The Flow Approach to Credit Markets: Methodology, Measurements, and Macro Perspectives*

Yasser Boualam† Clement Mazet-Sonilhac‡

June 24, 2022

We provide empirical foundations for a flow approach to credit markets and derive novel extensive/intensive margin decompositions for aggregate credit dynamics. Using bank-firm level data for commercial lending in France, we establish that the creation and destruction of credit relationship flows are (i) one order of magnitude larger than net flows, and (ii) volatile and pervasive throughout the cycle. Banks actively adjust their loan portfolios along the extensive margin, which (iii) contributes up to 46% of the cyclical and 90% of the long-run credit variations. We also document the distinct features of the extensive and intensive margin channels of monetary policy.

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

---

*First draft: Mar 3, 2020. The views expressed herein are those of the authors and do not necessarily reflect those of the Banque de France or the Eurosystem. The paper previously circulated under the title "Aggregate Implications of Credit Relationship Flows: A Tale of Two Margins." We are grateful to Paul Beaumont, Antonin Bergeaud, Thomas Chaney, Anne Duquerroy, Pietro Garibaldi, Erwan Gautier, Itay Goldstein, Andrei Gonçalves, Yunzhi Hu, Paul Hubert, Mathias Lé, Thibault Libert, Raoul Minetti, Jacob Sagi, and seminar participants at the University of North Carolina at Chapel Hill, Banque de France, Michigan State University, the 2020 UNC Junior roundtable, the 2020 World Meeting of the Econometric Society, the 2021 American Economic Association meetings, the 2021 Society for Economic Dynamics meeting, and the 2021 Money Macro and Finance Society meeting, for their insightful comments and feedback at various stages of the project. All remaining errors are our own.

†Kenan-Flagler Business School - University of North Carolina - Chapel Hill. Contact: boualam@unc.edu

‡SciencesPo - Banque de France. Contact: clement.mazet@sciencespo.fr

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 key aspect that has been widely 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 alleviating agency frictions and shaping credit at the lender-borrower level.[1] It has also emphasized the existence of cross-sectional heterogeneity in terms of match quality and duration, and formation and severance costs that can hinder banks' ability to adjust credit supply in a frictionless way. In this context, Boualam (2018) brings to life the distinct role of the extensive and intensive margins of credit through an equilibrium search framework featuring dynamic financial contracts. Since different economic mechanisms drive each margin, this generates heterogeneous responses to aggregate shocks. Among others, the model therein and its quantitative application highlight that adverse shocks that particularly lead to a significant destruction of relationship capital (i.e., a decline in the number of bank-firm relationships) can have more sluggish credit recoveries.

This paper builds on this novel perspective on credit intermediation and provides further empirical evidence on the unique roles of the intensive and extensive margins in shaping aggregate credit fluctuations. We attempt to look behind such fluctuations in order to address first-order questions such as: (i) When aggregate credit declines by 5%, is it because the average loan size (i.e., intensive margin) drops by 5%, or is it because 5% of bank-firm matches (i.e., extensive margin) are destroyed? (ii) Does the origin of credit fluctuations matter? (iii) Do monetary policy shocks impact these margins differently?

While the distinction between the extensive and intensive margins has been previously introduced in micro-empirical studies of the bank-credit supply (Jiménez et al. (2014)), to our knowledge, this paper is the first to provide a methodology for the measurement of credit relationship flows, document their properties, and quantify the contribution of each margin at the aggregate level over a two-decade horizon. We show that, through the continuous creation and destruction of credit matches, banks actively adjust

[1]See Boot (2000) and Degryse, Kim and Ongena (2009) for a survey of earlier work.

both the number *and* the intensity of their relationships and that both margins represent a significant source of variation in aggregate credit. These adjustments are somewhat analogous to the 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 remains limited, if not completely absent. Furthermore, we highlight that these margins have prominently different dynamics and argue that disentangling their effects can prove informative about the economic mechanisms at play 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. This longitudinal dataset contains granular, high-frequency, and nearly exhaustive records of bank-firm matches and corresponding credit exposures over the period 1998-2018, and provides an excellent basis for our analysis. To study the properties of credit relationship flows, we develop an empirical methodology akin to the one pioneered by Davis and Haltiwanger (1992) for labor flows. Our methodology and measurement efforts take 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 aggregate implications of bank-firm 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 cannot 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 properties of credit reallocation. Instead, we advance here a novel approach to exploit information available in credit registers, which is typically used in micro settings, to uncover new aggregate findings.

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

i. Extensive and intensive margins fluctuate continuously over time. While their persistence is

[2] To some extent, our analysis of 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.

roughly identical, the volatility of the intensive margin is relatively higher.

ii. Both margins are important at the business cycle frequency, with the extensive margin contributing about one quarter to one half of the variance in aggregate credit.

iii. In the long run, the extensive margin accounts for the bulk of aggregate credit variations.

Our analysis 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 are more volatile for small and short-term loans and credit relationships with duration of less than one year. Inflows are more volatile for relationships with small loans or lines of credit.

Our results also highlight that credit patterns observed during or in the aftermath of an economic downturn are driven potentially by multiple combinations of extensive and intensive margin sources, suggesting that different economic mechanisms may be at play. A better understanding of the extensive/intensive origin of a credit decline and its bottlenecks can thus be relevant to the design of effective and targeted policy tools. In this context, we investigate how monetary policy gets transmitted through both extensive and intensive margin channels. We show that the intensive margin responds immediately and strongly to monetary policy surprises. Conversely, the extensive margin's response is relatively more gradual and subdued during easing regimes, suggesting a potentially limited impact on newborn firms' access to credit. We also note that the extensive margin channel is at play mainly for relatively small banks or those with flexible balance sheets.

Our empirical framework also provides us with tools to better understand 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 yearly (excess) reallocation rates have been steadily declining over the past two decades. Such result may suggest the existence of factors hampering credit market fluidity and contain relevant theoretical and policy ramifications worthy of further investigation.

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 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 the role of bank net worth and balance sheet constraints.[3] Yet, both of these prominent strands generally abstract from long-term contracts, 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, albeit theoretical and empirical studies therein have focused mostly on the micro level with limited macroeconomic implications.

Our contribution resides in designing a transparent methodology, providing empirical foundations, and assessing the macroeconomic relevance of a flow-driven approach to credit markets. This approach posits the importance of credit match dynamics and has been introduced theoretically in Den Haan, Ramey and Watson (2003) and Becsi, Li and Wang (2005). More recently, Boualam (2018) builds an 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, due to the introduction of broadband internet, impacts bank-firm matching and aggregate credit.

Our work is also part of a nascent literature on credit flows and reallocation, which includes Dell'Ariccia and Garibaldi (2005), Herrera, Kolar and Minetti (2011), Craig and Haubrich (2013), and Contessi and Francis (2013). 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.[4] In the same vein, Herrera, Kolar and Minetti (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 Compustat data used in that analysis cannot fully capture the extent of reallocation across borrowers and lenders, nor account for relatively small firms. In marked contrast, our paper is the first to use loan-level data to carefully establish stylized facts about gross credit relationship flows and distinguish extensive and intensive margin effects. Our unit of observation is the bank-firm match, which allows us to precisely measure underlying 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

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

[4] For example, banks may well be reallocating credit across their borrowers even though their net credit growth is zero.

magnitudes of the underlying gross flows.[5] From a methodological standpoint, our approach is closely related to the one commonly used to examine job flows, and specifically to earlier studies conducted by Steven Davis and John Haltiwanger and partly summarized in Davis and Haltiwanger (1999).

The paper is also broadly related to the empirical literature quantifying the sources of bank-credit fluctuations and the transmission of shocks stemming from either borrowers or lenders.[6] Among others, three recent papers are connected to ours. Jiménez et al. (2014) identify the bank risk-taking channel of monetary policy through a bank-firm level analysis using Spanish loan application and credit register data. 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. Beaumont, Libert and Hurlin (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 relationship flows, and analyzes the extensive/intensive margin decompositions of credit from an aggregate perspective.

Finally, while we have focused almost entirely on aggregate outcomes here, an ongoing companion paper, Boualam and Mazet-Sonilhac (2022), analyzes the data from a disaggregated perspective and delivers complementary results on cross-sectional properties and credit reallocation.

Organization. The paper proceeds as follows. We start by outlining the conceptual foundations and empirical methodology behind our flow approach to credit markets in Section 2. We then present our core results for gross relationship flows (Section 3), and aggregate credit decompositions (Section 4). Section 5 explores the properties of credit during crises and recovery and Section 6 investigates macroeconomic implications. Section 7 discusses other relevant applications and Section 8 concludes.

2 The Flow Approach to Credit Markets

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 introduces conceptual foundations behind our

[5]A contemporaneous research work by Cuciniello and Di Iasio (2020) also investigates a credit decomposition into extensive/intensive margins using the Italian Credit Register data, and, in line with our results, confirms the prominent role played by the extensive margin throughout the business cycle.

[6]See, for example, Hubbard, Kuttner and Palia (2002), Khwaja and Mian (2008), Chodorow-Reich (2014), Becker and Ivashina (2014), and Greenstone, Mas and Nguyen (2020).

definitions and measurements, then discusses the data and lays out our empirical methodology.

2.1 Conceptual Foundations

The motivation for our flow measures comes from search theory and the literatures on credit relationships and credit reallocation, and relies more specifically on the theoretical insights from Boualam (2018). The function of a credit market is to assign the right borrower to the right lender and lending opportunity. The creation of a credit relationship thus consists of a bank's decision to deploy idle capital to an applying borrower at some cost. In the spirit of the labor market literature and Blanchard and Diamond (1992), a flow approach to credit markets relies on specifications for:

- Credit supply and demand through credit relationship creation and destruction flows.
- Process of application and lending through a matching function with a market tightness derived from the measure of searching borrowers and available loan opportunities.
- Long-term financial contract that determines the evolution of loan terms (e.g., credit amount, rates) which depend, among others, on market conditions and borrower and lender characteristics.

Boualam (2018) introduces the role of the extensive margin of credit through an equilibrium search framework that builds on the above specifications. In this context, credit relationship creations and destructions are inherent to a large process of adjustment and reallocation of capital across banks and firms. The theory therein posits that credit markets are subject to two forms of frictions, namely: (i) search frictions which affect the creation and severance of credit relationships (i.e., extensive margin), and (ii) agency frictions, which shape the dynamics of the financial contract (i.e., intensive margin).

The model and its quantitative application put forward the idea that these margins are driven by different economic mechanisms, and thus generate different responses to aggregate shocks. In particular, adverse shocks that lead to a significant decline in relationship capital (i.e., number of credit relationships) can have long-lasting effects. The model also accounts for the heterogenous response across borrowers with new or incumbent credit relationships further highlighting the importance of the duration or intensity of a credit relationship. As a consequence, aggregate credit dynamics do not only depend on the evolution of relationship capital but also on its composition.

Ultimately, it is important to recognize that both margins matter and that economies that are exclusively driven by either one may generate very distinct credit dynamics. This intuition is overall consistent with empirical findings. First, frictions along the extensive margin do matter. For example, Chodorow-Reich (2014) shows that during the financial crisis, firms that were unable to roll over their loans with their current bank had hard time finding a new lender and thus bore significant economic costs. Second, the intensive margin and credit relationships equally matter. In this context, Bolton et al. (2016) discusses how the nature of a credit match can lead to different treatments throughout crisis periods, with banks shielding their relationship borrowers from adverse shocks, while Duquerroy et al. (2022) highlight that firms with severed credit matches due to branch closures obtain worse contractual terms upon the formation of a new relationship with another branch of the same bank.

Our facts about extensive and intensive margins of credit suggest that bank loan provision is in general a more complex process. As we document throughout the paper, the very large magnitudes of credit relationship creations and destructions bring to the forefront the importance of credit reallocation and the fluid nature of credit markets. It also accentuates the importance of investigating questions related to the economic mechanisms behind the formation, retention, and severance of credit matches. Thus, we argue that one critically needs to account for *both* the dynamics of the extensive and intensive margins and composition of borrowers to understand aggregate credit dynamics. Importantly, a key dimension of heterogeneity across borrowers stems from the strength and duration of their lending relationship.

We focus 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 represents aggregate credit supplied by banks, C_t, as 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. Although this approach potentially masks compositional effects, 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:

$$N_{t+1} \quad = \quad N_t + \Gamma_{t+1} - \Delta_{t+1}, \tag{2}$$

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

2.2 Definitions and Measurements

Next we propose new measures for credit relationship flows, credit exposure, and relationship intensity and lay down their underlying assumptions and interpretations. Our definitions rely on the conceptual foundations above and follow in the footsteps of earlier studies of gross job flows (Davis et al. (1998)).

2.2.1 Credit Relationship (CR) Flows

We start with the definitions of creation and destruction flows and credit relationships.

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.*[7]
- ***Credit Relationship.*** *Existing bank-firm match at time t, whereby t lies within the creation and destruction dates.*

Our definitions put forward the theoretical construct of a credit relationship as the key economic aspect

[7] Our choice of a 4-quarter gap is informed by existing data and the fact that most "recalls" occur within the first year (for example, we find that only 10.5% of severed relationships are recreated 5 to 8 quarters later). Our results are qualitatively unchanged if we allow for the number of quarters to be 8 and 12, as shown in the Online Appendix.

behind the notion of extensive margin.[8] Figure 2 depicts possible configurations in the data and our measurement choices. We assume that borrower information is not lost immediately upon the expiration of a given credit facility, but only after an interaction-free period of several quarters. This approach helps to account for situations involving lengthy negotiations before a loan deal is closed, and also adjusts for cases where credit exposures temporarily decline below the mandatory reporting threshold and for potential reporting gaps in the data. Note that while the last occurrence of a bank-firm match may be at quarter t, the destruction of such match in fact happens some time between quarter t and $t+1$, and is thus accounted for at time $t+1$. Note also that our definitions do not preclude cases where banks and firms engage in several creation and destruction rounds throughout the sample.

