Working Paper Series

No 125 / September 2021

Determinants of the credit cycle: a flow analysis of the extensive margin

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Abstract

Using loan-level data covering almost all loans to households and businesses from banks in Italy over the past 20 years, we offer new empirical evidence that credit declines during a recession primarily because of the reduction in the net creation of borrowers. We then build on a flow approach to decompose the net creation of borrowers into gross flows across three statuses: (i) borrower, (ii) applicant and (iii) neither borrower nor applicant (i.e. inactive firms or households in the bank credit market). Along the macroeconomic dimension of these gross flows, we document four cyclical facts. First, fluctuations in the number of new borrowers (inflows) account for the bulk of volatility in the net creation of borrowers. Second, the volatility of borrower inflows is two times as large as the volatility of obligors exiting from the credit market (outflows). Third, borrower inflows are highly procyclical and tend to lead the business cycle. Fourth, decreases in the probability of a match between borrower and lender during recessions are a leading explanation for the role of borrower inflows.

JEL Classification: E51, E32, E44.
Keywords: Borrower flows, business cycles, credit cycles, credit market participation.

1 Introduction

There is extensive and solid-grounded evidence that private debt is closely intertwined with the business cycle.[1] However, what drives the expansion and contraction in private debt remains fundamentally unclear. In principle, a borrower may borrow from a new lender (extensive margin), from a pre-existing lender (intensive margin), or from both.[2] These possibilities raise several questions. What is the role of the extensive and intensive margins in shaping fluctuations in private debt? Are the number of borrowers that enter or exit from the credit market (the participation margin) a key driver of the extensive margin? Do search and matching frictions in the credit market matter for macro-financial linkages?

This paper proposes answers to these questions with four contributions. First, we offer new empirical evidence showing that debt expansions mainly result from changes in the number of borrowers rather than the average debt per borrower in Italy. Second, we propose a flow approach to decompose the net creation of borrowers into borrower inflows and outflows. Third, we quantify the size and the cyclical sensitivity of borrower gross flows. Inflows of borrowers play a key role in shaping the dynamic pattern of the participation margin in the credit market. Fourth, decreases in the probability of a match between borrower and lender during recessions are a leading explanation for the role of borrower inflows. This paper thus consists of four parts, one for each contribution, which we now describe in more detail.

In the first part of the paper, we examine the connection between private debt per capita and employment fluctuations at the regional level in Italy. We use the Italian Credit Register and the Italian Labor Force Survey data over the period 1999Q1-2019Q4. Private debt expansions typically last for three to four years and are associated with employment expansions. We then assess whether differences in debt fluctuations reflect differences between average debt per borrower versus the number of borrowers. Strikingly, movements in the borrower-to-population ratio emerge as the primary source of debt per capita differentials, accounting for 91% of the variation.

[1] Several studies show that rapid expansions in private debt are often followed by severe recessions (e.g. Schularick and Taylor, 2012; Jorda, Schularick and Taylor, 2013; Dell'Ariccia et al., 2012; Mian, Sufi and Verner, 2017; Greenwood et al., 2020).

[2] Although the role of nonbank financial firms in the provision of credit to the real economy has recently increased, bank credit still represents the main source of financing for households and corporations in most advanced and emerging economies.

In the second part of the paper, we propose a methodology to measure borrower flows. We classify individual households (HHs) and non-financial corporations (NFCs) into three non-overlapping statuses: (i) borrower, (ii) applicant and (iii) inactive HH or NFC in the credit market. We then build time series for the stock of HHs and NFCs in each status and compute transitions across groups (gross flows), e.g. the number of HHs that borrow at time t and become inactive at time $t+1$. Gross flows are of interest because provide insights into the mechanisms leading to borrowers' fluctuations. A simple numerical example can be useful to fully appreciate the relevance of focusing on both gross inflows and outflows of borrowers rather than just the net creation of borrowers. Consider one observes an increase of 10,000 units in the net creation of borrowers. These figures can be associated with two different extreme cases in the credit market. They can emerge in an economy in which 11,000 new borrowers enter the credit market and 1,000 pre-existing borrowers exit from the market or in an economy where 100,000 new borrowers enter and 90,000 pre-existing borrowers exit from the market. In the latter economy, bank credit reallocation among borrowers is clearly much higher than in the former one.

In the third part of the paper, we uncover three facts not previously reported in the literature. First, entries in the credit market by new obligors ("inflows") account for the bulk of volatility in the net creation of borrowers. Second, the volatility of borrower inflows is two times as large as the volatility of obligors exiting from the credit market ("outflows"). Third, borrower inflows move procyclically and tend to lead the business cycle. The dominant role of borrower inflows indicates that the number of borrowers declines during a recession because entering the credit market is particularly hard, not because borrowers exit from the market.

In the fourth part of the paper, we quantify the magnitude of informational and matching frictions in shaping the fluctuations in the inflows of borrowers, decomposing borrower inflows into the product of unknown borrowers and the probability for those borrowers of finding a new loan. We find that the bulk of volatility in borrower inflows is accounted for by the probability of matching with a new bank, i.e. frictions stemming from imperfect matching between borrowers and lenders.

To the best of our knowledge, a flow approach analysis in the credit market is novel to the literature. This kind of analysis can be carried out by other countries where individual loan data are collected as well. We see, however, four distinct advantages of using Italian data for assessing gross credit and borrower flows. First, the Central Credit Register records the individual loans of all resident banks as well as loan applicants. In this way, we can measure gross flows both for borrowers and for loan applicants to a new bank. Second, despite the Central Credit Register service is not an Italian specificity, the time series data set is quite unique in terms of historical length and granularity. Third, nearly all household mortgages are originated by banks and around three-quarter of business financial liabilities are liabilities to banks. Fourth, Italy's economy was severely hit by the double-dip recession following the global economic crisis of 2007 to 2009 and the sovereign debt crisis of 2010 to 2011. Both recessions were caused by factors that were largely exogenous to the banking sector. From 2007 to 2013 GDP fell by 9%, industrial production by almost a quarter, and investment by almost 30%. Both NFCs and HHs were affected by these large shocks and so we can assess whether the patters of borrower transitions have been different for consumers and producers.[3]

The distinction between the extensive and intensive margin is important because a bank in general faces more uncertainty regarding the creditworthiness of *new* borrowers than *known* clients. Over the course of a relationship the lender acquires private ("soft") information about their borrowers.[4] New borrowers are hence imperfect substitutes for pre-existing clients. This entails that the macroeconomic implications of credit fluctuations may differ depending on whether those involves new or pre-existing borrowers. For example, Dell'Ariccia and Marquez (2006) highlight that a rise in the number of unknown borrowers during a boom may lead to an easing of lending standards, thereby rendering banks more prone to financial distress in the event the economy experiences a downturn. Boualam (2018), instead, points out that recessions characterized by a sizable reduction in the number of pre-existing borrowers can trigger slowdown in economic recovery.[5]

[3] Researchers have highlighted that the increase in the household debt to GDP ratio predicts lower subsequent growth, whereas an increase in the firm debt to GDP ratio is uncorrelated with subsequent growth (Mian, Sufi and Verner, 2017; IMF, 2017).

[4] A literature review on the role of relationship banking in resolving problems of asymmetric information is for instance in Boot (2000). Liberti and Petersen (2018) review the importance of soft information in lending.

[5] den Haan, Ramey and Watson (2003) and Wasmer and Weil (2004) emphasize the existence of a match-

Related literature. Our paper is related to several strands of literature. First, our work complements the literature on gross credit flows. Dell'Ariccia and Garibaldi (2005) assess the dynamic properties of credit creation (destruction) by calculating debt growth rates of individual banks with rising (shrinking) debt.[6] Herrera, Kolar and Minetti (2011) apply a similar approach but focus on credit reallocation between firms. These studies document that credit expansion and contraction are sizeable and highly volatile, and coexist at any phase of the cycle. Our analysis is very much in the spirit of theirs, but our focus in on borrower flows rather than credit flows.

Ours is also the first paper to actually apply a flow approach to the credit market, thereby showing a conceptual similarity between the statuses of employee and borrower as well as between the statuses of unemployed and applicant. Marston (1976), Abowd and Zellner (1985), Poterba and Summers (1986), and Blanchard and Diamond (1990) exploit micro data on individuals' employment status and construct time series for the gross flow of workers between the statuses of employment, unemployment, and inactivity. In a similar vein, we construct gross flows between the statuses of borrower, applicant, and inactivity, analyzing their cyclical properties.

Third, by emphasizing the important role of the extensive margin in shaping bank credit dynamics, this paper is related to the literature on search and matching as well as to the literature on the informational structure of loan markets. den Haan, Ramey and Watson (2003), Wasmer and Weil (2004) and Petrosky-Nadeau and Wasmer (2013) introduce financial imperfections in a Mortensen-Pissarides economy with matching functions in the loan market. The introduction of financial frictions gives rise to an addition entry cost for firms, the cost of accessing finance, which amplifies the business cycle. Dell'Ariccia and Marquez (2006), instead, argue that changes in the informational structure of loan markets can lead to credit booms when the fraction of unknown borrowers rises. Our contributions to these theoretical studies is to show that the extensive margin magnifies fluctuations in total credit. Moreover, we provide some evidence on distinguishing alternative theories for credit fluctu-

ing frictions between bank funds and applicants that are not informational in nature, such as preferences for specific banks because of specialization across regions/industries or the presence of searching/switching costs.

