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The views expressed in this paper are those of the authors and do not reflect necessarily the position of the Central Reserve Bank of Peru

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

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Abstract

The risk-taking channel of the monetary policy has been extensively studied (see, e.g., [Adrian and Song Shin \(2010\)](#); [Borio and Zhu \(2012\)](#); [Jiménez, Ongena, Peydró and Saurina \(2014\)](#)). 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 a bank can allocate loans differently across risky markets after a monetary policy shock. First, by using a theoretical model we show that an expansionary monetary policy shock creates the risk-taking channel, by altering a bank's appetite for risk and to rebalance its loans portfolio by issuing more loans in more risky markets relative to lower risky markets. Second, we take our model predictions to the data. We reach identification by using branch-level and province-bank-level data to control for omitted variables. Our branch-level estimation confirms that the sensitivity of lending to MP changes is increasing in the riskiness of borrowers. At higher levels of aggregation, our results hold economical and statistical significance and show robustness that the risk-taking channel of MP has sizable impact on the total lending issued by financial firms.

Keywords: financial firms, risk-taking, monetary policy.

JEL Classification: G21, E44, E5.

Financial markets are important to understand the dynamics and amplification of the business cycles ([Bernanke, Gertler, and Gilchrist, 1999](#); [Kiyotaki and Moore, 1997](#)) and

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more importantly the risk-taking behavior of banks is key to understand the role of the exuberance on credit and business cycles. ([Jorda, Schularick and Taylor, 2013](#); [Jiménez, Ongena, Peydró and Saurina, 2014](#)). The Global financial crisis, during 2007-2009 showed us that the risk-taking behavior of banks determine how severe a crisis may be given the exposure of borrowers to risk to loose savings.

Relative to the existing literature, and consistent with our model, 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 general, in this paper we show a theoretical model and empirical estimates about the role of risk on the transmission of MP shocks: a bank's risk-taking mechanism.

We provide a model to rationalize the risk-taking channel of the monetary policy studied empirically in this paper. In particular, it 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.¹ 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 increase 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.

We test the predictions of the model in financial firm-level, and branch-level data for Peru. Given the limitations of aggregate data, we follow similar strategy as in [Pozo and Rojas \(2020\)](#) to show a direct causal effect as implied by our theory. In particular, we use branch-level and bank-province level data so we can control for omitted variables such as lending opportunities and credit demand conditions.

In particular, according to the risk-taking channel implied by our model, after an expansionary MP shock, banks can take advantage of the better outlook of the economy and lower funding costs banks have more appetite for risk and allocate more loans to more risky markets. This differential response is given by credit frictions on the credit supply side that create a bias in the way banks asses risk, and as a result value markets differently and take advantage of lending in risky but profitable markets. In this paper, the positive general equilibrium effects of low policy rate on bank default probability,

¹The theoretical framework is an extension of the closed-economy version model developed in [Pozo \(2019\)](#).

and with its expected profits, drives bank incentives to take excessive risk. To take the model predictions to the data we exploit the 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. Second, risk varies across markets. In particular, risk varies geographically, as heterogeneous inherent characteristics across markets persist. Thus, we consider credit markets at the province level, and compute measures of risk by computing non-performing loans (NPL) ratio at the province level.

A key idea in our identification strategy is that NPL, capturing the risk taking channel mechanism, signals banks to rebalance their lending portfolio and take advantage of profitable but riskier local markets. For our identification strategy to work, it is important to have variation in riskiness that is independent of bank's lending opportunities or demand factor influencing bank's decisions. To obtain such, we use a within-bank identification, by comparing across branches of the same bank, we are able to control for the bank's lending opportunities and identify the effects of the risk-taking channel on the sensitivity of lending to monetary policy.

Our branch-level estimation confirms that the sensitivity of lending to MP changes is increasing in riskiness of borrowers, even within a financial firm. After the MP rate decreases in 100 bps, a branch operating in an average high NPL market rises lending growth by 51.9 bps relative to a branch operating in an average low NPL market.² This result shows statistical and economical significance of our main prediction of our 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, risk-taking channel at the branch level is larger for banks than non banks. Our results do not change if we exclude the metropolitan area, the largest credit market, from the sample. Also, our results remain statistically significant if we control for sample selection or omitted variables such as bank concentration that may bias our results. The risk-taking channel is larger after we control for standard Herfindahl index, which shows the robustness of our results and that it is not picking bank concentration effects.

Our branch level results are partial equilibrium estimates, and risk-taking channel at the branch level may not be economically significant at higher level of aggregations. In fact, the average riskiness of the local markets where a financial firm operates may

²The average high (low) NPL corresponds to the average of markets with NPL above (below) the median.

determine the impact of risk-taking channel of MP. 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. To reach identification we compare the lending growth rate of different banks in the same province. The results of this within-province estimator, and consistent with our model predictions, show that after an expansionary monetary policy banks that operate in more risky markets increase lending by more relative to banks serving less risky markets. A one standard deviation increase in NPL-Bank increases lending by 62.2 bps per 100 bps fall in the MP rate.

Then, we aggregate our data to the province level to examine the overall effects of the risk-taking channel. We find that provinces whose banks lend in risky markets after an expansionary MP shock see a larger increases in lending relative to other provinces. We also find that the risk-taking channel has the predicted direction effects on province employment. But, we cannot show strong evidence that the risk-taking channel of MP increases real activity.

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

The remainder of this chapter is partitioned as follows. Section 1 presents the literature review. Section 2 we develop a theoretical model to understand the risk-taking channel and guide our empirical exploration. Section 3 present the sources and summary statistics of the data we use for our empirical estimations. Section 4 presents our main estimates of the risk-taking channel under our branch-level identification strategy. Section 5 shows estimates of the effects of the risk-taking channel under different levels of data aggregation. Finally, section 6 concludes.

1 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 using loans information at bank branch level in Peru. Next, we examine the literature that is closely related with the theoretical and empirical model developed in this paper.

This document 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 states. This in turn reduces banks’ incentives to take risk. The *leverage* channel suggests that the lower rate makes leverage less expensive. Then, banks have less of its own money (bank net worth) funding their risky loans. This means that the bank internalizes less of its risk-taking and increases its risk-taking incentives. [Dell’Ariccia, Laeven and Marquez \(2014\)](#) conclude that when leverage is endogenous, low interest rates lead to higher bank risk-taking.³ 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.

Also, this paper is related to the empirical literature that studies the risk-taking channel of monetary policy. This typically finds excess bank risk-taking increases after a reduction in the policy rate. [Maddaloni and Peydró \(2015\)](#) show that lending standards deteriorate after a reduction in the short-term interest rate. 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.

In particular, our 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 different econometric approach, which 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

³[Dell’Ariccia, Laeven and Marquez \(2014\)](#) assumes banks’ limited liability and asymmetric information, depositors cannot observe ex-ante the bank’s risk-taking level.

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.