We can then tabulate gross credit relationship flows, i.e., creation flows, Γ_t, and destruction flows, Δ_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:

$$\begin{aligned} \mathbb{N}_t &= \Gamma_t - \Delta_t \\ \mathbb{R}_t &= \Gamma_t + \Delta_t \\ \mathbb{X}_t &= \Gamma_t + \Delta_t - |\mathbb{N}_t|. \end{aligned}$$

In this context, excess reallocation 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 10% do not impact the stock of credit relationships, yet imply a large level of credit reshuffling across firms and banks and an excess reallocation of 20%. We eventually compute the corresponding flow rates (denoted with lowercase characters), 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}.

2.2.2 Relationship Intensity: Credit Exposure, Type, Maturity, and Duration

Besides bank and firm characteristics, the credit match can also be characterized by its intensity. Consistent with the empirical literature (Degryse, Kim and Ongena (2009)), we consider here three measures, namely (i) credit exposure, (ii) type/maturity, and (iii) duration.

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

Credit Exposure, Type and Maturity. We start by defining the credit exposure of a bank to a given borrowing firm, as the sum of withdrawn and undrawn credit, in addition to bank credit guarantees.[9] We further decompose the withdrawn component by maturity (i.e., short-term and long-term) and other, less common forms of credit (e.g., credit leasing, securitized debt, overdrafts limits).[10]

Definition 2. [11]

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

We characterize the intensity of the credit relationship based on the nature and maturity of credit involved. We define (i) the share of on-balance-sheet credit as a ratio over total credit exposure, and (ii) the share of long-term credit as a ratio over on-balance-sheet credit. These measures reflect the level of commitment from the bank's perspective. A credit relationship is less binding when consisting only of short-term or off-balance-sheet credit that banks can swiftly reduce following an adverse shock.

Relationship Duration. Next we consider relationship duration as another measure of the intensity of a bank-firm match. Indeed, the repeated interaction between borrowers and lenders can help gradually alleviate agency and informational frictions and eventually lead to higher credit supply over time.

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 quarters between time t and its creation date.*

2.3 The French Credit Register

Our analysis essentially relies on the French Credit Register, referred to as *Service Central des Risques* (henceforth SCR). This is a monthly database that contains bank credit exposures to borrowing firms

[9]A credit guarantee covers a debtor's liabilities in case of delinquency. It enables the borrower to contract third-party liabilities by transferring counterparty risk to the bank, thereby creating an implicit credit exposure.

[10]Ivashina, Laeven and Moral-Benito (2021) look more specifically at the aggregate implications of different loan types, which we abstract from in this analysis.

[11]On-balance-sheet credit also accounts for medium- and long-term leasing and factoring, while off-balance-sheet credit also accounts for securitized loans. We omit these items as they represent a negligible share of their respective categories.

over the period 1998-2018. This is the most comprehensive commercial credit dataset maintained by Banque de France and is used to monitor overall credit supply and risk exposures of domestic banks. The data are generated from detailed mandatory reports filed by all credit institutions (classified through a unique *Code Interbancaire* (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; banks' credit line and guarantee commitments; in addition to leasing, factoring, and securitized loans. Reporting financial intermediaries account for all resident credit institutions and investment firms. Thus, the dataset provides an extensive account of existing bank-firm linkages, provided that the credit exposure is above the 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 headquartered outside Metropolitan France, self-employed entrepreneurs, and certain types of entities such as nonprofit organizations.[12] 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.[13] We also exclude very small institutions with credit exposures averaging less than EUR 1 million quarterly.

We choose to work at the quarterly frequency given our analysis objective and the considerable size of available data. We also construct bank-firm relationships at the bank level (instead of branch or banking group levels). We deflate all credit variables using the GDP deflator for France.[14] We similarly define the reporting threshold in real terms. Furthermore, we focus on bank-firm pairs using the inflation-adjusted threshold (corresponding to EUR 75,000 in 1998) throughout the sample period in order to make sure that our analysis remains consistent over time despite the 2006 change in reporting.[15]

Our cleaned baseline dataset contains about 27 million bank-firm-quarter observations over the period 1998Q1-2018Q4, involving 715 unique banks (447 banks per quarter on average) and 940,554 unique firms (256,271 firms per quarter on average). Figures 3a and 3b report the evolution of the number of banks and firms and that of total credit and relationship capital, respectively. While the banking

[12] The Online Appendix provides additional details related to data filters and variable construction.

[13] 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 sample period.

[14] 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).

[15] The reporting threshold is fixed to EUR 75,000 at the beginning of the sample period and is adjusted over time. Given that inflation remains positive overall throughout the sample period, this means that we omit a small fraction of bank-firm relationships present in the data but that exhibit below-threshold credit exposures.

sector experienced intense consolidation over the sample period with the number of banks declining by a third, the number of firms relying on bank credit had almost doubled during that time.

Comparison with Aggregate Flow of Funds Data. Our final sample covers about 61% of total bank credit to non-financial companies as reported in the balance of payments available through the Flow of Funds data. 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 affect the level of relationship flows. These include (i) seasonality, (ii) bank and firm consolidations, and (iii) variations in the reporting threshold. We attempt to correct for these limitations and discuss them in detail in this section.[16]

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.[17]

Bank Consolidation. The French banking sector has undergone several rounds of consolidations throughout our sample period. As shown in Figure 3a, the number of banks declined from 547 to 342 from 1998 through 2017. This is due almost exclusively to mergers and acquisitions, as bank entry and exit events were negligible during this period. Bank consolidations may lead to spurious inflows and outflows when the acquiring bank starts reporting the credit relationships originally attributed to the acquired bank. For example, consider a merger where Bank A acquires Bank B between times $t-1$ and t. At time $t-1$, outflows stemming from bank B, $O_{B,t-1}$, are overestimated given that Bank B stops reporting. In a similar vein, inflows tabulated from Bank A at time t are overestimated by the same amount, $O_{B,t-1}$, as transferred relationships are treated as if they were newly formed.

[16] We relegate other minor issues such as those related to the change in the reporting of some categories (e.g., off-balance-sheet credit) and the classification of non-performing credit and ensuing adjustments to the Online Appendix.

[17] 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.

We remedy to this issue following the methodology in Dell'Ariccia and Garibaldi (2005) and using the list of bank merger events maintained by the French Supervision and Prudential Authority (ACPR). This list accounts for all banking M&A activity involving banks located in France over the period 1995 through 2016. We thus proceed by (i) setting acquired Bank B's outflows to zero at $t-1$ ($O_{B,t-1} = 0$) and (ii) reducing the time t inflows associated with acquiring Bank A by $O_{B,t-1}$. We omit mergers involving banks with missing identifiers, which account for less than 3% of M&A events. We also complement these adjustments by manually checking the database and accounting for more complex situations, such as the consolidation of Caisse d'Epargne and Banque Populaire.[18]

Firm Consolidation. M&A activity at the firm level could also generate spurious flows. For example, when Firm A absorbs Firm B that is linked to Bank C, our measurement definitions would record the simultaneous destruction of the B-C match and the creation of a new A-C match instead. While we cannot adjust directly for these flows in the absence of an exhaustive corporate M&A database for France, we can show that the M&A-induced flows represent a negligible fraction of our tabulated measures. We estimate the existence of fewer than 40,000 instances of firm consolidations in France over the period 1999-2018 through Bureau Van Dijk's Zephyr database, the most comprehensive dataset available to us. 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 considering only 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 that a conservative upper bound for the share of M&A-induced flows is around 5 to 6%. Finally, we note that our analysis is immune from other types of activity leading to ownership or name changes for standalone companies, given that their 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 not driven simply by threshold-crossing increases or declines in credit, which can mechanically generate a positive correlation between extensive and intensive 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

[18] 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 across all acquirers.

for an effective relationship separation only if a bank-firm match has been inactive (i.e., absent from the SCR database) for four consecutive 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 the average credit supplied at the time of creation or destruction of credit relationships hovers around EUR 500,000, about seven to eight times higher than the reporting thresholds, which further mitigates the extent of any related bias. The Online Appendix reports robustness tests associated with the reporting threshold.

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 has 802 distinct borrowing firms with an 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.

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 serviced 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, as seen in Panel (a) of Figure 4. We see that the percentage share of long-term credit (over total credit exposure) surprisingly increases while the share of short-term credit declines during crises, which potentially reduces banks' ability to adjust their credit exposure.

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.[19] Tabulating the weighted average

[19] This is in fact a lower-bound estimate, as we assign a duration of 0 to all bank-firm matches existing in 1998Q1, the starting date of the sample. We also do not count quarters in which the bank-firm match may be missing from the SCR

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 relationships classified as those with durations of below and above two years, in order to have a better sense of how the distribution of relationship durations evolves over time. Panel (b) in Figure 4 shows the steadily decline the fraction of relationships with duration below two years, consistent with a lower rate of bank-firm destruction.[20]

Credit exposures associated with newly created (destroyed) relationships, account for 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 (or previously supplied to exiting firms) is procyclical, 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.

3 Properties of Credit Relationship Flows

We now analyze the properties of credit relationship flows. Here, 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 5a exhibits the aggregate flow patterns. Gross credit relationship flows are inherent to credit markets and exhibit large magnitudes relative to the underlying net flows. 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 flows appear to closely track each other throughout the sample period. This observation further illustrates that the substantial process of credit reshuffling across financial institutions and borrowers is continuously reshaping credit markets. We also note that both gross flows exhibit downward trends, with quarterly flow rates of relationship creation and destruction declining from about 8.6% to 6% and from 6.8% to 5.8%, respectively, over the sample period.

when its credit exposure level drops below the reporting threshold.

[20] We select this threshold because the data show a distinct behavior for very young relationships relative to the rest. The two-year threshold is also chosen mainly so as to keep the longest possible time series.

3.2 Cyclical Properties

We 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. Figure 5b presents the corresponding cyclical deviations from the HP trend. We also tabulate the volatility, autocorrelation, and correlation with respect to log-growth of GDP, aggregate credit, and relationship capital, for each variable of interest. Table 2 formalizes these results.

First, we establish that creation flows (measured in levels or rates) are two to three times as volatile as their destruction counterpart. 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 (0.43), aggregate credit (0.47), and relationship capital (0.64). Conversely, destruction rates exhibit only a moderately negative correlation with GDP (-0.26), aggregate credit (-0.14), and relationship capital (-0.26). 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, n_t, using the following decomposition:

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

where $\gamma_t = \frac{\Gamma_t}{N_{t-1}}$ and $\delta_t = \frac{\Delta_t}{N_{t-1}}$ are the creation and destruction rates, respectively, and $n_t = \gamma_t - \delta_t$.

We show that positive flows account for about 84% of the variation in net flows while negative flows account for only about 16%. Thus, the creation margin is the key variable of adjustment for relationship capital, as banks may have limited control over destruction flows. This result is robust across sample periods, such as pre- and post- 2008.[21] It confirms earlier findings in Boualam (2018) for the U.S., based on Dealscan data, but disagrees with that reported in Dell'Ariccia and Garibaldi (2005) and Herrera, Kolar and Minetti (2011), who use bank-level and loan-level data, respectively.[22,23]

[21] The relative importance of gross flows is also visible in the scatter plot in Figure B.7 in the Online Appendix.

[22] 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.

[23] 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)).

3.3 What Drives the Creation and Destruction of Credit Relationships?

Figure 6 presents the decomposition of creation and destruction of credit matches as follows:

- Creation flows: (i) bank switches and multi-bank firms experiencing a relationship gain ("positive reallocation") and (ii) 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 (multiple) pre-existing relationship(s). We also choose to report bank switches along with relationship gains/losses, as some firms appear to switch from one lender to another gradually, generating transitory periods where 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 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. Furthermore, despite the substantial volume of their gross flows, incumbent borrowers who are either switching or adding/dropping credit relationships have net flows comprising only about one fourth the volume of those exhibited by 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., the 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.[24] While the flows of entrant firms and those that obtain credit for the first time are highly correlated (84%), their ratio

[24] Unfortunately, there is no table linking firm identifiers in SIRENE and SCR datasets. Thus, we cannot track the outcome of each individual entrant firm.

exhibits stark dynamics. As shown in Figure 7, 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.[25]

3.4 Cross-sectional Decomposition at the Relationship Level

We further uncover the determinants behind gross flow fluctuations by analyzing the cross-section of credit relationships with regards to key characteristics, namely (i) credit exposure, (ii) credit type and maturity, and (iii) duration. Figure 8 shows the times series associated with gross flows and Table 3 presents the results pertaining to their cyclical properties.[26]

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.[27] 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) account for about 61%, 19%, 10%, and 10% of total relationships, respectively. 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 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 credit fluctuations 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. We classify all credit lines within one category, given the limited availability of information about their maturity.[28] We observe that 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

[25] 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.

[26] The cross-sectional properties at the firm- and bank-level are reported in Boualam and Mazet-Sonilhac (2022).

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

[28] 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.

credit types offer more 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 flows remain relatively stable.