[6] They adapt the methodology employed by Davis and Haltiwanger (1992) in studying the aggregate consequences of heterogeneous labor adjustment to construct job flows data.

ations. Specifically, we disentangle the relative importance of matching probabilities from the number of unknown borrowers in shaping borrower inflows, thereby evaluating their contribution to aggregate changes in the number of borrowers.

Other empirical studies have focused on the link between aggregate debt in the non-financial private sector and the business cycle (Mendoza and Terrones, 2008; Schularick and Taylor, 2012; Jorda, Schularick and Taylor, 2013; Krishnamurthy and Muir, 2017; Mian, Sufi and Verner, 2017). However, the micro determinants of credit cycle remain largely under-explored. For example, to quote Jorda, Schularick and Taylor (2016) "a natural question to ask is whether this surge in household borrowing occurred on the intensive or extensive margin. In other words, did more households borrow or did households borrow more? Ideally, we would have long-run household-level data to address this question, but absent such figures we can nonetheless infer some broad trends from our data." The methodological approach and implementation in this paper are novel to the macro-finance literature and use a large and clean panel dataset on individual loans over the past 20 years.

Layout. The paper is organized as follows. Section 2 describes the data. Section 3 presents the connection between debt per capita expansion and employment fluctuations at the regional level. Section 4 assess whether differences in debt per capita fluctuations reflect differences between average debt per borrower versus borrower-to-population ratio. Section 5 proposes a flow approach to decompose the net creation of borrowers in the borrower inflows and outflows. Section 6 and 7 present the main results. Section 8 concludes. Additional details and robustness can be found in the Appendix.

2 Data and Summary Statistics

The primary level of aggregation in our dataset is the borrower. From about 8 million borrowers in the banking system (2.4 million NFCs and 5.6 million HHs), we then construct a balanced panel of region-level bank loan disbursements to HHs and NFCs in Italy. The Italian region is the first-level constituent entities of the Italian Republic, constituting its second NUTS administrative level. The country is organized in 20 regions, of which five have greater autonomy than the other fifteen.[7] The final dataset covers 20 regions from 1999:Q1 to 2019:Q4.

2.1 Central Credit Register

The empirical analysis relies on HHs' and NFCs' debt towards the banking and financial systems available from the Italian Central Credit Register (CCR). The CCR is an information system operated by the Bank of Italy, the Italian central bank, which contains all loans extended by all credit institutions to individuals. Jointly with the European Central Bank, the Bank of Italy supervises the Italian banking system. Every month each bank or financial company reports the debtor position of all its clients whose exposure is equal or higher than €30,000. In the rest of the paper, the term 'bank' is used indifferently to refer to bank or financial company.[8]

As of January 2009 the minimum bank's exposure to each client, which was previously set to €75,000, has been lowered to €30,000. To appropriately control for this discontinuity, we limit the analysis to borrowers whose total credit exposures to a bank exceeds €75,000. Credit exposures between €30,000 and €75,000 account for around 5% of total credit to HHs and NFCs. Note that the threshold of €75,000 implies *de facto* that the analysis captures only mortgages for HHs.[9] Producer households (i.e. firms with up to 5 employees) are included among NFCs.

Is the private debt dynamics considerably altered by the €75,000 threshold? Figure 1 compares our borrower-based dataset ("censored") to banks' balance sheet data ("uncensored"). Specifically, the uncensored line shows the annual growth rates of loans to the non-financial private sector using banks' balance sheet data drawn from the Bank of Italy's Statistical Database.[10] The censored line contains data from the CCR with a €75,000 thresh-

[7] In order to take into account cultural differences and protect linguistic minorities, Sardinia, Sicily, Trentino-Alto Adige/Südtirol, Aosta Valley and Friuli Venezia Giulia have special forms and conditions of autonomy in terms of legislative, administrative and financial power.

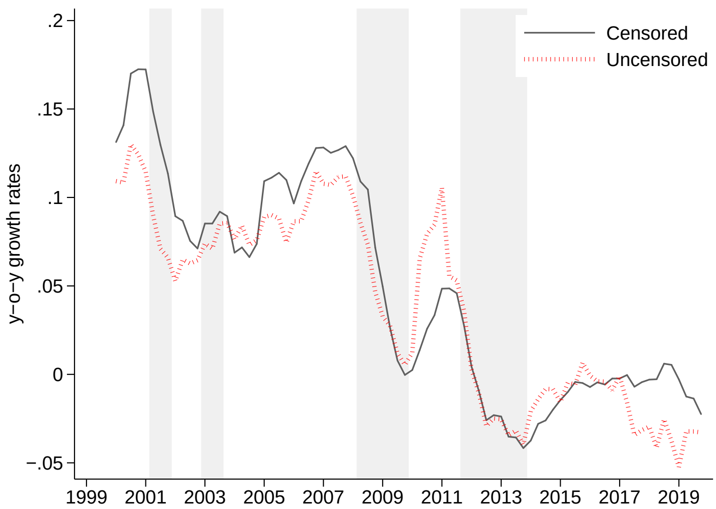
[8] Banks are by far the major lenders to HHs and NFCs.

[9] Pursuant to Article 122 of Legislative Decree No. 385 of 1 September 1993 (the "Banking Act"), only loans granted for amounts lower than €75,000 are considered consumer loans.

[10] Beyond not having a reporting threshold, the Statistical Dataset differs from the CCR in three respects mainly. First, they contain reverse repos. Second, the "banking perimeter" is the banking group and accordingly excludes business activities conducted through financial corporations. Third, loans include those not reported on banks' balance sheets because they have been securitized or otherwise transferred.

old. All in all, our censored series is a very good approximation to the uncensored one. The correlation between the two series is 0.93. Henceforth, we will use this strong relationship to just focus on censored data for studying the dynamics of bank credit in Italy.

Figure 1: Bank credit to households and businesses



Notes: "Censored" loans include total bank exposures to one borrower exceeding €75,000. "Uncensored" loans are drawn from the Bank of Italy's Statistical Database. Shaded regions represent recessions which are identified as periods of at least two consecutive quarters of negative real GDP q-o-q growth.

We collect all types of bank loans to the private sector as end-of-quarter outstanding amounts, deflated by the GDP deflator. The CCR records information on the loan type, loan amount, date of origination, maturity, default status, and guarantees. In our analysis we consider all loan types, namely loans backed by account-receivables, term loans, credit lines, and bad loans ("sofferenze").[11] We supplement these data with additional firm- and household-specific information on the region of residence, guarantees, loan applications.[12] Whenever banks receive a loan application from new potential clients, they can access individual credit reports to assist in their decision. Each time they request a credit report for credit-related purposes an inquiry is listed in the CCR (the so-called preliminary information

[11] Bad loans are exposures to insolvent counterparties (even if not legally ascertained), regardless of any loss estimate made by the bank and irrespective of any possible collateral or guarantee. A €250 threshold applies for reporting bad loans.

[12] To deal with heterogeneity issues, in Section 7 we show some results at the provincial level. There are 107 Italian provinces distributed in 20 regions.

request or "servizio di prima informazione").[13]

2.2 Italian Labor Force Survey

In order to assess the connection between private debt and the regional business cycle, we consider the number of employed workers aged 15 and over. We draw on the official information on regional labor markets released by the Italian Institute of Statistics. Specifically, we combine the total number of both independent and payroll employees resident in each region as gathered from the Italian Labour Force Survey. This is one of the major surveys carried out on national territory on the evolution of the Italian labour market and detects the number of employed, unemployed and inactive persons in the labor market. The official evaluations of the main aggregates of the job offer are produced and disseminated monthly at the national level and on a quarterly basis at the regional level.[14]

2.3 Summary Statistics

Panels A, B, and C of Table 1 report summary credit statistics for the region-level sample in December 2011. There are 20 regions, and they partition the Italian territory. The average private debt in each region amounted to €72 bln. The guaranteed share of private debt was about 50%. On average each NFC borrowed €1 mln. The NFC default rate was 11% and guarantees amounted to 36% of NFC debt. As to HHs, they borrowed €145,000 per capita. The HH default rate was about 7% and 92% of HH debt was guaranteed. Panel D reports summary labor statistics. Average employment rate was 67% in each region and average population was roughly 2 million people aged 15 and over.

Italy experienced a particular rapid expansion in NFC and HH credit prior to the global financial crisis 2008-2009. Figures 2 and 3 show that between 1999 and 2008 the NFC debt to GDP ratio increased by 30 percentage points and the HH debt to GDP ratio by 13 percentage points. NFC and HH lending was accompanied by a fall in the debt risk premium. Figure 4 displays the spread between the bank interest rates and the euro 1-year OIS. This measure

[13] Banks use this service only when the loan application originates from a new potential borrower, as the CCR regularly updates banks with information on the overall credit position of existing clients.

[14] Provincial data are disseminated annually.

Table 1: Summary statistics

A: Private debt (NFCs+HHs)	Mean	Std. dev.	10th	Median	90th
Credit disbursement (million euros)	72,285	90,265	4,702	41,130	163,658
Borrowers	172,686	181,013	14,150	95,828	347,205
Bad loans (million euros)	7,583	7,639	1,208	4,383	18,238
Guarantees (million euros)	35,941	43,178	2,283	20,401	76,554

B: NFC debt	Mean	Std. dev.	10th	Median	90th
Credit disbursement (million euros)	55,094	70,970	3,525	31,386	127,677
Borrowers	55,665	53,480	5,569	38,392	116,272
Bad loans (million euros)	6,440	6,402	1,063	3,734	15,857
Guarantees (million euros)	20,161	25,244	1,297	12,534	42,825

C: HH debt	Mean	Std. dev.	10th	Median	90th
Credit disbursement (million euros)	17,191	19,463	1,177	8,943	37,500
Borrowers	117,021	128,308	8,582	61,177	242,791
Bad loans (million euros)	1,143	1,289	137	649	2,445
Guarantees (million euros)	15,780	18,111	986	8,289	34,401

D: Labor market	Mean	Std. dev.	10th	Median	90th
Employment (thousands)	1,109	984	142	609	2,095
Unemployment (thousands)	118	100	18	104	282
Population (thousands)	1,955	1,622	294	1,217	3,799

Notes: All panels report summary statistics for region-level variables in December 2011. Column "10th" and "90th" denote respectively the 10th and 90th percentile. Employment, unemployment, and population are measured for persons aged 15 and over.

of the debt risk premium fell by over 100 basis points between 2004 and 2008.