2 A Model of the Risk-Taking Channel

Here we develop a two-period model with a continuum of measure one identical banks, identical households, and non-identical firms. Banks operate in competitive 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.⁴ These two provinces are different because of type of firms that exist within each provinces. There is an infinity 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 firms. 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 borrowing from others 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.⁵ 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.⁶ 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

⁴This framework can be easily extended to a more than two provinces and hence more than two bank branches; however, there are not gains in terms of intuition or qualitative results by doing so.

⁵I am assuming 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.

⁶The risk-taking involves the volume and not the type of credit.

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 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, an capital and labor is combined to produce. Also, the (state-contingent) bank loan interest rate is realized. Finally, bank loans and workers are repaid and.

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:⁷

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

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

⁷For simplicity, since supply of labor force is inelastic, we can omit labor factor.

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,

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

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 avoid 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,

$$l_h + l_l = d + n. \quad (2)$$

Since banks have limited liability, banks resources available to payback 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 repay 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,

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

and hence $\pi^b = 0$. It follows that the endogenous probability that bank defaults at $t = 1$

is given by,⁸

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

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

$$r_h^{l*} = \max \left\{ 0, \frac{rd - r_l^l l_l}{l_h} \right\} \quad (3)$$

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

$$\mathbb{E}\{\beta (\max\{0, r_h^l l_h + r_l^l l_l - rd\})\}. \quad (4)$$

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 (4) subject to the bank balance sheet, (2). 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,⁹

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

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

which can be rewritten, respectively, as¹⁰

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

In the general equilibrium, using (1), these yield,

$$r = (1 - \delta_h) + \alpha_h \mathbb{E}\{z_h | (z_h, z_l) \in \Omega'_z\} l_h^{\alpha_h - 1}, \quad r = (1 - \delta_l) + \alpha_l \mathbb{E}\{z_l | (z_h, z_l) \in \Omega'_z\} l_l^{\alpha_l - 1}, \quad (5)$$

⁸We calibrate the model so the limited liability binds and hence bank default probability is positive.

⁹Proof in Appendix A.1.

¹⁰ Ω' is the complement of Ω .

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,

$$r = (1 - \delta_h) + \alpha_h \mathbb{E}\{z_h\} l_h^{\alpha_h - 1}, \quad r = (1 - \delta_l) + \alpha_l \mathbb{E}\{z_l\} l_l^{\alpha_l - 1}. \quad (6)$$

Comparing (5) and (6), we find that when there is limited liability and deposit insurance, (5), 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 (5) are clearly higher than the unconditional expectations in (6). 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.¹¹

Furthermore, under unlimited liability, equation (5), 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 (4) the *profit* channel consists that a lower r increases bank profits

¹¹Proof in Appendix A.2.

and hence reduces bank incentives to take risk so bank can benefit the most from the positive profits. And from (3) 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 (6) 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 model supports the empirical findings of Jiménez et al. (2014). This is, as suggested in figure 5 in Appendix A.3 lowly capitalized banks (i.e., banks with low bank equity to asset ratio) grants 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 is possible, and simulate changes on r .¹² 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 $\sigma_l = 0.37$.

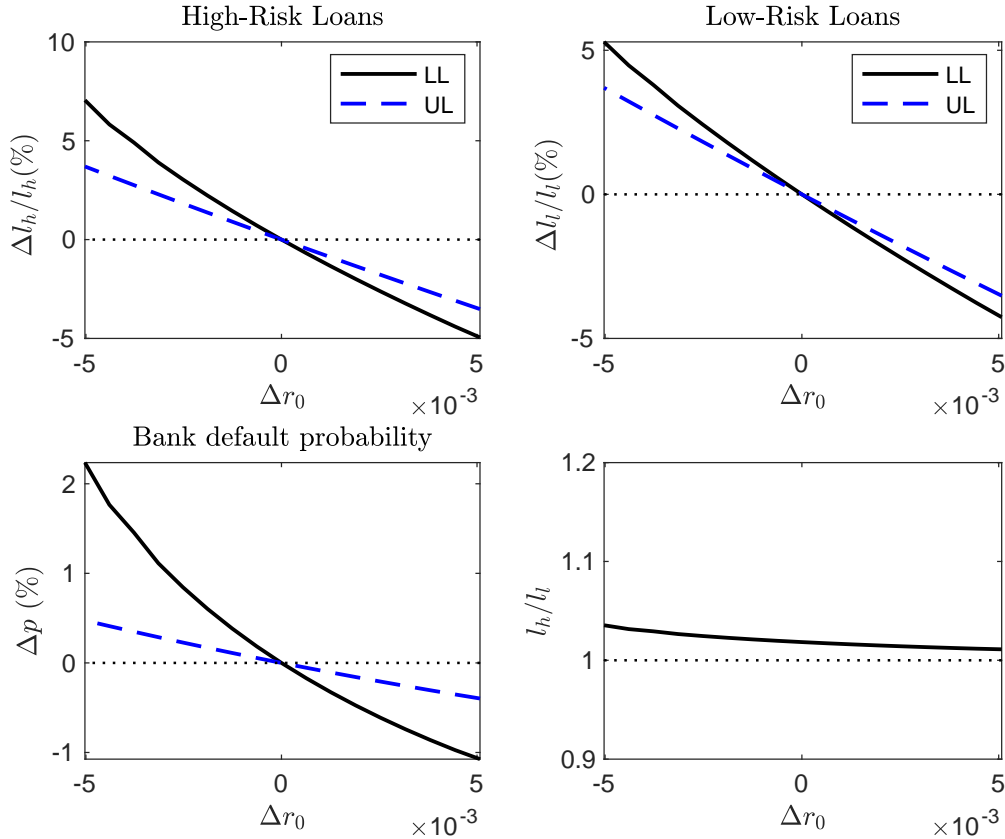
In equilibrium, high-risk loans are 4.3% inefficiently high and low-risk loans are 2.5% inefficiently high. This implies that there is a stronger preference for high-risk loans. Since banks might default with a positive probability, they do not internalize the losses when the return on the loans is very 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 1 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

¹²In 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.

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 1. This, as explained before, increases bank incentives to take more excessive risk and hence to excessively supply more of low-risk and high-risk loans to firms.

Figure 1. *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 1 reports that a monetary policy easy produces a stronger increase of high-risk loans. Hence, this model provides evidence that after a monetary policy easy, banks raise their preferences of holding a larger share of high-risk loans on their loan portfolio.¹³ 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.

¹³In fact, figure 1 shows that the ratio of high-risk to low-risk loans is always higher than one.

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 4 and 5 in Appendix A.3, respectively.

In the empirical section of these paper we use this result to test the risk-taking channel mechanism underpinning our model. Ideally we would like observe risk directly, but we consider non-performing loans ratio in a local market as one degree of variation in riskiness.

3 Data

The Peruvian credit market is segmented locally, as there is heterogeneity in the number of institutions serving a given province. But, there are large financial institutions with 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*. The latter four groups are non-banks and intermediates small amount of loans and mainly focused in credit to small firms and consumers, and offer limited financial services.¹⁴ In our empirical analysis we focus on all these bank and non-banks.