Decomposition by Relationship Duration. We examine the effect of relationship duration on outflows. 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 years. The average shares associated with each category are 17%, 16%, 26%, and 41%, respectively. While outflows appear to increase across all categories during most recessions (one exception is a decline in outflows for one- to two-year 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. This is, for example, consistent with Bolton et al. (2016) who highlight that relationship borrowers are better shielded from financial shocks relative to transaction borrowers. These credit relationships are also potentially more difficult to initiate, as their inflow rates are substantially lower. These findings are not necessarily surprising in light of the positive relationship between duration and credit size and the negative relationship between duration and separation probability.[29] As a result, the gross flow 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 size, type, maturity, and duration. Indeed, it may be easier to sever a young or small bank-firm match if the lost value from such a relationship is relatively minimal. Similarly, it is easier to approve relatively small loans if this marginally impacts the credit and/or counterparty risk faced by the bank.

4 How Do Banks Adjust Their Credit Supply Along Extensive and Intensive Margins?

What levers do banks use to adjust their credit supply? What is the relative importance of extensive and intensive margins in credit fluctuations? These questions are inherent to the macro-finance literature, yet they have surprisingly received little attention. In this section, we attempt to address them by exploring two complementary decompositions of credit variations that account for different definitions of each margin. The first decomposition is the simplest possible raw decomposition and treats all bor-

[29]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.

rowers as homogenous, in which case the extensive and intensive margins are defined as the number of credit relationships (i.e., relationship capital) and average credit per match, respectively. The second decomposition goes one step forward and accounts for credit amount differences observed across incumbent borrowers and those involved in new or severed relationships. In this case, the extensive margin is defined as reflecting credit flows related to new and severed relationships, while the intensive margin captures flows associated with remaining incumbent borrowers.

In both decompositions, we establish that accounting for the extensive margin is critical for the proper inference of bank lending behavior in the aftermath of an aggregate shock or a new policy implementation. Thus, grasping and measuring the channel through which market participants form or sever matches is key to understanding credit dynamics.

4.1 Simple Credit Decomposition (Decomposition 1)

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 9 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 through 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.[30] 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 to boost 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 the 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 10a 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 spirit of Fujita and Ramey (2009) and formally quantify the contribution of each margin, as follows:

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

[30] 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.

Ultimately, we can write:

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

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

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

$$\Delta\log(N_t) = \log(1 + n_t) \simeq 1 + n_t = 1 + \gamma_t - \delta_t. \tag{7}$$

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:

$$\text{var}(\log(1 + n_t)) \simeq \text{var}(n_t) \simeq \text{cov}(\gamma_t, n_t) + \text{cov}(-\delta_t, n_t). \tag{8}$$

Thus, we obtain:

$$\begin{aligned}\beta_{Ext} &\simeq \frac{\text{cov}(\Delta\log(N_t), \Delta\log(C_t))}{\text{var}(\Delta\log(C_t))} \\ &= \underbrace{\frac{\text{cov}(\gamma_t, \Delta\log(C_t))}{\text{var}(\Delta\log(C_t))}}_{\beta_c} + \underbrace{\frac{\text{cov}(-\delta_t, \Delta\log(C_t))}{\text{var}(\Delta\log(C_t))}}_{\beta_d}.\end{aligned}$$

Panel A in Table 5 reports the results of this variance decomposition. The intensive margin accounts for 73% of the total credit variation while the extensive margin accounts for the remaining 27%. In addition, positive flows drive the bulk of the variation in the extensive margin, while negative flows are much less important. With the first-difference decomposition, we also note that the contribution of negative flows reduces, rather than increases, the variance of credit, as gross flows trend downward throughout the sample period. Once we detrend flow variables, we see that negative flows have a negligible impact on the extensive margin and aggregate credit more generally.

4.3.2 HP Filter Approach

We complement these results by studying cyclical deviations from HP trends. Table 4 reports the correlation structure while Figure 10 illustrates the evolution of the two margins for both the first-difference and HP filter approaches.[31] As shown earlier, the relative contributions are about one quarter for the extensive margin and three quarters for the intensive margin (Panel B in Table 5). We highlight 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 extensive and intensive 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 Alternative Decomposition: Incumbent vs. New and Severed Credit Relationships and the Importance of the Sub-extensive Margin (Decomposition 2)

Next, we complement our first decomposition with an alternative and more refined version that accounts 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 extensive and intensive margins.

In order to justify the role of the sub-extensive margin, we first show in Figure 11 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.[32]

We denote by N^ϵ, and $\bar{c}^\epsilon$, with $\epsilon \in \{\iota, \nu, \sigma\}$, the number of relationships and the average credit associated with incumbent (ι), new (ν), and severed (σ) 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:

$$\begin{aligned} C_t &= N^\iota_{t+1}\bar{c}^\iota_t + N^s_{t+1}\bar{c}^\sigma_{t+1} \\ C_{t+1} &= N^\iota_{t+1}\bar{c}^\iota_{t+1} + N^n_{t+1}\bar{c}^n_{t+1}, \end{aligned}$$

[31] While the decomposition into extensive/intensive margins remains straightforward, disentangling the respective effects of gross relationship flows requires additional derivations and approximations, detailed in the Online Appendix.

[32] These observations are consistent with credit that is increasing, and separation probability that is decreasing with relationship duration, as we show in Figure B.3 in the Online Appendix.

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

$$\Delta C_{t+1} = C_{t+1} - C_t \quad = \quad N^{\iota}_{t+1}\Delta\bar{c}^{\iota}_{t+1} + N^{\nu}_{t+1}\bar{c}^{\nu}_{t+1} - N^{\sigma}_{t+1}\bar{c}^{\sigma}_{t+1}. \tag{9}$$

With $\alpha^{\nu}_t = \frac{N^{\nu}_t}{N^{\iota}_t}$, $\alpha^{\sigma}_t = \frac{N^{\sigma}_t}{N^{\iota}_t}$, $c^{\nu}_t = \frac{\bar{c}^{\nu}_t}{\bar{c}^{\iota}_t}$, and $c^{\sigma}_t = \frac{\bar{c}^{\sigma}_t}{\bar{c}^{\iota}_{t-1}}$, we can write the counterpart to equation (5) as:

$$\Delta\log(C_{t+1}) \quad = \quad \underbrace{\Delta\log(\bar{c}^{\iota}_{t+1})}_{\text{Incumbent bank-firm effect}} + \underbrace{\log(1+\alpha^{\nu}_{t+1}c^{\nu}_{t+1})}_{\text{New bank-firm effect}} - \underbrace{\log(1+\alpha^{\sigma}_{t+1}c^{\sigma}_{t+1})}_{\text{Severed bank-firm effect}}. \tag{10}$$

We decompose the variance in aggregate credit, in terms of an incumbent relationship effect (intensive margin), and a new and severed relationship effects, which jointly account for the extensive margin:

$$\begin{aligned} \text{var}(\Delta\log(C_t)) \quad = \quad & \text{cov}(\Delta\log(\bar{c}^{\iota}_{t+1}), \Delta\log(C_t)) \\ & + \text{cov}(\log(1+\alpha^{\nu}_{t+1}c^{\nu}_{t+1}), \Delta\log(C_t)) \\ & + \text{cov}(-\log(1+\alpha^{\sigma}_{t+1}c^{\sigma}_{t+1}), \Delta\log(C_t)). \end{aligned} \tag{11}$$

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

$$\beta_{Incumbent} \quad = \quad \frac{\text{cov}(\Delta\log(\bar{c}^{\iota}_{t+1}), \Delta\log(C_t))}{\text{var}(\Delta\log(C_t))}; \tag{12}$$

$$\beta_{New} \quad = \quad \frac{\text{cov}(\log(1+\alpha^{\nu}_{t+1}c^{\nu}_{t+1}), \Delta\log(C_t))}{\text{var}(\Delta\log(C_t))} \simeq \frac{\text{cov}(\alpha^{\nu}_{t+1}c^{\nu}_{t+1}, \Delta\log(C_t))}{\text{var}(\Delta\log(C_t))}; \tag{13}$$

$$\beta_{Severed} \quad = \quad \frac{\text{cov}(-\log(1+\alpha^{\sigma}_{t+1}c^{\sigma}_{t+1}), \Delta\log(C_t))}{\text{var}(\Delta\log(C_t))} \simeq \frac{\text{cov}(-\alpha^{\sigma}_{t+1}c^{\sigma}_{t+1}, \Delta\log(C_t))}{\text{var}(\Delta\log(C_t))}, \tag{14}$$

with $\beta_{Incumbent} + \beta_{New} + \beta_{Severed} = 1$.

Figure 12 reports the corresponding time series, and Panel B in Table 5 reports the decomposition results.[34] The results for this decomposition 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 confirm as well the

[33] 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 Online Appendix.

[34] Section C.3 in the Online Appendix presents a third decomposition (referred to as "gross intensive credit flows"), which further disentangles the positive and negative flows within the intensive margin. Its results (for both first-difference and HP filter approaches) are reported in Table C.1 and are overall consistent with the ones presented in this section.

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 procyclical 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. Through our first decomposition, we estimate that such contribution is on the order of one quarter. When we also take into account the extent of heterogeneity (in terms of credit size) existing between incumbent and new or severed credit relationships, the relative contribution of the extensive margin becomes even larger and jumps to about one half. This additional variation stemming from the sub-extensive margin is informative about the sources of financial constraints faced by unfunded firms. In particular, it highlights that borrowers may face two layers of uncertainty and constraints when searching for credit, inline with the theory in Boualam (2018). For example, at the onset of a crisis, those that are unfunded not only have more difficulty forming new credit relationships but also only obtain relatively smaller credit amounts upon a match.

5 Anatomy of a Credit Crisis and Recovery

We have so far highlighted the importance of both extensive and intensive margins in 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 economic downturns with a focus on the second decomposition approach. 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. Figure 13 shows the unconditional results while Figure 14 zooms into each recession period separately. The aggregate credit time series we report corresponds to the sum of the detrended extensive and intensive margins. Here, all variables of interest are normalized to 0 at the onset of a recession and their dynamics are then reported over the subsequent three years.

We see that aggregate credit gradually declines on average to about 7% three years after the quarter of recession onset. This decline is equitably due to both extensive and intensive margins, which fall by about 3.5% each. Interestingly, we show that the intensive margin is the main driver of aggregate credit decline in the short-run, while the contribution of the extensive margin is concentrated between the fifth and twelfth quarters. Both margins appear to be particularly persistent and start reverting back toward pre-crisis levels only after about three-and-a-half years.

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 halfway from their pre-crisis level after seven to eight quarters. The persistently low level of credit supplied to newly formed relationships further amplifies the role of the creation margin during crisis and recovery periods. Conversely, outflows observe only a modest and short-lived increase in downturns. The magnitude of their change is roughly one-sixth that of inflows and they revert back to their pre-crisis levels in about four quarters. Furthermore, the relationships severed during downturns in general consist of smaller loans relative to normal periods, which further mitigate the impact of the credit destruction component.

When we zoom into each recession separately, we observe that the credit declines experienced have different origins, namely: (i) the extensive margin as in the crisis of 2008-2009, (ii) a combination of extensive and intensive margins as in 2001-2003, and (iii) the intensive margin as in 2012-2013 and 2014-2016.[35] For example, in 2001-2003, when aggregate credit fell by about 12 log-points over the ten quarters following its peak, the intensive margin declined by eight log-points, while the extensive margin declined only by four log-points. Conversely, the credit decline of about five log-points observed in 2008-2009 was explained principally by the four log-point decline in the extensive margin, while the intensive margin component experience an increase of up to one log-point in the first quarters of the crisis. These findings extend results in Ivashina and Scharfstein (2010) who focus only on commercial loans to large borrowers in the U.S. and show that the significant decline in new lending was accompanied with drawdowns from pre-committed credit lines during the financial crisis. Importantly, it confirms the importance of distinguishing the effect experienced by incumbent and new/severed borrowers.

6 The Extensive/Intensive Margin Channels of Monetary Policy

In this section, we ask how does monetary policy impact aggregate credit dynamics through the lens of the extensive and intensive margins. While the bank lending channel has been widely analyzed for aggregate credit, only a few studies have specifically discussed the role of the extensive margin and credit composition. For example, Jiménez et al. (2014) investigate the role of the extensive margin by

[35]These results extend to the first credit decomposition, as reported in the Online Appendix.

analyzing the implications for the formation of new relationships, while Greenwald, Krainer and Paul (2021) highlight the distinction between incumbent borrowers who are able to draw down credit lines and other borrowers following monetary tightening.[36] Our analysis complements these studies insofar we argue that disaggregated information is critical to uncover the heterogeneous effects associated with credit match characteristics. Markedly, we take a long-horizon perspective rather than focus on a particular period, and provide a more complete view of the extensive/intensive margin channels by accounting for both creation and destruction aspects in addition to the sub-extensive component.

We address this question by estimating impulse responses using the local projection methods of Jordà (2005). Throughout this section, we focus on the extensive/intensive margins, as determined by our second decomposition approach, described in section 4.4, and on the effects of monetary policy surprises over a horizon h from zero to eight quarters. Our analysis is first conducted at the aggregate level. We then complement our findings with micro-level results and further investigate how bank characteristics can affect monetary policy transmission along both credit margins.

