Income inequality and capital reallocation in the presence of financial frictions*

Matias Ossandon Busch†

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Abstract

Does income inequality affect banks' credit-risk reallocation when facing financial distress? Using novel branch-level data on Colombian banks I find that facing a large liquidity shock, exposed banks shift more credit towards low-risk borrowers in municipalities with higher income inequality. For identification I compare branches' reaction to a foreign funding shock within banks and across regions by simultaneously absorbing local demand. Collateral frictions play a key role: while the overall effect is stronger in regions with higher collateral constraints, credit backed by better collateral remains consistently shielded. Regional-level estimates suggest that this 'inequality risk-taking channel' can account for a significant share of consumption growth in crisis periods.

Keywords: Income inequality, credit risk, collateral constraints, consumption.

JEL Codes: D31, E21, F34, G21.

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†Correspondence: Financial Markets Department, Halle Institute for Economic Research – Member of the Leibniz Association, Kleine Maerkerstrasse 8, 06108 Halle an der Saale, Germany; and Center for Latin American Monetary Studies (CEMLA), Durango 54, Colonia Roma Norte, Alcaldía Cuauhtémoc, 06700, Mexico City. Email: mossandon@cemla.org.

1 Introduction

A striking fact about recent financial crises is the low growth path followed by consumer expenditure relative personal income in the crises' aftermath. In the US, for instance, this phenomenon has occurred since 2008 even in the presence of a decline in overall debt, financial deleveraging, and low interest rates. A body of literature has related the slow recovery of consumption to the pre-crisis debt overhang or to credit constraints in the banking sector (Mian et al., 2013, Dynan, 2012). These explanations converge in assigning a crucial role to credit markets, either because of weak credit demand or because of supply-side constraints triggered by a run to safety, in which credit rationing shifted credit out of borrowers with a higher marginal propensity to consume (Kaplan and Violante, 2014).

If credit rationing and risk shifts matter for macroeconomic performance in a crisis' aftermath, a question that arises is whether in the presence of imperfect capital markets the distribution of income may affect the reallocaiton of credit risk. This question builds on the notion that in the presence of agency frictions, collateral requirements become a mechanism to circumvent borrowers' limitation to pledge future cash flows. Provided that the distribution of collateral resembles the distribution of wealth and income within a pool of borrowers, a higher income inequality may allow banks to shift credit towards wealthier agents with available collateral. This dynamic may occur when higher inequality makes borrowers' income an increasingly precise signal about their creditworthiness, as suggested by Coibion et al. (2016). If in place, this channel could affect aggregate consumption by reallocating capital to arguably wealthier agents less prone to consume.

In this paper I investigate whether the distribution of income interacts with underlying financial frictions (i.e. collateral constraints) in affecting credit risk shifts in a context of financial distress. For this purpose I use bank-level balance sheet data to inspect whether, faced with a sudden disruption in their available funding, banks shift credit towards low-risk borrowers, and whether they do so especially in the presence of high income inequality at a regional level. While this effect may indirectly indicate that financial frictions are driving the results, I move on to test whether collateral constraints can explain the relationship between inequality and risk shifts. This analysis provides first evidence on a previously unexplored risk-taking channel of inequality, with implications for both financial stability and macroeconomic outcomes.

Why should we expect the distribution of income to affect banks' risk-taking? At first glance, financial intermediaries should aim at assessing borrowers' future cash flows. If borrowers can effectively pledge future cash flows, the effect of collateral becomes negligible and the distribution of wealth and income would not influence banks' behavior (Campbell and Cocco, 2007, Khwaja et al., 2010). Moreover, even if a risk shift can be linked to income inequality, the relationship could be arguable driven by credit demand constraints, for instance if simultaneously the level of employment in low-income groups decreases. In reality, however, institutional weaknesses – especially in EMEs – are likely to limit borrowers' capacity to assess borrowers' risk, leading banks to demand collateral to secure loans. In this context income inequality may induce larger (supply-driven) risk shifts when banks become liquidity constrained. To find whether this latter narrative can find support in the data is the main objective of this paper.

Shedding light on a risk-taking channel of income inequality comes with strong empirical challenges related to the availability of data as well as to several identification concerns. Firstly, exploring the link between inequality and economic outcomes is likely to be subjected to omitted variable biased due to the correlation between inequality and other aggregated economic characteristics. Second, one would need to unravel the presence of financial frictions affecting banks' risk taking in regions with a different income distribution. Such frictions are in general unobserved variables difficult to account for. Finally, obtaining measures of income inequality and banks' risk taking at a sub-national level is difficult as no such data can be obtained from standard public or commercial data sources.

I address these challenges by exploiting a combination of novel micro-level datasets tracing bank balance sheets in Colombia at a regional (municipal) level, the same level at which income inequality and other macroeconomic outcomes can be observed. I follow the established literature (e.g., Chodorow-Reich, 2014, Ongena et al., 2015) in using the collapse in Lehman Brothers in the third quarter of 2008 as an exogenous shock to the Colombian banking system that triggered a capital flows reversal reducing the available foreign interbank funding for banks. I match banks' balance sheet data including their foreign funding exposures to an administrative register reporting banks' credit portfolio by risk categories and aggregated at the bank-municipality level. I then look for traces of a funding shock that is exogenous from municipal branches' perspective and that could affect their risk-taking behaviour in either way conditional on the shape of the income distribution.

Armed with these data, I estimate branches' credit-risk ratio (i.e. the share of high-risk to total credit) using a difference-in-difference model for the period between 2005 and

2009. I rely on banks' pre-shock foreign funding to asset ratio (foreign funding exposure henceforth) to assess their exposure to the sudden stop in foreign funding triggered by the Lehman collapse in 2008Q3. Then I focus the analysis on whether the adjustment in credit risk by branches from banks differentially exposed to the shock varies along the distribution of local income inequality.

Two key characteristics of the empirical setting allow to unravel the size and sign of a risk-taking channel of income inequality. First, by tracing a liquidity shock over two layers of a bank's organizational structure – the headquarters and the municipal branches – I can saturate the model with time-variant bank fixed effects. Thereby the model performs a within-bank estimation, in which branches from the same bank but whose pool of borrowers has a different ex-ante income distribution can be compared over time. Second, the fact that several branches can be traced over the quarterly data within municipalities allows to control for common demand trends and other characteristics within regions.

The results provide robust evidence on the existence of a risk-taking channel of income inequality, which explains a sizeable share of branches' risk shifts when facing a funding shock. The identified effect is not only statistically robust but also economically meaningful, with two standard deviations (SD) more in the Gini index leading to a 1.3 percentage points (pp.) extra shift from high- to low-risk credit, which represents 13 percent of a SD in the credit-risk ratio. This economic effect explains a significant share of the cross-regional differences in branches' adjustment after the shock. Overall this result suggests that the risk-taking channel of inequality can provide a new explanation for the shifts in credit from high- to low-risk borrowers observed in contexts of financial distress.

If collateral constraints explain the main effect, a number of testable predictions can be derived. First, ceteris paribus, the effect should be stronger in regions in which banks tend to historically demand better collateral, presumably due to stronger agency problems. Second, within branches' balance sheets the effect should be stronger for credit segments that are more likely to rely on weaker collateral. For example, commercial and consumer loans should react by more than mortgages. Third, within branch-credit segment 'buckets', risk-shifts should concentrate in credits where loan officers allow borrowers to rely on less liquid collateral when issuing the loan. I find support for these three testable predictions in the sample of 1,330 bank-municipality pairs.

Whether the identified effect matters for macroeconomic outcomes depends on borrowers' capacity to substitute away affected banks' risk shifts. For example, collateral-constrained borrowers may tap liquidity from other banks or from informal sources, so that the effect on aggregate outcomes becomes negligible. However, estimations at the municipal level of aggregation show that this is unlikely to be the case: regions with higher inequality face in the aggregate a significant increase in risk shifts from high- to low-risk credit, which translates into a weaker growth rate in total consumption. Notably, this latter consequence is absent in regions where households in the top 80 percentile of the income distribution are relatively 'poor' in the cross-section of municipalities. This result suggests that the identified risk shift is more harmful for consumption when capital is reallocated into agents with a lower marginal propensity to consume.

This latter finding provides a novel explanation for the moderate growth rate of consumption observed after major financial shocks (see, e.g., Onaran et al., 2011, Carvalho and Rezai, 2016, Cynamon and Fazzari, 2016). This study highlights that usual explanations related to credit deleveraging such as in Mian et al. (2013) may hide a previously unexplored interaction between income inequality and financial frictions that fuels the direction and size of capital reallocation during a period of financial distress.

This paper is mainly related with strands in the literature exploring the linkages between inequality and finance, and the implications of collateral constraints in banking. A large literature aimed at exploring an inequality-finance nexus. Most of these studies focus though on the effect of finance on income or wealth inequality, looking at aspects such as financial development from a cross-country perspective (see, e.g., Demirgüç-Kunt and Levine, 2009, Beck et al., 2010, for a review). Closer to this paper are studies investigating whether inequality affects macroeconomic outcomes via its effect on the financial system. Political economy narratives, as in Rajan (2009) or Degryse et al. (2018), suggest, for instance, that wealthy elites may repress financial development as a rent preservation device, affecting economic growth. Other studies explore whether inequality affects financial crises' run-up by leading poor households to borrow more.[1] This paper extends this literature by providing first evidence linking inequality with credit risk shifts at the bank level.