Province Lending: Our 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 financial regulator from Peru, *Superintendencia de Banca, Seguros y Administradoras de Fondos de Pensiones* (SBS).

Financial firms data: The financial firms data comes from balances reported to the financial regulator from Peru, *Superintendencia de Banca, Seguros y Administradoras de Fondos de Pensiones* (SBS). We access to data available from 2002m1 to 2017m09.

Non-Performing loans: Our 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 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.¹⁵ The data is available in quarterly frequency for the 2003Q1-2010Q3 period and

¹⁴CAMCs 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

¹⁵This information is restricted. We thank to the Central Bank of Peru, BCRP, for giving us access to use the datasets.

in 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 match the credit registry data with geographic location, in a province. We use geographic location of a debtor provided by the Peruvian tax administration (SUNAT) and match this information to Location codes (UBIGEO).¹⁶ 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 the 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 B shows the results of this matching process. In general, our sample to compute NPL captures very well the dynamics of aggregate credit market in Peru.

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

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

Employment: We collect data on employment from administrative data provided by SUNAT.¹⁷ 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).

¹⁶Once we have a UBIGEO, we use the Peruvian Bureau of statistics' information on location of a UBIGEO in a region.

¹⁷This information is restricted. We thank to the Central Bank of Peru, for giving us access to use this dataset.

Monetary Policy rate: We use Interbank interest rate as our measure of Monetary policy rate. We obtain this information from the BCRPData.¹⁸

3.1 Summary Statistics

Table 1 presents the descriptive statistics for the main variables in our analysis. It shows the cross-section and time averages. Our empirical analysis uses variation on lending at branch-level. There are 3682 branches located in 451 districts and 189 provinces.

Our identification strategy uses variation in riskiness of local credit markets, which we measure using the Non-Performing Loans (NPL) at the given province, NPL-Branch. The NPL-Branch is calculated by summing up all non-performing loans in a given province in a given year, and then averaging over all years. We then assign to each financial firm branch in our data the NPL of the province in which it is located.

Figure 2 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.

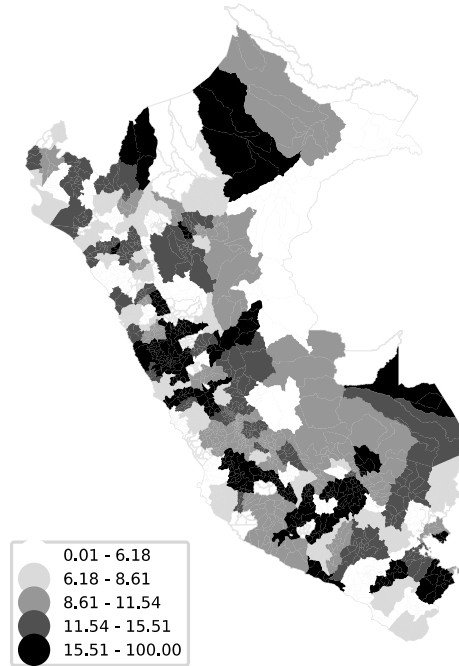
All panels in Table 1 provide a breakdown by high and low non-performing loan (NPL) using the median NPL as a threshold value to divide the respective samples. Panel A of Table 1 shows statistics of the data for all provinces with at least one financial firm branch. It is noticeable that low-risk local 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 1. Branches in low-risk provinces are larger (146.5 thousand Pen Soles versus 26.4 thousand Pen Soles). The average branch holds loans worth 86.4 thousand Pen Soles. However, branches in low-risk and high-risk show similar credit growth in average.

Panel C of Table 1 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 a financial firm's branches, using branch lending for the 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.

¹⁸BCRPData is online database provided by the Central Bank of Peru and available at: <https://estadisticas.bcrp.gob.pe/estadisticas/series/>

Figure 2. *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 $\frac{\sum_t NPL_{p,t}}{T}$, where T is the number periods in the sample. Sample: 2003m1-2017m12.

4 Empirical Estimates of the Risk-Taking Channel

In this section we look to establish a direct causal effects of the risk-taking channel of monetary policy on lending using Peruvian Data. [Carrera \(2011\)](#); [Pozo and Rojas \(2020\)](#) present evidence of monetary policy on the credit markets, but with aggregate data is very difficult to show which mechanisms are operating. Due to identifications problems from using aggregate data, we follow similar strategy as in [Pozo and Rojas \(2020\)](#) to show that a direct causal effect as implied by our theory. In particular, we use branch-level and bank-province level data so we can control for omitted variables such as lending opportunities and credit demand conditions.

4.1 Identification Strategy

We exploit geographic variation in Non-Performing Loans (NPL) induced by differences in riskiness of local credit markets. Thus, we use the Non-Performing Loans (NPL) as a measure of the riskiness of a local credit market.

A key idea in our identification strategy is that that NPL, capturing the risk taking

Table 1. 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/)	86.4	792.4	146.5	1,115.9	26.4	59.7
Loan growth (%)	3.0	11	3.1	11	3.0	10.0
Obs.(branch × month))	317,386		158,657		158,729	
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.(branch × 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 the median NPL for the 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 data on formal employment. 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.

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 by 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 our identification strategy to work, it is important to have variation in riskiness that is independent of a financial firm's lending opportunities or demand factor influencing financial firm's decisions. To obtain such variation we compare lending across branches of

the same financial firm located in different provinces. This is a within-financial identification, and we refer to it as branch-bank estimation. By comparing across branches of the same financial firm, we are able to 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.

4.2 Branch-Bank estimation

Equation 7 shows 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 our indicator of riskiness of the local credit market in province p . Δi_t is the change of the monetary policy rate, measured by changes in the interbank market. This variable enters in the regression with a lag to control for a problem of simultaneity. We include bank-time fixed effects, α_{bt} , for bank b that owns a branch j ; and $\alpha_j, \alpha_{p(j)}, \alpha_{r(j)t}$ are branch j , province and region-time fixed effects.

$$\Delta y_{b(j)pt} = \rho \Delta y_{b(j)pt-1} + \alpha_j + \alpha_{p(j)} + \alpha_{r(j)t} + \alpha_{bt} + \beta \text{NPL-Branch}_p \times \Delta i_{t-1} + \epsilon_{b(j)pt} \quad (7)$$

We also include a one-period lag to control for the mean reversion property of credit at the branch level. However, results are robust to adding this autoregressive element.

The key set of fixed effects are the bank-time fixed effects, α_{bt} , which absorbs all time differences across banks, to control for bank’s lending opportunities. So, we compare across branches of same bank. $\text{NPL-Branch}_p \times \Delta i_t$ captures the MP risk-taking channel. Basically, after a expansionary MP change, branches operating in more risky 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 the specific region level. If we omit bank-time fixed effects, we add time fixed effect to control for country level trends.

