in levels of riskiness. Based on a theoretical model with supply side frictions, we show that changes in monetary policy introduce additional incentives for financial firms to rebalance their lending portfolio across different local markets that varies in levels of riskiness. According to the risk-taking channel after an expansionary monetary policy shock, financial firms operating in more risky markets tend to expand lending by more relative to banks operating in less risky markets. We test this theoretical implication using micro-data. With branch-level data at hand, we show causal evidence that the risk-taking channel works even within financial firms. The incentives to rebalance lending portfolio to riskier loans does not disappear at higher levels of aggregation, and across the different types of financial institutions. The impact of monetary policy on total credit via the risk-taking channel is important, and there is evidence of its effects on real variables, as employment. This finding of an operative risk-taking channel in Peru is robust to different specifications and sample definitions underlying the estimations.

Also, using branch-level data we show causal evidence that the risk-taking channel works even within financial firms. The incentives to rebalance lending portfolio to more risky loans does not disappear at higher level of aggregation

As far as policy implications are concerned, the risk-taking channel may also work on the extensive margin by including riskier borrowers that otherwise may not have access to the credit market. However, we also show that the credit response dynamics via the risk-taking channel operate for those credit markets below the 80 percentile of the risk distribution. Thus, the perils on financial stability from a risk-taking channel may be compensated by the financial inclusion of riskier borrowers with limited access to formal credit markets. It also demonstrates the limitations of monetary policy as a tool for attracting new riskier borrowers from the top of the risk distribution.

On the other hand, the mechanism we show in this chapter brings the concept of financial fragility due to excessive risk-taking. The estimates show that expansionary MP shocks tend to generate more than proportionally profits to banks operating in riskier markets. A regulator should be mindful about the excessive profit obtained by banks. Also, under the risk-taking channel, financial firms tend to prefer to loans in foreign currency, which may pose a sort of balance sheet fragility for a partially dollarized economy as Peru.

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Appendices

A Monetary Policy Shocks Identification

A.1 Macroeconomic forecasts

This appendix describes the set of macroeconomics forecast we use in the estimation of regression (1). The Central Bank of Peru's monetary policy is based on an inflation targeting scheme that has been adopted since 2003. From September 2003 the Central Bank of Peru sets a benchmark rate, the Reference Rate, for the interbank lending market each month, according to a previously announced schedule. Accordingly, from 2003m1 until 2019m12 we obtain the Central Bank's forecast from the Inflation Reports. These forecasts are publicly available.[38] We collect annual GDP and inflation forecasts because they are consistently published over the sample period.

From 2003 to 2008, the Central Bank of Peru issued forecasts three times a year; beginning in 2009, forecasts were issued four times a year. The release of these forecasts sometimes coincided with a policy meeting. However, if the release of forecasts do not coincide with a date of policy decision, we assign forecast iteratively. we use forecasts published in the same month as the meeting or, if available, the previous month. For all remaining meetings, we follow Cloyne and Huertgen (2016); Holm, Pascal and Tischbirek (2021) in using forecasts by professional forecasters to proxy for the forecasts of the central bank. We specifically use data from the Expectations Survey of analysts and financial entities, which is conducted during the last two weeks of each month.[39] We resort to the mean of those projections. These forecasts are released at the end of each month, and monetary policy meetings are usually held before the middle of the following month.

Data from the Expectations Survey is a good proxy for Central Bank of Peru's forecast. Both sets of forecasts, Profesional forecasters forecasts and Central Bank forecasts show a high level of correlation. Monthly projections of current and next year GDP forecasts have a correlation coefficient of 0.99 and 0.91, and of 0.93 and 0.68 for inflation, respectively.

[38] The historical reports are available at the Central Bank of Peru Web Page.

[39] The Central Reserve Bank of Peru conducts the Expectation Survey to economic analysts and executives of financial and non-financial companies. The historical surveys are available at the Central Bank of Peru Web Page.

Table 9. *Forecasts Assignment available for monetary policy meetings*

Central Bank Forecasts from the Inflation Report	
Prepared for a policy meeting	11
Same month before the meeting	1
One month before the meeting	48
Professional Forecasts from the Expectation Survey	
Month before the meeting	135
Total number of monetary policy meetings	195

Note: This table shows all forecasts available for the monetary policy meetings held between 2003m9 and 2019m12.

Table 9 shows that for a 195 monetary policy meetings held between 2003m9 and 2019m12 in the sample we assign Central Bank of Peru forecast to 60 meetings and the remaining 135 are filled in using professional forecasters form the Expectations Survey. Finally, we exclude the policy meetings that occurred between 2009m4 and 2009m8 from the estimation. The consequences of Global Financial Crisis was unfolding rapidly during this period, and the available forecasts may not capture the evolution of these rapid changes in the expectations about the future path of the economy. Thus, we may incorrectly assign a larger proportion of policy rate changes to a monetary policy shock if we include this period in the analysis. Also we exclude meetings on February 2005 and February 2007 due to lack of next year forecasts releases. At the end, the sample estimation is restricted to 188 meetings during the period 2003m9 and 2019m12.

A.2 Policy Rate

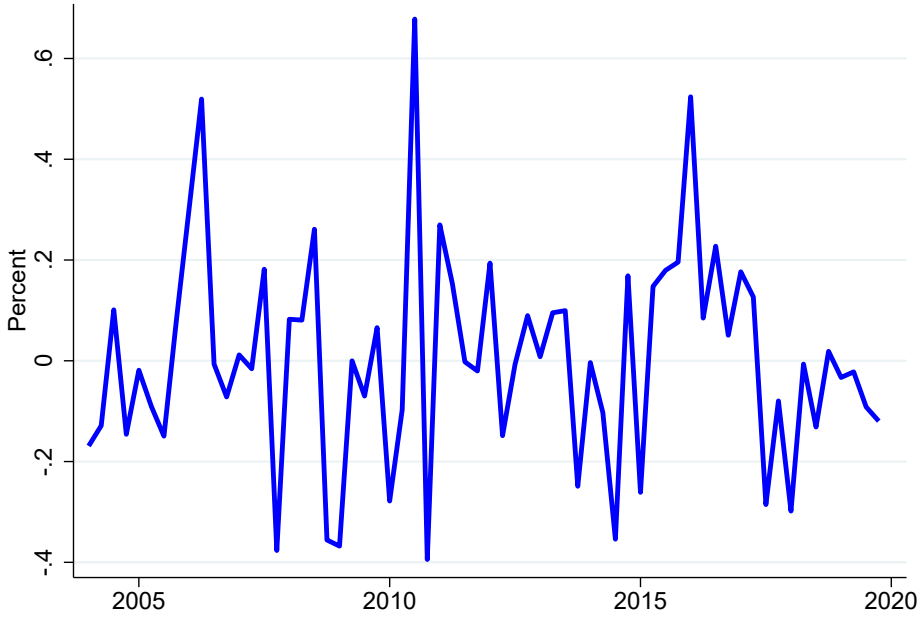
Figure 9. *Central Bank of Peru's Policy Rate (Reference Rate)*



Note: This figure shows the Central Bank of Peru's Policy Rate for the period 2003m9-2018m12.