After the strong growth of credit in the decade before 2008, Italy experienced a large fall in the growth rates of private debt because of the legacy of the Global Financial Crisis and the subsequent Sovereign Debt Crisis. From 2008 to 2013 the Italian GDP fell by 9% and fixed investment fell by a third in real terms. The subdued growth continued in 2010-2012 and the number of NFC borrowers fell by about 100,0000 units (Figure 5). The number of HH borrowers remained quite constant between 2012 and 2014, suggesting that HHs were less negatively affected by the sovereign debt crisis in this respect. The double-dip recession in Italy had a severe impact on labor markets, too. Figure 6 displays that unemployment increased sharply in the aftermath of the 2008 global recession. Similarly, employment rate decreased by 4 percentage points over 2008-2014.

The share of loans to HHs in the portfolios of banks has been steadily increasing since the early 2000s and reached about 30% of total non-financial private sector lending in December 2019 (Figure 7). The incidence of HH lending in Italy was much lower than that of other large euro area countries at the beginning of 1999. This suggests that the Italian market for housing finance was small by international standards at the launch of the single-currency in January 1999. The entry of foreign banks in the late 1990s introduced new products and put pressure on the large domestic banking groups, which reacted promptly by taking advantage of their large customer base and branch networks.

3 On the connection between debt per capita expansion and employment fluctuations

Figure 8 shows that regions with higher debt per capita are those with higher employment rates. Each observation represents the level of employment rate and the level of real debt per capita in 2017 for each region. The dotted line is the estimated non-parametric relation between employment rate and private debt per capita. Moving from a level of real debt per capita of €35,000 to €50,000 (a one standard deviation increase) is associated with an increase in employment rate from 64 to 69%. This seems to suggests that increases in private

Figure 2: Disbursement

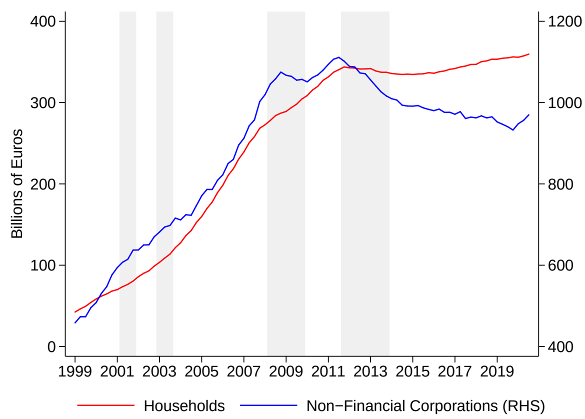


Figure 3: Debt-to-GDP ratios

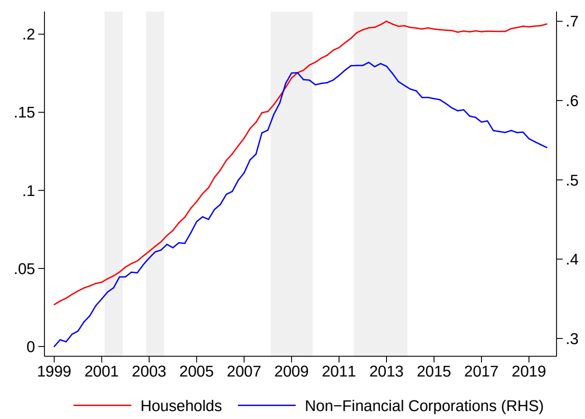


Figure 4: Debt risk premium

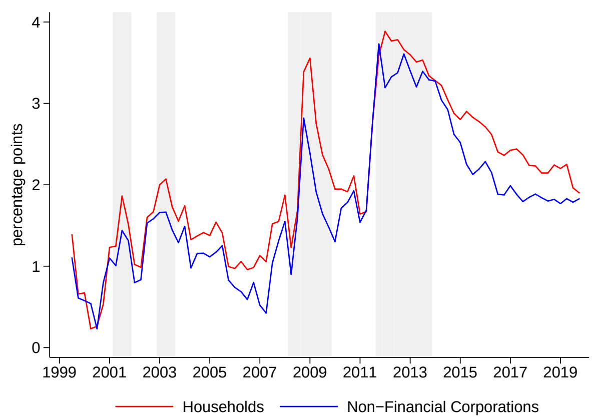


Figure 5: Borrowers

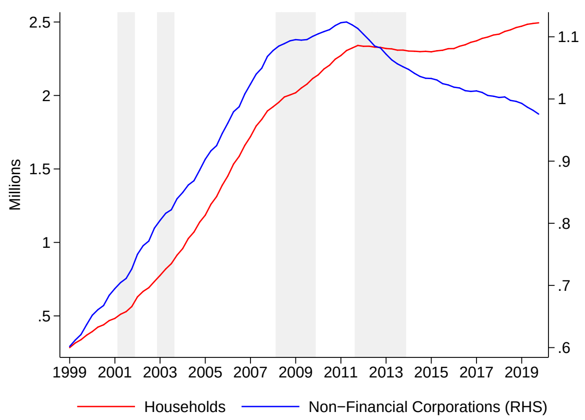


Figure 6: Labor market developments

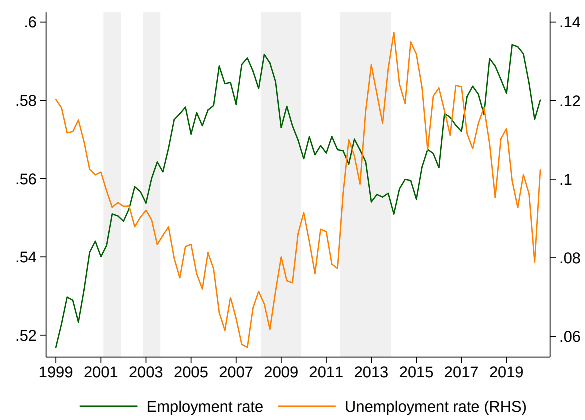
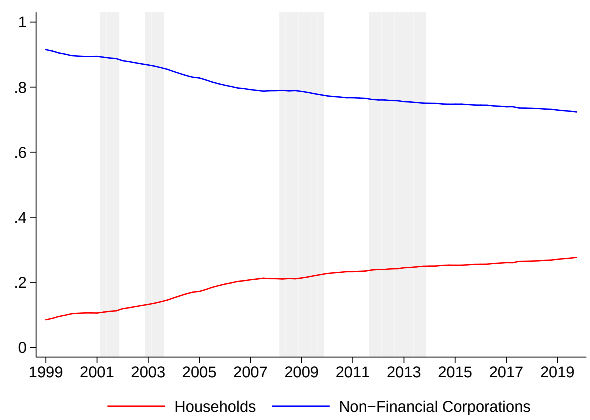
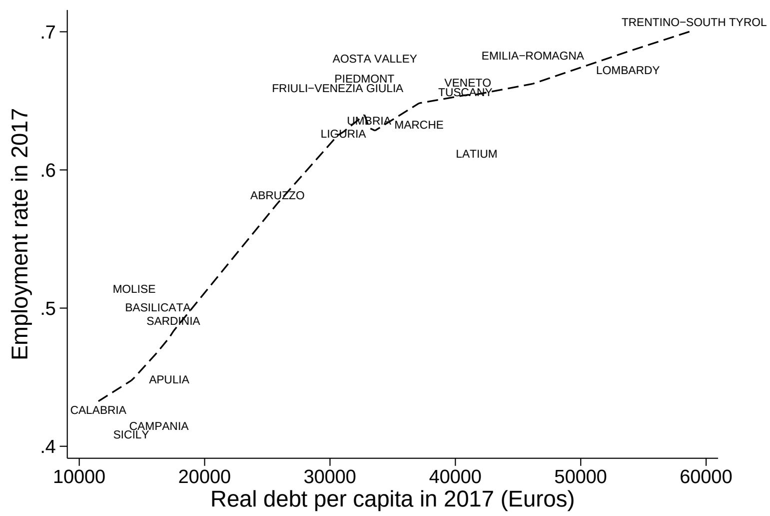


Figure 7: Shares of the total credit disbursed



Notes: GDP in Figure 3 and labor market data in Figure 6 are drawn from the Italian National Institute of Statistics. Bank lending rates in Figure 4 are the spread between lending rates and EURO 1-year OIS drawn from the Bank of Italy's Bank and Money: National Data; these data are issued monthly and include aggregated national data on the banking system, which follow the Eurosystem's harmonized definitions. Shaded regions in all panels represent recessions which are identified as periods of at least two consecutive quarters of negative real GDP q-o-q growth.

Figure 8: Debt per capita and employment



Notes: Both variables are measured in the fourth quarter of 2017 and in terms of persons aged 15 and over.

debt are associated with accelerating economic activities in our sample.