Results

Table 2 shows the results of the estimation of equation (7). Our sample include all branches from all financial firms, banks and non-banks. Our monthly sample covers the period from 2002m1 to 2018m12. Lending data was winsorized at the 2% to control

bias our results due to outliers. From columns (1) to (4), we add regressors or take out regressors. Our prefer specification is in Column (2). Overall, we intend to control for variables that might influence the lender decision that may be also correlated with a financial firm ownership, firm size, regional economic conditions or managerial decisions.

Table 2. *Branch-level estimation: Results*

	Dependent variable: Δy_{bdt}			
	(1)	(2)	(3)	(4)
NPL-Branch $\times \Delta i$	-0.0276** (0.0120)	-0.0279** (0.0113)	-0.0174* (0.0101)	-0.0221** (0.0101)
Δy_{t-1}		0.177*** (0.00173)	0.180*** (0.00172)	0.220*** (0.00167)
Bank-Time FE	✓	✓	✓	
Region-Time FE	✓	✓		
Branch FE	✓	✓	✓	✓
province FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
R^2	0.278	0.291	0.274	0.155
Observations	315345	311445	311445	313237

Note: This table estimates the effect of the Peruvian monetary policy rate changes on lending growth, $\Delta y_{b(j)pt}$. Monthly Sample: 2002m1-2018m12 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. Δi is the change in Peruvian interbank rate. Fixed effects are described at the bottom of the table. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Columns (1) and (2) show that allowing for the autoregressive component of branch lending growth rates make no 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. When MP rate decreases in 100 bps, financial firms raise lending growth rates by 2.79 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 the MP rate decreases in 100 bps, a branch operating in an average high NPL market (24.7) rises lending growth by 51.9 bps relative to a branch operating in an average low NPL market (6.1).¹⁹ This result presents evidence of the main prediction of our model: higher

¹⁹The average high (low) NPL corresponds to the average of markets with NPL above (below) the median.

lending inflows into more risky 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 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. All these results show that the risk-taking channel is economically and statistically significant.

In general, all these results are consistent with the profit maximization of financial firms as required by our model. In particular, higher profits from increasing lending by more with the monetary policy rate in more risky markets.

We report the results from robustness tests in Appendix C. First, Table 6 in the Appendix C.1 shows that the effects of monetary policy on lending are bit larger if we include in the sample all financial firms and not only those financial firms serving more than two province markets. Table 7 shows that the direction of the risk-taking channel of monetary policy on branch lending is consistent across of banks, non-banks, large banks and the exclusion of branches operating in the metropolitan area, which is the largest credit market in the country. Second, the risk-taking channel is larger for banks than non banks. This sensitivity on lending is similar for the sample of large banks, although not statistically significant which could be a result that some large banks centralize risk not at local market but at bank level and they are more prudent and decide not to take excessive risk. Third, results are similar if we exclude the metropolitan area, the largest credit market, from the sample.

Table 8 in the Appendix C.2 shows that our results remains statistically significant if we control for sample selection or omitted variables such as bank concentration that may bias our results. Fourth, effect of risk-taking channel remains statistically significant if we exclude from the sample the initial years, 2002-2004, which have measurement problems and have a low representation of the aggregate credit dynamics. Fifth, restricting the sample, before and the Great Financial Crisis (GFC) to control for monetary stance, international liquidity availability and international rates does not change the direction of the risk-taking channel, but it shows that it has been much stronger pre-GFC. Sixth, the risk-taking channel is larger after we control for bank competition, which shows the robustness the our results and that it is not picking bank concentration effects. Risky but profitable markets would be also those markets were large banks prefer to operate or market power is higher, which make funding easier to get. However, this robustness check shows that the risk-taking channel is independent of the degree of concentration of local markets.

5 Aggregation of the Risk-Taking Channel

A proposition of our model is that after monetary policy rate fall, banks expand credit to take advantage of riskier lending opportunities and if producers cannot costlessly replace bank loans with other ways to finance production, real activity declines. To identify the impact of the risk-taking channel on real activity we need to revisit our estimates at higher levels of aggregation.

Our previous results are at the branch level, and they are partial equilibrium estimates. The risk-taking channel at the branch level may not be economically significant at higher level of aggregations, as financial firms can allocate lending across branches. Thus, the average riskiness of the local markets where a financial firm operate must determine the impact of risk-taking channel of MP. 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 our model is that after an expansionary monetary policy change banks operating in risky markets (high NPL-Bank) expand lending my 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.

5.1 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:

$$\Delta y_{bpt} = \alpha_{bp} + \delta_{pt} + \gamma \text{NPL} - \text{Bank}_{bt-1} + \beta \Delta i_{t-1} \times \text{NPL} - \text{Bank}_{bt-1} + \varepsilon_{bpt} \quad (8)$$

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 . $\text{NPL} - \text{Bank}_{b,t}$ is our indicator of riskiness of markets that a bank faces from $t - 4$ to t . Δi_t is the change of the monetary policy rate, measured again by changes in the interbank market. This variable enters in the regression with a lag to control for a problem of simultaneity. We include bank-province fixed effects, α_{bp} , and province-time fixed effects, which are the key set of controls to absorb changes in local lending opportunities or local market demand conditions.

Table 3 shows the results. Column (1) includes all the set of fixed effects controls.

It shows that after an expansionary monetary policy banks that operate in more risky markets increase lending by more relative to banks serving less risky markets. After a 100 bps fall in the MP rate, a one standard deviation increase in NPL-Bank (5.1) increases the positive effect on lending growth by 62.2 bps. In other words, financial firms that operate in a market with a NPL-Bank that is one standard deviation above the mean, increases lending by 62.2 bps more than the average financial firm per 100 fall in the MP rate. This estimate of the risk-taking channel is quantitatively larger, that those estimates at the branch level. It provides evidence that through the risk-taking channel, monetary policy rate affects lending in given province via changes in the lending incentives of financial firms that take more risk.

Table 3. *Bank-Province estimation: Results*

	Dependent variable: Δy_{bdt}		
	(1)	(2)	(3)
NPL-Bank $\times \Delta i$	-0.122* (0.0662)	-0.117* (0.0614)	-0.134** (0.0620)
NPL-Branch $\times \Delta i$		-0.0180 (0.0134)	-0.0179 (0.0135)
NPL-Bank	0.101*** (0.0352)	0.111*** (0.0310)	0.0574* (0.0302)
Δy_{t-1}	0.150*** (0.00448)	0.146*** (0.00416)	0.214*** (0.00401)
Province-Time FE	✓		
Bank FE	✓	✓	✓
Bank-Province FE	✓	✓	
Province FE	✓	✓	✓
Time FE	✓	✓	✓
R^2	0.276	0.171	0.121
Observations	51852	53531	53557

Note: This table show estimates of the effect of the risk-taking channel on total 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-Branch is the average NPL-branch using lending shares across branches as weights. Fixed effects are denoted at the bottom. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In column (2) we include our measure of local riskiness (NPL-Branch) interacting with monetary policy rate change.²⁰ Local riskiness has similar magnitude as those obtained in

²⁰To do so, we have to drop out the province-time fixed effects.

branch-level estimation, but is no longer statically significant. In contrast, the bank-level measure of risk-taking (NPL-bank) is almost unchanged from column (1) and remains statistically significant. This result implies that banks can allocate lending across branches, as it indicates that portfolio lending decisions are made at the bank level.