Several studies have investigated the determinants of collateral constraints when borrowers face limitations to pledge future cash flows (see, e.g., Kerr and Nanda, 2009). These studies

[1] Kumhof et al. (2015) study for instance crisis periods across the XX century and present a theoretical model in which higher inequality increases leverage by poor households, affecting the occurrence of crises. Iacoviello (2008) also links increases in inequality with household debt and the business cycle. This view has been recently challenged by Coibion et al. (2016) who use micro data to show that higher inequality may increase credit rationing against poorer households.

identify factors such as firms' size (Banerjee and Duflo, 2014) or credit limit constraints (Khwaja et al., 2010) as drivers of borrowers' constraints. Closer to this article are recent studies by Braggion et al. (2015, 2018) using US data to investigate whether inequality affects the structure of the banking sector (i.e. number of branches) at the MSA level. The authors suggest that wealthy elites may limit the development of local capital markets, exacerbating the effect of collateral constraints. In opposite to these papers my approach does not require taking a particular stance on regional-level proxies for collateral constraints, as I can directly trace over time changes in branches' risk exposure within buckets of their credit portfolio with different underlying collateral. Moreover, the within-bank estimation I perform allows me to isolate a risk-taking channel of inequality previously unexplored in this literature.[2]

As my empirical setting traces liquidity shocks across bank branches, I also contribute to a growing literature exploring internal capital markets and (sub-national) financial market integration as a channel that propagates liquidity risk. While most of these studies use regional banking data for the US (see, e.g., Gilje et al., 2016, Cortés and Strahan, 2017, Dursun-de Neef, 2018, or Levine et al., 2018), a few papers have use Brazilian data to explore the transmission of productivity shocks (Bustos et al., 2016) and liquidity dry-ups (see, e.g., Coleman and Feler, 2015 or Noth and Ossandon Busch, 2017) to municipal bank branches.

The remainder of the paper proceeds as follows. Section 2 describes the institutional background and the nature of the financial shock that affected Colombia in 2008. Section 3 presents the identification strategy, describe the data and reports benchmark results. Section 4 explores the role of collateral constraints. Section 5 reports regional-level estimates of credit risk and consumption. Section 6 report a robustness analysis and Section 7 concludes.

[2]My focus on branches' risk taking also links this work with a broader literature studying the determinants and consequences of risk-taking channels at the bank level. Since the seminal study by Borio and Zhu (2012), other studies have looked at the effect of monetary policy, bank leverage, and government guarantees as drivers of banks' risk attitudes, mostly in the US (see, e.g., Dell'Ariccia et al., 2017, Cordella et al., 2017). My focus on inequality extends this literature by unravelling a different mechanism of banks' risk taking.

2 Background & stylised facts

2.1 Macroeconomic background

This section describes the macroeconomic situation in Colombia in the run-up to the 2008-2009 global financial crisis and the subsequent foreign funding shock. Important for my empirical setting is that the crisis hit Colombia in a context of relatively strong economy growth: in 2006 and 2007 the GDP had grown by an average of 7 percent per year, 2 pp. above the overall GDP expansion in Latin America. The credit market accompanied this expansion with year-on-year increases in outstanding credit of around 18 percent between 2006 and 2007. As many Latin American countries, Colombia had experienced major reforms to financial markets' institutions throughout the 1990s, moving to a framework with an independent central bank following an inflation-targeting rule and a floating exchange rate.[3]

The crisis affected Colombia via three main channels: a drop in exports (10 percent), in remittances (20 percent), and in total cross-border debt (28 percent).[4] A sound pre-crisis fiscal and financial situation allowed authorities to react to increasing pressures with expansionary monetary and fiscal interventions. The central bank decreased the monetary policy rate from 10 to 3.5 percent between 2008 and 2009, while government spending rose by 6 percent in 2009 in the backdrop of a GDP expansion of only 1.2 percent. Notably, Colombia did not experience an economic recession during the crisis, despite of experiencing only moderate growth rates in 2008 and 2009. By the end of 2010 the traces of the crisis were vanished, with the economy expanding by 5.4 percent on annual basis. These numbers depict a situation of an overall sound economy affected by a major external shock.

2.2 Stylised facts on the capital flows reversal

The events that followed the collapse of Lehman Brothers in September 2008 led to a sudden reversal in banks' available foreign funding, resulting in a major loss in available liquidity. For an average bank, the peak-to-trough drop in foreign funding accounted for 9 percent

[3]The impact of these reforms can be illustrated by the long term trend followed by domestic interest rates. For instance the monetary policy rate moved from numbers above 40 percent in the middle of the 1990s to 7 percent in 2007.

[4]Annual variation between 2007 and 2009. These numbers are computed from the IMF International Financial Statistics, the Colombian Central Bank, and the BIS Locational Banking Statistics.

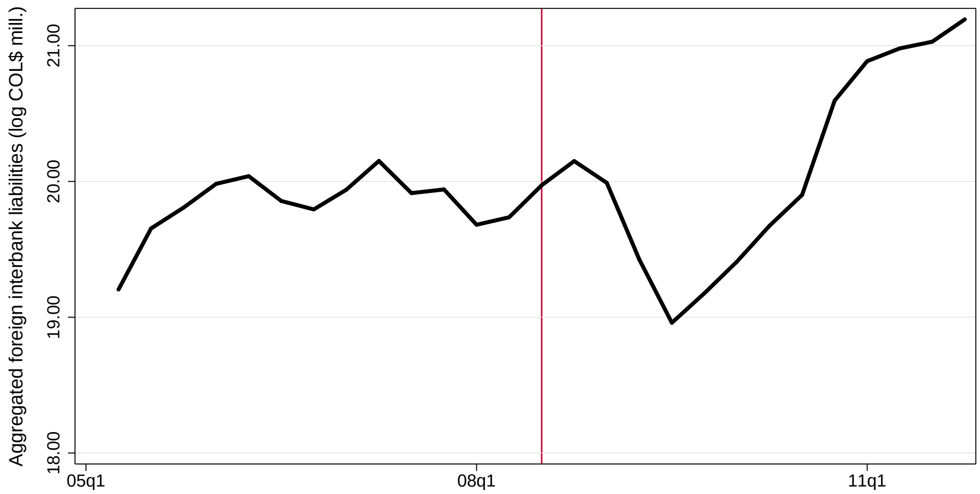

Figure 1 Foreign interbank funding by Colombian banks

Notes: Author's elaboration based on data from the Colombian Banking Authority (SFC). The graph depicts the log of aggregate foreign interbank liabilities reported in Colombian banks' balance sheets. The vertical line is set at 2008Q2, the last quarter before the outbreak of the crisis.

of pre-crisis total assets, representing the largest drop across banks' liabilities around the crisis. In contrast, the only moderate effect of the crisis on aggregate output implied that deposits still grew at an average annual rate of 3.7 percent during the same period. The importance of this shock is illustrated in Figure 1, which depicts the evolution of aggregate foreign interbank liabilities from 2005 to 2012. After remaining at stable levels in the crisis' run-up, the volume of foreign debt plunged in the fourth quarter of 2008, reaching its lowest level in the third quarter of 2009. This period coincides with the one where traces of the crisis can be found in the main macroeconomic indicators in Colombia. Foreign funding experienced then a rebound beginning in 2010, fuelled by the global recovery phase and by a search for yield in international capital markets.

Did this shock matter for the performance of the Colombian banking system? At least the 'big picture' of banks' adjustment to the crisis seems to support the notion this was indeed the case. While aggregate credit volumes increased on an annual basis by 6.9 percent on average before 2008, during the crisis (2008-2009) this number plunged to only 2.2 percent. Credit risk shooted up rapidly, with the credit-risk ratio almost doubling from 4 to 8 percent between 2007 and the height of the crisis. This latter effect reflects two forces at work. First, with higher cost of funding and a weakening aggregate demand firms and households found it difficult to roll-over existent debt, delaying interest payments during the crisis. Second, on the supply side a perceived fear of liquidity risk and decreasing returns on credit may have incentivized a riskier credit supply, especially at the outbreak of the crisis when its consequences for the Colombian economy were still unclear (see Figure A.2 in the Appendix).

Notably, a relevant heterogeneity in this risk-adjustment across banks can be observed in the data: while banks with a higher ex-ante exposure to foreign funding (above the median) reported an average increase in the credit-risk ratio of only 0.1 pp., for other banks the increase was of 0.6 pp. This differential adjustment may reflect that banks' directly exposed to the shock tended to shift risk towards safer borrowers, whereas other banks may have seized the opportunity in a 'gambling for profits' fashion to gain market power.

3 Identification, data & benchmark results

3.1 Identification

The objective of this article is to provide a causal estimate of the effect of income inequality on the extend of banks' risk-taking adjustment following a large liquidity shock. For expositional purposes, the identification strategy can be divided into three main dimensions of analysis: an exogenous event that provides a quasi-experimental setting in which banks are suddenly faced with a disruption in their established funding sources; a mechanism to disentangle the effect of inequality from other local conditions; and a mechanism to disentangle the potential supply-driven adjustment in credit risk from demand factors. In what follows, I briefly explain these identification steps.

While in theory we could analyse the role of inequality in banking in any period and without the need of an external shock (as for example in Braggion et al., 2015), capturing the effect of frictions related to collateral constraints is more feasible in a setting in which banks are exogenously moved towards credit risk shifts. Under normal conditions, collateral constraints are likely not to be binding, so that any correlation between inequality and banks' risk could be driven by other structural characteristics correlated with inequality but not affecting directly borrowers capacity to pledge cash flows. An unanticipated and large liquidity shock, on the contrary, allows to compare bank risk before and after the event, so that risk shifts can be traced over a period in which underlying frictions become binding. I therefore follow Khwaja et al. (2010) in using an external shock to make the constraints under study 'visible'.

To partial out periods where we would expect collateral constraints to be differentially binding, I follow a body of literature (see, e.g., Aiyar, 2012, Ongena et al., 2015, Dursun-de Neef, 2018) that has used the collapse in Lehman Brother in 2008 as an unanticipated and exogenous shock to banks' foreign interbank funding to investigate the consequences of the crisis. To reduce further reverse-causality concerns I measure banks' exposure to the crisis by their pre-crisis ratio of foreign interbank liabilities to total assets. While the analysis below uses 2008Q3 as the cut-off point between pre-crisis and crisis periods in the quarterly data, I also explore alternative definitions for the crisis period in Section 6.

Two forces explain the importance of foreign funding as a transmission channel of the crisis. First, the largest portion of cross-border claims vis-á-vis Colombian banks originated in the US (87 percent according to BIS data as of 2007), opening a cross-country liquidity-risk transmission channel well documented in the literature (see, e.g., Buch and Goldberg, 2015, for a review). Second, being Colombia a relatively open economy, affected banks held a large portion of foreign funding in their balance sheets: the average bank reported a ratio of 6 percent of foreign funding to total assets before 2008Q3, funding approximately 10 percent of its credit portfolio with this source.[5]

The core of the identification strategy relies on separating banks' balance sheets between their core (i.e. headquarters) and their municipal branches distributed throughout Colombia. This setting represents an important departure from previous attempts to empirically link inequality with financial frictions (Braggion et al., 2018). First, I exploit this feature in the data to implement a within-bank estimation saturating a difference-in-difference model with bank-time fixed effects. This procedure reduces concerns that inequality or the risk-adjustment itself may be affecting in a reverse-causality fashion banks' demand for foreign funding during the crisis. This approach focus the comparison across branches of a given affected bank, which lend to pools of borrowers that differ in their income distribution.