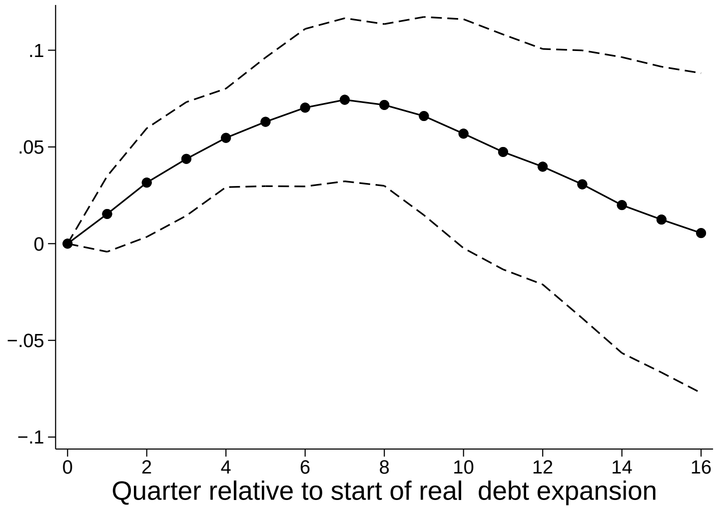
In order to assess whether private debt expansion predicts higher subsequent employment growth, Figure 9 displays estimates of β^h from

$$y_{rt-4+h} - y_{rt-4} = \beta^h \Delta_4 d^P_{rt} + \alpha_r + \epsilon_{rt}, \qquad h = 1, \ldots, 16, \tag{1}$$

where y_{rt} is the employment rate in region r, d^P_{rt} is the log real debt per capita, and α_r is a region fixed effect. Note that in eq. 1 expansion in private debt per capita is fixed from year-quarter $t-4$ to t and we examine its correlation with changes in the employment rate from $t-4$ to $t-3$, $t-2$, $\ldots$, and $t+12$. Figure 9 shows that private debt expansions typically last for three to four years and are associated with employment expansions.

Earlier studies examining the impact of increases in the debt-to-GDP ratio on subsequent growth using country-level panel data find a positive relation (e.g. Levine, Loayza and Beck, 2000; Loayza and Ranciere, 2006). Our result is largely complementary to these papers. Instead of focussing on cross-country analysis, we argue that debt expansions and the business cycle (measured in terms of employment rates) are strictly intertwined at the regional level. In Appendix A we show that the positive relationship between credit expansion and

Figure 9: Private debt expansion and employment



Notes: This figure presents the dynamics of employment rate around log real debt per capita expansions, estimated using eq. (1). Dashed lines represent 95% confidence intervals computed using standard errors that are two-way clustered on region and year-quarter.

employment growth also holds for HH debt or the service sector debt.

As highlighted by Reinhart and Rogoff (2009) there are many episodes of boom-bust financial cycles but not all of them result in a costly economic contraction. Some boom-bust cycles, such as those in Japan and the Scandinavian countries in the 1990s, and the subprime crisis of 2007-2009, led to banking crisis and a serious recession. But on other well known occasions such as the 1987 crash or the dot-com bubble of 1999-2000, the collapse of asset prices did not result in a banking crisis and a severe contraction of real economic activity.[15] The double-dip recession that hit the Italian economy between 2008 and 2013 has indeed caused severe difficulties for the banking sector. However, both recessions were caused by factors that were largely exogenous to the banking system. Moreover, the banking sector weathered these shocks better in Italy than in other countries, where substantial public intervention was required (e.g. Visco, 2018).[16]

[15]Disentangling good from bad credit booms is beyond the scope of this paper.

[16]At the end of 2011, the impact of public intervention amounted to 0.2 percentage points of GDP in Italy, whereas in Ireland, Germany, and Netherlands was respectively 48, 11, and 7 points.

4 On the importance of the credit participation margin for debt per capita fluctuations

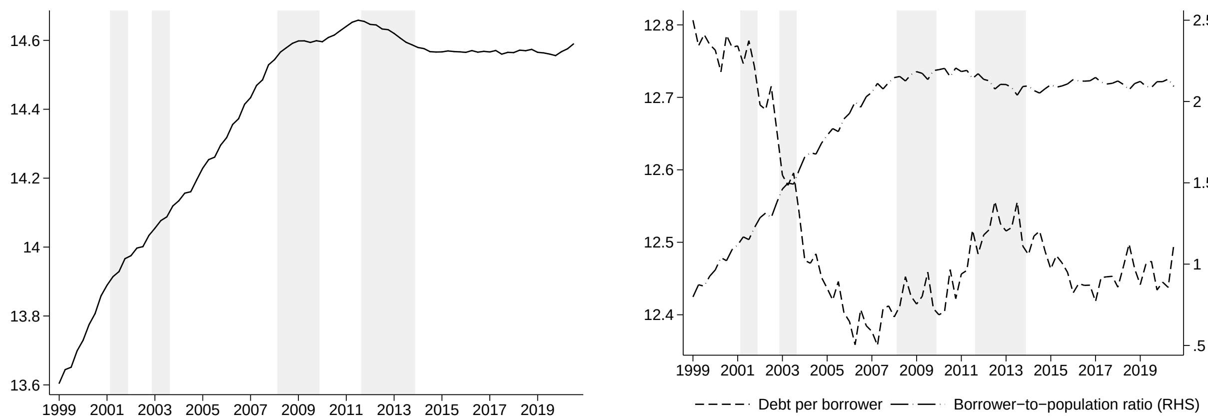
Debt per capita predicts higher employment rates in Italy. Here we try to understand two key mechanisms through which debt per capita may increase. Specifically, we answer the following question. Is the debt per capita expansion associated with an increase in the number borrowers in the credit market or with a rise in the average debt per borrower?

To answer this question we can write the log debt per capita d_t as the sum of the (log) average debt per borrower and the (log) ratio of borrowers to population as follows.

$$d_t \equiv \log\left(\frac{D_t}{B_t}\frac{B_t}{P_t}\right) = \underbrace{\log\frac{\sum_{r=1}^{20} D_{rt}}{\sum_{r=1}^{20} B_{rt}}}_{\text{Average debt per borrower}} + \underbrace{\log\frac{\sum_{r=1}^{20} B_{rt}}{\sum_{r=1}^{20} P_{rt}}}_{\text{Borrower-to-population ratio}}, \tag{2}$$

where D_{rt} denotes the real private debt in region r, B_{rt} is the total number of borrowers in the non-financial private sectors, and P_{rt} indicates the total population aged 15 and older.

Figure 10: Debt per capita decomposition



Debt per capita Decomposition

Notes: The left panel reports the term on the left-hand side of eq. (2). The right panel reports the terms on the right-hand side of eq. (2). Shaded regions represent recessions which are identified as periods of at least two consecutive quarters of negative real GDP q-o-q growth.

The left panel of Figure 10 illustrates the path of log private debt per capita since 1999 and the right panel decomposes private debt per capita into the average debt per borrower and the borrower-to-population ratio as in eq. (2). There is almost a one-to-one relationship between movements in the private debt per capita and those in the borrower-to-population ratio. The strong correlation between these two variables holds at the regional level as well (Table 2).

To formally assess the contribution of changes in the borrower-to-population ratio and average debt per borrower to the volatility of private debt per capita, we use the estimated coefficient β from the following OLS regression

$$\Delta_4 \log(X_{rt}) = \alpha_r + \alpha_g + \beta_X \Delta_4 \log(D_{rt}/P_{rt}) + e_{rt} \qquad X_{rt} \in \{D_{rt}/B_{rt}, B_{rt}/P_{rt}\},$$

where the independent variable is annual change in the log private debt per capita, the dependent variable is either the annual variation in the borrower-to-population ratio or the annual variation in average debt per borrower at the regional level, α_r is a region fixed effect, α_g is a borrower-type fixed effect, and e_{rt} is a residual. To account for small borrowers, who might be more procyclical (e.g. small businesses) than credit flows at the aggregate level, we consider three borrower types g: consumer households, businesses with fewer than 20 employees, and businesses with 20 or more employees.

Table 2: Descriptive statistics

	debt per capita ($\Delta_4 \log D_{rt}/P_{rt}$)	**average debt per borrower** ($\Delta_4 \log D_{rt}/B_{rt}$)	**borrower-to-population ratio** ($\Delta_4 \log B_{rt}/P_{rt}$)
Standard deviation (%)	5.77	3.27	6.45
Correlation with debt per capita	1.00	0.12	0.86
β-decomposition, β_X	1.00	0.09	0.91

Notes: The row labeled "β-decomposition, β_X" reports the estimated coefficient β from an OLS regression where the independent variable is log private debt per capita at the regional level and the dependent variable is either the average debt per borrower or the borrower-to-population ratio defined in eq. (2).

The OLS is a linear operator, which implies that the coefficients for the average debt per borrower and the borrower-to-population ratio sum to 1. In this sense, the beta coefficient can be interpreted as a measure of the contribution of each margin to private debt per capita swings. Table 2 reports a simple "β-decomposition" of the contribution of changes in the average debt per borrower and of the borrower-to-population ratio to variations in private debt per capita at the regional level. Movements in the borrower-to-population ratio–namely the credit market participation margin–explains 91% of the fluctuations in private debt per capita. This result conveys the message that movements in the credit market participation margin are the key driver of private debt swings.