In column (3) we omit province-time fixed effects and our result maintains similar in magnitude and is still statistically significant.

These results indicate that the effect of financial firm-level risk-taking on the sensitivity of local lending to monetary policy is robust. Further, the Table 9 from Appendix C.3 shows that the financial-firm level risk-taking channel operates mainly through non-banks. For the sample of large banks and banks, bank-level risk is not relevant but local risk-taking channel is more important and statistically significant. This may be due to the fact that banks are more prudent than non-banks.

5.2 Province-level estimation

In this section we look for effects of the risk taking channel on lending and employment at the province level. Thus, we aggregate our data to the province level. A prediction of our model is that, after an expansionary monetary policy, provinces, or local markets, served by banks that lend in more risky markets experience larger lending expansions relative to provinces served banks operating in less risky markets.

Thus, we construct a measure of exposure to banks that take more risk at the province level: NPL-Province. It is computed as the weighted average of NPL-Bank across all financial firms operating in a given province, using their lending shares as weights. We estimate the following OLS regression:

$$\Delta y_{pt} = \rho \Delta y_{pt} + \alpha_p + \delta_t + \beta \text{NPL-Province}_{p,t-1} + \gamma \Delta i_{t-1} \times \text{NPL-Province}_{p,t-1} + \varepsilon_{pt} \quad (9)$$

where Δy_{pt} is change in the log of lending or the log of employment in province p at time t . Δi_t is the change in the monetary policy rate, which enter in the regression with one lag. 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.

Column (1) in Table 4 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 increases in lending relative to other provinces. After a 100 bps fall in the MP rate, a one standard deviation increase

in NPL-Province (4.57) increases the positive effect on total lending growth by 164 bps. This result is statistically significant and its magnitude is high. In column (2) we add local riskiness as a control (NPL-Branch) the main estimates remains very similar and statistically significant. These results support our proposition that the risk-taking channel affects bank lending.

Columns (3) and (4) in Table 4 present the results for log employment growth. We find that the risk-taking channel has the predicted direction effects on province employment. In particular, the increase in riskiness of a province rises employment growth after a fall in MP rates. But, the results are not statistically significant.²¹ Thus, we cannot show strong evidence that the risk-taking channel increases real activity.

Table 4. *Province-Level estimation: Results*

	$\Delta Loans$		$\Delta Employment$	
	(1)	(2)	(3)	(4)
NPL-Province $\times \Delta i$	-0.362** (0.163)	-0.352** (0.163)	-0.631 (0.523)	-0.572 (0.524)
NPL-Branch $\times \Delta i$		-0.0214 (0.0135)		-0.0762** (0.0381)
NPL	-0.0565 (0.0556)	-0.0565 (0.0556)	-0.358 (0.380)	-0.353 (0.380)
$\Delta Loans_{t-1}$	0.146*** (0.0111)	0.146*** (0.0111)		
$\Delta Employment_{t-1}$			-0.133*** (0.0153)	-0.134*** (0.0153)
Province FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
R^2	0.203	0.203	0.0556	0.0565
Observations	7626	7626	4388	4388

Note: This table show estimates of the effect of the risk-taking channel on Δy_{pt} : log total lending growth rate or log employment growth rate in a given province p and quarter t . The data are at the province-quarter level from 2004Q1 to 2018Q4. 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 lending shares across provinces as weights. Fixed effects are denoted at the bottom. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

²¹The non significance of our results may come from the fact the employment data is short and there are some measurement concerns that can be playing against us.

5.3 Bank-level estimation

In this section we seek for evidence of the effects of the risk taking channel on loans and profits at the financial firm-level. We show how banks change lending after monetary policy rates fall. The unit of observation is a financial firm-quarter.

In particular, our model predicts that after an expansionary monetary policy, banks operating in more risky markets increase lending by more and obtain more profits relative to banks operating in less risky markets. We run the following regression:

$$\begin{aligned} \Delta y_{bt} = & \rho \Delta y_{bt-1} + \alpha_b + \delta_t + \gamma \text{NPL-bank}_{b,t-1} \\ & + \beta_1 \Delta i_{t-1} \times \text{NPL-bank}_{b,t-1} + \beta_2 \Delta i_{t-2} \times \text{NPL-bank}_{b,t-2} + \varepsilon_{bt} \end{aligned} \quad (10)$$

where Δy_{bt} is 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 our measure of a financial firm profits and it is defined as the ratio of the financial income net of financial expenses to total assets. Δi_t is the change in the monetary policy rate, which enters in the regression with one lag. NPL-Bank is the weighted average of NPL-Branch for all financial institution's branches weighted by their lending shares. α_b are financial firm fixed effects and δ_t are time fixed effects. We include two lags of the MP rate and report the sum of the coefficients. By doing so, we control for the fact that at this level of aggregation the impact of MP rate changes have a lag.

Column (1) in Table 5 shows that when the monetary policy rate falls financial firms that operate in more risky markets expand lending by more. The estimated coefficient are of similar magnitude of our previous estimates using bank-province data. 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 than domestic currency lending. These result may not be surprising, as lending in foreign currency tend to be riskier than domestic currency lending²².

Finally, column (4) in Table 5 shows that after an expansionary monetary policy shock, financial firms operating in more risky markets tend to have more that proportionally profits, measured by the financial margin, relative to financial firms operating in more less risky markets. After a 100 bps fall in the MP rate, a one standard deviation increase in NPL-Bank (5.1) increases the positive effect on lending growth by 404.1 bps. Consistent with our model, this show that changes in monetary policy introduce additional incentives for banks to rebalance their lending portfolio by expanding more credit into more risky markets.

²²For example, loans in foreign currency involve exchange rate risk.

Table 5. *Bank-Level estimation: Results*

	Total loans	Domestic currency loans	Foreign currency loans	Financial margin
NPL-Bank $\times \Delta i$	-0.1878** (0.0951)	-0.0861 (0.1095)	-0.449** (0.213)	-0.8645** (0.291)
Bank FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
R^2	0.296	0.317	0.246	0.99
Observations	2358	2344	2137	2,358

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

6 Conclusions

We have shown that the risk-taking channel is operative in Peru and it is heterogeneous across banks. Using 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. 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. We show that the impact on monetary policy on total credit via the risk-taking channel is important, but there is not strong evidence of its effects on real variables, as employment. This finding of and operative risk-taking channel in Peru is robust to different specifications and sample definitions underlying our estimations.