A.3 Quarterly Monetary policy shocks

Figure 10. *Peru: Quarterly Monetary policy shocks*

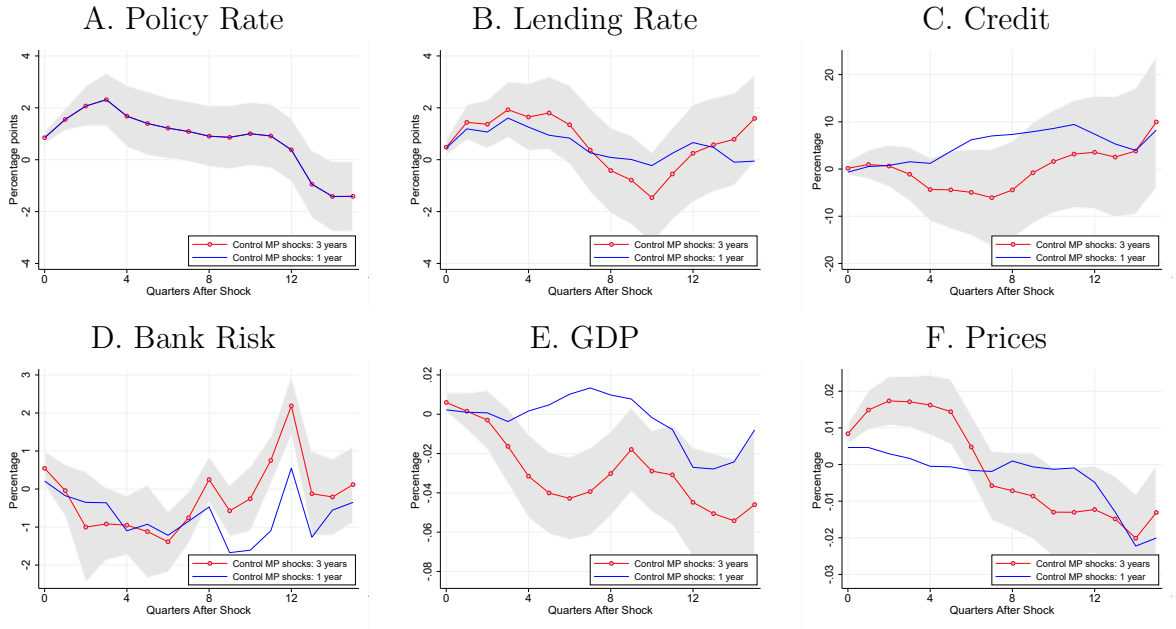


Note: This figure shows quarterly monetary policy shocks, by summing up monthly monetary policy shocks shows in figure 1.

B Robustness: Local Projections on Macro Variables

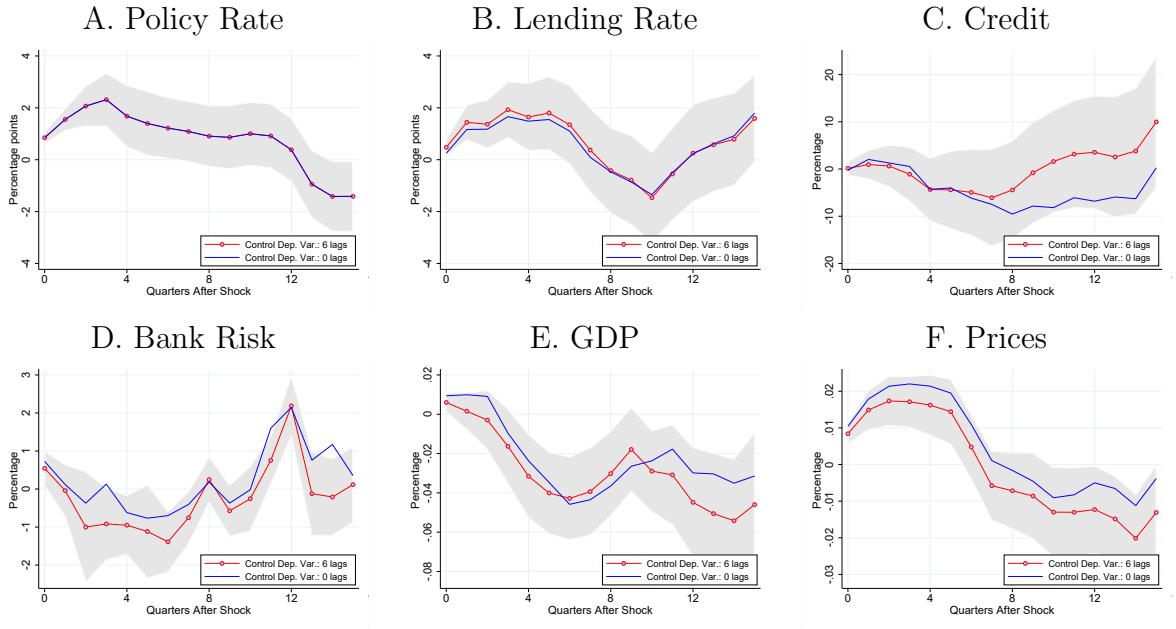
In this section we conduct some of robustness checks to the results shown in Section 4.1. Figure 11 shows that the impulse responses for credit and GDP and CPI prices are sensible to including only one year of lagged values of the monetary policy shock. However, the response of the lending rate and bank risk are not sensitive. From the intuition developed in Section 4 evidence for the monetary policy transmission via the credit supply side requires that the lending rate rises after a contractionary monetary policy shock, and evidence for the bank risk-taking channel requires a fall in bank risk. As a result, evidence for the findings of a supply side via a risk-taking mechanism remains robust to changes in the lag length of monetary policy shocks. Also Figure 12 shows that the results are robust to changes in the controls of the dependent variable's lagged growth rate. Finally, 13 shows that excluding Central Bank of Peru's forecasts from the process of identification described in Section 3 has little effects on the impulse responses.

Figure 11. *Local Projections on Macro variables: Robustness to lag length of Monetary Policy shocks*



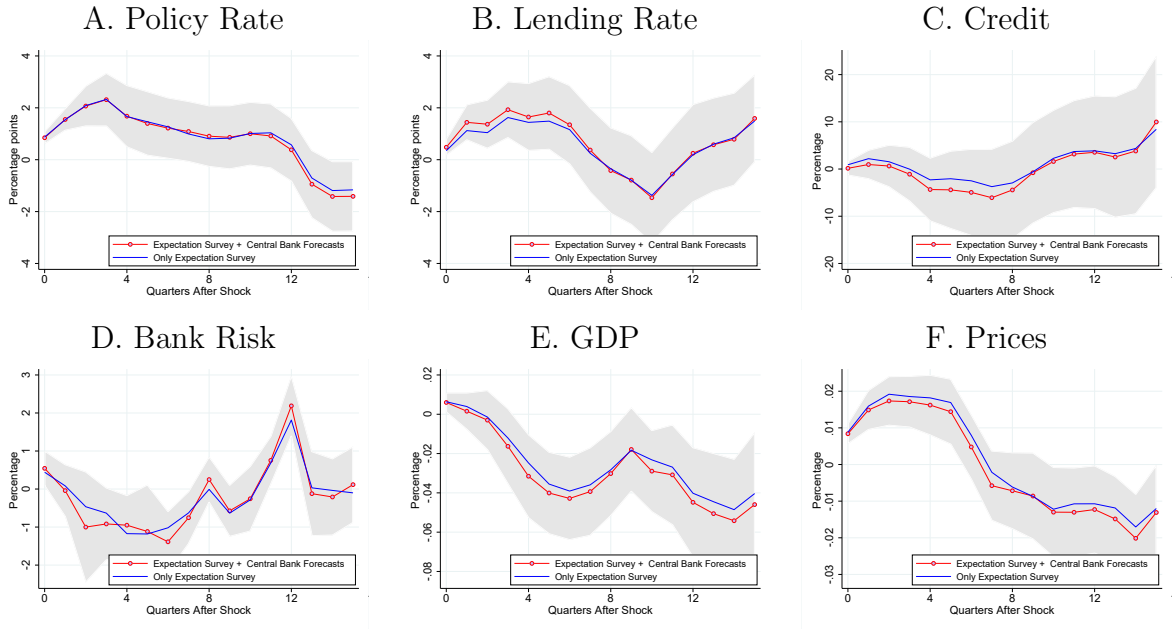
Note: This figure shows the impulse response functions to a contractionary monetary policy shocks of 100 basis points. Sample period 2003q4 - 2019q4. Light gray bands are 68% confidence bands using Newey and West (1987) standard errors. "Control MP shocks: 3 years"indicates the baseline model with three years of lagged monetary policy shocks as controls. "Control MP shocks: 1 year" add only shocks from the previous year as controls.

Figure 12. *Local Projections on Macro variables: Robustness to lag length of depend variable as controls*



Note: This figure shows the impulse response functions to a contractionary monetary policy shocks of 100 basis points. Sample period 2003q4 - 2019q4. Light gray bands are 68% confidence bands using Newey and West (1987) standard errors. "Control Dep. Var.: 6 lags"indicates the baseline model with 6 quarters of lagged dependent variable as controls. "Control Dep. Var.: 0 lags" add no lags as controls.

