Heterogeneous Monetary Policy Pass-Through to Consumer Credit Along the Income Distribution*

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Using loan-level data from the Brazilian credit registry, this paper investigates whether the pass-through of monetary policy to consumer credit is heterogeneous along the income distribution. We find three novel results on how monetary policy affects different consumers' credit costs. Firstly, the pass-through of monetary policy to consumer interest rates is stronger for lower-income borrowers than for higher earners. Secondly, we decompose the results into a *direct heterogeneity effect* and portfolio composition channels. We show that the direct heterogeneity effect is operational, implying that pass-through of monetary policy would still be higher to lower-income individuals even if all borrowers had identical loan portfolios. Thirdly, we show that this pass-through heterogeneity is asymmetric between periods of monetary loosening and tightening. During the post-Covid tightening cycle, the pass-through of monetary policy hikes to consumers' borrowing costs was stronger for individuals with lower incomes. Conversely, during the previous loosening cycle, the pass-through of cuts to lower earners was *weaker* than for higher earners. These results therefore shed light on a potential transmission mechanism whereby monetary policy exacerbates inequality through consumers' borrowing costs.

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1 Introduction

What are the mechanisms through which monetary policy may affect inequality? Using Brazilian credit registry data between 2018 and 2022, we present three novel results which show significant heterogeneity in the pass-through of monetary policy to consumer credit along the income distribution.

Firstly, we document that the pass-through of monetary policy to interest rates on an individual's consumer credit portfolio is stronger for lower-income borrowers than for higher-income borrowers. This means that a change in the policy rate leads to a larger change in borrowing costs for lower earners than for higher earners. These results hold even when controlling for individual characteristics (such as indebtedness, risk, and the length of the financial relationship with the lender) and the responses of loan portfolio characteristics (such as size and average maturity) to monetary policy.

We then show theoretically that the heterogeneous effect of monetary policy on borrowing costs along the income distribution can be decomposed into a *direct heterogeneity effect*, and portfolio composition channels. The direct heterogeneity effect captures the extent to which the pass-through of monetary policy is heterogeneous even when comparing "like-for-like" loan portfolios – that is, loans of the same type, volume and maturity. An implication of the direct heterogeneity effect is that pass-through of monetary policy would still be higher for lower-income individuals even if all individuals held identical loan portfolios. Empirically, we find evidence that the direct heterogeneity effect is operational and driven by the personal and payroll loans market, which are the two largest consumer credit types in Brazil.

Thirdly, we find that heterogeneity in pass-through was asymmetric between the post-Covid tightening cycle and the previous loosening cycle. While the pass-through of monetary policy *contractions* during the hiking cycle was stronger for lower-income borrowers, the pass-through of monetary policy cuts during the loosening cycle was *weaker* for lower-income borrowers than for higher earners. This suggests that lower-income borrowers suffered larger increases in borrowing costs following a hike, but received smaller reductions in interest rates following a cut. Using our decomposition, we find that the direct heterogeneity effect is also operational in determining asymmetry in pass-through heterogeneity. Monetary policy therefore increases credit cost inequality across the income distribution, and would still do so even if all individuals held identical loan portfolios.

We point to the role of bank lending practices as the key driver of our results rather than the response of consumer credit demand to monetary policy. We argue that our

regression specification controls for *observable* demand by including a measure of each borrower's total indebtedness. We suggest that heterogeneity in pass-through is also unlikely to be driven by *unobserved* increases in loan demand in the form of rejected loan applications, as heterogeneity in pass-through is present even at the top end of the income distribution and in loans with wage consignment that carry minimal default risk. We also note that our results focus on impact pass-through, so the longer-term general equilibrium mechanisms through which monetary policy can affect consumer credit demand (such as a reduction in employment and wage earnings) are unlikely to drive our results.

In theory, monetary policy can directly affect consumer demand by changing household credit costs and thus, disposable income.[1] Heterogeneity in pass-through to credit rates is therefore a direct channel through which monetary policy can impact inequality – if the weight of rising borrowing costs is disproportionately borne by low-income borrowers, then the effect of a monetary contraction directly exacerbates inequality along the income distribution. Our results on the asymmetry in pass-through heterogeneity suggests that increases in inequality during hiking cycles would be further exacerbated during subsequent loosening cycles due to larger reductions in borrowing costs for higher-income individuals. As such, monetary policy may have lasting implications for inequality. These distributional effects are particularly important in our context, as Brazil is one of the world's most unequal countries (with the 8th highest Gini coefficient globally).

Heterogeneity in pass-through could also have implications for the aggregate effects of monetary policy. If the lower-income borrowers who see the largest increases in credit costs have higher marginal propensities to consume, then heterogeneous pass-through to consumer credit could amplify the effects of monetary tightening on aggregate consumption and output. Furthermore, asymmetry in pass-though heterogeneity could generate parallel asymmetry in aggregate monetary transmission. If the pass-through of cuts is weaker for high-MPC, low-income borrowers, this would dampen expansionary monetary policy. This asymmetry would then imply that policy hikes are more effective at inducing contractions than cuts are in generating expansions.

Our investigation into how monetary policy affects consumer credit rates heterogeneously is facilitated by the granularity of our data source. The results primarily use data from the credit registry maintained by the *Banco Central do Brasil*, which provides loan-level data on 99% of the universe of formal loans in Brazil. We use a 1% sample of the

[1]This channel is especially relevant for Brazil, with Minella and Souza-Sobrinho (2013) suggesting that 62% of the output fall following a monetary contraction is attributable to household interest rate channels. This highlights the importance of consumer credit responses for monetary policy transmission.

credit registry's detailed loan and individual data, which provides a comprehensive view of the terms of each loan as well as the personal characteristics of each borrower. This allows us to construct a dataset of individual-bank level loan portfolios which captures the composition of these portfolios and the contemporaneous individual characteristics of the borrower.

This paper proceeds as follows. Section 2 places the contribution in the context of the existing literature. Section 3 provides a detailed overview of the datasets and variables used. Section 4 outlines the empirical specification and presents our three key results on pass-through heterogeneity along the income distribution. Section 5 discusses the potential sources of pass-through heterogeneity. Section 6 concludes.

2 Literature Review

This paper primarily relates to a growing literature on the effects of monetary policy on inequality (Coibion et al. 2017, Kaplan et al. 2018, Auclert 2019, Slacalek et al. 2020). Empirical papers in this literature have suggested that the general equilibrium effects of monetary policy can increase inequality, with recent contributions using datasets sourced from individual-level tax records to obtain information on household balance sheets (Flodén et al. 2021, Andersen et al. 2023). While much of the existing literature focusses on individuals' net asset positions and interest expenditure, the granularity of our data allows us to study the effect of monetary policy on different individuals' credit costs.[2] The key contribution of our paper is therefore in empirically documenting a new transmission mechanism through which monetary policy can exacerbate inequality through consumer credit markets. We show that the pass-through of monetary policy to consumer credit rates varies with an individual's income such that lower-income individuals are adversely affected by monetary policy. Our use of detailed individual and loan-level data allows us pinpoint this relationship between income and monetary policy pass-through by controlling for changes to the loan portfolio or borrower characteristics.

Our introduction of a novel analytical decomposition to identify the "direct" and portfolio composition channels of pass-through heterogeneity further clarifies the heterogeneous relationship between pass-through and income.[3] The combination of our theoret-

[2]Another novelty of our paper therefore relates to the existing literature's focus on individuals' differing exposure to *homogenous* increases in interest rates; for example, due to differences in net asset positions. Our paper instead focusses on measuring the exposure of individuals' interest rates on liabilities to monetary policy along the income distribution. That is, how individual's interest rates are *heterogeneously* exposed to changes in the policy rate (conditional on the same volume of liabilities). Theoretically, this heterogeneous pass-through channel would introduce an additional layer of heterogeneity to the analytical decomposition in Auclert (2019).

[3]In formalising the notion that heterogeneity in pass-through may be partially caused by systematic

ical decomposition with our loan-level data source allows us to compare the pass-through of monetary policy across like-for-like loan portfolios and isolate the direct heterogeneity effect. Consequently, this informs on the extent to which the pass-through of monetary policy along the income distribution would still be heterogeneous even if all borrowers had identical loan portfolios.

A secondary contribution to this literature is our ability to inform on these heterogeneous effects of monetary policy along the income distribution in the context of an emerging market. Existing empirical evidence focusses on high-income countries, where the level of household data granularity needed for empirical analysis on monetary policy and inequality is typically more available. However, inequality is arguably a more pressing and relevant issue in emerging market economies like Brazil. Our granular dataset therefore allows us not only to extend the existing literature, but to do so using data from a large, emerging-market economy with very high levels of inequality.

In measuring the heterogeneous effect of monetary policy on credit rates along the income distribution, this paper also builds upon the empirical literature measuring the average pass-through of monetary policy to consumer and firm lending rates (Andries and Billon 2016, Gregor et al. 2021, Beyer et al. 2024). These studies examine pass-through at an aggregated level, so borrower characteristics are controlled for indirectly through the use of macroeconomic variables (as proxies for average borrower characteristics) and location-time fixed effects. The examination of how pass-through may vary *heterogeneously* across the income distribution is novel to the literature. Our ability to investigate this heterogeneity in pass-through is facilitated by our use of loan-level data, which allows the empirical specification to directly observe the income associated with a loan, as well as control for individual borrower and loan portfolio characteristics.

Finally, our paper also relates to the literature on monetary policy pass-through and the bank lending channel of transmission (Bernanke and Blinder 1992), which posits that monetary policy tightening generates increases in interest rates due to a reduction in banks' credit supply. This literature uses detailed bank balance sheet data to examine how monetary policy affects total bank lending, and how the degree of *average* interest rate pass-through varies systematically with bank characteristics such as size (Kashyap and Stein, 1995), liquidity (Kashyap and Stein, 2000), capitalisation (Kishan and Opiela, 2000), and deposit market power (Drechsler et al. 2017). This paper contributes to the bank lending literature by examining how monetary policy pass-through to credit rates varies across a *consumer* characteristic (income). Our results also relate to the bank

differences in loan portfolio compositions across the income distribution, our decomposition is able to further identify a static, a dynamic and a mechanical portfolio composition effect.

lending literature in that the documented heterogeneity in pass-through to consumer credit rates along the income distribution is inconsistent with being driven by changes in credit demand, suggesting that bank lending behaviour may play an important role in determining the relationship between income and pass-through.

3 Data

The main data source for this paper is the *Sistema de Informações de Créditos* (SCR), the Brazilian credit registry managed by the *Banco Central do Brasil* (BCB). The credit registry contains loan-level data from all financial institutions in Brazil at monthly frequency since 2003, for all loans above a given threshold.[4] The threshold is sufficiently low such that the dataset covers over 99% of the universe of formal loans in Brazil. The dataset records the cross-section of consumer loans at each monthly observation, providing detailed data on both the terms of the loan and the characteristics of the borrower as recorded by the lender institution. The granularity of the dataset on both loan and borrower characteristics enables us to investigate heterogeneity in the pass-through of monetary policy to different borrowers.

We conduct our analysis using a 1% sample of individuals from January 2018 to December 2022. After data cleaning, this sample covers 3,714,422 new loans made to 749,407 individuals. This sample period observes one loosening and one tightening cycle in the policy rate (the Selic), with the tightening cycle observed in 2021 associated with the post-Covid-19 global tightening cycle. Figure 1 shows the path of the Selic and the targeted consumer price inflation rate during the sample period.

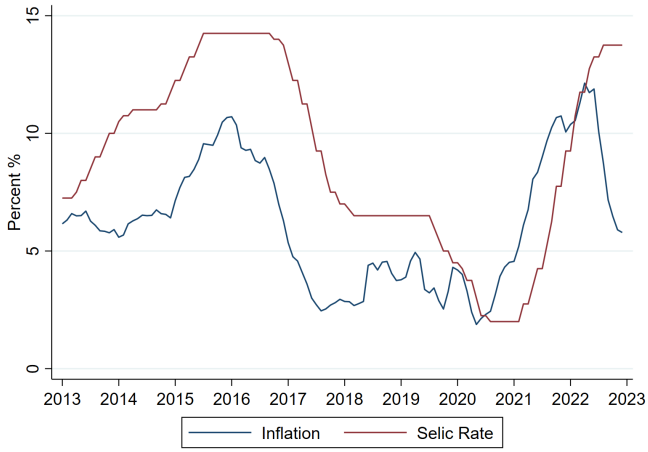


Figure 1: Path of the Selic and consumer price inflation for Brazil, 2013-2023

[4]This threshold was 5,000 BRL (1445 USD) from 2003-2011, 1,000 BRL (536 USD) from 2012-2016, and has been 200 BRL (57 USD) since 2016.

Loan Data (SCR)

For our analyses into heterogeneous pass-through of monetary policy to individuals' credit rates, we consider individuals' portfolios of traditional, non-housing loans. These fall into four broad loan types: payroll loans (i.e. loans with wage consignment), personal (non-payroll) loans, auto loans and goods loans. We exclude non-traditional loans such as credit cards and overdrafts as these forms of credit do not have a clear issuance date or maturity. We also exclude housing and home equity loans, as a significant majority of housing loans subject lenders to funding requirements that are likely to affect bank lending behaviour in response to monetary policy.[5] Due to the prominence of these four selected loan types, our portfolios of traditional, non-housing loans serve as a good proxy for consumers' total loan portfolios – at the beginning of our sample in 2018, these four loan types accounted for over 62% of the total outstanding consumer credit in Brazil. Furthermore, newly issued loans in these loan types accounted for an average of over 24% of total outstanding credit in the credit registry throughout the sample period. This means that the selection of these four key loan types allows us to capture the effect of monetary policy at the level of an individual's portfolio while also maintaining the flexibility to investigate the drivers of pass-through within a loan type.

Each of the four loan types has defining characteristics. Of the four, payroll and personal loans are the two largest loan types, as measured by either the total number or the total value of loans issued.

Payroll Loans (loans with wage consignment)

The payroll loan market is the largest consumer credit market in Brazil, accounting for almost 49% of the total lending in our sample. These are loans with wage consignment, where debt service payments are taken directly out of an individual's wages or monthly pension payment. Only individuals working for or receiving a pension from the government or an eligible company (which must have a pre-arranged agreement with the payroll loan lender) have access to this credit type. As such, a large proportion of payroll loan borrowers are civil servants and retired pensioners. Due to the wage consignment provision, payroll loans are subject to a 30% payment-to-income limit. Payroll loans are therefore characterised by longer maturities and lower annualised interest rates. See Figure 2 for a comparison of the average interest rates for each of the four loan types.

[5]Note that the mortgage market in Brazil is relatively small, with outstanding mortgages worth less than 20% of GDP. In comparison, the outstanding mortgage-to-GDP ratio is over 70% in the United States.

Personal Loans (loans without wage consignment)

The personal loans market is the second largest consumer credit market in Brazil, encompassing all non-earmarked consumer credit without wage consignment. Personal loans account for over 27% of the total lending volume in our sample. As these loans are uncollateralised, this loan type is associated with the highest interest rates out of our selected loan types, as well as the largest variance in interest rates. The average interest rate is over 145% during the sample period.

Auto Loans

Auto loans are specifically borrowed for the purpose of purchasing motor vehicles. Due to the size of the loan needed to purchase a vehicle, these loans have the highest average loan principal of our four selected loan types. Auto loans account for 22% of total lending in our sample. As these loans are also collateralised, they are also associated with lower interest rates.

Goods Loans

Goods loans encompass any loan borrowed for the specific purchase of any non-auto good or service. This is the smallest loan category in our sample, both by volume and by number of loans issued. Goods loans account for approximately 2% of the total lending volume in our sample.