Let us denote by Y_t the dependant credit variable. The general specification we use is as follows:

$$Y_{t+h} = \alpha_h + \beta_h V_t + u_{t,h}, \tag{15}$$

with V_t, the treatment variable representing the instrument for exogenous variations in the monetary policy stance at time t, and the error term $u_{t,h}$. The estimated coefficients $\{\beta_h\}_{h=1..8}$ determine the cumulative impulse response path of the credit variables of interest following a change in the treatment variable. Given the nature of the credit decomposition (10), the dependent variable Y_{t+h} stands for (i) $\Delta\log(C_{t,t+h}) = \log(C_{t+h}) - \log(C_t)$ for aggregate credit, (ii) $\sum_{l=1}^{h} \log(1+\alpha^n_{t+l}c^n_{t+l}) - \log(1+\alpha^s_{t+l}c^s_{t+l})$ for the extensive margin, and (iii) $\Delta\log(\bar{C}^i_{t,t+h}) = \log(\bar{C}^i_{t+h}) - \log(\bar{C}^i_t)$ for the intensive margin.

6.1 Measurement of Monetary Policy Shocks

Our analysis relies on the Eurozone monetary policy shocks constructed in Jarociński and Karadi (2020) over the period 2002-2018. These shocks are determined building on the high-frequency identification (HFI) methodology established in Gürkaynak, Sack and Swanson (2005). The HFI approach is particularly useful given that short-term monetary policy, as reflected in the Euro Overnight Index Average (EONIA), remained anchored at the zero lower bound for a significant portion of our sample period, and

[36] Jiménez et al. (2020) also show that a credit supply boom leads to increased bank risk-taking through the expansion of credit to new borrowers.

that monetary policy decisions are correlated with macroeconomic conditions. The identified monetary policy shocks combine surprise movements in the three-month to two-year EONIA swap rates. The surprises are tabulated within short intraday windows surrounding policy announcements (30 minutes) and press conferences (90 minutes) following the monetary policy meetings of the European Central Bank's (ECB's) Governing Council. The identification assumes that changes in interest rates and asset prices occurring within these time windows ought to be due solely to monetary policy news.

Furthermore, the ECB's transparent communication may convey substantial information about both monetary policy stance and economic outlook. Such confounding information can lead to counterintuitive results. As a result, Jarociński and Karadi (2020) disentangle these surprises into "purified" monetary policy and central bank information components by exploiting the differentiated reaction of stock market prices using the EURO STOXX 50 index and imposing co-movement restrictions into their VAR specification. The key idea is that positive shocks attributed to "purified" monetary policy generate a positive response to interest rates but a negative one to asset prices, while positive shocks attributed to central bank information generate a positive response for both interest rates and asset prices. Ultimately, our analysis delves extensively into credit responses to monetary policy shocks associated with the"purified" monetary policy surprises.[37] The shocks are aggregated from the ECB meeting to the quarterly frequency to be consistent with the remaining variables in the specification.

6.2 Aggregate Response

We estimate the specification (15) for aggregate credit in addition to its extensive and intensive margin components. Figure 15 reports the impulse response results based on the estimated $\{\beta^h\}_{h=1..8}$.[38] Panel (a) shows that a 100 basis point contractionary monetary policy shock produces a gradual decline in aggregate credit, reaching about 20% after seven quarters. Notably, our findings suggest that the bank lending channel operates through both extensive and intensive margins, albeit with different sensitivities and timing, as shown in Panels (b) and (c). The bulk of the credit variation appears to be driven by the intensive margin in the short run, with the extensive margin's response initially muted. Ultimately, the effect on the extensive margin becomes more prominent between the fourth and eighth quarters. Finally, Panels (d) and (e) report differentiated responses for the creation and destruction components of the

[37] Figure E.1 reports these time series in the Online Appendix. We thank Peter Karadi for sharing these data with us.

[38] We also report the results obtained for the Central Bank information component in the Online Appendix. We also provide further robustness tests. In particular, we highlight that our results are robust to (i) introduction of two lags of monetary policy surprises as controls, and (ii) using shocks constructed in Kerssenfischer (2019), with methodology that notably allows for a wider time window around ECB announcements and uses German Bund futures.

extensive margin. More specifically, we show that monetary policy surprises are channelled initially through the formation of new relationships and only start impacting the destruction side after five to six quarters. This observation further confirms earlier results highlighting the importance of creation flows, given that banks may have limited ability to sever credit relationships featuring long-term loans. One interpretation of the time lag between extensive and intensive margins is that it reflects higher adjustment costs related to search frictions or information asymmetry associated with the creation or destruction of bank-firm matches. As a result, monetary policy easing conducted in the aftermath of a downturn could appear to benefit solely incumbent borrowers through their existing credit relationships, at the expense of first-time borrowers. This may generate inefficiencies in credit allocation and impact small- and medium-size businesses as they delay entry decisions and access to credit.

Easing vs. Tightening Effects. We also test whether credit variable responses are subject to non-linearities conditional on the easing or tightening nature of the shocks using the adjusted specification:

$$Y_{t+h} = \alpha_h + \beta_h^1 \times \delta_T + \beta_h^E V_t + \beta_h^T \delta_T \times V_t + u_{t,h}, \tag{16}$$

with a dummy variable, δ_T, that equals 0 for an easing shock and 1 for a tightening shock; $\{\beta_h^E\}_{h=1..8}$, the estimated response to an easing shock, and $\{\beta_h^T\}_{h=1..8}$, the estimated response to a tightening shock. Figure 16 shows the results. While the effects appear to be roughly of the same order of magnitude, only the responses to tightening shocks are statistically significant. Thus, the overall effect of monetary policy shocks on total credit (-10%) and the extensive margin are mainly driven by the negative effect implied by tightening surprises, as easing surprises generate non-significant changes.[39] These results are in line with Jiménez et al. (2012) who show that tighter monetary conditions affect the extensive margin through a decline in new loans, particularly for banks with lower capital or liquidity ratios.

6.3 Bank-level Response

Next we revisit our impulse response results and analyze micro-level responses using bank-level information. The adjusted specification we use for local projections is as follows:

$$Y_{i,t+h} = \alpha_{i,h} + \beta_h V_t + u_{i,t,h}, \tag{17}$$

[39] This result is particularly strong for the pre-2008 period. In auxiliary results, we show that the simultaneous Long-Term Refinance Operations announcements significantly mitigate the effects of conventional monetary policy surprises.

with V_t, the treatment variable representing the monetary policy shock and the error terms $u_{i,t,h}$.

We estimate the above panel regression (17) and show the estimated cumulative impulse responses in Figure 17.[40] Overall, the estimated $\{\beta^h\}_{h=1..8}$ coefficients (derived based on equal weights across banks) are estimated with tighter confidence intervals, given bank-level heterogeneity. The results are qualitatively in line with those estimated at the aggregate level, with the exception of the destruction component. At the bank level, we find that a 100 basis point contractionary monetary policy shock leads to an average decline in credit of about 38% after seven quarters. This is due overall to a 14% decline in the extensive margin combined with a 24% decline in the intensive margin. The notably different pattern for the destruction component of the extensive margin (Panel (e)) illustrates potentially distinct lending behaviors across the bank size distribution and suggest that smaller banks may respond to monetary policy tightening by severing fewer credit relationships or relationships that feature relatively small credit exposures, as opposed to larger banks.

What is the role of bank characteristics in the transmission of monetary policy shocks? We take advantage of the bank-level approach and investigate the above results by classifying banks into subgroups associated with (i) bank size, (ii) share of long-term loans, and (iii) share of off-balance-sheet credit items. Banks are reclassified on a quarterly basis in below- and above-median groups. We re-estimate our local projection specification (17) and report the corresponding results in Figure 18.

While credit variable responses appear to consistently follow similar paths across all subgroups, the magnitude of the effects can differ substantially. For example, banks that are smaller, with fewer long-term loans, or with more off-balance-sheet credit exposure appear to be twice as reactive to monetary policy changes relative to their counterparts. This effect is visible along the intensive margin across all characteristics. It is all the more stark for the extensive margin given that banks that are larger, with a large share of long-term loans, or with a small share of off-balance-sheet items, exhibit only a muted response, as opposed to a significant decline experienced by their counterparts. Thus, banks that retain sufficient flexibility in their balance sheet may be able to react more swiftly to monetary policy surprises. From a policy perspective, these banks may play a key role during credit recoveries. Indeed, monetary easing rounds in the aftermath of an economic downturn could specifically benefit incumbent borrowers of such banks, all else being equal. In a similar vein, these banks are likely to expand their loan supply along their extensive margin and offer better access to credit for first-time borrowers.

Taken together, our findings show that the extensive margin is critical in the transmission of monetary

[40] The results are qualitatively similar when including bank fixed-effects, as shown in the Online Appendix.

policy to commercial credit. The extensive margin channel we uncover is central for small banks and those with flexible balance sheets and ample lending capacity.

7 Discussion - Credit Reallocation and Theoretical Implications

In light of the above results, we complement our analysis by discussing implications for credit reallocation process and how our flow approach could be useful for our understanding of credit markets overall.

7.1 The Secular Decline in Credit Reallocation

In light of earlier results, we start by highlighting the long-run trend in bank credit reallocation. Given that our analysis is at the bank-firm level, we can draw a more complete picture of the process of credit reallocation relative to previous studies conducted at either the bank level (Dell'Ariccia and Garibaldi (2005)) or the firm level (Herrera, Kolar and Minetti (2011)).

We establish that French credit markets have become much less fluid over the past two decades. As implied by Figure 5, both reallocation (from 15.4% to 11.8%) and excess reallocation (from 13.6% to 11.6%) rates have declined significantly during that period, with the small credit segment and low-duration matches being particularly impacted.

Exploring the determinants of this substantial decline in credit market reallocation is beyond the scope of this paper. However, we elaborate below on potential contributing factors. First, a lower degree of 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 resulting from 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 also be at play in the long run. These include bank consolidation, increased competition, tightened regulatory requirements, securitization, development of secondary markets, and improved creditor protection, and can also relate to innovations in lending technology. For example, easier access to more information, while lowering matching costs, might also prompt more precise screening, and thus to tightened lending standards. This could lead to longer credit search periods for firms, as banks become pickier, but could also generate a lower incidence of destruction of bank-firm pairs as match quality improves.

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 the reallocation slowdown. More specifically, while an increase in duration can add value for a healthy credit relationship, it could also be detrimental in the case of unhealthy ones. The lack of 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, and consequently hamper productivity.

A deeper understanding of the properties and key drivers behind the dynamics of credit reallocation requires a more refined cross-sectional analysis, which we pursue in Boualam and Mazet-Sonilhac (2022).

7.2 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 extensive and intensive margins. Indeed, the macrofinance literature has typically modelled credit dynamics either through the lens of the intensive margin with a focus on the demand-side and firm-specific shocks (e.g., Kiyotaki and Moore (1997) and Bernanke, Gertler and Gilchrist (1999)) or directly from an aggregate standpoint, with a focus on the supply-side and bank net worth and balance sheet constraints (e.g., Gertler and Kiyotaki (2010), Corbae and D'Erasmo (2019)). This means that aggregate credit dynamics are attributed to one particular margin, thus potentially misinterpreting the quantitative relevance of a given channel and the effects of policy prescriptions.

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 tackle the explanation of the finer grain of the credit (re)allocation process and the aggregate implications of long-term financial contracts.[41] These models are also silent about firms' ability to gain credit access or credit rationing, the potential mismatch between demand and supply, and the allocative role of financial intermediaries. Given their quantitative importance, we argue that a successful theory of aggregate credit fluctuations should take into account bank-firm match heterogeneity in addition to both extensive and intensive 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

[41] Papers such as Brunnermeier and Sannikov (2014), Gertler, Kiyotaki and Prestipino (2016), model adjustment costs in order to generate richer dynamics and break the mapping between aggregate credit and balance sheet constraints. More recently, Begenau et al. (2020) introduce an accounting delays related to the speed of loan loss recognition to rationalize slow-moving nature of leverage dynamics, with loans driven by variations in net worth and leverage.

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 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 and 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 bank-firm-specific relationship capital, which can be detrimental to both parties. This is the case, for example, 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 adverse shocks, but that may have some flexibility in partially adjusting their short-term credit and credit lines.

Second, the credit relationship flows we uncover result from firms' and banks' search, approval, and rollover decisions. This provides a novel perspective on the intermediation process in credit markets and the frictions therein. Thus, decisions related to the creation and destruction of credit relationships, but also to credit market entry and exit, may themselves be subject to time-varying costs linked to aggregate or idiosyncratic shocks and frictions hindering swift adjustments.[42]

In the spirit of arguments laid out by Rogerson and Shimer (2011) highlighting the utility of search theory in labor, a similar approach can help make sense of empirical regularities and provide predictions about borrower and credit flows. It can also be useful in terms of the modeling of agents' decisions and can thus provide further understanding of the dynamics of aggregate credit variables that are typically studied. For example, a decline in aggregate credit relationships may be due to the fact that borrowers are not entering credit markets, are not searching intensively, or are simply more picky with respect to lenders and corresponding contractual terms. On the other hand, it can also be due to the fact that banks are implementing 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 banking models abstracting from search.

[42] 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.

Search-and-matching frictions also provide microfoundations for adjustment costs faced by banks along the extensive margin, and thus a relevant framework that can generate some dampening but also further persistence in credit dynamics following adverse aggregate shocks, as it is the case in Boualam (2018). 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.

8 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. It is a first step toward leveraging the richness of credit register data and uncovering the properties and implications of credit relationship flows. While our results are restricted to a single country, France, our empirical approach is also applicable to the study of other markets and countries with similar datasets.

While we focus mostly on establishing stylized facts and identifying the distinctive features of extensive/intensive margins, we believe that fleshing out the potential economic mechanisms behind these dynamics can provide additional connections to the macro-finance literature, and in particular the role played by collateral and bank balance-sheet channels. Indeed, the finding that up to 46% of the variation in aggregate credit is driven by the extensive margin is novel and leads support to theories that can rationalize credit relationship flows and their dynamics. However, our results do not imply that the intensive margin is not important. Rather, we highlight that each margin may respond differently to macroeconomic shocks and have distinct behavior across each crises.

