Aggregate Implications of Credit Relationship Flows: a Tale of Two Margins

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Abstract

This paper documents the aggregate properties of credit relationship flows within the commercial loan market in France from 1998 through 2018. Using detailed bank-firm level data from the French Credit Register, we show that banks actively and continuously adjust their credit supply along both intensive and extensive margins. We particularly highlight the importance of gross flows associated with credit relationships and show that they are (i) volatile and pervasive throughout the cycle, and (ii) can account for up to 48 percent of the cyclical and 90 percent of the long-run variations in aggregate bank credit.

Keywords: Credit Flows; Financial Institutions; Relationship Lending; Search and Matching.

JEL Classification: E51; G21; E52; E32

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NON-TECHNICAL SUMMARY

What drives the fluctuations of credit over the business cycle and in the long run? How do banks adjust their credit supply in response to aggregate shocks or policy changes? These questions have been at the forefront of macro-finance and banking research at least since the seminal work of Bernanke (1983). Yet, our understanding of aggregate credit fluctuations and their implications for the real economy remains incomplete on several fronts. Bank credit is a significant source of financing for the majority of businesses. One particularly important aspect that has been extensively studied at the micro level, yet overlooked in macro, has to do with bank-firm credit relationships. Indeed, a vast theoretical and empirical literature has long highlighted the role of these relationships in terms of alleviating agency frictions and shaping credit supply at the lender-borrower level. It also emphasized the existence of cross-sectional heterogeneity in terms of match quality and inherent relationship characteristics such as duration, which can potentially hinder banks' ability to adjust their credit supply in a frictionless way. Conversely, the common view across most macro-finance models either simply assumes homogeneous borrowers and/or lenders, or abstracts from the long-term nature of financial contracts and any market frictions that may prevent banks from costlessly forming or severing these credit matches. These models thus downplay the value of relationships and their aggregate consequences and imply that banks can swiftly adjust the number of their borrowers in response to shocks. They also leave little room for analysing the process of credit reallocation across bank-firm matches and its dynamics throughout the cycle.

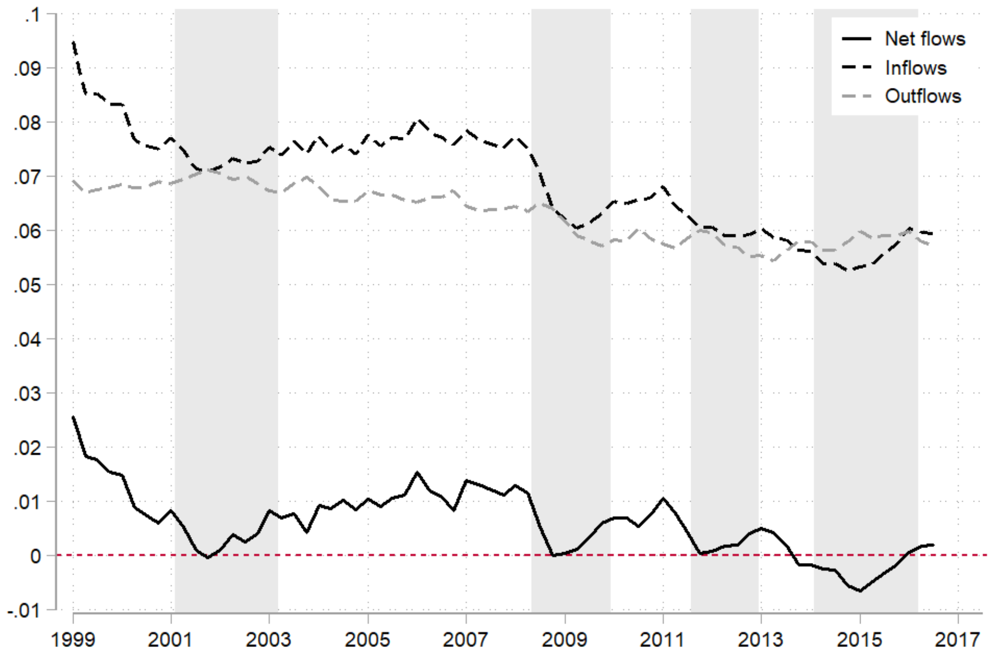
This paper proposes a novel macro perspective on the process of credit intermediation. It aims to provide further empirical evidence on the key and distinctive roles played by both the intensive and extensive margins in shaping aggregate credit fluctuations. Here, we attempt to look behind such fluctuations in order to address first-order questions such as: (i) When aggregate bank credit declines by five percent, is it because the average loan size (i.e., intensive margin) drops by five percent, or is it because five percent of bank-firm matches (i.e., extensive margin) are destroyed? (ii) Does the origin of aggregate credit fluctuations matter? (iii) Do monetary policy shocks impact these margins differently?

To answer those questions, we leverage a key source of information, the French Credit Register, which covers the commercial loan market in France, and is maintained by Banque de France. The data contains granular and nearly exhaustive records of bank-firm matches and corresponding credit exposures over the period 1998 - 2018. To study the properties of credit relationships flows, we develop an empirical methodology akin to the one pioneered by Davis and Haltiwanger (1992) for labor flows. Our methodology takes into consideration specific characteristics associated with credit market structure and available data. For example, we track data entries for each bank-firm match to determine the time of creation and inferred time of destruction in order to construct the associated gross credit relationship flows. We also account for cross-sectional heterogeneity and the nature of financial contracts through key attributes such as loan size, credit type and maturity, and relationship duration. Our empirical investigation establishes the following stylized facts about the extensive and intensive margins of credit: (i) extensive and intensive margins fluctuate continuously over time, (ii) although both margins are important at the business cycle frequency, the intensive margin plays a more prominent role, contributing about one half to three quarters of the variance in aggregate credit, (iii) in the long run, the extensive margin accounts for the bulk of aggregate credit variations (i.e., 90+%), and (vi) the intensive margin displays higher volatility relative to the extensive margin, while their persistence is roughly identical. It also highlights the following features pertaining to gross credit relationship flows: (i) the creation, destruction, and reallocation of bank-firm relationships coexist throughout the cycle, (ii) creation (inflows) and destruction (outflows) of relationships show greater volatility compared to net flows. Variations in net flows are driven mainly by inflows, and (iii) outflows exhibit greater volatility for small and short-term loans and credit relationships with duration of less than one year. Inflows exhibit greater volatility for relationships involving small loans and lines of credit.

Our empirical framework also provides us with tools to better understand the nature of the reallocation process occurring in credit markets and the channels through which bank shocks get

transmitted to the real economy. In particular, we show that the excess reallocation rate of credit relationships is countercyclical, in line with the cleansing effect of recessions. In addition, yearly (excess) reallocation rates have been steadily declining over the past two decades. These results indicate the existence of factors hampering credit market fluidity and contain relevant theoretical and policy ramifications worthy of further investigation.

Credit Relationship Flows



Effets macroéconomiques des flux de relations de crédit

RÉSUMÉ

Cet article documente les propriétés agrégées des flux de relations de crédit bancaire au sein du marché français des prêts aux entreprises, de 1998 à 2018. En utilisant des données détaillées au niveau banque-entreprise du registre de crédit de la Banque de la France, nous montrons que les banques ajustent activement et continuellement leur offre de crédit selon des marges intensives et extensives. Nous soulignons l'importance des flux bruts associés aux relations de crédit et montrons qu'ils sont (i) volatils et omniprésents tout au long du cycle, et (ii) peuvent représenter jusqu'à 48 % des variations cycliques et 90 % des variations à long terme du crédit bancaire global.

Mots-clés : marchés du crédit ; institutions financières; relations bancaires; recherche et appariement.

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1 Introduction

What drives the fluctuations of credit over the business cycle and in the long run? How do banks adjust their credit supply in response to aggregate shocks or policy changes? These questions have been at the forefront of macro-finance and banking research at least since the seminal work of Bernanke (1983). Yet, our understanding of aggregate credit fluctuations and their implications for the real economy remains incomplete on several fronts.

Bank credit is a significant source of financing for the majority of businesses. One particularly important aspect that has been extensively studied at the micro level, yet overlooked in macro, has to do with bank-firm credit relationships. Indeed, a vast theoretical and empirical literature has long highlighted the role of these relationships in terms of alleviating agency frictions and shaping credit supply at the lender-borrower level.[1] It also emphasized the existence of cross-sectional heterogeneity in terms of match quality and inherent relationship characteristics such as duration, which can potentially hinder banks' ability to adjust their credit supply in a frictionless way (Boualam (2018)). Conversely, the common view across most macro-finance models either simply assumes homogeneous borrowers and/or lenders, or abstracts from the long-term nature of financial contracts and any market frictions that may prevent banks from costlessly forming or severing these credit matches. These models thus downplay the value of relationships and their aggregate consequences and imply that banks can swiftly adjust the number of their borrowers in response to shocks. They also leave little room for analyzing the process of credit reallocation across bank-firm matches and its dynamics throughout the cycle.

This paper proposes a novel macro perspective on the process of credit intermediation. It aims to provide further empirical evidence on the key and distinctive roles played by both the intensive and extensive margins in shaping aggregate credit fluctuations. Here, we attempt to look behind such fluctuations in order to address first-order questions such as: (i) When aggregate bank credit declines by five percent, is it because the average loan size (i.e., intensive margin) drops by five percent, or is it because five percent of bank-firm matches (i.e., extensive margin) are destroyed? (ii) Does the origin of aggregate credit fluctuations matter? (iii) Do monetary policy shocks impact these margins differently?

To our knowledge, we are the first to show that banks actively adjust both the number *and* the intensity of their relationships, in response to macroeconomic shocks, and that both of these margins represent a significant source of variations in bank lending. These adjustments are somewhat analogous to the

[1] See Boot (2000) and Degryse et al. (2009) for a survey of earlier work.

ways in which firms constantly adjust both quantity of hours worked and employment, or their capacity utilization and new capital investment.[2] This view may sound intuitive, yet — and surprisingly — a thorough analysis of the dynamics of these margins, and their macroeconomic implications remain limited, if not completely absent. Furthermore, we not only establish the quantitative importance of these margins, but we also argue that they are subject to prominently different aggregate behaviors. Thus, disentangling the effects associated with each margin can prove informative about the economic mechanisms at play and the role of credit reallocation, and ultimately yield relevant policy implications.

To shed light on this process, we leverage a key source of information, the French Credit Register, which covers the commercial loan market in France, and is maintained by Banque de France. The data contains granular and nearly exhaustive records of bank-firm matches and corresponding credit exposures over the period 1998 - 2018. To study the properties of credit relationships flows, we develop an empirical methodology akin to the one pioneered by Davis and Haltiwanger (1992) for labor flows. Our methodology takes into consideration specific characteristics associated with credit market structure and available data. For example, we track data entries for each bank-firm match to determine the time of creation and inferred time of destruction in order to construct the associated gross credit relationship flows. We also account for cross-sectional heterogeneity and the nature of financial contracts through key attributes such as loan size, credit type and maturity, and relationship duration.

Understanding the implications of bank-firm credit relationships is a natural undertaking. However, a dearth of empirical evidence documenting their macro-level properties exists due to the paucity of extensive micro datasets over a sufficiently long period of time. In fact, earlier studies such as Dell'Ariccia and Garibaldi (2005) relied on bank-level call report data. Thus, they can identify the involved borrowers and can observe net intensive flows only at the bank level. As a consequence, these studies cannot disentangle extensive from intensive margins, nor precisely capture the underlying magnitude and cyclical properties of credit reallocation. Instead, we advance here a novel framing for the information available in the French Credit Register, which is typically exploited in micro settings, to uncover new findings at the aggregate level.

Our empirical investigation establishes the following stylized facts about the extensive and intensive margins of credit:

i. Extensive and intensive margins fluctuate continuously over time.

[2] To some extent, our analysis for credit markets follows in the footsteps of Lilien and Hall (1986), who first decomposed the fluctuations in total hours worked into changes in employment and changes in hours worked per employed worker.

ii. Although both margins are important at the business cycle frequency, the intensive margin plays a more prominent role, contributing about one half to three quarters of the variance in aggregate credit.

iii. In the long run, the extensive margin accounts for the bulk of aggregate credit variations (i.e., 90+%).

iv. The intensive margin displays higher volatility relative to the extensive margin, while their persistence is roughly identical.

It also highlights the following features pertaining to gross credit relationship flows:

i. The creation, destruction, and reallocation of bank-firm relationships coexist throughout the cycle.

ii. Creation (inflows) and destruction (outflows) of relationships show greater volatility compared to net flows. Variations in net flows are driven mainly by inflows.

iii. Outflows exhibit greater volatility for small and short-term loans and credit relationships with duration of less than one year. Inflows exhibit greater volatility for relationships involving small loans and lines of credit.

Our empirical framework also provides us with tools to better understand the nature of the reallocation process occurring in credit markets and the channels through which bank shocks get transmitted to the real economy. In particular, we show that the excess reallocation rate of credit relationships is countercyclical, in line with the cleansing effect of recessions. In addition, yearly (excess) reallocation rates have been steadily declining over the past two decades. These results indicate the existence of factors hampering credit market fluidity and contain relevant theoretical and policy ramifications worthy of further investigation. For example, it would be interesting to explore whether the observed credit reallocation slowdowns are problematic and whether newly implemented policies and structural reforms may have hindered markets' ability to redirect capital towards the most productive matches.

Literature review. This paper aims to connect two distinct yet complementary approaches to bank credit: macroeconomic research on credit cycles and microeconomic literature on relationship banking. The literature on credit cycles has long emphasized the role of credit constraints stemming from the borrower side (starting with Bernanke and Gertler (1989) and Kiyotaki and Moore (1997)). More recently, this literature has shifted focus toward analyzing bank constraints and decisions.[3] Yet, both

[3] See for example, Corbae and D'Erasmo (2019) and Begenau and Landvoigt (2018).

of these prominent strands generally abstract from long-term contracts and omit frictions stemming from market structure, and can hardly relate the role of bank or firm heterogeneity to the process of credit reallocation. At the same time, the banking literature has largely demonstrated the importance of relationships in shaping credit, but its theoretical and empirical studies haven focused mostly on the micro level with limited macroeconomic implications.

The paper's contribution resides in both providing empirical foundations to and assessing the macroeconomic relevance of a complementary line of research that puts forward a flow-driven approach to credit markets. This approach posits the essential role of bank-firm match dynamics in aggregate credit and has been introduced theoretically in Den Haan et al. (2003) and Becsi et al. (2005). More recently, Boualam (2018) builds a general equilibrium model featuring frictional credit markets and long-term contracts and argues that the destruction of bank-firm relationships during crises can significantly slow down recoveries. In a related micro approach, Mazet-Sonilhac (2020) empirically investigates how the reduction in search frictions, driven by the introduction of broadband internet, impacts the matching of banks and firms and aggregate credit flows. From a methodological standpoint, our empirical approach is closely related to the one, common in the literature, that is used to examine on job flows, and in particular earlier studies conducted by Steven Davis and John Haltiwanger and partly summarized in Davis and Haltiwanger (1999).

Our work is also part of a nascent literature on credit flows and reallocation, which includes Dell'Ariccia and Garibaldi (2005), Herrera et al. (2011), Craig and Haubrich (2013), and Contessi and Francis (2013).[4] One closely related paper to ours is by Dell'Ariccia and Garibaldi (2005), who use bank-level information to track credit flows along the intensive margin. We argue that the use of bank-level data, while informative about flows "on the surface", in fact masks the extent of credit reallocation and cannot provide information about the dynamics of bank-firm relationships.[5] In the same vein, Herrera et al. (2011) work with firm-level data to measure inter-firm credit reallocation. Although that paper provides a valuable first step toward our understanding of credit reallocation, its focus is not on bank credit, but rather on a broad definition encompassing all forms except trade credit. In addition, the data from Compustat used for that analysis cannot fully capture the extent of reallocation across borrowers and lenders nor account for relatively small firms. In contrast, our paper is the first to use loan-level data to carefully establish patterns and stylized facts about gross credit relationship flows in order to distinguish

[4]More broadly, it is also related to the literature on capital reallocation such as Ramey and Shapiro (1998) and Eisfeldt and Rampini (2006), who conduct their flow analyses at the firm level.

[5]In particular, banks may well be reallocating credit across their borrowers even though their net credit growth is zero.

extensive and intensive margin effects and uncover the underlying reallocation dynamics. Indeed, our unit of observation is the bank-firm match, which allows us to precisely measure credit reallocation at the loan level. This level is key because inter-bank reallocation or inter-firm credit reallocation measures tend to significantly underestimate the magnitudes of the underlying gross flows.

The paper is also broadly related to the literature quantifying the sources of aggregate credit fluctuations and more generally the transmission of shocks stemming from either borrowers or lenders.[6] Among others, two recent papers connected to ours include Amiti and Weinstein (2018) and Beaumont et al. (2019). Amiti and Weinstein (2018) use matched bank-firm loan-level Japanese data with a focus on publicly listed companies to measure the importance of idiosyncratic granular bank supply shocks and their implications for credit and firm investment overall. In a similar vein, Beaumont et al. (2019), with whom we share the use of the French Credit Register, suggest additional effects stemming from granular borrower shocks. Our paper differs from these in that it focuses on the role played by credit relationships and their associated gross flows, and instead proposes an extensive/intensive margin decomposition of aggregate lending.

Finally, while we have almost entirely focused on aggregate outcomes here, a companion paper, Boualam and Mazet-Sonilhac (2020), analyzes the data from a disaggregated perspective and delivers complementary cross-sectional results.

Organization. The paper proceeds as follows. We first start by outlining our empirical methodology and its conceptual foundations in Section 2. We then present our core results for gross relationship flows (Section 3), and aggregate credit decompositions (Section 4). Section 5 explores implications for crises while Section 6 further discusses relevant applications and extensions. Section 7 concludes.

2 Empirical methodology

The central objective of this paper is to shed light on the importance of the extensive margin of credit, and to document aggregate patterns and cyclical properties of gross credit relationship flows along with their intensive margin counterpart. This section first discusses the conceptual foundations behind our measurements. It then introduces the data and sample construction and lays out our credit flow concepts, definitions, and empirical methodology.

[6] See, for example, Hubbard et al. (2002), Khwaja and Mian (2008), Chodorow-Reich (2014), and Chen et al. (2017).

2.1 Conceptual foundations: a flow approach to credit markets

Our focus is on the aggregate implications behind the dynamics of bank-firm relationships. It is thus essential to disentangle the extensive and intensive margins of credit. We start with a simple credit market identity, which states that total aggregate credit supplied by banks, C_t, is the product of the number of credit relationships (i.e., extensive margin), N_t, which we refer to as *relationship capital*, and the average credit exposure per relationship (i.e., intensive margin), $\bar{c}_t$:

$$C_t \quad = \quad N_t \times \bar{c}_t. \tag{1}$$

This decomposition presupposes that all firms are ex-ante identical, and that credit relationships are all homogeneous, thus potentially masking compositional effects. Yet it has the merits of being straightforward and easy to interpret and measure. In that sense, the underlying changes in the extensive and intensive margins shape the dynamics of aggregate credit.

Furthermore, we can write down the dynamics of relationship capital as follows:

$$N_{t+1} \quad = \quad N_t + \mathbb{C}_{t+1} - \mathbb{D}_{t+1}, \tag{2}$$

where $\mathbb{C}_{t+1}$ and $\mathbb{D}_{t+1}$ represent creation and destruction flows materialized between times t and $t+1$, respectively. These creation and destruction flows can take multiple forms within credit markets. Figure 1 represents them conceptually from the firms' perspective. In particular, We consider that firms can be in one of two states: (i) funded, or (ii) unfunded. Creation flows can thus represent the formation of a bank-firm relationship (as the unfunded firms becomes funded), but also situations where already funded firms switch banks or accumulate multiple banking relationships. In a similar vein, destruction flows represent the severance of credit relationships. These destructions can be viewed as "internal" to the credit market as it is the case for firms transitioning from the funded to unfunded states, switching banks, or separating from part of their established banking relationships. These flows can also be "external" whereby the bank-firm match destruction is due to permanent firm exit or default.

In the spirit of the labor market literature, we rely on search theory insights to provide the conceptual grounds underlying our measurements of gross credit relationship flows. We also follow general insights from Boualam (2018), who posits that credit markets are subject to imperfections, akin to search frictions, and that this may lead to a form of asymmetric adjustment costs in bank relationship capital. In addition, the total credit intermediated is a function of the number of relationships but also of their intensity and composition. As search is costly, banks and firms spend time looking for matches. Frictions affecting the matching, severance, and reallocation of bank-firm pairs acts as a form of credit adjustment cost. We view credit relationship creations and destructions as inherent to a large process of adjustment and reallocation of capital across banks and firms. One key insight is that these adjustments are time-varying, with potentially asymmetric costs associated with creation and destruction and extensive and intensive margins. These costs may also depend on bank, firm, and credit relationship characteristics. Thus, we exploit concepts laid out by this flow-driven approach, and construct novel measures that shed light on the structure of credit markets and bank-firm relationships.

2.2 Definitions and measurement

Next, we introduce our notations and proposed measures for credit relationship flows, credit exposure, and relationship intensity.

2.2.1 Credit Relationship (CR) flows

Relying on our conceptual foundations, and following in the footsteps of earlier studies on gross job flows (e.g., Davis et al. (1998)), we introduce our definitions of credit relationship creations and destructions and their associated measures.[7] It is important here to lay down our interpretation of these statistics and their underlying assumptions. We start by defining the creation and destruction of a bank-firm match and the notion of credit relationship as follows:

Definition 1.

- ***Credit Relationship Creation (inflow).*** *First occurrence of a bank-firm match with strictly positive credit exposure at time t, assuming no previous match over the preceding 4 quarters, i.e., between $t-4$ and $t-1$.*
- ***Credit Relationship Destruction (outflow).*** *Last occurrence of a bank-firm match, assuming no further match for at least the next 4 quarters, i.e., between $t+1$ and $t+4$.*
- ***Credit Relationship.*** *Existing bank-firm match at time t, whereby t lies within the creation and destruction dates.*

Figure 2 represents possible situations encountered in the data. Our definitions capture the theoretical

[7] An earlier version of these flow definitions was proposed in Boualam (2018).

construct put forward in the relationship banking literature.[8] In particular, they reflect the idea that information is revealed mostly through bank screening and monitoring (even though the firm may already have an account or a transaction-based relationship with a given bank). They also allow for the fact that information about a firm is not necessarily lost immediately upon the maturity of a given credit facility, but only after a relatively long interaction-free period. Our definitions thus help us account for the fact that banks and firms may engage in lengthy negotiations before closing a loan deal and also for potential reporting gaps in the data. It also adjusts for temporary declines in credit exposure below the mandatory reporting threshold.

Note that while the last occurrence of a bank-firm match in the SCR dataset may be at quarter t, the destruction of such match in fact happens sometime between quarter t and $t+1$, and is thus accounted for at time $t+1$. We further test the robustness of our definitions and results by allowing for the number of quarters to be 8 and 12. It is also worth noting that a bank and a firm could engage in several credit relationship creation and destruction rounds throughout the sample, as shown in Figure 2.[9]

With these definitions in mind, we can now tabulate gross credit relationship flows, i.e., creation flows, $\mathbb{C}_t$, and destruction flows, $\mathbb{D}_t$, based on the sum of all bank-firm relationships that are either created or destroyed between times $t-1$ and t. In the same vein, we can define, at time t, the net credit relationship flows, $\mathbb{N}_{t+1}$ as the difference between inflows and outflows, the reallocation flows, $\mathbb{R}_t$, as the sum, of inflows and outflows, and excess reallocation flows, $\mathbb{X}_t$, as the sum of inflows and outflows minus the absolute value of net flows:

$$\begin{aligned}
\mathbb{N}_t &= \mathbb{C}_t - \mathbb{D}_t \\
\mathbb{R}_t &= \mathbb{C}_t + \mathbb{D}_t \\
\mathbb{X}_t &= \mathbb{C}_t + \mathbb{D}_t - |\mathbb{N}_t|
\end{aligned}$$

In the spirit of the interpretation put forward in Davis and Haltiwanger (1992) for labor flows, excess reallocation for credit relationships measures the extent of reallocation in excess of that needed to generate the corresponding net changes in total credit relationships. For example, simultaneous creation and destruction flows on the order of ten percent do not impact the stock of credit relationships in the economy, yet imply a large level of credit reshuffling across firms and banks and an excess reallocation of 20%. We can eventually compute the corresponding flow rates (denoted with lowercase characters),

[8] Throughout the paper, we refer to credit relationships and bank-firm matches interchangeably.