The matched bank-branch structure also matters to partial out a supply-driven adjustment in credit risk from demand-driven effects. To this regard two dimensions of demand confounders should be considered. First, local economic conditions may affect the demand

[5]Even though the reported shock could partially reflect banks' own reduction in foreign funding demand, two reasons should reduce concerns that this is the case. First, exposed banks never fully halted foreign funding during the crisis. Second, by the third quarter of 2009 the economy was already back in a strong growing path. This latter adjustment in expectations should have made banks increase their demand for external funding.

for credit if, for example, unemployment increases. Second, even keeping the overall economic conditions in the economy constant, the inequality channel I seek to unravel can also operate via demand: borrowers below a certain moment of the income distribution may react to economic conditions differently, leading to diverging demand trends in two regions sharing the same overall economic performance but differing in terms of income distribution. I address these concerns by saturating the econometric model with municipality-time fixed effects, which capture common demand shocks to branches in a given region, that are themselves differentially exposed to the shock via their headquarters banks.

With these considerations in mind, I estimate the following empirical model, where the dependent variable $Crisk_{i,m,t}$ is defined as the quarterly credit-risk ratio[6] in a branches' balance sheet:

$$
\begin{aligned}
Crisk_{i,m,t} = &\alpha + \beta_1 \left[Exposure_i^{<08} \times Shock_t \times Ineq_m^{05}\right] + \\
&\beta' Bank_{i,m,t-1} + \mu_{m,t} + \gamma_{i,t} + \varepsilon_{i,m,t}
\end{aligned} \tag{1}
$$

Eq. (1) represents a panel at the bank i, municipality m, and quarter t level. The main variable of interest is a triple-interaction term between banks' pre-crisis foreign funding to assets ratio ($Exposure_i^{<08}$), a time-variant dummy variable equal to 1 in the period after 2008Q2 ($Shock_t$), and a pre-crisis measure of income inequality ($Ineq_m^{05}$). The variable $Exposure_i^{<08}$ is computed as an average of the pre-crisis period, between 2005Q1 and 2008Q2. $Ineq_m^{05}$ measures income inequality as the Gini index at the municipal level as of 2005. The overall sample period ranges between 2005Q1 to 2009Q4. I winsorize all variables in Eq. (1) at the 1st and 99th percentiles.

The identification is sustained in the simultaneous inclusion of municipality-quarter ($\mu_{m,t}$) and bank-quarter ($\gamma_{i,t}$) fixed effects in a difference-in-difference setting estimated at the branch level. I purposefully exclude other constitutional terms of the triple-interaction as they become absorbed by the fixed-effects structure. Eq. (1) includes a vector of bank and branch control variables $Bank_{i,m,t}$, although specifications with the full set of fixed effects also control for time-varying factors at the bank level. These controls enter the model with a one quarter lag to reduce endogeneity concerns. In the main specification I cluster standard

[6]The credit-risk ratio is computed as the ratio of non-A to total credit as defined by credit risk categories of the Colombian Banking Authority (SFC). See definition in Section 3.2.

errors (se) at the bank and quarter level (in Section 6 alternative cluster options are tested.).[7]

If a more unequal distribution of income lead branches to shift more credit towards low-risk borrowers, we would expect β_1 to have a negative sign. This result could be interpreted as evidence that branches whose parent banks are more exposed to the shock reduce the share of their high-risk credit by more than other banks, and that they do so to a larger extent in regions with an unequal distribution of income.

It should be noted that this narrative may also hold for the case of wealth instead of income inequality, which would put the focus on the stock of collaterizable assets. Even though my choice of income inequality is restricted by the available data, this approach prevents problems of assets' under-reporting. Also, informality may lead valuable assets not to be properly recorded.[8] The focus on income inequality also follows previous studies linking inequality with financial markets' performance (see, e.g., Larraín, 2015, Azzimonti et al., 2014) and is likely to provide rather conservative estimates of the effect of inequality on credit, as wealth inequality tends to be larger than income inequality in cross-country comparisons (see, e.g., Balestra and Tonkin, 2018).

3.2 Data & sampling procedure

I fill the empirical model represented by Eq. (1) with a dataset that combines three main types of information: balance sheet data at the bank level, a registry of credit and deposits at the bank-municipality level (i.e. bank branch), and newly constructed expenditure data at the household-municipality level.[9] These sources can be described as follows.

I use data from the regulatory register 'Financial Statements of the Monitored Entities' reported by the Colombian Regulatory Authority (or *Superintendencia Financiera de Colombia*, SFC). The SFC publishes on a quarterly basis a summary of banks' balance sheets and

[7]Following conventional use in the empirical banking literature, the regressions control at the bank level for the log of total assets, the capital-to-assets ratio, the liquid-to-total assets ratio, banks' RoA, a ratio of administrative costs to assets, and an NPL rario. At the branch level the regressions control for the log of total assets, their share in the banking group's total assets, and the ratio of liquid to total deposits, where the latter ones refer to current account, interbank, and term deposits. All variables with their corresponding sources are defined in Table A.6

[8]In Colombia a large share of the labour market was reported as informal before 2008. Official reports from the DANE suggest that around 52 percent of the working age population was informally employed as of 2006. This share did not significantly change in the subsequent years (see DANE, 2019).

[9]It should be noted that all the data in this article stems from open administrative registers available for the public, ensuring the possibility to replicate the results.

income statements at the bank-country level. While some variables such as credit and deposit are aggregated from each bank's regional units, other variables such as capital and foreign funding represent only the balance sheet of the core of the bank (i.e. headquarters), as both capital and foreign funding activities are conducted in a centralized fashion. To ensure the comparability of the different sources, I transformed all variables to millions of (current) Colombian Pesos (henceforth COL$). Foreign funding – a variable obtained from this source – is defined by the SFC as 'foreign credit from other financial institutions'.

Using a manually computed identifier, I match the balance sheet data for banks with the corresponding credit and deposit balances reported at the municipality level. For this purpose I use data from the regulatory register 'Deposits and Loans by Municipality' (henceforth DLM), that contains similar balance sheets positions as the ones reported at the national level. It should be noted that these data contains information aggregated at the municipal level. I therefore refer henceforth to 'branches' as an aggregated municipal entity that may represent the banking activity of different offices of a bank within a municipality. Hereby I follow similar approaches as for instance by Coleman and Feler (2015) or Bustos et al. (2016). While these data is reported by banks to the SFC on a quarterly basis, the information is made public by the National Administrative Statistical Department of Colombia (or *Departamento Administrativo Nacional de Estadistica*, DANE).

The DLM data provides a useful tool to trace banks' risk-taking over time. This source records detailed information of branches' credit portfolio with disaggregation by credit type, risk category, and quality of the underlying collateral. Outstanding balances for each out of 4 credit types are reported by risk category. Credit types include commercial, consumer, housing and micro-credit. The SFC imposes banks a reporting standard that divides each credit type into risk categories – ranging from A to E – reflecting the probability of loans becoming non-performing. The risk assessment, which changes over the life-cycle of a loan, is determined by the loan officer.[10] Officers are also required to report the quality of loans' collateral, which is either 'acceptable' (i.e. below the bar of an ideal collateral) or 'normal'. Whereas no strict rules exist to determine a threshold, the definition depends crucially on how liquid the underlying collateral is and with which certainty it can be liquidated in short

[10] In this categorization, type E represents a non-performing loan. Categories B to D represent loans that are still being repaid but where the loan officer considers that the probability of repayment has changed. The categories are defined by the SFC as follows. B credits report an acceptable but higher than normal risk of non-repayment, given uncertainty about the borrower's financial situation. C credits are the ones with a medium to high probability of default, formally an 'appreciable risk'. D credits are the ones reporting a 'significant' risk, which occurs in cases where certain components of the loan contract are violated.

notice.

The third pillar of the database are measures of income inequality at the municipal level. Given the non-existence of inequality measures at this subregional level, I use the Small Area Estimation (SAE) approach (Elbers et al., 2003) to simulate proxies for income inequality in each municipality. This procedure requires combining income surveys (typically representative at the county/federal state level) with census data covering the whole population of each municipality. The intuition of this approach is to match households' observable characteristics in both datasets that can be empirically linked to household per capita income. I follow similar applications of the SAE approach (see, e.g., Tarozzi and Deaton, 2009, Enamorado et al., 2016) and use information from the Colombian 2003 National Life Quality Survey (*Encuesta Nacional de Calidad de Vida*, ENCV) and from the Colombian 2005 Census (*Censo General de 2005*) to perform this simulation. While the micro-data for the ENCV is publicly available from the DANE, the micro-data for the census is regrettably not publicly available. I therefore use a sample of the census representative at the municipal level provided by IMPUS International.[11]

I implement the SAE approach as follows. First, I identify observable variables reported both in the ENCV and the census that have a similar distribution and can potentially explain the expenditure per capita in the data.[12] Second, I run so called 'consumption models' at the state level using the ENCV. These (OLS) estimations regress total expenditure per capita (observed at the household level) on a large set of explanatory variables.[13] Third, I run Monte Carlo simulations that extract the coefficients from the consumer models to impute a given expenditure per capital to each household in the census data. This latter variable is finally used to compute a Gini index per municipality.[14]

[11]The census data is reported at the household level for an harmonized group of municipalities that keeps constant the municipal borders throughout the years. I therefore collapse the 827 municipalities in 29 states ('departamentos') in Colombia where some banking activity is reported into 458 municipalities in 23 states. This approach, even though conditioned by the available data, has the advantage that combines regions historically similar and reduces concerns of changes in administrative boundaries affecting the analysis.

[12]In particular, I identify variables in which the sample mean is statistically equivalent to the population mean.