Figure 13. *Local Projections on Macro variables: Robustness to forecast sets - Only Expectations Surveys forecasts*



Note: This figure shows the impulse response functions to a contractionary monetary policy shocks of 100 basis points. Sample period 2003q4 - 2019q4. Light gray bands are 68% confidence bands using Newey and West (1987) standard errors. "Expectation Survey + Central Bank Forecasts"indicates the baseline approach we use in the analysis in section 3. "Only Expectation Survey " excludes Central Bank of Peru's forecasts from the process of identification in the baseline approach.

C Aggregate Data Sources

This appendix describes the data we use in the aggregate analysis in Section 4 and Appendix D. The Peruvian data was obtained from Peruvian Central Bank of Peru's macroeconomic data repository, BCRPData.

- Peruvian GDP (PN02538AQ): Real gross domestic output, millions of 2007 PEN soles. Data seasonally adjusted by using X13.
- Peruvian CPI: (PN01270PM): Consumer price index, 2009=100. Quarterly average from monthly data.
- Total Credit (PN00505MM): Total credit to private sector from depository institutions, in millions of PEN soles. End of quarter.
- Domestic interbank interest rate (PN07819NM): Quarterly average from monthly data.
- M1 (PN00181MM): Money, in millions of PEN soles. End of period. Data seasonally adjusted by using X13.

- Nominal exchange rates(PN01206PM): Nominal Foreign Exchange rate PEN soles per US dollar, interbank market, Bid.
- Stock Exchange price index, Índice General Bursátil BVL (PD04694MD).
- Lending rates, computed as a credit-weighted average of financial institutions' 1-year outstanding loan contracts, or 30-days outstanding loan contracts. Interest rates by currency (local and foreign) are weighted by the last year stock of credit. Interest rates in dollars are expressed in dollars by using the 12-ahead data on expected depreciation (BCRP Expectations Survey).
  - Stock local currency interest rates (PN07807NM): Bank average lending rates from the 1-year outstanding loan contracts, PEN soles denominated contracts.
  - Stock Foreign currency interest rates (PN07827NM): Bank average lending rates from the 1-year outstanding loan contracts, US dollars denominated contracts.
  - Flow local currency interest rates (PN07808NM): Bank average lending rates from the last 30-days outstanding loan contracts,PEN soles denominated contracts.
  - Flow Foreign currency interest rates (PN07828NM): Bank average lending rates from the last 30-days outstanding loan contracts, US dollars denominated contracts.
- Bank risk is computed as a quarterly realized volatility of the S&P/BVL Financials Index (PEN).
- Global commodity prices correspond to the Global Price Index of All Commodities from FRED Data (PALLFNFINDEXM).

D VAR Aggregate Analysis:

This appendix provides more details about the aggregate analysis shown in Section 4. In particular, it complements the estimation of local projections in specification 2 by estimating a VAR to identify impulse responses to monetary policy shocks. In particular we specify a recursive VAR with impulse responses from a Cholesky identification scheme. The main purpose of this exercise is to describe and show the robustness of the relationship between credit markets and monetary policy and document risk-taking behavior. We want to be clear that from this VAR analysis we do not pretend to go after a strong causal identification, as we do in Section 4.1, but it shows additional evidence for the arguments in section 4

We estimate a VAR for the Peruvian economy with and exogenous foreign external sector. The variables in the VAR model includes the log of Global commodity prices, log of US CPI, log of domestic GDP, log of domestic GDP, log of domestic CPI, log of total credit, the domestic interbank interest rate as the MP policy variable, log of Money (M1), a measure of lending rates,

a measure of overall bank risk and log of nominal exchange rates. The measure for for bank risk-taking as explained in Section 4 is given by the quarterly realized volatility of the S&P/BVL Financials Index (PEN), calculated as standard deviation of daily returns of the index over each quarter. Since daily data on S&P/BVL Financials Index (PEN) in only available from 01/01/2011 onward, we estimate the VAR for the sample period 2011Q1-2019Q4. Appendix C shows a detail description of the variables we use.

Given the sample period 2011Q1-2019Q4, the specification assumes the Peruvian economy is a small open economy prone commodity and US spillovers shocks. In particular, during this period several global shocks (for example terms of trade shocks and the *taper tantrum*) had impact on the peruvian economy. So, Consistently, we estimate a VARX with exogenous variables: log US GDP, Fed Funds Rate and Commodity prices. We restrict these variables to follow a VAR(1) process independent of domestic variables.

All previous selection of domestic variables follows in part Castillo, Pérez and Tuesta (2011), who developed a VAR to study monetary policy in Peru, but we extended it to include variables for determination of credit market as in Pozo and Rojas (2023b) and a variable for risk-taking behavior of banks.

Thus, the structural VAR in levels is given by

$$A_0 Y_t = a + \sum_{i=1}^{p} A_i Y_{t-i} + \epsilon_t$$

where c is a matrix with a constant, a linear trend and exogenous variables, A_i's are the structural coefficients of the dynamic system, ϵ_t is the vector of structural shocks with $E(\epsilon_t \epsilon_t') = I$, and I is an identity matrix. The reduced form representation can be written as:

$$Y_t = c + \sum_{i=1}^{p} B_i Y_{t-i} + u_t$$

where $c = A_0^{-1} a$, $B_i = A_0^{-1} A_i$ and $u_t = A_0^{-1} \epsilon_t$ is the vector of reduced form residuals. Based on BIC information criterion we set $p = 1$. that includes a constant and a linear trend. The identification assumption, by imposing a Cholesky decomposition on A_0, set the foreign variables ordered first, followed by the most exogenous and slow-moving domestic variables, with the foreign exchange rate ordered last, as the most endogenous variable. The monetary policy proxy is ordered after such that GDP, prices and credit respond with one lag to a MP shock. This estimation strategy follows similar ordering as in Christiano, Eichenbaum and Evans (1999). Robustness to the variable ordering, the inclusion or omission of variables or identification assumptions are shown in the appendix D.2

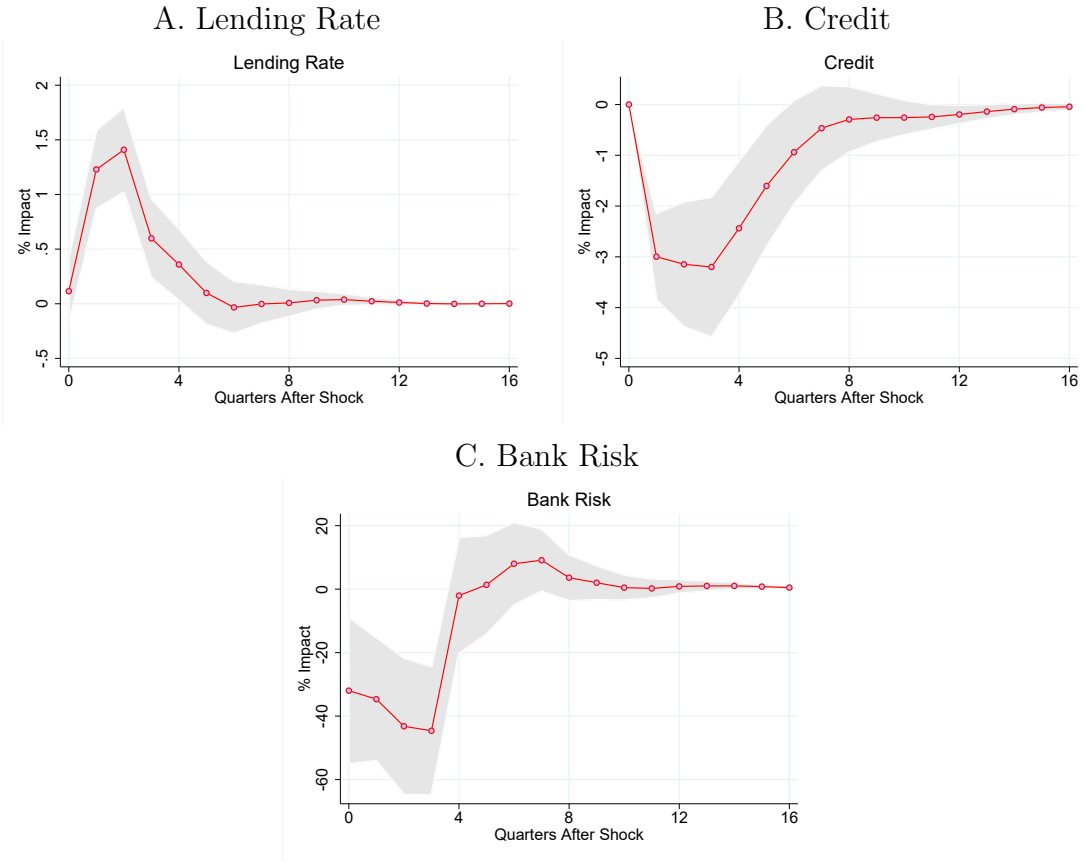
The impact of a contractionary monetary policy shock of 100 basis points on credit variables outcomes are show in Figure 14. Panel A shows an increment in lending rates after of a 100 basis