[9] In fact, we find that only 10.5% of severed relationships are recreated 5 to 8 quarters later.

by dividing the measure of flows experienced between times $t-1$ and t, by the relationship capital stock at time $t-1$, N_{t-1}.[10]

2.2.2 Relationship intensity: credit exposure, maturity, type, and duration

Besides banks' and firms' characteristics, the credit relationship itself can be characterized along several dimensions that define how binding and intense the match is. We consider here three measures that reflect relationship intensity, namely (i) credit exposure, (ii) maturity/type, and (iii) duration.

Credit exposure, maturity, and type. We start by defining the credit exposure of a bank to a particular borrowing firm, as the sum of withdrawn and undrawn credit, in addition to bank credit guarantees.[11] We further decompose the withdrawn component by maturity (i.e., short-term and long-term) and other less common forms of credit (i.e., credit leasing, securitized debt, overdrafts limits).

Definition 2.

- ***On-Balance-sheet credit.*** *Accounts for long-term (> 1 year) and short-term credit (< 1 year).*[12]
- ***Off-Balance-sheet credit.*** *Accounts for lines of credit and credit guarantees.*[13]
- ***Credit Exposure.*** *Sum of on-balance sheet credit and off-balance sheet credit.*

In addition to the size of the credit exposure, we can further characterize the intensity of the credit relationship based on the nature and maturity of credit involved. In particular, we define (i) the share of on-balance-sheet credit as the ratio of on-balance-sheet credit to total credit exposure, and (ii) the share of long-term credit as the ratio of long-term credit to on-balance-sheet credit. These measures both reflect the level of flexibility and commitment from the bank's perspective. Thus, we posit that a credit relationship is more binding when banks supply long-term credit. Conversely, it is less binding when it consists predominantly of short-term or off-balance-sheet credit that a bank can more swiftly adjust downward in anticipation of or following a negative shock.

[10] We adopt this definition at the aggregate level throughout the paper for consistency. Results remain qualitatively unchanged if these rates are computed using the mid-point $0.5(N_{t-1}+N_t)$, instead of N_{t-1}.

[11] A credit guarantee ensures that a debtor's liabilities will be covered by the lending institution in case of delinquency. It thus enables the borrower to contract third-party liabilities (e.g., trade credit) through the transfer of counterparty risk to the bank, thereby creating an implicit credit exposure.

[12] Formally, this definition also accounts for medium- and long-term leasing and factoring, but these categories are omitted from our calculations as they represent less than one percent of on-balance-sheet credit.

[13] Formally, this definition also accounts for securitized loans. We omit this category from our calculations as it is represents a negligible share of off-balance-sheet credit.

Relationship Duration. Next we consider relationship duration. Relying on extensive micro literature on credit relationship (Degryse et al. (2009)), the repeated interaction between borrowers and lenders can help gradually alleviate agency and informational frictions that may initially be present. This eventually leads to higher credit supply over time. Thus, duration can serve as a proxy for bank-firm match quality.

Definition 3.

- ***Credit Relationship Duration.*** *The duration $d_{ij,t}$ of an ongoing credit relationship between bank i and firm j corresponds to the number of years/quarters between time t and its (latest) creation date.*

2.3 Data

Our analysis relies on multiple sources of bank-firm level micro data obtained from Banque de France and the French Institute of Statistics (INSEE). These include the French Credit Register, which is at the heart of our analysis, in addition to sources such as French firms balance-sheet data (FIBEN and BRN) and SIRENE, which are used for complementary analyses, and introduced in later sections.

The French Credit Register. The French Credit Register, referred to as *Service Central des Risques* (henceforth SCR), is a monthly database that contains bank credit exposures to borrowing firms over the period 1998-2018. This is the most comprehensive commercial credit dataset maintained by Banque de France and used to monitor overall credit supply and risk exposures of domestic banks. The data are generated from detailed mandatory reports filled by all credit institutions (classified through a unique CIB identifier) and which list any credit commitment or risk exposure to any borrowing firm (as defined by a legal unit and referenced by a unique national identification number, SIREN). Reports encompass the funds made available or drawn credits, the bank's commitments on credit lines and guarantees as well as medium and long-term leasing, factoring and securitized loans.

Commercial borrowers include single businesses, corporations, sole-proprietorship engaged in professional activities, which may be registered in France or abroad. Reporting financial intermediaries account for all resident credit institutions, investment firms, and other public organizations. Thus, the dataset provides an extensive account of existing bank-firm linkages, as long as the bank credit exposure is above the legal nominal reporting threshold of EUR 75,000 for the period 1998 - 2005 or EUR 25,000 from 2006 onward.

Data construction. Our sample excludes firms with headquarters outside Metropolitan France, self-employed entrepreneurs, and certain types of entities such as nonprofit organizations.[14] It also omits observations related to public credit institutions, non-traditional banking groups, and non-credit intermediaries, which may have different objectives compared to more standard banks.[15] We also exclude some very small institutions whose aggregate credit exposure averages less than EUR 1 million on a quarterly basis.

We choose to work at the quarterly frequency given our analysis objective and the considerable size of available data. We also work with bank-level data instead of branch or banking group levels in order to focus on bank-firm relationships.[16] We also choose to work in real terms to capture real credit exposure within a match and hence deflate all credit variables using the GDP deflator for France.[17] Similarly, we adjust the reporting threshold to reflect real terms. Furthermore, to make sure that our analysis remains consistent over time despite the change in the reporting threshold, we focus on bank-firm pairs using the inflation-adjusted threshold (corresponding to EUR 75,000 in 1998) throughout the whole sample period.[18] While such restriction does not drastically affect total aggregate credit (our final dataset accounts for 97% of total bank credit), it accounts for only 57% of existing bank-firm relationships, suggesting that a non-negligible number of credit relationships are in fact very small in nature.[19]

Our cleaned baseline panel dataset contains about 27 million bank-firm-quarter observations over the period 1998Q1-2018Q4, includes 715 unique banks (447 banks per quarter on average), and 940,554 unique firms (256,271 firms per quarter on average). Figure 3 reports the evolution of the number of banks and firms. While the banking sector experienced intense consolidation over the sample period,

[14] Appendix A provides additional details related to data filters and variable construction.

[15] These include Caisse des Depots et Consignations, Oseo, and Banque de Developpement des PME, which later became Banque Publique d'Investissement (BPI) in 2015. Credit supplied through public banks accounts for about 15% of the total credit over the period.

[16] The Online Appendix contains further robustness tests using data consolidated at the banking group level. Our results remain qualitatively unchanged.

[17] Appendix A provides further technical details about the construction of credit variables. All credit variables are reported in terms of 1998 EUR based on the GDP implicit price deflator in France constructed by the OECD and retrieved from FRED (FRAGDPDEFQISMEI).

[18] The reporting threshold is fixed to EUR 75,000 at the beginning of the sample period and is then adjusted over time. Given that inflation remains overall positive throughout the sample period, this means that we omit a small fraction of bank-firm relationships with available data, but for which the credit exposure is below the inflation-adjusted threshold. We discuss and report in the Online Appendix our results based on nominal terms. Our results remain overall consistent and robust to such adjustments.

[19] We further run robustness checks using the lowest reporting threshold for the period 2006-2018. As we show in the Online Appendix, this adjustment does not qualitatively affect our results.

with the number of banks declining by a third, the number of firms (relying on bank credit) has almost doubled in the meantime.

Comparison with aggregate Flow of Funds data. Our final sample covers about 61% of total bank credit to non-financial companies reported in the balance of payments on average. Also, as shown in Figure 4, the two time series exhibit similar aggregate patterns overall, with correlations of 0.99 for total credit and 0.98 for long-term credit.

2.4 Issues and adjustments

Our data and empirical methodology are subject to certain limitations and other standard issues, which may tend to over-estimate the level of relationship flows. These include (i) seasonality, (ii) bank and firm consolidation, (iii) variations in the reporting threshold, and (iv) change in the reporting of some categories (e.g., off-balance-sheet credit) and the classification of non-performing credit.[20] We attempt to correct for these limitations and discuss them in detail in this section.

Seasonality. The flow data exhibit strong seasonality patterns with higher creation flows in quarter 1 and higher destruction flows in quarter 4. We use the standard X-13 procedure to generate seasonally adjusted time series. Furthermore, and although such issues appear to be negligible, we smooth the data using a centered moving average (-1,1) to control for potentially mistimed reports of credit exposures.[21]

Bank consolidation. The French banking sector has undergone several rounds of consolidations throughout our sample period. As shown in Figure 5, the number of banks declined from 547 to 342 from 1998 through 2017. This is due almost exclusively to mergers and acquisitions (M&As) as the effects of bank entry and exit remain relatively marginal during this period. We use the bank merger list maintained by Banque de France and gathered by the French Supervision and Prudential Authority (ACPR), which reports all banking M&As over the period 1995 through 2016. This dataset includes the dates of mergers and covers all instances involving banks located within the French territory. We first correct for M&As and bank consolidations, following the same methodology as in Dell'Ariccia and Garibaldi (2005), as they may lead to spurious overestimation of inflows and outflows. For example, consider a merger occurring between Bank A (absorbing bank) and Bank B (absorbed bank), in the

[20] See Appendix A for more details.

[21] For example, a loan deal that closes on December 31 might not be officially reported until the following quarter. Similarly, a relationship that gets terminated on January 1 might not be accounted for until the next quarter.

period between time $t-1$ and time t. At time $t-1$, outflows are overestimated by the stock of relationship capital of Bank B, $O_{B,t-1}$, as Bank B gets removed from the SCR dataset, thus generating an artificial destruction of all its credit relationships. At time t, inflows are in turn overestimated by the same amount $O_{B,t-1}$ because the transferred credit relationships from the mergers are accounted as ones that have been newly created by Bank A. We thus proceed to correct raw changes by (i) setting to zero outflows of Bank B due to absorption at $t-1$ (i.e., $O_{B,t-1}=0$), and (ii) reducing inflows of Bank A, at time t, by $O_{B,t-1}$ (i.e., $I^{net}_{A,t}=I_{A,t}-O_{B,t-1}$). We omit mergers involving banks with missing identifiers (CIB), which account for less than three percent of M&A events. We also complement these adjustments by manually checking our database, and taking into account more complex situations, such as the consolidation of Caisse d'Epargne and Banque Populaire.[22]

Firm consolidation. Mergers and acquisitions activity at the firm level could also generate spurious accounts of creation and destruction flows.[23] Indeed, when Firm A linked to Bank C absorbs Firm B linked to Bank D, our measurement definitions would record the simultaneous destruction of the B-D match and the creation of a new A-D match instead. While one can argue whether these flows are economically meaningful, we cannot make direct adjustments given that we are not aware of any exhaustive database of firm M&A activity in France. However, we can show that such M&A-induced flows represent a negligible fraction of our tabulated flow measures. Indeed, we estimate through Bureau Van Dijk's Zephyr database (which is the most comprehensive firm consolidation database available) the existence of less than 40,000 instances of firm consolidations in France over the period 1999-2018. This number represents less than 0.15% of bank-firm credit relationships and about 2% of total gross flows over the sample period. Furthermore, when only considering the subsample of larger firms reported in FIBEN (i.e., the universe of firms for which balance sheet information is collected by Banque de France), we estimate a conservative upper bound for the share of M&A-induced flows to be around 5 to 6%. Finally, it is also worth noting that our analysis is immune from other types of activity leading to ownership or name changes for standalone companies given that their the legal identifier (SIREN) is unique and remains constant irrespective of ownership or other legal adjustments.

Reporting threshold. Given that we consider only those bank-firm relationships for which the total credit exposure exceeds EUR 75,000, we check that the flows of relationship creation and destruction are

[22] This case corresponds to the absorption of one banking subsidiary by multiple acquiring banks. Here, we correct for this merger through a uniform adjustment of inflows for all acquirers.

[23] We thank Pietro Garibaldi for raising this point.

not driven simply by threshold-crossing increases or declines in credit, which can mechanically generate a positive correlation between intensive and extensive margins.

While we cannot fully rule out this possibility, we carefully address it and estimate its extent through the following tests. First, our definition of creation and destruction flows is conservative, as it accounts for an effective relationship separation only if a bank-firm match has been inactive (i.e., absent from the SCR) for 4 quarters. That way, temporary declines in credit, below the reporting thresholds, do not generate spurious episodes of relationship destruction followed by creation. Second, we re-run our analysis based on a EUR 25,000 reporting threshold over the period 2006-2018 and show that the obtained patterns are qualitatively and quantitatively in line with our benchmark results. Third, we can trace back a large fraction of relationship creation and confirm that a vast majority is due to either new entrant firms (based on their creation dates obtained from the SIRENE database) or bank switches. Similarly, a large fraction of relationship destruction is due to defaulting or exiting firms in addition to switches. Fourth, we show that average credit supplied at the time of creation or destruction of credit relationships hovers around EUR 700,000, about nine to ten times higher than the reporting thresholds, which further mitigates the extent of any related bias. The Online Appendix reports several robustness tests associated with the reporting threshold.

Other reporting issues. The reporting methodology of the SCR has evolved constantly over the past two decades. We document here some of the issues that directly impact our tabulations and our corresponding adjustment. For example, in 2003 Q3, the French Central Bank credit grading scale was amended (going from *cotation BDF* to *cotation NEC*); we use a correspondence table provided by Banque de France to ensure a consistent measure of the credit quality of borrowers. In 2012 Q1, the reporting of non-performing loans was modified, which creates a minor discontinuity in some of our aggregate series. All the non-performing credit was indeed previously allocated to long-term credit (even if the maturity was shorter than one year), but, after 2011Q4, its reporting was broken down into long-term and short-term categories. This evolution directly affects our measures of the number of existing relationships with short-term vs. long-term credit. We decided to artificially keep the pre-2012 norm active until the end of our sample and to re-classify relationships based on their initial maturities. Finally, and despite our efforts, we were unable to properly deal with a change in the reporting methodology for credit guarantees, occurring at the end of 2005, that led to a spike in gross flows around 2005Q4 and 2006Q1. For each gross flow time series, we manually replace this one data point at time t based on the midpoint derived from the time $t-1$ and $t+1$ data. That said, working with this data point or simply omitting it from the analysis doesn't substantially affect any of our results.

2.5 Summary statistics and aggregate time series

Table 1 reports summary statistics for key variables pertaining to banks, firms, and credit relationships. The average bank in our sample has 802 distinct borrowing firms with a average credit exposure of EUR 1.03 million each (based on 1998 EUR). Furthermore, this exposure consists of about EUR 413 thousand in long-term debt, EUR 214 thousand in short-term debt, and EUR 413 thousand in undrawn credit lines.

Figure 5 shows the close link between the dynamics of aggregate credit and those of bank-firm relationships, while Figure 6 exhibits the evolutions of the number of banks per firm and vice versa. The average number of banking relationships exhibited a slight decline from around 1.45 to 1.32, with the fraction of firms engaged in a single relationship hovering around 80%. On the other hand, banks have grown bigger, and service about two and a half times more firms in 2016 relative to 1999. Perhaps more surprising is that the average credit exposure per firm remained relatively stable (in real terms) throughout the sample period, around EUR one million. The composition of debt has shifted, however, toward long-term credit and credit lines at the expense of short-term credit (see Figure 7).

Panel (a) in Figure 7 shows the evolution of alternative proxies for relationship intensity. We see that the percentage share of long-term credit (over total credit exposure) actually increases while the share of short-term credit declines during crises, which potentially makes banks even less flexible in terms of their ability to adjust credit supply. This finding is consistent with firms mostly withdrawing from their long-term, pre-committed credit lines, in line with U.S. evidence (Ivashina and Scharfstein (2010)).

Banks and firms engage in relatively long-term relationships. We estimate the average duration of a match to be on the order of 15 quarters, a bit shorter than four years.[24] Tabulating the weighted average relationship duration in the economy may be subject to some biases that could lead to spuriously large (resulting from a small subset of relationships with extremely long duration) or low numbers. We therefore choose instead to track the fractions of relationships with durations below one year, between one and three years, and above three years, in order to have a better sense of the evolution of the distribution of relationship durations over time.[25] Panel (b) in Figure 7 shows these results.

[24] This is in fact a lower-bound estimate, as we assign a duration of 0 to all bank-firm matches existing in 1998Q1, which is the starting date of the sample. We also do not count quarters where the bank-firm match may be missing from the SCR when its credit exposure level drops below the reporting threshold.

[25] We select these thresholds because the data show a distinct behavior for very young relationships relative to the rest. The three-year threshold is arbitrary and is chosen mainly so as to keep the longest possible time series.

It is also worth noting that the credit exposures associated with newly created (destroyed) relationships, account for about 57% (45%) of that of incumbents, which corresponds to about EUR 570 (450) thousand, well above the reporting threshold. Furthermore, the average credit amount supplied to newly created relationships (and that was previously supplied to exiting firms) appears to follow procyclical dynamics, suggesting that the sub-extensive margin may play an important role in aggregate credit fluctuations. We will get back to this point in Section 4.1.

Cross-section. Eventually, Table 2 reports additional summary statistics in the cross-section. We note that overall there is a significant degree of heterogeneity across banks, firms, and bank-firm matches, further highlighting the importance of jointly analyzing the intensive and extensive margins of credit.[26] For example, bank size (as measured by the number of serviced borrowers or total credit exposure) is heavily skewed with a median of 77 borrowers (or equivalently EUR 137 million), with the 95$^{\text{th}}$ percentile standing at over 4000 borrowers (or EUR 3.8 billion). In the same vein, relationship duration and credit exposure measures also exhibit a large degree of dispersion across relationships with interquartile ranges spanning 5.9 - 24.4 quarters, and 116 - 429 thousand EUR, respectively.

3 Properties of credit relationship flows

We are now ready to analyze the properties of credit relationship flows. In particular, we show that the processes of creation, destruction, and reallocation of credit relationships are (i) significantly large, (ii) volatile, (iii) asymmetric, and (iv) inherent to credit markets at all times.

3.1 Aggregate patterns

Figure 8 exhibits the aggregate patterns for the flow times series (Panel (a)). Gross credit relationship flows are inherent to credit markets and exhibit relatively large magnitudes and volatilities. They are also quite large relative to the underlying net flows. Indeed, our results suggest that about 1 in 14 credit relationships is created and 1 in 16 is destroyed on a quarterly basis. On average, 23,407 positive flows (6.94%) and 21,497 negative flows (6.32%) combine to generate 1,910 net flows (0.62%) per quarter. As a result, the excess reallocation rate is on the order of 12.51% per quarter. Moreover, these gross

[26] On the one hand, if bank-firm matches were all identical and financial contracts were rigid (e.g., credit per match is constant throughout the relationship), then we should care only about counting the number of credit relationships in the economy (i.e., extensive margin would be a sufficient statistic for aggregate credit). On the other hand, if the processes behind the creation and destruction of bank-firm matches were frictionless and the value/quality of relationship portable, then only the intensive margin would matter.

flows appear to closely track each other throughout the sample period. This again illustrates that the substantial process of credit reshuffling across financial institutions and borrowers is continuously reshaping credit markets. We also observe that both gross flows exhibit downward trends with quarterly flow rates of relationship creation and destruction declining respectively from about 8.6% to 6%, and from 6.8% to 5.8% over the sample period.

3.2 Cyclical properties

We now examine the cyclical properties of gross credit relationship flows, and characterize the magnitude of their fluctuations. We detrend all flow rates using the Hodrick-Prescott (HP) filter, with a smoothing parameter of 1600. Panel (b) in Figure 8 presents the corresponding cyclical deviations from HP trend. We also compute the corresponding volatility, autocorrelation, and correlation with respect to log-growth of GDP, aggregate credit, and relationship capital, for each variable of interest. Table 3 formalizes these results.

First, we establish that creation flows (in levels or rates) of credit relationships are two to three times as volatile as their destruction counterpart. As shown in Table 3, the standard deviation of creation flows is 0.044 for levels (0.0027 for rates), while the volatility of destruction flows is 0.026 for levels (0.0013 for rates). Second, and maybe unsurprisingly, rates of creation flows are positively correlated with growth rate of GDP (0.44), aggregate credit (0.47), and relationship capital (0.64). On the other hand, rates of destruction flows exhibit only a moderately negative correlation with GDP (-0.084), aggregate credit (-0.14), and relationship capital (-0.26). We find similar results when looking at the levels of creation and destruction flows. Third, we establish that the variations of net flows are relatively large, with a volatility of 0.051. Indeed, the procyclical nature of inflows and the countercyclical nature of outflows combine to generate large movements in net flows. Fourth, we can measure the relative contribution of each component toward the overall variance of (detrended) net flows using the following decomposition:

$$1 = \underbrace{\frac{\text{cov}(c_t, n_t)}{\text{var}(n_t)}}_{\beta_{pos}} + \underbrace{\frac{\text{cov}(-d_t, n_t)}{\text{var}(n_t)}}_{\beta_{neg}}, \tag{3}$$

and show that positive flows account for about 84% of the variation in net relationship flows while negative flows account for only about 16%. This result is also robust to the sample periods.

The relative importance of creation and destruction flows is also visible in the scatter plot, shown in Figure 9. Taking the periods pre- and post- 2008 separately, we observe that the creation margin drives net flows, while the destruction rates remain relatively stable. Furthermore, this figure also highlights a regime shift taking place around the financial crisis, with negative flow rates, in particular, declining from their 6.5-7 percent range pre-crisis, to a 5.5-6 percent range.

Overall, and from an aggregate perspective, this finding suggests that the critical adjustment variable for relationship capital is along the creation margin, as banks may have limited control over destruction flows, especially when the supplied credit is long-term. This result confirms earlier findings obtained in Boualam (2018) for the U.S., based on Dealscan data. However, they disagree with those reported in Dell'Ariccia and Garibaldi (2005) and Herrera et al. (2011), who use bank-level and loan-level data, respectively.[27,28]

3.3 What drives the creation and destruction of credit relationships?

Figure 10 presents the decomposition of creation (Panel (a)) and destruction (Panel (b)) of credit matches as follows:

- Creation flows: (i) bank switches and multi-bank firms experiencing a relationship gain ("positive reallocation"), and (iii) new firm entry (with credit exposure above the threshold).
- Destruction flows: (i) bank switches and multi-bank firms experiencing a relationship loss ("negative reallocation"), (ii) firm default, and (iii) firm exit (excluding default) or with a loan below the reporting threshold closed.

A bank switch is defined as the simultaneous move from one lender to another, which corresponds to the destruction of the original relationship and the creation of a new one within a four-quarter interval. We define multi-bank firm relationship gains (losses) as the incremental addition (drop) of a credit relationship induced by firms with a (two) pre-existing relationship(s). Here, we choose to report bank switches along with relationship gains/losses, as some firms appear to switch from one lender to another at a gradual pace, generating transitory periods in which they are formally associated with two banks.

Overall, we show that about two thirds of creation flows are due to new entrants, while one third is due to incumbent firms switching to or matching with additional lenders. On the other hand, we report that destruction flows are due to bank switches and multi-bank firms experiencing a relationship loss (about

[27]Arguably, several differences across our samples may explain this discrepancy. Among others, these studies focus on U.S. data and different sample periods. Equally important, they use data aggregated at the bank or firm levels instead of working at the credit relationship level, as we do.

[28]Interestingly, this result is also different from labor market studies which suggest that job destruction rates are more volatile and relatively more important for net labor flow fluctuations (Davis and Haltiwanger (1992)).

40%), firm exit (about 40%), and firm default (20%). These contributions appear to be relatively stable across the sample period and each component generally inherits the cyclical properties of the underlying gross flow. However, this picture looks slightly different for net flows, which appear to be explained mostly by the spread between entry and exit flows. And, despite the substantial amount of their gross flows, incumbent borrowers who are either switching or adding/dropping credit relationships have net flows about four times smaller compared to entering and exiting firms.

How important are firm entry and exit? We complement our analysis by using the SIRENE database to help us determine the dates of firm entry (i.e., firm's legal incorporation date) into the French economy. We then tabulate the ratio of first-time borrowers (i.e., firms appearing in the SCR for the first time) over newly created firms (entrants) within the same quarter.[29] While the flows of entrant firms and those that obtain credit for the first time are highly correlated (84%), their ratio exhibits stark dynamics. As shown in Figure 11, the share of first-time borrowers over entrants presents a downward secular trend (declining from about 26% to 20%) and procyclical patterns, suggesting that newly created firms have harder time getting credit during crisis periods.[30]

3.4 Cross-sectional decomposition at the relationship level

We further uncover the determinants behind these fluctuations by analyzing the dynamics of credit relationships as a function of their key characteristics, namely (i) credit exposure, (ii) credit type and maturity, and (iii) duration. Figure 12 shows the times series associated with gross flows and Table 4 presents the results pertaining to their cyclical properties.