[13]The coefficients obtained from these estimations cannot be economically interpreted due to their potential endogeneity. Still, if their inclusion can reduce the error term in the model including these variables improves the precision of the simulations run afterwards. The variables included cover information on households' socio-demographic traits, living standards, and dwelling characteristics.

[14]Note that the use of household expenditure to proxy for income has the advantage of providing a more comprehensive picture of borrowers' available income, as the informal labour market would not be represented by administrative wage records. The importance of informal labour markets in Colombia has been widely documented in the literature and in local policy debates (see, e.g., Bernal, 2009).

Table 1 DESCRIPTIVE STATISTICS

					Exposure:		
	Mean	**S.d.**	**Min.**	**Max.**	**Large**	**Low**	**Diff.**
	I	II	III	IV	V	VI	VII
Dependent variables:							
Credit-risk ratio	0.10	0.09	0.00	0.50	0.09	0.10	0.01
Foreign funding / Total assets	0.05	0.04	0.00	0.14	0.09	0.02	-0.07
Gini index	0.58	0.04	0.31	0.66	0.57	0.58	0.00
Headquarters controls:							
Size (log assets)	16.51	1.13	11.64	19.41	16.21	15.93	-0.28
Capital / Total assets	0.13	0.06	0.05	0.92	0.12	0.09	-0.03*
Liquidity / Total assets	0.06	0.02	0.01	0.55	0.05	0.05	0.00
Deposits / Total assets	0.65	0.13	0.00	0.89	0.68	0.72	0.04*
RoA	0.01	0.01	-0.05	0.04	0.01	0.01	0.00
Adm. Cost / Total assets	0.28	0.10	0.02	5.69	0.30	0.34	0.04*
NPL / Credit	0.05	0.02	0.00	0.57	0.05	0.05	0.01
Branch controls:							
Size (log assets)	9.59	2.09	0.00	16.98	9.05	9.10	0.05
Ratio of liq. deposits	0.73	0.23	0.01	1	0.71	0.73	0.02
Share in bank assets	0.02	0.07	0.00	0.82	0.02	0.02	0.00

NOTES: This table reports the summary statistics for our working sample. While the first four columns report the mean, the standard deviation (S.d.), the minimum and the maximum value for each variable for the entire sample period, the next two columns report the mean of each variable for the group of affected and non-affected branches separately in the pre-shock period. The final column reports the difference in means between the control group (non-affected) and affected branches. Employing the normalized difference in means method of (Imbens and Wooldridge, 2009), * denotes whether the respective difference is statistically significant.

After matching the inequality and banking data I impose a number of filters aimed at fulfilling the identification requirements of Eq. (1). This sampling procedure is as follows. I start from a raw dataset containing information on 35 banks operating in 428 municipalities between 2005 and 2009, adding a total of 2,207 bank-municipality pairs. I then keep only branches operating 'around the crisis', that is, those reporting at least some activity both before and after the cut-off point in 2008Q3. As a second filter, I focus only on municipalities hosting branches from at least 2 different banks. This filter allows saturating Eq. (1) with municipality-time fixed effects. This procedure results in a final sample of 20 banks operating in 237 municipalities (1,330 bank-municipality pairs). Despite the observation loss, the analysis still covers an average of 78.2 percent of total credit in Colombia over the sample period.

Table 1 reports descriptive statistics for the final sample. To shed light on possible systemic sorting between banks affected and not by the foreign funding shock, the table also reports the pre-crisis average for each variable for banks below and above the sample median of the pre-crisis foreign funding exposure (columns V and VI). Column VII reports the differences in means between these groups of banks. Statistically significant differences according to a test of normalized differences (Imbens and Wooldridge, 2009) are marked with a *.

This descriptive analysis shows that more exposed banks were on average ex-ante more capitalized (3 pp. higher capital ratio), had a smaller deposit share (4 pp.), and were slightly more efficient in terms of the ratio of administrative cost to assets (4 pp. lower). Banks from these two groups do not differ in terms of other observable characteristics. Notably, these differences emerge only in bank-level variables, whereas no statistically significant differences can be found at the level of branches. To the extent that Eq. (1) includes bank-time fixed effects, these differences should not be a reason for major concerns.[15]

3.3 Benchmark results

Table 2 reports the benchmark results from estimating Eq. (1). The evidence reported in the table is consistent with the notion that affected banks shift credit to low-risk borrowers in regions with higher income inequality. Empirically, the risk shift is interpreted out of the triple interaction term on the top line of Table 2, which reports throughout all specifications a negative and statistically significant sign. This means that affected bank branches report after the cut-off point (2008Q3) a stronger decrease in the credit-risk ratio compared to other banks in regions with higher values of the Gini index.

Column I in Table 2 shows the results of a plain estimation focusing on average differences between branches differentially exposed to the shock. This regression shows that in an average municipality affected branches tend to take on more risk. A supply-driven interpretation of this result would be in line with risk-shifting models in financial intermediation. To this

[15]Table 1 additionally tests for a potential violation of the parallel trend assumption during the pre-crisis period. This assumption is important in difference-in-difference models as they require the dependent variable to be in a parallel trajectory between groups of entities differentially exposed to a 'treatment'. Table 1 shows that the credit-risk ratio (the dependent variable in Eq. (1) does not significantly differ between both groups of banks before the crisis.

Table 2 RESULTS – BENCHMARK ESTIMATION

Dep. var:	**Credit-risk ratio**				
	I	**II**	**III**	**IV**	**V**
Shock x Exposure x Ineq		-2.400***	-2.300***	-2.162***	-2.066***
		(0.558)	(0.546)	(0.471)	(0.461)
Shock x Exposure	0.212**	0.870***	0.892***		
	(0.102)	(0.180)	(0.171)		
Shock x Ineq		0.024	0.018	0.076**	
		(0.040)	(0.041)	(0.033)	
Exposure x Ineq		1.265***	1.111***		
		(0.349)	(0.331)		
Controls	No	No	Yes	Yes	Yes
Branch FE	No	No	No	Yes	Yes
Bank x Time FE	No	No	No	Yes	Yes
Region x Time FE	No	No	No	No	Yes
Obs.	21078	20728	20464	20412	20338
R-squared	0.026	0.028	0.082	0.625	0.724

NOTES: This table reports the empirical results of the baseline estimation (see: Eq. (1)). The variable of interest is the triple interaction term represented by $[Exposure_i^{<08} \times Shock_t \times Ineq_m^{05}]$. While Column I reports the results when including only an interaction between $Shock_t$ and $Exposure_i^{<08}$, the subsequent columns include the triple differences term of interest (II), further control variables (III), branch and bank-time FE (IV), and municipality-time FE (V). Given that ordinary time and municipality fixed effects are nested in the municipality-time fixed effects, these terms are not additional included in the model. For all equations, I cluster se. at the headquarters and quarter level. ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

regard, the pressure of the liquidity shock can lead to distorted financial risk-taking incentives (see, e.g., Keeley, 1990), via exacerbated agency problems.

Column II reports a baseline specification with the triple interaction term of interest but excluding any other control variable or fixed effect. Interestingly, we see a flip in the coefficient pinned down in the plain regression from Column I: in regions with a larger Gini coefficient, affected branches shift a larger portion of their credit portfolio towards low-risk borrowers as compared to their peers. That is, if we hypothetically shift a unit of income from poor to rich borrowers, banks providing credit to this pool of borrowers will shift their credit supply towards borrowers with a higher creditworthiness if facing a liquidity shock. Columns III and IV add a set of bank and branch level control variables and a first fixed-effect specification including branch (i.e. bank-municipality) and bank-time fixed effects. This model further tightens the specification by absorbing potential bank and branch time-variant confounders. The inclusion of time fixed effects also absorbs country-level macroeconomic trends (i.e. currency devaluations, aggregate demand, changes in expectations). Despite of these controls, the estimated coefficient of interest remains unaltered.

Finally, Column V reports the benchmark specification of Eq. (1) adding municipality-time fixed effects. This model follows recent studies relying on a similar data structure (e.g., Bustos et al., 2016, Dursun-de Neef, 2018) in absorbing municipality-specific trends affecting all branches operating in that market. These 'common shocks' can then be ruled out as drivers of the estimation. Most importantly, this estimation departs from previous studies in combining this type of 'within borrowing region estimation' with a 'within bank estimation' that controls for trends at the bank level. It is reassuring to see that the coefficient of interest remains fairly stable throughout the specifications. While the estimation assumes that demand shocks are homogeneously distributed across branches and within municipalities, the evidence from Table 2 suggests that this assumption should not be a source of major concern: demand-driven effects that artificially inflate the coefficient of interest should show-up in the estimation as differences in the estimated β_1 coefficient between columns IV and V, with the latter one being significantly larger. The fact that these two coefficients are fairly similar suggests that demand considerations do not play a major role.

How large are the magnitudes of this risk-taking channel of inequality? To illustrate the result consider a region with a Gini index one SD below the average (0.53). Here, an affected branch would have reported a 9.2 pp. larger decrease in the credit-risk ratio compared to a low affected bank. On the contrary, in a region with a large Gini (1 SD above the average) this differential adjustment would have been of 10.5 pp. Hence, increasing the Gini index by 2 SD leads to a 1.3 pp. larger differential adjustment in the credit-risk ratio between affected and not-affected banks. This differential effect is economically sizeable when compared to the SD of the dependent variable (10.5 pp.).[16] These benchmark results are unaltered when considering a number of alternative specifications and robustness checks, described in detail in Section 6.

[16]Large and low affected banks are defined for this exercise as those with a foreign funding exposure 1 SD above and below the average, respectively.

4 Inequality and collateral constraints

The results in Section 3.3 say little about the underlying mechanism linking the distribution of income with branches' risk taking. Exploring the mechanism in place is important as the results are by no means obvious, as larger funding pressures may well lead banks to increase the riskiness of their credit portfolio, not to reduce it. In this section I exploit the rich structure in the data to unravel whether financial frictions in the form of collateral constraints drive the benchmark findings. In exploring this hypothesis I build on a large body of literature discussing how income distribution can have macroeconomic impacts provided that credit market frictions exist, as it has been discussed by Piketty (1997) and more recently by Blaum (2012) or Coibion et al. (2016).