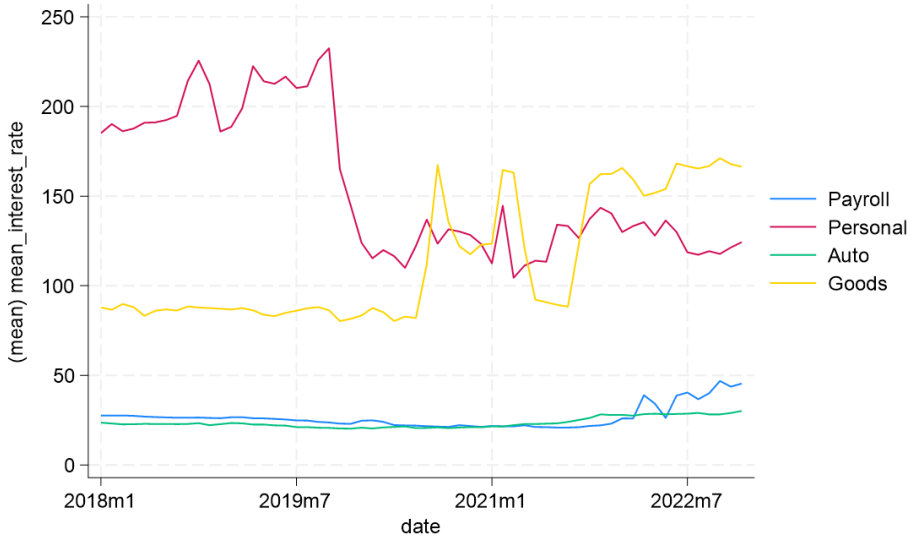


Figure 2: Average nominal interest rate (unweighted) across new loans by loan type in the 1% SCR sample.

For each loan in our sample, we obtain data on the loan type, the loan start date (to identify newly issued loans), the loan volume (principal), the maturity (in days), and

the annualised nominal interest rate agreed in the contract. To conduct our empirical analysis, we aggregate the dataset of loans in our four loan types to the individual-bank level. We define the average interest rate on an individual's portfolio of new loans at a bank as the average of each loan's annualised nominal interest rate weighted by the loan volume as a proportion of the total new loans portfolio in that month. Similarly, we obtain a size-weighted average portfolio maturity. To account for differences in lending behaviour between banks, we also obtain the unique identifier of the lender issuing each loan. We use the identifier at the level of the bank holding company (referred to as the "conglomerate" in the credit registry), such that loans from subsidiaries of the same parent bank are recorded as being issued by the same lender.

Individual Data

Income Data

Our measures of borrowers' incomes are based upon the incomes recorded by the lender in the credit registry. At the time of loan origination, the lender enters two income values: a continuous income variable (that simply records the borrower's monthly income), and a categorical income variable that assigns borrowers to an income group based on their earnings as a multiple of the minimum wage on that date. The nine income categories are defined as:

1. Income information unavailable.
2. No income.
3. 0 to 1 multiple of minimum wage.
4. 1 to 2 multiples of minimum wage.
5. 2 to 3 multiples of minimum wage.
6. 3 to 5 multiples of minimum wage.
7. 5 to 10 multiples of minimum wage.
8. 10 to 20 multiples of minimum wage.
9. More than 20 multiples of minimum wage.

This categorical income measure effectively enables us to control for the effect of inflation on incomes, as the Brazilian minimum wage is uprated annually.

As income is recorded at the loan level (instead of the individual level), we find that a significant proportion of individuals have incomes that are stated inconsistently across

loans.[6] These income inconsistencies can arise for a number of reasons, including recording errors (loans with incomes which are erroneously recorded as zero or missing), timing differences and differences in the frequency at which lenders update their records on borrowers' incomes. For example, as payroll loan repayments are deducted directly from borrowers incomes, these loans require lenders to verify and monitor borrowers' incomes more closely. As a result, the incomes recorded in the credit registry are often updated for the whole lifespan of the payroll loan. This means that the incomes recorded for payroll loans are often more up to date than the incomes recorded for other loan types, even when the other loans have been issued more recently.

Due to the centrality of income for this paper, we ensure that these income inconsistencies do not drive our results by rectifying conflicts in nine different ways. For a given individual at a given date, we first identify all of the income values that have been recorded for the individual in the full SCR dataset (i.e., all new and existing loans in all loan types, including non-traditional and housing loans) from the beginning of the sample up to that month. We then clean the income variables by applying different combinations out of: (1) selecting the income from the newest open loan, (2) choosing the most recently updated income value, and / or (3) taking the most recently entered non-zero or non-missing income value. For example, the continuous income variable used in our benchmark regressions resolves conflicts by selecting the newest non-missing income value from the most recently originated loan or the most recent update to an existing loan (with new loans taking precedence). The steps and varying combinations are designed to ensure that the most current information in the credit registry is included in our measure of the individual's income, without allowing data entry errors to bias results. The process gives rise to nine alternative continuous income variables, and four distinct categorical income variables. The full details of these income cleaning procedures can be found in the appendix.[7]

To obtain a measure of an individual's relative income in each month, we also calculate each individual's percentile in the cross-sectional income distribution. These measures enable us to measure how both absolute and relative incomes affect the pass-through of monetary policy to consumer credit. To ensure that the data cleaning methodology does not bias results, we create three versions of the income percentile variable from three different continuous income variables. For every regression presented in this paper, we run the specification for each of our nineteen (eleven continuous, five categorical and three percentile) income variables. This procedure verifies that the results are robust to

[6]These inconsistencies in stated income are seen both across newly issued loans and between newly issued loans and the income recorded for a pre-existing loan.

[7]We further supplement our set of income measures by also including the categorical and continuous income variables in the FCR dataset, an alternative internal BCB database based on the credit registry.

the different cleaning steps, and ensures that the impact of erroneous income records on the results is minimised.

Non-Income Personal Characteristics

We use three data sources to obtain a comprehensive overview of every borrower's personal characteristics. The SCR contains personal information on gender, birth date, whether a customer is new to the credit registry (i.e., with no previous formal credit history) and the length of the financial relationship between the individual and the lender. By aggregating across SCR loan-level data, we are able to create variables measuring individual-level indebtedness. For each individual, we calculate their total (in-period) credit use recorded in the credit registry (i.e., the individual's total loan portfolio, including non-traditional and housing loans), their total volume of non-performing credit and the total volume of credit they have written off within a period. Using this data, we create several flags for characteristics associated with risky borrowers. We create a "multimodality" dummy, which indicates if an individual uses multiple types of interest-accruing, revolver credit lines (i.e., credit cards and overdrafts). We create a "defaulter" dummy, which indicates if the individual has any delayed payments in the current period. We also create a "past defaulter" dummy for if the individual has previously been in arrears or defaulted.

We also take data from an internal BCB dataset, the "FCR". This is a secondary data source calculated using data from the credit registry, and contains information on individuals' debt-to-income, debt-service-to-income and interest-to-income ratios. Using this data, we create a "high service" dummy, which indicates whether an individual has debt service exceeding 50% of income.

To obtain data on the municipality where the borrower resides, we match the credit registry data to tax records from the tax authorities (*Secretaria da Receita Federal*). As Brazil has 26 states and over 5500 municipalities, using municipality data allows us to control for geographical differences at a very disaggregated level. Due to the frequency of the tax records, municipality is the only variable that we obtain on an annual basis instead of monthly.[8] When contemporaneous information on municipality of the borrower is not available, we use municipality from the most recent tax year (2024).

A table of summary statistics for the dependent variable and each of the regressors used is available in appendix A.3.

[8]Our data shows that borrowers are static, with only a very small fraction of our sample moving between municipalities across years. This suggests that annual municipality data is sufficient to capture locational effects.

4 Results

Empirical Specification

To measure heterogeneity in the pass-through of monetary policy to consumer credit rates along the income distribution, we estimate the following regression for the sample of new loans issued in each month:

$$\begin{aligned} r_{i,b,m,t} = {} & \alpha_1 \mathbf{Income}_{i,t} + \alpha_2 \mathbf{X^{HH}}_{i,t} + \alpha_3 \mathbf{X^{L}}_{i,b,m,t} \\ & + \beta_1 \mathbf{Selic}_t \times \mathbf{Income_{i,t}} + \beta_2 \mathbf{Selic}_t \times \mathbf{X^{HH}}_{i,t} + \beta_3 \mathbf{Selic}_t \times \mathbf{X^{L}}_{i,b,m,t} \\ & + \epsilon_{b,t} + \gamma_{m,t} + \varepsilon_{i,b,m,t}. \end{aligned} \tag{1}$$

The dependent variable $r_{i,b,m,t}$ is the average (weighted by loan volume) nominal interest rate charged on new loans issued to individual i by bank b in municipality m during month t. Alongside the income variable $\mathbf{Income_{i,t}}$, we include vectors of other individual and loan characteristics denoted by $\mathbf{X^{HH}}_{i,t}$ and $\mathbf{X^{L}}_{i,b,m,t}$, respectively. We interact all variables with the policy rate, where $\mathbf{Selic}_t$ denotes the level of the central bank's policy rate at the start of the month. The baseline specifications include both bank-time and municipality-time fixed effects, which are denoted by ϵ_{bt} and γ_{mt}. As a robustness measure, we also estimate a specification including individual fixed effects (δ_i) in lieu of municipality-time fixed effects.

The key coefficient of interest is β_1, which is the coefficient on the interaction between the policy rate and income, and the empirical approximation of $\frac{\partial^2 r_{ibmt}}{\partial \mathbf{Selic}_t \, \partial \mathbf{Income}_{it}}$.[9] This indicates whether there is a relationship between pass-through of the policy rate and the borrower's income, as β_1 is the estimated additional change to a consumer's credit rate in response to the policy rate (relative to the average pass-through[10]) for an additional unit of income. A negative β_1 would suggest that pass-through is stronger for lower-income individuals – i.e. when the policy rate rises, credit rates for lower-income individuals rise by more than credit rates for higher-income individuals. Conversely, a positive β_1 would suggest that pass-through is stronger for higher-income individuals.

We repeat the specification using a continuous income variable, a categorical income

[9]Note that the panel specification means β_1 does not vary across individuals. β_1 can therefore be interpreted as reflecting the average $\frac{\partial^2 r_{ibmt}}{\partial \mathbf{Selic}_t \, \partial \mathbf{Income}_{it}}$ across our panel.

[10]Our time fixed effects absorb the average pass-through of the policy rate. That is, $\epsilon_{b,t}$ and $\gamma_{m,t}$ effectively capture a $\alpha_4 \mathbf{Selic}_t$ term, where α_4 measures average pass-through of the Selic, $\frac{\partial r_{ibmt}}{\partial \mathbf{Selic}_t}$. In appendix A.4, we verify that the average pass-through of the policy rate to consumer credit rates at the bank-municipality level is positive, in line with standard assumptions and the standard result from the empirical literature on pass-through.

variable and an income percentile variable for $\mathbf{Income}_{i,t}$.[11] As the categorical income variable and the income percentile variable are both relative measures of income, this prevents trends in absolute income levels or extreme income outliers from driving our results. The income percentile variable indicates the relative income of an individual within our sample of individuals at the cross-section. Alternatively, the categorical income variable measures income in multiples of the annually adjusted minimum wage, therefore providing an income measure relative to the whole population in Brazil. The categorical income variable also has the advantage of relaxing the linear assumption implicitly imposed on the relationship between pass-through and credit rates by the continuous income and income percentile variables. As the categorical income variable allows us to estimate how pass-through differs across different minimum wage multiples, this indicates the extent to which heterogeneity in pass-through occurs along different points of the income distribution.

The loan portfolio controls included are the total loan volume (in logarithms) and the volume-weighted average maturity of the individual's new loans portfolio in each period. Recall that we focus on an individual's loan contracts for four loan types, and we use these four loan types as a proxy for the individual's total loan portfolio. As an additional measure to account for this approximation, we also include as a control the remaining volume of loan contracts; i.e., the total value of an individual's outstanding credit recorded in the credit registry not captured by new loans issued in our four observed loan types. This control could also be thought of as an individual characteristic capturing existing level of indebtedness.

The individual-level controls included are age, gender[12], the length of the individual's financial relationship with the lender bank, a dummy variable indicating whether an individual is new to the credit registry, the total current volume of non-performing credit (late or defaulted payments) recorded in the credit registry, and three further risk dummies. In addition to the volume of non-performing credit, we capture the extensive margin of defaults through a "defaulter" dummy, which indicates whether an individual has any recorded payments in arrears in the credit registry. The second risk dummy variable indicates whether the individual has a debt service-to-income ratio of over 50%. The third is a "multimodality" dummy, which shows whether an individual is using more than one revolving line of credit, such as an overdraft or the revolving portion of a credit card. These individual characteristic variables attempt to control for observable measures

[11] As discussed in section 3, the specification is also repeated for variants of each of the continuous, categorical and income percentile variables generated through different cleaning methodologies as a robustness check.

[12] The relationship between gender and interest rates is captured by the individual fixed effects. In our specification with individual fixed effects, gender is only directly included in the interaction term.

of loan demand and default risk by capturing measures of indebtedness, existing credit risk and characteristics associated with riskier borrowers.[13]

The specification is repeated using bank-time fixed effects in addition to either municipality-time or individual fixed effects. The inclusion of bank-time fixed effects controls for the effect of the bank's aggregate lending behaviour. The inclusion of municipality-time fixed effects captures regional differences, which are allowed to vary over time. This is particularly important in a large and diverse country like Brazil, where a municipality covering rural farmland in the Amazonas is very different to the city of São Paulo. The alternative use of individual fixed effects is intended to account for time-invariant unobserved risk and inherent differences in loan demand not captured by our individual characteristics. Note that the inclusion of individual fixed effects has a substantial trade-off with the variation of our dependent variable, as variation in credit rates would be measured relative to the average rate charged on new loans for a given individual in our 5 year sample period. This means that only within-individual interest rate variation is used to estimate β_1, and the sample is restricted to individuals who take out multiple new loans over our sample. As there is little movement of individuals across municipalities in our sample, individual fixed effects are also able to roughly capture municipality fixed effects.

Result 1: The pass-through of monetary policy to credit rates is stronger for lower-income individuals.

We find that the pass-through of monetary policy to consumer credit rates is negatively correlated with an individual's income. This means that lower-income individuals are more exposed to changes in their borrowing costs when the central bank changes its policy rate. A rise (fall) in the monetary policy rate is associated with a larger increase (decrease) in interest rates for borrowers with lower incomes.

Table 1 shows the coefficients for the interactions between the Selic and the three alternative income variables from our baseline specification. Column 1 shows that the coefficient on the interaction term between the continuous income variable and the policy rate is negative and significant ($\hat{\beta}_1 < 0$ in the empirical specification). This indicates that the positive effect of an increase in the policy rate on individuals' credit rates is decreasing in income ($\frac{\partial r_{ibmt}}{\partial \mathbf{Selic}_t}$ is decreasing in income, or $\frac{\partial^2 r_{ibmt}}{\partial \mathbf{Selic}_t \, \partial \mathbf{Income}_{it}} < 0$). In the case of a monetary policy hike, this means that the interest rates charged on new loans to lower-income borrowers rise by more than the interest rates on loans to higher-income

[13]These characteristics are partially chosen in line with the Banco Central do Brasil's research into risky borrower characteristics (BCB Departamento de Promoção da Cidadania Financeira, 2023).

borrowers. The magnitude of the $\hat{\beta}_1$ estimate means that the pass-through of a 100 basis point (bps) increase in the Selic is estimated to be 32 bps weaker for every additional 10,000 BRL in monthly earnings.[14]

Column 2 of Table 1 shows the results for the same specification using the income percentile variable. As before, the negative coefficient on the interaction term under this specification indicates that that the pass-through of monetary policy to a borrower's average interest rate is stronger for lower-income borrowers. As the income percentile variable is calculated for each monthly cross section within our sample, this indicates that pass-through is negatively correlated to *relative* income as well as absolute income earnings. That is, as well as absolute nominal income, an individual's relative income position matters in determining the strength of monetary policy pass-through. The magnitude of the coefficient shows that the pass-through of a 100 bps monetary policy hike is reduced by 12 bps for every decile of the within-sample cross-sectional income distribution.