point rise in the monetary policy rate: at impact the lending rate rises and reaches a maximum increment of 1.45% after two quarters and it is still up at around 0.25% one year later. Panel B displays the persistent and economically significant negative response of aggregate credit after a monetary policy shock: credit declines by around 3% two quarters after the shock, and reaches a decline of around 1.6% after a year. As we show in the appendix D.2 the increment of lending rates and the decline in credit after a MP shock is robust to several specifications, ordering of variables, detrending or scheme identification (Figure 16). More importantly, Panel C shows that after the MP shock the measure of overall risk of bank, perceived by investors, falls by around 40 pbs after a 4 quarters. In particular, investor perceive that banks allocate loans to less risky borrowers during monetary policy tightening.

This aggregate empirical evidence add to the finding in Section 4 and also points out to a supply side mechanism of adjustment in credit markets that is consistent with the existence of a risk-taking channel after a MP shock.

The full set of results from the estimated VAR is shown in Appendix D.1.

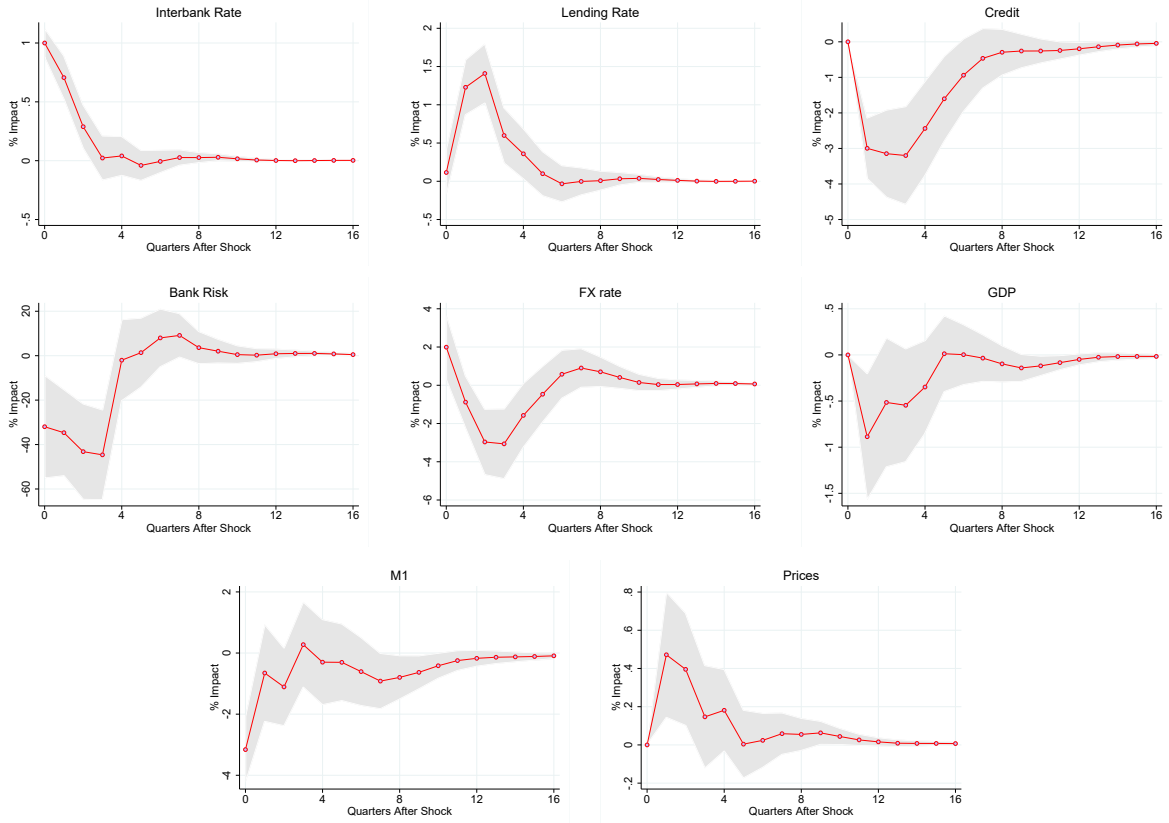
Figure 14. *VAR Results: Monetary Policy Shock, Credit Market and risk-taking*



Note: This figure shows the impulse response functions to a 1 percent increment in the domestic MP policy rate (RR). VAR identified under the recursive assumption, with the following ordering: log of Global commodity prices, log of US GDP, log of US CPI, log of domestic GDP, log of domestic CPI, log of total credit, the domestic interbank interest rate as the MP policy variable, log of Money (M1), a measure of overall bank risk, a measure of lending rates, and log of nominal exchange rates. log US GDP, Fed Funds Rate and Commodity prices are restricted to follow a VAR(1) process independent of domestic variables. VAR(1) includes a constant and a linear trend. Sample period 2011q4 - 2019q4.

D.1 Baseline VAR: Full set of results

Figure 15. *Real, nominal and credit markets after a Monetary Policy Shock*



Note: This figure shows the impulse response functions to a 1 percent increment in the domestic MP policy rate (RR). VAR identified under the recursive assumption, with the following ordering: log of Global commodity prices, log of US GDP, log of US CPI, log of domestic GDP, log of domestic CPI, log of total credit, the domestic interbank interest rate as the MP policy variable, log of Money (M1), a measure of overall bank risk, a measure of lending rates, and log of nominal exchange rates. log US GDP, Fed Funds Rate and Commodity prices are restricted to follow a VAR(1) process independent of domestic variables. VAR(1) includes a constant and a linear trend. Sample period 2011q4 - 2019q4. Light gray bands are 95% confidence bands.

