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

Abstract

We use monthly data on individual loans from the Italian Credit Register over the period from 1997 to 2019 and show that bank credit expansions in the non-financial private sector are mostly explained by variations in the extensive margin calculated either in credit flows or headcount of new borrowers. We then build on a flow approach to decompose changes in the net creation of borrowers into gross flows across three states: (i) borrowers, (ii) applicants and (iii) others (neither debtors nor applicants). The paper investigates the macroeconomic dimension of these gross flows and documents three key cyclical facts. 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 are highly pro-cyclical, lead the economic cycle, and their fluctuations are mainly driven by the probability of getting a loan from new banks. We read these results in light of the macrofinance literature on search frictions and on competition with lender-lender informational asymmetries. Overall, our findings support theoretical predictions of these models, but search frictions seem to play a major role in shaping movements along the extensive margin.

Non-Technical Summary

Bank credit booms often sow the seeds of subsequent credit crunches. Not surprisingly, understanding the determinants of credit cycle is a key priority in both academic and policy circles. The burst of credit bubble at the onset of the global financial crisis has further increased policymakers awareness of the risks associated with prolonged periods of buoyant credit growth. Since then, bank regulators have introduced more effective tools - both borrower-based and lender-based - for curbing lending.

This work uses data from the Italian Credit Register from 1997 to 2019 and shows that credit cycle in the non-financial private sector is mainly explained by variations in the number of borrowers entering and exiting the credit market. The model builds a methodology to disentangle variations in the number of households and non-financial corporations participating in the credit market based on the transitions across three states: (i) borrowers, (ii) applicants and (iii) others (neither debtors nor applicants).

Our key results are the following. Entry in the credit market by new obligors (inflows) accounts for the bulk of fluctuations in the number of borrowers. The volatility of borrower inflows is two times as large as the volatility of obligor exiting the credit market (outflows). The obligor inflows into the borrower category are highly pro-cyclical and lead the economic cycle. Therefore the size of gross flows of households and corporates that participate in the credit market can explain aggregate credit market dynamics and also provide timely information on cyclical turning points.

Movements in borrower inflows are mainly driven by the probability of getting a loan from new banks. We read these results in light of the macrofinance literature on search frictions and on competition with lender-lender informational asymmetries. Our findings support theoretical predictions of these models, but search frictions seem to play a major role in shaping changes in the number of borrowers.

In conclusion, the rise in inflows of borrowers during the buoyant phase should not be overlooked by regulators. Conversely, strong regulatory focus on the evolution in the outflows - in particular the deleveraging during the downturn phase - seems not supported because of their minor role for the dynamics of the credit markets.

"First, how did our economy reach this point? Well, most economists agree that the problems we're witnessing today developed over a long period of time. For more than a decade, [...] more families [were allowed] to borrow money for cars, and homes, and college tuition, some for the first time. [M]ore entrepreneurs [were allowed] to get loans to start new businesses and create jobs."

U.S. President George W. Bush's Speech to the Nation on the Economic Crisis

(September 24, 2008)

1   Introduction

Bank credit boom often sow the seeds of subsequent credit crunches (e.g. Schularick and Taylor, 2012; Dell'Ariccia, Laeven, Igan, and Tong, 2012; Baron and Xiong, 2017). Not surprisingly, understanding the determinants of credit cycle is a key priority in academic and policy circles (e.g. Reinhart and Rogoff, 2011; Gourinchas and Obstfeld, 2012; Mian, Sufi, and Verner, 2017; Basel Committee on Banking Supervision, 2010).[1] A borrower can increase her debt by borrowing from new lenders (extensive margin), by borrowing more from pre-existing lenders (intensive margin) or both. Yet, banks offering credit to new borrowers face more uncertainty about their creditworthiness than about the creditworthiness of known clients because of "inside information" generated by the history of bank-client interactions (relationship lending).[2] In other words, the relative importance of the extensive and intensive margins in shaping credit dynamics interacts with competition under adverse selection but also depends on the probability of applicants of finding a new lender, namely search frictions.[3] Although a large literature has studied the dynamic adjustment of aggregate bank credit, little is known about the relative importance of the intensive and extensive margin as well as the role of borrowers entering and exiting from the credit market in explaining credit expansions. (Jorda, Schularick, and Taylor, 2017). This paper is an attempt to fill that gap.

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[1]Global regulators have introduced macroprudential tools for curbing credit dynamics and required banks to build capital buffers when "there are signs that credit has grown to excessive levels" Basel Committee on Banking Supervision (2010).

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

[3]Dell'Ariccia and Marquez (2006) show under asymmetric information competition generates an adverse selection problem for banks. When the number of unknown borrower in the economy is relatively high, banks cannot distinguish applicants with new projects and those rejected by competitor banks, thereby reducing lending standards to increase market share. den Haan, Ramey, and Watson (2003) and Wasmer and Weil (2004) emphasize the role of search frictions in the credit market, and the existence of a matching problem between bank funds and applicants.

We propose a simple methodology to decompose changes in aggregate bank credit along the intensive and extensive margin as well as a flow approach to analyze cyclical properties of fluctuations in the number of borrowers. We use monthly information on individual households (HHs) and non-financial corporations (NFCs) from the Italian Credit Register over the period from 1997 to 2019 and present five new key results.[4] First, the bulk of aggregate credit expansions is accounted for by movements along the extensive margin. Second, fluctuations in the extensive margin are tightly linked to fluctuations in the net creation of borrowers. Third–focussing on the net creation of borrowers–we compute the number of borrowers entering (inflows) and exiting (outflows) the bank credit market. In each month, as explained in Section 2, we classify our individual HHs and NFCs into three non-overlapping states: (i) borrowers, (ii) applicants and (iii) inactive HHs or NFCs in the credit market. We build time series for the number of HHs and NFCs belonging to each category and compute transitions across groups (gross flows), e.g. the number of HHs that borrow at time t and become inactive at time $t + 1$. The distinction is crucial from a policy perspective because, in general, the choice of policy tools depends on the type of imbalances and shocks.[5] It turns out that aggregate dynamics in the net creation of borrowers is mainly driven by gross inflows of borrowers. Fourth, borrower inflows move procyclically, are highly volatile, and tend to lead the business cycle. Fifth, the bulk of volatility in borrower inflows is explained by the probability of matching with a new bank, i.e. search frictions, while a minor role is played by competition stemming from fluctuations in the number of unknown borrowers in the market.

Our methodology is purposefully agnostic as we do not want to impose any structure on booms and busts, since there is no theory to guide us. We prefer to let the data inform us. Booms and busts in credit markets are respectively explained by large increase and decline in the gross inflows of borrowers. Conversely, gross outflows of borrowers contributes much less to credit dynamics. A simple numerical example is 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 quite different scenarios in the credit market participation. They can emerge in an economy where 10,000 new borrowers enter the credit market while no pre-existing borrower exits the market or

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[4]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.

[5]For understanding the impact of interest rate changes is key for instance to assess new mortgage borrowing dynamics. Similarly, LTV caps only affect a targeted set of new borrowers.

in an economy where 100,000 new borrowers enter and 90,000 pre-existing borrowers close all their banking relationships. Credit dynamics (e.g. turnover, market tightness, resource allocation ...) in the two economies differ sharply.