Fluctuations in the participation margin, however, may reflect variations in the number of borrowers ($\Delta_4 \log B_{rt}$) or in the total population ($\Delta_4 \log P_{rt}$). To study these issues we break the participation margin down into variation in the number of borrowers and in the total population and then estimate their contribution to the participation margin by the following β-decomposition:

$$\Delta_4 \log X_{rt} = \alpha_r + \alpha_g + \beta_X \Delta_4 \log B_{rt}/P_{rt} + e_{rt}, \qquad X_{rt} \in \{B_{rt}, P_{rt}\}.$$

We find that 99% of the volatility in the credit market participation margin is explained by changes in the number of borrowers. Henceforth, we will focus on the net borrower creation.

5 A Flow Approach: Concepts and Methods

A complete decomposition of private debt per capita into the borrower-to-population ratio and average debt per borrower in Section 4 showed that the bulk of fluctuations in private debt per capita is accounted for by the extensive margin. Changes in the number of borrowers, in turn, play the dominant role in shaping the pattern of the extensive margin. In this section we propose a flow approach to get further insights into understanding movements in the number of borrowers by assessing their gross flows, namely borrower inflows and outflows.

5.1 Stocks

We start by dividing the population into three non-overlapping groups reflecting different credit market statuses (stocks): (i) borrower (ii) applicant and (iii) neither borrower nor applicant (i.e. inactive NFCs or HHs). Specifically, the three credit market statuses are defined as follows.

Borrower. HHs or NFCs that have a credit relationship with a bank at the reporting date.

Applicant. HHs or NFCs that submit a loan application *and* do not have any credit relationship at the reporting date.

Inactive. HHs or NFCs that are neither borrowers nor applicants at the reporting date.

The above definitions mirror those commonly used in the labor market. As the employed person has a job, the borrower has a loan. As the job-seeker looks for a job, the applicant searches for a loan.[17] The concept of inactivity in the credit market adopted here is that of a marginally attached person or firm who have had or have looked for a loan sometime in the prior 12 months.

Exits from the credit market occur when the borrower's total exposure toward the banking system is zero and does not apply for new loans. A zero banking exposure may in turn happens when borrowers repay their loans or banks write-off their total exposure due to the conclusion of the workout process of a non-performing loan.[18] Note that performing and non-performing borrowers are used in the paper as synonyms of defaulted and non-defaulted obligors respectively. With reference to the Italian banking system the difference between these concepts is not material because of the historical attitude of aligning prudential and accounting classification with reporting criteria.

Two natural questions at this point are should defaulted debtors be counted as part of the pool of borrowers? Can defaulted debtors apply for a loan to a new bank? We argue that defaulted debtors have to be included in the pool of borrowers for at least two reasons. First, the classification in default cannot be considered an event that ends the credit relationship because both parties remain engaged and, from the bank's perspective, the credit granted remains freezed until the defaulted loan is at least partially recovered (unless it is cured). Second, although outright elimination of non-performing loans would in principle imply larger contractions in the number of borrowers during a recession, it should be taken into account that this practice has been until very recently quite uncommon among

[17] The borrower has at least one bank relationship at t and the applicant does not have any bank relationship at t. Our main results are not significantly affected by assuming that applicants have a bank relationship at t (see Appendix C).

[18] Our data set also reveals a zero banking exposure when the amount borrowed is below the CCR reporting threshold. In Section 2 we showed that these loans do not have a substantial impact on aggregate credit dynamics.

Italian banks, especially for collateralized and large exposures which are included within the scope of our analysis due to the CCR reporting threshold.

To answer the second question on loan applications by non-performing borrowers, note that in principle a defaulted borrower may apply for a loan to a new bank. As a matter of fact, the initial information service permits the intermediaries to know the global (i.e. related to all reporting banks) risk position of all non-performing borrowers, with no threshold on bad loans and with a maximum look-back period of 36 months.[19] This may discourage non-performing borrowers from applying for a loan to a new bank because their credit history can be forwarded to the banking system as a whole.

5.2 Flows

After having defined stocks, namely borrower, applicant, and inactive HHs and NFCs, we now define gross flows, namely transitions across these three credit market statuses. In Table 3 the first letter in each cell of the matrix represents the credit market status of HHs or NFCs in the current period, the second letter is the status in the next period. The cells on the main diagonal of the matrix (BB, AA, II) stand for the number of HHs or NFCs that remained in the same status between two consecutive periods. Other cells (BA, BI, AB, AI, IB, and IA) indicate HHs or NFCs changing their status. In our baseline, the transition period between credit market status is 4 quarters.[20]

The net creation of borrowers $\Delta_4 B_{t+4}$ can be decomposed into the difference between borrower inflows and borrower outflows:

$$\underbrace{\Delta_4 B_{t+4}}_{\text{net flows}} = \underbrace{AB_{t+4} + IB_{t+4}}_{\text{gross inflows}} - \underbrace{(BA_{t+4} + BI_{t+4})}_{\text{gross outflows}}, \tag{3}$$

where XY_{t+4} are calculated as the gross flows XY between period t and $t+4$. For example, the gross flow AB_{t+4} between applicant and borrower is the number of HHs or NFCs

[19] See footnote 11.

[20] In general there are several factors that determine the duration of a loan-application process. For instance, loan complexity, data collection, valuation of collateral and of applicant's documentation affect the decision process of loan applications. In this respect, we take a conservative approach by assuming that the time needed to complete the loan decision making process and, in case of acceptance, the credit disbursement is twelve months. In Appendix B we show some key results during 1-quarter and 2-quarter transitions.

Table 3: Transition Matrix

	Status in next period		
	Borrower	*Applicant*	*Inactive*
Status in current period			
Borrower	BB	BA	BI
Applicant	AB	AA	AI
Inactive	IB	IA	II

Notes: The letter B stands for Borrower, A stands for Applicant and I for Inactive in the credit market.

applicants at time 4 that becomes borrowers at time $t + 4$.

6 Results

After having defined gross flows at the individual level, in this section we first analyze the aggregate size of borrower gross flows, i.e. inflows and outflows in eq. (3). Next, we turn to their dynamic properties and relative contribution to the business cycle.

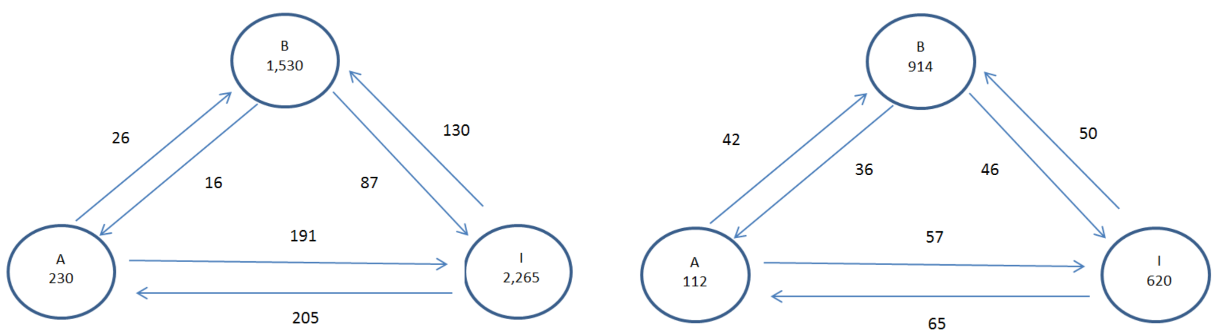
6.1 Size

Figure 11 reports the average size of gross flows and stocks in the period from 1999 to 2019. All numbers are in thousand units and refer to status changes in a 4-quarter period.

Figure 11: Gross Flows and Stocks (Thousands)

Households

Non-Financial Corporations



Notes: The variable A stands for Applicant, B for Borrower, and I for Inactive.

On average around 655 thousand HHs and 296 thousand NFCs changed their credit status after 4 quarters. 156 thousand HHs and 92 thousand NFCs became borrower, and 103 and 82 thousand respectively leaved the borrower status 4 quarters later. Moreover, 221 thousand HHs become applicant and 217 thousand respectively leaved the applicant status. For NFCs, applicant inflows are 101 thousand and applicant outflows amount to 99 thousand.

Two facts stand out from Figure 11. First, the net creation of HH borrowers is five times as large as the net creation of NFC borrowers. Second, borrower inflows are between three and five times as large as the net creation of borrowers. This indicates that gross borrower flows have economic relevance.

Table 4 reports the average weight of each flow in terms of the credit market population, measured by $B + A + I$; 33% of HHs and 52% of NFCs are and remain borrower. The percentages are 49 and 30 respectively for inactive HHs and NFCs. While the gross flow from B to A account for 0.4% of total HHs, the corresponding figures for NFCs is 2.2%.

Table 4: Credit market transitions (percent of $A + B + I$)

	Status in next period		
Households	B_{t+4}	A_{t+4}	I_{t+4}
Status in current period			
B_t	33.2	0.4	2.4
A_t	0.6	0.3	4.9
I_t	3.9	5.4	48.9

	Status in next period		
Non-Financial Corporations	B_{t+4}	A_{t+4}	I_{t+4}
Status in current period			
B_t	51.5	2.2	2.9
A_t	2.5	0.7	3.4
I_t	3.3	3.8	29.5

Notes: The variable A stands for Applicant, B for Borrower, and I for Inactive in the credit market.

6.2 The cyclical sensitivity of borrower inflows and outflows

After having established the existence of sizable borrower flows, we now turn our focus explicitly to measuring the cyclical sensitivity of each flow. We obtain three important results from our flows-based analyses. First, borrower inflows are procyclical and account for the bulk of decline in the number of borrowers during recessions. Second, the volatility of borrower inflows is two times as large as the volatility of borrower outflows and accounts for most of fluctuations in the number of borrowers. Third, borrower inflows are mainly driven by flows from inactivity.