Decomposition by relationship credit exposure. We specify fixed dollar thresholds at 250 thousand, 500 thousand, and 1 million EUR throughout the sample, and classify bank-firm matches into small, medium, or large credit size categories on a quarterly basis.[31] Credit relationships classified by credit exposure into (i) small (below 0.25 million Euro), (ii) medium (0.25 to 0.5 million Euro), (iii) large (0.5 to 1 million Euro), and (iv) very large (above 1 million Euro) respectively account for about 61%, 19%, 10%, and 10% of total relationships. We show that gross and net flows associated with small loans exhibit a larger volatility relative to the largest ones. They also exhibit the largest decline in inflows

[29] Unfortunately, there is no connecting table between firm identifiers in SIRENE and the SCR and thus we cannot individually track the outcome of each entrant firm.

[30] While we cannot completely rule out the possibility of a significant procyclical shift in credit exposure to new entrants, our results remain unchanged even when considering the lower reporting threshold in the second half of the sample.

[31] Adjusting the size classification thresholds for inflation does not qualitatively alter the results.

during downturns. This suggests that banks consider their smaller relationships as a key variable of adjustment throughout the cycle and reiterates the additional vulnerability of small borrowers during crises. Thus, small loans have a significant impact on aggregate fluctuations in bank credit, given their relative importance in terms of share in aggregate credit relationships and lending volume.

Decomposition by credit type and maturity. We decompose relationships by credit type and maturity as follows: (i) credit line, (ii) short-term, (iii) long-term, and (iv) short & long-term. Here, we will classify all credit lines within one category, given the limited availability of information about their maturity.[32] We observe that credit relationships based solely on short-term credit or credit lines experience significantly larger gross flows than relationships involving long-term credit. This suggests that these credit types offer more adjustment/reallocation flexibility to banks, as they may be cheaper to originate and/or less costly to break up. This interpretation is further supported by evidence that these two categories are subject to large increases in outflows across all four crises, while long-term credit relationships flows remain relatively stable.

Decomposition by relationship duration. We examine the effect of relationship duration on outflows. To see this, we classify relationships into four buckets: duration of (i) below one year, (ii) between one and two, (iii) between two and five, and (iv) above five. The average shares associated with each category are 17%, 16%, 26%, and 41%. While outflows appear to increase across all categories during most recessions (one exception being a decline in outflows for one- to two-year duration relationships in 2008), the most sensitive relationships are those that have been active for less than one year.

To summarize, mature credit relationships with large and long-term credit exposures are overall more resilient during crisis periods relative to younger and smaller ones. They are also potentially more difficult to initiate as their inflow rates are substantially lower. These results are not necessarily surprising in light of the positive relationship between duration and credit size and the negative relationship between duration and separation probability, as shown in the literature, and as confirmed in Figure 13.[33] As a result, the gross flows patterns we uncover may imply that different adjustment costs are at play and depend on the value of the credit relationships, as measured by their duration, credit size, type, and maturity. Indeed, it may be easier to sever a young or small bank-firm match if the lost value from

[32] One could partially infer such maturity once the firm draws from the credit line and the corresponding bank later reports the corresponding amount as short or long-term credit.

[33] Using loan-level Japanese data, Nakashima and Takahashi (2018) link relationship destruction rates to bank capital constraints and show that these are more prevalent for younger matches.

ending such a relationship is relatively minimal. In the same vein, it is also easier to approve relatively small loans if this only marginally impacts the credit and/or counterparty risk faced by the bank.

4 How do banks adjust their credit supply in the long run and throughout the cycle? Intensive vs. extensive margins of credit

What levers do banks use to adjust their credit supply? What is the relative importance of intensive and extensive margins in credit fluctuations? These questions are inherent to the macro-finance literature, yet they have surprisingly received very little attention. In this section, we attempt to address them by exploring three relatively close decompositions of bank credit variations. In particular, we establish that accounting for the extensive margin of credit and ensuing process of reallocation is absolutely critical in order to properly infer bank lending behavior in the aftermath of an aggregate shock or a new policy implementation. Thus, grasping and measuring the channel through which credit market participants form or sever matches is essential for the understanding of aggregate credit dynamics.

4.1 A simple decomposition

We start with the simple credit market identity described in equation (1) and operate a log-transformation so as to make this decomposition additive:

$$\log(C_t) \quad = \quad \log(N_t) + \log(\bar{c}_t). \tag{4}$$

We detrend our aggregate credit variables using the HP filter with a smoothing parameter of 1600. The standard deviation of detrended aggregate credit (in log) is 2.58%, while the standard deviation of the number of relationships is 1.14%, and that of average credit per relationship is 1.93%. The correlation of aggregate bank credit with the two latter series is 0.71 and 0.91, respectively.

4.2 Secular trends

Figure 14 reports the long-run trends associated with our three variables of interest (in logs). The trends show a significant increase (about 50%) in aggregate credit (in real terms) over the past 20 years. Interestingly, this pattern has been accompanied by an almost equivalent increase in relationship capital (about 45%), and a minimal increase in average credit per match (about 5%, which corresponds to the average credit rising from about 977 thousand to 1.02 million EUR from 1999 to 2016). In fact, while the trend in the intensive margin was relatively evident in the first half of the sample (+12%), the advent of the financial crisis has led to a gradual decline over the period 2008-2017 and thus an overall negligible contribution to aggregate credit in the long run.

This relative stability of the average credit per match may suggest that firm size composition and corresponding financing needs also remained stable throughout the sample period.[34] Hence, such finding establishes that low-frequency changes in the number of relationships may be the dominant force for long-run fluctuations in aggregate credit. As a consequence, policies that aim at boosting aggregate credit in the long run may be more effective when targeting structural changes that impact the matching process between borrowers and lenders and gross relationship flows in general.

4.3 Cyclical fluctuations

We now move on to the cyclical properties. Here we start with a simple and straightforward approach based on first differences before complementing it with an analysis of log-deviations from HP trend.

4.3.1 First-difference approach

Based on the identity derived in (4), we can apply a first difference between time t and $t+1$ to get:

$$\Delta \log(C_{t+1}) = \log(C_{t+1}) - \log(C_t) = \Delta \log(N_{t+1}) + \Delta \log(\bar{c}_{t+1}), \tag{5}$$

where $\Delta X_{t+1} = X_{t+1} - X_t$. Figure 15 illustrates the evolution of the aggregate credit (log-growth) in addition to its two extensive and intensive margin components over the sample period. For the most part, the large credit declines observed during crisis periods are due to the joint effect of both margins. In addition, the extensive margin seems to exhibit a "smoother" pattern and maybe a slower reaction over time, which highlights possible differences in adjustment behaviors and costs for each margin. In addition, such decomposition can also help characterize credit recoveries. For example, the nearly creditless recovery observed in 2010-2012 was due to a relatively subdued average credit per bank-firm pair while the number of bank-firm relationships was actually growing over the same period. We further elaborate on these crisis/recovery patterns in Section 5.

Interestingly, given that the log-transformation allows for the extensive and intensive margins to be additively separable, we can write a linear decomposition of the variance of total credit flows in the

[34] Note that only a small fraction of firms relies on more than one relationship; thus, the average credit per match is a reasonable proxy for the total credit per given firm.

spirit of Fujita and Ramey (2009) and formally quantify the contribution of each margin, as follows:

$$\text{var}(\Delta \log(C_t)) = \text{cov}(\Delta \log(N_t), \Delta \log(C_t)) + \text{cov}(\Delta \log(\bar{c}_t), \Delta \log(C_t)). \tag{6}$$

Ultimately, we can write:

$$\beta_{Ext} = \frac{\text{cov}(\Delta \log(N_t), \Delta \log(C_t))}{\text{var}(\Delta \log(C_t))}, \tag{7}$$

$$\beta_{Int} = \frac{\text{cov}(\Delta \log(\bar{c}_t), \Delta \log(C_t))}{\text{var}(\Delta \log(C_t))}, \tag{8}$$

with $\beta_{Ext} + \beta_{Int} = 1$.

Moreover, we can rewrite the change in relationship capital (in logs) in terms of flow rates:

$$\Delta \log(N_t) = \log(1 + n_t) \simeq 1 + n_t = 1 + c_t - d_t. \tag{9}$$

Assuming that n_t is relatively small, we can derive the following first-order approximation to further decompose the contribution of the extensive margin into creation and destruction components:

$$\begin{aligned} \text{var}(\log(1 + n_t)) &\simeq \text{var}(n_t) \\ &= \text{var}(c_t) + \text{var}(d_t) - 2\text{cov}(c_t, d_t) \\ &= \text{cov}(c_t, n_t) + \text{cov}(-d_t, n_t), \end{aligned} \tag{10}$$

where c_t, and d_t are the credit relationship creation and destruction rates, respectively, and thus obtain:

$$\begin{aligned} \beta_{Ext} &\simeq \frac{\text{cov}(\Delta \log(N_t), \Delta \log(C_t))}{\text{var}(\Delta \log(C_t))} \\ &= \frac{\text{cov}(c_t, \Delta \log(C_t))}{\text{var}(\Delta \log(C_t))} + \frac{\text{cov}(-d_t, \Delta \log(C_t))}{\text{var}(\Delta \log(C_t))} \\ &= \beta_c + \beta_d \end{aligned}$$

Table 7 reports the results of this variance decomposition (for both first-difference and log-deviations from trend). We show that the intensive margin accounts for 73% of the total variation in credit, while the extensive margin accounts for the remaining 27%. In addition, positive flows account for the bulk of the variation in the extensive margin, while negative flows are much less important, as they exhibit relatively smaller variations over the cycle. With the first-difference decomposition, we also note that the contribution of negative flows lowers, rather than increases, the variance of credit, as gross flows trend downward throughout the sample period. Once we de-trend flow variables, we see that negative flows have very little impact on the extensive margin, or aggregate credit more generally.[35]

4.3.2 HP filter approach

We complement these results by studying cyclical deviations from HP trends. While the decomposition into extensive/intensive margins remains straightforward, disentangling the respective effects of gross relationship flows requires additional derivations and approximations, detailed in section B of the Appendix. Figure 16 illustrates the evolution of the two margins while Tables 5 and 8 report the correlation structure and the variance decomposition results, respectively. As shown earlier, the relative contributions are about one quarter for the extensive margin and three quarters for the intensive margin. This result is also apparent in Figure 17, which represents a scatter plot of the deviations in aggregate credit vs. deviations in intensive and extensive margins. It highlights that a non-negligible number of quarters with minor fluctuations in aggregate credit may actually be experiencing counteracting extensive and intensive margin effects. Furthermore, the relatively low correlation between intensive and extensive margins (0.25 based on log-growth, and 0.46 for log-deviations) also suggests that each component responds differently to aggregate shocks.

4.4 An alternative decomposition: Incumbent vs. new vs. severed credit relationships and the role of the sub-extensive margin (decomposition 2)

Next, we complement our first decomposition with alternative and more refined versions in order to account for heterogeneity across incumbent, new, and severed bank-firm relationships, which is prevalent across our data. We define and quantify the role of the sub-extensive margin and show that it further amplifies the distinctive features of intensive and extensive margins. While we report in the core part of the paper the derivations for the first-difference approach, the details associated with the HP filter approach are in the Appendix.

In order to justify the role of the sub-extensive margin, we first show in Figure 18 that the average credit size of entering and exiting borrowers corresponds to about 50% and 40% of that of the average incumbent, respectively. Moreover, this credit ratio for new borrowers is volatile and procyclical, consistent with theory in Boualam (2018). Similarly, the credit ratio for severed relationships also exhibits a procyclical pattern, albeit with slightly less volatility. Overall, these observations are consistent with

[35] The formal derivations are in the Appendix.

credit dynamics that are increasing, and separation probabilities that are decreasing, with relationship duration, as we show in Figure 13.

With this in mind, we denote by n^ν, and $\bar{C}^\nu$, with $\nu \in \{i, n, s\}$, the number of relationships and the average credit associated with incumbent (i), new (n), and severed (s) bank-firm relationships, and observe that we can write the total credit C_t at time t, based on (future) surviving relationships (i.e., $t+1$ incumbents), combined with credit lost from relationships severed between t and $t+1$. We can also write C_{t+1} at time $t+1$, based on the existing relationship (i.e., the same $t+1$ incumbents) combined with the credit supplied to relationships newly formed between t and $t+1$. We can then formulate the following alternative decomposition of credit flows:

$$\begin{aligned} C_t &= n^i_{t+1}\bar{C}^i_t + n^s_{t+1}\bar{C}^s_{t+1} \\ C_{t+1} &= n^i_{t+1}\bar{C}^i_{t+1} + n^n_{t+1}\bar{C}^n_{t+1}, \end{aligned}$$

and write the corresponding first-difference identity for aggregate credit:

$$\Delta C_{t+1} = C_{t+1} - C_t = n^i_{t+1}\Delta C^i_{t+1} + n^n_{t+1}\bar{C}^n_{t+1} - n^s_{t+1}\bar{C}^s_{t+1}. \tag{11}$$

Eventually, with $\alpha^j_t = \frac{n^j_t}{n^i_t}$ and $c^j_t = \frac{\bar{C}^j_t}{\bar{C}^i_t}$ for $j \in \{n, s\}$, we can write the counterpart to equation (6) for log-growth in credit as:

$$\Delta \log(C_{t+1}) = \underbrace{\Delta \log(\bar{C}^i_{t+1})}_{\text{Incumbent bank-firm effect}} + \underbrace{\log(1+\alpha^n_{t+1}c^n_{t+1})}_{\text{New bank-firm effect}} - \underbrace{\log(1+\alpha^s_{t+1}c^s_{t+1})}_{\text{Severed bank-firm effect}} \tag{12}$$

Similarly, we can then decompose the variance in aggregate credit, in terms of an incumbent relationship effect (i.e., intensive margin), and a new and severed bank-firm relationship effects, which combined account for the extensive margin:

$$\begin{aligned} \text{var}(\Delta \log(C_t)) = &\ \text{cov}(\Delta \log(\bar{C}^i_{t+1}), \Delta \log(C_t)) \\ &+\text{cov}(\log(1+\alpha^n_{t+1}c^n_{t+1}), \Delta \log(C_t)) \\ &+\text{cov}(-\log(1+\alpha^s_{t+1}c^s_{t+1}), \Delta \log(C_t)) \end{aligned} \tag{13}$$

More importantly, this decomposition accounts for the sub-extensive margin of credit, by allowing for time-variation in the average credit size supplied to entering or exiting firms, relative to incumbents.

Eventually, we can write the betas associated with each component and the final decomposition as:

$$\beta_{Incumbent} = \frac{\text{cov}(\Delta\log(\bar{C}^i_{t+1}), \Delta\log(C_t))}{\text{var}(\Delta\log(C_t))}; \tag{14}$$

$$\beta_{New} = \frac{\text{cov}(\log(1+\alpha^n_{t+1}c^n_{t+1}), \Delta\log(C_t))}{\text{var}(\Delta\log(C_t))} \simeq \frac{\text{cov}(\alpha^n_{t+1}c^n_{t+1}, \Delta\log(C_t))}{\text{var}(\Delta\log(C_t))}; \tag{15}$$

$$\beta_{Severed} = \frac{\text{cov}(-\log(1+\alpha^s_{t+1}c^s_{t+1}), \Delta\log(C_t))}{\text{var}(\Delta\log(C_t))} \simeq \frac{\text{cov}(-\alpha^s_{t+1}c^s_{t+1}, \Delta\log(C_t))}{\text{var}(\Delta\log(C_t))} \tag{16}$$

with

$$\underbrace{\beta_{Incumbent}}_{Intensive} + \underbrace{\beta_{New} + \beta_{Severed}}_{Extensive} \simeq 1. \tag{17}$$

Figures 19 and 20 report the corresponding time series, and Tables 7 and 8 report the decomposition results.[36] The results for this decomposition are in line as we show that the incumbent effect accounts for 54% while the extensive margin (i.e., the combination of new-bank-firm and severed-bank-firm effects) accounts for 46%. The approximative results obtained for the HP filter decomposition equally confirm the relatively balanced contribution between the two margins. Looking at the effects of new and severed relationships separately, we find that their βs are 0.62 and -0.17 (0.57 and -0.17 for the HP filter approach), respectively. The negative sign associated with $\beta_{Severed}$, while surprising, comes in part from the fact that the average credit of recently destroyed relationships is pro-cyclical and the corresponding fluctuations actually dominate those associated with the flow component.

In summary, we note that the extensive margin contributes significantly to aggregate credit fluctuations at the business cycle frequency. In fact, through our first decomposition, we estimate that such relative contribution is on the order of one quarter. When we also take into account the sub-extensive margin, and hence the extent of heterogeneity (in terms of credit size) existing between incumbent and new or severed credit relationships, we see that the relative contribution of the extensive margin is actually even larger and jumps to about one half.

[36]Section B.3 in the Appendix also presents a third decomposition (referred to as "gross intensive credit flows") that further disentangles the positive and negative flows within the intensive margin. Its results (for both first-difference and HP filter approaches) are reported in Tables 7 and 8 under "Decomposition 3". They are overall consistent with the ones presented in this section.

5 Anatomy of a credit crisis and recovery

We have so far highlighted the importance of both extensive and intensive margins in terms of explaining fluctuations of aggregate credit. In this section, we trace out the anatomy of a credit cycle by constructing the average cyclical fluctuations of our variables around crisis periods. The French economy experienced four recessions over the period 1998-2018 according to the OECD: (i) 2001-2003, (ii) 2008-2009, (iii) 2011-2013, and (iv) 2014-2016. We focus on the first extensive/intensive decomposition. Figure 21 shows the aggregated results while Figure 22 zooms into each recession period separately. Here, all variables of interests are normalized to one, based on the timing of the pre-crisis peak of aggregate credit, and their dynamics are then reported over the following ten quarters.

We see that the average decline in bank credit was about 5.5%, due to a 3% decline in average credit, and a 2.5% decline in the stock of credit relationships. Over the course of the past four recessions, the aggregate total credit returned to its previous trend following the 2001-2003 recession after about ten quarters, while the severity and proximity of the succeeding crisis (i.e., the European debt crisis) prevented a full recovery. Twelve quarters after the end of the financial crisis, aggregate credit was still well below its pre-crisis peak. With respect to gross credit relationship flows, we show that a typical recession is characterized by a sharp and prolonged decline in inflows that persists over the first four quarters. In addition, inflows remain subdued for a relatively long period, recovering only "half-way" from their pre-crisis level after seven to eight quarters. On the other hand, outflows observe only a modest and short-lived increase in downturns. Indeed, the magnitude of their change is roughly one-sixth the size relative to inflows and they revert back to their pre-crisis levels in about four quarters.

Interestingly, when we zoom into each one of the four recession periods, we notice a distinctive behavior for each component. As highlighted by the left panels in Figure 22, we show the existence of two distinct types of credit crises: (i) those particularly driven by the intensive margin as in the crises of 2001-2003 and 2012-2013, and (ii) those combining the effects of extensive and intensive margins as in the crises of 2008-2009 and 2014-2016.

For example, in 2001-2003, when aggregate credit fell by about 11 log-points over the ten quarters following its peaks, average aggregate credit declined by nine log-points, and relationship capital by two log-points. In 2008-2009, aggregate credit fell by about 6.5 log-points over the ten quarters following its peaks, with average credit declining by four log-points, and relationship capital by 2.5 log-points. We also note that decline in relationship capital seems to lead the decline in other aggregate variables by one to two quarters, with the exception of the 2008 - 2009 recession, and that the decline in both margins is not always synchronized, as is the case in the first two recessions in the sample.

6 Discussion - Relevance and implications of credit relationship flows

6.1 Macroeconomic implications

How do innovations to key aggregate variables impact the dynamics of extensive and intensive margins? We attempt to address this question through a simplified VAR structure accounting for five variables in the following order: (i) real GDP, (ii) aggregate credit, (iii) market volatility, (iv) net interest margin, and (v) Euro Overnight Index Average (EONIA). We also run a second VAR specification where we simply replace the time series for aggregate credit, by associated (ii-a) intensive and (ii-b) extensive margins.[37] Market volatility is used to proxy for uncertainty and is determined based on the standard deviation of the previous 90 daily log-returns of the CAC40 index, multiplied by $\sqrt{250}$. We proxy business lending profitability for banks using a measure of net interest margin. This measure is tabulated based on the difference between excess bond premia on nonfinancials and financials.[38] Excess bond premia correspond to the average spread between interest rates on recently issued debt obligations and the same-maturity German Bunds, following the methodology in Gilchrist and Zakrajšek (2012). Finally, we use EONIA as a proxy for monetary policy.

We view our analysis as a first step toward understanding the joint dynamics behind these variables. Thus, we work with a simple identification based on Cholesky decomposition, rather than imposing an extensive structural approach or identifying strategies. The particular order selected above suggests that innovations to output impact credit margins contemporaneously, while shocks stemming from other variables have a one quarter lagged effect. Output and credit variables are in log-difference. All variables described above are available only from 1999 Q1 through 2017 Q1. We estimate the VAR over this sample period, allowing for two lags. The short period of available data explains the relatively large confidence intervals.

Figure 23 illustrates the cumulative impulse response functions of credit variables to orthogonalized shocks. We start with the first VAR specification, which includes aggregate credit, only. The results

[37] The relative order between the two margins does not qualitatively alter the results.

[38] An alternative approach would be to include separately both excess bond premia in the VAR. We compute net interest margin using excess bond premia for nonfinancials, because the time series for average loan interests are available only since 2003. That said, the two time series are highly correlated (0.94). In addition, the VAR estimation using loan interest rates over the period 2003-2017 delivers similar results.

are intuitive overall. We observe that aggregate credit increases, with output and net interest margin innovations, and declines with market volatility. The latter effects are large in terms of magnitude and persistence. However, the effect due to monetary policy shocks is relatively subdued. It is initially positive over the first eight quarters, but turns negative afterwards.

We now turn to the specification including both average credit and relationship capital. We find several distinct effects across the two aspects, consistent with our earlier results. First, an unanticipated shock to output leads to a large and persistent increase in relationship capital. This is likely induced by an increase in firm entry, which leads to higher demand for credit and the formation of new bank-firm pairs. For average credit, however, we first observe a slight decline before a positive impact occurs about three quarters later. We attribute this pattern to two rationales related to composition and cash flow effects. When economic prospects improve, the increase in relationship formation may be heavily concentrated among small entrant firms, which skews the average credit downward. Average credit eventually rises gradually, as these relationships grow and as other incumbent loan contracts get rolled over with more favorable terms. Another argument may be that positive output shocks improve firm cash flows and balance sheets. Thus, firm reliance on credit may decline in the near term. It ultimately rises in the medium term as new investments in need of bank financing are implemented.

Second, a positive shock to uncertainty leads to a decline in both credit margins. The impact is immediate and sizable for the intensive margin, but more limited and only visible after six to seven quarters for the extensive margin. These results may find their origin in the relative adjustment costs associated with each margin. With respect to the intensive margin, existing firms may swiftly halt their investments and demand for credit, while banks may quickly become reluctant to increase their credit supply. With respect to the extensive margin, the existence of sizable search costs associated with the creation of new bank-firm pairs may lead to a considerable inactivity in uncertain times, whereby banks have less incentive to form new relationships, but also have less incentives to sever existing ones.

Third, a positive innovation to bank profitability impacts both margins positively and with similar magnitude. This result is not surprising and is driven by possibly different sources affecting both margins simultaneously. For example, increased bank profitability may be associated with lower bank funding costs and increased deposits. This not only allows banks to offer more favorable terms and larger loans, but it also allows them to relax their lending standards and approve more new loans on the margin.

Fourth, unanticipated positive shocks associated with monetary policy only appear to impact the intensive margin. The effect is positive, albeit moderate and limited to the first six quarters following the shock. It is also somewhat opposite to the one observed for real output. However, it doesn't seem to be induced primarily by compositional effects, given the limited impact on the extensive margin. These results are not surprising, in light of the lack of variability of EONIA, especially during the second half of our sample period.

All in all, this exercise highlights the driving forces behind aggregate credit dynamics. In particular, it shows that the response to market uncertainty and bank profitability is due to joint extensive and intensive effects. In contrast, the response to output shocks is in fact driven mainly by the extensive margin, while the response to monetary policy tends to be induced by the intensive margin.