The paper is organized as follows. Section 2 describes the data. Section 3 decomposes the growth rate of aggregate credit into the intensive and extensive components. Section 4 discusses the flow approach to decompose the net creation of borrowers in the borrower inflows and outflows. Section 5 and 6 present the main results as well as some robustness checks and extensions. Section 7 concludes.

Related literature. Our paper is related to several strands of literature. To our knowledge, it is the first contribution that applies a flow approach developed in the labor market literature to the credit market. 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 status of employment, unemployment, and inactivity. In a similar vein, we construct gross flows between the status borrower, applicant, and inactivity so as to analyze their cyclical movements.

This paper also complements recent papers on gross credit flows using bank-level balance sheet information (Dell'Ariccia and Garibaldi, 2005) or firm-level balance sheet information (Herrera, Kolar, and Minetti, 2011). These studies assess the dynamic properties of credit creation (destruction) by calculating debt growth rates of individual firms *or* banks with rising (shrinking) debt. They document that credit expansion and contraction are sizeable and highly volatile, and coexist at any phase of the cycle. Our study is very much in the spirit of theirs, though the lack of individual loan information does not allow them to account for the simultaneous credit expansion and contraction within banks or within firms and so to disentangle the contribution of the intensive and extensive margins to aggregate credit growth.

Several 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). However, the micro determinants of credit cycle remain largely under-explored. The methodological approaches used and the new empirical facts uncovered in this paper add to this macro-finance literature studying the dynamics of credit over the cycle.

Our decomposition of borrower inflows quantifies the relative importance of the probability of finding a new bank and of the number of unknown borrowers in shaping fluctuations of borrower inflows. In this respect, we contribute by measuring the role of search frictions and competition under adverse selection highlighted in the theoretical literature in explaining credit swings (den Haan, Ramey, and Watson, 2003; Wasmer and Weil, 2004; Dell'Ariccia and Marquez, 2006).

2   Data and Basic Patterns

The empirical analysis relies on information requests and data on credit volumes reported to the Italian Central Credit Register (CCR) for individual HHs and NFCs in the period January 1997-June 2019. The main object of interest is the net creation of borrowers and its determinants. CCR is an information system operated by the Bank of Italy, the Italian central bank that, jointly with the European Central Bank, 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. The threshold was lowered in December 2008 from €75,000 to €30,000.[6] To appropriately control for this discontinuity, we limit the analysis to customers whose total credit exposures to a bank (a term used henceforward to include all intermediaries since banks are by far the major participants in these activities) exceeds €75,000. The data set includes about 2.4 million NFCs and 5.6 million HHs borrowing from at least one bank.

Total credit exposure includes credit granted and credit disbursed (drawn) which, in turn, are disaggregated by loan type (loan backed by account-receivables, term loans, credit lines). NFCs include both small firms (i.e. firms with less than 5 employees) and corporates. As for HHs, the threshold of €75,000 implies *de facto* that the analysis captures mortgages only. Indeed, 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.

Our results are however robust to the inclusion of borrowers with bank exposure between €30,000 and €75,000. These on average account for around 6 percent of total credit to the non-financial private sector. Figure 1 shows that the pattern of aggregate lending from our censored data exhibits year-to-year fluctuations similar to those uncensored, namely the official economywide

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[6]As far as bad loans ("sofferenze") are concerned, the reporting threshold is much lower (€250) and was not affected by the change.

statistics, used by the Bank of Italy for assessing the Italian economy's macro-financial conditions to set the countercyclical capital buffer accordingly.[7]

Figure 1: Bank credit to the private non-financial sector
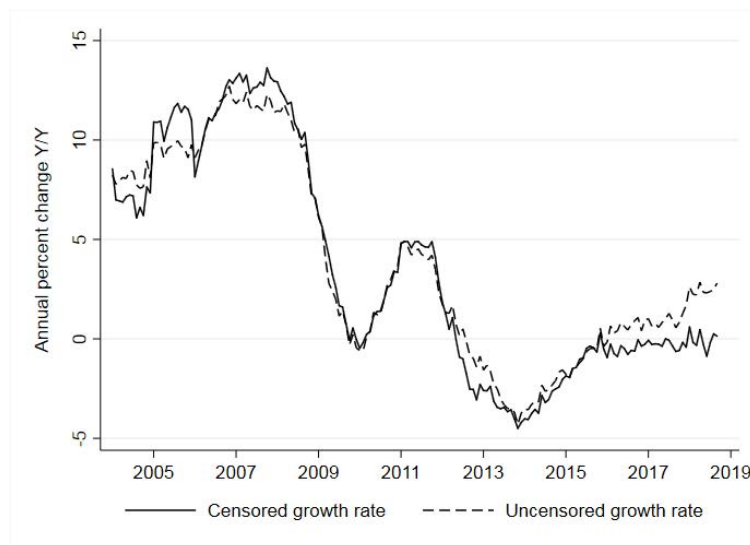
Source: Authors' calculations on the Italian Credit Register data for the censored growth rate. Bank of Italy's calculation on the Italian Credit Register data for the uncensored growth rates.
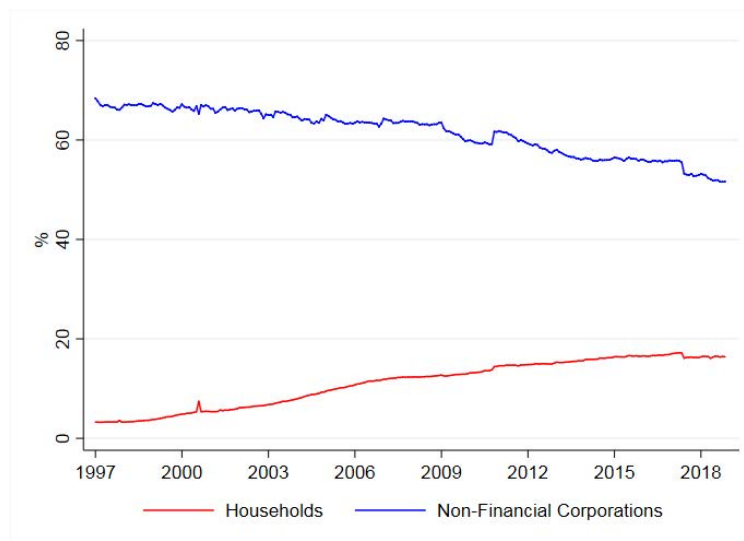*Notes*: Censored growth rate data include only individual exposures exceeding €75,000.

From CCR it is also possible to extract information on loan applications. Specifically, whenever a bank receives a loan application from a new potential client—i.e. a household or a firm that is not already a client of that lender—it can lodge an enquiry to obtain information on the current credit position of the applicant (the so-called preliminary information request or "servizio di prima informazione").

We highlight four key patterns in the data. First, the share of loans to HHs in the portfolios of banks from CCR has been steadily increasing since the early 2000s and reached 17% in November 2018 (Figure 2). While fairly stable at around 65% until 2009, the share of loans to NFCs started to decrease and was roughly 52% in November 2018.

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[7]Bank of Italy's calculation on the CCR data for uncensored growth rates are available at the Bank of Italy website https://www.bancaditalia.it/compiti/stabilita-finanziaria/politica-macroprudenziale/index.html.