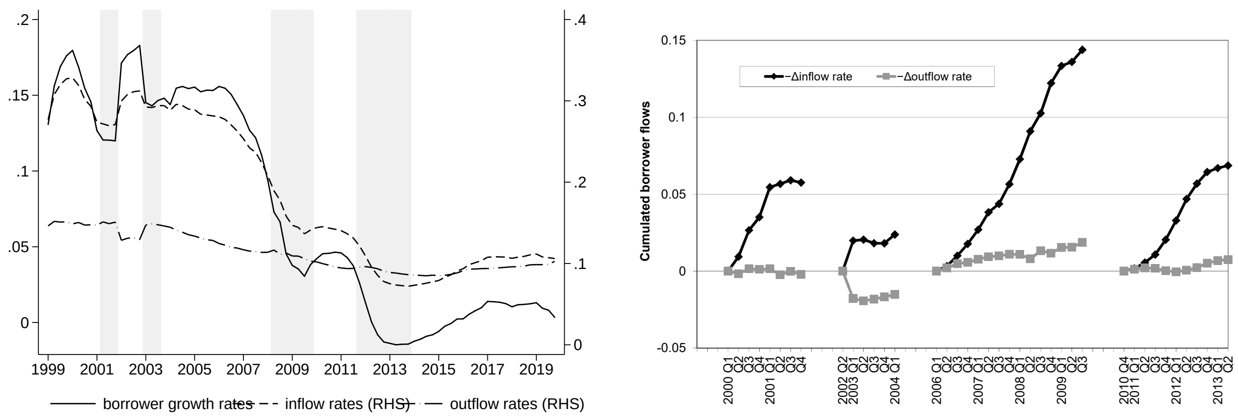
6.2.1 Relationship with GDP fluctuations

We start by having a look at the annual growth rates in the number of borrowers and their corresponding inflows and outflows calculated as follows.

$$\underbrace{\Delta_4 \frac{B_{t+4}}{B_t}}_{\text{borrower growth rate}} = \underbrace{\frac{AB_{t+4} + IB_{t+4}}{B_t}}_{\text{inflow rate}} - \underbrace{\frac{BA_{t+4} + BI_{t+4}}{B_t}}_{\text{outflows rate}}. \tag{4}$$

Inspection of Figure 12 reveals substantial decline in borrower inflows in all recessions.

Figure 12: Borrower flows during recessions



Notes: Borrower growth, inflow, and outflow rates are defined in eq. (4). $-\Delta$inflow rate and $-\Delta$outflow rate respectively indicate the cumulative peak-to-trough decline in the inflow and outflow rate. Shaded regions represent recessions which are identified as periods of at least two consecutive quarters of negative real GDP q-o-q growth.

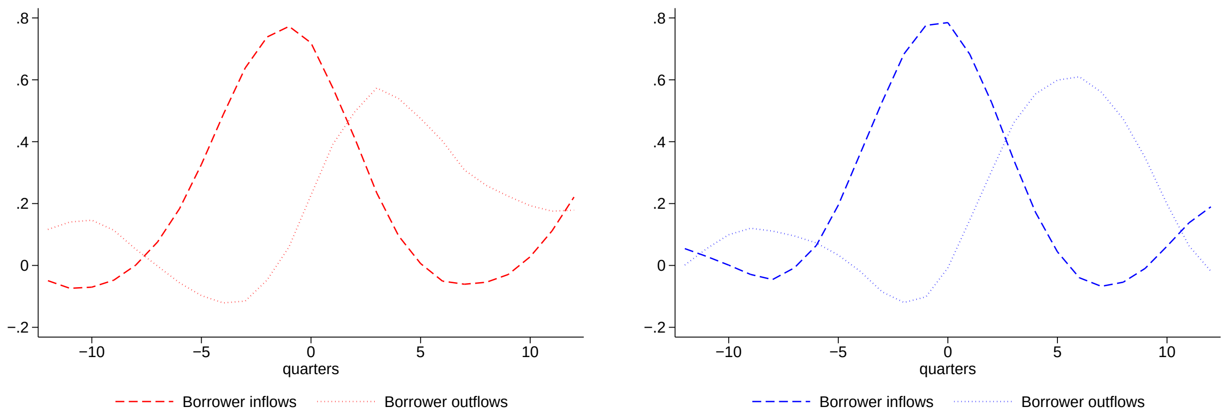
We can use the decomposition (4) to assess the fraction of the reduction in the number of borrower during a recession due to fluctuations in the inflow rate and outflow rate.[21] We first identified start and end dates for borrower decline in each recession and then we

[21] The start dates were determined by the highest annual borrower growth rate preceding each recession and the end dates by the minimum borrower growth rate following each recession end date.

calculated the difference in the inflow rate and outflow rate relative to their start-of-recession values for each recession. In this way, we capture how a worsening in aggregate conditions is systematically associated with the pattern of borrower inflows and outflows.

The right panel of Figure 12 shows that the borrower inflow rate fell in each recession by about 7 percentage points. Moreover, variations in the inflow rate explained almost all the cumulative peak-to-trough decrease in the number of borrowers. Inflow rates were very large during the global financial crisis. They declined by about 15 percentage points. This result suggests that borrower inflows and the business cycle are strictly intertwined (see Section 3). Figure 13 confirms that borrower inflows are highly pro-cyclical both for HHs and NFCs. More specifically, borrower inflows have peak correlation of 0.8 at a lag of 1 quarters. Conversely, borrower outflows have a peak correlation of 0.6 with GDP at a lead of 4 or 6 quarter, respectively in the HH and NFC sector.

Figure 13: Cross-correlations



HHs NFCs

Notes: Correlation between $\widehat{GDP}_t$ and $\widehat{\text{borrower inflows}}_{t+i}$ and between $\widehat{GDP}_t$ and $\widehat{\text{borrower outflows}}_{t+i}$, where $i \in [-12, 12]$. The cyclical component of each series X is obtained by transforming it in four-quarter growth rate denoted by $\widehat{X}_{t+4} \equiv \ln(X_{t+4}/X_t)$. Borrower inflows and outflows are defined in eq. (3).

Figure 13 shows that the dynamic properties of borrower inflows and outflows are intrinsically different. It is worth noticing that borrower inflows are affected by both lenders and applicants' decisions. Both in buoyant times and adverse phases, they naturally tend to lead the business cycle, also in light of the strict link between credit and macroeconomic outlook.

On the flip side, borrower outflows are mainly affected by lenders' decisions. As a matter of fact, even in the worst case, when lenders are forced to comply with short-term market or regulatory constraints during a recession, deleveraging opportunities for the bank would be prevented by the worse creditworthiness of borrowers. In fact, the probability of finding a loan from a new bank to refinance the credit is low as well as the possibility for the borrower of getting other sources to reimburse the amount already drawn. As a consequence, borrower outflows naturally tend to lag the business cycle.

6.2.2 Volatility decomposition

Table 5 reports the volatility of borrower inflows and outflows. Borrower inflows are two times as volatile as borrower outflows. This result confirms that the borrower inflows and outflows may react asymmetrically to macroeconomic shocks. Moreover, the volatility of these flows is much larger than that of GDP by an order of magnitude. Thus, their dynamic behavior is not simply the mirror image of GDP dynamics.

Table 5: Standard deviation

GDP	2.13	
	HH	**NFC**
borrower inflows	17.24	11.51
borrower outflows	11.51	5.61

Notes: Numbers are in percentage. All series are annual growth rates. Borrower inflows and outflows are defined in eq. (3).

Employing OLS regressions, we can calculate the contribution of borrower inflows and outflows to the volatility of the net creation of borrowers. Table 6 reports that fluctuations in borrower inflows account for 79% and 90% of the volatility in borrower variations, respectively in the HH and NFC sector. This evidence suggests that swings in new borrowers are mostly accounted for by movements in borrower inflows.[22]

[22] This result also holds whether we consider Hodrick-Prescott filtered data. See Appendix D.

Table 6: β-decomposition of the net creation of borrowers

	HH sector	
β^{AB+IB}	borrower inflows	0.79
β^{BA+BI}	borrower outflows	0.21
β^{AB}	*AB flows*	0.05
β^{IB}	*IB flows*	0.73
β^{BA}	*BA flows*	0.00
β^{BI}	*BI flows*	0.21
	NFC sector	
β^{BA+BI}	borrower inflows	0.90
β^{BA+BI}	borrower outflows	0.10
β^{AB}	*AB flows*	0.09
β^{IB}	*IB flows*	0.81
β^{BA}	*BA flows*	-0.02
β^{BI}	*BI flows*	0.12

Notes: The third column of the row labeled "β^j" reports the OLS estimated coefficient from running a regression of the variable j against the annual growth of borrowers, i.e. $Cov(j, \Delta_4 B)/Var(\Delta_4 B)$ with $j \in \{BA + BI, AB + IB, AB, IB, BA, BI\}$. Net flows, $\Delta_4 B$, and j variables are defined in eq. (3).

Table 6 also reports that the volatility of borrower inflows is mainly explained by the IB component. In principle, a lender may minimize the risk of lending to a new borrower in two ways. First, a bank may screen or evaluate new business projects. Second, lenders may be tempted to require the borrower having more "skin in the game" through collateralization (Asriyan, Laeven and Martín, 2018). In the latter case, loan origination without an inquiry in the CCR may occur when the inquiry is expected not to affect the credit decision. For example, this might happen when the credit proposal respects a series of predefined parameters of low risk and is standardized in terms of product characteristics or the type of guarantees and collateral. In these cases, the preparation of the proposal can follow a simplified and "fast" procedure.