I approach this question by tracing the role of collateral constraints over three distinct dimensions. First, in a cross-regional check I test whether the findings vary across municipalities in which banks have (ex-ante) higher collateral requirements. Second, I look whether credit types more reliant on collateral, such as commercial or consumer loans, report a different risk shift as compared to mortgage or micro-credit loans. Finally, I use within-credit type sample splits according to the quality of loans' underlying collateral to explicitly check whether a better collateral shields portions of branches' credit portfolio from risk shifts.

4.1 Cross-regional collateral reliance

I first implement a test at the regional level to search for traces of collateral constraints in the benchmark results. For this purpose I split the sample of municipalities according the the median of the average pre-crisis ratio of credit with 'normal' (i.e. good quality) collateral to total credit. This variable is aggregated at the municipality level by adding-up branches' positions in their portfolio of consumer and commercial loans. I exclude mortgages and micro-credits as in these segments no collateral split is provided given the specific nature of these loans. In an average municipality 44.6 percent of credit (commercial + consumer) is reported with collateral that, following a loan officer's assessment, can be liquidated in short notice.

I replicate Eq. (1) separately for the subsamples of municipalities below and above the median. The results are reported in Panel A in Table 3. Considering potential concerns with the sample split procedure, I report results both with and without the preferred municipality-time fixed effects structure. Column I replicates for comparison the benchmark specification from Table 2, Column V. A consistent pattern emerges: while the benchmark result is confirmed with a fairly stable size for the group of municipalities above the threshold, it does not longer hold for municipalities below the threshold (those with less strict collateral requirements). This finding shows that banks exposed to stronger agency frictions – and therefore requiring more high-quality collateral – are more sensible to the risk-taking channel documented in the previous section.

4.2 Cross-credit type collateral reliance

Within branches, the effect of collateral could be visualized also in the cross-section of credit types differentially exposed to agency frictions. To test for this hypothesis, I run separate regressions estimating Eq. (1) for specific credit segments, namely, commercial, consumer, mortgage, and micro-credit loans. Since the underlying panel structure remains unaltered, this estimation can be performed using the preferred setting with municipality- and bank-time fixed effects. These loans are likely to expose banks to different risks. For example, given the fact that Colombia did not experience a housing price shock during 2008-2009, mortgage lending remained a relatively safe activity linked to valuable collateral. Micro-credits in general tend not to require high value collateral, as they typically represent credits of small volumes. On the contrary, both consumer and commercial loans rely to a larger extent on collateral whose value became arguably difficult to asses during the crisis.

Panel B in Table 3 shows the results for the four credit types in which branches' credit portfolio can be divided. Again, the first column replicates the benchmark results from Table 2, Column V. Columns II to V report the results for commercial, consumer, mortgage, and micro-credit loans, respectively. The results are consistent with the idea that credit types that expose banks to higher agency frictions – implying that borrowers face stronger collateral constraints – are the ones explaining the results. In fact, when estimating Eq. (1) for mortgages or micro-credit I cannot longer find evidence of risk shifts towards low-risk borrowers in regions with a more unequal income distribution. Hence, I interpret this result as evidence that even within a given affected branch, the reallocation of risk occurs differentially depending on the exposure of credit segments to agency risks.

Table 3 RESULTS – INEQUALITY AND COLLATERAL CONSTRAINTS

Panel A		Share good collateral:		Share good collateral:	
		High	Low	High	Low
	I	II	III	IV	V
Shock x Exposure x Ineq	-2.074***	-2.984***	-1.065	-2.967***	-1.071
	(0.460)	(0.553)	(0.653)	(0.654)	(0.664)
Region x Time FE	Yes	No	No	Yes	Yes
Obs.	20338	10436	9964	10364	9962
R-squared	0.724	0.608	0.662	0.746	0.714

Panel B					
Credit type:	All	Com.	Cons.	Mortg.	Micro
	I	II	III	IV	V
Shock x Exposure x Ineq	-2.066***	-1.879***	-2.161***	-1.466	0.030
	(0.461)	(0.678)	(0.447)	(1.813)	(1.412)
Obs.	20338	20261	20319	13793	15784
R-squared	0.724	0.658	0.718	0.849	0.685

Panel C		Reported quality of collateral:		Reported quality of collateral:	
		Good	Normal	Good	Normal
Credit type:	All	Cons.	Cons.	Com.	Com.
	I	II	III	IV	V
Shock x Exposure x Ineq	-3.297***	-3.856***	-4.662***	-1.041	-0.963*
	(0.877)	(0.914)	(1.691)	(1.204)	(0.607)
Obs.	19661	19669	19513	18621	18621
R-squared	0.640	0.618	0.675	0.555	0.649

NOTES: This table reports different estimations of Eq. (1). Panel A splits the sample according to the municipaliy-level share of good collateral before 2008Q3. Panel B runs separare regressions for commercial (Com.), consumer (Cons.), mortgages (Mortg.), and microcredit (Micro) loans. Panel C estimates separate regressions for commercial and consumer credits with good and normal collateral. Fixed-effects are at the municipality-time and branch level if not stated otherwise. Se. are clustered at the bank-time level. ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

4.3 Within-credit type collateral reliance

Even though the previous tests are suggestive of a direct link between the benchmark results and underlying collateral constraints, still the actual quality of collateral remains unobserved. Therefore, a third approach consist in exploiting the collateral-quality disaggregation of branches' credit to test whether the effect is stronger in loans backed by weaker collateral. Importantly, I implement this test within branches' credit segments, the level at which I can trace portions of the credit portfolio with different quality of collateral. Therefore, for both commercial and consumer loans I separately compute the credit-risk ratio for credits with 'good' and 'normal' collateral as defined above. Then, I replicate Eq. 1 in four 'buckets' of branches' credit portfolio: commercial and consumer loans, both with good and normal collateral. I focus on commercial and consumer loans as the analysis above highlights that these categories are the ones driving the results.

The results are reported in Panel C in Table 3, where Column I replicates the benchmark result from Table 2, Column V. Interestingly, the case of consumer credit reported in Columns II and III shows that Eq. (1) delivers statistically significant results for the risk-taking channel of inequality for both subsamples with good and normal collateral, respectively. However, a closer analysis of the estimated magnitudes indicate that the effect is economically larger for loans with normal collateral. Hence, the quality of collateral affects the intensive margin of the risk-shift effect. Columns IV and V depict a slightly different picture for commercial loans. Whereas the effect remains in place for commercial loans with normal collateral, the triple-differences term becomes statistically insignificant for loans with good collateral.[17]

The results reported in this section provide compelling evidence that collateral constraints and agency problems matter when explaining the empirical findings from the benchmark estimation. The three dimensions of analysis deliver consistent estimates in line with a narrative in which agency frictions lead banks to shift credit towards safer agents in more unequal regions. Consistent with this argument, the effect does not hold when banks are less strict in their demand for collateral.

[17] An unreported T-test confirms that the results in Cols. IV and V are not statistically significantly different from each other.

5 Risk reallocation and aggregate consumption

The branch-level results provide evidence on differential risk-shifts – even in the cross-section of branches within banks – triggered by income inequality. This conclusion does not mean, however, that aggregate effects for the local economies in which branches operate exist. If borrowers can substitute credit across banks, risk-shifts by one institution may not have implications for the aggregate economy.

A natural question is therefore whether municipality-level estimates can shed light on the macroeconomic dimension – at a subnational level – of the documented risk-taking channel of income inequality. Moreover, if substitution is limited so that risk shifts can be even verified in aggregate credit, the question remains whether the reallocation of capital to low-risk borrowers affects aggregate consumption. Assuming that low-risk borrowers are likely to represent households in the upper part of the income distribution, one could conjecture that capital is being reallocated towards agents with a lower marginal propensity to consume. In this context, we could expect to observe a link between the documented risk shifts and aggregate consumption at the municipal level.

In what follows I report a simple exercise that adjusts Eq. (1) to estimate regressions at the municipality level. Hereby I focus on two central questions: did other lenders net out the effect identified at the bank level? And if not, did risk shifts affect aggregate consumption at the municipality level? To perform this analysis I aggregate the banking data at the municipality level, weighting each branch variable by its respective credit market share. That is, I create a variable measuring branches' exposure to the shock that equals the average of the pre-crisis exposure by all branches in municipality m weighted by their average pre-crisis market shares. The same procedure is followed to aggregate other time-variant control variables.

I operationalize the questions outlined above by computing two dependent variables: the aggregate credit-risk ratio and the growth rate in aggregate consumption in municipality m.[18] This latter variable is proxied by the growth rate of the municipality-level collection of the 'tax on industry and commerce', which taxes the net income of commercial activities with a fixed rate. This variable — based on administrative data from the Colombian National

[18]While other macroeconomic variables could also be potentially affected by the risk shift, the focus on consumption reflects the fact that consumption credit seems to be particularly sensible to the identified channel, as discussed in Section 4. Moreover, as I discussed below, this focus has identification advantages.

Directorate of Taxes and Customs (DIAN) — has the advantage of being indexed to the volume of sales, allowing to trace consumption dynamics.[19] I estimate the following adjusted version of Eq. (1):

$$Crisk_{m,t} = \alpha + \eta_1 \left[Exposure_m^{<08} \times Shock_t \times Ineq_m^{05}\right] + \tag{2}$$

$$\beta' Bank_{m,t-1} + \mu_{r,t} + \gamma_m + \varepsilon_{m,t}$$

In Eq. (2) I first estimate the aggregate credit-risk ratio as a function of a triple-interaction estimator following the same structure as in Eq. (1). The subscripts denote that the units of observation are aggregated at the municipal level. I saturate the model with municipality (γ_m) and macro-region-time ($\mu_{r,t}$) fixed effects. The latter ones capture trends at the department level in which each municipality is located. In a second step I replace the dependent variable by the quarter-to-quarter log change in aggregate consumption. To facilitate interpreting the results, I replace the continuous variable $Exposure_m$ by a dummy equal to one for municipalities above the median of the distribution of $Exposure_m$. Even though credit demand cannot be absorbed as clearly as in Eq. (1), the choice of consumption growth as a dependent variable reduces concerns that heterogeneous demand across branches or municipalities (after controlling for regional trends) affect the estimates: while commercial credit is likely a relatively heterogeneous contract depending on firms' sector, size, or export orientation, consumer credit is arguably a more homogeneous product.