Figure 2: Share of total bank credit granted

Second, the share of credit exposures of banks towards HHs was quite low in Italy in 1999 (Figure 3). A diverging trend - as compared to euro area peers - is observed for the share of loans of Italian banks to NFCs, amid the deep and long recession that hit the Italian economy. From 2008 to 2013 the Italian GDP fell by 9%, fixed investment fell by a third in real terms, and the number of NFCs decreased by 100,000 units.

Figure 3: Aggregate debt as a ratio of GDP

| Households | Non-Financial Corporations |
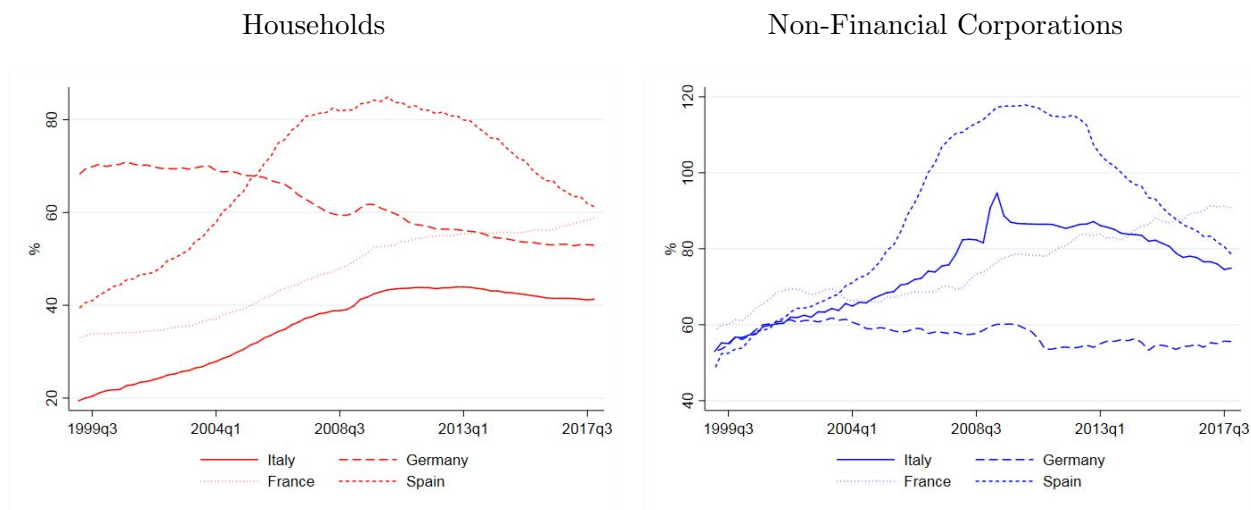
Source: Authors' calculations on ECB Statistical Data Warehouse.

Notes: Debt-to-GDP ratios for NFCs are based on consolidated banking data. All series are neither seasonally adjusted nor calendar adjusted. Households include small firms with less than 5 employees ("famiglie produttrici") as well.
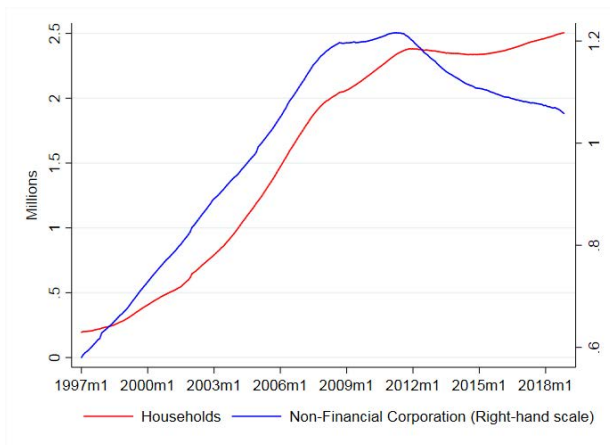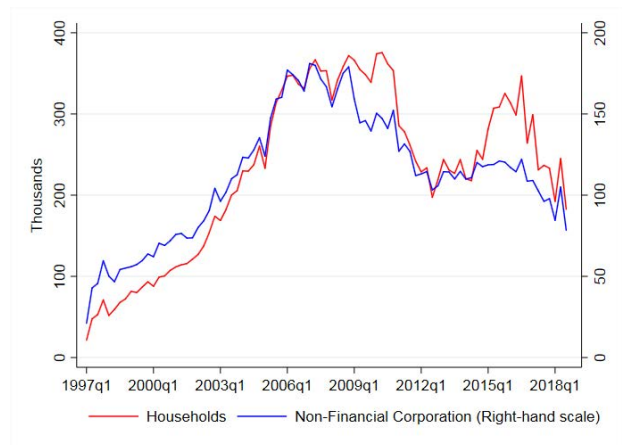
Figure 4: Borrowers

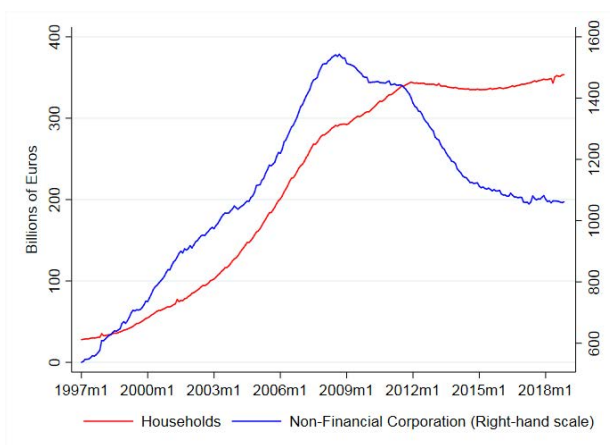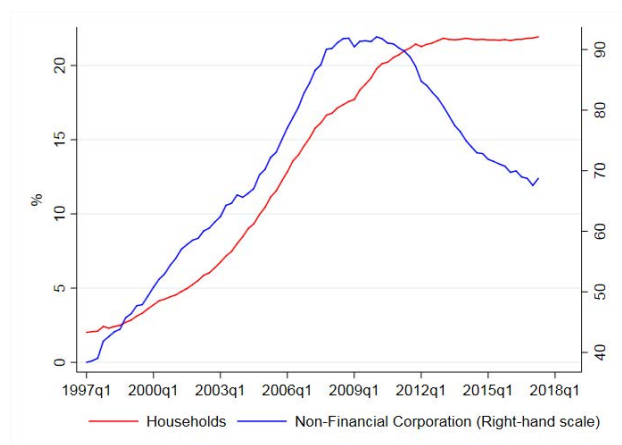
Figure 5: Applicants

Figure 6: Credit Granted

Figure 7: Credit-to-GDP ratio

Source: Authors' calculations.
Notes: GDP in Figure 7 is the four-quarter cumulated flow drawn from the Italian National Institute of Statistics.

Third, as far as it concerns borrowers, NFCs and HHs have followed diverging trends since the onset of the sovereign debt crisis in 2011 (Figure 4). Figure 5 reports the evolution of applicants, with both NFCs and HHs on an increasing pattern in the run-up of the GFC.

Forth, Figures 6 and 7 show the evolution of the amount of credit granted (so called "accordato") to NFCs and HHs, in nominal terms and as share of GDP. Since the burst of the GFC the path for NFCs and HHs widely diverges, with the latter remaining substantially flat and the former experiencing a sharp decline.