As far as policy implications are concerned, our results point that, the risk-taking channel works on the extensive margin by including riskier borrowers that otherwise may not have access to the credit market. Even though in our model we do not model constrained and unconstrained firms, in our empirical exploration we show that high risky market tend to be smaller, with high levels informal employment shares, and smaller loan quantities. Thus, the perils on financial stability from a risk-taking channel may be compensated by benefits from financial inclusion of riskier borrowers with limited access to formal credit markets.

On the other hand, the mechanism we show in this paper brings the concept of financial fragility due to excessive risk-taking. Our 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 to balance sheet fragility for the economy.

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A Appendix: Model derivation

A.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 (4), 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,

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

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

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

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

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

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

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

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,

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

A.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 their 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.,

$$r = \mathbb{E}\{x\}\bar{r}, \quad (11)$$

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 (11) 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 (11), which is no longer perfectly elastic. This is, the bank is going to internalize 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,

$$r_h^{l*} = \max \left\{ 0, \frac{\bar{r}d - r_l^l l_l}{l_h} \right\}. \quad (12)$$

Similarly, the supply curve of deposits, faced by banks, equation (11), can be rewritten as,

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

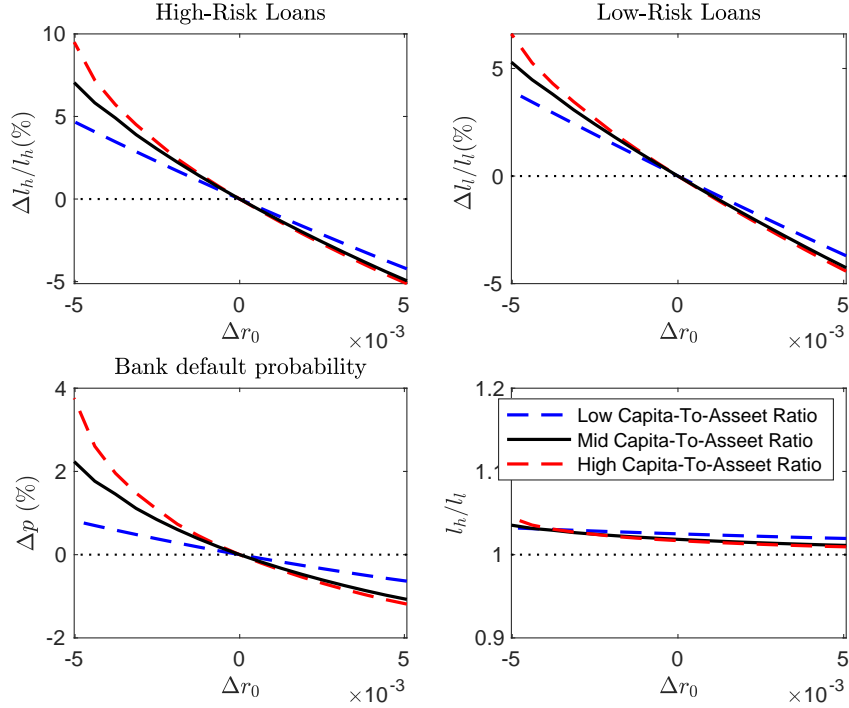
Inserting the supply curve of deposits into bank profits, the latter results in,

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

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.

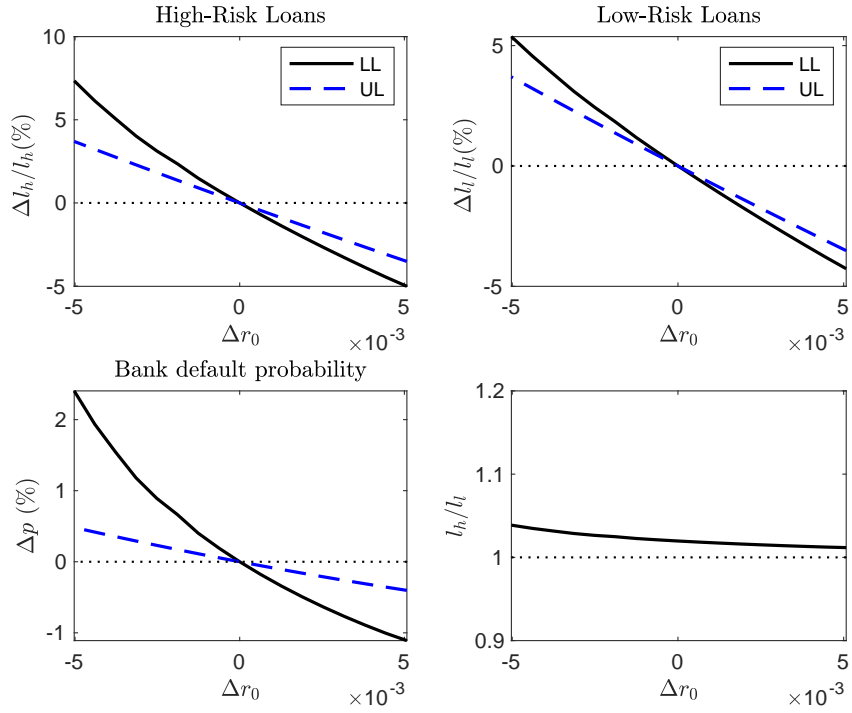
A.3 Additional Figures

Figure 3. *Monetary Policy Impact and Capital to Asset Ratio*



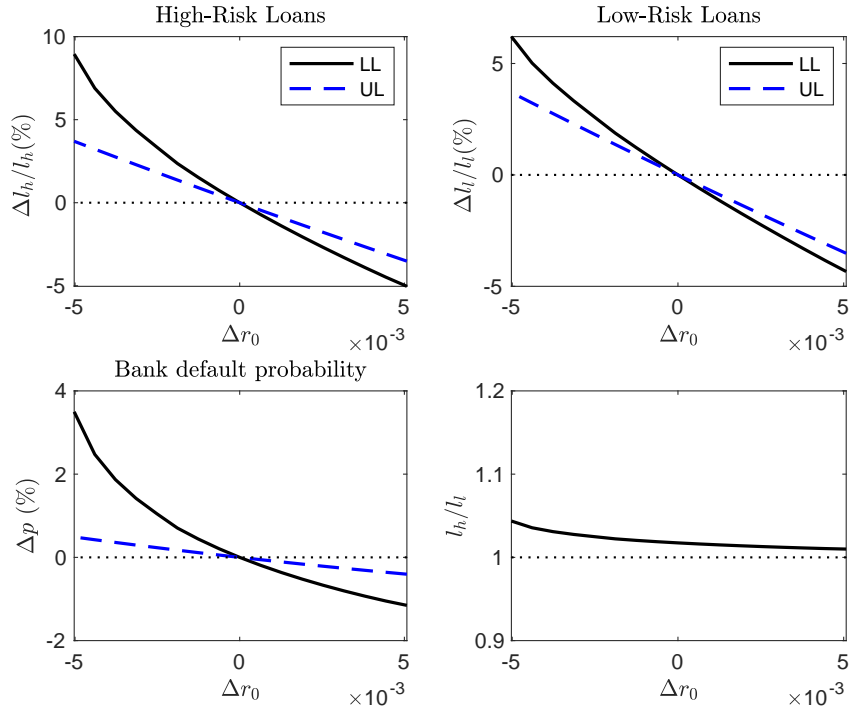
Note: Figure shows the responses of some variables to changes of the monetary policy rate under limited Liability. In general, we set $\rho = 0$, $\beta = 0.99$, $\delta_h = \delta_l = 0.20$, $\alpha_h = \alpha_l = 0.33$. In the baseline calibration (solid black line), the other parameters n and σ_h 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 4. *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 5. *Monetary Policy Impact: $\rho < 0$*