6.2 Credit reallocation and credit market fluidity

Trend. French credit markets have become much less fluid over the past two decades. As shown in Figure 8, credit market fluidity, which we define as the average credit relationship reallocation rate (i.e., the sum of creation and destruction rates), has declined from about 15.4% to 11.8% during that time period. The decline in reallocation is driven particularly by the small credit segment and low-duration matches.

Exploring the determinants of this substantial decline in credit market fluidity and its relative lack of dynamism is beyond the scope of the paper. However, we elaborate on several contributing factors, some of which may resemble those proposed in the labor literature (Davis and Haltiwanger (2014)). First, a slower reallocation can be interpreted as a slower arrival of new credit opportunities and potentially longer credit search periods for newly created businesses. It can also be viewed as due to higher switching costs for incumbent borrowers (with potentially more monopoly rents extracted by banks), which can limit their ability to grow or to find a banking partner that better matches their needs.

Various government policies and recent banking developments may be at play for these long-term trends. These include bank consolidation, increased competition, tightened regulatory requirements, securitization, development of secondary markets, and improved creditor protection. These developments also include technological progress and information costs. For example, easier access to more information, while lowering matching costs, might also prompt more precise screening, and thus to increased bank lending standards. This would lead to longer credit search periods for firms, as banks become pickier, but also generate lower destruction of bank-firm pairs, as match quality improves. On the other hand, other policies such as government guarantees, which lower the credit risk faced by banks, can help promote reallocation.

Ultimately, it is unclear whether such a trend is a considerable source of concern without a more refined exploration of bank-firm match quality and the reasons behind its slowdown. Indeed, while an increase in duration can add value for a healthy credit relationship, it could also be detrimental to the economy in the case of unhealthy ones. The slowdown in credit market fluidity could also have indirect implications for firm entry if borrowing is impeded and search periods are long, and for firm exit if capital remains allocated to low-quality borrowers for too long, consequently hampering productivity growth.

Cyclical properties. A substantial literature has focused on exploring the sullying or cleansing effects of crises. Indeed, a procyclical reallocation is associated with a sullying effect to the extent that lower-quality matches tend to last longer during downturns. In the context of credit markets, this could materialize in terms of a firm's decreased ability to switch lenders as bank entry and competition decline in bad times. It could also illustrate that certain capital-constrained banks have incentives to prolong credit to distressed borrowers (i.e., zombie lending). On the other hand, the cleansing effect associated with countercyclical reallocation can emerge when bad matches (be they due to bad banks or borrowers) are severed and capital is efficiently reallocated toward higher quality and more resilient matches.

In the data, we find that credit reallocation is procyclical while credit churning (i.e., excess reallocation) exhibit mildly countercyclical dynamics. Table 5 shows that reallocation is positively correlated with the growth rate of GDP, credit, and relationship capital. It also shows that excess reallocation is negatively correlated with GDP (both in levels and rates. It is however surprisingly overall uncorrelated to total credit or relationship capital over our sample period. This finding highlights the assumption that credit reshuffling across firms and banks is an essential mechanism and a potential determinant behind the overall evolution of the economy. These results are in line with studies performed in other contexts. For example, the excess reallocation of jobs (Davis and Haltiwanger (1992), Davis et al. (1998), and Nakamura et al. (2018)) and capital (Ramey and Shapiro (1998)) are shown to be countercyclical. A deeper understanding of these effects requires a more refined cross-sectional analysis, which we pursue in Boualam and Mazet-Sonilhac (2020).

6.3 Implications for theories of banking and credit

Our results call for a deeper understanding of the process of credit intermediation and tradeoffs faced by banks along both intensive and extensive margins. This is critical for the development of macro-finance models that appropriately capture credit dynamics.

Most macroeconomic banking models have so far focused on broad indicators such as aggregate credit and interest rates as their central variables, and have rarely tackled the underpinnings of credit intermediation and the aggregate implications of long-term financial contracts. Thus, since these models typically assume one-period same-size loans to which banks can make frictionless adjustments in response to shocks, they are unlikely to provide economic grounds for the existence of credit relationship flows across firms or banks, nor distinguish the role of bank-firm match heterogeneity. Given their quantitative importance, we argue that a successful theory of aggregate credit fluctuations (at either business cycle or long-run frequencies) should take into account both intensive and extensive margins, and carefully lay out the driving forces that may affect them differently.

First, several mechanisms and constraints could potentially shape economic tradeoffs between these two margins. On the one hand, banks may be interested in making loans to as many borrowers as possible so as to diversify idiosyncratic risk, learn more about their local environment, or to supply credit beyond the limited demand of their existing customers. On the other hand, banks may be willing or simply constrained to focus on a small number of important relationships, when borrower acquisition or monitoring costs, or the marginal benefit of in-depth credit relationships simply outweighs diversification. In the same vein, if credit relationships turn profitable only in the long run, banks may be willing to spend extra effort to retain their incumbent borrowers, instead of creating new relationships. The severance of credit relationships could also lead to the destruction of a bank-firm-specific relationship capital, which can be detrimental to both parties. This is particularly the case when the match quality cannot be transferable due to informational frictions or other agency problems.

Other constraints can influence the extensive/intensive margin tradeoff. For example, the adjustment in bank credit is lumpy due to the very nature of bank-firm relationships and loan contracts. This is the case for banks with long-term credit exposures that cannot be reduced immediately following negative shocks, but that may have flexibility in adjusting intensive margins (at least for short-term credit and credit lines).

Second, the credit relationship flows we uncover result from firms' and banks' search, approval, and rollover decisions and thus may provide a novel perspective on the process of intermediation in credit markets and the frictions therein. Thus, the decisions related to the creation and destruction of credit relationships, but also related to credit market entry and exit, may themselves be subject to time-varying costs related to aggregate or idiosyncratic shocks and frictions hindering swift upward or downward adjustments.[39]

In the spirit of arguments laid out by Rogerson and Shimer (2011) highlighting the utility of search models in labor, a search-theoretic approach can help make sense of empirical regularities and make predictions about borrower flows between unfunded and funded stages and across banks. It can also be useful in terms of the modeling of agents' decisions and can thus provide further understanding of the dynamics of aggregate variables (e.g., aggregate credit, interest rates) that are typically analyzed in the context of models abstracting from search frictions. For example, a decline in aggregate credit relationships may be due to the fact that borrowers are not entering the credit markets, are not searching intensively, or are simply more picky with regards to the lenders and corresponding contractual terms. On the other hand, it can also be due to the fact that banks have implemented higher lending standards resulting in higher rejection rates, or have decided to stop rolling over certain loans. Such alternative possibilities would be difficult to identify and quantify in standard banking models.

Search-and-matching frictions also provide new foundations for adjustment costs faced by banks along the extensive margin, and thus a relevant framework that can potentially generate some dampening but can also further persistence in the evolution of credit following aggregate shocks. Thus, when the formation of new matches is costly and shocks are small or transitory, banks may focus on adjusting credit along the intensive margin. On the other hand, banks may ultimately downsize their relationship portfolio when subject to more severe or permanent shocks. This could lead to the severance of relationships, the loss of match-specific capital, and more persistent effects, especially when relationships are time-consuming and costly to rebuild.

7 Conclusion

Our analysis highlights the role and importance of the extensive margin in aggregate credit fluctuations. The methodology we develop for relationship flows extends that of labor research to account for the specificities of credit markets and is applicable to the study of other markets and countries with available

[39]If credit relationships were homogeneous and banks could adjust them symmetrically and frictionlessly, then studying relationship flows may not be of the first order, but this is not the case.

credit register data. We also view our empirical methodology and dataset as a novel laboratory and as a first step toward uncovering more properties of credit relationships and their aggregate implications.

While we mostly focused on establishing stylized facts and identifying the distinctive features of extensive/intensive margins, we believe that further delving into the potential economic mechanisms behind these dynamics can further provide connections to the macro-finance literature, and in particular the role played by collateral and bank balance-sheet channels.

More broadly, given the key role played by the extensive margin of credit along the business cycle frequency and in the long run, this analysis raises the issue of whether banking models abstracting from such a quantitatively important dimension provide a reasonable benchmark for the study of aggregate credit fluctuations. Thus, building models that account for both margins is, in our opinion, critical when thinking about credit. We leave the implications of these arguments for future research.

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Appendix A Data and variable construction

A.1 French Credit Register (SCR)

Our raw database excludes (i) sole entrepreneurs; and (ii) all firms belonging to the financial sector and public administrations. We keep only those firm-branch observations with non-missing data on firm and bank identifiers. We also remove (i) observations for bank branches located in Corsica as well as in overseas departments and territories, and (ii) branch-firm linkages for non-resident firms. We then follow standard filters for firms within our sample and delete observations for (i) various legal firm categories under French civil, commercial, or administrative law that are irrelevant for our analysis (e.g., parishes, unions, cooperatives, etc.); and (ii) financial and insurance companies, public administration, and various liberal professions. Finally, we allocate banks in our sample to a unique banking group identifier: we drop all banks that belong to nontraditional banking groups or non-credit intermediaries (e.g., public banks and financial institutions).

A.2 Balance sheet data (FIBEN & BRN)

We use two different datasets in order to gather information on French firms' balance sheets. First, FIBEN (*Fichier Bancaire des Entreprises*) accounting data are extracted from the individual company accounts. These are collected yearly through the branch network of Banque de France based on fiscal documents (i.e., balance sheet and income statements). The data collection covers all companies conducting business in France whose annual turnover exceeds EUR 0.75 million or whose bank debt exceeds EUR 0.38 million. We exploit this database to obtain relevant firm-level variables such as firm total assets, leverage, and employment. The dataset also provides information about about the age of the firm, its 2-digit industry, and whether it is part of a group or a standalone company. It also contains a unique firm identifier that allows for the merge with the SCR. Second, the BRN (*Benefices Industriels et Commerciaux - Regime Normal*) dataset is produced by the INSEE and gathers balance sheet information of firms that opt for the *standard fiscal regime*. It provides information on employment, sales, value added, and the breakdown of investment for all firms of all sectors from 1998 to 2016.

A.3 Banking Mergers and Acquisitions (M&As)

In order to keep track of bank M&As, we rely on data from the French Supervision and Prudential Authority (ACPR). Our dataset gathers all the M&A operations involving banks located within the French territory and includes the date of the transaction as well as the identity of acquiring and acquired banks.

A.4 Public banks

Due to their "nonstandard" objectives, we remove the following public banks from the sample:

- *Caisse nationale des Telecom* (Bank identifier: 15379)
- *Caisse nationale des autoroutes* (Bank identifier: 15389)
- *Groupe banque de development des PME* (BPI (initially titled OSEO), with bank identifiers: 10048, 13328, 13810, 14138, 18710, 19510, 13880, and 18359)
- *Groupe CDC* (Bank identifiers: 23930, 40031, 60030, and 60070)
- *Groupe credit logement* (Bank identifier: 19230)

Appendix B HP filter decompositions

B.1 Simple decomposition

This section provides additional derivations related to the variance decomposition of aggregate credit, based on the HP-filtered cyclical log-deviations. We start with the following identities:

$$\begin{aligned}\log(C_t) &= \log(N_t) + \log(\bar{c}_t)\\ \log(\tilde{C}_t) &= \log(\tilde{N}_t) + \log(\tilde{\bar{c}}_t).\end{aligned}$$

We can thus write:

$$\begin{aligned}\Delta\log(C_t) &= \log(C_t) - \log(\tilde{C}_t)\\ &= \Delta\log(N_t) + \Delta\log(\bar{c}_t),\end{aligned} \tag{18}$$

where $\tilde{X}$ is the HP-filtered trend and $\Delta X_t = X_t - \tilde{X}_t$ correspond to the cyclical deviations. We can then determine the associated betas based on this decomposition, similar to the one derived in Equations (12 - 15):

$$\begin{aligned}1 &= \frac{\mathrm{cov}(\Delta\log(N_t), \Delta\log(C_t))}{\mathrm{var}(\Delta\log(C_t))} + \frac{\mathrm{cov}(\Delta\log(\bar{c}_t), \Delta\log(C_t))}{\mathrm{var}(\Delta\log(C_t))}\\ &= \beta_{Ext} + \beta_{Int}.\end{aligned}$$

Furthermore, we can write the following recursive expression connecting the cyclical deviations of the number of relationships to those of gross flows:

$$\begin{aligned}\Delta\log(N_{t+1}) &= \log(N_t + Pos_{t+1} - Neg_{t+1}) - \log(\tilde{N}_t + \tilde{Pos}_{t+1} - \tilde{Neg}_{t+1})\\ &= \Delta\log(N_t) + \log(1 + c_{t+1} - d_{t+1}) - \log(1 + \tilde{c}_{t+1} - \tilde{d}_{t+1}),\end{aligned} \tag{19}$$

where Pos_t and Neg_t correspond to positive and negative relationship flows (in level) at time t. We can then iterate this relationship up until the time origin and rewrite the cyclical deviations in the extensive margin as follows:

$$\begin{aligned}\Delta\log(N_{t+1}) &= \Delta\log(N_0) + \sum_{i=1}^{t+1}\log(1+c_i-d_i) - \sum_{i=1}^{t+1}\log(1+\tilde{c}_i-\tilde{d}_i)\\ &\simeq \Delta\log(N_0) + \sum_{i=1}^{t+1}(c_i-\tilde{c}_i) - \sum_{i=1}^{t+1}(d_i-\tilde{d}_i)\\ &\simeq \Delta\log(N_0) + \sum_{i=1}^{t+1}\Delta c_i - \sum_{i=1}^{t+1}\Delta d_i, \qquad (20)\end{aligned}$$

where the last two approximations assume small $\{c_i\}_{i=1,t+1}$ and $\{d_i\}_{i=1,t+1}$. We thus have β_{Ext} further decomposed into:

$$\begin{aligned}\beta_{Ext} &\simeq \frac{\text{cov}(\sum_{i=1}^{t+1}\Delta c_i, \Delta\log(C_t))}{\text{var}(\Delta\log(C_t))} + \frac{\text{cov}(-\sum_{i=1}^{t+1}\Delta d_i, \Delta\log(C_t))}{\text{var}(\Delta\log(C_t))} \qquad (21)\\ &\simeq \beta_{Pos} + \beta_{Neg} \qquad (22)\end{aligned}$$

B.2 Alternative decomposition

The same logic applies for the alternative decompositions. We start with:

$$C_{t+1} = C_t + \underbrace{n_{t+1}^i\Delta C_{t+1}^i}_{T_{1,t+1}} + \underbrace{n_{t+1}^n\bar{C}_{t+1}^n}_{T_{2,t+1}} - \underbrace{n_{t+1}^s\bar{C}_{t+1}^s}_{T_{3,t+1}}.$$

Assuming small $\frac{T_{1,t+1}}{C_t}$ $+\frac{T_{2,t+1}}{C_t}$ and $\frac{-T_{3,t+1}}{C_t}$, we can write:

$$\begin{aligned}\Delta\log(C_{t+1}) &= \Delta\log(C_t) + \Delta\log(1+\frac{T_{1,t+1}}{C_t}+\frac{T_{2,t+1}}{C_t}+\frac{-T_{3,t+1}}{C_t})\\ &\simeq \sum_{i=1}^{t+1}\Delta\frac{T_{1,i}}{C_{i-1}} + \sum_{i=1}^{t+1}\Delta\frac{T_{2,i}}{C_{i-1}} + \sum_{i=1}^{t+1}\Delta\frac{-T_{3,i}}{C_{i-1}}.\end{aligned}$$

Hence,

$$\text{var}(\Delta\log(C_t)) \simeq \text{cov}(\sum_{i=1}^{t}\Delta\frac{T_{1,i}}{C_{i-1}}, \Delta\log(C_t)) + \underbrace{\text{cov}(\sum_{i=1}^{t}\Delta\frac{T_{2,i}}{C_{i-1}}, \Delta\log(C_t))}_{Entry} + \underbrace{\text{cov}(\sum_{i=1}^{t}\Delta\frac{-T_{3,i}}{C_{i-1}}, \Delta\log(C_t))}_{Exit},$$

and, after dividing each side by $\text{var}(\Delta\log(C_t))$:

$$1 \simeq \beta_{Int} + \underbrace{\beta_{Entry} + \beta_{Exit}}_{\beta_{Ext}}.$$

B.3 A third decomposition: gross intensive credit flows (decomposition 3)

We finally present another alternative decomposition allowing for the distinction between positive and negative (intensive) credit flows for incumbent, new, and severed relationships. This version is based on gross intensive flows, rather than on "pure" extensive vs. intensive margin. It is somewhat close to decomposition 2, although it comes with some minor adjustments. We start with the following identity:

$$C_{t+1} = C_t + Pos^i_{t+1} + Pos^n_{t+1} - Neg^i_{t+1} - Neg^s_{t+1}, \tag{23}$$

where Pos^i_t, and Neg^i_t, represent positive and negative flows of incumbent credit relationships, while Pos^n_t represents positive flows associated with new relationships, and Neg^s_t represents the negative flows associated with newly severed ones.

We can then derive the log-growth in credit as:

$$\begin{aligned}\Delta\log(C_{t+1}) &= \log(1 + \frac{Pos^i_{t+1}}{C_t} + \frac{Pos^n_{t+1}}{C_t} - \frac{Neg^i_{t+1}}{C_t} - \frac{Neg^s_{t+1}}{C_t}) \\ &\simeq 1 + \frac{Pos^i_{t+1}}{C_t} + \frac{Pos^n_{t+1}}{C_t} - \frac{Neg^i_{t+1}}{C_t} - \frac{Neg^s_{t+1}}{C_t}. \end{aligned} \tag{24}$$

And, similar to previous decompositions, we get:

$$1 \simeq \beta_{\text{Pos}^i} + \beta_{\text{Neg}^i} + \beta_{\text{Pos}^n} + \beta_{\text{Neg}^s}.$$

For the HP filter approach, we can equivalently write:

$$C_{t+1} = C_t + Pos^i_{t+1} + Pos^n_{t+1} - Neg^i_{t+1} - Neg^s_{t+1}. \tag{25}$$

and, assuming small $\frac{Pos^i_{t+1}}{C_t}$, $\frac{Pos^s_{t+1}}{C_t}$, $\frac{Neg^i_{t+1}}{C_t}$ and $\frac{Neg^s_{t+1}}{C_t}$,

$$\begin{aligned}
\Delta\log(C_{t+1}) &= \Delta\log(C_t) + \Delta\log(1 + \frac{Pos^i_{t+1}}{C_t} + \frac{Pos^n_{t+1}}{C_t} - \frac{Neg^i_{t+1}}{C_t} - \frac{Neg^s_{t+1}}{C_t}) \\
&\simeq \Delta\log(C_0) + \sum_{i=1}^{t+1}\Delta\frac{Pos^i_i}{C_{i-1}} + \sum_{i=1}^{t+1}\Delta\frac{Pos^n_i}{C_{i-1}} - \sum_{i=1}^{t+1}\Delta\frac{Neg^i_i}{C_{i-1}} - \sum_{i=1}^{t+1}\Delta\frac{Neg^s_i}{C_{i-1}}. \qquad (26)
\end{aligned}$$

We can eventually derive the variance decomposition as:

$$\begin{aligned}
\mathrm{var}(\Delta\log(C_t)) &= \mathrm{cov}(\sum_{i=1}^{t}\Delta\frac{Pos^i_i}{C_{i-1}}, \Delta\log(C_t)) + \mathrm{cov}(-\sum_{i=1}^{t}\Delta\frac{Neg^i_i}{C_{i-1}}, \Delta\log(C_t)) \\
&\quad + \mathrm{cov}(\sum_{i=1}^{t}\Delta\frac{Pos^n_i}{C_{i-1}}, \Delta\log(C_t)) + \mathrm{cov}(\sum_{i=1}^{t}-\Delta\frac{Neg^s_i}{C_{i-1}}, \Delta\log(C_t)), \qquad (27)
\end{aligned}$$

and write after diving each side by $\mathrm{var}(\Delta\log(C_t))$:

$$1 \simeq \underbrace{\beta_{Pos_i} + \beta_{Neg_i}}_{\beta_{Int}} + \underbrace{\beta_{Pos_n} + \beta_{Neg_s}}_{\beta_{Ext}}.$$

Appendix C Tables and Figures

Table 1: Summary statistics: aggregate results

This table reports summary statistics aggregated at the quarter level for the period 1999Q1-2016Q4. All credit variables are in thousands of Euro unless specified otherwise and are deflated using the French seasonally adjusted GDP Implicit Price Deflator obtained from the FRED database. We display the mean and standard deviation for all variables over the full sample period in addition to the first (1999) and last (2016) complete years in our sample.

	Full sample		1999		2016	
	Mean	SD	Mean	SD	Mean	SD
Number of banks	447.02	60.85	541.98	3.89	360.49	6.57
Number of firms	256271.62	44836.66	182126.04	4433.08	301378.04	1428.21
Number of credit relationships	345678.89	50645.87	264776.49	5594.82	399220.31	2253.39
Aggregate credit exposure (Eur Bn)	358.13	60.52	258.77	9.38	408.86	5.20
Number of relationships per firm	1.36	0.05	1.45	0.00	1.32	0.00
Number of relationships per bank	802.50	219.30	488.57	14.52	1107.74	25.90
Fraction of firms with 1 bank	80.30	1.95	76.41	0.15	81.47	0.05
Fraction of firms with 2 banks	12.19	0.78	13.70	0.03	11.81	0.03
Fraction of LT only	45.71	1.26	42.42	0.61	44.91	0.51
Fraction of ST only	30.83	3.89	37.77	0.29	25.96	0.34
Fraction of ST + LT only	14.20	1.60	16.75	0.25	13.71	0.19
Fraction of undrawn only	9.26	4.87	3.06	0.31	15.42	0.25
Relationship duration (in quarters)	14.64	4.79	4.91	0.79	21.52	0.32
Credit exposure per match	1032.93	48.84	977.08	16.14	1024.11	7.29
Short-term debt per match	214.05	71.33	329.22	4.02	149.24	0.46
Long-term debt per match	413.96	51.85	334.44	7.29	454.65	3.23
Undrawn credit line per match	396.14	55.37	311.60	7.88	406.95	6.01
Share of long-term credit per match	50.05	1.22	48.57	0.57	49.73	0.28
Share of drawn credit per match	81.45	6.10	89.45	0.32	74.99	0.20
Fraction of credit to new entrants	4.15	1.10	5.27	0.21	3.14	0.34
Fraction of credit to incumbents	95.85	1.15	94.86	0.50	96.82	0.54
Average credit per entering firm / incumbent	57.48	8.26	58.67	2.29	50.27	1.55
Average credit per exiting firm / incumbent	44.77	6.68	50.00	4.52	38.28	1.38
Creation flow	23407.40	1950.81	22502.74	877.01	23812.29	828.83
Destruction flow	21497.35	1992.70	17672.60	312.80	23223.42	417.51
Net flow	1910.05	2288.60	4830.14	568.97	588.86	1124.07
Excess reallocation	42464.36	3618.07	35345.20	625.59	46129.19	528.46
Creation rate	6.94	1.04	8.63	0.30	5.98	0.22
Destruction rate	6.32	0.52	6.78	0.14	5.83	0.10
Net flow rate	0.62	0.75	1.85	0.20	0.15	0.28
Excess reallocation rate	12.51	1.14	13.56	0.27	11.58	0.10
Fraction of switching firms	0.42	0.08	0.54	0.01	0.35	0.01
Firm entry rate	4.57	0.54	4.99	0.21	4.14	0.09
Firm exit rate	3.79	0.21	3.47	0.03	3.84	0.02
Firm entry / firm creation	22.82	2.39	27.25	1.68	19.70	0.44

Table 2: Summary statistics: cross-sectional results

This table reports cross-sectional summary statistics for the period 1999Q1-2016Q4. Relationship duration is measured in quarters. All credit variables are in thousands of Euro unless specified otherwise and are deflated using the French seasonally adjusted GDP Implicit Price Deflator obtained from the FRED database. We display the mean, 25th, 50th, 75th, 95th and 99th percentiles for all variables over the sample period.