Our point, however, is not to deny the importance of CCR inquires for the risk of lenders.

Our point is that, in order to assess the roles of borrower inflows, one must understand the economic determinants of inflows from inactivity in the credit market, IB. To provide a sense of this, we calculate – as a proxy – the collateral share in credit debt for borrower inflows. Loans for IB flows have a mean collateral proportion of 87% while the mean collateral share for AB flows amounts to 75% in the HH sector. Similarly, the loan average collateral share for IB flows is 42% and that for AB flows amounts to 27% in the NFC sector.

7 Toward understanding borrower inflows

The preceding sections have highlighted that borrower inflows are very procyclical and account for the bulk of volatility in the net creation of borrowers. An important question, then, is what might explain the observed cyclicality of these flows. The inflow of borrowers can increase either because, at a given acceptance rate, the number of potential borrowers rises or because the acceptance rate itself rises. In this section, we distinguish the role of these two components in shaping the pattern of borrower inflows and we delve into the pattern of heterogeneity in borrower flows at the participation margin that can be observed in available data.

There is ample evidence that firms, particularly small businesses like the ones in our sample (and thus a fortiori single individuals) are tied to their local credit markets. For instance, Petersen and Rajan (2002) show that lending to small businesses is a highly localized activity as proximity between borrowers and lenders facilitates information acquisition. Segmentation of local credit markets is thus very likely to occur. The disaggregated analysis in this section uses data on borrower inflows at the provincial level.

The Italian province is an administrative unit roughly comparable to a US county. There are 107 provinces, and they partition the Italian territory. This geographical unit properly measures local banking markets for at least three reasons. First, this was the definition of a local market when the Bank of Italy authorized the opening of new branches throughout the country.[23] Second, according to the Italian Antitrust authority the province is still the

[23] Until the beginning of the 1990s the birth of new banks and the opening of new branches by the existing banks in Italy were strictly regulated by the Bank of Italy.

'relevant market' in banking for antitrust purposes. Third, the bankers' rule of thumb is to avoid lending to a client located more than three miles from the branch.

In principle, borrower inflows are not only affected by aggregate shocks but also by different local industry and sector mix. To guide the analysis, start with a simple decomposition of the inflow of unknown borrowers into the pool of borrowers. Suppose that borrower inflows are affected by the loan finding rate per unit of time, f, and the proportion of unknown borrowers, u. The borrower inflow rate, ins, satisfies

$$\underbrace{\log \frac{AB_{jt+4} + IB_{jt+4}}{A_{jt} + B_{jt} + I_{jt}}}_{ins_{jt+4}} = \underbrace{\log \frac{AB_{jt+4} + IB_{jt+4}}{A_{jt} + I_{jt}}}_{f_{jt+4}} + \underbrace{\log \frac{A_{jt} + I_{jt}}{A_{jt} + I_{jt} + B_{jt}}}_{u_{jt}}, \qquad j \in \{p, s\} \tag{5}$$

where p denotes a province and s is a two-digit industry.[24] ins is defined as the ratio borrower inflows to the credit market population, i.e. $A+I+B$, and $A+I$ is the number of unknown clients in the market.[25]

Table 7 reports the decomposition of borrower inflows in terms of the loan finding probability and of non-borrower fluctuations at the provincial and industry level. Almost all volatility in borrower inflows is explained by the probability of finding a loan at the provincial level. More than two-thirds of borrower inflows are explained by the probability of matching with a new bank at the industry level. This result indicates that matching frictions (namely credit finding probability) are quantitatively important in accounting for fluctuations in borrower inflows and, as shown in Section 4, for credit swings as well.

Table 7: Decomposition of borrower inflows

	province	2-digit industry
β^f	0.97	0.73
β^u	0.03	0.27

Notes: the row "β^j" reports the OLS estimated coefficient from running a regression of the variable j against ins, i.e. $Cov(j, ins)/Var(ins)$ with $j \in \{f, u\}$, where f, u, ins are defined in eq. (5).

From a theoretical viewpoint, Dell'Ariccia and Marquez (2006) show that when the num-

[24] Actually, we have 85 industries and the consumer household sector.

[25] Definition of B, A, and I and their transition flows across states are provided in Section 5.

ber of *unknown borrowers* in the market is high, banks cannot distinguish between applicant entrepreneurs with new or untested projects and those rejected by competitor banks. In this case, lenders find profitable to undercut bank competitors and increase their market share by lending more to unknown borrowers.[26] den Haan, Ramey and Watson (2003), Wasmer and Weil (2004), and Petrosky-Nadeau and Wasmer (2013) emphasize instead the role of *matching frictions* in the credit market, and the existence of a matching problem between bank funds and applicants. A key point in this literature is the powerful nature of the amplification and propagation mechanism associated with search and matching frictions.

The new facts we hope to have clarified in this paper lend some support to models that emphasize search and matching frictions in the credit market. We argue that theoretical and empirical analyses aimed at explaining economic determinants of credit cycle cannot prescind from understanding why loans are hard to find rather than why borrowers exit from the credit market during a recession.

8 Concluding Remarks

In this study, we use loan-level information on the population of households and non-financial firms that borrow from banks operating in Italy to quantify the magnitude of the extensive margin in shaping the pattern of aggregate credit dynamics. We make contributions both from a methodological and from an empirical perspective.

On the methodological side, exploiting the interplay between cross-sectional and longitudinal dimension of loan-level data, we implement a flow approach methodology commonly used in the labor market literature. We then construct new time series for the transitions between three statuses: borrower, applicant to a new bank, and inactivity in the credit market.

On the empirical side, the analysis here uncovers five new facts not previously reported in the literature. First, the bulk of fluctuations in bank credit to households and businesses

[26] Dasgupta and Maskin (1986) and Bester (1985), for instance, assume that the willingness of banks to screen borrowers depends on the distribution of applicant borrowers. In Asriyan, Laeven and Martín (2018) banks can fund projects either by screening borrowers or by collateralization. When the price of collateral is low, lenders rely largely on screening (see the discussion in Section 6.2).

is accounted for by the extensive margin. We show that the net creation of borrowers is of paramount importance to explain changes along the extensive margin. Second, fluctuations in the net creation of borrowers are largely accounted for by gross inflows of borrowers. Third, borrower inflows are twice as volatile as borrowers outflows. Fourth, borrower inflows are procyclical, highly volatile, and tend to lead the business cycle. Fifth, the volatility of borrower inflows is mainly explained by matching frictions (captured by the borrower probability of matching with a new bank).

As borrower inflows are calculated from micro data, they can be a key metric that bank supervisors with loan-level data can easily track and monitor. For instance, effective macro-prudential tools aimed at smoothing fluctuations in the credit cycle (such as LTV or DTI ratios) should address the rise in inflows of new borrowers in the boom or their sharp decline in the subsequent bust. Many countries have recently introduced large macroeconomic measures to support liquidity conditions and help to sustain the flow of credit to households and firms in the wake of the economic dislocations caused by the COVID-19 crisis.

The evidence here suggests that loans granted to new borrowers have been important drivers of credit swings in Italy over the last two decades. This raises interesting issues regarding the relationship between aggregate demand stabilization and monetary policy actions that effectively can ensure the smooth functioning of the financial system and help set the stage for a speedier reallocation of credit, workers, and capital to their most efficient uses; we look forward to future research addressing these questions.

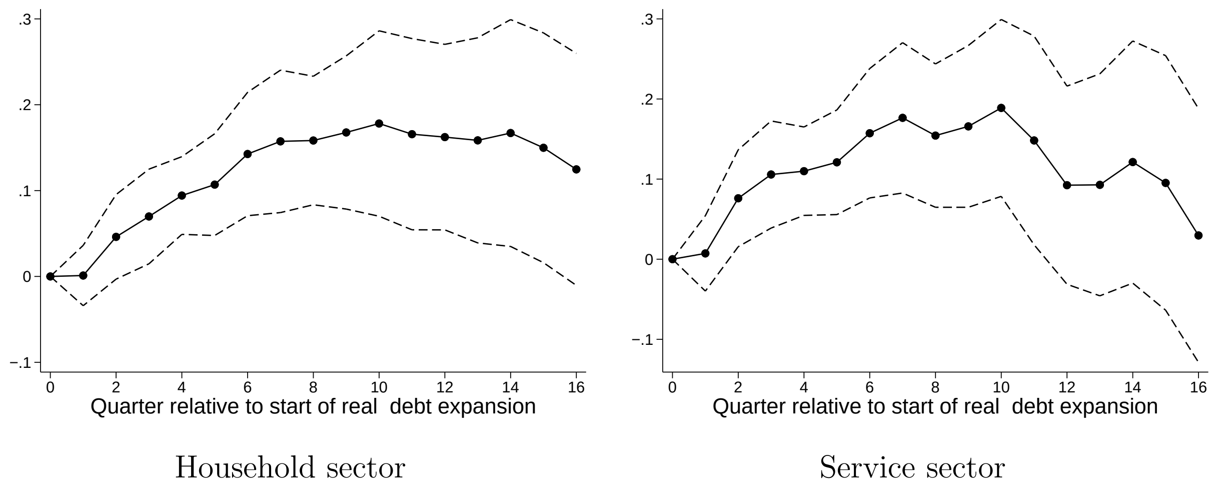
APPENDIX

In this Appendix we consider the sensitivity of our findings to some assumptions in our baseline analysis.