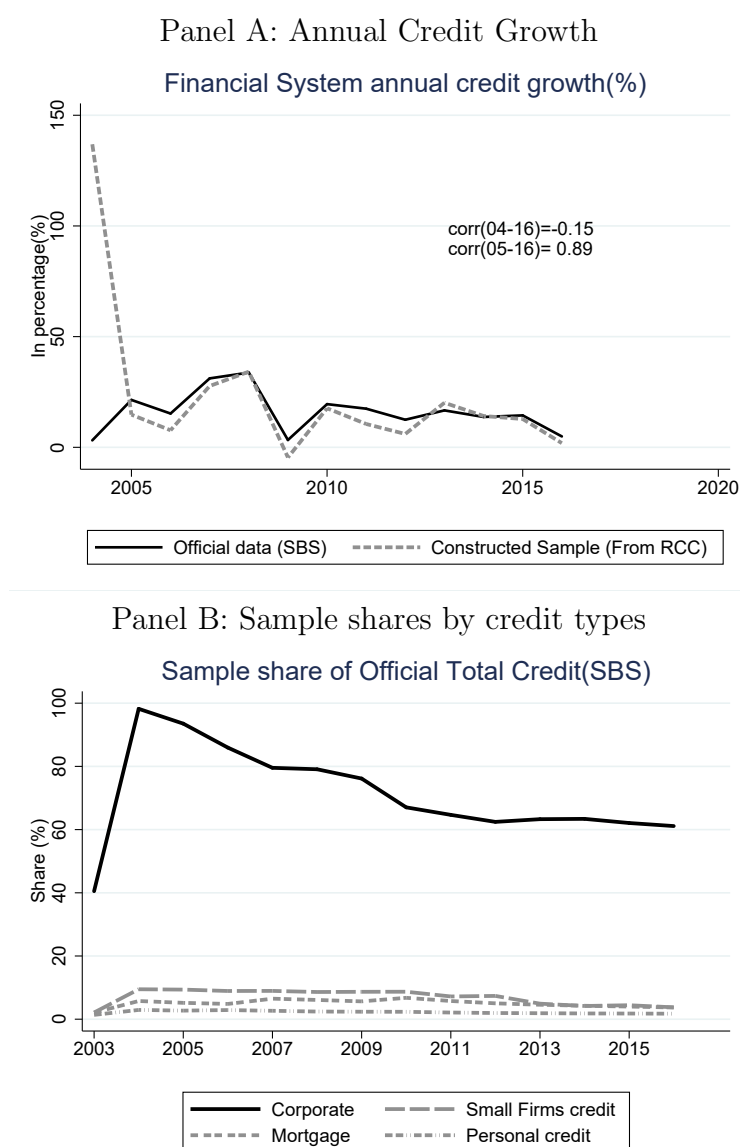


Note: Figure shows the responses of some variables to changes of the monetary policy rate under LL and UL. LL: Limited Liability, UL: Unlimited Liability. In the baseline calibration, we set $\rho = -0.50$, $\beta = 0.99$, $\delta_h = \delta_l = 0.20$, $\alpha_h = \alpha_l = 0.33$. The other parameters 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 $\sigma_l = 0.45$.

B Appendix: Sample Data

In this section we show results from our marching process. Figure 6 shows that our sample mimics very well the dynamics of the total bank credit. Aggregating our sample at the financial system level, its correlation with the official data shows a high level of correlation, 0.89, after we omit observations from the year 2004, where the quality of data is not very good. Panel B of Figure 6 shows, in average, our sample represents around 48 percent of the official total credit. Despite this low share, we can say that our sample is representative of the aggregate credit dynamics.

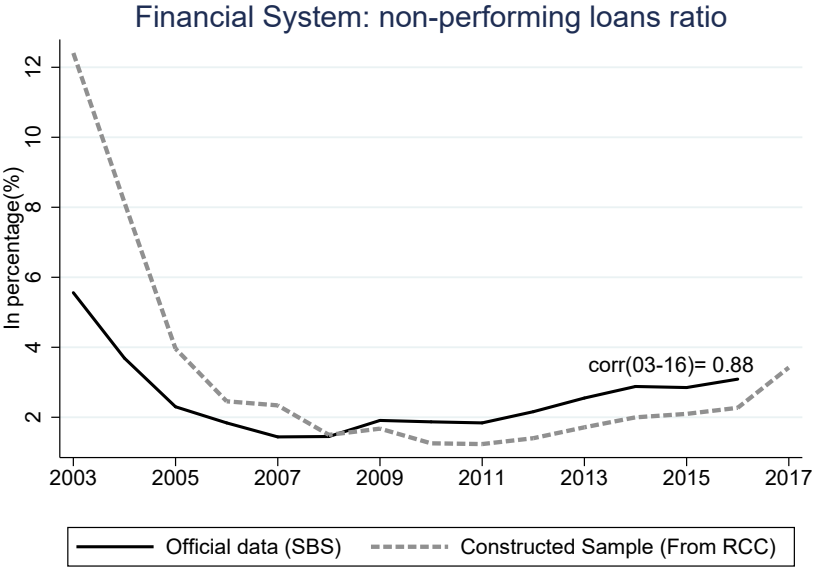
Figure 6. *Representativeness of the sample - Aggregate credit*



Note: Annual Sample 2004-2016. SBS Official Data from http://www.sbs.gob.pe/app/pp/seriesHistoricas2/Paso3_Mensual.aspx?cod=6&per=7&passo=2&secu=01

Figure 7 also show that in aggregate, our sample follows similar dynamics of the NPL ratio published in official statistics.