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 complete benchmark for the study of aggregate credit fluctuations. Thus, building models that account for both margins is, in our opinion, critical when thinking about bank credit. We leave the implications of these arguments for future research.

References

Amiti, Mary, and David Weinstein. 2018. "How much do idiosyncratic bank shocks affect investment? Evidence from matched bank-firm loan data." *Journal of Political Economy*, 126(2): 525–587.

Beaumont, Paul, Thibault Libert, and Christophe Hurlin. 2019. "Granular borrowers." Universite Paris-Dauphine Research Paper No. 3391768.

Becker, Bo, and Victoria Ivashina. 2014. "Cyclicality of credit supply: Firm level evidence." *Journal of Monetary Economics*, 62: 76–93.

Becsi, Zsolt, Victor Li, and Ping Wang. 2005. "Heterogeneous borrowers, liquidity, and the search for credit." *Journal of Economic Dynamics and Control*, 29(8): 1331–1360.

Begenau, Juliane, and Tim Landvoigt. 2018. "Financial regulation in a quantitative model of the modern banking system." Available at SSRN 2748206.

Begenau, Juliane, Saki Bigio, Jeremy Majerovitz, and Matias Vieyra. 2020. "A Q-Theory of Banks." *NBER Working Paper w27935.*

Bernanke, Ben, and Mark Gertler. 1989. "Agency costs, net worth, and business fluctuations." *The American Economic Review*, 79(1): 14–31.

Bernanke, Ben S. 1983. "Non-monetary effects of the financial crisis in the propagation of the Great Depression." NBER Working Paper.

Bernanke, Ben S, Mark Gertler, and Simon Gilchrist. 1999. "The financial accelerator in a quantitative business cycle framework." *Handbook of Macroeconomics*, 1: 1341–1393.

Blanchard, Olivier Jean, and Peter Diamond. 1992. "The flow approach to labor markets." *The American Economic Review*, 82(2): 354–359.

Bolton, Patrick, Xavier Freixas, Leonardo Gambacorta, and Paolo Emilio Mistrulli. 2016. "Relationship and transaction lending in a crisis." *The Review of Financial Studies*, 29(10): 2643–2676.

Boot, Arnoud. 2000. "Relationship banking: What do we know?" *Journal of Financial Intermediation*, 9(1): 7–25.

Boualam, Yasser. 2018. "Credit markets and relationship capital." Working Paper.

Boualam, Yasser, and Clement Mazet-Sonilhac. 2022. "Credit market fluidity." Working Paper.

Brunnermeier, Markus K, and Yuliy Sannikov. 2014. "A macroeconomic model with a financial sector." *American Economic Review*, 104(2): 379–421.

Chodorow-Reich, Gabriel. 2014. "The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis." *The Quarterly Journal of Economics*, 129(1): 1–59.

Cieslak, Anna, and Andreas Schrimpf. 2019. "Non-monetary news in central bank communication." *Journal of International Economics*, 118: 293–315.

Contessi, Silvio, and Johanna Francis. 2013. "U.S. commercial bank lending through 2008: Q4: new evidence from gross credit flows." *Economic Inquiry*, 51(1): 428–444.

Corbae, Dean, and Pablo D'Erasmo. 2019. "Capital requirements in a quantitative model of banking industry dynamics." NBER Working Paper No. 25424.

Craig, Ben, and Joseph Haubrich. 2013. "Gross loan flows." *Journal of Money, Credit and Banking*, 45(2-3): 401–421.

Cuciniello, Vincenzo, and Nicola Di Iasio. 2020. "Determinants of the credit cycle: a flow analysis of the extensive margin." *Bank of Italy Temi di Discussione (Working Paper) No. 1266.*

Davis, Steven, and John Haltiwanger. 1992. "Gross job creation, gross job destruction, and employment reallocation." *The Quarterly Journal of Economics*, 107(3): 819–863.

Davis, Steven, and John Haltiwanger. 1999. "Gross job flows." *Handbook of Labor Economics*, 3: 2711–2805.

Davis, Steven, John Haltiwanger, Scott Schuh, et al. 1998. *Job creation and destruction.* Vol. 1, The MIT Press.

Degryse, Hans, Moshe Kim, and Steven Ongena. 2009. *Microeconometrics of banking: methods, applications, and results.* Oxford University Press.

Dell'Ariccia, Giovanni, and Pietro Garibaldi. 2005. "Gross credit flows." *The Review of Economic Studies*, 72(3): 665–685.

Den Haan, Wouter, Garey Ramey, and Joel Watson. 2003. "Liquidity flows and fragility of business enterprises." *Journal of Monetary Economics*, 50(6): 1215–1241.

Duquerroy, Anne, Clément Mazet-Sonilhac, Jean-Stephanen Mesonnier, and Daniel Paravisini. 2022. "Bank Local Specialization." *Banque de France Working Paper Series*, 865.

Fujita, Shigeru, and Garey Ramey. 2009. "The cyclicality of separation and job finding rates." *International Economic Review*, 50(2): 415–430.

Gertler, Mark, and Nobuhiro Kiyotaki. 2010. "Financial intermediation and credit policy in business cycle analysis." In *Handbook of monetary economics.* Vol. 3, 547–599. Elsevier.

Gertler, Mark, Nobuhiro Kiyotaki, and Andrea Prestipino. 2016. "Wholesale banking and bank runs in macroeconomic modeling of financial crises." In *Handbook of Macroeconomics.* Vol. 2, 1345–1425. Elsevier.

Greenstone, Michael, Alexandre Mas, and Hoai-Luu Nguyen. 2020. "Do credit market shocks affect the real economy? Quasi-experimental evidence from the great recession and 'normal' economic times." *American Economic Journal: Economic Policy*, 12(1): 200–225.

Greenwald, Daniel L, John Krainer, and Pascal Paul. 2021. "The credit line channel." Federal Reserve Bank of San Francisco.

Gürkaynak, Refet, Brian Sack, and Eric Swanson. 2005. "Do actions speak louder than words? The response of asset prices to monetary policy actions and statements." *International Journal of Central Banking.*

Herrera, Ana Maria, Marek Kolar, and Raoul Minetti. 2011. "Credit reallocation." *Journal of Monetary Economics*, 58(6-8): 551–563.

Hubbard, Glenn, Kenneth Kuttner, and Darius Palia. 2002. "Are there bank effects in borrowers' costs of funds? Evidence from a matched sample of borrowers and banks." *The Journal of Business*, 75(4): 559–581.

Ivashina, Victoria, and David Scharfstein. 2010. "Bank lending during the financial crisis of 2008." *Journal of Financial Economics*, 97(3): 319–338.

Ivashina, Victoria, Luc Laeven, and Enrique Moral-Benito. 2021. "Loan types and the bank lending channel." *Journal of Monetary Economics*.

Jarociński, Marek, and Peter Karadi. 2020. "Deconstructing monetary policy surprisesthe role of information shocks." *American Economic Journal: Macroeconomics*, 12(2): 1–43.

Jiménez, Gabriel, Atif Mian, José-Luis Peydró, and Jesús Saurina. 2020. "The real effects of the bank lending channel." *Journal of Monetary Economics*, 115: 162–179.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina. 2012. "Credit Supply and Monetary Policy: Identifying the Bank Balance-Sheet Channel with Loan Applications." *American Economic Review*, 102(5): 2301–26.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina. 2014. "Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking?" *Econometrica*, 82(2): 463–505.

Jordà, Òscar. 2005. "Estimation and inference of impulse responses by local projections." *American Economic Review*, 95(1): 161–182.

Kerssenfischer, Mark. 2019. "Information effects of euro area monetary policy: New evidence from high-frequency futures data." Deutsche Bundesbank Discussion Paper.

Khwaja, Asim Ijaz, and Atif Mian. 2008. "Tracing the impact of bank liquidity shocks: Evidence from an emerging market." *American Economic Review*, 98(4): 1413–42.

Kiyotaki, Nobuhiro, and John Moore. 1997. "Credit cycles." *Journal of Political Economy*, 105(2): 211–248.

Lilien, David, and Robert Hall. 1986. "Cyclical fluctuations in the labor market." *Handbook of Labor Economics*, 2(Part C): 1001–1035.

Mazet-Sonilhac, Clément. 2020. "Information frictions in credit markets." Working Paper.

Nakashima, Kiyotaka, and Koji Takahashi. 2018. "The real effects of bank-driven termination of relationships: Evidence from loan-level matched data." *Journal of Financial Stability*, 39: 46–65.

Newey, Whitney, and Kenneth West. 1987. "A Simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix." *Econometrica*, 55(3): 703–708.

Rogerson, Richard, and Robert Shimer. 2011. "Search in macroeconomic models of the labor market." *Handbook of Labor Economics*, 4: 619–700.

Appendix A 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 long-term only	45.71	1.26	42.42	0.61	44.91	0.51
Fraction of short-term only	30.83	3.89	37.77	0.29	25.96	0.34
Fraction of short-term + long-term 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: 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 panel shows the results in rates. All flow variables are detrended using an HP filter with a smoothing parameter of 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)
				A. 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
				B. 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

Table 3: 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 flow variables are detrended using an HP filter with a smoothing parameter of 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)
			A. 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
			B. 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
			C. 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 4: 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 a smoothing parameter of 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).

	A. 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
	B. 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 5: Variance Decomposition: Intensive vs. Extensive Margins

This table reports the results of variance decompositions of aggregate credit fluctuation over the period 1999-2016. The intensive/extensive margin decompositions are derived based on first-differences (Panel A) and log-deviations from trend (Panel B) obtained from an HP filter with a smoothing parameter of 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).

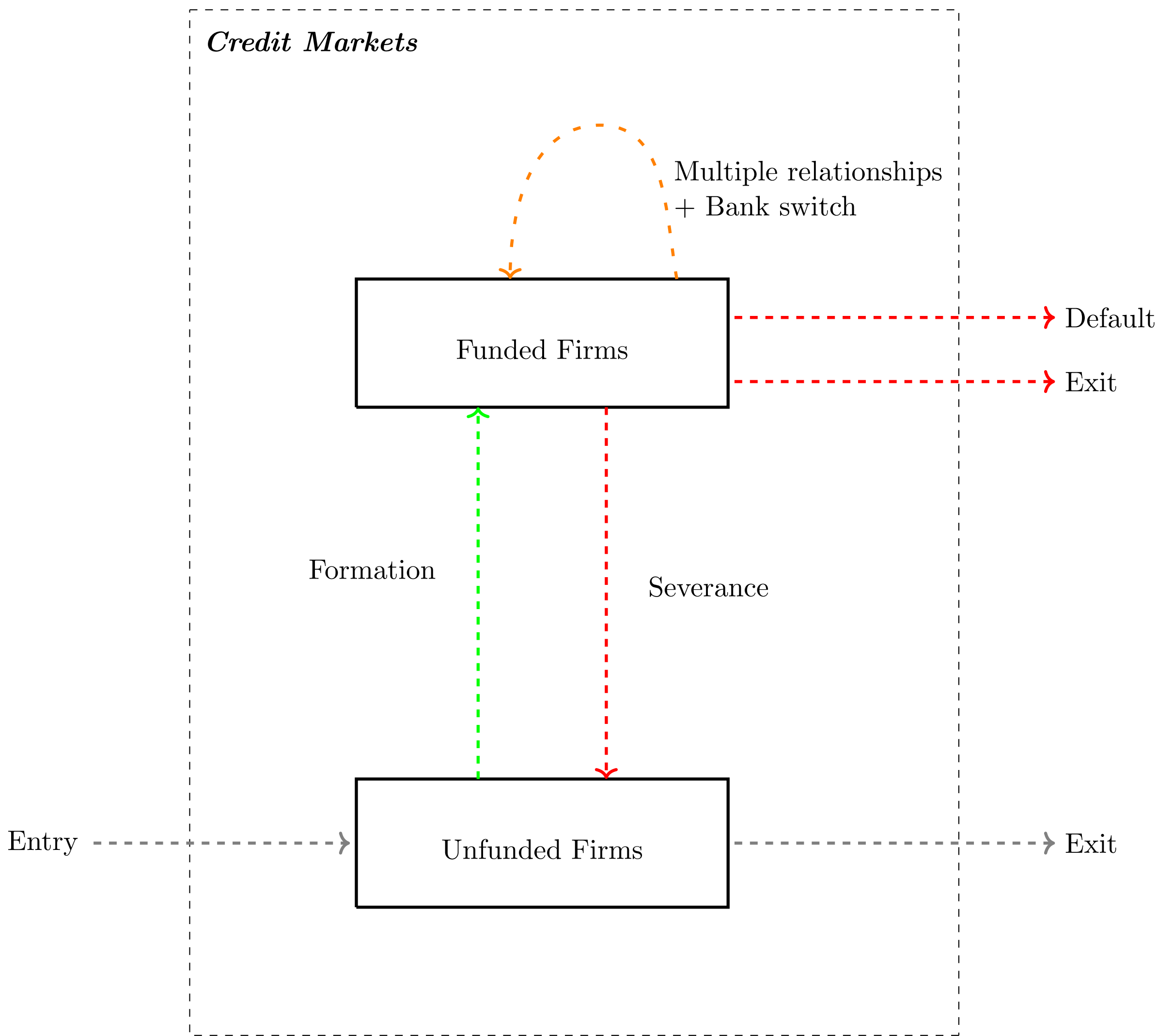
A. Decomposition 1

First-Difference Approach	Intensive Margin	Extensive Margin	
	0.73	0.27	
		Creation Flows	Destruction Flows
		0.43	-0.16
HP Filter Approach	Intensive Margin	Extensive Margin	
	0.76	0.22	
		Creation Flows	Destruction Flows
		0.23	-0.03