Column 3 shows the coefficients on the interaction term between income and the policy rate for the specification using a categorical income variable. These coefficients show the additional response of credit rates to monetary policy for individuals in each income category relative to individuals in the highest income category (20+ multiples of minimum wage). The estimated interaction coefficients are positive and significant for all income categories, indicating that individuals in all income categories see stronger pass-through of monetary policy to their borrowing costs relative to individuals in the highest income category. The coefficients on the interactions between the Selic and the income categories are also larger for lower income categories, showing that the negative gradient between pass-through and income is observed throughout the income distribution. The magnitude of the coefficients suggests that the pass-through of a 100 bps increase in the Selic to the credit rates charged to individuals earning between 0 and 1 times the minimum wage is 180 bps higher than for individuals in the highest income category. For individuals in the second highest income category earning between 10 and 20 times the minimum wage, the pass-through of a 100 bps hike is estimated to be 71 bps stronger than for the highest income group. Pass-through is therefore stronger for lower-income individuals relative to both the highest earners and higher income categories. While not significantly different, the clear increase in the estimated coefficients as income falls in the 5 lowest income categories (income multiples 0 to 5), even as these categories are defined very narrowly, suggests a steep gradient at the bottom end of the income distribution.

The largest coefficient estimate in column 3 is for individuals for whom the lender bank

[14] 10,000 BRL is approximately equal to USD 2,000 - 3,000 at 2018-2022 exchange rates.

has recorded income as "N/A", indicating no available income information. Relative to borrowers in the highest income category, the pass-through of a 100 bps increase in the Selic is almost 370 bps higher for borrowers with no income information. This suggests that a second dimension of pass-through heterogeneity along the income distribution is higher pass-through for individuals with more income uncertainty.

Recall that our specification controls for the interaction of loan portfolio and individual characteristics with the Selic, including variables that capture the volume and maturity of the portfolio, the individual's total indebtedness and the total volume of the individual's payments in default. The negative relationship between income and monetary policy pass-through is therefore independent of the responses of individual indebtedness to monetary policy. Our finding of stronger pass-through to lower-income individuals is robust to controlling for increases in loan portfolio size, including increases in loans outside of our selected loan portfolio[15], as well as the shortening of maturities if lower-income individuals switch to shorter-term credit. It is also robust to the possibility that lower-income individuals are more likely to use expensive short-term, unarranged financing such as overdrafts and the revolver section of credit cards.[16] The use of these short-term measures would be captured by our indebtedness variables, while the interest rates on these financing measures would not affect the dependent variable (which is the average interest rate of our *selected* loan portfolio).

The above results therefore suggest that the effect of monetary policy on credit rates is heterogeneous such that credit rates for lower-income individuals are disproportionately responsive to the policy rate. In the absence of offsetting effects in other markets, this implies that heterogeneity in pass-through causes contractionary monetary policy to directly reduce disposable income by more for lower-income individuals, increasing disposable income inequality. Given the increasing evidence that monetary policy contractions increase inequality in general equilibrium (Flodén et al. 2021; Andersen et al. 2023), these (partial equilibrium) results may be an important channel through which monetary policy can directly exacerbate inequality.

[15]This is because we include both the volume of the selected loan portfolio as well as the (remaining) total volume of credit outstanding recorded in the credit registry.

[16]Note that the results could reflect portfolio composition choices across our four chosen loan types. This is discussed in depth in the decomposition section below.

Coefficient on Selic and Income Interaction Terms.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic	-3.18e-05***		
	(6.48e-06)		
Income percentile × Selic		-0.0118***	
		(0.00315)	
(Income = N/A) × Selic			3.690***
			(0.658)
(Income multiple = 0) × Selic			1.718***
			(0.534)
(Income multiple = 0-1) × Selic			1.828***
			(0.360)
(Income multiple = 1-2) × Selic			1.873***
			(0.347)
(Income multiple = 2-3) × Selic			1.482***
			(0.308)
(Income multiple = 3-5) × Selic			1.244***
			(0.275)
(Income multiple = 5-10) × Selic			0.853***
			(0.234)
(Income multiple = 10-20) × Selic			0.712***
			(0.208)
(Income multiple = 20+) × Selic			0
			(0)
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Municipality-Time FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	3,618,601	3,618,601	3,618,601
R-squared	0.695	0.695	0.695

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1: Coefficient estimates from regression specification 1 for the full sample of individual loan portfolios.

The Decomposition of Pass-Through Heterogeneity Along the Income Distribution

Result 1 documents the negative correlation between income and the pass-through of monetary policy, which is robust to controlling for the impact of an individual's loan portfolio characteristics (total loan volume and average maturity). These results do not, however, control for the composition of the individual's portfolio across loan types.[17] This means that observed pass-through heterogeneity in Result 1 could be driven by either a *direct heterogeneity effect*, or indirect forces relating to the composition of loan portfolios. Directly, Result 1 could reflect that there is heterogeneity in pass-through of interest rates *within* each loan type, such that the interest rates for lower-income individuals are more responsive to the policy rate even when comparing loans of the same type, volume and maturity. This "true" heterogeneity in pass-through would mean that the pass-through of the policy rate to credit rates would be stronger for lower-income individuals even if all individuals held the exact same loan portfolios. Indirectly, pass-through heterogeneity could also arise as a result of differences in the composition of low-income and higher-income borrowers' portfolios.

To investigate the role of these direct and compositional effects in driving our result, we show theoretically that heterogeneity in pass-through can be decomposed into a *direct heterogeneity effect*, a portfolio composition channel, and an additional mechanical effect. Our knowledge of the exact composition of loan portfolios then allows us to empirically test for the operation of the direct heterogeneity effect.

Our dependent variable is the size-weighted average interest rate on an individual's portfolio of new loans. Equivalently, this can be thought of as the size-weighted average of interest rates across the individual's portfolios of different loan types. That is:[18]

$$r_i = \sum_l (\text{share}_{l,i} \times r_{l,i}) \tag{2}$$

where r_i is the average interest rate on individual i's portfolio of loans[19], $\text{share}_{l,i}$ is loan type l's share of individual i's total portfolio of newly issued loans, and $r_{l,i}$ is the (size-weighted) average interest rate across loans of type l issued to individual i.[20]

[17] As an example of why this may matter, note that a loan portfolio containing only payroll loans is likely to behave differently to a loan portfolio containing only goods loans, even if the two portfolios are of the same size and have the same average maturity.

[18] For ease of notation, we drop $\{b, m, t\}$ subscripts. Dropping time subscripts is possible because we focus on the *impact* pass-through of monetary policy.

[19] The b, m, t subscripts would add that the individual is living in municipality m, and the portfolio of loans would be borrowed from bank b at time t.

[20] Where $l \in$ {payroll loans, personal loans, auto loans, goods loans}.

Using this definition, the change in an individual's interest rate (r_i) in response to a change in the policy rate (the Selic) can be expressed as:

$$\frac{\partial r_i}{\partial \textbf{Selic}} = \sum_l \left[\frac{\partial r_{l,i}}{\partial \textbf{Selic}} \times \text{share}_{l,i} + \frac{\partial \text{share}_{l,i}}{\partial \textbf{Selic}} \times r_{l,i} \right]. \tag{3}$$

Recall that our coefficient of interest, β_1, is the empirical approximation of $\frac{\partial^2 r_i}{\partial \textbf{Selic}\, \partial \textbf{Income}_i}$. Taking the partial derivative of (3) with respect to income gives us:

$$\begin{aligned}\frac{\partial^2 r_i}{\partial \textbf{Selic} \partial \textbf{Income}_i} = \sum_l \Bigg[& \underbrace{\frac{\partial^2 r_{l,i}}{\partial \textbf{Selic} \partial \textbf{Income}_i} \times \text{share}_{l,i}}_{\textbf{(1) Direct heterogeneity effect}} \\ & + \underbrace{\frac{\partial^2 \text{share}_{l,i}}{\partial \textbf{Selic} \partial \textbf{Income}_i} \times r_{l,i} + \frac{\partial \text{share}_{l,i}}{\partial \textbf{Income}_i} \times \frac{\partial r_{l,i}}{\partial \textbf{Selic}}}_{\textbf{(2) Portfolio composition effects}} \\ & + \underbrace{\frac{\partial \text{share}_{l,i}}{\partial \textbf{Selic}} \times \frac{\partial r_{l,i}}{\partial \textbf{Income}_i}}_{\textbf{(3) Mechanical effect from interest rate inequality}} \Bigg].\end{aligned}$$

This illustrates that there are three potential effects driving the observed heterogeneity in pass-through of the policy rate along the income distribution.

Firstly, the heterogeneity may be caused by a direct heterogeneity effect, where the pass-through to interest rates on type l loans is stronger for lower-income individuals relative to higher-income individuals. This channel can be thought as capturing the "true" heterogeneity in pass-through, whereby pass-through to average credit costs for lower-income individuals is higher even when comparing identical loans. An implication of this is that pass-through to lower-income individuals would be higher even if all individuals held the exact same loan portfolios. Effect **(1)** contributes to higher pass-through for lower-income individuals if $\sum_l (\frac{\partial^2 r_{l,i}}{\partial \textbf{Selic} \partial \textbf{Income}_i} \times \text{share}_{l,i}) < 0$. That is, if the net effect of heterogeneities in pass-through *within* loan types is such that the responsiveness of the (size-weighted) average interest rate to monetary policy is higher for lower-income individuals. This could be due to much stronger heterogeneity in loan types where the correlation between income pass-through is negative, or if these negative-correlation loan types account for a larger share of loan portfolios.

Secondly, effect **(2)** in our decomposition shows that heterogeneity in pass-through can be driven by differences in the composition of loan portfolios across low- and high-income individuals, or in the responses of portfolio compositions to monetary policy. To

see this, note that the terms in effect **(2)** can be rewritten as:

$$\underbrace{\underbrace{\frac{\partial^2 \text{share}_{l,i}}{\partial \textbf{Selic} \partial \textbf{Income}_i} \times r_{l,i}}_{\textbf{2(i)}} + \underbrace{\frac{\partial \text{share}_{l,i}}{\partial \textbf{Income}_i} \times \frac{\partial r_{l,i}}{\partial \textbf{Selic}}}_{\textbf{2(ii)}}}_{\textbf{(2)}} = \frac{\partial}{\partial \textbf{Selic}} \left(\frac{\partial \text{share}_{l,i}}{\partial \textbf{Income}_i} \times r_{l,i} \right)$$

The term $\frac{\partial \text{share}_{l,i}}{\partial \textbf{Income}_i} \times r_{l,i}$ represents the spread of average credit costs across the income distribution attributable to differences in loan portfolio composition across loan types (as loan types charge different interest rates). Taking the partial derivative of this with respect to the Selic therefore represents how the part of the credit spread that is due to differences in loan composition changes with the policy rate.

Taken separately, the decomposition reveals that there are two portfolio composition channels that may affect heterogeneity in pass-through. The term labelled **2(i)** shows that there is a dynamic portfolio composition channel, where different income groups may adjust their portfolio shares of each loan type differently in response to changes in the policy rate. For example, this would encompass the effect of lower-income individuals disproportionately increasing their share of high interest rate loan types after a monetary policy hike. The term labelled **2(ii)** indicates there is also a static loan composition channel where different income groups may hold different proportions of loan types that vary in their responsiveness to monetary policy. For example, if low-income individuals disproportionately borrow in loan types that have more responsive interest rates to monetary policy, then the responsiveness of their average interest rate would be correspondingly higher. Each of these channels would cause lower-income borrowers to see a larger increase in their average interest rates than higher-income borrowers after a monetary contraction.

Finally, the decomposition shows that a mechanical effect **(3)** stemming from fundamental interest rate inequality could contribute to the observed heterogeneity in pass-through. That is, if interest rates in a loan type l are higher for lower-income individuals than higher-income individuals, then an increase in loan l's share of loan portfolios during a monetary policy contraction would increase credit rates by more for lower-income individuals. Changes in portfolio compositions therefore mechanically amplify or dampen the prominence of pre-existing interest rate inequality, which in turn affects heterogeneity in pass-through of the policy rate.

Empirical Estimation of the Direct Heterogeneity Effect of Monetary Policy

The granularity of our data means that we are able to observe the type of every loan in an individual's portfolio, enabling us to examine how each channel in our decomposition may contribute to the observed heterogeneity in pass-through. In particular, a key advantage of this granularity is that we can re-estimate our empirical specification when restricting our sample by loan type. This provides us with empirical estimates of $\frac{\partial^2 r_{l,i}}{\partial \mathbf{Selic} \partial \mathbf{Income}_i}$ for every l, which in turn allows us to inform on the existence and importance of the direct heterogeneity effect. The empirical specification for these within loan type regressions is:

$$\begin{aligned} r_{l,i,b,m,t} = {} & \alpha_{1,l}\mathbf{Income}_{i,t} + \alpha_{2,l}\mathbf{X^{HH}}_{i,t} + \alpha_{3,l}\mathbf{X^{L}}_{l,i,b,m,t} \\ & + \beta_{1,l}\mathbf{Selic}_t \times \mathbf{Income_{i,t}} + \beta_{2,l}\mathbf{Selic}_t \times \mathbf{X^{HH}}_{i,t} + \beta_{3,l}\mathbf{Selic}_t \times \mathbf{X^{L}}_{l,i,b,m,t} \\ & + \epsilon_{l,b,t} + \gamma_{l,m,t} + \varepsilon_{l,i,b,m,t}. \end{aligned} \tag{4}$$

There are two important implications of performing the pass-through analysis at the disaggregated loan-type level. Firstly, as the dependent variable for this regression is the average interest rate on an individual's interest rates of new type l loans ($r_{l,i,b,m,t}$), our coefficient of interest $\beta_{1,l}$ now directly corresponds to the $\frac{\partial^2 r_{l,i}}{\partial \mathbf{Selic} \partial \mathbf{Income}_i}$ terms in **(1)**. Secondly, as we only examine the portion of the loan portfolio that is made up of type l loans and we control for the total volume of these loans, we effectively switch off any loan portfolio composition effects **(2)** and their resulting mechanical effects **(3)**. The disaggregated regression therefore allows us to isolate the direct effect **(1)**, and test for the presence of "true" heterogeneity in monetary policy pass-through.

Result 2: The direct heterogeneity effect is operational, and is driven by personal and payroll loans.

We find that heterogeneity in pass-through can be seen even when restricting the sample by loan type and controlling for loan characteristics, with both personal loans and payroll loans exhibiting a negative correlation between pass-through and income. This relationship is particularly strong for personal loans. In contrast, we do not see any significant heterogeneity in pass-through when restricting the sample to auto or goods loans. This indicates that the direct heterogeneity effect is operational and contributes to Result 1 (as the net effect across loan types is unequivocally negative), and that this channel is driven by personal and payroll loans. As personal and payroll loans together account for over 75% of credit in our observed loan portfolios, we suggest that the direct

heterogeneity effect accounts for a meaningful proportion of the overall heterogeneity in pass-through.

The results when restricting the sample to personal loans are shown in Table 2. For each of the three income variables used, the results show that the pass-through of monetary policy to personal loan interest rates is decreasing in the borrower's income. The coefficient point estimates are all larger in magnitude compared to those in the unrestricted sample (Table 1) and those for any other loan type (Tables 3 to 5), suggesting that personal loans are the driver of the direct heterogeneity effect.[21]

In Table 2 column 1, the coefficient on the interaction between the policy rate and the continuous income variable is negative and statistically significant. This shows that the pass-through of the Selic to the interest rate on new personal loans is strongest for low-income borrowers. For every additional 10,000 BRL in monthly income, the pass-through of a 100 bps Selic hike is estimated to weaken by 39 bps. Pass-through is also stronger for *relatively* low-income individuals in our sample. In column 2, the coefficient on the income percentile variable is also negative and significant, supporting that pass-through is stronger as individuals move down the income distribution. The point estimate here suggests that every additional decile of income sees pass-through weaken by 21 bps (for a 100 bps Selic increase). The results from the regression using the categorical income variable are shown in column 3. As in Result 1, the coefficients on all interaction terms between the Selic and each income category are positive and significant. As before, this shows that the pass-through of monetary policy to personal loan interest rates is weakest for borrowers in the highest income category relative to borrowers in all other income categories. The coefficient estimates again exhibit a significant negative gradient, with the point estimates decreasing for higher income categories. After a 100 bps increase in the Selic, the interest rate on new personal loans for borrowers earning less than the monthly minimum wage rises by over 300 bps more than for borrowers in the highest income group. For borrowers with incomes between 10 and 20 times the minimum wage, the increase is approximately 99 bps more than for those in the highest income group. This illustrates that monetary policy is passed-through most strongly to the personal loan interest rates of borrowers at the lower end of the income distribution.[22]

[21]The finding that personal loans drive Result 2 may also hold implications for the distributional effects of monetary policy. As personal loans are neither subject to debt servicing limits nor collateralised (as payroll loans are), personal loans have the highest interest rates of the four loan types, with an average interest rate of over 146%. The results therefore show that lower-income consumers who have large proportions of high-interest rate personal loans in their portfolio (and so, correspondingly higher debt servicing costs) also disproportionately bear the weight of monetary policy.