The approach outlined in Eq. (2) follows a body of literature using regional data in macroeconomics (see, e.g., Autor et al., 2013, Huber, 2018, Giroud and Mueller, 2018, for notable recent examples). Even though Eq. (2) is estimated at a higher level compared to Eq. (1), it still has the advantage of using a shock occurring outside a given municipality to trace aggregate adjustments in an identification that operates in the cross-section of municipalities but controlling for trends at a subnational level. Thus, a substantial share of regional-specific shock components can still be controlled for.

The results from estimating Eq. (2) are reported in Table 4. Column I reports the result when estimating the aggregate credit-risk ratio using Eq. (2). It suggests that municipalities with a larger exposure to the shock via the presence of exposed banks observe a larger decrease in the credit-risk ratio, provided that they report a relatively large Gini index. Hence, the

[19] Alternatively, I replicate this exercise in unreported results using the tax collection for the gasoline tax, recorded also at the municipal level.

Table 4 Results – Municipality-level estimates

Dep. var:	$Crisk_{m,t}$	Δ Consumption		
			Income 80th ptile:	
Sample:	Full	Full	Low	High
	I	**II**	**III**	**IV**
Shock x Exposure x Ineq	-0.136*	-0.257***	0.003	-0.419**
	(0.073)	(0.066)	(0.133)	(0.177)
Shock x Exposure	0.048**	0.056**	-0.015	0.094*
	(0.022)	(0.020)	(0.035)	(0.047)
Shock x Ineq	-0.187***	0.187	-0.134	0.251
	(0.063)	(0.124)	(0.164)	(0.164)
Mun FE	Yes	Yes	Yes	Yes
Region x Time FE	Yes	Yes	Yes	Yes
Obs.	8446	8446	3360	3414
R-squared	0.643	0.099	0.098	0.130

Notes: This table reports the empirical results of regressions performed at the municipality level (see: Eq. (2)). The variable of interest is the triple interaction term represented by $[Exposure_m^{<08} \times Shock_t \times Ineq_m^{05}]$. Column I estimates as the dependent variable the aggregated credit-risk ratio per municipality. Columns II to IV replace the dependent variable by the quarter-to-quarter growth rate in aggregate consumption. This latter variable is proxied by the collection of the "tax on industry and commerce". Columns III and IV split the sample according to the sample median of the average income of households on top of the 80th percentile of the income distribution. All regressions include municipality and region-quarter FE, se. are clustered at the quarter level. ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

risk-taking channel documented in the previous sections can be verified at a regional level of aggregation despite of substitution possibilities across banks. Columns II to IV extend the analysis by estimating the quarter-to-quarter growth rate in aggregate consumption under the same specification. The negative and statistically significant result on Column II highlights that the risk-taking channel of income inequality can also be associated with larger decreases in the growth rate of aggregate consumption.

What explains the link between the inequality risk-taking channel and consumption? Columns III and IV show regressions that provide a tentative answer to this question. Instead of running Eq. (2) for the full sample of municipalities, I split the sample between municipalities with a relatively 'rich' and a relatively 'poor' wealthy group of households, represented by the average income of the top 20 percentile of households' income distribution. I split the sample according to the median of municipalities' top 20 percentile average income and run separate regressions estimating aggregate consumption for these two subsamples. Notably, the negative effect on consumption stems from municipalities where wealthy households report a relatively large average income. This results is intuitive as we would expect credit shifts towards households with a lower marginal propensity to consume to affect aggregate consumption the most. This result shows how the reallocation of credit fuelled by income distribution – in the presence of financial frictions – leads to a weaker aggregate consumption growth in periods of financial distress.

The magnitude of this aggregate effect can be visualized as follows. Consider the differential effect of the shock in municipalities with a low (1 SD below the average, 0.55) vs. large (1 SD above the average, 0.60) Gini index. While in the former case the differential decrease in the consumption growth rate is of -14 pp. (0.55 * 1 * 0.26), in the latter case the decrease is of -16 pp. (0.60 * 1 * 0.26). Hence, an increase in the Gini from 'low' to 'high' levels increases the differential effect of the shock's exposure by 2 p.p., what represents aprox. 13 percent of a SD in the growth rate of consumption. A tentative extension of this exercise suggests that a downward shift in the Gini index between these two levels would have lead an average municipality to mitigate 8 percent of the peak-to-trough drop in consumption during the crisis (see Figure A.4).

6 Robustness tests

I first examine the sensibility of the analysis to alternative econometric specifications of Eq. (1). One interesting vein of analysis is whether the effect changes depending on how long the post-crisis period is defined. From a policy perspective, this question matters to inform discussion on how to calibrate the speed and timing of policy interventions when crises occur. This question is also important to address the speed of adjustment in branches' risk assessment: since I rely on ex-post realization measures of credit risk recorded locally by loan officers, it may be the case that a 'riskier' loan decision only realizes as a penalty in the risk category some quarters after the loan issuance. Therefore, the results may capture a riskier credit supply in the quarters close to the cut-off point, wrongly attributing the effect to a post-crisis reaction. I address this concern by dividing the post-shock period into a short (2008Q3-2009Q1) and a long (2009Q2-2009Q4) period of adjustment, replicating then the estimation of Eq. (1). The results, reported in Table A.1 in the Appendix, show that the effect remains in place regardless of the period used. However, the estimated effect is stronger in the 'long run', i.e. the period between 2009Q2-2009Q4. This result reduces concerns of a biased interpretation of the main findings, highlighting that the effect stems from a gradual adjustment in risk taking during the shock period.

I also test the sensibility of the error terms in the benchmark estimation when using alternative clustering options. The main analysis relies on clusters at the bank and time level recognizing that the shock affects all banks simultaneously and that branches from the same bank are likely to have an error term correlated in the cross-section. However, alternative approaches may consider using only bank or even municipality clusters, as branches within are region can be arguable subjected to common unexplained variation over time. These alternatives are tested in Table A.1, finding that the results remain in place regardless the clustering option. Concerning the definition of the crisis period, I implement placebo tests in which I test for fictitious cut-off points in each quarter of the available data, re-estimating Eq. (1) and plotting the coefficients of interest in Figure A.3. This exercise confirms that only cut-off points in the immediate neighbourhood of 2008Q3 lead to similar results, otherwise the estimation becomes statistically insignificant.

Another concern relates to credit-demand shocks that may be not properly captured by the fixed effects structure in Eq. (1). To this regard one limitation of my dataset is that, in opposite to studies using loan-level credit registers (see, e.g., Iyer et al., 2014, Jiménez et al., 2014, or Ioannidou et al., 2015), I cannot control for borrower-specific fixed effects. While the flip side of this limitation is the advantage of tracing branch level credit portfolios weighted by risk (my observational unit under study), it should be recognized that the model may fail to capture demand shocks if they are not relatively homogeneously distributed across branches within municipalities. To address this concern I exploit the several layers of balance-sheet information in the data to expand the panel structure in one further dimension, that is, I bring it to a bank-municipality-credit type-quarter structure that allows for the use of municipality-credit type-quarter fixed effects in an adjusted version of Eq. (1). Hereby each branch's series of the credit-risk ratio are transformed into four series, representing the ratios for commercial, consumer, mortgage, and micro-credit loans. I test this alternative panel under different fixed effects specifications and report the results in Table A.2, with results remaining fairly stable as compared to the benchmark.

In a further test I explore whether alternative measures of income inequality my lead to different results. While the Gini index is widely accepted as a proper proxy for the shape of income distribution, this variable has its own limitations. For instance, the Gini index fails to capture the effect of absolute differences in income, and it can lead to an inequality rank across regions in which different income distributions report the same Gini coefficient. To address the sensibility of the analysis to the definition of income inequality I replicate Eq. (1) using as inequality measures the 80-20 ratio, the 90-10 ratio, the 90-50 ratio, and a generalized entropy index.[20] The results from this replication is reported in Table A.3, showing that different inequality measures (that put different weights on the skewness of the distribution), do not alter the results.

Finally, another concern is that components of the triple-differences coefficient could be correlated with other variables. For example, instead of capturing the effect of foreign funding reliance, the exposure measure could absorb the sensibility of branches to an overall increase in credit risk (or other weak fundamentals) at the bank level. This problem could generate an omitted variable bias in which the exposure measure is actually reflecting an endogenous relationship between a bank's financial health and the effect of the crisis on branches. Similarly, the Gini index could be correlated with other municipality level fundamentals, such as poverty or rule of law. In this case, the model could wrongly attribute an heterogeneous difference-in-difference response to the Gini index.

To address this type of systemic sorting I run multiple 'horse-races' in which a competing triple interaction term is included in Eq. (1). I separate these tests into two approaches: regressions where the competing term includes a bank-level alternative to the foreign funding ratio, and others where this term replaces the Gini index by other municipality-level variables.[21] The results from this exercise are reported in Tables A.4 and A.5 in the Appendix and confirm the conclusion that the specific combination of banks' exposure and local income inequality is driving the results.

[20]While the Gini index compares cumulative shares of the population with the share of income they receive, the 80-20 Ratio is the ratio of the average income of the 20 percent richest against the 20 percent poorest share of the population. The 90-10 Ratio divides the upper bound value of the ninth decile of the income distribution by the one of the first decile. Similarly, the 90-50 Ratio divides the upper bound value of the ninth decile by the income of the median household. The generalized entropy index is a proxy for the redundancy in household per capita income (estimated here with a parameter of $\alpha = 1$).

[21]At the bank level, I run specifications for bank size (log assets), capital ratio, NPL ratio, liquid assets ratio, and deposit ratio. At the municipality-level I consider the geographic size (in log km2), the alphabetization rate, the log of the geographic area with coca plantations, the poverty rate, and all these options simultaneously combined.

7 Conclusion

This article documents the existence of a risk-taking channel of income inequality when banks are affected by sudden liquidity shocks. Using an *ad hoc* constructed dataset tracing bank activities in Colombia to the municipality level, the analysis shows robust evidence that branches of banks affected by a foreign funding shock shift credit towards low-risk borrowers by more in high-inequality regions. In opposite to the few previous studies exploring the relationship between inequality and financial intermediation, I use a combination of administrative registers that allows tracing the role of collateral constraints as the financial friction underlying the main results.