B. Decomposition 2

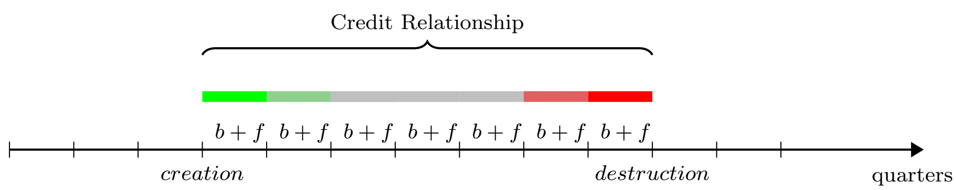
First-Difference Approach	Intensive Margin	Extensive Margin	
	0.54	0.46	
	Incumbent effect	New bank-firm effect	Severed bank-firm effect
	0.54	0.62	-0.17
HP Filter Approach	Intensive Margin	Extensive Margin	
	0.46	0.40	
	Incumbent effect	New bank-firm effect	Severed bank-firm effect
	0.46	0.57	-0.17

Figure 1: The Flow Approach to Credit Markets

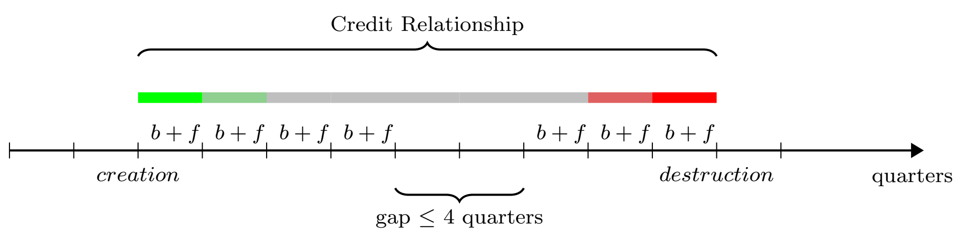


Note: This figure displays the multiple forms of flows associated with unfunded and funded firms within credit markets.

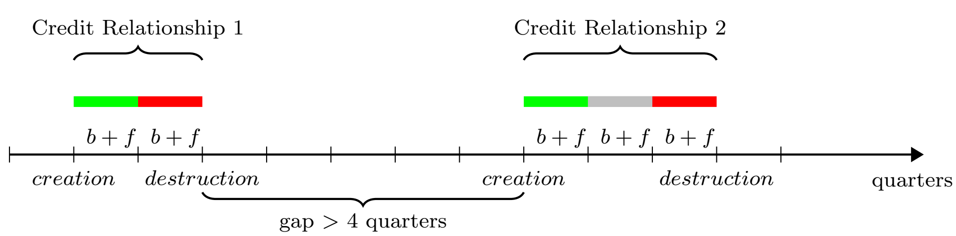
Figure 2: Credit Relationships: Concepts and Measurements



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



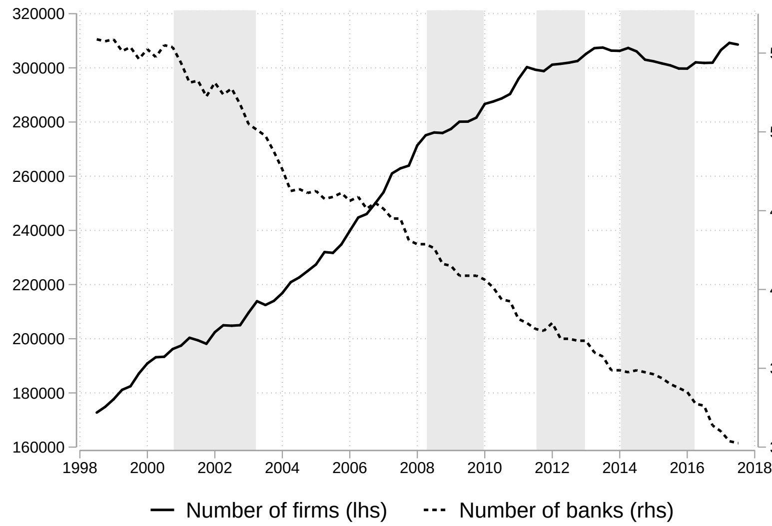
(b) Case 2: Contiguous credit relationship (gap below 4 quarters)



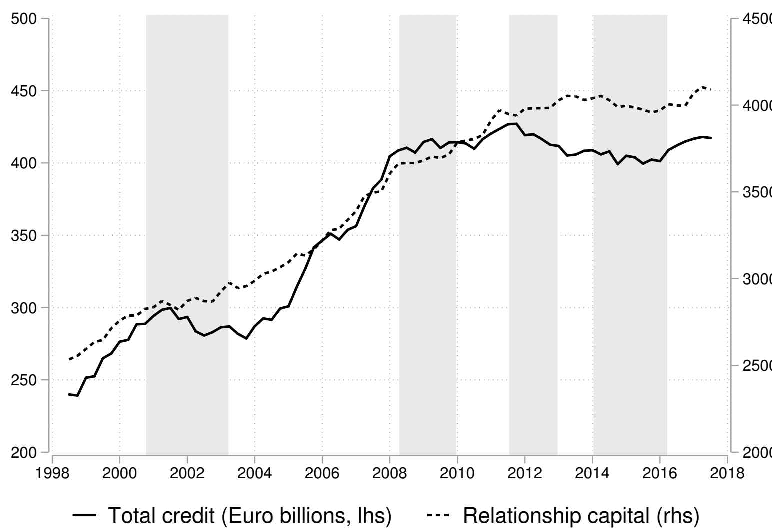
(c) Case 3: Non-contiguous credit relationships (gap exceeding 4 quarters)

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: Evolution of Banks, Firms, Bank-firm Relationships, and Credit



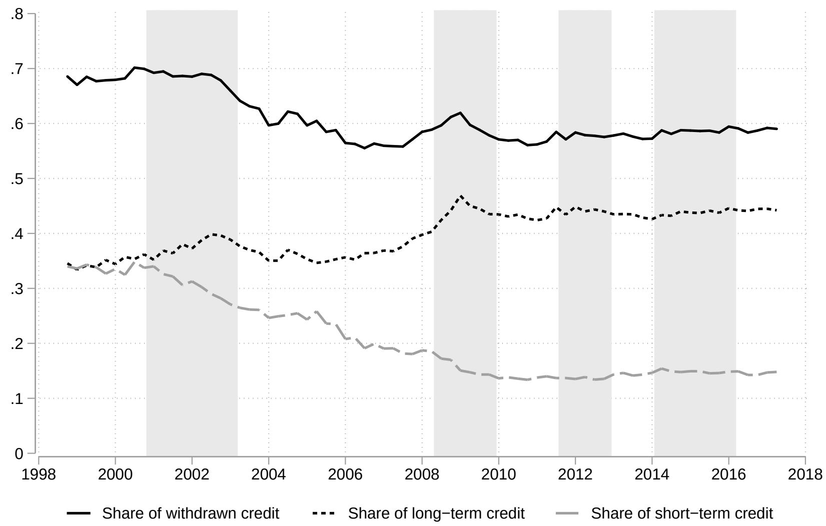
(a) Total banks and firms



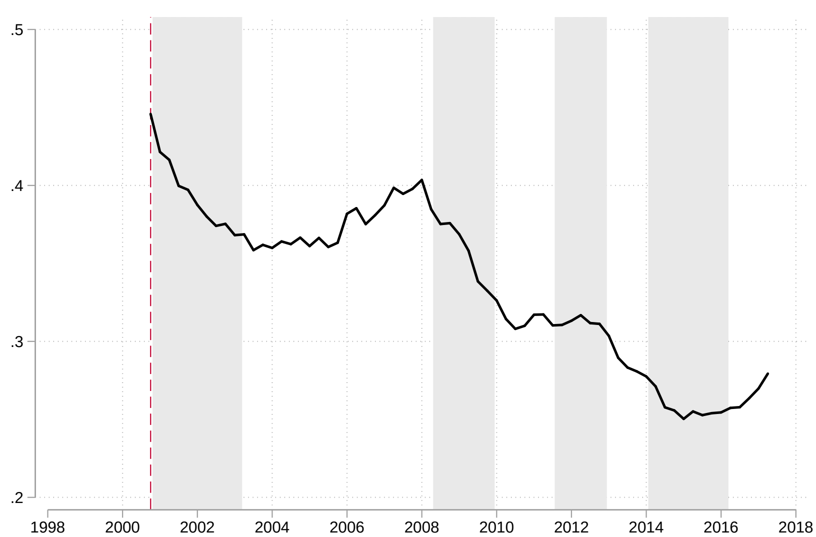
(b) Aggregate credit and number of bank-firm relationships

Notes: Panel (a) shows the evolution of the number of unique firms and active banks. Only those banks and firms involved in credit relationships with credit exposure above the reporting threshold are taken into account. Panel (b) 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. The sample period is 1999-2017 . 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 4: Share of Credit Relationships by Type and Duration



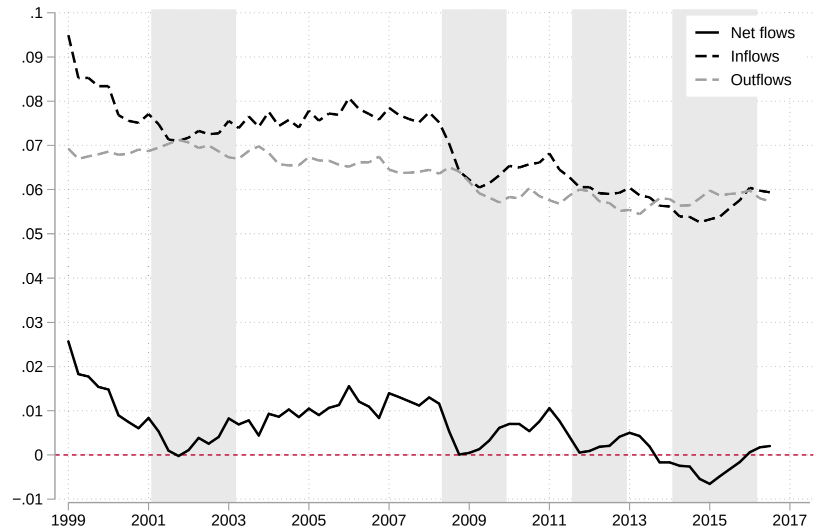
(a) Decomposition by type/maturity



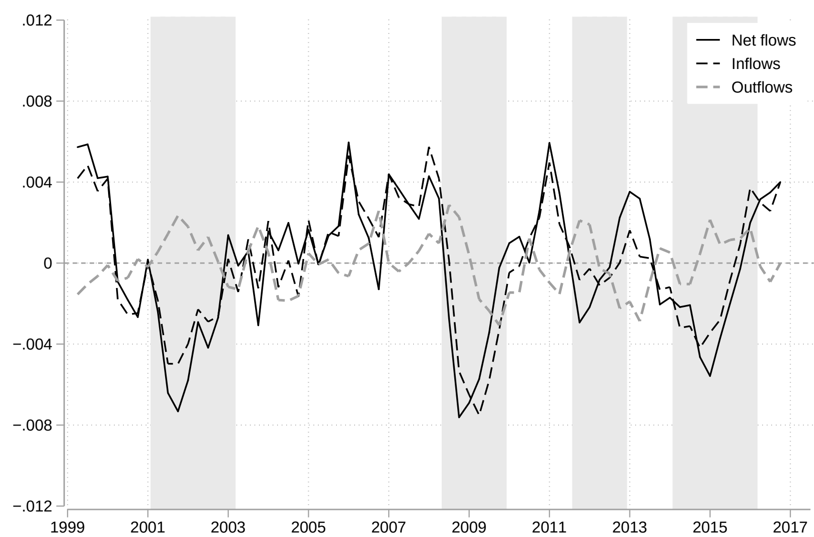
(b) Share of relationships below two-year duration

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 1999-2017. Gray-shaded areas correspond to recession periods.

Figure 5: Credit Relationship Flows



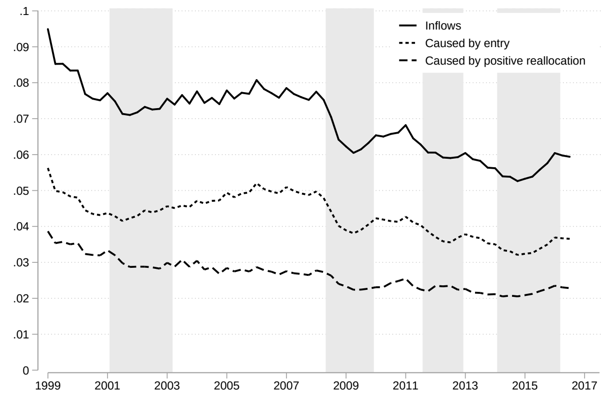
(a) Raw net and gross flows



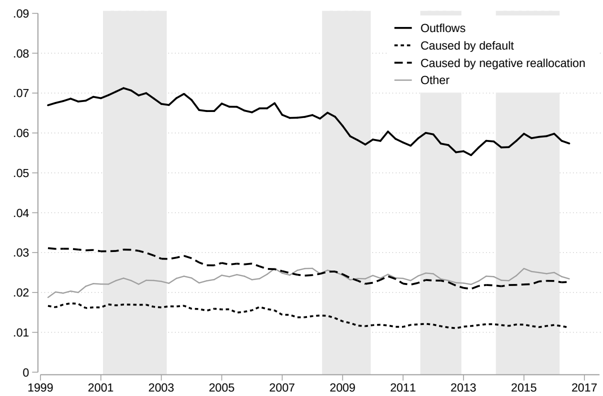
(b) Cyclical deviations of net and gross flows

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 a smoothing parameter of 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.