3 Intensive and Extensive Margins

In the expanding phase, do more borrowers borrow (extensive margin) or do borrowers borrow more (intensive margin)? In this section we provide an answer to this question. We decomposes the growth rate of aggregate credit to non-financial private sector into the intensive and extensive components, and show that the bulk of the aggregate bank credit boom in the non-financial private sector in Italy is accounted for by the extensive margin.[8]

The intensive margin at date t is defined as the annual growth rate of credit due to pre-existing bank-borrower relations in both year t and year $t-1$. The extensive margin is defined as the annual growth rate of credit due to the formation and severance of bank-borrower relationships. Specifically, aggregate growth in outstanding loans can be written as follows:

$$\frac{\Delta L_t}{L_{t-1}} = \underbrace{\sum_{f \in \mathcal{F}} \sum_{b \in \mathcal{B}} \frac{l^I_{fbt} - l^I_{fbt-1}}{L_{t-1}}}_{\text{Intensive margin}} + \underbrace{\sum_{f \in \mathcal{F}} \sum_{b \in \mathcal{B}} \frac{l^C_{fbt} - l^D_{fbt-1}}{L_{t-1}}}_{\text{Extensive margin}}, \tag{1}$$

where l^I_{fbt} denotes total outstanding loan amount (loan backed by account-receivables, term loans, credit lines) granted by financial intermediary f to borrower b whose relationships was active in t and in $t-1$. l^C_{fbt} is total outstanding loan stemming from a fb relationship active in t and not in $t-1$, while l^D_{fbt} is total outstanding loan amount with a fb relationship not active in t and active in $t-1$. The formation of new bank-borrower relationships have a positive impact on credit growth while severance of relationships push the growth rate down, and the net impact is proportional to their share of credit in aggregate credit.

To account for mergers and acquisitions among banks, we build pro-forma consolidated data for all merged banks when calculating annual changes. This implies that we are not overestimating the extensive margin by recording spurious formation and severance of bank-borrower relationships due to merger and acquisitions.

A simple "β-decomposition" of the contribution of each margin to aggregate credit growth indicates that the extensive margin explains 65% of the fluctuations in credit growth in Figure 8. Formally, this is the estimated coefficient β from an OLS regression where the independent variable is credit growth, $\Delta L_t / L_{t-1}$, and the dependent variable is the extensive margin term in

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[8]Section 2 contains details on data

eq. (1). Note that OLS is a linear operator, which implies that the coefficients for the intensive and extensive margin sum to 1. In this sense, the beta coefficient can be interpreted as a measure of the contribution of the margin to the cyclical fluctuation in credit growth.[9]

Figure 8: The intensive and extensive contributions to bank credit growth

Non-financial private sector
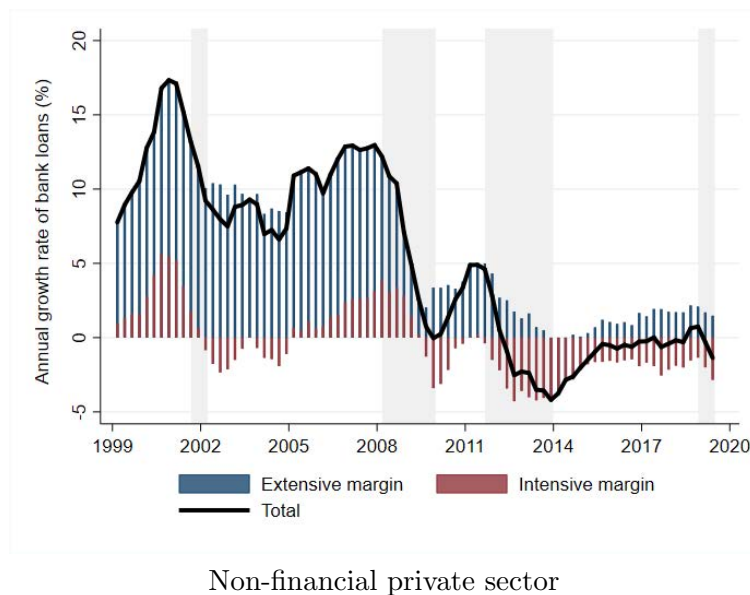
Source: Authors' calculations on the Italian Credit Register data.

Figure 8 displays that the global financial crisis 2008-09 and the European sovereign debt crisis of 2010-12 resulted in an unprecedented fall in the growth rates of Italian household (HH) and non-financial corporation (NFC) bank credit. Moreover, the growth rates of credit reached negative territory in the wake of the sovereign debt crisis. Specifically, the contribution of the extensive margin to credit growth has always been positive since 1997, while the contribution of the intensive margin was negative during slowdowns in credit growth or with negative credit growth rates.

Table 1 presents the decomposition of the two margins when credit is on expanding phases, namely when both the intensive and the extensive margin contribution are positive. We focus on expanding phases because credit booms may sow the seeds of subsequent credit crunches (e.g. Schularick and Taylor, 2012; Dell'Ariccia, Laeven, Igan, and Tong, 2012; Baron and Xiong, 2017). Column "bank-borrower" indicates the average contribution when *bank-borrower relations* active

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[9]Of course, there is heterogeneity in the extensive margin across sectors. The contribution of each margin to aggregate credit growth indicates that the extensive margin explains 55% and 92% of the fluctuations in credit growth, respectively for non-financial corporations and for households.

in t and $t-1$ are included in the intensive margin, while the remaining ones are in the extensive margin. More than 80% of credit fluctuations are accounted for by the extensive margin. Column "borrower" indicates the average contribution when *borrowers* active in t and $t-1$ are included in the intensive margin, while the remaining ones are in the extensive margin. In this case, the bulk of contribution to credit growth (i.e. 60%) is still due to the extensive margin.

Table 1: Intensive and extensive contributions to credit expansion

	bank-borrower	borrower
Intensive margin	17.6	40.4
Extensive margin	82.4	59.6

Notes: The extensive and intensive margin are calculated according to eq. (1). In column "bank-borrower" *bank-borrower relations* active in t and $t-1$ are included in the intensive margin, while the remaining ones are in the extensive margin. In column "borrower" *borrowers* active in t and $t-1$ are included in the intensive margin, while the remaining ones are in the extensive margin. The average contribution of each margin to aggregate credit growth is calculated when both margins are positive.

All told, the conclusion that we draw from the above analysis is that the key driver of credit expansion is the extensive margin, i.e. the difference between flow of loans to new borrowers and flow of loans lost due to borrowers exiting. However, the extensive margin in turn depends on the net change in the average loan to new borrowers and on the net change in the number of borrowers. To quantify the cyclicality of the extensive margin component, Table 2 reports the correlation between the extensive margin and net change in the number of borrowers as well as the correlation between the extensive margin and the net change in average loan to new borrowers. It turns out that the correlation between the net change in the number of borrowers and the extensive margin ranges from 0.92 to 0.94, while the average loan to new borrowers is weakly correlated to the extensive margin. For sake of simplicity, we will focus henceforth on the entry and exit of borrowers from the credit market.