From a macro perspective, regional estimates at the municipality level suggest that while borrowers cannot substitute away the risk shift across lenders, the reallocation of capital to high-income agents (i.e agents with a lower marginal propensity to consume) negatively affects the growth rate of aggregate consumption. While the linkages between inequality and the macroeconomy have drawn much attention in recent years, this paper provides first evidence linking banks' credit risk and income inequality with drops in consumption observed during crisis periods.

Overall, my results suggest that an increase in inequality makes easier for banks to disentangle between 'good' and 'bad' type borrowers, improving the information signal represented by household income. While the regional estimates highlight that this risk shifting dynamic may be detrimental for consumption, the results reported here should not be taken as highlighting an inefficient financial intermediation outcome. In fact, banks' decision may be constrained efficient, accelerating a deleveraging process that ultimately leads to 'clean' branches' credit portfolio. The identified channel may also have further unwelcome implications for credit-rationed borrowers and the macroeconomy, considering for instance socio-economic impacts or a potential economy-wide effect on incentives to save. Exploring these follow-up questions can provide a fruitful field for future research.

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A Appendix: Additional figures and tables

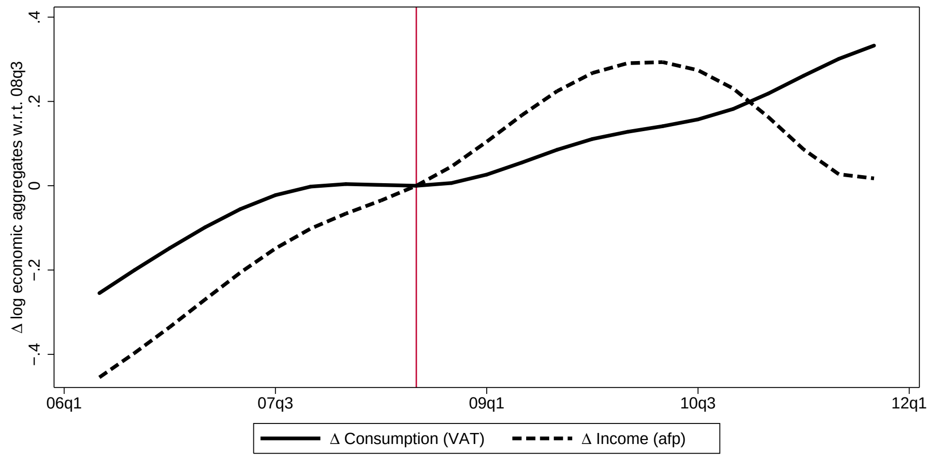

Figure A.1 Consumption vs. disposable income

Notes: Author's elaboration based on data from the Colombian DANE (National Statistical Office). The graph depicts the log change in per capita consumption vs. disposable income with respect to 2008Q2. Underlying series are expressed in COL$ millions. Per capita expenditure is proxied by the total VAT collection at the country level, divided by the population. Disposable income is proxied by total (compulsory) deposits in the Colombian pension fund system. The vertical line is set at 2008Q2, the last quarter before the cutoff point. Source: DANE.

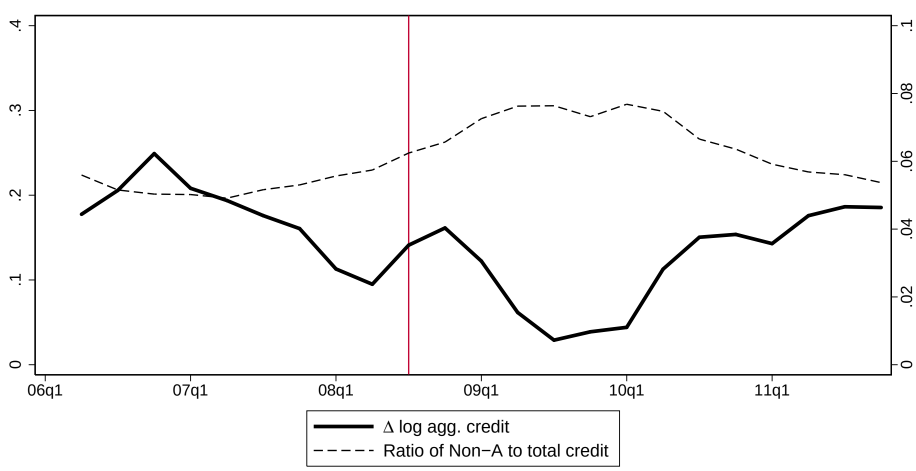

Figure A.2 Credit growth and credit-risk ratio

Notes: Author's elaboration based on data from the SFC. The graph depicts the quarter-to-quarter log change in total outstanding credit as aggregated from the bank branch level sample (left axis). The dashed line represents the aggregate credit-risk ratio by all Colombian banks (left axis). The vertical line is set at 2008Q3, the last quarter before the cutoff point. Source: SFC.

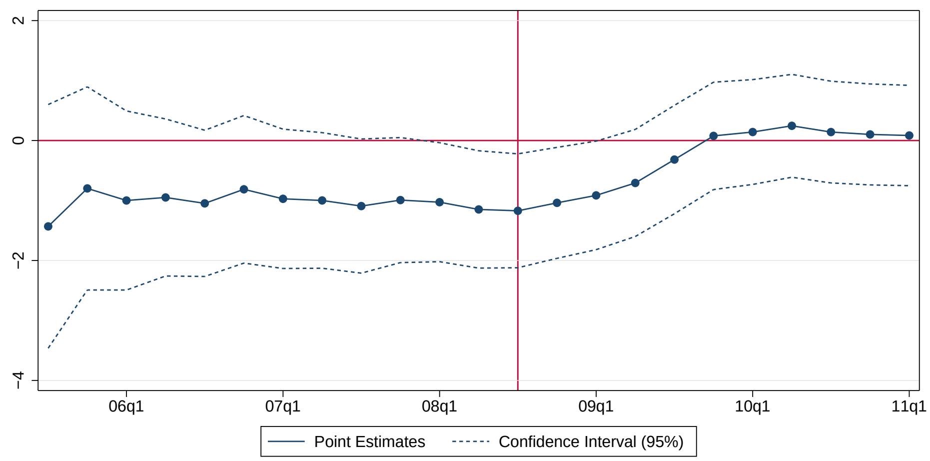

Figure A.3 Placebo test with alternative crisis definitions

Notes: Author's elaboration based on data from the SFC. The graph depicts the estimated coefficients with its 95 percent C.I. of β_1 in Eq. (1) for different definitions of the crisis period. The point estimates are depicted at the dates in which the beginning of the crisis is defined in each regression. The vertical line is set at 2008Q2, the last quarter before the cutoff point. Source: SFC.

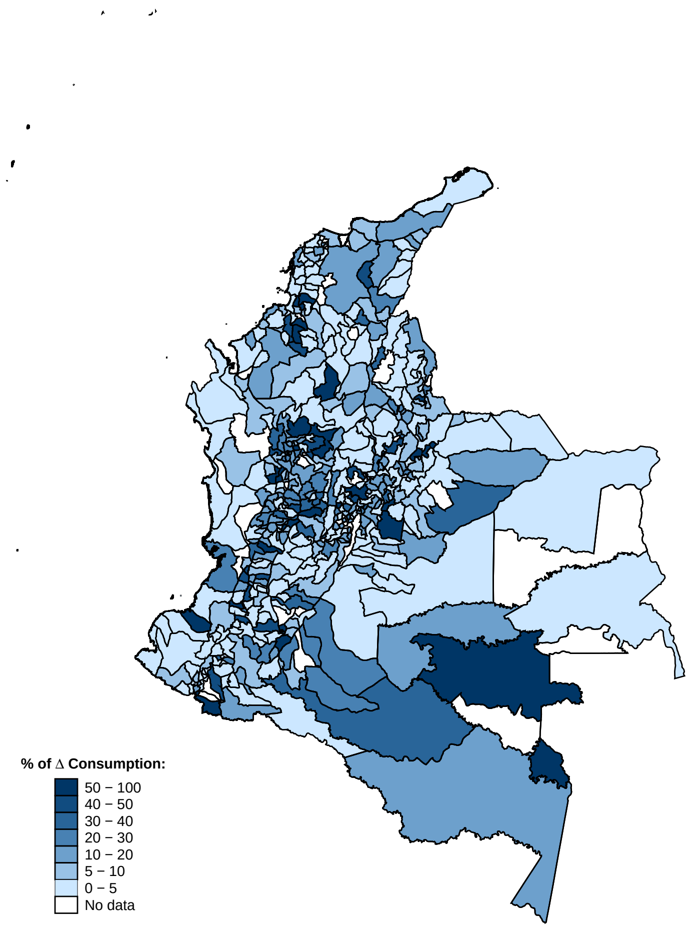

Figure A.4 Economic magnitudes on consumption estimates

Notes: Author's elaboration based on data from the SFC. The graph depicts a heatmap in which darker regions represent a stronger economic impact on aggregate consumption growth of the results from Eq. (2). The economic effet is reported as a percent of the peak-to-trough drop in consumption in a given municipality around the crisis period. The average economic effect around 8.3 percent can be interpreted as the share of the fall in consumption that would have been mitigated, would the Gini index have been 1 SD lower in the pre-crisis period (assuming that municipality m was largely exposed to the shock).