[22]Note that the coefficient for the interaction between the Selic and the 'N/A' income category is once again large and statistically significant. Relative to the highest income group, the pass-through of a 100 bps increase in the Selic is over 375 bps stronger for borrowers with 'N/A' income. This provides evidence to suggest that there is also a direct heterogeneity effect driving the income uncertainty heterogeneity

The direct heterogeneity effect is also present in the market for payroll loans (loans with wage consignment). Table 3 displays the results for the regression using data for payroll loans. The coefficient estimates again show evidence of pass-through heterogeneity along the income distribution, though the coefficient magnitudes and the level of statistical significance are both smaller than for personal loans. This suggests that it is personal loans which primarily drive the results at the individual portfolio level.

In Table 3 column 2, the coefficient on the income percentile interaction is negative and significant, indicating that the pass-through of monetary policy to payroll loan interest rates is higher for individuals who are lower down in the income distribution. While we still observe a negative relationship between income and pass-through, the absolute size of the point estimates is roughly one order of magnitude smaller than the results for personal loans. For every decile of the income distribution, the pass-through of a 100 bps Selic increase to payroll loan interest rates is estimated to fall by approximately 1.8 bps. In column 3, the categorical income variable regression results reinforce that pass-through is stronger to lower-income borrowers. Again, all but one of the coefficient estimates for the interaction between the Selic and the income categories are positive and significant, and the coefficients are also decreasing in the level of the income category. For individuals earning less than the minimum wage, the pass-through of a 100 bps increase in the Selic is 35 bps more than for the highest earners. This point estimate is twice as large as the point estimate for borrowers earning between 10 and 20 times the minimum wage, for whom the pass-through of a 100 bps Selic increase is around 17 bps higher relative to the highest income group.[23]

In contrast to personal and payroll loans, heterogeneity in pass-through is not observed when restricting the sample to auto and goods loans. The results for auto loans and goods loans are shown in Tables 4 and 5. In both cases, the results do not show clear evidence of pass-through heterogeneity along the income distribution – point estimates are small and largely insignificant, as well as inconsistent across the continuous, percentile and categorical income variables.

These results indicate that the pass-through of monetary policy to interest rates is heterogeneous even when partialling out the effects of differing portfolio compositions along the income distribution. Recall that our decomposition showed that the direct heterogeneity effect generates stronger pass-through to lower-income customers if the weighted average of within-loan type heterogeneity in pass-through across loan types is negative.

observed on an individual level.

[23]Pass-through is also stronger to individuals with 'N/A' income, with pass-through of a 100 bps rise in the Selic associated with an additional 76 bps increase in payroll loan interest rates for these borrowers.

Empirically, this requires that the weighted sum of the coefficient estimates for the interactions between income and the policy rate is negative. Given that the correlation between income and pass-through is negative for both personal and payroll loans (the two largest loan types) and insignificantly different from zero for auto and goods loans, the weighted sum across loan types is unequivocally negative. A back-of-the-envelope calculation based on the point estimates and the in-sample share of each loan type suggests that the direct heterogeneity channel accounts for over 33% of the overall pass-through heterogeneity when using the continuous income variable, and almost 55% when using the income percentile variable.[24] This indicates that there is substantial "true" heterogeneity in pass-through driven by the presence of personal and payroll loans within loan portfolios – even when looking within these loan types and controlling for differences in loan volumes or maturity, lower-income individuals are still more exposed to the policy rate. This means that lower earners would still see larger changes in their interest rates following a change in the Selic even if all individuals held identical loan portfolios.[25]

[24]To estimate the total contribution of the direct heterogeneity effect, we calculate the sum of the four $\hat{\beta}_{1,l}$ estimates weighted by loan type l's share of total new lending in the sample. The direct heterogeneity effect share is the ratio of this weighted sum to the $\hat{\beta}_1$ estimate from Table 1.

[25]As discussed in Result 1, our specification already controls for the effects of different loan portfolio characteristics such as total volume and average maturity.

(**Personal loans**) Coefficient on Selic and Income Interaction Terms.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic	-3.90e-05***		
	(9.89e-06)		
Income percentile × Selic		-0.0213***	
		(0.00360)	
(Income = N/A) × Selic			3.751***
			(0.713)
(Income multiple = 0) × Selic			3.823***
			(0.672)
(Income multiple = 0-1) × Selic			3.066***
			(0.585)
(Income multiple = 1-2) × Selic			2.478***
			(0.549)
(Income multiple = 2-3) × Selic			1.974***
			(0.517)
(Income multiple = 3-5) × Selic			1.690***
			(0.468)
(Income multiple = 5-10) × Selic			1.086***
			(0.420)
(Income multiple = 10-20) × Selic			0.986***
			(0.363)
(Income multiple = 20+) × Selic			0
			(0)
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Municipality-Time FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	2,104,493	2,104,493	2,104,493
R-squared	0.785	0.785	0.785

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Coefficient estimates from regression specification 1 for the sample restricted to individual portfolios of personal loans (without wage consignment).

(**Payroll loans**) Coefficient on Selic and Income Interaction Terms.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic	-5.06e-06		
	(3.12e-06)		
Income percentile × Selic		-0.00176**	
		(0.000754)	
(Income = N/A) × Selic			0.760***
			(0.205)
(Income multiple = 0) × Selic			-0.848
			(1.048)
(Income multiple = 0-1) × Selic			0.349***
			(0.132)
(Income multiple = 1-2) × Selic			0.290**
			(0.129)
(Income multiple = 2-3) × Selic			0.298**
			(0.119)
(Income multiple = 3-5) × Selic			0.274**
			(0.109)
(Income multiple = 5-10) × Selic			0.232**
			(0.105)
(Income multiple = 10-20) × Selic			0.174*
			(0.102)
(Income multiple = 20+) × Selic			0
			(0)
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Municipality-Time FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	1,019,097	1,019,097	1,019,097
R-squared	0.844	0.844	0.845

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Coefficient estimates from regression specification 1 for the sample restricted to individual portfolios of payroll loans (loans with wage consignment).

(**Auto loans**) Coefficient on Selic and Income Interaction Terms.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic	-3.30e-07		
	(6.88e-07)		
Income percentile × Selic		0.000299	
		(0.000387)	
(Income = N/A) × Selic			-0.173*
			(0.101)
(Income multiple = 0) × Selic			-0.0532
			(0.119)
(Income multiple = 0-1) × Selic			-0.0123
			(0.0472)
(Income multiple = 1-2) × Selic			0.00489
			(0.0438)
(Income multiple = 2-3) × Selic			0.0156
			(0.0406)
(Income multiple = 3-5) × Selic			0.0174
			(0.0382)
(Income multiple = 5-10) × Selic			0.0152
			(0.0357)
(Income multiple = 10-20) × Selic			-0.0118
			(0.0406)
(Income multiple = 20+) × Selic			0
			(0)
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Municipality-Time FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	174,404	174,404	174,404
R-squared	0.635	0.636	0.637

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Coefficient estimates from regression specification 1 for the sample restricted to individual portfolios of auto loans.

(**Goods loans**) Coefficient on Selic and Income Interaction Terms.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic	1.54e-05		
	(1.74e-05)		
Income percentile × Selic		0.00854	
		(0.0129)	
(Income = N/A) × Selic			-0.356
			(0.985)
(Income multiple = 0) × Selic			-2.626*
			(1.562)
(Income multiple = 0-1) × Selic			-1.416
			(1.191)
(Income multiple = 1-2) × Selic			-0.754
			(0.888)
(Income multiple = 2-3) × Selic			-0.715
			(1.399)
(Income multiple = 3-5) × Selic			-2.130
			(1.451)
(Income multiple = 5-10) × Selic			-0.744
			(1.028)
(Income multiple = 10-20) × Selic			1.485
			(1.174)
(Income multiple = 20+) × Selic			0
			(0)
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Municipality-Time FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	234,286	234,286	234,286
R-squared	0.310	0.310	0.310

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Coefficient estimates from regression specification 1 for the sample restricted to individual portfolios of goods loans.

Asymmetry in Pass-Through Heterogeneity Along the Income Distribution

Result 1 shows that the pass-through of monetary policy is heterogeneous along the income distribution, with lower-income borrowers seeing larger changes in borrowing costs for a given change in the policy rate. Result 2 decomposes this heterogeneity in pass-through into different channels, and shows that the direct heterogeneity channel is present and driven by the markets for personal and payroll loans. In order to understand the distributional implications of these results, we next examine whether heterogeneity in pass-through to credit costs is symmetric across monetary tightening and loosening cycles.

While stronger pass-through of monetary policy hikes to low-income borrowers increases (credit cost) inequality, stronger pass-through of interest rate cuts alleviates this inequality by reducing the debt service costs for lower-income individuals. If the observed pass-through heterogeneity across the income distribution is symmetric across hikes and cuts, we would expect the effect of monetary policy on consumer credit rates to worsen inequality during a hiking cycle and alleviate inequality during a cutting cycle. However, if heterogeneity in pass-through is asymmetric, monetary policy hikes and cuts can have the *same* effect on inequality. That is, monetary policy could always increase inequality or always decrease inequality, regardless of whether the policy rate rises or falls. For example, consider the benign case where cuts to the policy rate are passed-through more strongly to lower-income individuals while hikes are passed-through more weakly.[26] Here, pass-through heterogeneity would alleviate credit cost inequality in both tightening and loosening cycles as lower-income borrowers receive larger reductions in credit costs in response to policy rate cuts and smaller increases in response to hikes. Conversely, monetary policy could always worsen credit cost inequality if heterogeneity in pass-through is asymmetric such that the pass-through of hikes is stronger for lower-income borrowers, while the pass-through of cuts is stronger for higher-income borrowers. In this case, lower earners would suffer larger increases in borrowing costs following a hike and receive smaller reductions in interest rates following a cut. Monetary policy would therefore exacerbate inequality during both hiking and cutting cycles.

To investigate these distributional concerns, we amend our baseline individual-level specification to allow for asymmetry between the pre-Covid loosening cycle and the post-Covid hiking cycle. This enables us to examine whether pass-through heterogeneity along the income distribution differs between the two periods. The regression specification is

[26]Note that this could still consistent with Result 1 if the negative correlation between pass-through and income during a cut is stronger than the positive correlation between pass-through and income during a hike.

as follows:

$$
\begin{aligned}
r_{i,b,m,t} = {} & \mathbb{1}_{hike}\alpha_1^{hike}\mathbf{Income}_{i,t} + \mathbb{1}_{hike}\alpha_2^{hike}\mathbf{X^{HH}}_{i,t} + \mathbb{1}_{hike}\alpha_3^{hike}\mathbf{X^{L}}_{i,b,m,t} \\
& + \mathbb{1}_{hike}\beta_1^{hike}\mathbf{Selic}_t \times \mathbf{Income_{i,t}} + \mathbb{1}_{hike}\beta_2^{hike}\mathbf{Selic}_t \times \mathbf{X^{HH}}_{i,t} + \mathbb{1}_{hike}\beta_3^{hike}\mathbf{Selic}_t \times \mathbf{X^{L}}_{i,b,m,t} \\
& + \mathbb{1}_{cut}\alpha_1^{cut}\mathbf{Income}_{i,t} + \mathbb{1}_{cut}\alpha_2^{cut}\mathbf{X^{HH}}_{i,t} + \mathbb{1}_{cut}\alpha_3^{cut}\mathbf{X^{L}}_{i,b,m,t} \\
& + \mathbb{1}_{cut}\beta_1^{cut}\mathbf{Selic}_t \times \mathbf{Income_{i,t}} + \mathbb{1}_{cut}\beta_2^{cut}\mathbf{Selic}_t \times \mathbf{X^{HH}}_{i,t} + \mathbb{1}_{cut}\beta_3^{cut}\mathbf{Selic}_t \times \mathbf{X^{L}}_{i,b,m,t} \\
& + \epsilon_{b,t} + \gamma_{m,t} + \varepsilon_{i,b,m,t}
\end{aligned} \tag{5}
$$

where $\mathbb{1}_{hike}$ and $\mathbb{1}_{cut}$ are indicator functions for the tightening and loosening cycles:[27]

$$
\mathbb{1}_{hike} = \begin{cases} 0 & \text{if } t < \text{March 2021} \\ 1 & \text{if } t \geq \text{March 2021} \end{cases}
$$

$$
\mathbb{1}_{cut} = \begin{cases} 1 & \text{if } t < \text{March 2021} \\ 0 & \text{if } t \geq \text{March 2021.} \end{cases}
$$

The key coefficients of interest are β_1^{hike} and β_1^{cut}, which show the relationship between individual income and the pass-through of monetary policy to the borrower's interest rates during the tightening and loosening cycle:

$$
\beta_1^{hike} = \left.\frac{\partial^2 r_{ibmt}}{\partial \mathbf{Selic_t}\ \partial \mathbf{Income_{it}}}\right|_{\mathbb{1}_{hike}=1}
$$

$$
\beta_1^{cut} = \left.\frac{\partial^2 r_{ibmt}}{\partial \mathbf{Selic_t}\ \partial \mathbf{Income_{it}}}\right|_{\mathbb{1}_{cut}=1}.
$$

In both cases, a positive coefficient estimate indicates that the pass-through of the policy rate to consumer interest rates is increasing with income, while a negative value indicates that pass-through is decreasing with income. A sufficient condition for the pass-through heterogeneity to differ significantly between the hiking and cutting periods is that β_1^{hike} and β_1^{cut} have different signs and are both individually statistically significant.

[27] The beginning of the hiking cycle is chosen as March 2021, which was the month of the BCB's first hike during the sample.

Result 3: Pass-through heterogeneity along the income distribution was asymmetric between the pre-Covid loosening and the post-Covid tightening cycles.

We find that the heterogeneity in pass-through along the income distribution was asymmetric between the periods of monetary tightening and loosening within our sample. During the post-Covid tightening cycle, the pass-through of monetary policy was stronger for lower-income borrowers. During the previous loosening cycle, the pass-through of monetary policy was stronger for higher-income borrowers. That is, in our sample period of 2018-2022, credit rates for lower-income borrowers rose by more in response to policy rate hikes and fell by less in response to policy rate cuts.[28]

The results for the regression with asymmetric heterogeneity are shown in Table 6. The results show substantial asymmetry in pass-through heterogeneity along the income distribution. During the recent hiking cycle, increases in the policy rate were passed through more to lower-income borrowers. However, during the previous loosening cycle, the pass-through of cuts was stronger for *higher-income* borrowers. Column 1 shows the regression coefficient estimates for the triple interaction between the continuous income variable, the Selic, and the dummy variable indicating whether the month falls in the tightening or loosening cycle. For the hiking period, the coefficient estimate is negative and statistically significant. This shows that the pass-through of a monetary policy hike to consumer interest rates is decreasing with income, meaning that pass-through is stronger for lower-income borrowers. In contrast, during the cutting cycle, this coefficient is *positive* and significant. This shows that the pass-through of monetary loosening was stronger for higher-income borrowers. The magnitude of the coefficient shows that, for every additional 10,000 BRL in monthly income, credit rates fall by 26 bps more in response to a 100 bps cut to the Selic.