Table 2: Correlation between extensive margin and its components

	bank-borrower	borrower
net average loan to new borrowers	0.17	-0.27
net change in the number of borrowers	0.92	0.94

Notes: All series are divided by their corresponding standard deviation. The extensive margin is calculated according to eq. (1). In column "bank-borrower" *bank-borrower relations* active in t and $t-1$ are included in the intensive margin, while the remaining ones are in the extensive margin. In column "borrower" *borrowers* active in t and $t-1$ are included in the intensive margin, while the remaining ones are in the extensive margin. The net average loan to new borrowers is difference between the average loan to new borrowers (relationships) and the average loan to exiting borrowers (relationship severances). The net change in the number of borrower is the difference between the number of new borrowers (relationships) and the number of exiting borrowers (relationship severances).

The difference between the two columns in Table 1 points out that around 20% contributions to credit fluctuations stems from creation and severance of bank relationships of borrowers with at least one bank relationship in $t-1$. Large NFCs in Italy usually have multiple bank relationships and can form or sever bank relationships as well. Conversely, HHs usually borrow from just one bank. We will assess how multiple relationships for NFCs affect our results in Section 6. Here, it is worth stressing that the effects of macroprudential or monetary policies could be mitigated if borrower can obtain credit from the less affected banks. Hence, to assess the macro relevance of changes in policy tools, it is in principle important to consider the possibility for current bank client of forming new bank relationships as well. Our main results however hold when we assume a bank-borrower relationship rather than a borrower perspective of the extensive margin.

4 A Flow Approach

A complete decomposition of the total credit growth into extensive and intensive margin in Section 3 showed that the large majority of aggregate movement is accounted for by the extensive margin and that the net change in the number of borrowers is strongly correlated to the extensive margin. Since we are interested in the impact of the extensive margin on aggregate correlations, we restrict attention to the net change in the number of borrowers.

We divide the population into three non overlapping groups reflecting different credit market

status: *Borrower*, *Applicant* and *Inactive*. The three credit market statuses are defined as follows.

Borrower. HHs and NFCs that have at least one credit relationship with a bank.

Applicant. HHs and NFCs that submit at least one loan application to a new bank *and* do not have any credit relationship with a bank at the reporting date.

Inactive. HHs and NFCs that are neither borrowers nor applicants during the period but are classified as applicants or borrowers in the previous *or* next six months.

Table 3: Baseline definition

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

Table 3 reports that under our baseline new borrowers are those entering the bank credit market. In other words, new borrowers do not have any preexisting bank relationship.[10] Conversely, borrowers exit the market when their total exposure toward the banking system is zero and do not apply for loans to a new bank.[11] This may occur when the borrower repays her loans or because banks write-off or cancel her total exposure due to the conclusion of the workout process of a non-performing loan. Note that performing and non-performing 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 due to the historical attitude of aligning prudential and accounting classification and reporting criteria.

Our approach, however, implies that we may underestimate the drop of borrowers during the early stages of a recession. We argue that the exclusions of defaulted debtors is not correct in our context for at least two reasons. First, the classification in default cannot be considered an event

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[10]In Section 6 we relax this assumption by considering new borrowers relative to a single bank instead of the credit market as a whole. Therefore under our alternative definition new borrowers may have pre-existing bank relationships.

[11]Our classification mirrors the one commonly used in the labor market. Borrowers in the credit market can be associated with the employed of the labor market while, as the unemployed are workers that are looking for a job, applicants are seeking a loan.

that ends the credit relationship, since both parties remain engaged and, in particular from the bank's perspective, the credit granted remains frozen 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 Italian banks, in particular for collateralized and large exposures (which are included within the scope of our analysis due to the CCR reporting threshold).

By the same token, the inclusion of non-performing borrower among applicants may overestimate the total number of loan applicants. As a matter of fact, the initial information service permits the intermediaries to know for a fee 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. This may discourage non-performing borrowers from applying for a loan to a new bank because they will anticipate that the probability of acceptance is almost nil.

Having defined stocks, we then compute transitions (flows) across the three credit market status. In Table 4 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 six months. 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, to disburse the credit is six months.[12]

The net creation of borrowers $\Delta_6 B_{t+6}$ can be decomposed into the difference between borrower inflows and borrower outflows:

$$\Delta_6 B_{t+6} = \underbrace{AB_{t+6} + IB_{t+6}}_{\text{borrower inflows}} - \underbrace{(BA_{t+6} + BI_{t+6})}_{\text{borrower outflows}}, \tag{2}$$

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[12]Our main results are qualitatively unaffected when we consider a year or a three-month transition period.

Table 4: 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.

where XY_{t+6} are calculated as the gross flows XY between period t and $t + 6$. For example, the gross flow AB_{t+6} between applicant and borrower is the number of HHs or NFCs that switch from applicants to borrowers from time t to $t + 6$.

5 Results

In this Section we first analyze the magnitude of borrower gross flows, i.e. inflows and outflows. We then turn to their dynamic properties and relative contribution to the business cycle.

5.1 Size

Figure 9 reports the average values of the gross flows and stocks in the period from 1997 to 2019. All numbers are in thousand units and refer to status changes in a six-month period.

In an average month around 655 thousand HHs and 296 thousand NFCs change their credit status after six months. 156 thousand HHs and 92 thousand NFCs become borrower, and 103 and 82 thousand respectively leave the borrower status six months later. Moreover, 221 thousand HHs become applicant in an average month and 217 thousand respectively leave the applicant status. For NFCs, applicant inflows are 101 thousand and applicant outflows amount to 99 thousand.

Two facts stand out from Figure 9. First, the net creation of HH borrowers is 53 thousand in an average month, while the net creation of NFC borrowers amounts to 10 thousand. Second, borrower inflows are between three and five times as large as the net creation of borrowers, thereby pointing out the relevance of gross borrower flows *per se*.

Table 5 reports the average weight of each monthly flow in terms of credit market population,

Figure 9: Gross Flows and Stocks (Thousands)
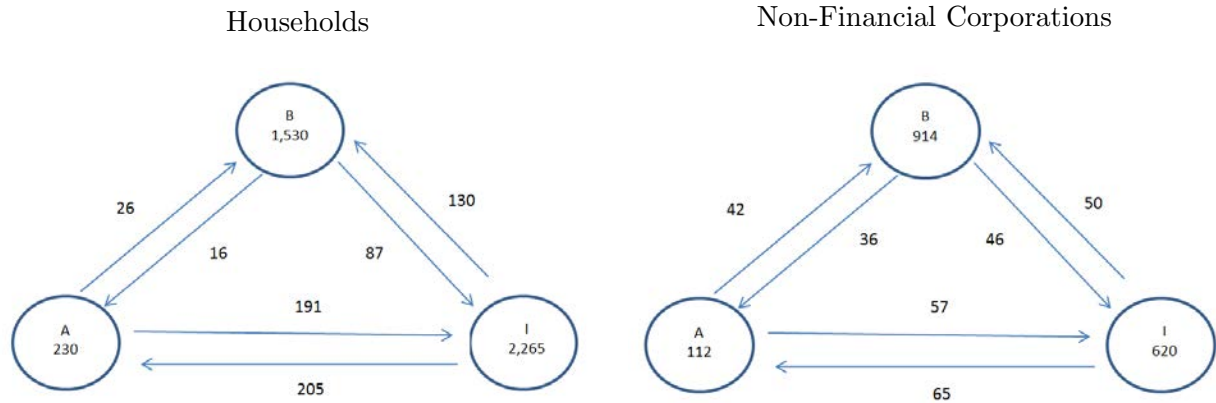
Households   Non-Financial Corporations

Notes: Averages of not seasonally adjusted monthly series. The variable A stands for Applicant, B for Borrower, and I for Inactive in the credit market.