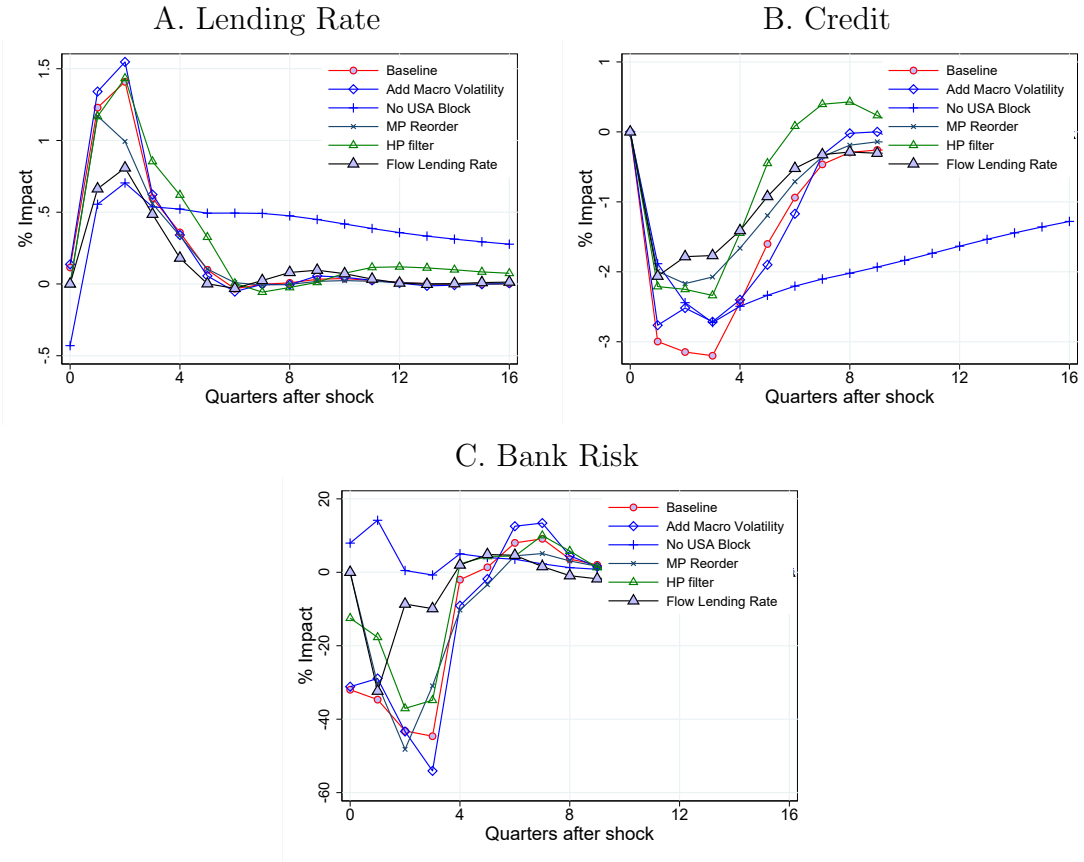
This section presents the full set of impulse responses after a MP shock, from estimating the VAR described in Section D. Figure 15 shows both the credit market adjustment and real response of the economy after of a monetary shock. The responses are not persistent as the monetary policy shock is transitory and start to die out after the fourth quarter. The GDP negative response is more persistent than the monetary policy shock and economically significant; after 1 quarters GDP drops by around 0.8% and reaches -0.45% after 1 year. There is a price puzzle, which points to an incomplete empirical model provided by the VAR. Rather than being a problem of misspecification, we attribute this to the specific sample period of estimation. In the first part of the period 2011q4 - 2019q4 the peruvian economy was hit by supply shocks such that the core inflation was above the upper level of the target range for inflation of 3 per cent. Only

after the end of 2017 inflation was starting to fall and be closer to 2 percent (see Rojas (2019) for a more detailed description of inflation in Peru during this period). Although initially the nominal exchange rate depreciates, after 1 quarter of the MP shock it is appreciated by around 3 percent.

D.2 VAR Robustness

Figure 16 displays a list of robustness results to the VAR analysis. It shows the impulse responses of the lending rate, credit and bank risk to a 1% rise in the policy rate.

Figure 16. *Monetary Policy Shock, Credit Market and risk-taking: VAR Robustness*



Note: This figure shows the impulse response functions to a 1 percent increment in the domestic MP policy rate (RR). VAR identified under the recursive assumption. VAR(1) includes a constant and a linear trend. Sample period 2011q4 - 2019q4. Baseline impulse responses (filled circle symbol) with the following ordering: log of Global commodity prices, log of US GDP, log of US CPI, log of domestic GDP, log of domestic CPI, log of total credit, the domestic interbank interest rate as the MP policy variable, log of Money (M1), a measure of overall bank risk, a measure of lending rates, and log of nominal exchange rates. log US GDP, Fed Funds Rate and Commodity prices are restricted to follow a VAR(1) process independent of domestic variables. Also, it present a specification including realized volatility of the Peruvian Stock Exchange price index (diamond symbols); a specification were we drop the influence of the US economy (+ symbols); a specification in which the MP variable is ordered last (x symbols); a specification in which all variables but the interest rates and the bank risk measure are HP filtered (hollow triangle symbols); and a specification in which lending rates are computed from loan contracts signed by financial institutions in the last 30 days (filled triangle symbols).

In particular, it shows the baseline impulse responses (filled circle symbol), a specification that includes realized volatility of the Peruvian Stock Exchange price index to control for overall economy risk and uncertainty (diamond symbols); a specification were we drop the influence of the US economy (+ symbols); a specification in which the MP variable is ordered last (x symbols); a specification in which all variables but the interest rates and the bank risk measure are HP filtered (hollow triangle symbols); and a specification in which lending rates are computed from loan contracts signed by financial institutions in the last 30 days (filled triangle symbols). The effects of the monetary policy shock in the credit market and risk-taking are robust to the

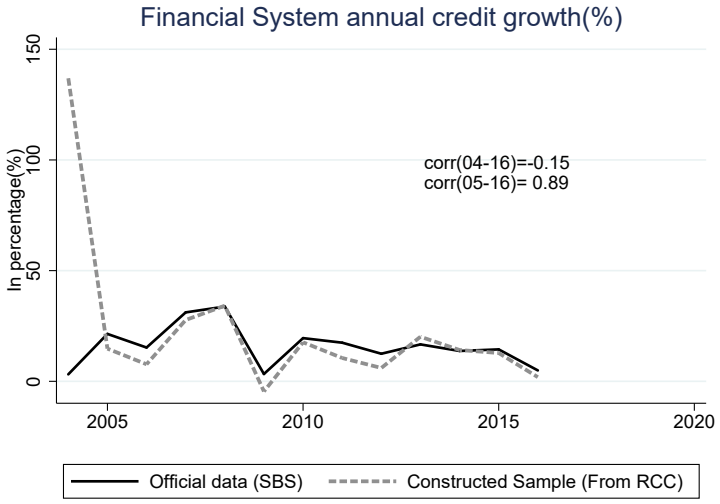
different specifications. Bank risk is not robust to the omission of the US block, which in the sample period is a problem of misspecification, as during the 2011-2018 US economy spillovers in the peruvian economy were important. In general, the robustness results shows that there is a compelling evidence that MP shocks are transmitted via the supply side of the credit market and there is a risk-taking channel under operation.

E Appendix: Sample Data

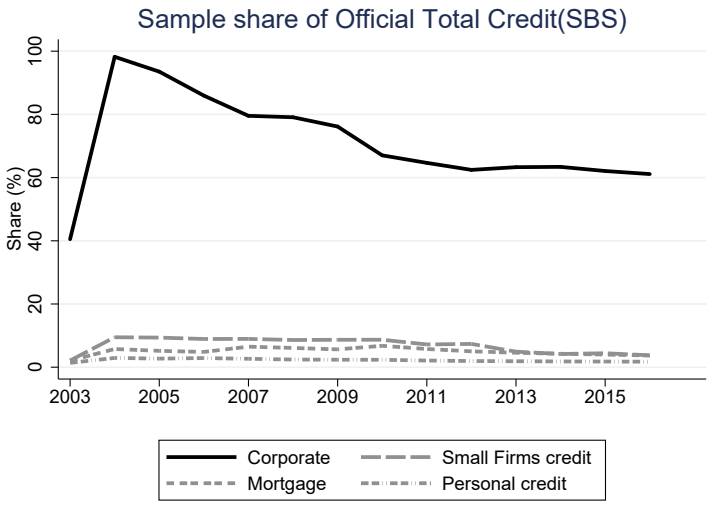
In this section we show results from the matching process. Figure 17 shows that the sample mimics very well the dynamics of the total bank credit. When the micro-data sample is aggregated at the financial system level, its correlation with the official data shows a high level of correlation, 0.89, after excluding observations from 2004, where the data quality is not very good. Panel B of Figure 17 shows, in average, that the sample represents around 48 percent of the official total credit. Despite this low share, we can say that the sample is representative of the aggregate credit dynamics.