In column 2, the coefficient for the interaction between the Selic and the income percentile variable during the hiking cycle is negative and significant. Once again, this illustrates that an increase in the Selic was followed by a larger rise in borrowing costs for borrowers at the lower end of the income distribution. In contrast, the coefficient on the interaction during the cutting period is positive (though insignificant), indicating that low-income borrowers did not benefit from stronger pass-through of monetary policy cuts.

The results for the categorical income variable in column 3 also suggest that pass-

[28]Taken together with Result 1, this suggests that the negative correlation between income and pass-through during hikes is stronger than the positive correlation between income and pass-through during cuts.

through heterogeneity along the income distribution is asymmetric between the two periods. For the hiking period, the coefficient estimates are positive and significant for all income categories with income values up to 10 times the minimum wage. This means that, relative to the highest income group, the pass-through of a policy rate increase is stronger for borrowers in lower income categories. The results also exhibit a negative gradient. Relative to the highest income category, the pass-through of a 100 bps Selic increase is over 120 bps stronger for borrowers earning between 1 and 2 times the minimum wage. For individuals earning between 5 and 10 times the minimum wage, the rise in interest rates is only 42 basis points higher than for the highest income group. This shows that increases in the Selic during the hiking cycles were passed-through most strongly to borrowers at the bottom end of the income distribution.

During the cutting cycle, the results in column 3 show that the pass-through of a cut in the policy rate is instead *positively* correlated with income. The coefficients on the interactions between the Selic and the income category are all negative and largely significant. This indicates that, relative to the highest earners, borrowers in lower income groups see a smaller fall in their borrowing costs following a monetary policy cut. In line with the continuous income variables, the estimates exhibit a broadly increasing gradient. For individuals earning less than the minimum wage, the fall in their interest rates following a 100 bps increase in the Selic is 163 bps smaller than that of the highest earners. For borrowers earning between 10 and 20 times the minimum wage, the cut is 91 bps smaller. This shows that cuts in the Selic during the loosening cycle were passed-through most strongly to borrowers at the top end of the income distribution.

The asymmetry in pass-through heterogeneity has important implications for credit cost inequality. The asymmetric results suggest that lower-income borrowers suffered larger increases in their borrowing costs during the period of monetary tightening, but received smaller reductions in their borrowing costs during the previous loosening cycle. As a result, pass-through heterogeneity along the income distribution exacerbates credit cost inequality as lower earners experience less favourable changes in their borrowing costs than higher earners in both hiking and cutting periods.

Furthermore, this partial equilibrium asymmetry in the effects of monetary policy on different individuals' borrowing costs could also generate asymmetry in the aggregate general equilibrium effects of monetary policy. If lower income borrowers have higher marginal propensities to consume, then a larger fall in disposable incomes due rising credit costs during a hike would amplify the aggregate consumption and output effects of monetary tightening. Conversely, if lower-income borrowers see a smaller rise in disposable income following a cut, the aggregate effects of monetary loosening would be

Coefficient on Selic and Income and Hike or Cut Interaction Terms.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic × cut	2.59e-05**		
	(1.06e-05)		
Income × Selic × hike	-1.51e-05**		
	(6.07e-06)		
Income percentile × Selic × cut		0.00216	
		(0.00504)	
Income percentile × Selic × hike		-0.00847***	
		(0.00318)	
(Income = N/A) × Selic × cut			-0.877
			(1.156)
(Income multiple = 0) × Selic × cut			-0.711
			(0.878)
(Income multiple = 0-1) × Selic × cut			-1.627**
			(0.638)
(Income multiple = 1-2) × Selic × cut			-0.694
			(0.546)
(Income multiple = 2-3) × Selic × cut			-0.959*
			(0.506)
(Income multiple = 3-5) × Selic × cut			-1.264***
			(0.460)
(Income multiple = 5-10) × Selic × cut			-0.854**
			(0.397)
(Income multiple = 10-20) × Selic × cut			-0.907***
			(0.322)
(Income multiple = 20+) × Selic × cut			0
			(0)
(Income = N/A) × Selic × hike			2.359***
			(0.750)
(Income multiple = 0) × Selic × hike			0.908*
			(0.549)
(Income multiple = 0-1) × Selic × hike			0.980***
			(0.370)
(Income multiple = 1-2) × Selic × hike			1.216***
			(0.346)
(Income multiple = 2-3) × Selic × hike			0.852***
			(0.315)
(Income multiple = 3-5) × Selic × hike			0.608**
			(0.285)
(Income multiple = 5-10) × Selic × hike			0.415*
			(0.242)
(Income multiple = 10-20) × Selic × hike			0.347
			(0.213)
(Income multiple = 20+) × Selic × hike			0
			(0)
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Municipality-Time FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	3,618,601	3,618,601	3,618,601
R-squared	0.696	0.696	0.696

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Coefficient estimates from regression specification 5 (with asymmetry) for the full sample of individual loan portfolios.

dampened. Asymmetry in the heterogeneity of pass-through to credit rates could therefore have corresponding asymmetric implications for the aggregate effects of monetary policy.

Result 3b: The direct heterogeneity effect is asymmetric, and this asymmetry is driven by personal loans.

Result 3 suggests that lower-income consumers receive larger increases in borrowing costs following hikes, and smaller decreases in borrowing costs following cuts. Our decomposition of heterogeneity shows that this could be because of asymmetries in the direct heterogeneity channel, or because of asymmetry in portfolio composition effects. To determine the extent to which asymmetry is a feature of the direct heterogeneity effect, we re-estimate the asymmetric regression specification (5) separately by loan type.

The results show that there is asymmetry in the direct channel of pass-through heterogeneity, so low-income individuals are not adversely impacted by monetary policy simply because of their loan portfolio composition. That is, we find that $\sum_l (\frac{\partial^2 r_{l,i}}{\partial \mathbf{Selic} \partial \mathbf{Income}_i} \times \text{share}_{l,i})|_{\text{hike}} < 0$, but $\sum_l (\frac{\partial^2 r_{l,i}}{\partial \mathbf{Selic} \partial \mathbf{Income}_i} \times \text{share}_{l,i})|_{\text{cut}} > 0$. This implies that lower-income individuals would still have seen higher rises in credit costs in response to a policy hike and smaller falls in response to a policy cut even if all individuals held identical loan portfolios. We show that this is driven by the market for personal loans, where the post-Covid tightening cycle saw a sharper rise in the interest rates charged to low-income borrowers than for higher earners. During the loosening cycle, however, low-income borrowers received smaller reductions in borrowing costs from personal loan lenders. Conversely, we also show that pass-through asymmetry was partially offset by the direct pass-through heterogeneity in payroll loans (loans with wage consignment), where lower-income individuals are more exposed to the policy rate in both the tightening and loosening periods.

Table 7 shows the asymmetric regression results when restricting the sample to personal loans. In column 1, the interaction between the Selic and the continuous income variable has a positive and significant coefficient estimate during the loosening period and a negative coefficient during the tightening period. This illustrates that it is higher earners who see a larger fall in their borrowing costs following a cut in the monetary policy rate, while the pass-through of cuts is weaker for lower earners. Compared to the full sample, the positive correlation between pass-through and income during the loosening cycle when restricting the sample to personal loans is roughly four times greater. For every additional 10,000 BRL of monthly income, the interest rates on personal loans are estimated to fall by over 83 bps more after a 100 bps cut in the Selic. In contrast

to this, the negative coefficient during the hiking period shows that higher earners do *not* see a symmetric larger increase in their borrowing costs following a monetary policy hike. Instead, the negative coefficient on the interaction term during a hike estimates that pass-through (of a 100 bps hike) is 12 bps weaker for every additional 10,000 BRL in monthly income. Hence, we find that higher earners receive more of the benefits from a monetary policy cut while being shielded from the worst of the costs of a monetary policy hike even when comparing loans of the same type and controlling for differences in loan volume and maturity. The direct heterogeneity effect of monetary policy attributable to personal loan rates is therefore asymmetric.

Table 7, column 2 shows the results from the regression using the income percentile. For personal loans, the coefficient on the interaction with the Selic is negative and significant for the hiking cycle, but positive for the cutting cycle. For every additional decile of the income distribution, the pass-through of a 100 bps Selic increase falls by over 15 bps. However, the positive coefficient for the loosening cycle indicates that poorer households do not receive stronger pass-through of monetary policy cuts. This illustrates again that a monetary policy contraction is followed by a larger rise in personal loan interest rates for borrowers at the lower end of the income distribution, whereas a policy expansion is associated with larger falls in personal loan rates for higher-income borrowers.

The asymmetry in heterogeneous pass-through along the income distribution for personal loans is illustrated most clearly by the results for the categorical income variable (Table 7, column 3). Consider first the interaction coefficients during the cutting cycle. All but one of the coefficient estimates are significant and negative. This shows that pass-through of monetary policy cuts was weaker for all individuals outside the highest income group. The coefficient estimates also exhibit a positive gradient, with higher point estimates for higher income groups, illustrating that poorer borrowers see weaker pass-through than borrowers with higher incomes all along the income distribution. Relative to the highest income group, the pass-through of a 100 bps Selic cut to a borrower earning less than the minimum wage is almost 450 bps weaker. For borrowers earning between 10 and 20 times the minimum wage, the pass-through of a cut in the Selic is over 180 bps weaker relative to the highest income group. Hence, the lowest earners receive significantly lower reductions in their personal loan borrowing costs following a monetary contraction.

During the hiking period, the results indicate that the opposite relationship between income and pass-through holds. The coefficient estimates for the three lowest income groups are positive and significant. The point estimates also now exhibit a negative gradient, with higher income groups seeing a lower point estimate. This illustrates that the

lowest earners suffer a larger rise in their personal loan interest rates following a rise in the Selic compared to the highest earners. Following a 100 bps increase in the Selic, the interest rates charged on new loans to individuals with no income rise by 200 bps more than the interest rates charged for the highest earners. For borrowers earning between 1 and 2 times the minimum wage, the pass-through of the hike is almost 96 bps stronger. These results indicate that personal loan borrowers at the bottom of the income distribution received the largest increases in personal loan borrowing costs during the tightening cycle and the smallest reductions in borrowing costs during the loosening cycle.

Table 8 shows the results for payroll loans, which highlight that payroll loans do not exhibit the same asymmetry across the two periods as personal loans. Instead, the results suggest that both the hiking and cutting periods saw stronger pass-through for lower-income borrowers. In column 1, the coefficient estimate for the interaction between the Selic and the continuous income variable is negative for both the tightening and loosening cycle. Similarly, the point estimates for the interaction with the income percentile are negative for both periods in column 2. This shows that the correlation between pass-through and borrower income is negative, meaning that the pass-through of both Selic cuts and hikes to payroll interest rates was stronger for lower-income borrowers.

The symmetric pass-through heterogeneity for payroll loans are also observed most clearly when using the categorical income variable (Table 8, column 3). For both the hiking and cutting period, the coefficient estimates for all non-zero income groups are positive and statistically significant. This shows that all individuals earning less than the highest income group received stronger pass-through of both increases and decreases in the Selic. The coefficient point estimates are of very similar magnitudes across each of the periods.[29] Relative to the highest earners, the results show that the pass-through of a 100 bps cut was 32 bps stronger for borrowers earning less than the minimum wage. Similarly, during the hiking period, the pass-through of a 100 bps hike to the interest rates on new payroll loans was 34 bps stronger for individuals in this income group. Hence, in the case of payroll loans, lower earners received both larger falls in their borrowing costs during the loosening cycle and larger increases in their interest rates during the tightening cycle.

Taken together, these results mean that the contribution of the direct heterogeneity effect to asymmetry in pass-through heterogeneity is entirely driven by personal loans, and partially offset by the symmetric pass-through heterogeneity in payroll loans.[30] For

[29]Tests for statistical significance confirm that there is no significant difference between these coefficients, as seen by the very similar point estimates.

[30]Sections A.5 and A.6 in the appendix show the results when restricting the sample to automobile and goods loans. Loans within these types do not exhibit significant heterogeneity in pass-through during either tightening or loosening cycles.

both personal and payroll loans, the results show that monetary policy hikes during the post-Covid tightening cycle were passed-through more strongly to lower-income borrowers. This means that the direct heterogeneity effect unequivocally contributes to the higher pass-through of monetary policy to lower-income borrowers during a hike ($\sum_l(\frac{\partial^2 r_{l,i}}{\partial \mathbf{Selic} \partial \mathbf{Income}_i} \times \text{share}_{l,i})|_{\text{hike}} < 0.$). A back-of-the-envelope calculation of the weighted average of the point estimates shows that the direct heterogeneity effect accounts for over 34% of the pass-through heterogeneity observed during the hiking cycle when we use the continuous income variable in the regression. The contribution of the direct heterogeneity effect rises to over 51% when we use the income percentile variable.[31] This implies that lower-income individuals would always see larger increases in interest rates in response to a hike in the policy rate even if all individuals held the same loan portfolios.

However, the results show that the pass-through of Selic to lower earners during the cutting cycle was instead considerably *weaker* than for higher earners in the market for personal loans. This asymmetry was not seen in the market for payroll loans, where lower earners also received stronger pass-through of the cuts in the Selic. Recall that for the direct heterogeneity effect to explain the asymmetry in Result 3, we require that $\sum_l(\frac{\partial^2 r_{l,i}}{\partial \mathbf{Selic} \partial \mathbf{Income}_i} \times \text{share}_{l,i})|_{\text{cut}} > 0$. Whether the direct heterogeneity channel contributes to the asymmetry found in Result 3 thus depends on the extent to which the negative correlation between pass-through and income in the payroll loans market during a cut offsets the corresponding positive correlation in the personal loans market. Using the point estimates in Result 3b and the average portfolio shares of each loan type, we find that the weighted average of point estimates is positive for the loosening cycle. The positive correlation between income and pass-through during the cutting cycle when restricting the sample to personal loans outweighs the opposing negative correlation when restricting the sample to payroll loans, which is consistent with the much larger magnitudes of $|\beta^{cut}_{1,Personal}|$. In fact, the direct heterogeneity effect accounts for over 77% of the heterogeneity observed in Result 3 when using the continuous income variable, and over 83% of the heterogeneity when using the income percentile variable.[32]

Result 3b therefore illustrates that the net direct heterogeneity effect of monetary policy is asymmetric due to the behaviour of personal loans. The implication of this result is that average borrowing costs in low-income individuals' portfolios would have

[31] For this estimate, we calculate the sum of the $\hat{\beta}^{hike}_{1,l}$ estimates weighted by loan type l's share of total new loans during the hiking period. The direct heterogeneity effect share is the ratio of this weighted sum to the $\hat{\beta}^{hike}_{1}$ estimate in Table 6.

[32] These results show that the contribution of the direct heterogeneity effect to the total observed pass-through heterogeneity was larger during the cutting period than during the hiking period. That is, portfolio composition and mechanical effects played a smaller part in determining the stronger pass-through of cuts to higher-income individuals (in comparison to their role in determining higher pass-through of hikes to lower-income individuals).

risen by more during the hiking cycle and fallen by less during the loosening cycle even if individuals held the same average loan portfolio, and that this asymmetry is driven by the response of interest rates on personal loans to changes in the policy rate.