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%.

5.2 The cyclical properties

Having established the existence of sizable borrower flows, we turn to examining their dynamic properties. In this section we follow the business cycle literature and look at the dynamic properties of borrower flows by studying the correlations of their cyclical components with respect to the cyclical component of GDP at various leads and lags as well as their volatility.

Before proceeding to the analysis of the cyclical components, it is useful to have a look at the patterns of the net creation of borrowers and their corresponding inflows and outflows calculated according to eq. (2). Figure 10 displays that borrower outflows are roughly constant over time, while inflows of borrowers sharply decline during downturns.

To corroborate this result, let b_{t+4} denote the annual rate of change of borrowers, i.e $\Delta B_{t+4}/B_t$, at *quarterly frequency*. Using eq. (2) we can rewrite b in terms of cumulative annual inflows and

Table 5: Credit market transitions (percent of $A + B + I$)

Households	Status in next period		
	B_{t+6}	A_{t+6}	I_{t+6}
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

Non-Financial Corporations	Status in next period		
	B_{t+6}	A_{t+6}	I_{t+6}
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

Source: Authors' calculations.
Notes: Averages of not seasonally adjusted monthly series. The variable A stands for Applicant, B for Borrower, and I for Inactive in the credit market.

outflows of borrowers as follows.

$$b_{t+4} = \underbrace{\frac{\sum_{i=1}^{2} AB_{t+2^i}}{B_t}}_{\bar{AB}_{t+4}} + \underbrace{\frac{\sum_{i=1}^{2} IB_{t+2^i}}{B_t}}_{\bar{IB}_{t+4}} - \underbrace{\frac{\sum_{i=1}^{2} BA_{t+2^i}}{B_t}}_{\bar{BA}_{t+4}} - \underbrace{\frac{\sum_{i=1}^{2} BI_{t+2^i}}{B_t}}_{\bar{BI}_{t+4}}, \tag{3}$$

where $\sum_{i=1}^{2} AB_{t+2^i}$ and $\sum_{i=1}^{2} IB_{t+2^i}$ denote cumulative annual inflows of borrowers from the status of applicant and inactive, respectively. Similarly, $\sum_{i=1}^{2} BA_{t+2^i}$ and $\sum_{i=1}^{2} BI_{t+2^i}$ respectively denote the cumulative annual outflows of borrowers to applicant and inactive status. The sum of the $\bar{AB}$ and $\bar{IB}$ captures the contribution of gross inflows to the annual net creation rate of borrowers, while the sum of $\bar{BA}$ and $\bar{BI}$ indicates the contribution of gross outflows.

In what follows the cyclical component of each series X is obtained by transforming it in four-quarter growth rate denoted by $\widehat{X}_{t+4} \equiv \ln(X_{t+4}/X_t)$. For rates the transformation is $X_{t+4} - X_t$.

5.2.1 Relationship with GDP fluctuations

Figure 11 shows that b_t is procyclical, signals future changes in economic activity, has peak correlation of 0.66 with GDP at a lag of 4 quarters. These results adds to the evidence that in advanced economies credit dynamics are positively related with the business cycle (Schularick and Taylor, 2012; Jorda, Schularick, and Taylor, 2013).
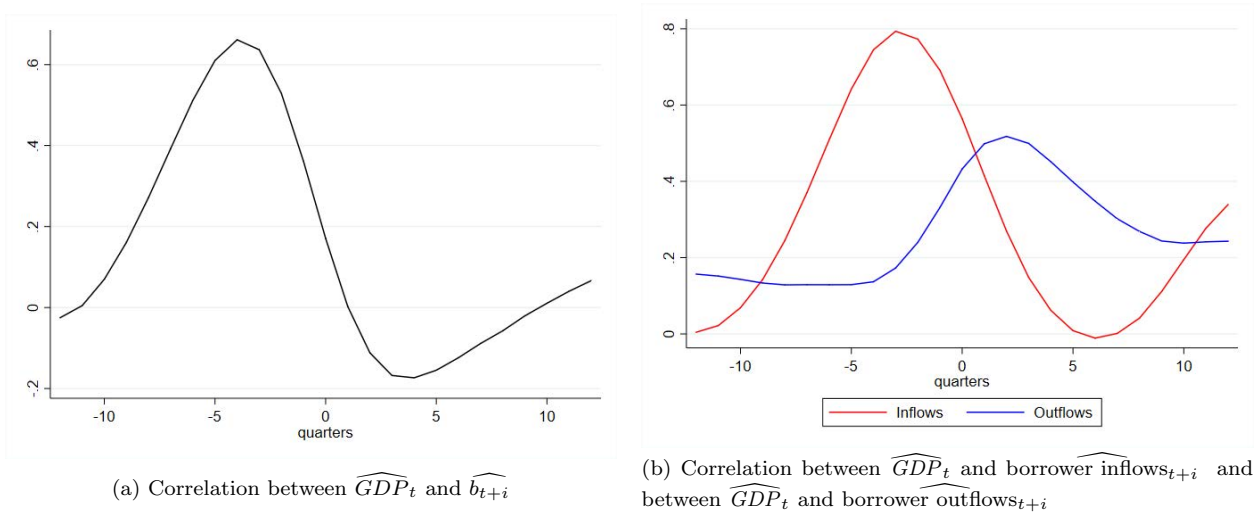
Figure 10: Borrower Flows (Annual Changes)

(a) HH Borrowers

(b) NFC Borrowers
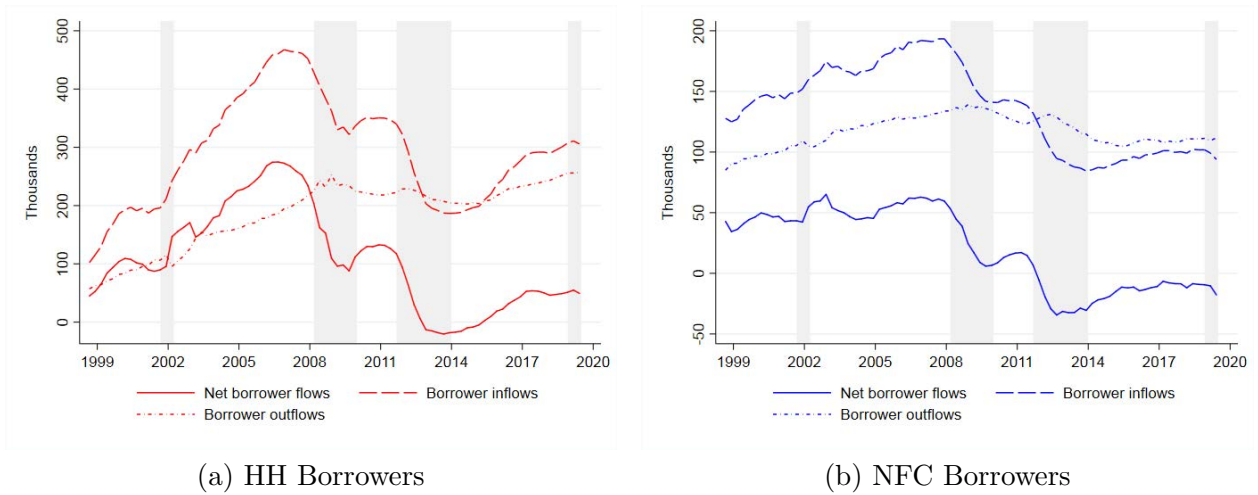
Sources: Authors' calculations.
Notes: The variable $\Delta_4 B$ denotes the 4-quarter borrower difference. Inflows and outflows are two-semiannual cumulated gross flows. Shaded regions represent recessions which are identified as periods of at least two consecutive quarters of negative real GDP q-o-q growth.