Figure 17. *Representativeness of the sample - Aggregate credit*

Panel A: Annual Credit Growth



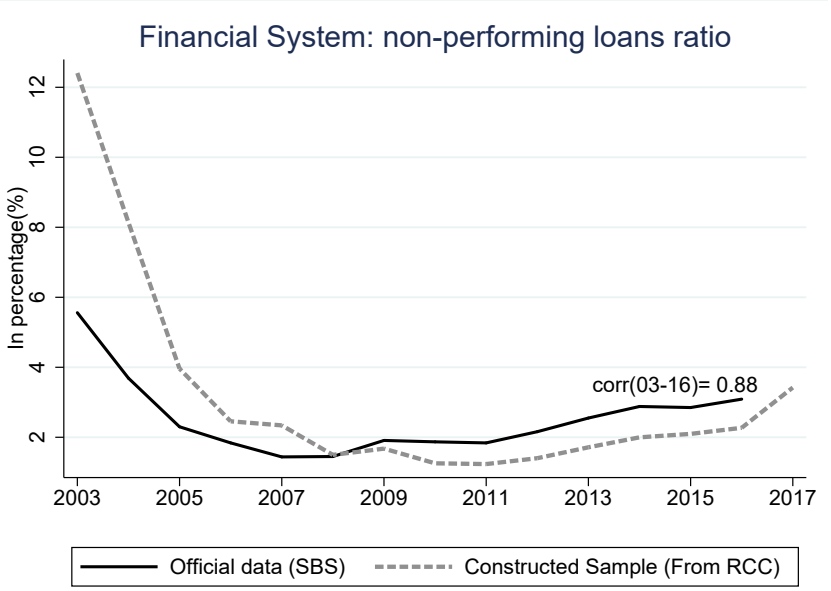
Panel B: Sample shares by credit types



Note: Annual Sample 2004-2016. SBS Official Data available for period 2002-2016.

Figure 18 also show that in aggregate, the sample follows similar dynamics of the NPL ratio published in official statistics.

Figure 18. *Representativeness of the sample - Non Performing Loans ratio*



Note: Annual Sample 2004-2016. SBS Official Data available for period 2002-2016.

F Appendix: Additional regressions and Robustness

F.1 Branch-bank estimation: All banks sample

This section presents robustness of the regression specification (10) by using the sample all banks, not only those serving more than one local province market. In specific, we estimate the following specification:

$$\Delta y_{b(j)pt} = \alpha_j + \alpha_{p(j)} + \alpha_{r(j)t} + \beta \,\text{NPL-Branch}_p \times \epsilon_t^{MP} + \sum_{k=1}^{K} \gamma_k^h X_{b(j)p,t-k} + \epsilon_{b(j)pt} \tag{15}$$

Table 10 shows that the effect of monetary policy on lending via the risk-taking channel is slightly larger when we do not include bank-time fixed effects.

Table 10. *Branch-level estimation: All banks sample*

	Dependent variable: Δy_{bdt}			
	(1)	(2)	(3)	(4)
NPL-Branch $\times \epsilon_t^{MP}$	-0.104*	-0.181**	-0.177**	-0.162*
	(0.0591)	(0.0767)	(0.0812)	(0.0826)
y_{t-1}	-0.106***	-0.109***	-0.109***	-0.0147***
	(0.00465)	(0.00511)	(0.00496)	(0.00144)
Controls Lag Dep.		✓	✓	✓
Region-Time FE	✓	✓		
Branch FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Time FE				✓
R^2	0.201	0.198	0.179	0.0522
Observations	69373	65724	65724	65802

Note: This table estimates the effect of the Peruvian monetary policy shocks on lending growth, $\Delta y_{b(j)pt}$. Quarterly Sample: 2004Q1 to 2018Q12 at the branch-level. The sample includes all financial firms with branches in one or more provinces. Lending growth is the log change in credit at the branch level. NPL-Branch measures market riskiness in the province where a branch is located. ϵ_t^{MP} is the monetary policy shock. Fixed effects are described at the bottom of the table. Standard errors clustered at time and bank-level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

F.2 Branch-Bank estimation: Robustness

Table 11 shows additional robustness to the main specifications due to sample selection or due to omitted variables such as bank concentration that may bias the results. The effect of risk-taking

channel remains statistically significant in all specifications.

Table 11. *Branch-level estimation: Robustness II*

	Dependent variable: Δy_{bdt}			
	(1) After 2005m1	(2) Before GFC	(3) After GFC	(4) Control HH
NPL-Branch $\times \epsilon_t^{MP}$	-0.112*	-0.170	-0.150*	-0.111**
	(0.0588)	(0.102)	(0.0870)	(0.0551)
HH-Branch $\times \epsilon_t^{MP}$				-0.341
				(4.096)
y_{t-1}	-0.118***	-0.178***	-0.112***	-0.118***
	(0.0154)	(0.00851)	(0.0176)	(0.0154)
Bank-Time FE	✓	✓	✓	✓
Region-Time FE	✓	✓	✓	✓
Branch FE	✓	✓	✓	✓
province FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
R^2	0.336	0.362	0.343	0.336
Observations	64325	16614	53851	64325

Note: This table estimates the effect of the Peruvian monetary policy shocks on lending growth, $\Delta y_{b(j)pt}$. Quarterly Sample: 2004Q1 to 2018Q12 at the branch-level. The sample includes only banks with branches in two or more provinces. Lending growth is the log change in credit at the branch level. NPL-Branch measures market riskiness in the province where a branch is located. ϵ_t^{MP} is the monetary policy shock. Fixed effects are described at the bottom of the table. After 2005Q1 sample drops observations from 2002 to 2004. Before GFC sample corresponds to 2004Q1-2008Q4 period, but because the sample spam is only four years long, as controls it considers four quarters of lags for the monetary policy shock and two quarters of lags for the dependent variable. After GFC sample corresponds to 2009Q4-2018Q4 period. HH-Branch is calculated in a similar way to NPL-Branch. Control HH adds the standard Herfindahl index and it is referred as HH-Branch. HH-Branch and is computed by summing up the squared credit-market shares of all banks participating in a given province in a given year, and then averaging over all years. Standard errors clustered at time and bank-level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Column(1) drops observations from 2002 to 2004. The initial years in our sample have measurement problems and have a low representation of the aggregate credit dynamics. This columns shows not a big difference with respect to the main estimates.

In columns (2) and (3) we try to control for the availability of international liquidity, and low international interest rates and expansionary monetary policy stance. In particular, before the Great Financial Crisis (GFC) monetary policy rates and economic growth rates were higher in Peru, and international interest rates were not low. After the GFC, with expansionary monetary policy stance from almost all major central banks in the world, international liquidity has been high and interest rates have been lower. Also, The monetary policy rates in Peru, in average,

are lower during this period. In this context, the risk-taking behavior of banks can be a result of high liquidity and lower interest rates, than from changes in monetary policy rates. In column (2) we only consider the sample period before the Great Financial Crisis (GFC). In column (3) we only consider the sample period during and after the GFC. The results show that the direction of the risk-taking channel of monetary policy on branch lending is consistent across sample periods, but it is much stronger after-GFC. After GFC, the same expansionary monetary policy rate change, a branch rise lending growth rates by 15.6 bps more in a high risky location relative to a branch operating in a low risky location, per unit of NPL.

In column (4) we control for bank concentration or competition in the credit market by adding the standard Herfindahl index, which we refer as HH-Branch. HH-Branch and is computed by summing up the squared credit-market shares of all banks participating in a given province in a given year, and then averaging over all years. Bank competition may confounding the result, as risky but profitable markets would be also those markets were large banks operate or market power is higher. The results in Column(4) show that the risk-taking behavior of banks is still present and very similar in magnitude as the main specification after we control for bank concentration.