Figure 7. *Representativeness of the sample - Non Performing Loans ratio*



Note: Annual Sample 2004-2016. SBS Official Data from http://www.sbs.gob.pe/app/pp/seriesHistoricas2/Paso3_Mensual.aspx?cod=6&per=7&paso=2&secu=01

C Appendix: Additional regressions and Robustness

C.1 Branch-bank estimation: All banks sample

In this section we check the robustness of our regression specification (7) by including in the sample all banks. In specific, we estimate the following specification:

$$\Delta y_{b(j)pt} = \rho \Delta y_{b(j)pt-1} + \alpha_j + \alpha_{p(j)} + \alpha_{r(j)t} + \beta \text{NPL-Branch}_p \times \Delta i_t + \epsilon_{b(j)pt} \quad (13)$$

Table 6 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 6. *Branch-level estimation: All banks sample*

	Dependent variable: Δy_{bdt}			
	(1)	(2)	(3)	(4)
NPL-Branch $\times \Delta i$	-0.0389*** (0.0150)	-0.0319*** (0.0115)	-0.0221* (0.0114)	-0.0249** (0.0110)
Δy_{t-1}		0.218*** (0.0140)	0.220*** (0.0139)	0.282*** (0.0140)
Region-Time FE	✓	✓		
Branch FE	✓	✓	✓	
Province FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
R^2	0.137	0.172	0.155	0.113
Observations	317158	313237	313237	313259

Note: This table estimates the effect of the Peruvian monetary policy rate changes on lending growth. Monthly Sample: 2002m1-2018m12 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. Δi is the change in Peruvian interbank rate. Fixed effects are described at the bottom of the table. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.2 Branch-Bank estimation: Robustness

Table 7 shows robustness to our main specification in equation (7): in column(1) it consider only the sample of banks, in column (2) we only consider large banks, in column (3) it considers the sample of non-bank financial institutions and column (4) excludes from the sample the metropolitan area, the union of Lima and Callao, which is largest credit market in the country.

Table 7. *Branch-level estimation: Robustness I*

	Dependent variable: Δy_{bdt}			
	(1) Banks	(2) Large Banks	(3) Non-Banks	(4) No Metropolitan Area
NPL-Branch $\times \Delta i$	-0.0840*** (0.0304)	-0.0281 (0.0432)	-0.0154 (0.00955)	-0.0193* (0.0105)
Δy_{t-1}	0.00193 (0.00277)	-0.108*** (0.00389)	0.420*** (0.00203)	0.259*** (0.00201)
Bank-Time FE	✓	✓	✓	✓
Region-Time FE	✓	✓	✓	✓
Branch FE	✓	✓	✓	✓
province FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
R^2	0.218	0.171	0.493	0.371
Observations	133366	69390	177710	218919

Note: This table shows robustness of the estimated effect of the Peruvian monetary policy rate changes on lending growth, in our main specification. Monthly Sample: 2002m1-2018m12 at the branch-level. The sample includes all financial firms 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. Δi is the change in Peruvian interbank rate. 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 areas in the Peru. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The direction of the risk-taking channel of monetary policy on branch lending is consistent across all samples. Although, for some samples this effect of monetary policy is not statistically significant. The risk-taking channel is larger for banks than non banks. For the sample of banks, after a rise in the monetary policy rate in 100 bps, a branch rise lending growth rates by 8.4 bps more in a high risky location relative to a branch operating in a low risky location, per unit of NPL. For the sample of non-banks, the magnitude of the risk taking channel is smaller even relative to main estimates, but it not statistically significant. An explanation for this result may be due to fact may non-banks have fewer branches, which works against our identification strategy. However, when we consider different sub samples of non-banks, or other specifications our results are similar in magnitude to our original estimates and they are statistically significant.²³ For the large banks sample, the magnitude of the risk taking channel is similar to our main estimate, but not statistically significant. Even though large banks have more branches and operate in almost all provinces in the country, the reallocation effect on loans

²³Basically, if we exclude EDPYMES, which focus on lending to small firms and highly concentrated in the Metropolitan Area, the results are statistically significant. These results are not shown but are available upon request from the authors.

due to MP changes across different markets may be absent if they centralize risk not at local market but at bank level. Also, the fact that some large banks are more prudent and decide not to take excessive risk may act against the results. In addition, large banks tend to be less sensitive to MP rate changes, since they have access to more alternative funding options.

Table 8 shows additional robustness to our main specifications due to sample selection or due to omitted variables such as bank concentration that may bias our results. The effect of risk-taking channel remains statistically significant in all specifications.

Table 8. *Branch-level estimation: Robustness II*

	Dependent variable: Δy_{bdt}			
	(1) After 2005m1	(2) Before GFC	(3) After GFC	(4) Control HH
NPL-Branch $\times \Delta i$	-0.0219* (0.0114)	-0.126* (0.0718)	-0.0192* (0.0111)	-0.0549** (0.0249)
HH-Branch $\times \Delta i$				-3.368*** (0.952)
NPL-Branch \times HH-Branch $\times \Delta i$				0.0684* (0.0380)
Δy_{t-1}	0.199*** (0.00177)	-0.0304*** (0.00560)	0.220*** (0.00187)	0.177*** (0.00173)
Bank-Time FE	✓	✓	✓	✓
Region-Time FE	✓	✓	✓	✓
Branch FE	✓	✓	✓	✓
province FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
R^2	0.310	0.350	0.320	0.291
Observations	290600	34104	256461	311445

Note: This table shows robustness of the estimated effect of the Peruvian monetary policy rate changes on lending growth, in our main specification. Monthly Sample: 2002m1-2018m12 at the branch-level. The sample includes all financial firms 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. Δi is the change in Peruvian interbank rate. Fixed effects are described at the bottom of the table. After 2005m1 sample drops observations from 2002 to 2004. Before GFC sample corresponds to 2005m1-2008m6 period. After 2008 sample corresponds to 2008m7-2018m12 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 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 as our sam-

ple have measurement problems and have a low representation of the aggregate credit dynamics. This column shows not a big difference with respect to our main estimates.

In columns (2) and (3) we try to control for the availability of international liquidity, international interest rates and 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 has been much stronger pre-GFC. Before GFC, after MP rate decreases in 100 bps more, a branch rise lending growth rates by 1.92 bps in a high risky location relative to a branch operating in a low risky location, per unit of NPL. After GFC, after the same expansionary monetary policy rate change, a branch rise lending growth rates by 12.6 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 our 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 it is larger than our main specification after we control for bank concentration: After MP rate decreases in 100 bps, a branch rise lending growth rates by 5.49 bps more in a high risky location relative to a branch operating in a low risky location, per unit of NPL.

C.3 Bank-Province estimation: Robustness

Table 9. *Bank-Province estimation: Robustness*

	Dependent variable: Δy_{bdt}			
	(1) Banks	(2) Large Banks	(3) Non-Banks	(4) No Metropolitan
NPL-Bank $\times \Delta i$	0.366 (0.285)	-4.104 (2.838)	-0.255*** (0.0870)	-0.130* (0.0677)
NPL-Bank	-0.328* (0.181)	-1.741* (0.913)	-0.0207 (0.0488)	0.0966*** (0.0359)
Δy_{t-1}	0.126*** (0.00807)	-0.0759*** (0.0120)	0.178*** (0.00576)	0.148*** (0.00460)
Province-Time FE	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Bank-Province FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
R^2	0.309	0.449	0.363	0.276
Observations	18216	9408	32125	49591

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 in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.