Figure 11: Cross-correlations

(a) Correlation between $\widehat{GDP}_t$ and $\widehat{b_{t+i}}$

(b) Correlation between $\widehat{GDP}_t$ and borrower $\widehat{\text{inflows}}_{t+i}$ and between $\widehat{GDP}_t$ and borrower $\widehat{\text{outflows}}_{t+i}$

Sources: Authors' calculations.
Notes: Correlation is between the cyclical component of each series. Inflows=$\bar{A}B + \bar{I}B$ and Outflows=$\bar{B}A + \bar{B}I$ are given in eq. (3).

Moreover, as reported in eq. (3), net changes in the number of borrower are the result of two

different gross flows. Borrower inflows, namely the number of borrowers entering the market, have a positive impact on b, while borrower outflows, namely the number of borrowers exiting the market, have a negative impact. Figure 11 reports that borrower inflows have peak correlation of 0.80 at a lag of 3 quarters, while borrower outflows have a peak correlation of 0.51 with GDP at a lead of 2 quarter. It turns out that the dynamic properties of these flows are intrinsically different.

5.2.2 Volatility

In the reference period, the standard deviation of GDP is 1.93% and the standard deviation of the net creation of borrowers is 2.83% (Table 6). The volatility of gross inflows of borrowers is two times as large as the one of gross outflows of borrowers, and it is much larger than that of GDP by an order of magnitude.

Table 6: Standard deviation

GDP		1.93	
Net creation of borrowers b		2.83	
-borrower inflows		15.85	
-borrower outflows		8.40	
	HH		**NFC**
Net creation of borrowers b	10.66		3.85
-borrower inflows	19.79		11.29
-borrower outflows	11.72		6.06

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

Employing OLS regressions, we find that fluctuations in gross inflows account for 96% and 89% of the volatility in the net creation respectively of HH and NFC borrowers (Table 7).

Table 7: Decomposition of the net creation of borrowers

	HH sector	
$\beta^{\bar{A}B+\bar{I}B}$	borrower inflows	0.96
$\beta^{\bar{B}A+\bar{B}I}$	borrower outflows	0.04
	NFC sector	
$\beta^{\bar{A}B+\bar{I}B}$	borrower inflows	0.89
$\beta^{\bar{B}A+\bar{B}I}$	borrower outflows	0.11

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 cyclical component of the annual growth rate of borrowers, i.e. $Cov(\widehat{j},\widehat{b})/Var(\widehat{b})$ with $j \in \{\bar{B}A + \bar{B}I, \bar{A}B + \bar{I}B\}$. Borrower growth rates, b, and j variables are defined in eq. (3).

This evidence highlights that swings in the number of borrowers is accounted for by movements in borrower inflows. Moreover, inflows of borrowers are the key determinant of the net creation of borrowers both for HHs and NFCs. Interestingly, gross inflows of borrowers for NFCs are mainly driven by AB flows, while for HHs the IB component is predominant. In general, the origination of a credit without an inquiry in the CCR may occur when the inquiry is expected not to affect the credit decision. The relevance for HHs of gross flows from inactive to borrowers could be explained by factors related to the way local banks grant credit for mortgages. Usually banks have private information on households that apply for a loan, so that lodging an enquiry in the CCR is not necessary. In particular, this might happen when the credit proposal respects a series of predefined parameters of low risk and is standardized in terms of product characteristics and of the type of guarantees and collateral. In these cases, the preparation of the proposal can follow a simplified and 'fast' procedure.

5.3 Searching Friction and Unknown Borrowers

Where do fluctuations in borrower inflows originate from? Our results so far points out the inherent asymmetry in the net creation of borrowers and relative importance of forces behind the inflow/outflows, i.e. credit creation and credit destruction. These forces are in turn subject to different sources of frictions. Since borrower inflows are the key determinants of credit booms, we

focus on those flows and two sources of frictions.

First, Dell'Ariccia and Marquez (2006) show that under asymmetric information *competition* stemming from an increase in the number of unknown borrower in the market generates an adverse selection problem for banks. When the proportion of unknown borrowers is high banks cannot distinguish between applicant entrepreneurs with new or untested projects and those rejected by competitor banks. In this case it may be profitable to reduce lending standards so as to under-cut bank competitors and increase market share.[13] A second strand of literature in theoretical macroeconomics has emphasized the role of *search frictions* in the credit market, and the existence of a matching problem between bank funds and applicants. This friction is captured here by the probability of forming a credit relationship (e.g. den Haan, Ramey, and Watson, 2003; Wasmer and Weil, 2004).

To investigate relative importance of competition and search friction in shaping the dynamics of borrower inflows, we use the following relation.

$$(\widehat{AB + IB})_{t+4} = \widehat{f}_{t+4} + (\widehat{A + I})_t, \tag{4}$$

where $f \equiv \frac{AB+IB}{A+I}$ denotes the probability of finding a loan and A and I is the stock of unknown clients. Table 8 reports the decomposition of borrower inflows in terms of the loan finding probability and non-borrower fluctuations. More than two-thirds of borrower inflows are explained by the probability of finding a loan. This result holds both for NFCs and HHs and indicates that search friction (credit finding probability) is quantitatively important in accounting for fluctuations in borrower inflows and so for credit swings as well.

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[13]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. Information generated through screening is long-lived, while collateralized projects depend on the price of collateral and are accompanied by a 'depletion' of information. However, our results hold whether we just focus on borrowers with uncollateralized debt.

Table 8: Decomposition of borrower inflows

HH sector		
β^f	loan finding probability	0.68
β^{A+I}	non borrowers	0.29
NFC sector		
β^f	loan finding probability	0.73
β^{A+I}	non borrowers	0.25

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 cyclical component of the annual growth rate of borrower inflow, i.e. $Cov(\widehat{j}, \widehat{AB+IB})/Var(\widehat{AB+IB})$ with $j \in \{f, A+I\}$. The cyclical component of borrower inflows and of j variables are defined in eq. (4).

6 Robustness and Extensions

Having established that borrower inflows are an important source of the net borrower creation, in this Section we consider the sensitivity of our findings to some of our baseline analysis.

Alternative definition of borrower and applicant. So far we have investigated the inflows of new borrowers with no bank relationship. However, most of large NFC in Italy have multiple bank relationships and can start new bank relationships as well.[14] In order to account for this feature, we discuss the following alternative definition of borrower and applicant.