Percentile	p25	p50	p75	p95	p99	Mean
Number of banks per firm	1	1	1	3.1	5.4	1.36
Number of firms per bank	10.8	77.7	772.8	4,016.4	8,951.8	802.5
Bank size (EUR M)	16.4	137.2	820.9	3,839.1	12,856.6	853.1
Firm size (EUR M)	0.1	0.2	0.5	2.5	12.6	1.4
Duration	5.9	13.3	24.4	40.7	43	16.4
Credit exposure per match	116.4	196.2	429.4	2,179.8	12,753.1	1,032.9
Short-term debt per match	0	6.2	86.4	611.2	2,834.7	214.1
Long-term debt per match	13	101.4	223.9	1,103.3	5,180.2	413.9
Credit lines and guarantees per match	0	0	31.6	423.1	3,697.1	396.1

Table 3: Cyclical properties of credit relationship flows

This table reports the results for auto-correlation, standard deviation of detrended credit relationships flows and their correlation with respect to the log-growth of GDP, total credit, and relationship capital, over the period 1999-2016. The top panel shows results for flows, in levels, while the bottom shows the results in rates. All flow variables are detrended using an HP filter with smoothing parameter 1600. All nominal credit variables are deflated using the French GDP deflator, deseasonalized using the X-13 seasonal adjustment procedure, and smoothed based on MA(-1, 1).

	Autocor(x)	Stdev(x)	cor(x, GDP)	cor(x, Total credit)	cor(x, Relationship capital)
Levels					
Creation flows	0.749	0.044	0.354	0.445	0.629
Destruction flows	0.673	0.026	-0.374	-0.155	-0.278
Net flows	0.754	0.051	0.494	0.458	0.678
Reallocation	0.701	0.050	0.107	0.300	0.394
Excess reallocation	0.683	0.025	-0.278	-0.057	-0.045
Rates					
Creation flows	0.730	0.003	0.432	0.474	0.639
Destruction flows	0.589	0.001	-0.261	-0.138	-0.258
Net flows	0.738	0.004	0.498	0.485	0.683
Reallocation	0.677	0.004	0.288	0.378	0.479
Excess reallocation	0.604	0.003	-0.141	-0.013	0.008

Table 4: Cyclical properties of credit relationship flows: cross-sectional decomposition

This table reports the results for auto-correlation; standard deviation of detrended credit relationships flows decomposed by (i) credit size, (ii) credit type, and (iii) relationship duration and their cross-correlation with log-growth GDP, total credit and relationship capital, over the period 1999-2016. All flows variables are detrended using an HP filter with smoothing parameter 1600. All nominal credit variables are deflated using the French GDP deflator, deseasonalized using the X-13 seasonal adjustment procedure, and smoothed based on MA(-1, 1).

	Autocor(x)	Stdev(x)	cor(x, GDP)	cor(x, Total credit)	cor(x, Rel. capital)
			Credit size		
Creation flows: Small	0.841	0.003	0.493	0.478	0.709
Destruction flows: Small	0.674	0.002	-0.296	-0.088	-0.141
Net flows: Small	0.786	0.004	0.480	0.546	0.645
Creation flows: Medium	0.863	0.003	0.501	0.485	0.644
Destruction flows: Medium	0.745	0.001	-0.332	-0.106	0.123
Net flows: Medium	0.852	0.003	0.622	0.511	0.569
Creation flows: Large	0.886	0.003	0.562	0.508	0.590
Destruction flows: Large	0.660	0.001	0.040	-0.059	0.271
Net flows: Large	0.858	0.003	0.561	0.542	0.506
Creation flows: Very large	0.906	0.003	0.497	0.614	0.562
Destruction flows: Very large	0.580	0.001	0.153	0.283	0.200
Net flows: Very large	0.818	0.002	0.476	0.534	0.524
			Credit type		
Creation flows: Long-term	0.879	0.003	0.656	0.578	0.610
Destruction flows: Long-term	0.659	0.001	0.315	0.282	0.098
Net flows: Long-term	0.826	0.003	0.592	0.519	0.650
Creation flows: Short-term	0.841	0.004	0.178	0.225	0.412
Destruction flows: Short-term	0.838	0.004	-0.516	-0.386	-0.086
Net flows: Short-term	0.826	0.005	0.523	0.465	0.396
Creation flows: Credit line	0.627	0.014	0.356	0.120	0.367
Destruction flows: Credit line	0.600	0.008	-0.430	0.102	-0.189
Net flows: Credit line	0.616	0.016	0.497	0.051	0.393
			Relationship duration		
Destruction flows: < 1 year	0.782	0.003	-0.370	-0.269	-0.437
Destruction flows: $1 < 2$ years	0.642	0.002	0.178	-0.064	-0.058
Destruction flows: $2 < 5$ years	0.755	0.002	0.183	0.189	0.111
Destruction flows: ≥ 5 years	0.712	0.002	-0.252	0.247	0.165

Table 5: Cyclical properties of aggregate variables

This table reports the results for auto-correlation; standard deviation and correlation of GDP, total credit, and relationship capital, over the period 1999-2016. In the top panel of the table, results are based on the log-growth of the variables. In the bottom panel, results are based on log-deviations from HP trends, obtained using an HP filter with smoothing parameter 1600. All nominal credit variables are deflated using the French GDP deflator, deseasonalized using the X-13 seasonal adjustment procedure, and smoothed based on MA(-1, 1).

	Log-growth				
	Autocor(x)	Stdev(x)	cor(x, GDP)	cor(x, Total credit)	cor(x, Relationship capital)
GDP	0.868	0.004	1.000	0.378	0.443
Total credit	0.831	0.013	0.378	1.000	0.640
Relationship capital	0.769	0.006	0.443	0.640	1.000
Average credit	0.719	0.010	0.230	0.904	0.250
	Cyclical deviations				
	Autocor(x)	Stdev(x)	cor(x, GDP)	cor(x, Total credit)	cor(x, Relationship capital)
GDP	.926	0.009	1.000	0.480	0.558
Total credit	0.935	0.029	0.480	1.000	0.707
Relationship capital	0.908	0.010	0.558	0.707	1.000
Average credit	0.923	0.023	0.364	0.954	0.462

Table 6: Cyclical properties: lead-lag structure

This table reports the results for cross-correlation of leads (+2 to +8) and lags (-8 to -2) for detrended credit relationship flows, relationship capital and average credit with respect to GDP, total credit, and relationship capital, over the period 1999-2016. GDP, total credit, relationship capital, and average credit refer to the log-growth of these variables. All flows variables are detrended using an HP filter with smoothing parameter 1600. All nominal credit variables are deflated using the French GDP deflator, deseasonalized using the X-13 seasonal adjustment procedure, and smoothed based on MA(-1, 1).

	Cross-correlation of GDP with:						
	x(-8)	x(-4)	x(-2)	x	x(+2)	x(+4)	x(+8)
Relationship capital	-0.36	-0.10	0.16	0.44	0.42	0.21	-0.06
Average credit	0.07	-0.04	0.16	0.23	0.32	0.35	-0.04
Creation flows	-0.29	-0.13	0.11	0.43	0.44	0.18	-0.28
Destruction flows	0.06	-0.26	-0.37	-0.26	0.14	0.40	0.21
Net flows	-0.30	-0.02	0.24	0.50	0.34	0.00	-0.34
Reallocation rate	-0.24	-0.22	-0.05	0.29	0.45	0.33	-0.16
Excess reallocation	-0.05	-0.22	-0.32	-0.14	0.19	0.37	0.16

	Cross-correlation of Total credit with:						
	x(-8)	x(-4)	x(-2)	x	x(+2)	x(+4)	x(+8)
Relationship capital	-0.06	0.47	0.53	0.64	0.50	0.35	0.34
Average credit	0.12	0.17	0.55	0.90	0.56	0.23	-0.10
Creation flows	0.05	0.36	0.47	0.47	0.29	-0.03	-0.10
Destruction flows	0.13	-0.13	-0.07	-0.14	0.11	0.37	-0.07
Net flows	-0.01	0.38	0.46	0.48	0.22	-0.18	-0.06
Reallocation rate	0.09	0.29	0.40	0.38	0.31	0.12	-0.12
Excess reallocation	0.08	-0.11	0.11	-0.01	0.12	0.30	-0.04

	Cross-correlation of Relationship capital with:						
	x(-8)	x(-4)	x(-2)	x	x(+2)	x(+4)	x(+8)
Relationship capital	0.26	0.56	0.53	1.00	0.53	0.56	0.26
Average credit	0.29	0.13	0.34	0.25	0.37	0.27	-0.22
Creation flows	0.09	0.37	0.41	0.64	0.27	0.03	-0.30
Destruction flows	0.14	0.01	-0.04	-0.26	0.12	0.11	0.03
Net flows	0.03	0.34	0.39	0.68	0.19	-0.02	-0.29
Reallocation rate	0.13	0.35	0.36	0.48	0.29	0.07	-0.27
Excess reallocation	0.06	0.10	0.17	0.01	0.25	0.10	-0.12

	Cross-correlation of Average credit with:						
	x(-8)	x(-4)	x(-2)	x	x(+2)	x(+4)	x(+8)
Relationship capital	-0.22	0.27	0.37	0.25	0.34	0.13	0.29
Average credit	-0.01	0.14	0.50	1.00	0.50	0.14	-0.01
Creation flows	0.01	0.24	0.35	0.24	0.21	-0.06	0.03
Destruction flows	0.08	-0.17	-0.06	-0.03	0.07	0.40	-0.10
Net flows	-0.02	0.29	0.35	0.23	0.17	-0.22	0.07
Reallocation rate	0.04	0.16	0.30	0.21	0.23	0.11	-0.01
Excess reallocation	0.07	-0.19	0.04	-0.02	0.01	0.33	0.02

Table 7: Variance decomposition: intensive vs. extensive margin (first-difference)

This table reports the results for variance decompositions of aggregate credit fluctuation over the period 1999-2016. The three intensive/extensive margin decompositions are derived in Section 4.1 based on first-differences. All nominal credit variables are deflated using the French GDP deflator, deseasonalized using the X-13 seasonal adjustment procedure, and smoothed based on MA(-1, 1).

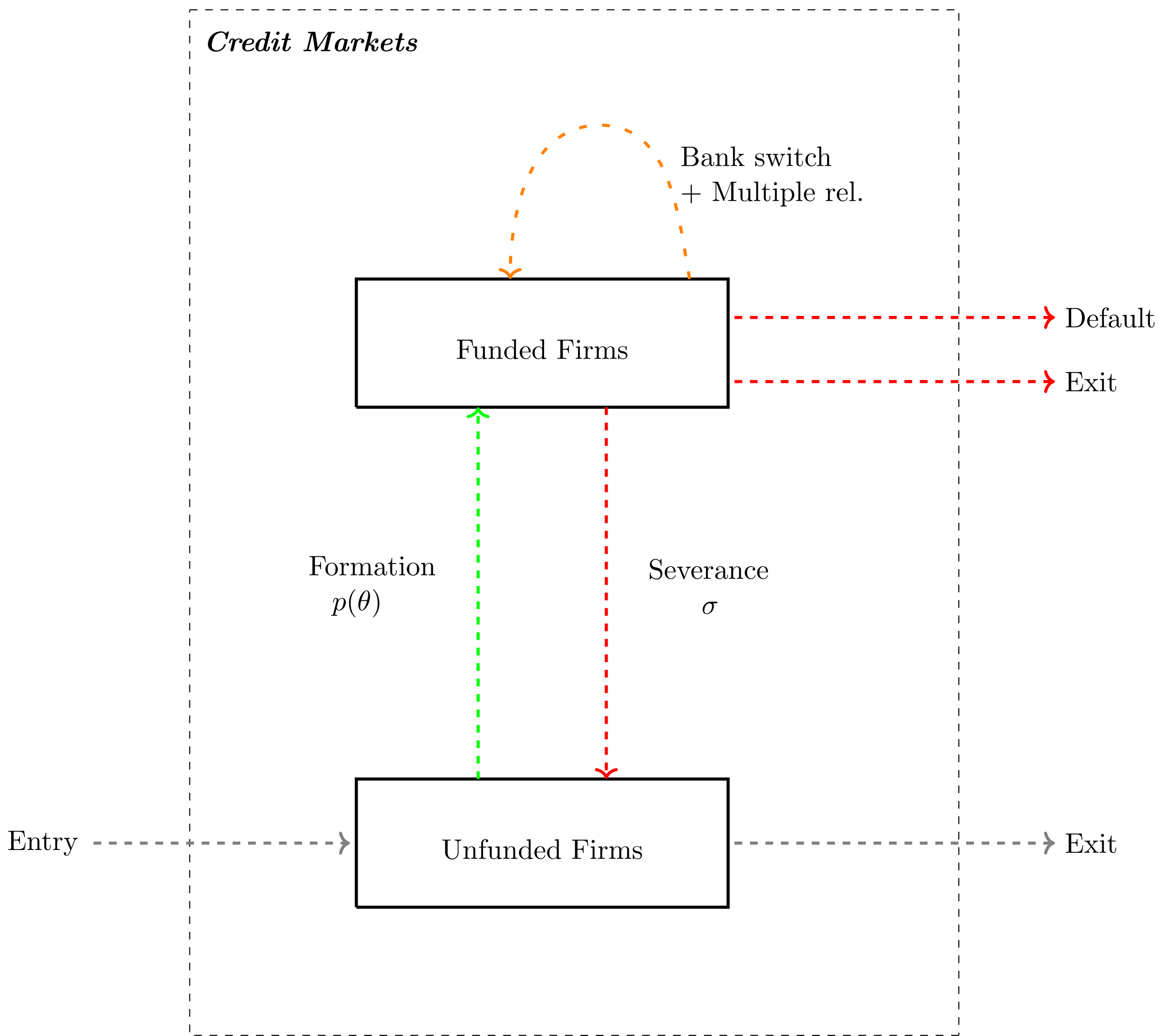
Decomposition 1	Intensive Margin		Extensive Margin	
	0.73		0.27	
			Creation Flows	Destruction Flows
			0.43	-0.16
		Trend (Net Flows)	Creation Flows	Destruction Flows
		0.17	0.13	0.01
Decomposition 2	Intensive Margin		Extensive Margin	
	0.54		0.46	
	Incumbent effect		New bank-firm effect	Severed bank-firm effect
	0.54		0.62	-0.17
Decomposition 3	Intensive Margin		Extensive Margin	
	0.52		0.48	
	Pos. flows - Incumbent	Neg. flows - Incumbent	New bank-firm effect	Severed bank-firm effect
	0.79	-0.27	0.74	-0.26

Table 8: Variance decomposition: intensive vs. extensive margin (HP filter)

This table reports the results for variance decompositions of aggregate credit fluctuation over the period 1999-2016. The three intensive/extensive margin decompositions are derived in Section B in the appendix, based on log-deviations from trend (obtained from HP filter with smoothing parameter 1600). All nominal credit variables are deflated using the French GDP deflator, deseasonalized using the X-13 seasonal adjustment procedure, and smoothed based on MA(-1, 1).

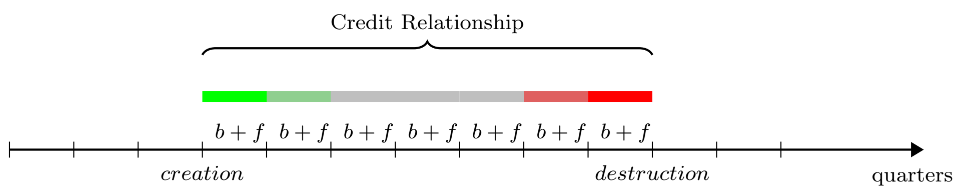
Decomposition 1	Intensive Margin		Extensive Margin	
	0.76		0.22	
			Creation Flows	Destruction Flows
			0.23	-0.03
Decomposition 2	Intensive Margin		Extensive Margin	
	0.46		0.40	
	Incumbent effect		New bank-firm effect	Severed bank-firm effect
	0.46		0.57	-0.17
Decomposition 3	Intensive Margin		Extensive Margin	
	0.61		0.42	
	Pos. flows - Incumbent	Neg. flows - Incumbent	New bank-firm effect	Severed bank-firm effect
	0.53	0.08	0.72	- 0.30

Figure 1: The Flow Approach to Credit Markets

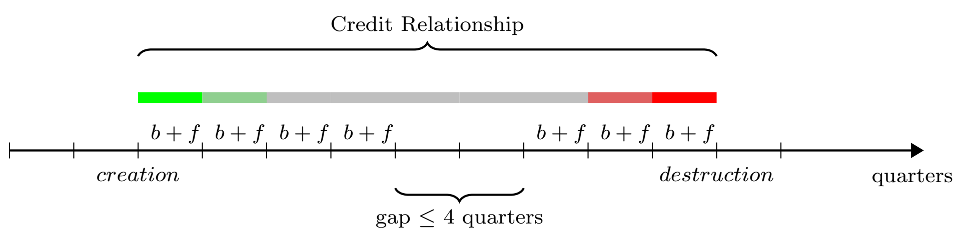


Notes: This figure displays the multiple forms of flows associated with unfunded and funded firms within credit markets.

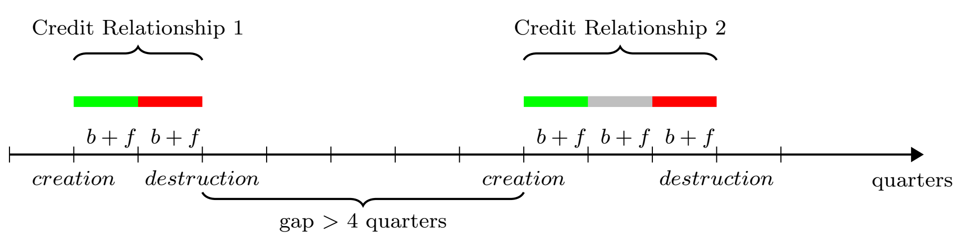
Figure 2: Credit relationships: Concepts and Measurements



(a) Case 1: Contiguous credit relationship (no gap)



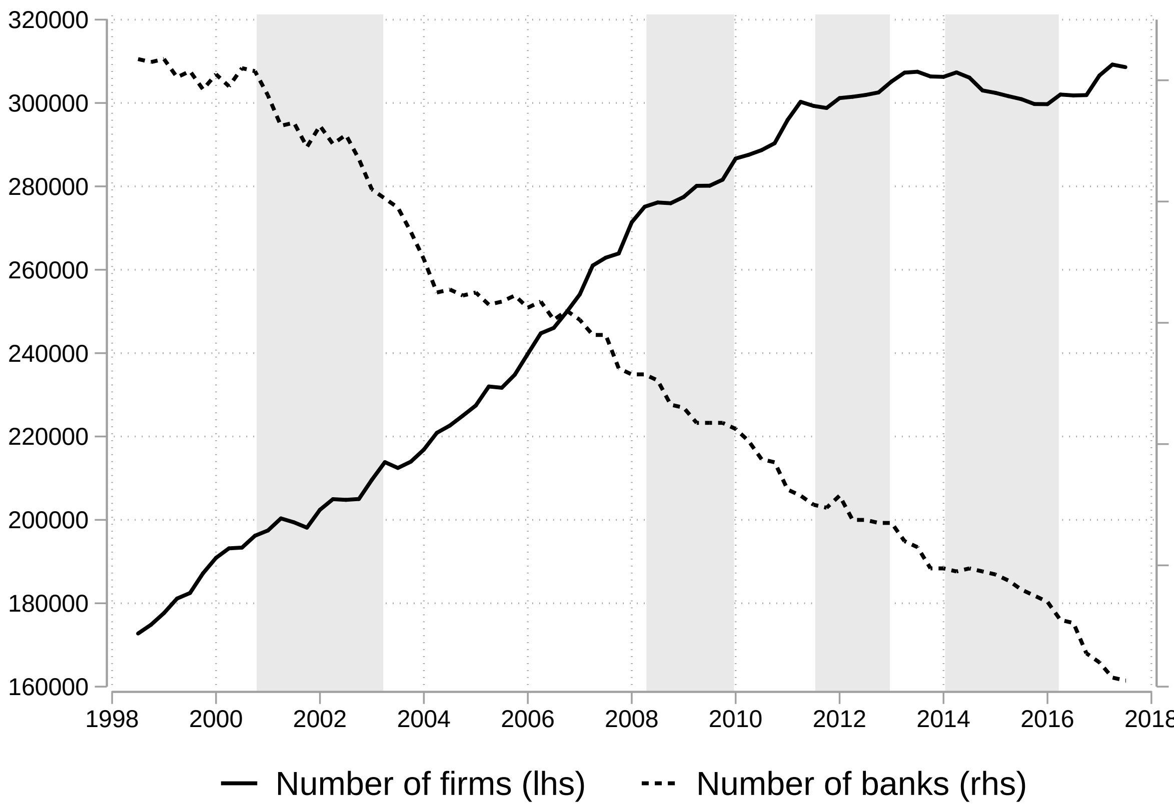
(b) Case 2: Contiguous credit relationship (gap below 4 quarters)



(c) Case 3: Non-contiguous credit relationships (gap exceeding 4 quarters)

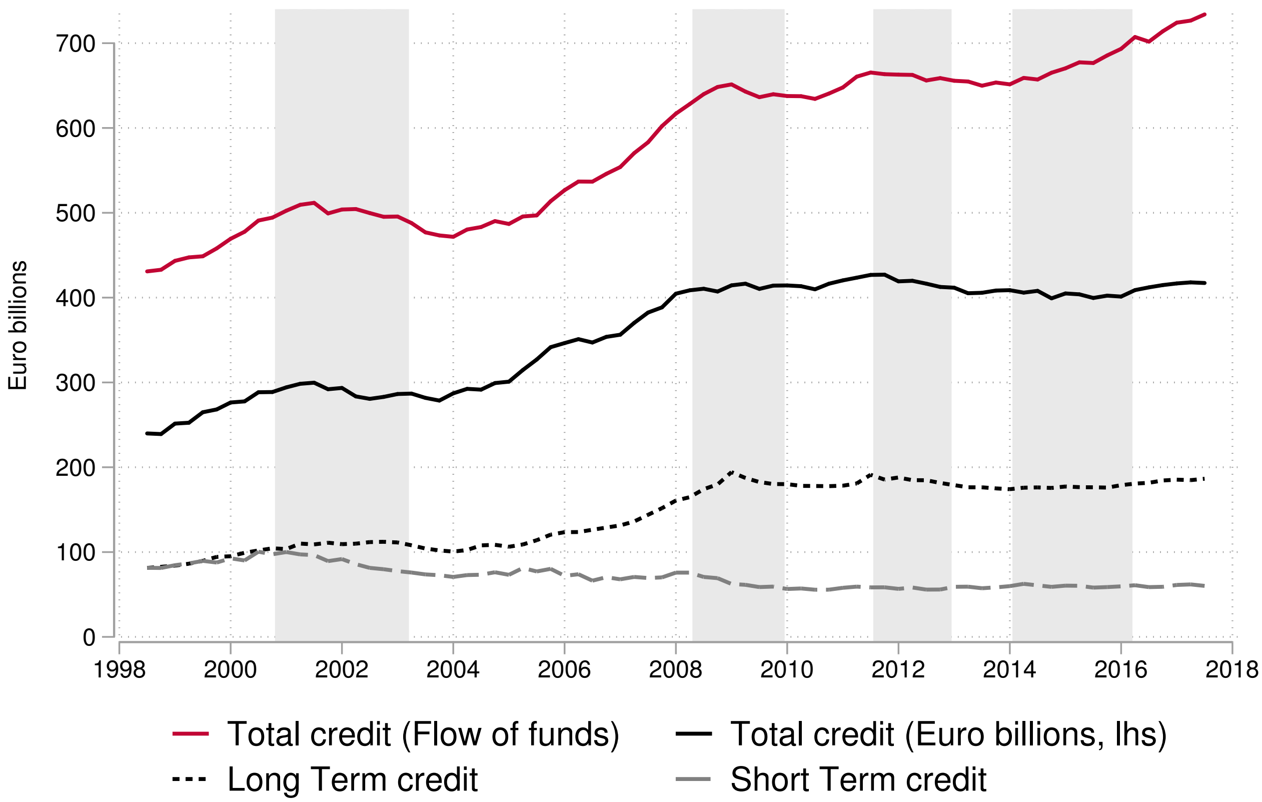
Notes: These figures represent potential situations for bank-firm (b+f) match data entries and the corresponding definitions for credit relationships and gross flows. We consider that a credit relationship is "contiguous" as long as the data entries are available with a reporting gap below 4 quarters (cases (a) and (b)). When the reporting gap is above 4 quarters, we consider that the bank-firm entries generate 2 non-contiguous credit relationships with independent creation and destruction dates (case (c)).