A Sectoral credit allocation and employment outcomes

Section 3 showed that expansions in private debt have a predictive content for future employment at the regional level. However, it is important to understand whether sectoral credit allocation may drive different patters. For instance, Muller and Verner (2021) points out that lending to HH or non-tradable sector predicts lower future output growth.

Figure 14: Debt expansion and employment



Notes: This figure presents the dynamics of employment rate around log real debt per capita expansions in the household and servicesector, estimated using eq. (1). Dashed lines represent 95 percent confidence intervals computed using standard errors that are two-way clustered on region and year-quarter.

Figures 14 examine the link between sectoral credit allocation and employment outcome at the regional level. Consistent with our result in the main text, we find that both credit to HHs and to the service sector predict higher medium-run growth in employment.

B Alternative transition periods

Table 8: β-decomposition of the net creation of borrowers

	4-quarter	2-quarter	1-quarter
β^{AB+IB}	0.79	0.90	0.93
β^{BA+BI}	0.21	0.10	0.07

Notes: The first column reports the OLS estimated coefficient from running a regression of the variable j against variation in the number of borrowers with $j \in \{BA + BI, AB + IB\}$. The second column reports $Cov(j, \Delta_4 B)/Var(\Delta_4 B)$. The third column reports $Cov(j, \Delta_2 B)/Var(\Delta_2 B)$. The fourth column reports $Cov(j, \Delta B)/Var(\Delta B)$. j variables are defined in eq. (3).

C Alternative definition of borrower and applicant

The main text focused on the inflows of new borrowers with no pre-existing bank relationship. Large NFCs in Italy usually have multiple bank relationships and can form or sever bank relationships.[27] Conversely, HHs usually borrow from one lender.

To account for this feature, we discuss the following alternative definition of borrower and applicant.

Borrower. HHs and NFCs have at least one credit relationship with a bank *and* do not apply for a loan to a new bank at the reporting date.

Applicant. HHs and NFCs submit at least one loan application to a new bank at the reporting date.

The difference between the baseline and alternative definition affects HHs and NFCs with at least one bank relationship and applying for a loan to a new bank, i.e. those in the top row and in the first column in Table 9. In our baseline, they are considered as borrowers, while in the alternative definition they are applicants. In Figure 15 we compare our baseline and the alternative definition of borrower and applicant for NFCs and for HHs. As expected, the number of NFC borrowers (applicants) is lower (higher) under our alternative definition than under our baseline definition because firms usually have at least one lending relationship with a bank. Conversely, the difference between our baseline and alternative definition of HH applicant/borrower is quite negligible.

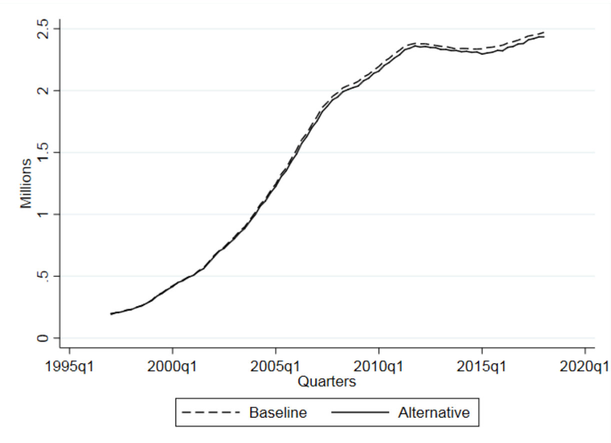
Using the alternative definition of borrowers and applicants, however, does not affect our main results. In terms of volatility decomposition, for instance, Table 10 reports that the contribution of borrower inflows to borrower fluctuation is key both for NFCs and HHs.

[27]Large NFCs on average borrowed from more than 10 banks in the period before the GFC.

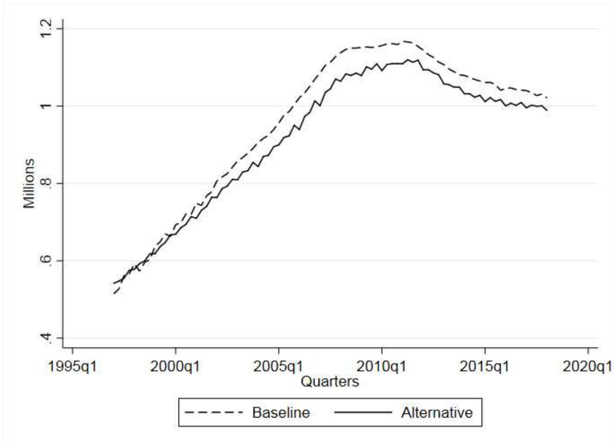
Table 9: Alternative definition

	Looking for a new bank loan? Yes	No
Borrowing?		
Yes	Applicant	Borrower
No	Applicant	Inactive

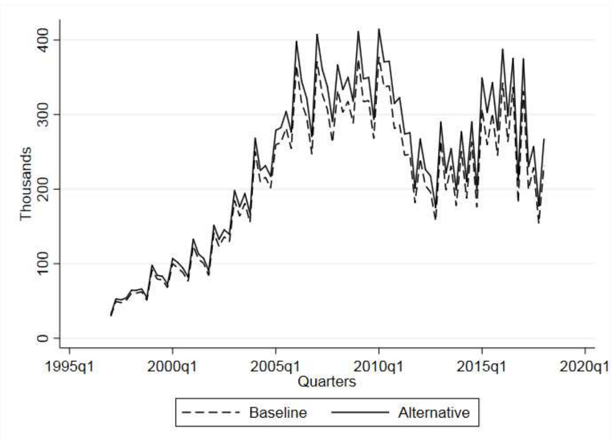
Figure 15: Borrower and Applicant - Baseline vs Alternative Definition



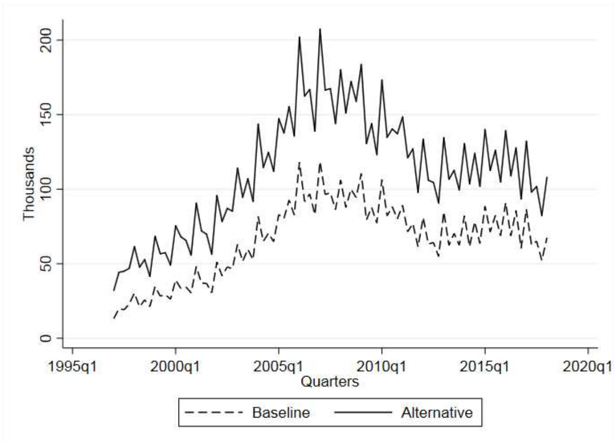
(a) HH borrowers



(b) NFC borrowers



(c) HH applicants



(d) NFC applicants

Table 10: Decomposition of borrower growth rates - Alternative definition ($\bar{B}$)

	HH sector	
$\beta^{\bar{A}\bar{B}+\bar{I}\bar{B}}$	borrower inflows	0.99
$\beta^{\bar{B}\bar{A}+\bar{B}\bar{I}}$	borrower outflows	0.01
	NFC sector	
$\beta^{\bar{A}\bar{B}+\bar{I}\bar{B}}$	borrower inflows	0.74
$\beta^{\bar{B}\bar{A}+\bar{B}\bar{I}}$	borrower outflows	0.26

Notes: The third column of the row labeled "β^j" reports the OLS estimated coefficient from running a regression of the variable $\widehat{j}$ against the annual growth rate of borrowers, i.e. $Cov(j, \Delta_4\bar{B})/Var(\Delta_4\bar{B})$ with $j \in \{\bar{B}\bar{A} + \bar{B}\bar{I}, \bar{A}\bar{B} + \bar{I}\bar{B}\}$. The upper bar denotes the alternative definition of borrower and applicant.

D Hodrick-Prescott filter

We consider the sensitivity of our results to employ HP filtering as method for detrending the data. In the macro literature the cyclical component of each series is usually defined as the deviation of its log from its HP-filtered logged values. In the HP filtered data, fluctuations in borrower inflows still explain the bulk of overall fluctuations in the net creation of borrowers. This result holds when we use a smoothing parameter of 1,600 or of 400,000.[28] Moreover, the correlation of borrower inflows with GDP is even larger in magnitude than the correlation obtained using the first difference filter.

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[28] The value usually used in the literature on business cycle with quarterly data is 1,600; however, the European Systemic Risk Board suggests to set the smoothing parameter to 400,000 to capture the long-term trend in the behavior of the credit-to-GDP ratio (European Systemic Risk Board, 2014). The CRD IV introduced the Basel III package in Europe and delegated the European Systemic Risk Board to guide member states in the operationalization of the countercyclical capital buffer.

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Imprint and acknowledgements

This paper is based on our previous work Cuciniello and di Iasio (2020). We are grateful to Luisa Carpinelli (discussant), Giovanni di Iasio, Xavier Freixas, Luigi Paciello, José-Luis Peydró, Alexey Ponomarenko (discussant), Victoria Vanasco, and seminar participants at Universitat Pompeu Fabra, the 2020 American Economic Association Meetings, the 2020 European Economic Association Congress, the Bank of Russia, and the Bank of Italy for valuable comments and discussions. Part of this research was conducted while Vincenzo Cuciniello was a Visiting Scholar at Universitat Pompeu Fabra. The views expressed in the paper are those of the authors and do not necessarily reflect those of the Bank of Italy or the European Central Bank. All errors are our own.

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ISSN	2467-0677 (pdf)
ISBN	978-92-9472-232-4 (pdf)
DOI	10.2866/688937 (pdf)
EU catalogue No	DT-AD-21-012-EN-N (pdf)