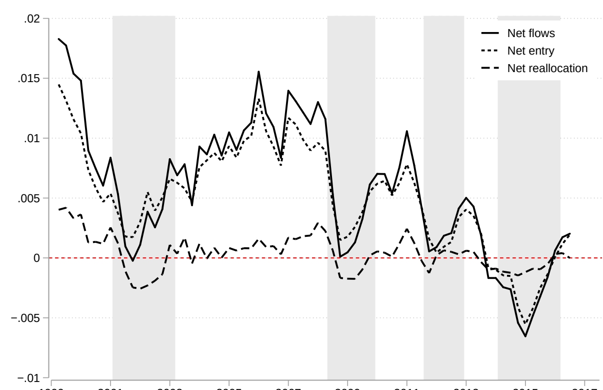
Figure 6: Sources of Relationship Creation and Destruction



(a) Decomposition of inflows



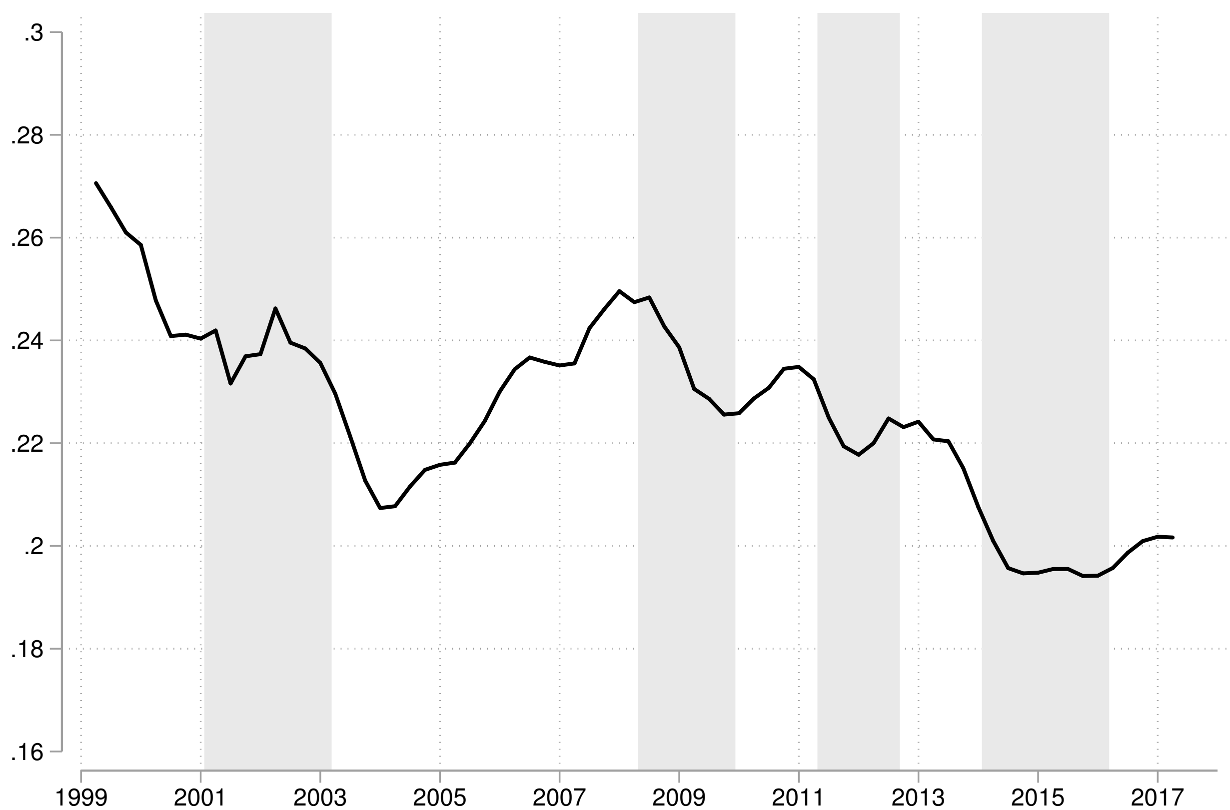
(b) Decomposition of outflows



(c) Decomposition of net flows

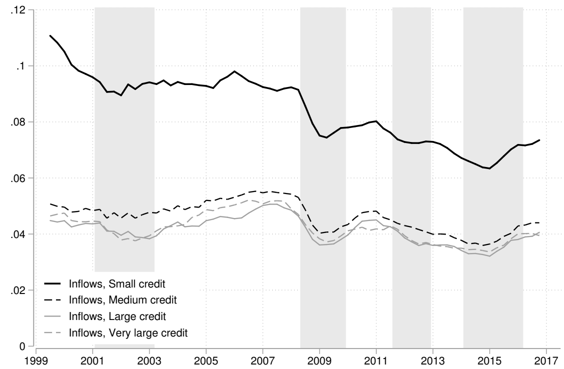
Notes: This figure shows the decomposition of raw creation (Panel (a)), destruction (Panel (b)), and net (Panel (c)) flows due to firms (i) entering or exiting the relationship, (ii) switching borrowers, or (iii) experiencing multi-bank relationship gains or losses. Our sample period is 1999-2016. Results 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 7: First Credit Relationship and Firm Entry

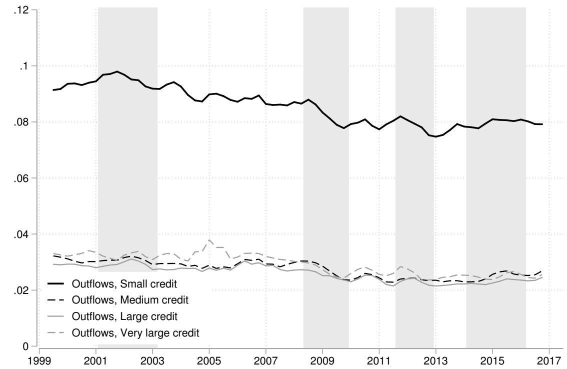


Notes: This figure reports the ratio of first-time borrowers over total number of newly created firms. Our sample period is 1999-2016. Results are based on relationships above the reporting threshold (adjusted for inflation). Gray-shaded areas correspond to recession periods.

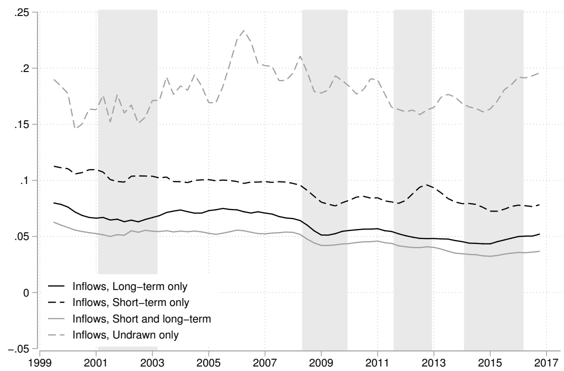
Figure 8: Gross Flows, by Credit Size, Type, and Duration



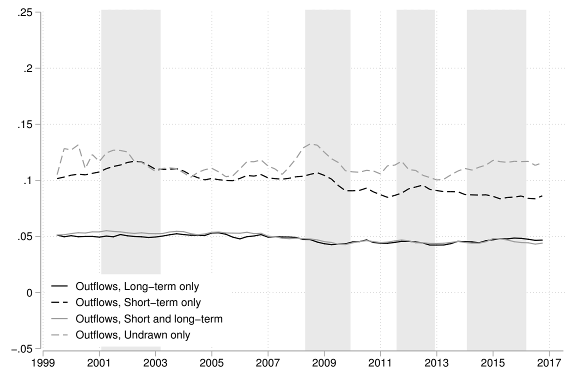
(a) Inflows by credit size



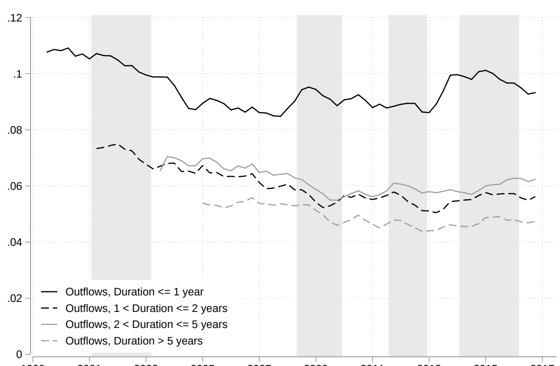
(b) Outflows by credit size



(c) Inflows by credit type



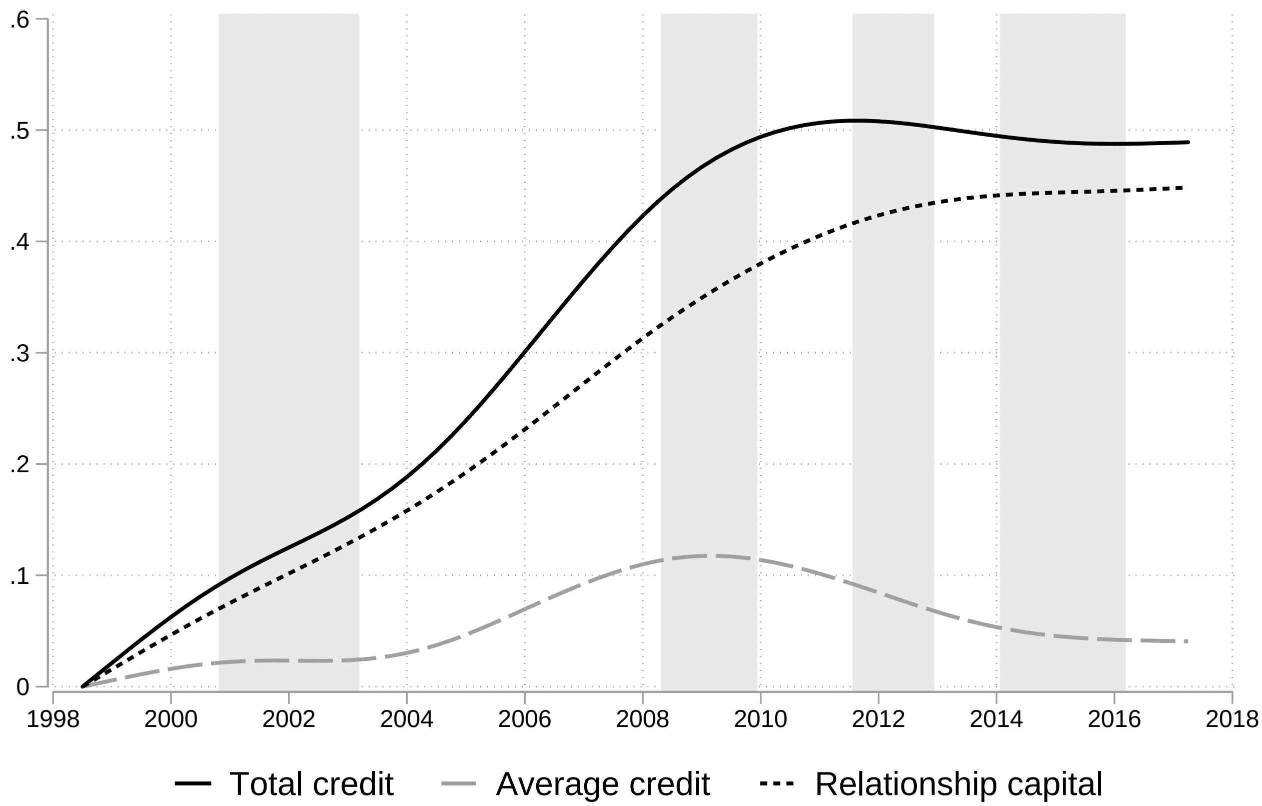
(d) Outflows by credit type



(e) Outflows by relationship duration

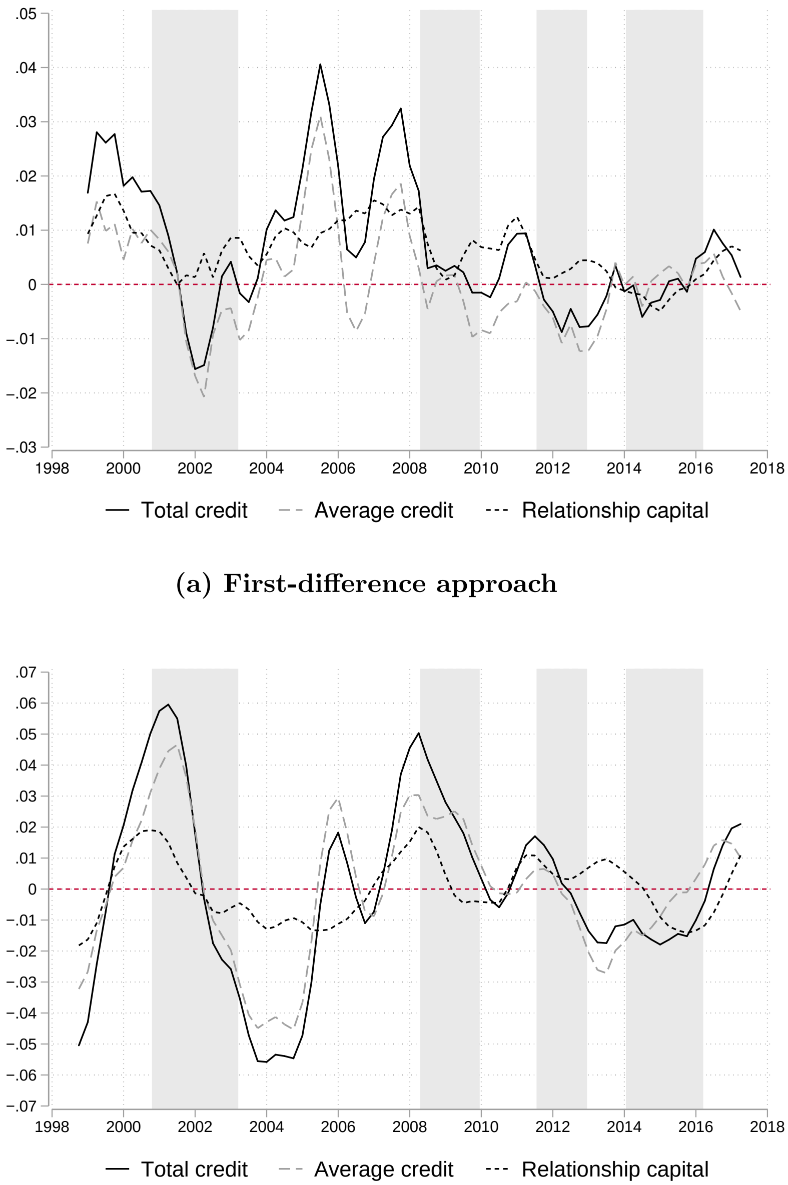
Notes: This figure shows the decomposition of raw creation (left panels) and destruction (right panels), by credit size (Panels (a) & (b)), by type (Panels (c) & (d)), and by relationship duration (Panel (e), for outflows only). Our sample period is 1999-2016. Results are based on relationships above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