Figure 3: Total banks and firms



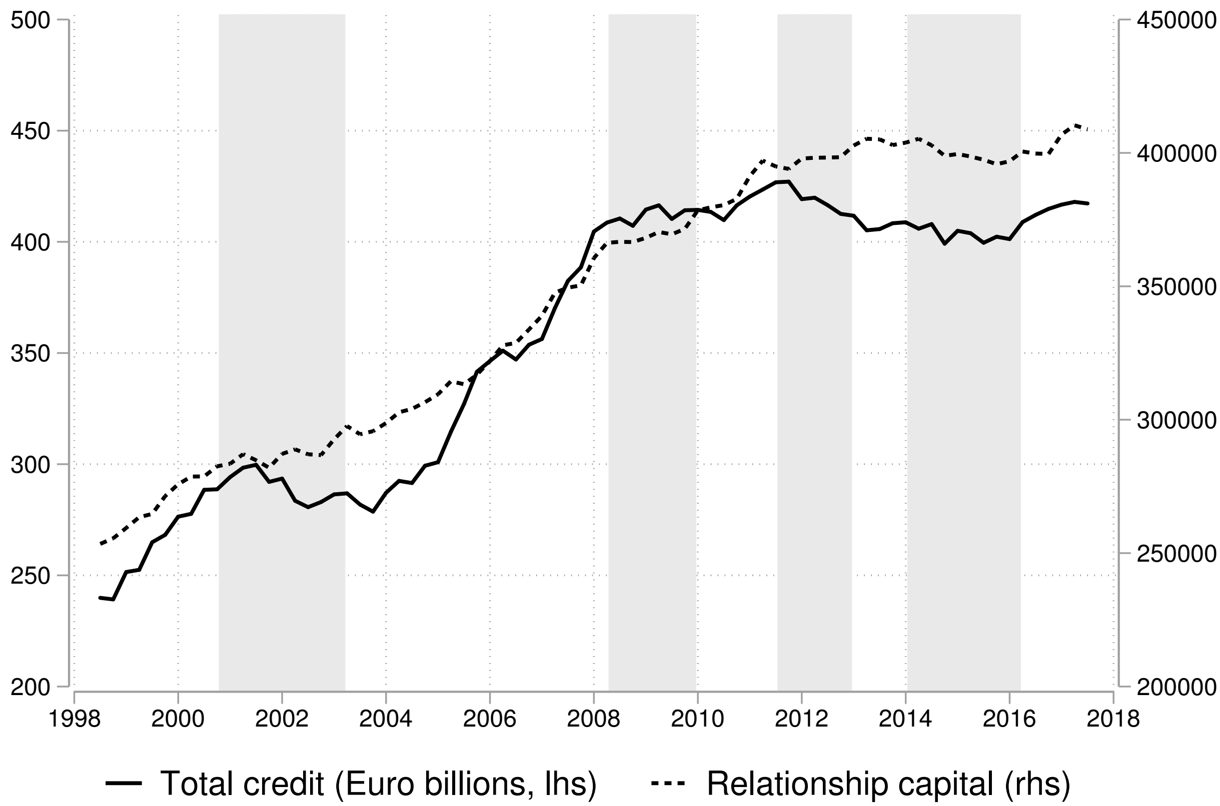
Notes: This figure shows the evolution of the number of unique firms and banks active over the period 1999-2016. Only those banks and firms involved in credit relationships with credit exposure above the reporting threshold are taken into account. Gray-shaded areas correspond to recession periods.

Figure 4: Aggregate Credit: French Credit Register (SCR) vs. Flow of funds



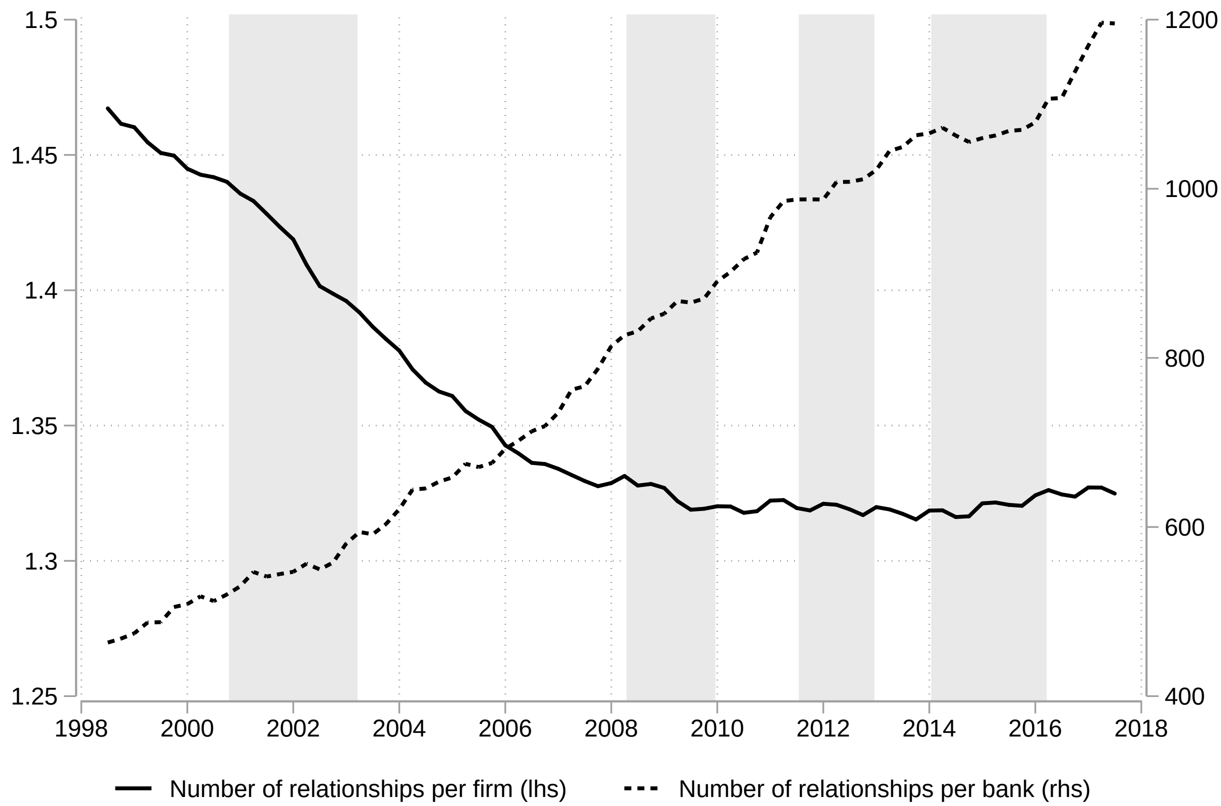
Notes: This figure compares the time series of aggregate bank credit obtained from the balance of payments (solid red line), aggregate credit obtained from the SCR after filters (solid black line). The black dashed curve presents the time series of aggregate long-term credit (initial maturity $\geq$ 1 year) while the gray dashed line represents the time series of short-term credit (initial maturity < 1 year). All nominal credit variables are deflated using the French seasonally adjusted GDP Implicit Price Deflator obtained from the FRED database. Gray-shaded areas correspond to recession periods.

Figure 5: Aggregate credit and number of bank-firm relationships



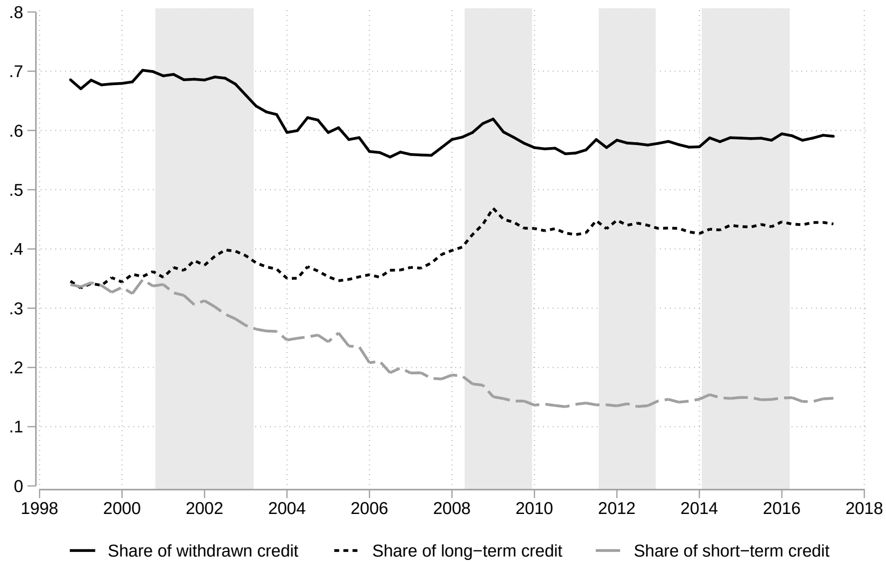
Notes: This figure shows the evolution of aggregate bank credit (solid line) and the number of bank-firm relationships (dashed line), with credit exposure above the reporting threshold, over the period 1999-2016. All nominal variables are deflated using the French seasonally adjusted GDP Implicit Price Deflator obtained from the FRED database. Gray-shaded areas correspond to recession periods.

Figure 6: Number of credit partners per bank and per firm

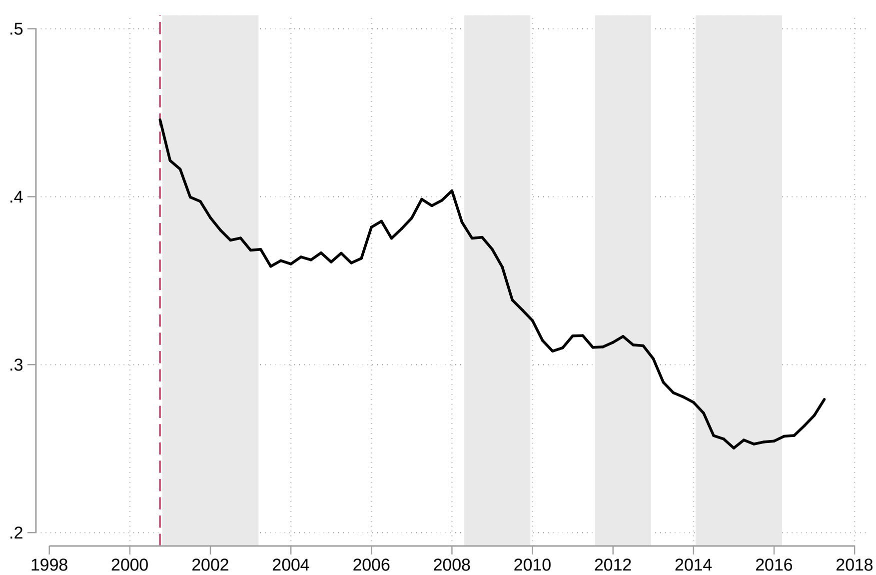


Notes: This figure reports the evolution of the number of relationships per firm (solid line) and the number of relationships per bank (dashed line) over the period 1999-2016. The sample accounts only for those relationships that are above the reporting threshold. Gray-shaded areas correspond to recession periods.

Figure 7: Share of credit relationships by type and duration



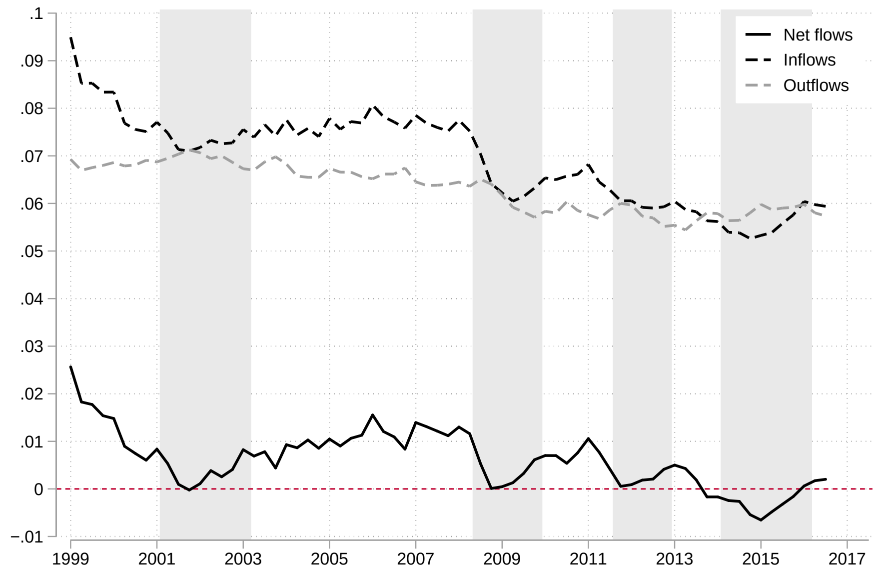
(a) Decomposition by Type/Maturity



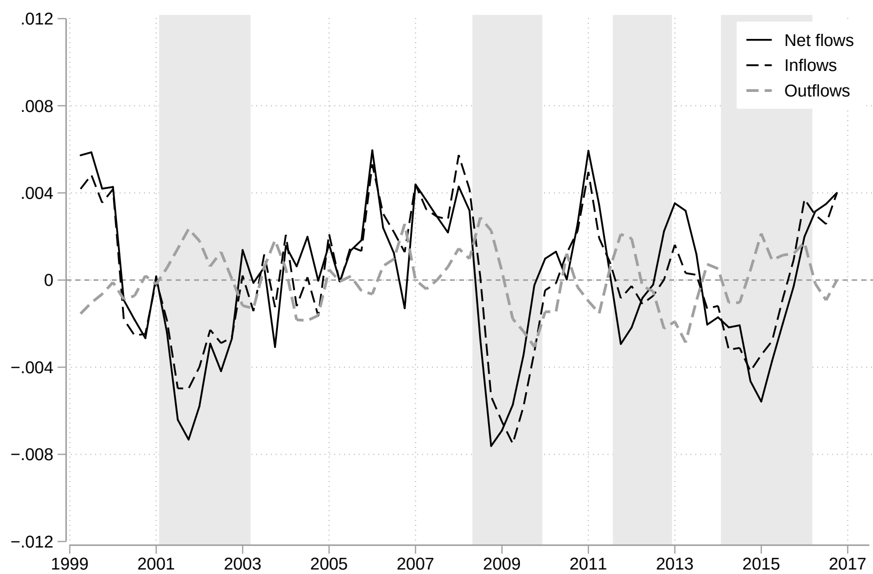
(b) Share of relationship below two-year Duration

Notes: Panel (a) shows the share of credit relationship per type and maturity over the sample period. Panel (b) shows the share of credit relationship by duration. Results are based on relationships above the reporting threshold (adjusted for inflation) and reported over the period 1999-2016. Gray-shaded areas correspond to recession periods.

Figure 8: Credit relationship flows



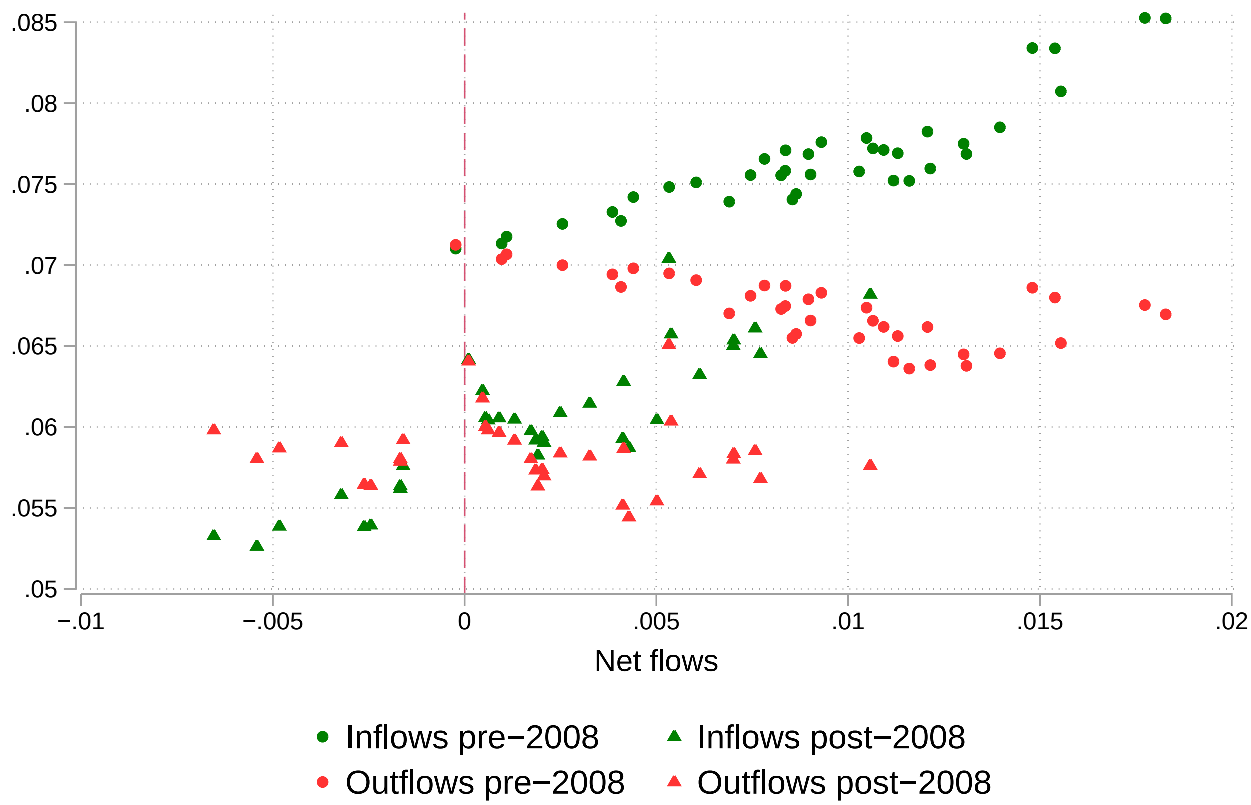
(a) Raw net and gross flows



(b) Cyclical deviations of net and gross flows

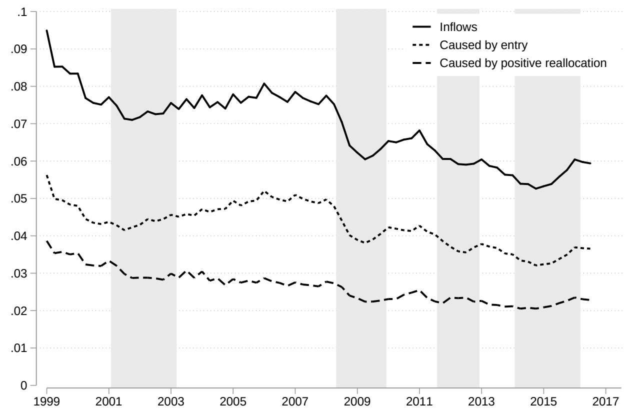
Notes: Panel (a) shows raw net (solid black line) and gross flows of credit relationships. Gross creation flows (inflows) are reported in dashed black line, while gross destruction flows (outflows) are reported in dashed gray line. Panel (b) shows the time series for cyclical deviations corresponding to the same three variables after applying an HP filter with smoothing parameter 1600. Our sample period is 1999-2016. Results are based on relationships above the reporting threshold (adjusted for inflation). Time series of relationship flows are first deseasonalized using the X-13 seasonal adjustment procedure and smoothed out using MA(-1,1). Gray-shaded areas correspond to recession periods.

Figure 9: Creation vs. destruction flows

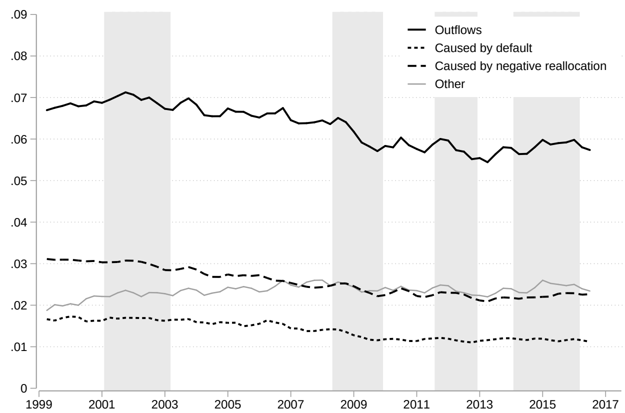


Notes: This figure shows a scatter plot of the cyclical deviations (in log) of average credit and the stock of relationship, as a function of their aggregate credit counterparts. Cyclical deviations are extracted using an HP filter with smoothing parameter 1600. Nominal variables are deflated using the French seasonally adjusted GDP Implicit Price Deflator obtained from the FRED database. Results are based on relationships above the reporting threshold (adjusted for inflation). Time series of relationship flows are first deseasonalized using the X-13 seasonal adjustment procedure and smoothed out using MA(-1,1). Our sample period is 1998-2017.

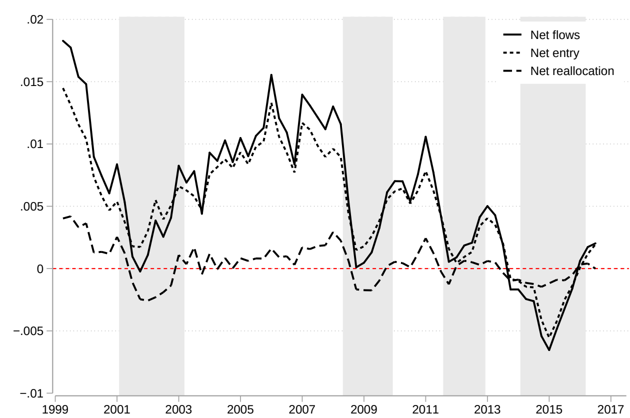
Figure 10: Decomposition of relationship creation and destruction



(a) Decomposition of inflows



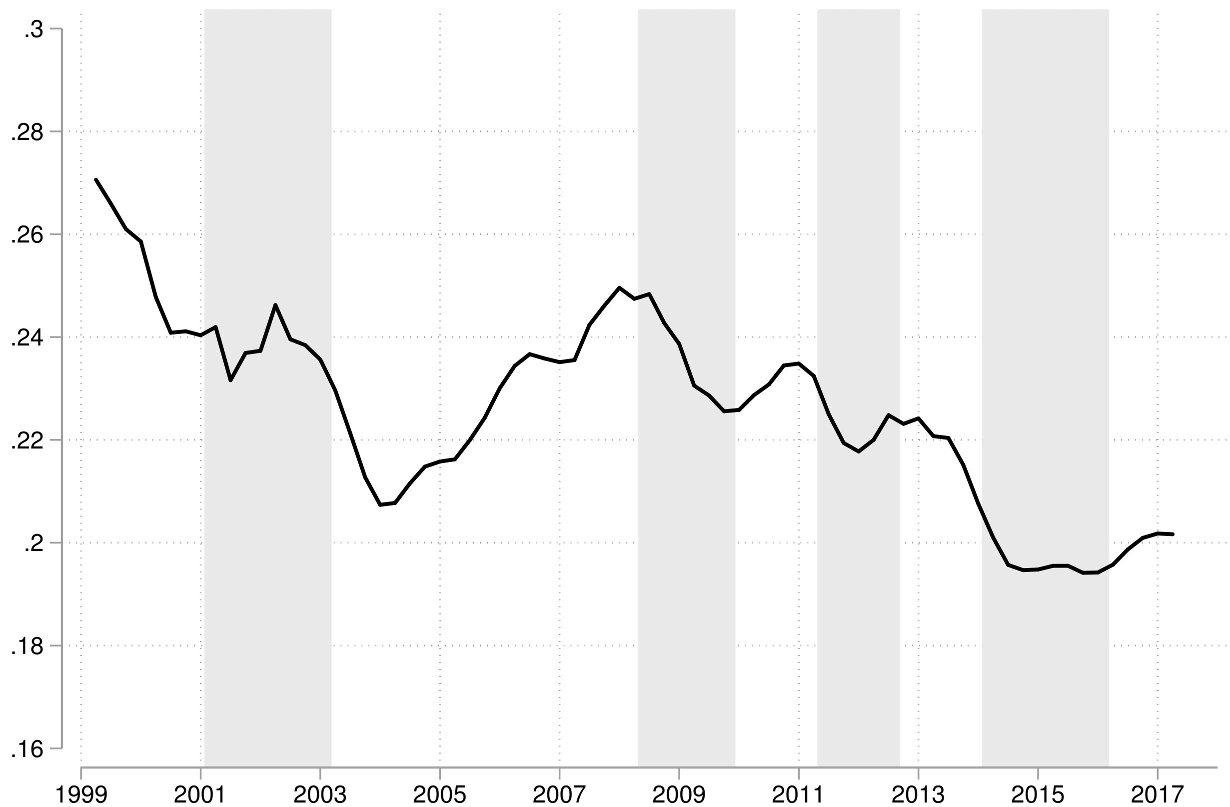
(b) Decomposition of outflows



(c) Decomposition of net flows

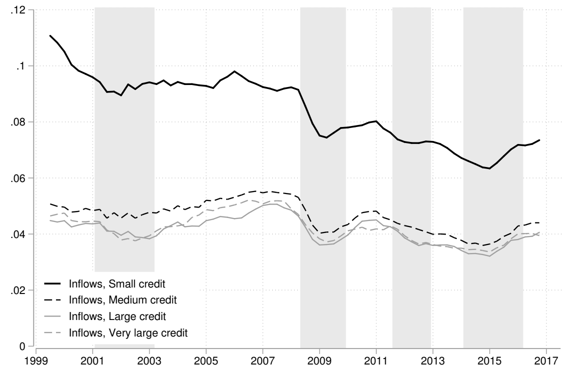
Notes: This figure shows the decomposition of raw creation (Panel (a)), destruction (Panel (b)), and net (Panel (c)) flows due to (i) entering or exiting firms, (ii) switching borrowers, or (iii) those experiencing multi-bank relationship gains or losses. Our sample period is 1999-2016. Results are based on relationships above the reporting threshold (adjusted for inflation). Time series of relationship flows are first deseasonalized using the X-13 seasonal adjustment procedure and smoothed out using MA(-1,1). Gray-shaded areas correspond to recession periods.