(**Personal loans**) Coefficient on Selic and Income and Hike or Cut Interaction Terms.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic × cut	8.31e-05***		
	(1.88e-05)		
Income × Selic × hike	-1.21e-05		
	(9.68e-06)		
Income percentile × Selic × cut		0.00748	
		(0.00758)	
Income percentile × Selic × hike		-0.0153***	
		(0.00362)	
(Income = N/A) × Selic × cut			2.836
			(1.798)
(Income multiple = 0) × Selic × cut			-2.438*
			(1.247)
(Income multiple = 0-1) × Selic × cut			-4.471***
			(1.163)
(Income multiple = 1-2) × Selic × cut			-4.225***
			(1.019)
(Income multiple = 2-3) × Selic × cut			-4.309***
			(0.949)
(Income multiple = 3-5) × Selic × cut			-3.825***
			(0.827)
(Income multiple = 5-10) × Selic × cut			-2.586***
			(0.697)
(Income multiple = 10-20) × Selic × cut			-1.860***
			(0.539)
(Income multiple = 20+) × Selic × cut			0
			(0)
(Income = N/A) × Selic × hike			3.116***
			(0.706)
(Income multiple = 0) × Selic × hike			2.010***
			(0.683)
(Income multiple = 0-1) × Selic × hike			1.355**
			(0.582)
(Income multiple = 1-2) × Selic × hike			0.956*
			(0.541)
(Income multiple = 2-3) × Selic × hike			0.536
			(0.505)
(Income multiple = 3-5) × Selic × hike			0.418
			(0.461)
(Income multiple = 5-10) × Selic × hike			0.217
			(0.414)
(Income multiple = 10-20) × Selic × hike			0.314
			(0.356)
(Income multiple = 20+) × Selic × hike			0
			(0)
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Municipality-Time FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	1,019,097	2,104,493	2,104,493
R-squared	0.845	0.787	0.787

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Coefficient estimates from regression specification 5 for the sample restricted to individual portfolios of personal loans (without wage consignment).

(**Payroll loans**) Coefficient on Selic and Income and Hike or Cut Interaction Terms.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic × cut	-3.56e-06*		
	(1.84e-06)		
Income × Selic × hike	-4.67e-06*		
	(2.81e-06)		
Income percentile × Selic × cut		-0.00129*	
		(0.000665)	
Income percentile × Selic × hike		-0.000441	
		(0.000810)	
(Income = N/A) × Selic × cut			1.217***
			(0.237)
(Income multiple = 0) × Selic × cut			-0.404
			(0.522)
(Income multiple = 0-1) × Selic × cut			0.323***
			(0.0918)
(Income multiple = 1-2) × Selic × cut			0.250***
			(0.0910)
(Income multiple = 2-3) × Selic × cut			0.278***
			(0.0873)
(Income multiple = 3-5) × Selic × cut			0.215**
			(0.0835)
(Income multiple = 5-10) × Selic × cut			0.246***
			(0.0850)
(Income multiple = 10-20) × Selic × cut			0.277***
			(0.0842)
(Income multiple = 20+) × Selic × cut			0
			(0)
(Income = N/A) × Selic × hike			0.863***
			(0.205)
(Income multiple = 0) × Selic × hike			-0.858
			(1.062)
(Income multiple = 0-1) × Selic × hike			0.341***
			(0.123)
(Income multiple = 1-2) × Selic × hike			0.278**
			(0.121)
(Income multiple = 2-3) × Selic × hike			0.290***
			(0.112)
(Income multiple = 3-5) × Selic × hike			0.265**
			(0.103)
(Income multiple = 5-10) × Selic × hike			0.233**
			(0.0997)
(Income multiple = 10-20) × Selic × hike			0.192**
			(0.0970)
(Income multiple = 20+) × Selic × hike			0
			(0)
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Municipality-Time FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	1,019,097	1,019,097	1,019,097
R-squared	0.845	0.845	0.845

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Coefficient estimates from regression specification 5 for the sample restricted to individual portfolios of payroll loans (loans with wage consignment).

Robustness Checks

We implement several robustness checks for all results discussed in this paper.[33] Firstly, we verify that our results hold when using individual fixed effects instead of time-varying municipality fixed effects (alongside bank-time fixed effects). As discussed in section 4, this allows us to control for unobserved differences across individuals at the cost of variation in our dependent variable.[34] We assert that our results and their statistical significance remain robust to the use of individual fixed effects, although point estimates are slightly smaller in magnitude under this specification. We include the results using individual fixed effects for Results 1 and 3 in appendix A.8 and A.9, respectively.

As discussed in section 3, we confirm that the choice of data cleaning methodology for the income variables does not drive our results. To do so, we verify that the results broadly hold across a total of nineteen cleaning methods (eleven cleaning methods for the continuous income variables, three different cleaning methods for the income percentile variable, and five different cleaning methods for the categorical income variable). As this exercise confirms that our results are not materially affected by the choice of data cleaning methodology, these results are not included here.

We also repeat all specifications at the loan level (rather than the individual level), and verify that our results hold. There are two key implications of this robustness check. Firstly, the difference between aggregating to the individual level and performing the regression at the loan level is the difference between weighting loan observations by volume and weighting all loans equally. Thus, while aggregating to the individual level is more appropriate for ease of economic interpretation, we perform the loan-level regressions to verify that our results are not only driven by the behaviour of larger loans. Secondly, while the individual-level regressions control for average loan characteristics in a portfolio, the loan-level regressions are able to control for the exact terms of every loan. The loan-level regressions therefore also ensure that our results are not driven by differences in higher-order moments across individuals' loan portfolio characteristics. We find similar results across loan-level and individual-level regressions, as illustrated by Table 14 in Appendix A.7, which displays results from the loan-level counterpart to Table 1.

Finally, we confirm that our benchmark Results 1 and 2 are robust to a "horse race" with inflation. Here, we supplement our baseline regression specification with interactions

[33]For the sake of brevity, not all the results from these robustness checks are included in the appendix but are available upon request.

[34]The inclusion of individual fixed effects rules out the case where individuals who happen to be low-income also experience higher pass-through – rather, individuals see larger reactions in their credit costs to the policy rate when they are earning a lower income in comparison to when their income is higher.

between the lagged value of the Banco Central do Brasil's reference inflation rate (*Índice Nacional de Preços ao Consumidor Amplo*, or the "IPCA") and all income variables, individual controls and loan portfolio characteristics. We repeat the same exercise when restricting the sample by loan type. The results for the inflation horse race are shown in Tables 17, 18 and 19 in Appendix A.10 (Result 1) and A.11 (Result 2). The coefficients on the interaction between the Selic and income when using the continuous, percentile or categorical income variable are displayed in columns 1, 2 and 3, respectively. In Table 17, the inflation horse race for Result 1, the coefficients remain negative and significant on the continuous and income percentile variable with slightly smaller coefficients than Table 1 (although this difference is insignificant). The coefficients across income categories are positive relative to the highest income level, largely significant and exhibit the same negative correlation between income and pass-through. Similarly, in Tables 18 and 19 (the inflation horse race for Result 2), the coefficients are mostly significant but of smaller magnitudes. This confirms that our results on the negative correlation between income and pass-through capture the heterogeneous response of consumer credit rates to monetary policy, rather than inflation.

5 Sources of Heterogeneity in Pass-Through

We find that the pass-through of monetary policy is heterogeneous in that lower-income individuals see stronger pass-through of the policy rate than higher-income individuals (Result 1). We emphasise that this result holds even when controlling for the role of individual characteristics and the responses of loan portfolio characteristics to monetary policy. We further find that this result holds when controlling for the role of loan portfolio compositions across different loan types (Result 2). That is, pass-through would still be higher to lower-income individuals even if all individuals held identical loan portfolios with the same composition across loan types and average portfolio characteristics. We then show that this heterogeneity in pass-through is asymmetric – while pass-through of monetary policy hikes was indeed stronger for lower-income individuals in the post-Covid tightening cycle, the pass-through of cuts in the pre-Covid loosening cycle was *weaker* for lower-income individuals (Result 3). We again find that these results hold when controlling for loan portfolio composition effects (Result 3b), and that this asymmetry is driven by asymmetry in pass-through to personal loans and partially offset by symmetric heterogeneity in pass-through to payroll loans. In this section, we discuss the potential causes of this results.

The Role of Loan Demand Explanations

As with other empirical studies on the effect of monetary policy on credit, we face an identification question as to whether the observed relationship between monetary policy pass-through and income is driven by changes in bank lending behaviour or shifts in credit demand. On the demand side, this relationship could be driven by disproportionate increases in credit demand from lower-income individuals in response to monetary policy contractions. However, our results are inconsistent with being primarily driven by loan demand for three key reasons. Firstly, the regression specification controls for *observable* loan demand. Secondly, the regression results on heterogeneity at the top end of the income distribution and when restricting the sample to payroll loans mean the results are also inconsistent with being driven by *unobservable* demand (i.e., demand that does not manifest as increased loan volumes due to credit constraints). Lastly, the results focus on heterogeneity in impact pass-through, meaning that the general equilibrium effects of monetary policy on loan demand through income are unlikely to be the key factor in generating pass-through heterogeneity. We therefore conclude that unaccounted demand-side factors are likely to be small and our results are inconsistent with being driven by demand-side explanations.

By including the interactions of the policy rate with loan portfolio and individual characteristics in our specification, we are able to explicitly capture many of the observable effects of monetary policy on individuals' credit demand. In including the total volume of the individual's new loans portfolio in each period as well as the total volume of outstanding credit recorded in the credit registry, the regression proxies for loan demand through an individual's indebtedness. The total outstanding credit variable includes revolving lines of credit such as overdrafts and credit cards, which can be accessed instantaneously by consumers and do not require pre-approval (conditional on a pre-arranged limit). These indebtedness variables are therefore responsive measures of loan demand for individuals who are not credit constrained.[35] Alternatively, an increase in credit demand could manifest as reduced debt service, with individuals delaying their existing loan payments. As this would negatively impact their creditworthiness, this behaviour is more likely to occur in credit-constrained individuals. This effect would also be controlled for by the interaction between total non-performing credit recorded in the credit registry and the Selic. The design of the regression specification therefore controls for observable loan demand.

[35]Note that while the use of credit types not included in our selected loan portfolio is captured by our total outstanding credit variable, switching to these credit types has no effect on the dependent variable (which only considers a selected portfolio of four loan types). The increased perceived risk of using revolving lines of credit on interest rates is also captured by a "multimodality" variable, which indicates whether multiple revolving lines of credit are in use. The results are therefore not driven by lower-income individuals switching to alternative, more expensive credit.

Moreover, we find that increased observable loan demand is not a key driver of heterogeneous pass-through. If higher pass-through to lower-income borrowers was the result of a surge in loan demand and loan volumes for low earners, then we would expect that lower-income individuals would increase credit volumes as much as possible in response to increases in the Selic, causing an increase in interest rates charged. In this scenario, changes in loan portfolios would exacerbate the heterogeneity in pass-through along the income distribution.[36] Removing the loan portfolio and Selic interactions that control for this effect should therefore result in coefficient estimates that are biased upwards, and so higher than those in Table 1. This is not the case. Table 9 shows that the coefficient estimates for the regression without loan portfolio characteristics and Selic interaction terms are smaller than in Result 1. The estimated β_1 coefficient on the continuous income variable shows that the pass-through of a 100 bps increase in the Selic is estimated to decline by 12 bps for every additional 10,000 BRL in monthly earnings, in contrast to the estimated 32 bps differential when including Selic and loan interaction terms. This implies that lower-income individuals are *not* disproportionately increasing their observable loan demand when the policy rate rises, which is inconsistent with loan demand driving our heterogeneity results.

The residual not captured by the interaction terms is the unobservable change in loan demand that does not manifest in an increase in credit (including easy-access credit that does not necessarily require pre-approval) or a reduction in debt service. As we are only able to observe credit accessed by an individual, our proxies for loan demand cannot capture the effects of *unrealised* loan demand, such as increased loan applications from lower-income, credit constrained individuals that are not approved but still affect credit rates for that income group. Nevertheless, we conclude that our results are inconsistent with being driven by unobservable credit demand in the form of rejected loan applications.

Crucially, the negative relationship between monetary policy pass-through and income is seen even at very high levels of income. Recall that column 3 of Table 1 shows that individuals earning between 10 and 20 times the minimum wage are estimated to see a 71 bps stronger response in their credit rates to a 100 bps monetary policy hike than the highest income group. As earning 10 to 20 multiples of minimum wage would place an individual in the top 7% of income in our sample (and in a similar percentile within the population of Brazil[37]), it is unlikely that these individuals are sufficiently credit

[36]The positive coefficient on the loan volume and Selic interaction term (which is omitted from the results table for brevity) verify that increases in loan volumes when the policy rate rises increase credit rates further – i.e., that $\frac{\partial^2 r_{ibmt}}{\partial \textbf{Selic}_t \, \partial \textbf{Loan Volume}_{ibt}} > 0$.

[37]See Engbom and Moser (2022).

constrained such that a rise in rejected loan applications could drive this difference in pass-through with the highest income category. This pass-through differential at the top end of the income distribution is also seen when restricting the sample to payroll loans, where the nature of wage consignment means that debt servicing payments are deducted directly from wages. Individuals at the top of the income distribution applying for loans with wage consignment are unlikely to be significantly credit constrained, even given the 30% cap on payment-to-income ratios for payroll loans. This means that unobserved credit demand is not likely to be the primary cause of pass-through heterogeneity.

The asymmetry in pass-through heterogeneity also casts doubt on unobservable credit demand as an explanation for the results. Results 3 and 3b show that the pass-through of monetary policy hikes was strongest for low-income borrowers, but the pass-through of cuts was strongest for high-income borrowers. For this result to be driven by credit demand, we would require that the credit demand of borrowers differs across the income distribution and that this difference is asymmetric. This implies that a monetary policy contraction causes a larger credit demand increase for low-income borrowers than high-income borrowers, but a monetary policy cut prompts a smaller credit demand fall for low-income borrowers than for higher earners. Hence, a credit demand explanation for this asymmetry would impose a corresponding asymmetric credit demand narrative which is inconsistent with empirical evidence on the cyclicality of income inequality (Patterson, 2023).

Lastly, the timing of our investigation limits the extent to which unobserved demand may be driving our results. The most obvious way for monetary policy contractions to generate a stronger credit demand response for lower-income borrowers is if a rise in the Selic generates a fall in the incomes earned by these individuals. However, this fall in incomes is a general equilibrium effect (for example, resulting from the impact of monetary policy on labour markets), which would primarily take effect after a time lag (Buda et al., 2025). The fall in incomes required to generate a rise in credit demand large enough to drive our results is not likely to materialise within one month of the monetary policy rate change. This further reduces the appeal of demand-side explanations as a driver of the observed pass-through heterogeneity.

As our results are inconsistent with being driven by demand side explanations, we point to the role of bank lending behaviours that disproportionately affect lower-income individuals in determining heterogeneity in pass-through.

Coefficient on Selic and Income Interaction Terms.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic	-1.20e-05**		
	(5.14e-06)		
Income percentile × Selic		-0.00522**	
		(0.00253)	
(Income = N/A) × Selic			2.745***
			(0.471)
(Income multiple = 0) × Selic			0.745
			(0.531)
(Income multiple = 0-1) × Selic			0.711**
			(0.317)
(Income multiple = 1-2) × Selic			0.855***
			(0.314)
(Income multiple = 2-3) × Selic			0.636*
			(0.332)
(Income multiple = 3-5) × Selic			0.543*
			(0.300)
(Income multiple = 5-10) × Selic			0.362
			(0.230)
(Income multiple = 10-20) × Selic			0.464**
			(0.211)
(Income multiple = 20+) × Selic			0
			(0)
Loan controls	✓	✓	✓
Loan controls × Selic	×	×	×
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Municipality-Time FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	3,618,601	3,618,601	3,618,601
R-squared	0.695	0.695	0.695

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Coefficient estimates from regression specification 1 **without** loan and Selic interaction terms, for the full sample of individual loan portfolios.

The Role of Relationship Lending

There exists a substantial literature on the role of relationship lending in credit access (Elyasiani and Goldberg 2004; Elsas 2005; Beck et al. 2018). While relationship lending is likely to contribute to heterogeneity in pass-through, the results discussed in this paper on the heterogeneous relationship between *income* and pass-through control for the potential role of relationship lending. That is, in our results, income does not proxy for the effects of relationship lending. Instead, pass-through is heterogeneous along the income distribution even when controlling for borrowers' differing financial relationships with lenders. This is due to the design of our empirical specification, where we include as a control variable the length of the financial relationship between an individual and a lender. As we also interact all control variables with the policy rate, we control for the case where individuals with longer financial relationships with lenders are more shielded from changes to the policy rate. As our specification for investigating asymmetry in pass-through heterogeneity also allows for asymmetry between hikes and cuts for all control variable interactions with the policy rate, Result 3 also controls for the case where individuals with longer financial relationships are shielded from policy rate hikes yet experience more favourable credit costs reductions in response to policy rate cuts. The inclusion of individuals' length of financial relationship with a lender therefore controls for the intensive margin effects of relationship lending on heterogeneity in pass-through across the income distribution.