Table A.1 Results – Alternative econometric specifications

	Benchmark **I**	<09Q1 **II**	>09Q2 **III**	Cluster:HDQ **IV**	Cluster:MUN **V**
Shock x Exposure	-2.066***	-1.304**	-2.314***	-2.066***	-2.066***
x Ineq	(0.461)	(0.591)	(0.507)	(0.459)	(0.611)
Branch controls					
Branch size	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Liq. Deposit	0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share in bank assets	1.150***	1.029***	1.077***	1.150**	1.150***
	(0.210)	(0.232)	(0.216)	(0.450)	(0.218)
Obs	20338	16229	18305	20338	20338
R-squared	0.724	0.754	0.727	0.724	0.724

Notes: This table reports the result from estimating Eq. (1) under alternative specifications. The variable of interest is the triple interaction term represented by $[Exposure_i^{<08} \times Shock_t \times Ineq_m^{05}]$. In all regressions the dependent variable is the credit-risk ratio at the branch level. Column I replicates the benchmark specification from Table 2, column V. Column II redefines the post-shock period as the one between 2008Q3 and 2009Q1. Column III follows the same approach but defines the crisis period between 2009Q2 and 2009Q4. Column IV estimates the model with se. clustered at the bank (headquarters) level (HDQ), whereas column V uses clusters at the municipality level (MUN). All regressions include a set of branch, municipality-time, and bank-time FE. ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

Table A.2 Results – Panel expansion with alternative FE

	Benchmark	Expanded panel:			
	I	**II**	**III**	**IV**	**V**
Shock x Exposure x Ineq	-2.066***	-1.395***	-1.469***	-1.755***	-1.755***
	(0.461)	(0.396)	(0.486)	(0.485)	(0.485)
Branch controls					
Branch size	0.001	0.004**	0.004**	0.002*	0.002*
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Liq. Deposit	0.000	0.002**	0.001***	0.002**	0.002**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Share in bank assets	1.150***	0.774***	0.658***	0.810***	0.810***
	(0.210)	(0.121)	(0.132)	(0.132)	(0.132)
Benchmark FE	Yes	Yes	Yes	Yes	Yes
Credit type x time FE	No	No	Yes	Yes	Yes
Branch x Credit type FE	No	No	No	Yes	Yes
Credit type x Mun x time FE	No	No	No	No	Yes
Obs.	20338	64668	64668	62107	62107
R-squared	0.724	0.243	0.237	0.694	0.694

Notes: This table reports the result from estimating Eq. (1) after expanding the panel structure to a bank-municipality-credit type level. Credit types are one out of four categories: commercial, consumer, mortgage, or microcredit loans. The variable of interest is the triple interaction term represented by $[Exposure_i^{<08} \times Shock_t \times Ineq_m^{05}]$. In all regressions the dependent variable is the credit-risk ratio at the branch level. Column I replicates the benchmark specification using the original panel structure from Table 2, column V. Columns II to V report the results from the expanded panel. Column II replicated the benchmark FE structure. Column III adds credit type-quarter FE. Column IV adds branch-credit type FE.Column V adds municipality-credit type-quarter FE. All regressions have se. clustered at the bank and quarter level. ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

Table A.3 Results – Alternative definitions of income inequality

	Alternative inequality measure:				
	Benchmark	80-20 Ratio	90-10 Ratio	90-50 Ratio	GE Index
	I	**II**	**III**	**IV**	**V**
Shock x Exposure x Ineq	-2.066***	-0.077***	-0.084**	-0.361***	-2.132***
	(0.461)	(0.028)	(0.035)	(0.108)	(0.536)
Branch controls					
Branch size (log COL Mill.)	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Liq. Deposit / Total deposits	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share in bank assets	1.150***	1.146***	1.145***	1.148***	1.153***
	(0.210)	(0.210)	(0.211)	(0.210)	(0.210)
Obs.	20338	20338	20338	20338	20338
R-squared	0.724	0.724	0.724	0.724	0.724

Notes: This table reports the result from estimating Eq. (1) with alternative variables defining municipalities' income inequality. The variable of interest is the triple interaction term represented by $[Exposure_i^{<08} \times Shock_t \times Ineq_m^{05}]$. In all regressions the dependent variable is the credit-risk ratio at the branch level. Column I replicates the benchmark specification from Table 2, column V. Columns II to V replace the Gini index by the following variables, respectively: 80-20 Ratio, 90-10 Ratio, 90-50 Ratio, and Generalized Entropy Index. All regressions include a set of branch, municipality-time, and bank-time FE. Se. are clustered at the bank and quarter level. ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

Table A.4 RESULTS – "HORSE-RACE" AGAINST BANK TRAITS

		Alternative bank traits:				
	Benchmark	Size	Cap. ratio	NPL ratio	Liq. ratio	Dep. Ratio
	I	**II**	**III**	**IV**	**V**	**VI**
Shock x Exposure	-2.066***	-1.911***	-2.322***	-2.255***	-1.982***	-1.901***
x Ineq	(0.461)	(0.520)	(0.621)	(0.556)	(0.477)	(0.491)
Shock x Exposure		-0.034	0.508	-1.805	-2.137	0.521
x Bank trait		(0.042)	(0.961)	(2.192)	(3.849)	(0.327)
Branch controls						
Branch size	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Liq. deposit	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share in bank assets	1.150***	1.152***	1.152***	1.149***	1.149***	1.153***
	(0.210)	(0.210)	(0.211)	(0.210)	(0.210)	(0.210)
Obs.	20338	20338	20338	20338	20338	20338
R-squared	0.724	0.724	0.724	0.724	0.724	0.724

NOTES: This table reports the result from estimating Eq. (1) by including competing triple-difference terms in which the variable $Exposure_i^{<08}$ is replaced by alternative pre-crisis average of bank level characteristics. These variables include banks' size (log assets, column II), capital ratio (column III), NPL ratio (column IV), liquid assets ratio (column V), and deposit ratio (column VI). The variable of interest is the triple interaction term represented by $[Exposure_i^{<08} \times Shock_t \times Ineq_m^{05}]$. In all regressions the dependent variable is the credit-risk ratio at the branch level. Column I replicates the benchmark specification from Table 2, column V. All regressions include a set of branch, municipality-time, and bank-time FE. Se. are clustered at the bank and quarter level. ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

Table A.5 Results – “Horse-race” against municipality traits

	Alternative municipal traits:						
	Base	Size	GDP	Alph.	Coca	Pover.	All
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**
Shock x Exp.	-2.066***	-1.899***	-2.244***	-2.391***	-2.206***	-1.945***	-1.567***
x Ineq	(0.461)	(0.410)	(0.486)	(0.454)	(0.455)	(0.435)	(0.425)
Shock x Exp.		-0.016	-0.000	0.009**	0.019*	0.062	
x Mun. trait		(0.021)	(0.004)	(0.004)	(0.010)	(0.183)	
Branch controls:							
Branch size	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Liq. Deposit	0.000	0.002*	0.002**	0.002*	0.002*	0.002*	0.002*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share in	1.150***	1.145***	1.134***	1.141***	1.140***	1.134***	1.128***
bank assets	(0.210)	(0.210)	(0.209)	(0.210)	(0.211)	(0.209)	(0.210)
Obs.	20338	20338	20338	20338	20338	20338	20338
R-squared	0.724	0.724	0.725	0.724	0.724	0.726	0.726

Notes: This table reports the result from estimating Eq. (1) by including competing triple-difference terms in which the variable $Ineq_m^{05}$ is replaced by alternative pre-crisis average of municipality level characteristics. These variables include the size (geo. area in km2, column II), GDP per capita (GDP,column III), alphabetization rate (column IV, Alph.), geo. area with coca plantations (i.e. Coca, column V), poverty rate (Pover, column VI), and all terms simultaneously (All, column VII). The variable of interest is the triple interaction term represented by $[Exposure_i^{<08} \times Shock_t \times Ineq_m^{05}]$. In all regressions the dependent variable is the credit-risk ratio at the branch level. Column I (Base) replicates the benchmark specification from Table 2, column V. All regressions include a set of branch, municipality-time, and bank-time FE. Se. are clustered at the bank and quarter level. ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

Table A.6 VARIABLES DEFINITION

	Definition	Source	Unit
Variables of interest:			
Credit-risk ratio (branch)	Ratio of Non-A to total credit as defined by credit risk categories of the Colombian Banking Authority (SFC).	SFC	share
Exposure	Average pre-crisis ratio of foreign interbank funding to total assets.	SFC	share
Shock	Dummy equal to 1 for the period between 2008Q3 and 2010Q1.	Author	0/1
Gini index	Gini index at the municipal level estimated using the Small Area Estimation approach as of 2005.	DANE (SAE)	share
Bank level:			
Size (log assets)	Total size of a bank's balance sheet computed as log of COL mill.	SFC	log
Capital / Total assets	Ratio of equity to total assets.	SFC	share
Liquidity / Total assets	Ratio of liquid (cash) to total assets at the parent-bank level.	SFC	share
Deposits / Total assets	Ratio of deposits (interbank, sight and savings deposits) to total assets.	SFC	share
RoA	Ratio of net returns to total assets.	SFC	share
Adm. Cost / Total assets	Ratio of administrative costs to total assets.	SFC	share
NPL / Credit	Ratio of non-A to total credit as defined by credit risk categories of the Colombian Banking Authority (SFC).	SFC	share

NOTES: This table provides a description of the main variables used for the empirical analysis reported in the paper, including their sources and unit of reporting. SFC stands for the Colombian Banking Authority, whereas DANE stands for the Colombian National Statistical Office.

Table A.6 Variables definition (continued)

	Definition	Source	Unit
Branch level			
Size (log assets)	Total size of a branches' balance sheet computed as log of COL mill. Branches are defined as aggregated positions at the bank-municipality level.	SFC	log
Liq. deposits ratio	Ratio of liquid to non-liquid deposits. Liquid deposits include current accounts, simple deposits, and term deposits. Non-liquid deposits comprise all types of saving deposits.	SFC	share
Share in bank assets	Ratio of deposits (interbank, sight and savings deposits) to total assets.	SFC	share
Municipality-level			
log area (km2)	Municipal area in log of squared kilometers.	DANE	log
GDP p.c.	Municipal GDP divided by municipal population (average 2005-2008).	DANE	share
Alphabet. rate	Share of the population that is illiterate (average 2005-2008).	DANE	percent
log coca	Area cultivated with coca plants as a share of the municipal territory (average 2005-2008).	DANE	share
Poverty rate	Share of the population below the poverty line (average 2005-2008).	DANE	share
80-20 Ratio	Ratio of the average income of the 20% richest to the 20% poorest as of 2005.	DANE (SAE)	share
90-10 Ratio	Ratio of the upper bound value of the ninth decile to that of the first decileas of 2005.	DANE (SAE)	share
90-50 Ratio	Ratio of the upper bound value of the ninth decile to the median income as of 2005.	DANE (SAE)	share
GE Index	Generalized entropy index with alpha set to 1 as of 2005.	DANE (SAE)	share

Notes: This table provides a description of the main variables used for the empirical analysis reported in the paper, including their sources and unit of reporting. SFC stands for the Colombian Banking Authority, whereas DANE stands for the Colombian National Statistical Office.