Figure 11: First credit relationship and firm entry

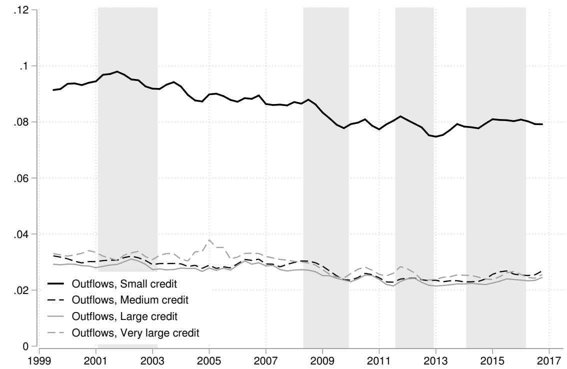


Notes: This figure reports the ratio of first-time borrowers over total number of newly created firms. Our sample period is 1999-2016. Results are based on relationships above the reporting threshold (adjusted for inflation). Gray-shaded areas correspond to recession periods.

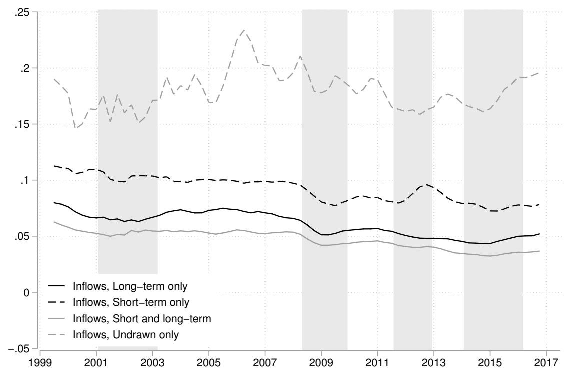
Figure 12: Gross flows, by credit size, type, and duration



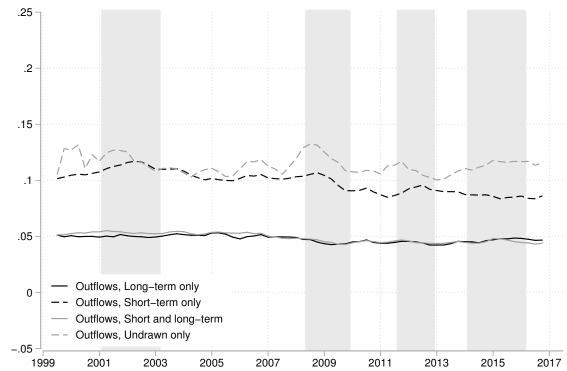
(a) Inflows by credit size



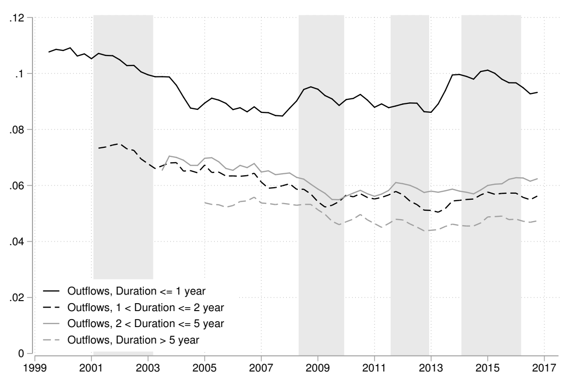
(b) Outflows by credit size



(c) Inflows by credit type



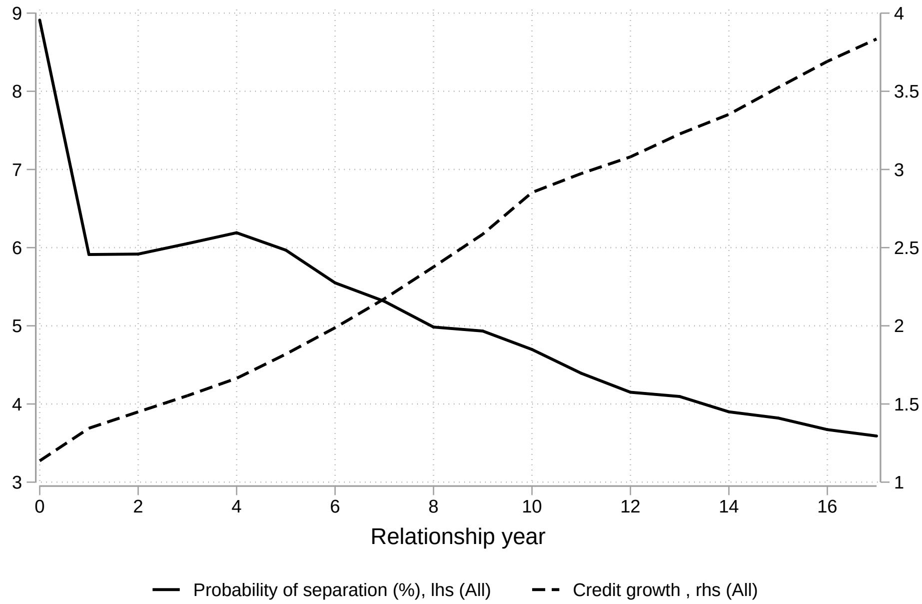
(d) Outflows by credit type



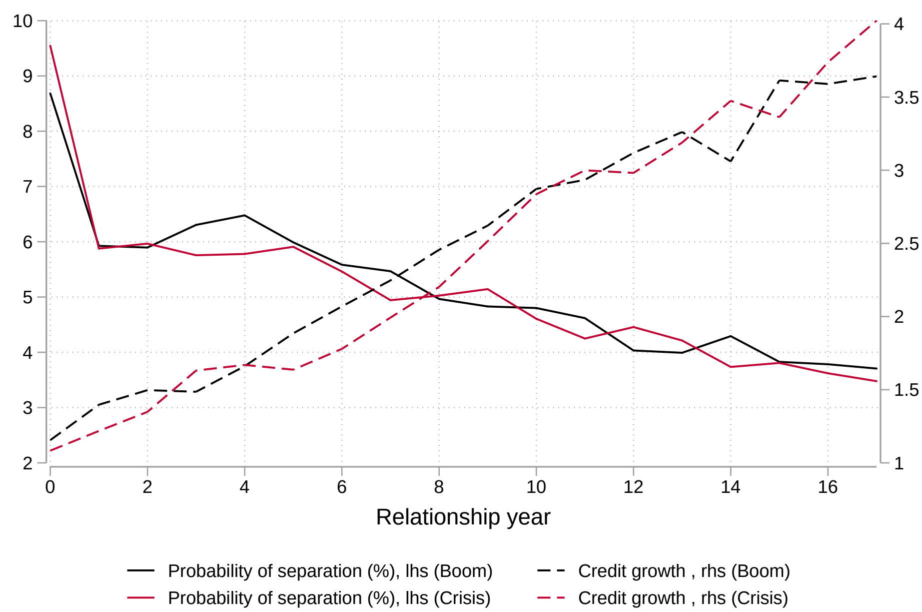
(e) Outflows by relationship duration

Notes: This figure shows the decomposition of raw creation (left panels) and destruction (right panels), by credit size (panels (a) & (b)), type (panels (c) & (d)), and relationship duration (panel (e), for outflows only). Our sample period is 1999-2016. Results are based on relationships above the reporting threshold (adjusted for inflation). Time series of relationship flows are first deseasonalized using the X-13 seasonal adjustment procedure and smoothed out using MA(-1,1). Gray-shaded areas correspond to recession periods.

Figure 13: Trajectories of credit growth and separation probability



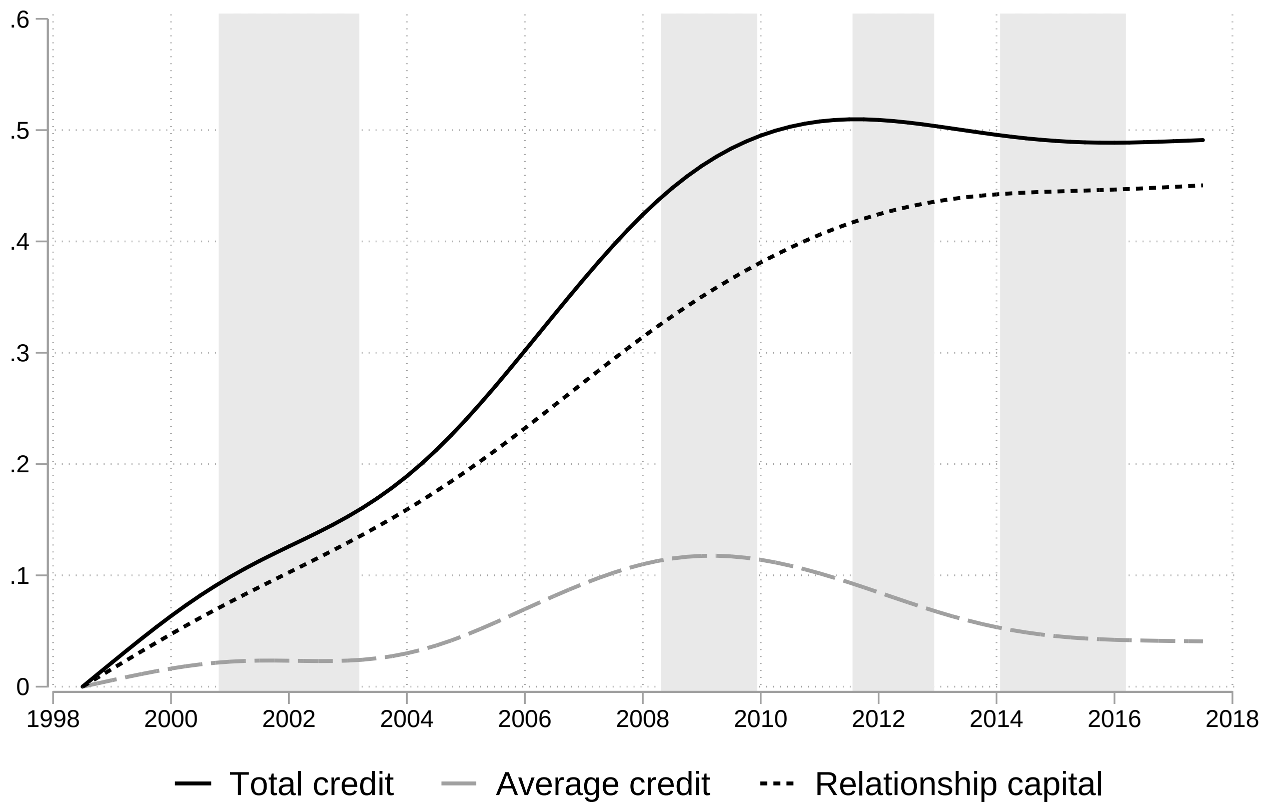
(a) Unconditional results



(b) Boom vs. Crisis periods

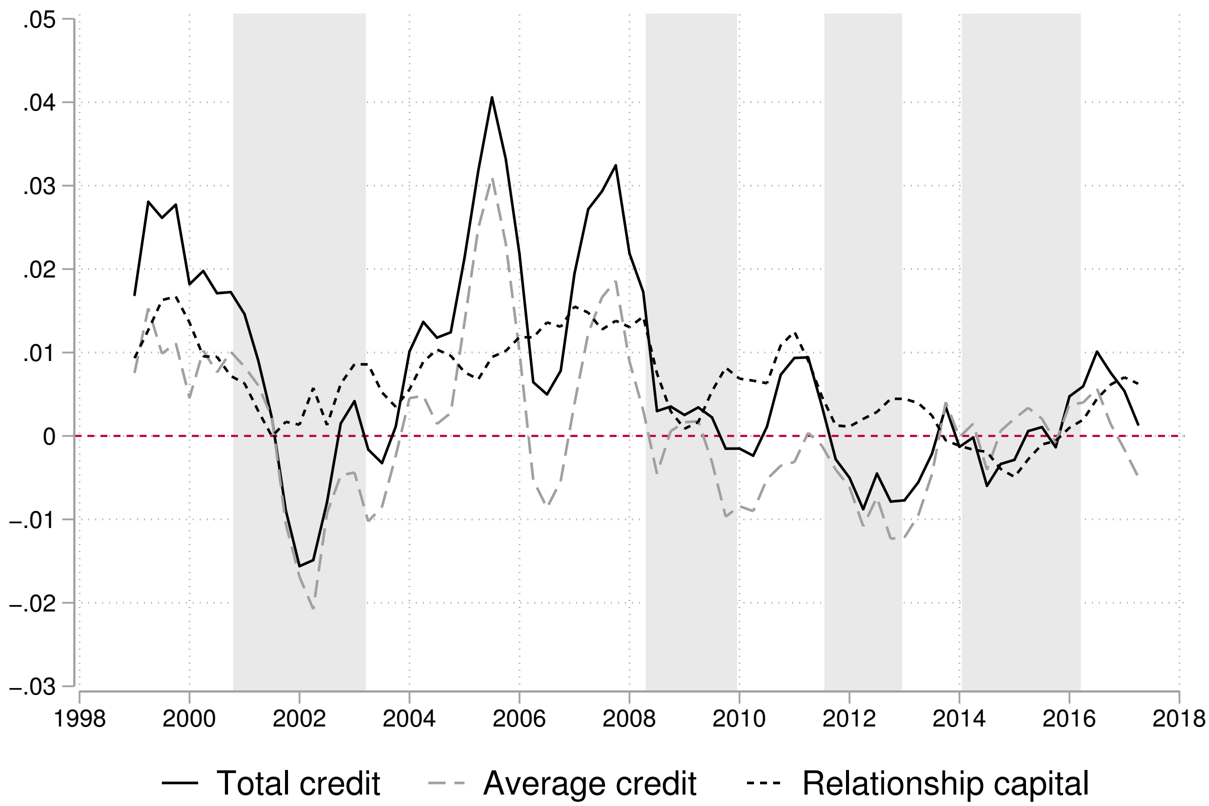
Notes: These figures show the trajectories of cross-sectional averages of credit, normalized to one at time 0 (dashed line) and separation probability (solid line) throughout the duration of a credit relationship. Panel (a) reports unconditional results, while Panel (b) reports the results for boom (in black) and crisis periods (in red). Results are based on relationships above the reporting threshold (adjusted for inflation) and within our sample period 1999-2016.

Figure 14: Extensive vs. intensive margins: long-run trends



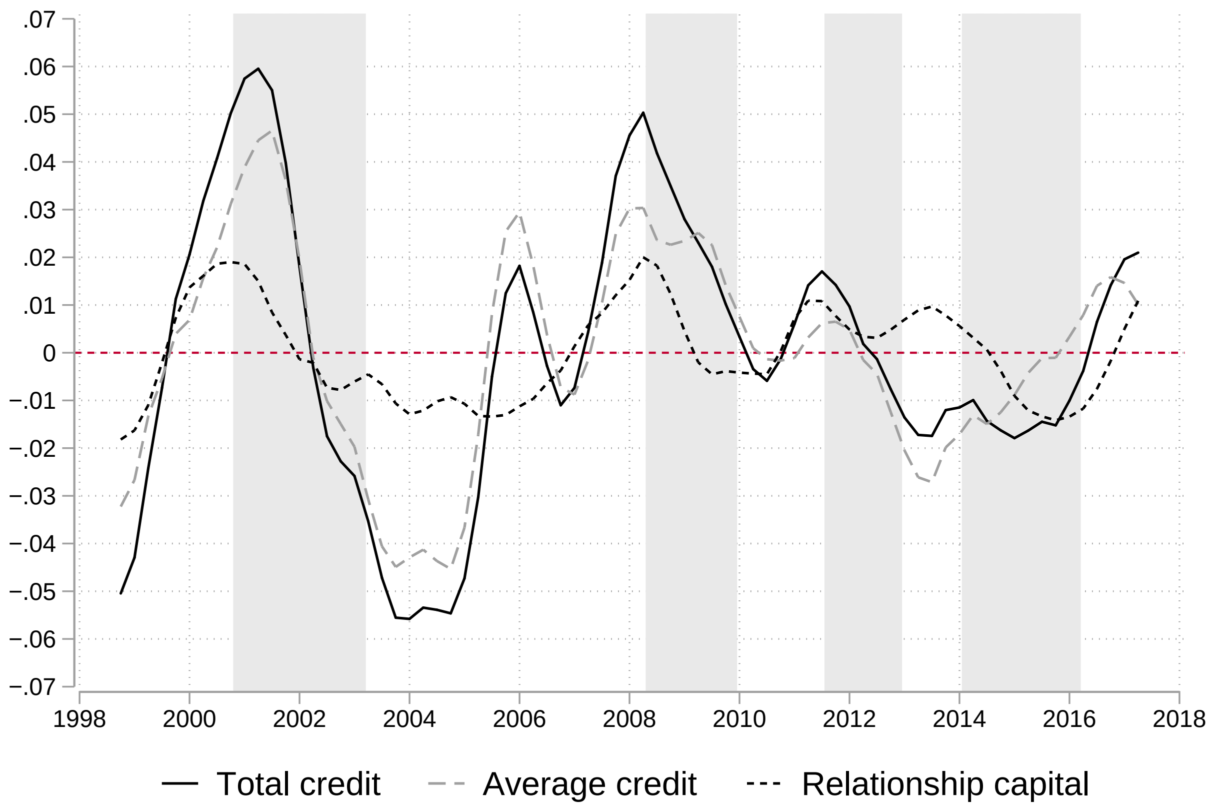
Notes: This figure reports the trends associated with aggregate credit, average credit, and the stock of relationship. The trends are extracted using an HP filter with smoothing parameter 1600. Nominal variables are deflated using the French seasonally adjusted GDP Implicit Price Deflator obtained from the FRED database. Results are based on relationships above the reporting threshold (adjusted for inflation). Time series of relationship flows are first deseasonalized using the X-13 seasonal adjustment procedure and smoothed out using MA(-1,1). Our sample period is 1999-2016. Gray-shaded areas correspond to recession periods.

Figure 15: Extensive vs. intensive margins of credit (first-difference)



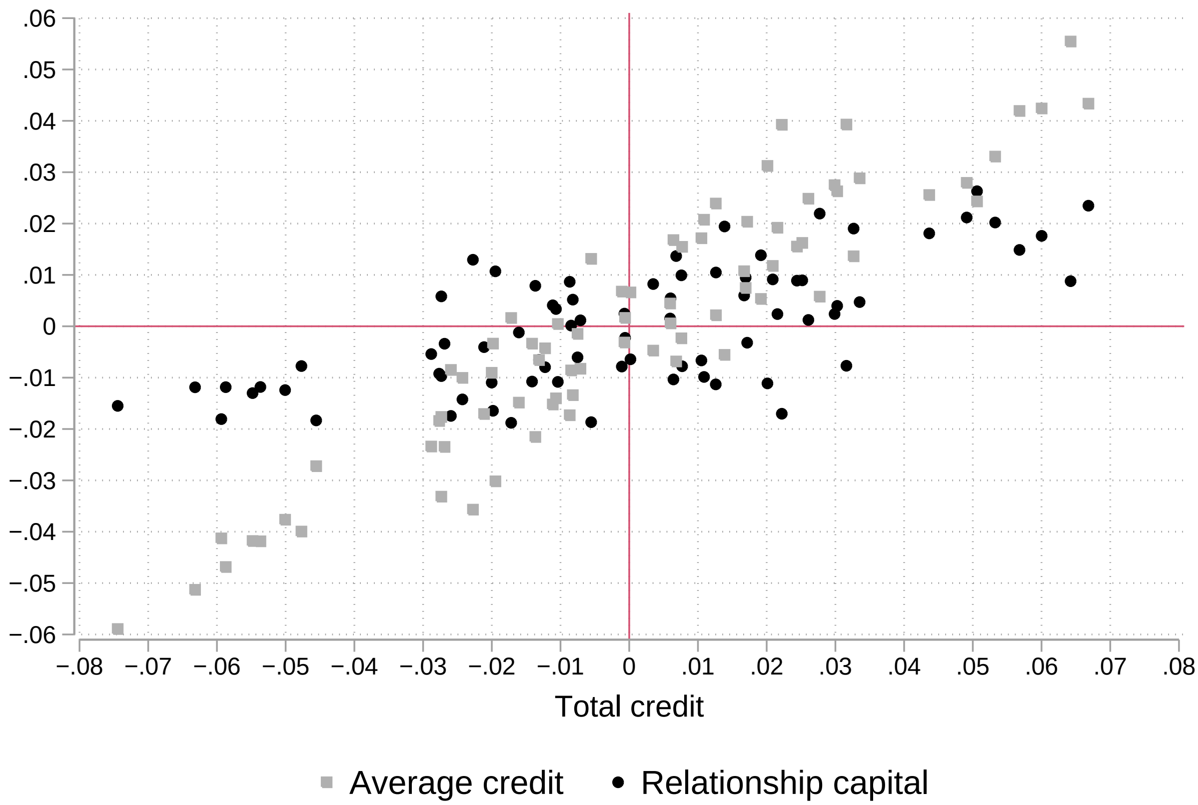
Notes: This figure shows the log-growth dynamics of aggregate credit (black solid line), average credit per relationship (gray dashed line), and the stock of credit relationships (black dashed line). Nominal variables are deflated using the French seasonally adjusted GDP Implicit Price Deflator obtained from the FRED database. Results are based on relationships above the reporting threshold (adjusted for inflation). Time series of relationship flows are first deseasonalized using the X-13 seasonal adjustment procedure and smoothed out using MA(-1,1). Our sample period is 1999-2016. Gray-shaded areas correspond to recession periods.

Figure 16: Extensive vs. intensive margins of credit (HP filter)



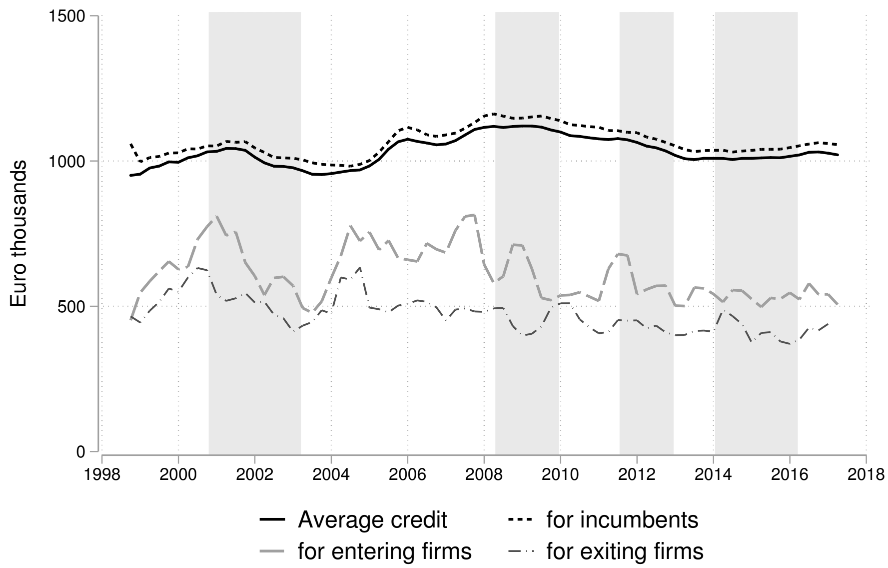
Notes: This figure shows the cyclical deviations (in log) of aggregate credit (black solid line), average credit per relationship (gray dashed line) and the stock of credit relationships (black dashed line). Nominal variables are deflated using the French seasonally adjusted GDP Implicit Price Deflator obtained from the FRED database. Results are based on relationships above the reporting threshold (adjusted for inflation). Time series of relationship flows are first deseasonalized using the X-13 seasonal adjustment procedure and smoothed out using MA(-1,1). Our sample period is 1999-2016. Gray-shaded areas correspond to recession periods.