Borrower. HHs and NFCs that 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 that 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 credit relationship established 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

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

the alternative definition they are applicants. In other words, the alternative borrower definition is narrower than the baseline borrower definition. Symmetrically, the definition of credit applicant is narrower under the baseline definition than under the alternative one.

Table 9: Alternative definition

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

In Figure 12 we compare our baseline and the alternative definition of borrower and applicant for NFCs and for HHs. Clearly, the number of NFC borrowers (applicants) is lower (higher) under our alternative 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. All in all, our main results are unaffected under the alternative definition. In terms of volatility and correlations, the results are in line with values discussed in the previous section. The contribution of borrower inflows to borrower volatility is still key for NFCs under our alternative definition as is illustrated in Table 10.
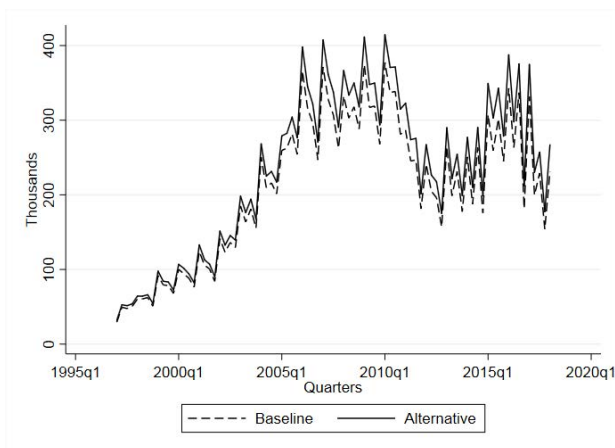
Figure 12: Borrower and Applicant - Baseline vs Alternative Definition
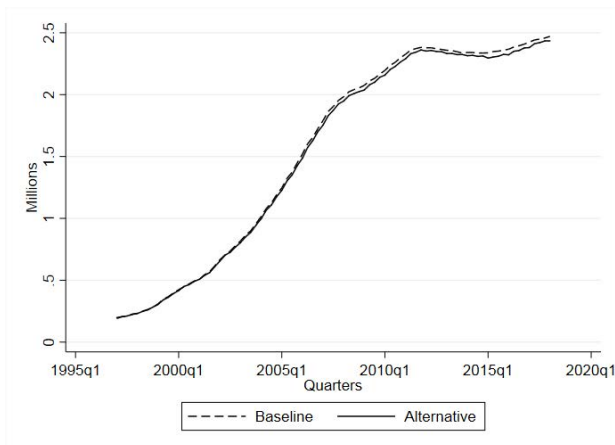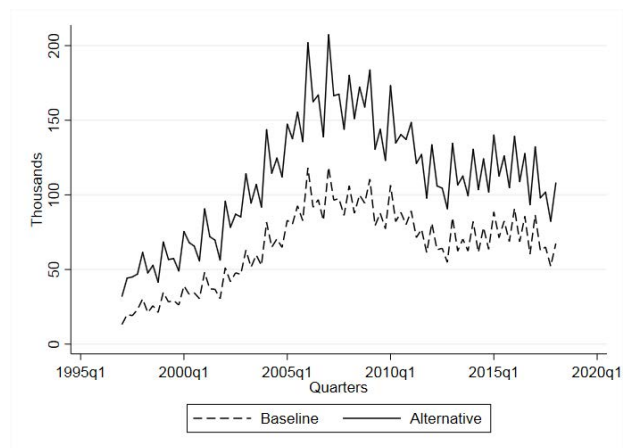

(a) HH borrowers
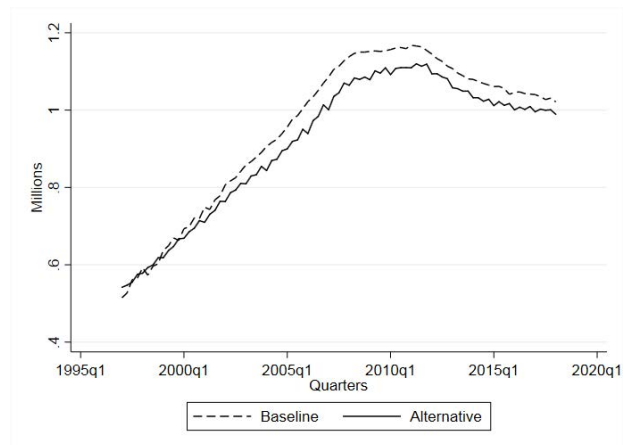
(b) NFC borrowers

(c) HH applicants

(d) NFC applicants

Sources: Authors' calculations.

Hodrick-Prescott filter. Having discussed the importance of our baseline definition of borrower and applicant, we now 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.[15] Moreover, the correlation

[15]The value usually used in the literature on business cycle with quarterly data is 1,600; however, the European

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

	HH sector	
$\beta^{\bar{A}B+\bar{I}B}$	borrower inflows	0.99
$\beta^{\bar{B}A+\bar{B}I}$	borrower outflows	0.01
	NFC sector	
$\beta^{\bar{A}B+\bar{I}B}$	borrower inflows	0.74
$\beta^{\bar{B}A+\bar{B}I}$	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 cyclical component of the annual growth rate of borrowers, i.e. $Cov(\widehat{j}, \widehat{b})/Var(\widehat{b})$ with $j \in \{\bar{B}A + \bar{B}I, \bar{A}B + \bar{I}B\}$. Borrower growth rates, b, and j variables are defined in eq. (3). Gross flows are calculated according to our alternative definition of borrower and applicant.

of borrower inflows with GDP is even larger in magnitude compared to when the first difference filter is used.

Cyclical indicators. In order to assess the robustness of findings to the choice of cyclical indicator, we repeat the exercise using unemployment in place of GDP. The dynamic pattern of borrower inflows is preserved in the first differenced data. Borrower inflows and unemployment exhibit strong negative correlation and borrower inflows lead unemployment fluctuations.

7 Concluding Remarks

We use granular information on the population of households and non-financial firms that borrow from banks operating in Italy to find new evidence on the role of the intensive and extensive margin in shaping the pattern of aggregate credit dynamics. Most of variation in the credit granted to the private non-financial sector occurs along the extensive margin, namely the net creation of borrowers.

In this respect, we construct new time series for the transition of HHs and NFCs between three

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.

statuses: borrower, applicant to a new bank and inactive. We underlie five new facts. First, the bulk of the aggregate bank credit dynamics is accounted for by movements along the extensive margin. Second, the contribution of extensive is of paramount importance to credit booms. Third, cyclical fluctuation in the extensive margin is strongly correlated to net creation borrowers which, in turn, is largely explained by gross inflows of borrowers. Fourth, gross inflows of borrowers are procyclical, highly volatile, tend to lead the business cycle, and are twice as volatile as borrowers outflows. Fifth, volatility of borrower inflows is mainly explained by search frictions stemming from changing in the probability of finding a loan.

We believe that our methodological approach and findings contribute to the empirical literature assessing the importance of search frictions and of competition with lender-lender asymmetric information in shaping bank credit dynamics. Moreover, since borrower inflows are easily measurable, they are a metric that bank supervisors could easily track monitoring lending in the economy and so useful to regulators. For instance, effective macroprudential 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. Conversely, the evolution of outflow of borrowers - and so a regulatory focus on the deleveraging during the downturn phase - seems not to be a key factor for aggregate credit dynamics.

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