The Role of Income Risk and Uncertainty

We suggest that income risk and uncertainty may play a part in amplifying heterogeneity in pass-through along the income distribution. However, risk is unlikely to fully explain our results on pass-through heterogeneity.

Recall that our results indicate that monetary policy pass-through is highest for individuals with no income information. Relative to borrowers in the highest income category, our estimates suggest that the pass-through of a 100 bps increase in the Selic is almost 370 bps higher for borrowers with no income information (column 3, Table 1). This estimate is substantially higher than the estimated 172 bps stronger pass-through for an individual earning no income (relative to the highest income level). The higher pass-through for individuals with no income information suggests that there is an *additional* uncertainty premium in the responsiveness of credit rates to monetary policy (as the most conservative assumption for individuals without income information is that they have no income). One explanation for this differential in pass-through could be that individuals with no income information have higher future income risk than individuals known to be

earning no income.

An income risk explanation could also be consistent with the documented negative correlation between income and pass-through if lower-income individuals have more income uncertainty.[38] If banks view low-income consumers as being subject to greater income risk following a monetary contraction, they may respond by increasing interest rates by more for these individuals to insure against this risk. The role of income risk in contributing to heterogeneity in pass-through is reinforced by our finding that the direct heterogeneity effect is driven by personal loans. As personal loans are uncollateralised and thus subject to higher rates of default, the stronger pass-through of Selic hikes to low-income borrowers for personal loans could be consistent with lenders responding to a larger rise in default and income risk among lower earners.

However, our results cannot be fully explained by changes in income risk. As shown in Table 3, the negative relationship between income and pass-through is still apparent when restricting the sample to loans with wage consignment. As payroll loans are predominantly available to current or retired public sector employees, individuals with payroll loans have relatively low levels of income risk. Defaulting on a payroll loan is also highly unlikely as debt service payments are deducted directly from wages. Even if a payroll loan borrower loses their job, outstanding payments can then be deducted from the borrower's legally mandated unemployment insurance fund. As the heterogeneity in pass-through along the income distribution is seen even when restricting the sample to a loan type with very marginal income and default risk concerns, this suggests that risk is an amplifying factor in our results rather than the primary explanation.

The Role of Market Segmentation

In theory, heterogeneity in pass-through along the income distribution could be driven by market segmentation between low-income and high-income individuals. For instance, individuals of different incomes could borrow in different credit types, from different banks, or in different municipalities. The design of our empirical specification and use of fixed effects means that our results are not driven by market segmentation at the bank or municipality level. However, market segmentation by credit type could lead to differences in loan portfolio composition along the income distribution that help explain the portfolio composition channel of pass-through heterogeneity.

[38]The empirical literature on income inequality has documented that low earners have more volatile and cyclical incomes – see Patterson (2023) for empirical evidence from the US.

Including bank-time fixed effects in our empirical specification ensures that the observed pass-through heterogeneity is not driven by bank-level segmentation across the income distribution. This is important as there may be differences in pass-through between the banks that lend to low-income and high-income borrowers. For example, if lower-income individuals borrow from banks which are more responsive to changes in the policy rate, this would cause low-income borrowers' average credit rates to respond more to monetary policy than those of high-income borrowers.[39] The inclusion of bank-time fixed effects means that we control for the average lending behaviour of every bank, so heterogeneity in pass-through is not driven by different levels of pass-through across banks that cater to different income groups. Instead, our observed pass-through heterogeneity is present relative to a bank's average pass-through rate.

Similarly, the use of time-varying municipality fixed effects means we are able to account for regional differences in credit market conditions that may also be correlated with income. For example, poorer areas may have higher credit market concentration and so experience greater pass-through of monetary policy. By including time-varying municipality fixed effects, we ensure that heterogeneity in pass-through is measured relative to the average pass-through in the local (geographical) credit market. Hence, our results are not driven by credit market segmentation at the geographical level.

However, market segmentation across different loan types could contribute to the portfolio composition channel of heterogeneity. Recall from our analytical decomposition in section 4 that changes in loan portfolio compositions along the income distribution form one of the three channels determining pass-through heterogeneity:

$$\frac{\partial^2 r_i}{\partial \mathbf{Selic} \partial \mathbf{Income}_i} = \sum_l \Bigg[\underbrace{\frac{\partial^2 r_{l,i}}{\partial \mathbf{Selic} \partial \mathbf{Income}_i} \times \text{share}_{l,i}}_{\textbf{(1) Direct heterogeneity effect}} + \underbrace{\frac{\partial}{\partial \mathbf{Selic}} \left(\frac{\partial \text{share}_{l,i}}{\partial \mathbf{Income}_i} \times r_{l,i} \right)}_{\textbf{(2) Portfolio composition effect}} + \underbrace{\frac{\partial \text{share}_{l,i}}{\partial \mathbf{Selic}} \times \frac{\partial r_{l,i}}{\partial \mathbf{Income}_i}}_{\textbf{(3) Mechanical effect from interest rate inequality}} \Bigg].$$

and that this portfolio composition effect of monetary policy can be separated into two

[39] If, as shown by Kashyap and Stein (1995), smaller banks have higher rates of pass-through, then pass-through heterogeneity could be driven by low-income individuals borrowing more from smaller banks. Bank-time fixed effects ensure that such scenarios do not drive our results.

components:

$$\frac{\partial}{\partial \textbf{Selic}}\left(\frac{\partial \text{share}_{l,i}}{\partial \textbf{Income}_i} \times r_{l,i}\right) = \underbrace{\frac{\partial^2 \text{share}_{l,i}}{\partial \textbf{Selic} \partial \textbf{Income}_i} \times r_{l,i}}_{\textbf{2(i)}} + \underbrace{\frac{\partial \text{share}_{l,i}}{\partial \textbf{Income}_i} \times \frac{\partial r_{l,i}}{\partial \textbf{Selic}}}_{\textbf{2(ii)}}.$$

The portfolio composition channel shows that, even in the absence of direct price discrimination in credit costs across low- and high-income individuals, pass-through heterogeneity can arise as a result of differences in loan portfolio composition across the income distribution. The static portfolio composition effect **2(ii)** shows that portfolio composition differences can generate stronger pass-through of monetary policy to low-income borrowers if lower-income borrowers disproportionately borrow in loan types that are more responsive to the policy rate. The dynamic portfolio composition effect **2(i)** shows that lower-income borrowers' interest rates will rise by more if lower earners disproportionately increase their portfolio shares of high interest rate loan types[40] in response to monetary policy.

Market segmentation across loan types could therefore exacerbate the portfolio composition channel in two ways. It could contribute to the static portfolio composition effect (**2(ii)**) if it causes lower-income individuals to disproportionately borrow in more responsive loan types. Additionally, it could contribute to the dynamic effect (**2(i)**) if lower earners are also unable to substitute away from loan types that charge higher interest rates. Indeed, our finding that pass-through heterogeneity is symmetric between the hiking and cutting cycle for payroll loans but not for personal loans suggests that low-income borrowers cannot easily switch between loan types[41] – if loan types were substitutes for low-income borrowers, we would expect that the stronger pass-through of cuts to the payroll interest rates offered to low earners would cause these borrowers to substitute away from personal loans. The fact that low earners receive much weaker pass-through from the Selic to personal loan interest rates implies that this substitution does not take place following a monetary policy contraction. Hence, market segmentation could contribute to pass-through heterogeneity through the portfolio composition channel, helping explain the portion of heterogeneity in pass-through not attributable to the direct heterogeneity effect.

[40] Where the possible loan types are payroll (with wage consignment), personal (without wage consignment), auto and goods loans.

[41] As does the large interest rate differential between payroll and personal loans.

6 Conclusion

Using granular loan-level data from the Brazilian credit registry, this paper finds three novel results on heterogeneity in the pass-through of monetary policy across the income distribution.

Firstly, we document that the pass-through of monetary policy to low-income borrowers' interest rates is stronger than for higher earners, even when controlling for individuals' characteristics and the responses of loan portfolio characteristics to monetary policy. In particular, we emphasise that this heterogeneity in pass-through is not caused by responses in loan volumes or maturities.

Secondly, we decompose the pass-through heterogeneity into three components – a direct heterogeneity effect, a portfolio composition effect, and a mechanical effect stemming from interest rate dispersion. We find evidence of a significant direct heterogeneity effect by documenting that the negative relationship between pass-through and income is present even when comparing "like-for-like" loans of the same type, volume and maturity, with the results being principally driven by heterogeneous pass-through to borrowers in personal and payroll loans. This indicates that our results are not simply driven by differences in loan portfolios or heterogeneous portfolio composition responses, and that lower-income individuals would see higher pass-through even if all individuals held identical loan portfolios.

Thirdly, we find that the heterogeneity in pass-through was asymmetric between the post-Covid hiking and pre-Covid loosening cycles covered in our sample period. During the hiking cycle, lower earners saw larger increases in their interest rates than higher earners. During the loosening cycle, however, the pass-through of monetary policy cuts was weaker for lower-income borrowers. This suggests that lower-income individuals saw credit rates fall by less in response to monetary policy expansions, but then experienced larger rises in credit rates when the policy rate increased. Applying insights from our decomposition, we document that this asymmetry is present in the direct heterogeneity effect, driven by asymmetric heterogeneity in pass-through in the market for personal loans and partially offset by symmetric pass-through in the market for payroll loans.

Taken together, Result 1 and 2 document a novel effect of monetary policy on consumer credit markets, whereby interest rates for lower-income individuals are more responsive to a rise in the policy rate than for higher-income individuals. This is not driven by differences in loan portfolio characteristics or composition, and would be present even if all individuals held identical loan portfolios. Result 3 then shows that heterogeneity in

pass-through differs across policy tightenings and loosenings, and that the pass-through of cuts is weaker for lower-income individuals. This suggests the effect of monetary policy in the consumer credit market directly exacerbates disposable income inequality, as debt service costs rise by more for lower-income individuals when the policy rate rises but fall by less in response to policy rate cuts. These heterogeneities in pass-through could translate into a new transmission channel through which monetary policy can directly impact inequality.

On the causes of pass-through heterogeneity, our results indicate that the role of income risk may have an amplifying effect on the observed heterogeneity, although it is unlikely to solely drive our results. We also argue that our results do not appear to be driven by consumer loan demand explanations, as we are able to control for changes in observable loan demand and the results are inconsistent with being driven by unobserved or unrealised increases in demand.

What remains to explain heterogeneity in monetary policy pass-through along the income distribution? We suggest a potential role for market segmentation in explaining the portfolio composition channel of heterogeneity, which stipulates that differences in portfolio compositions could lead to higher pass-through to lower-income individuals even in the absence of price discrimination along the income distribution. Primarily, however, we point to the role of bank lending behaviour in explaining our direct heterogeneity channel. We conclude that banks disproportionately target lower-income individuals to bear the adverse costs of monetary policy. Whether lower-income individuals are forced to bear these costs due to a lack of alternative credit options or inadvertently succumb to them due to inertia remains an open question. For future research, we therefore look to the role of credit supply, market segmentation and bank lending behaviours in determining heterogeneity in pass-through.

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A Appendix

A.1 Volume and Number of Loans by Loan Type

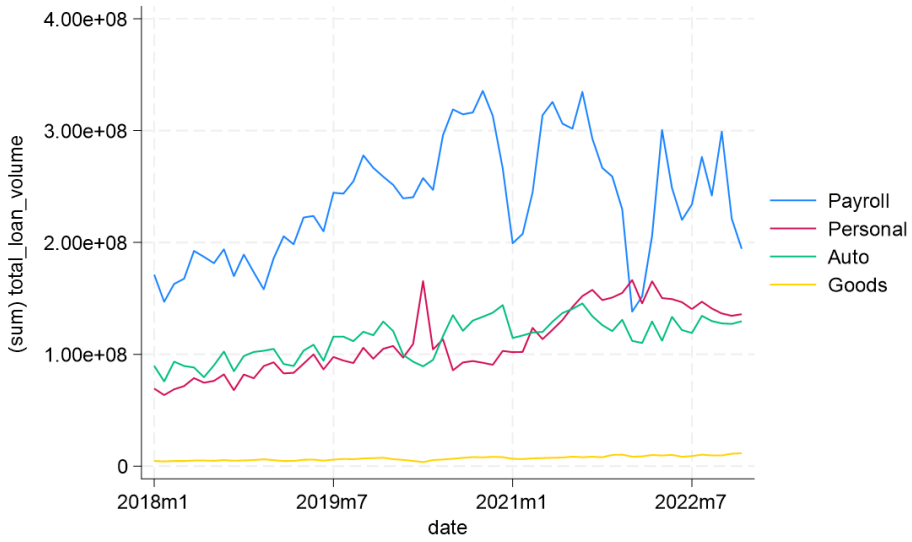


Figure 3: Total loan volume (principal) issued in each period (1% credit registry sample).

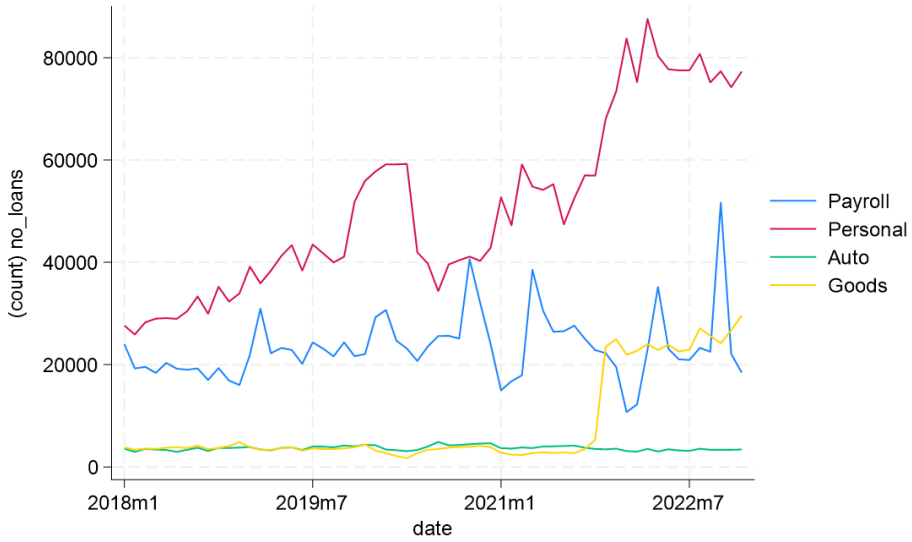


Figure 4: Total number of loans issued in each period (1% SCR sample).

A.2 Income Cleaning Methodology

Our 9 cleaning measures for the continuous income variables are listed below. Cleaning measures also applied to the categorical variable are marked with [CAT.].

1. Take income from newest open loan in each month. (This variable is also used to generate income percentiles.) [CAT.]
2. Take income from newest open loan with non-zero income each month. [CAT.]
3. Take income from newest open loan with nonmissing income in each month. [CAT.]
4. Take income from the newest loan with non-zero income (which may not be open).
5. Take income from the newest loan with non-missing income (which may not be open). [CAT.]
6. Take income from the most recent update – either a new loan with non-zero income or a non-missing update to an old loan. New loans take precedence over updated old loans. (This variable is also used to generate income percentiles.)
7. Option 6, but with updates taking precedence over new loans.
8. Take income from the most recent update (either a new loan with non-missing income or a non-missing update to an old loan. New loans take precedence over updated old loans.
9. Option 8, but with updates taking precedence over new loans.