F.3 Bank-Province estimation: Robustness

Table 12. *Bank-Province estimation: Robustness*

	Dependent variable: Δy_{bdt}			
	(1) Banks	(2) Large Banks	(3) Non-Banks	(4) No Metropolitan
NPL-Bank $\times \epsilon_t^{MP}$	-3.483***	-17.96*	-1.026*	-0.487*
	(1.290)	(7.134)	(0.560)	(0.242)
NPL-Bank	-1.457	-0.576	-0.552***	-0.315*
	(1.367)	(3.973)	(0.162)	(0.169)
y_{t-1}	-0.0563***	-0.0922***	-0.0593***	-0.0634***
	(0.0131)	(0.00502)	(0.00929)	(0.0104)
Province-Time FE	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Bank-Province FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
R^2	0.362	0.499	0.392	0.302
Observations	12535	7133	18526	29695

Note: This table estimates the effect of the risk-taking channel on total lending. The data are at the financial firm-province-quarter level from 2004Q1 to 2018Q3. Δy_{bpt} is the log change of the total amount of lending by a given financial firm in a given province and quarter. NPL-Bank is the last four quarters average of NPL-Bank measures from a given financial firm in a given quarter. NPL-Bank is the average NPL-branch using lending shares across branches as weights. Fixed effects are denoted at the bottom. Large Banks sample considers only the large four banks in Peru. Non-Banks includes CAMCs, CRACs, EDPYMES and *empresas financieras*. Non Metropolitan Area sample: excludes Lima and Callao, which form the largest metropolitan areas in the Peru. Standard errors clustered by time and bank in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

G Appendix: Model derivation

G.1 First order conditions

Here, we solve for the first order condition of the maximization problem of banks under limited liability and deposit insurance. Recall banks aim to maximize equation (6), which for convenience is rewritten as,

$$\int_0^{+\infty} \int_{r_h^{l*}}^{+\infty} \beta(r_h^l l_h + r_l^l l_l - rd) dF^{r,h}(r_h^l) dF^{r,l}(r_l^l),$$

where,

$$r_h^{l*} = max\left\{0, \frac{rd - r_l^l l_l}{l_h}\right\}.$$

For convenience, we rewrite it as,

$$\int_0^b \int_{r_h^{l**}}^{+\infty} \beta(r_h^l l_h + r_l^l l_l - rd) dF^{r,h} dF^{r,l} + \int_b^{+\infty} \int_0^{+\infty} \beta(r_h^l l_h + r_l^l l_l - rd) dF^{r,h} dF^{r,l} = 0,$$

where,

$$b = \frac{rd}{l_l} \qquad r_h^{l**} = \frac{rd - r_l^l l_l}{l_h}.$$

where $d = l_h + l_l - n$. Taking the partial derivative of the above expression with respect to l_h yields,

$$\int_0^b \left[\int_{r_h^{l**}}^{+\infty} \beta\left(r_h^l - r\right) dF^{r,h} - \beta(...) f^{r,h}(r_h^l)\Big|_{r_h^l = r_h^{l**}} \frac{\partial r_h^{l**}}{\partial l_h} \right] dF^{r,l} + \int_{r_h^{l**}}^{+\infty} \beta(...) dF^{r,h} f^{r,l}(r_l^l)\Big|_{r_l^l = b} \frac{\partial b}{\partial l_h} +$$

$$\int_b^{+\infty} \int_0^{+\infty} \beta\left(r_h^l - r\right) dF^{r,h} dF^{r,l} - \int_0^{+\infty} \beta(...) dF^{r,h} f^{r,l}(r_l^l)\Big|_{r_l^l = b} \frac{\partial b}{\partial l_h} = 0,$$

where $f^{r,i}(z_i)$ is the pdf of the random variable r_i^l. Solving,

$$\int_0^b \left[\int_{r_h^{l**}}^{+\infty} \beta\left(r_h^l - r\right) dF^{r,h} - \beta(r_h^l l_h + r_l^l l_l - rd) f^{r,h}(r_h^l)\Big|_{r_h^l = r_h^{l**}} \frac{\partial r_h^{l**}}{\partial l_h} \right] dF^{r,l} +$$

$$\int_b^{+\infty} \int_0^{+\infty} \beta\left(r_h^l - r\right) dF^{r,h} dF^{r,l} = 0,$$

Since, $(r_h^l l_h + r_l^l l_l - rd) f^{r,h}(r_h^l)|_{r_h^l = r_h^{l**}} = 0$, then

$$\int_0^b \int_{r_h^{l**}}^{+\infty} \beta\left(r_h^l - r\right) dF^{r,h} dF^{r,l} + \int_b^{+\infty} \int_0^{+\infty} \beta\left(r_h^l - r\right) dF^{r,h} dF^{r,l} = 0,$$

Then, it can be rewritten as,

$$\int_0^{+\infty} \int_{r_h^{l*}}^{+\infty} \beta(r_h^l - r) dF^{r,h}(r_h^l) dF^{r,l}(r_l^l) = 0,$$

Similarly, the first order condition for l_l is,

$$\int_0^{+\infty} \int_{r_h^{l*}}^{+\infty} \beta(r_l^l - r) dF^{r,h}(r_h^l) dF^{r,l}(r_l^l) = 0.$$

G.2 Limited liability and non-insured deposits

Under limited liability and in the absence of deposit insurance, the required return of bank deposits, $\bar{r}$, agreed at $t = 0$ is risk-sensitive. Since the bank defaults with a positive likelihood, households require a gross return for theirs bank deposits higher than the return of safe assets, i.e., $\bar{r}>r = 1/\beta$. Hence, $\bar{r}$ has to be high enough to compensate the reduced payment each time the bank defaults. Since households are risk neutral, the expected repayment of bank deposits has to be equal to the return of risk-free assets, i.e.,

$$r = \mathbb{E}\{x\}\bar{r}, \tag{16}$$

where x is known as the endogenous recovery ratio (see Gertler and Kiyotaki, 2015). This is defined as the fraction of the promised return that depositors receive in the event of default or, equivalently, as the fraction of bank agreed payment that is recovered by depositors. Equation (16) represents the deposit supply curve faced by banks. If at $t = 1$ the bank does not default, x=1 since depositors receive the full agreed payment; however, if the bank defaults, depositors only receive an endogenous fraction, $x = \frac{r_h^l l_h + r_l^l l_l}{\bar{r}d}$<1, of the agreed payment. In general, we can rewrite x as,

$$x = min\left\{1, \frac{r_h^l l_h + r_l^l l_l}{\bar{r}d}\right\}.$$

Therefore, $x\bar{r}$ represents the effective gross return of deposits. In this case, bank seeks to maximize the following profits,

$$\mathbb{E}\{\beta(max\{0, r_h^l l_h + r_l^l l_l - \bar{r}d\})\}.$$

where now the return of deposits is risk-sensitive, subject to supply curve of deposits, equation (16), which is no longer perfectly elastic. This is, the bank is going to internalizes the effects of its decisions on the promised interest rate of deposits, $\bar{r}$.

Bank profits can be rewritten as,

$$\int_0^{+\infty}\int_{r_h^{l*}}^{+\infty} \beta(r_h^l l_h + r_l^l l_l - \bar{r}d)dF^{r,h}(r_h^l)dF^{r,l}(r_l^l),$$

where,

$$r_h^{l*} = max\left\{0, \frac{\bar{r}d - r_l^l l_l}{l_h}\right\}. \tag{17}$$

Similarly, the supply curve of deposits, faced by banks, equation (16), can be rewritten as,

$$r = \int_0^{+\infty}\int_{r_h^{l*}}^{+\infty} \frac{r_h^l l_h + r_l^l l_l}{\bar{r}d}\bar{r}dF^{r,h}(r_h^l)dF^{r,l}(r_l^l) + \int_0^{+\infty}\int_{r_h^{l*}}^{+\infty} \bar{r}dF^{r,h}(r_h^l)dF^{r,l}(r_l^l).$$