Figure 17: Extensive vs. intensive margins: cyclical deviations

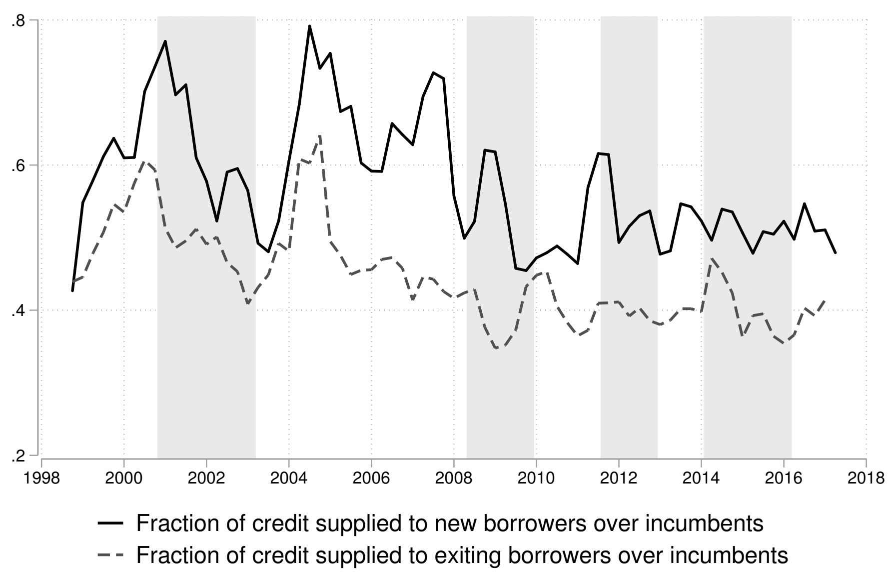


Notes: This figure shows a scatter plot of the cyclical deviations (in log) of average credit and the stock of relationship, as a function of their aggregate credit counterparts. Cyclical deviations are extracted using an HP filter with smoothing parameter 1600. Nominal variables are deflated using the French seasonally adjusted GDP Implicit Price Deflator obtained from the FRED database. Results are based on relationships above the reporting threshold (adjusted for inflation). Time series of relationship flows are first deseasonalized using the X-13 seasonal adjustment procedure and smoothed out using MA(-1,1). Our sample period is 1999-2016.

Figure 18: **Average credit for incumbents, entrants, and exiting firms**



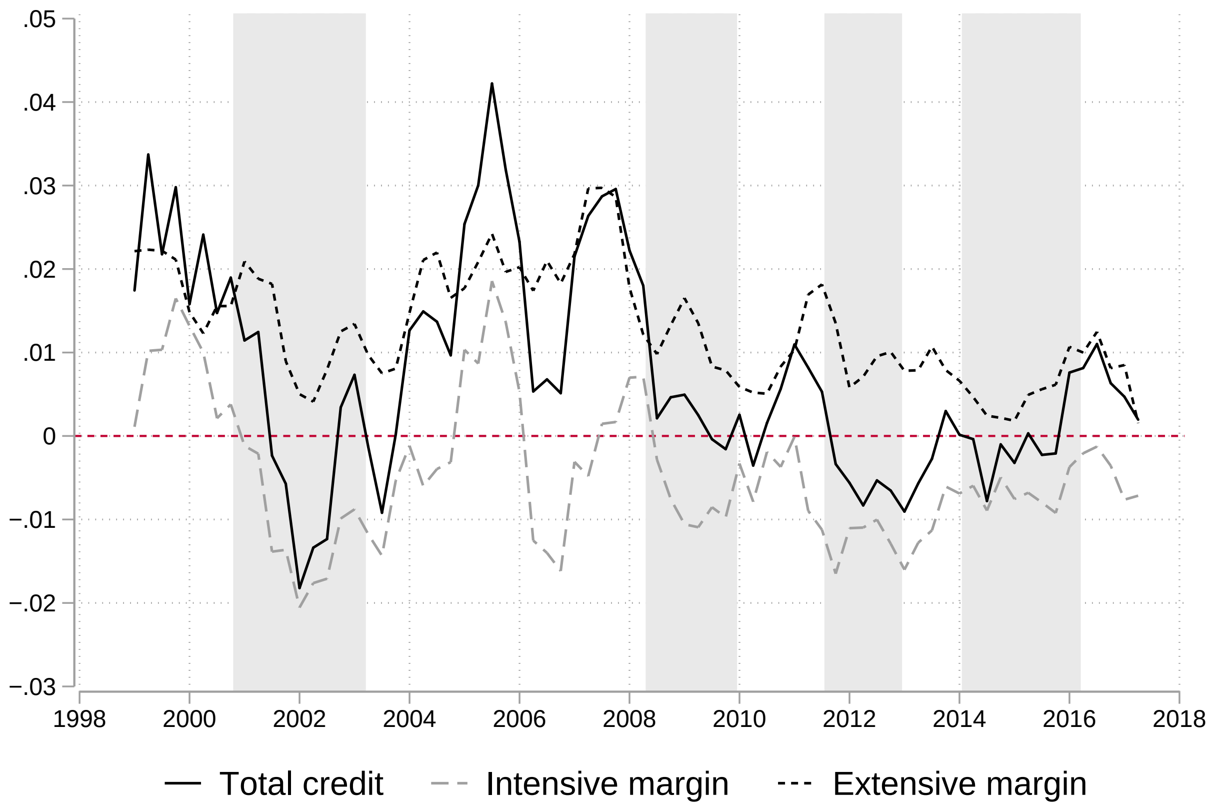
(a) Average credit for incumbents, entrants, and exiting firms, in thousand Euro



(b) Credit supplied to entering and recently exiting firms, as a fraction of incumbent credit

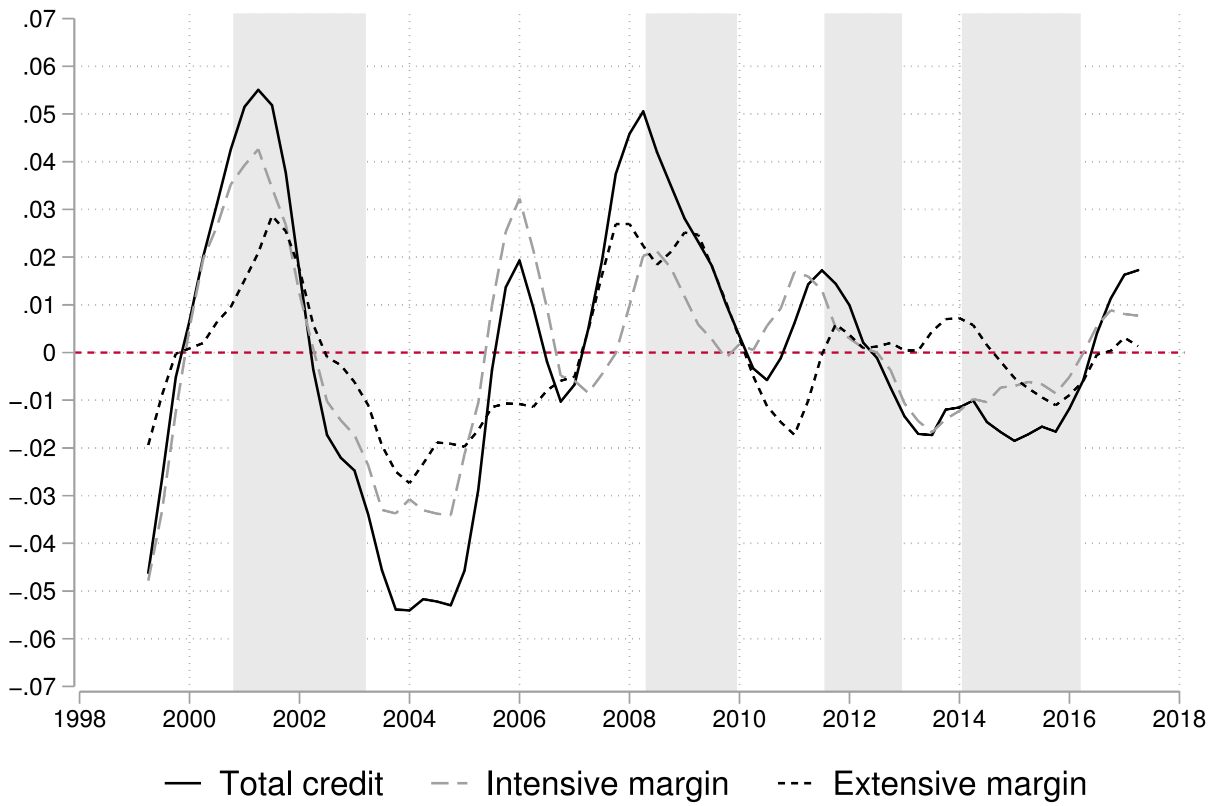
Notes: Panel (a) shows the time series of aggregate average credit per relationship (solid black line), in addition to the average credit supplied to (i) incumbent borrowers (black dotted line), (ii) new borrowers (light gray dashed line), and (iii) exiting borrowers (dark gray dashed line). Panel (b) shows the time series of the ratio of (i) average credit supplied to new borrowers over average credit supplied to incumbents (solid line) and (ii) average credit (previously) supplied to exiting borrowers over average credit supplied to incumbents (dashed line). Our sample period is 1999-2016. Results are based on relationships above the reporting threshold (adjusted for inflation). All nominal variables are deflated using the French seasonally adjusted GDP Implicit Price Deflator from the FRED database. Gray-shaded areas correspond to recession periods.

Figure 19: Incumbent vs. new/severed relationships (first-difference)



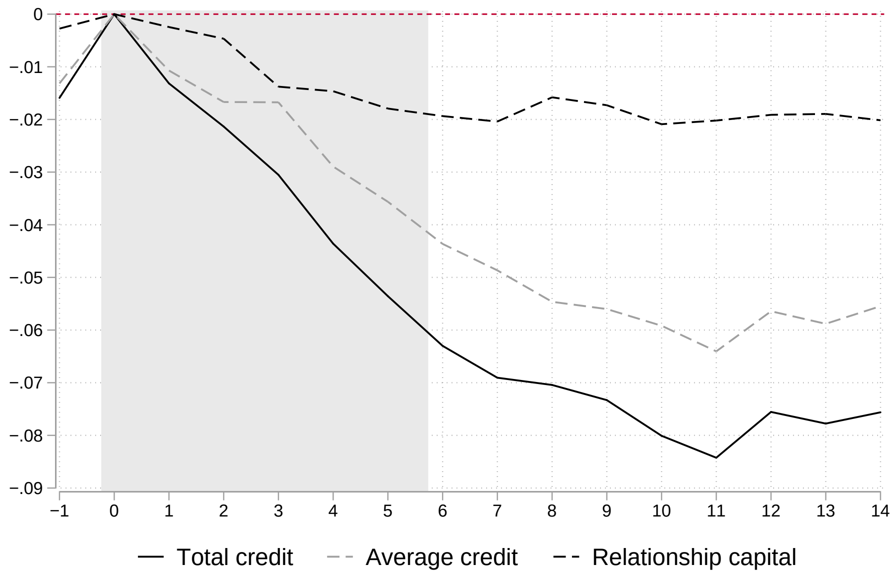
Notes: This figure shows the time series of total credit growth, intensive margin growth, and extensive margin growth. The intensive margin is the change in the average credit supplied to incumbents multiplied by the number of incumbents. The extensive margin is the number of new relationships multiplied by the average credit supplied to new firms minus the number of exiting relationships multiplied by the average credit supplied to exiting firms. Nominal variables are deflated using the French seasonally adjusted GDP Implicit Price Deflator obtained from the FRED database. Results are based on relationships above the reporting threshold (adjusted for inflation). Time series of relationship flows are first deseasonalized using the X-13 seasonal adjustment procedure and smoothed out using MA(-1,1). Our sample period is 1999-2016. Gray-shaded areas correspond to recession periods.

Figure 20: Incumbent vs. new/severed relationships (HP filter)

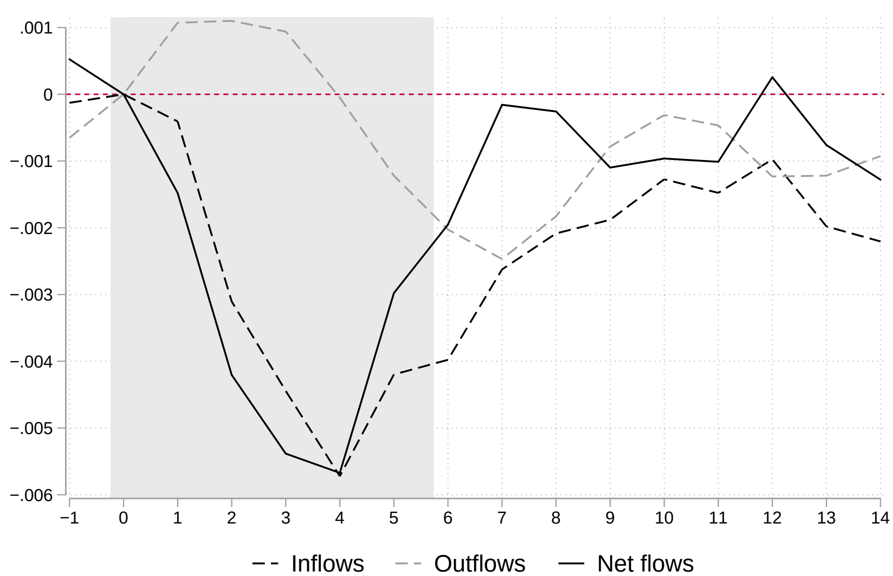


Notes: This figure shows the time series of total credit growth, intensive margin growth, and extensive margin growth. The intensive margin is the change in the average credit supplied to incumbents multiplied by the number of incumbents. The extensive margin is the number of new relationships multiplied by the average credit supplied to new firms minus the number of exiting relationships multiplied by the average credit supplied to exiting firms. Nominal variables are deflated using the French seasonally adjusted GDP Implicit Price Deflator obtained from the FRED database. Results are based on relationships above the reporting threshold (adjusted for inflation). Time series of relationship flows are first deseasonalized using the X-13 seasonal adjustment procedure and smoothed out using MA(-1,1). Our sample period is 1999-2016. Gray-shaded areas correspond to recession periods.

Figure 21: Anatomy of a crisis



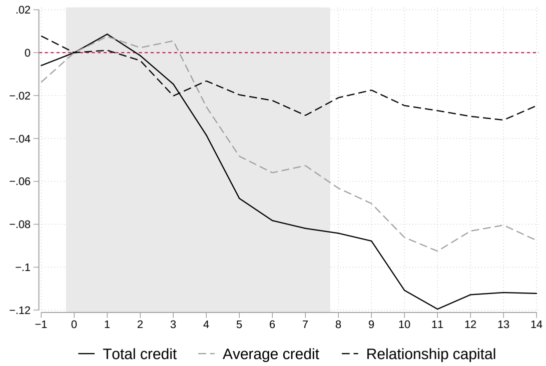
(a) Aggregate variables: credit vs. extensive and intensive margins



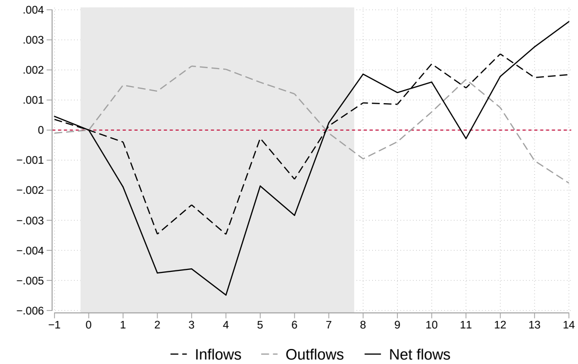
(b) Credit relationship flows: net vs. gross

Notes: These figures report the average evolution of (i) aggregate credit, average credit, and relationship capital (Panel (a)), and that of (ii) net and gross flows (Panel (b)) over the ten quarters following the onset of a recession. All variables are normalized to 0 based on the timing of the pre-recession peak for aggregate credit, and reported in terms of log-deviations from their corresponding HP trend (obtained with a smoothing parameter 1600). Gray-shaded areas correspond to the average recession period.

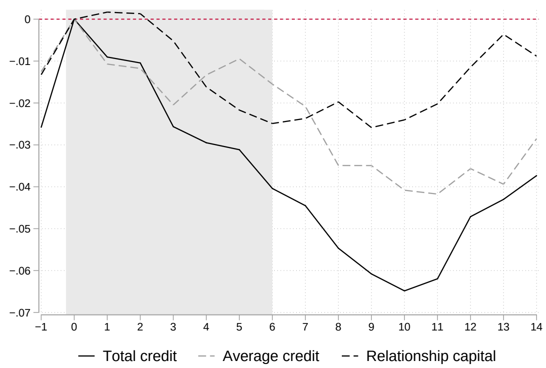
Figure 22: Anatomy of a crisis: details



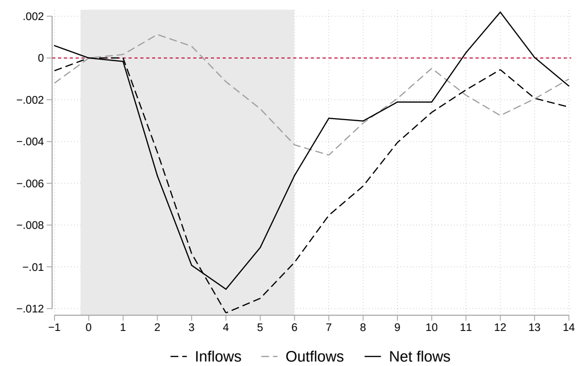
(a) Aggregate variables: 2001 - 2003



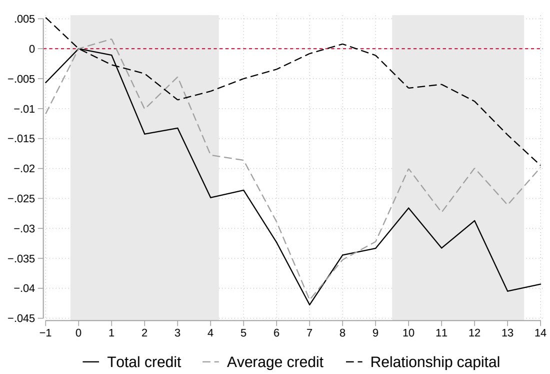
(b) Credit flows: 2001 - 2003



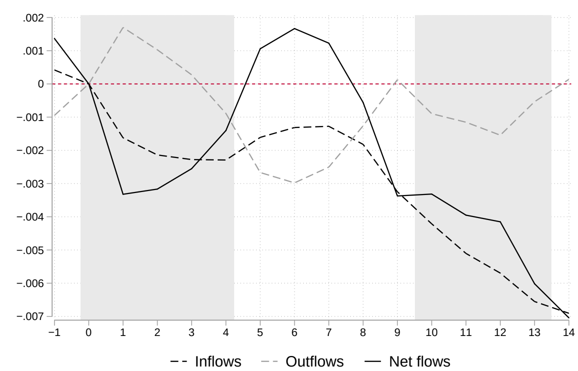
(c) Aggregate variables: 2008 - 2009



(d) Credit flows: 2008 - 2009



(e) Aggregate variables: 2012 - 2014

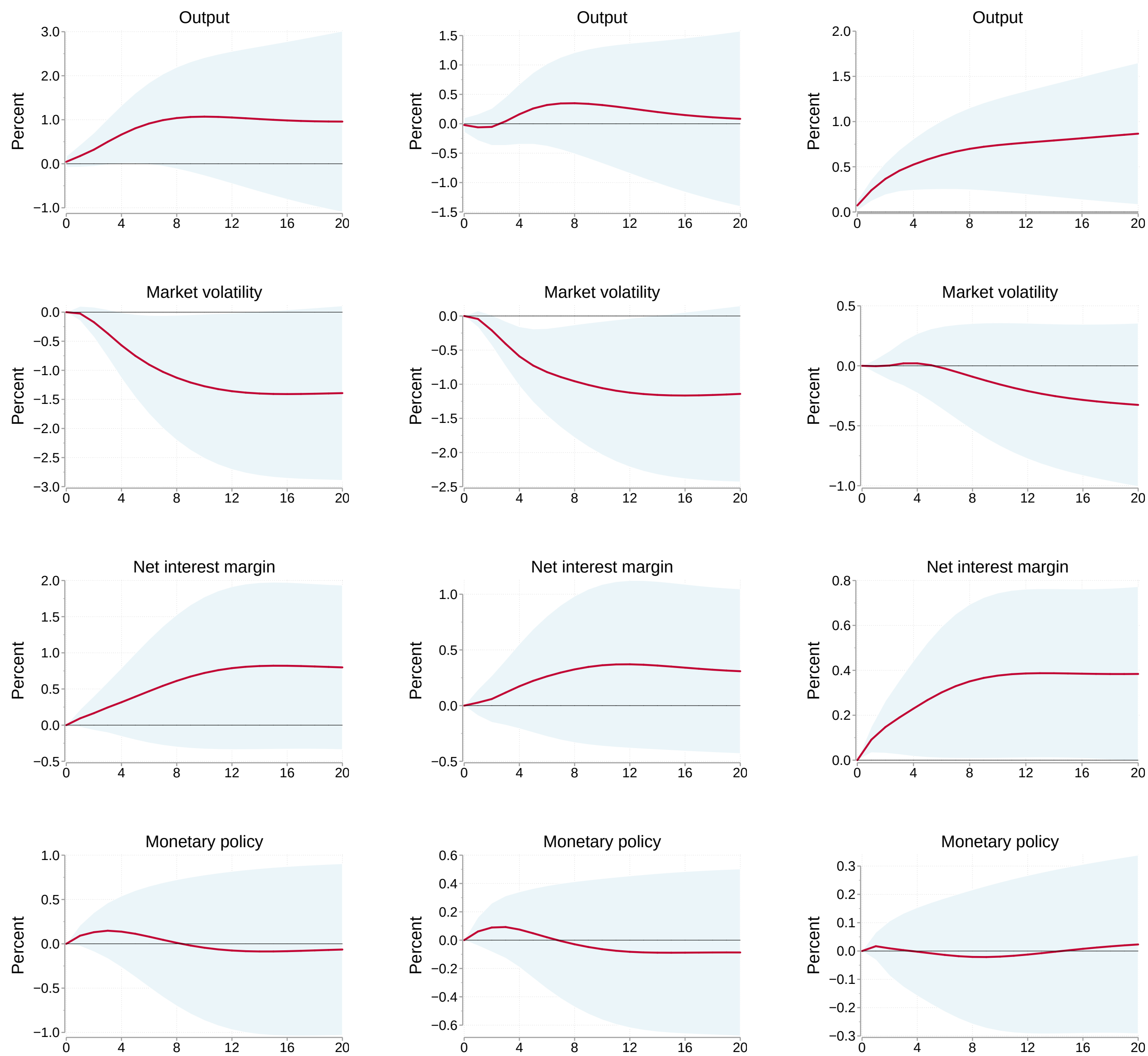


(f) Credit flows: 2012 - 2014

Notes: These figures report the evolution of (i) aggregate credit, average credit, and relationship capital (left-hand side panels), and that of (ii) net and gross flows (right-hand side panels) over the ten quarters following the onset of each recession. Due to their proximity, the recessions of 2012-2013 and 2014-2016 are shown combined in panels (e) and (f). All variables are normalized to 0 based on the timing of the pre-recession peak for aggregate credit, and reported in terms of log-deviations from their corresponding HP trend (obtained with a smoothing parameter 1600). Gray-shaded areas correspond to recession periods.

Figure 23: VAR analysis

(a) Aggregate credit **(b-0) Intensive margin** **(b-1) Extensive margin**



Notes: These figures illustrate impulse responses to a one standard deviation orthogonalized shock to (i) output, (ii) market volatility, (iii) net interest margin, and (iv) monetary policy. The results are obtained from two distinct VAR estimations: one including (a) aggregate credit (first column), and one including jointly the intensive (b-0, second column) and extensive (b-1, third column) margins. All responses are cumulative. The x-axis represents the number of quarters after the shock, and the y-axis represents percentages. The blue-shaded areas correspond to the 90-percent confidence intervals.