A.3 Summary Statistics

Variable	Mean	SD	P10	P25	Median	P75	P90
Volume	7314.911	29325.891	137.530	454.200	1577.920	5674.980	18265.777
Interest rate	105.448	180.973	15.953	22.275	32.301	127.500	240.000
Maturity	1007.417	1029.135	35.000	121.000	489.326	1848.000	2576.000
Relationship with bank (days)	91.768	107.809	0.000	5.000	45.000	154.000	255.000
Gender	0.480	0.500	0.000	0.000	0.000	1.000	1.000
Age	46.454	15.854	26.000	33.000	45.000	60.000	68.000
Income group	3.649	1.611	2.000	2.000	3.000	5.000	6.000
Income	3541.132	7085.043	855.520	1140.000	1976.000	3721.000	6994.000
Total outstanding credit	44372.341	84649.083	1346.190	4674.955	17049.311	46592.432	1.11e+05
Total non-performing credit	718.858	3134.517	0.000	0.000	0.000	0.000	1450.900
New to credit registry (Dummy)	0.013	0.111	0.000	0.000	0.000	0.000	0.000
Defaulter (Dummy)	0.385	0.487	0.000	0.000	0.000	1.000	1.000
High debt service to income ratio (Dummy)	0.352	0.478	0.000	0.000	0.000	1.000	1.000
Multimodality (Dummy)	0.217	0.412	0.000	0.000	0.000	0.000	1.000

Table 10: Summary statistics at the individual-bank loan portfolio level.

A.4 Average Pass-Through of Monetary Policy

To examine the average pass-through of monetary policy to interest rates and verify that pass-through is positive, we aggregate our results to the bank-municipality level and perform the following regression:

$$\mathrm{r}_{b,m,t} = \alpha \mathrm{Selic}_t + \beta_1 X_{b,m,t} + \beta_2 \chi_t + \gamma_b^1 + \gamma_m^2 + \epsilon_{b,m,t} \tag{6}$$

where $\mathrm{r}_{b,m,t}$ is the average interest rate, total loan volume (in logarithms) or average maturity issued on new loans by bank b in municipality m at time t. In line with the bank lending channel literature, we control for the leverage ratio of the lender and the weighted average (core) deposit HHI index over the municipalities where bank b raises its core deposits. We include inflation and economic activity controls (χ_t) to isolate the effect of the policy rate on consumer credit, as well as bank and municipality fixed effects (γ_b^1, γ_m^2) to further control for regional- and bank-specific differences in lending behaviour. The coefficient of interest is α, which informs on pass-through of the Selic to new loans.

In line with our investigation into the asymmetric relationship between monetary policy pass-through and income, we also estimate a specification that allows for average pass-through to differ between the cut and hike periods in our sample.

$$\mathrm{r}_{b,m,t} = \mathbb{1}_{cut}\alpha^{cut}\mathrm{Selic}_t + \mathbb{1}_{hike}\alpha^{hike}\mathrm{Selic}_t + \beta_1 X_{b,m,t} + \beta_2 \chi_t + \gamma_b^1 + \gamma_m^2 + \epsilon_{b,m,t} \tag{7}$$

Table 11 displays the estimated pass-through of the Selic to interest rates. In line with the standard assumption and empirical literature, we confirm that a rise in the Selic leads to a rise in the average interest rate on new loans ($\alpha > 0$). We also confirm that the positive pass-through holds in both our hike and cut periods ($\alpha^{hike} > 0$, $\alpha^{cut} > 0$), although the point estimate for pass-through during the cutting period is smaller and not significant.

Pass-through of the Selic at the bank-municipality level

	(1)	(2)	(3)	(4)
DEP. VARIABLE	Interest Rate	Interest Rate	Interest Rate	Interest Rate
Selic	1.167***	1.050***		
	(0.346)	(0.320)		
Selic × cut = 1			0.373	0.406
			(0.433)	(0.413)
Selic × hike = 1			1.389***	1.231***
			(0.388)	(0.358)
Macro Controls	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓
Municipality FE	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Loan Level	YES		YES	
Individual Level		YES		YES
Observations	243,568	243,568	243,568	243,568
R-squared	0.566	0.554	0.566	0.555

Two-way clustered standard errors at the (municipality-time, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1.

Table 11: Coefficient on Selic in regression specifications 6 and 7, estimated for the full sample aggregated to the bank-municipality level.

A.5 Result 3b: No Asymmetry or Heterogeneity in Auto Loans

(**Auto loans**) Coefficient on Selic and Income and Hike or Cut Interaction Terms.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic × cut	-2.95e-07		
	(1.43e-06)		
Income × Selic × hike	-2.82e-07		
	(6.90e-07)		
Income percentile × Selic × cut		0.00113	
		(0.000702)	
Income percentile × Selic × hike		0.000416	
		(0.000394)	
(Income = N/A) × Selic × cut			-0.271
			(0.183)
(Income multiple = 0) × Selic × cut			-0.187
			(0.143)
(Income multiple = 0-1) × Selic × cut			-0.0503
			(0.0862)
(Income multiple = 1-2) × Selic × cut			0.106
			(0.0744)
(Income multiple = 2-3) × Selic × cut			0.0865
			(0.0725)
(Income multiple = 3-5) × Selic × cut			-0.00854
			(0.0652)
(Income multiple = 5-10) × Selic × cut			0.0197
			(0.0613)
(Income multiple = 10-20) × Selic × cut			-0.0380
			(0.0666)
(Income multiple = 20+) × Selic × cut			0
			(0)
(Income = N/A) × Selic × hike			-0.182*
			(0.0990)
(Income multiple = 0) × Selic × hike			0.0900
			(0.128)
(Income multiple = 0-1) × Selic × hike			-0.0220
			(0.0483)
(Income multiple = 1-2) × Selic × hike			0.0123
			(0.0434)
(Income multiple = 2-3) × Selic × hike			0.0179
			(0.0406)
(Income multiple = 3-5) × Selic × hike			0.0105
			(0.0386)
(Income multiple = 5-10) × Selic × hike			0.0135
			(0.0358)
(Income multiple = 10-20) × Selic × hike			-0.0197
			(0.0408)
(Income multiple = 20+) × Selic × hike			0
			(0)
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Municipality-Time FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	174,404	174,404	174,404
R-squared	0.637	0.638	0.639

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Coefficient estimates from regression specification 5 for the sample restricted to individual portfolios of auto loans.

A.6 Result 3b: No Asymmetry or Heterogeneity in Goods Loans

(**Goods loans**) Coefficient on Selic and Income and Hike or Cut Interaction Terms.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic × cut	7.61e-05**		
	(3.82e-05)		
Income × Selic × hike	2.81e-05		
	(2.17e-05)		
Income percentile × Selic × cut		0.0505	
		(0.0315)	
Income percentile × Selic × hike		0.0207	
		(0.0180)	
(Income = N/A) × Selic × cut			2.876
			(2.556)
(Income multiple = 0) × Selic × cut			-4.272
			(3.882)
(Income multiple = 0-1) × Selic × cut			-4.418
			(2.752)
(Income multiple = 1-2) × Selic × cut			-1.955
			(2.101)
(Income multiple = 2-3) × Selic × cut			-1.272
			(3.736)
(Income multiple = 3-5) × Selic × cut			-2.483
			(3.592)
(Income multiple = 5-10) × Selic × cut			0.935
			(2.805)
(Income multiple = 10-20) × Selic × cut			4.943
			(3.005)
(Income multiple = 20+) × Selic × cut			0
			(0)
(Income = N/A) × Selic × hike			0.944
			(1.375)
(Income multiple = 0) × Selic × hike			-3.019
			(2.134)
(Income multiple = 0-1) × Selic × hike			-2.123
			(1.574)
(Income multiple = 1-2) × Selic × hike			-0.970
			(1.159)
(Income multiple = 2-3) × Selic × hike			-0.754
			(1.981)
(Income multiple = 3-5) × Selic × hike			-2.141
			(1.984)
(Income multiple = 5-10) × Selic × hike			-0.239
			(1.456)
(Income multiple = 10-20) × Selic × hike			2.391
			(1.597)
(Income multiple = 20+) × Selic × hike			0
			(0)
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Municipality-Time FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	234,286	234,286	234,286
R-squared	0.310	0.311	0.311

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Coefficient estimates from regression specification 5 for the sample restricted to individual portfolios of goods loans.

A.7 Loan-Level Counterpart to Table 1.

Coefficient on Selic and Income Interaction Terms.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic	-1.88e-05***		
	(4.91e-06)		
Income percentile × Selic		-0.00466**	
		(0.00218)	
(Income = N/A) × Selic			2.216***
			(0.444)
(Income multiple = 0) × Selic			1.517***
			(0.395)
(Income multiple = 0-1) × Selic			0.881***
			(0.298)
(Income multiple = 1-2) × Selic			1.206***
			(0.276)
(Income multiple = 2-3) × Selic			1.036***
			(0.249)
(Income multiple = 3-5) × Selic			0.792***
			(0.221)
(Income multiple = 5-10) × Selic			0.511***
			(0.197)
(Income multiple = 10-20) × Selic			0.424**
			(0.171)
(Income multiple = 20+) × Selic			0
			(0)
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Individual FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	4,613,529	4,613,529	4,613,529
R-squared	0.748	0.748	0.748

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Coefficient estimates from regression specification 1 performed at the loan-level, for the full sample of individual loan portfolios.

A.8 Individual Fixed Effects Counterpart to Table 1.

Coefficient on Selic and Income Interaction Terms.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic	-1.67e-05***		
	(4.76e-06)		
Income percentile × Selic		-0.00474**	
		(0.00231)	
(Income = N/A) × Selic			1.386***
			(0.444)
(Income multiple = 0) × Selic			1.284***
			(0.432)
(Income multiple = 0-1) × Selic			0.959***
			(0.305)
(Income multiple = 1-2) × Selic			1.252***
			(0.286)
(Income multiple = 2-3) × Selic			1.025***
			(0.258)
(Income multiple = 3-5) × Selic			0.814***
			(0.223)
(Income multiple = 5-10) × Selic			0.522***
			(0.196)
(Income multiple = 10-20) × Selic			0.506***
			(0.169)
(Income multiple = 20+) × Selic			0
			(0)
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Individual FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	3,453,304	3,453,304	3,453,304
R-squared	0.752	0.752	0.752

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Coefficient estimates from regression specification 1 with individual fixed effects, for the full sample of individual loan portfolios.

A.9 Individual Fixed Effects Counterpart to Table 6.

Coefficient on Selic and Income and Hike or Cut Interaction Terms.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic × cut	3.05e-05***		
	(8.69e-06)		
Income × Selic × hike	-6.95e-06		
	(4.69e-06)		
Income percentile × Selic × cut		0.0107***	
		-0.00386	
Income percentile × Selic × hike		-0.00168	
		(0.00231)	
(Income = N/A) × Selic × cut			0.870
			(0.883)
(Income multiple = 0) × Selic × cut			-0.149
			(0.676)
(Income multiple = 0-1) × Selic × cut			-1.715***
			(0.516)
(Income multiple = 1-2) × Selic × cut			-0.931**
			(0.450)
(Income multiple = 2-3) × Selic × cut			-0.893**
			(0.424)
(Income multiple = 3-5) × Selic × cut			-0.928**
			(0.372)
(Income multiple = 5-10) × Selic × cut			-0.473
			(0.328)
(Income multiple = 10-20) × Selic × cut			-0.185
			(0.281)
(Income multiple = 20+) × Selic × cut			0
			(0)
(Income = N/A) × Selic × hike			1.325***
			(0.483)
(Income multiple = 0) × Selic × hike			0.750*
			(0.424)
(Income multiple = 0-1) × Selic × hike			0.407
			(0.300)
(Income multiple = 1-2) × Selic × hike			0.813***
			(0.274)
(Income multiple = 2-3) × Selic × hike			0.641**
			(0.252)
(Income multiple = 3-5) × Selic × hike			0.460**
			(0.219)
(Income multiple = 5-10) × Selic × hike			0.309
			(0.193)
(Income multiple = 10-20) × Selic × hike			0.364**
			(0.172)
(Income multiple = 20+) × Selic × hike			0
			(0)
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Individual FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	3,618,601	3,453,304	3,453,304
R-squared	0.696	0.753	0.753

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16: Coefficient estimates from regression specification 5 (with asymmetry) with individual fixed effects for the full sample of individual loan portfolios.

A.10 Result 1: Selic Versus Inflation Horse Race

Coefficient on Selic and Income Interaction Terms with Inflation Horse Race.

	(1)	(2)	(3)
VARIABLES	Interest Rate	Interest Rate	Interest Rate
Income × Selic	-1.84e-05**		
	(7.52e-06)		
Income percentile × Selic		-0.00811**	
		(0.00394)	
(Income = N/A) × Selic			3.009***
			(0.800)
(Income multiple = 0) × Selic			1.334**
			(0.663)
(Income multiple = 0-1) × Selic			0.946**
			(0.460)
(Income multiple = 1-2) × Selic			1.374***
			(0.459)
(Income multiple = 2-3) × Selic			0.984**
			(0.404)
(Income multiple = 3-5) × Selic			0.672*
			(0.349)
(Income multiple = 5-10) × Selic			0.441
			(0.284)
(Income multiple = 10-20) × Selic			0.219
			(0.241)
(Income multiple = 20+) × Selic			0
			(0)
Inflation horserace	✓	✓	✓
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Municipality-Time FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	3,618,601	3,618,601	3,618,601
R-squared	0.695	0.695	0.695

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Coefficient estimates from regression specification 1 with additional inflation interaction terms for the full sample of individual loan portfolios.

A.11 Result 2: Selic Versus Inflation Horse Race

(**Payroll loans**) Coefficient on Selic and Income Interaction Terms with Inflation Horse Race.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic	-3.16e-06		
	(2.87e-06)		
Income percentile × Selic		-0.00190**	
		(0.000915)	
(Income = N/A) × Selic			0.779***
			(0.235)
(Income multiple = 0) × Selic			-1.170
			(1.203)
(Income multiple = 0-1) × Selic			0.287**
			(0.137)
(Income multiple = 1-2) × Selic			0.214
			(0.137)
(Income multiple = 2-3) × Selic			0.226**
			(0.115)
(Income multiple = 3-5) × Selic			0.191*
			(0.0985)
(Income multiple = 5-10) × Selic			0.190**
			(0.0910)
(Income multiple = 10-20) × Selic			0.120
			(0.0949)
(Income multiple = 20+) × Selic			0
			(0)
Inflation Horserace	✓	✓	✓
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Municipality-Time FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	1,019,097	1,019,097	1,019,097
R-squared	0.845	0.845	0.845

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Coefficient estimates from regression specification 1 with additional inflation interaction terms for the sample restricted to individual portfolios of payroll loans (loans with wage consignment).

(**Personal loans**) Coefficient on Selic and Income Interaction Terms with Inflation Horse Race.

VARIABLES	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
Income × Selic	-1.82e-05		
	(1.18e-05)		
Income percentile × Selic		-0.0155***	
		(0.00497)	
(Income = N/A) × Selic			2.902***
			(0.828)
(Income multiple = 0) × Selic			2.695***
			(0.830)
(Income multiple = 0-1) × Selic			1.484**
			(0.711)
(Income multiple = 1-2) × Selic			1.263*
			(0.677)
(Income multiple = 2-3) × Selic			0.832
			(0.613)
(Income multiple = 3-5) × Selic			0.597
			(0.538)
(Income multiple = 5-10) × Selic			0.371
			(0.455)
(Income multiple = 10-20) × Selic			0.352
			(0.377)
(Income multiple = 20+) × Selic			0
			(0)
Inflation Horserace	✓	✓	✓
Loan controls	✓	✓	✓
Loan controls × Selic	✓	✓	✓
Individual controls	✓	✓	✓
Individual controls × Selic	✓	✓	✓
Municipality-Time FE	✓	✓	✓
Bank-Time FE	✓	✓	✓
Observations	2,104,493	2,104,493	2,104,493
R-squared	0.786	0.786	0.786

Two-way clustered standard errors at the (individual, bank-time) level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Coefficient estimates from regression specification 1 with additional inflation interaction terms for the sample restricted to individual portfolios of personal loans (loans without wage consignment).