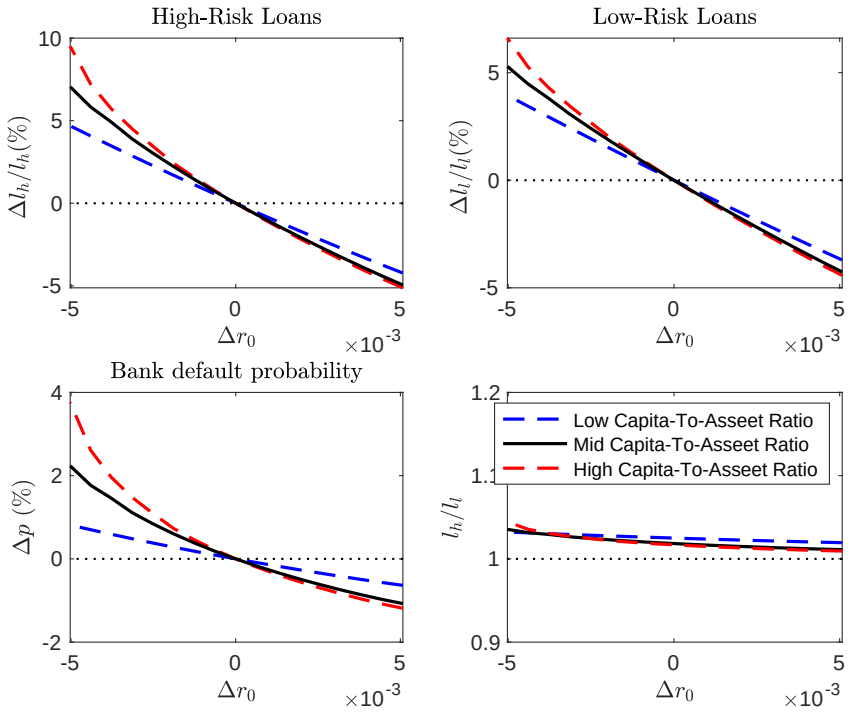
Inserting the supply curve of deposits into bank profits, the latter results in,

$$\mathbb{E}\{\beta(r_h^l l_h + r_l^l l_l - rd)\}.$$

This are the same bank profits that bank aim to maximize under unlimited liability. As a result, in this two period model allocation under limited liability and non-insured deposits is socially efficient as under unlimited liability.

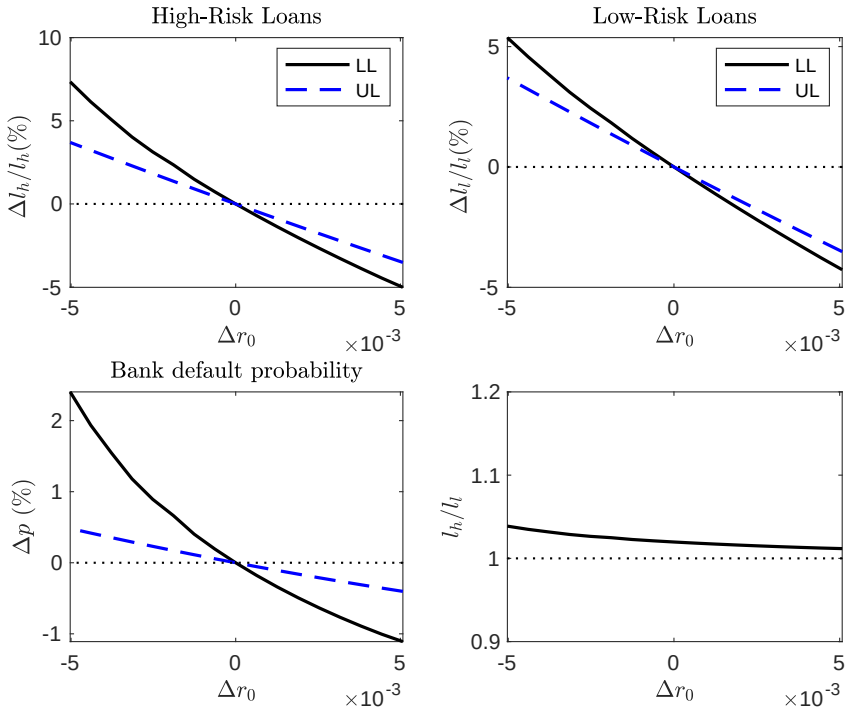
G.3 Additional Figures

Figure 19. *Monetary Policy Impact and Capital to Asset Ratio*



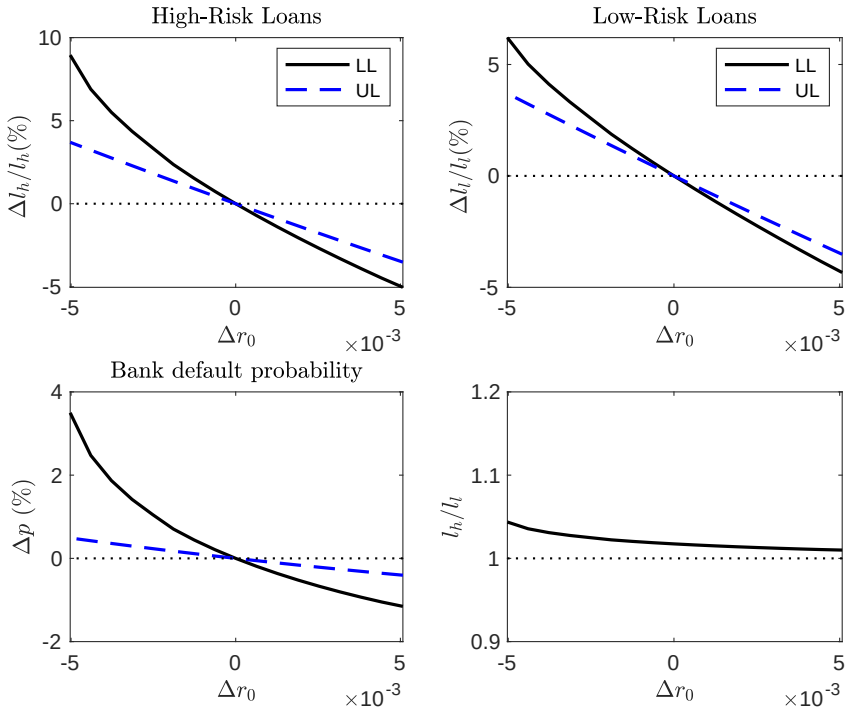
Note: Figure shows the responses of some variables to changes of the monetary policy rate under limited Liability. In general, we set $\rho = 0$, $\beta = 0.99$, $\delta_h = \delta_l = 0.20$, $\alpha_h = \alpha_l = 0.33$. In the baseline calibration (solid black line), the other parameters n and σ_h and σ_l are set so that bank default probability and capital to asset ratio $(n/(l_h + l_l))$ equate 3%, and 1/7, respectively, and $\sigma_l = 0.25\sigma_h$. It yields $n = 0.59$, $\sigma_h = 1.82$ and $\sigma_l = 0.45$. Similarly, in the dashed blue line, we set $n = 0.41$, $\sigma_h = 0.76$ and $\sigma_l = 0.19$ so that default probability and capital to asset ratio $(n/(l_h + l_l))$ equate 3%, and 1/10, respectively. Similarly, in the dashed red line, we set $n = 0.62$, $\sigma_h = 1.62$ and $\sigma_l = 0.40$ so that default probability and capital to asset ratio $(n/(l_h + l_l))$ equate 3%, and 1/6.7, respectively.

Figure 20. *Monetary Policy Impact:* $\rho > 0$



Note: Figure shows the responses of some variables to changes of the monetary policy rate under LL and UL. LL: Limited Liability, UL: Unlimited Liability. In the baseline calibration, we set $\rho = 0.50$, $\beta = 0.99$, $\delta_h = \delta_l = 0.20$, $\alpha_h = \alpha_l = 0.33$. The other parameters n and σ_h and σ_l are set so that bank default probability and bank leverage $((l_h + l_l)/n)$ equate 3%, and 7.0, respectively, and $\sigma_l = 0.25\sigma_h$. It yields $n = 0.59$, $\sigma_h = 1.26$ and $\sigma_l = 0.31$.

Figure 21. *Monetary Policy Impact:* $\rho < 0$



Note: Figure shows the responses of some variables to changes of the monetary policy rate under LL and UL. LL: Limited Liability, UL: Unlimited Liability. In the baseline calibration, we set $\rho = -0.50$, $\beta = 0.99$, $\delta_h = \delta_l = 0.20$, $\alpha_h = \alpha_l = 0.33$. The other parameters n and σ_h and σ_l are set so that bank default probability and bank leverage $((l_h + l_l)/n)$ equate 3%, and 7.0, respectively, and $\sigma_l = 0.25\sigma_h$. It yields $n = 0.59$, $\sigma_h = 1.82$ and $\sigma_l = 0.45$.