Figure 9: Extensive vs. Intensive Margins: Long-run Trends



Notes: This figure reports the trends associated with aggregate credit, average credit, and relationship capital, obtained through the simple decomposition 1. The trends are extracted using an HP filter with a smoothing parameter of 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 1999-2017. Gray-shaded areas correspond to recession periods.

Figure 10: Extensive vs. Intensive Margins of Credit – Decomposition 1

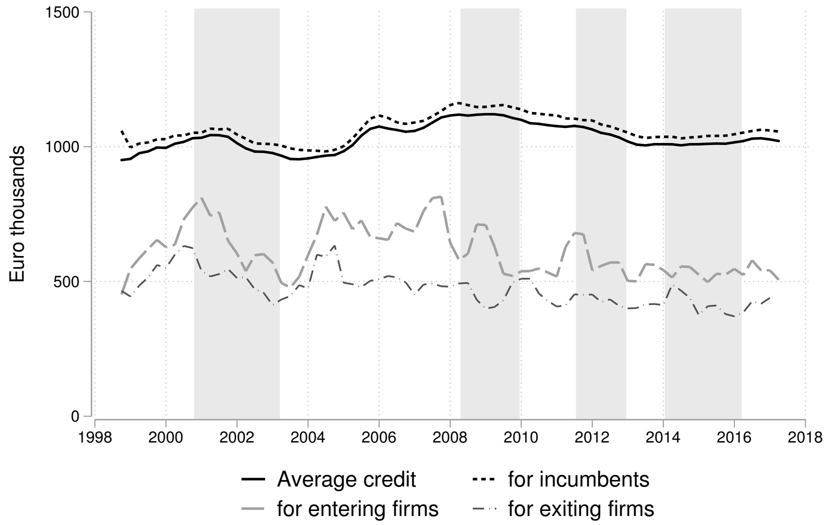


(a) First-difference approach

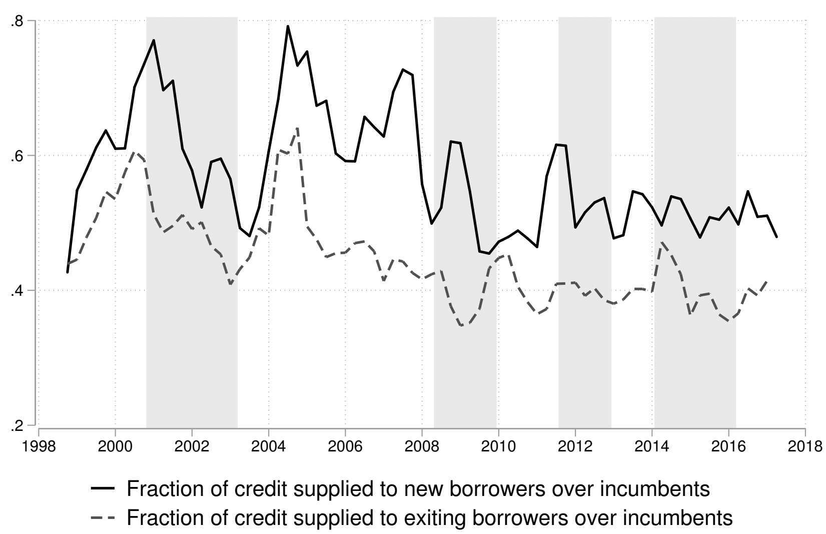
(b) HP Filter approach

Notes: These figures show the log-growth dynamics (Panel (a)) and cyclical deviations (in log, Panel (b)) of aggregate credit (black solid line), average credit per relationship (gray dashed line), and relationship capital (black dashed line), obtained through the simple decomposition 1. 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 11: Credit for Incumbents vs. Entering and Exiting Firms



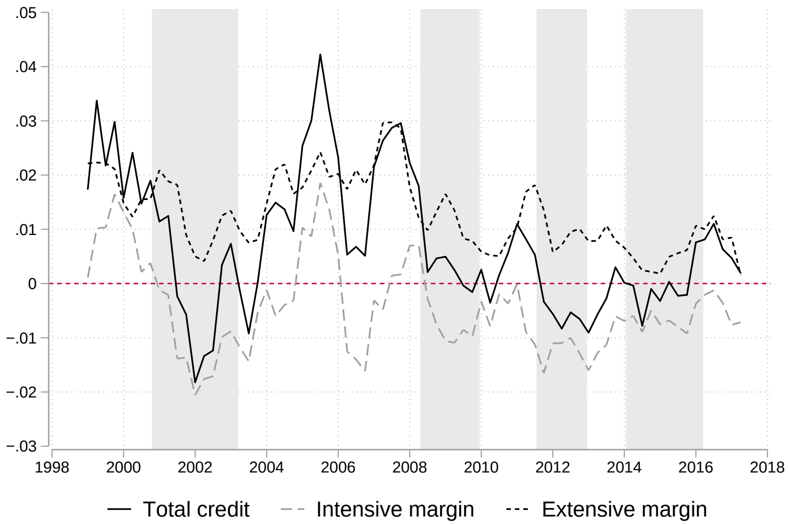
(a) Average credit for incumbents vs. entering and exiting firms



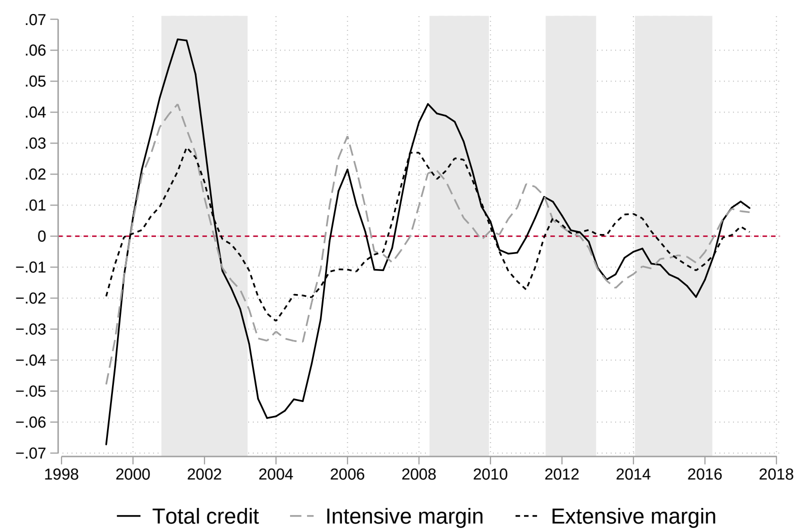
(b) Credit supplied to entering and exiting firms, as a fraction of incumbent credit

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 12: Extensive vs. Intensive Margins of Credit – Decomposition 2



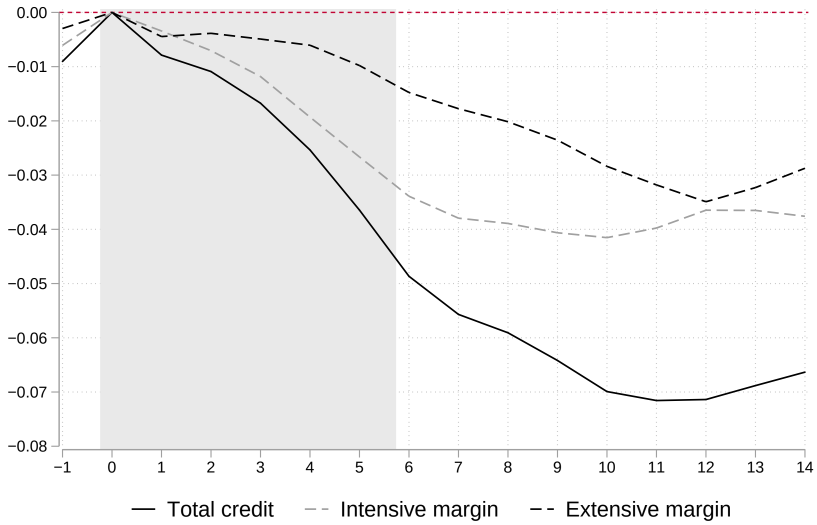
(a) First-difference Approach



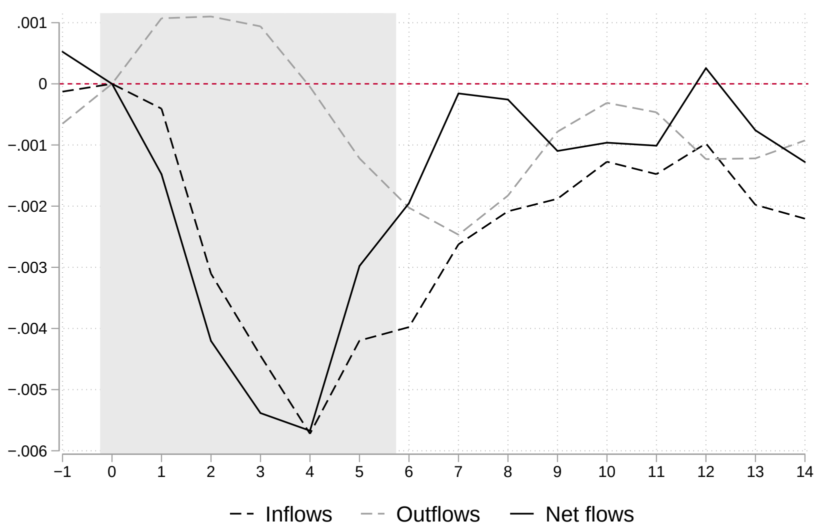
(b) HP Filter Approach

Notes: These figures show the time series of the log-growth dynamics (Panel (a)) cyclical deviations (in log, Panel (b)) for total credit (solid black line), intensive margin (gray dashed line), and extensive margin (black dashed line), obtained through the refined decomposition 2. 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 13: Anatomy of a Crisis: Unconditional Patterns



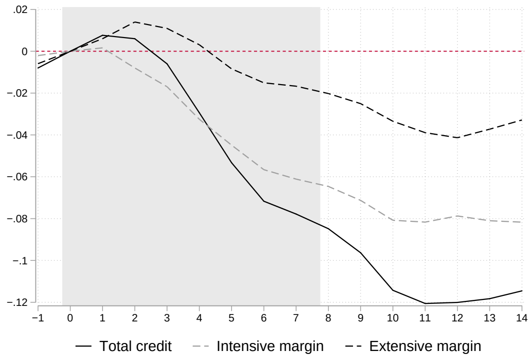
(a) Aggregate variables: credit vs. intensive and extensive margins



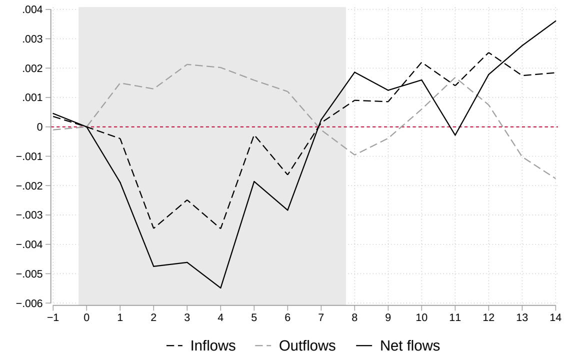
(b) Credit relationship flows: net vs. gross

Notes: These figures report the unconditional evolution of (i) aggregate credit, intensive, and extensive margins capital (top panel), and that of (ii) net and gross flows (bottom panel) over the fourteen quarters following the onset of a recession. The intensive/extensive margins are constructed based on the refined credit decomposition 2 specified in equation (10). The aggregate credit dynamics reported are based on the sum of the extensive and intensive margins. 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 of 1600. Gray-shaded areas correspond to the average recession period.

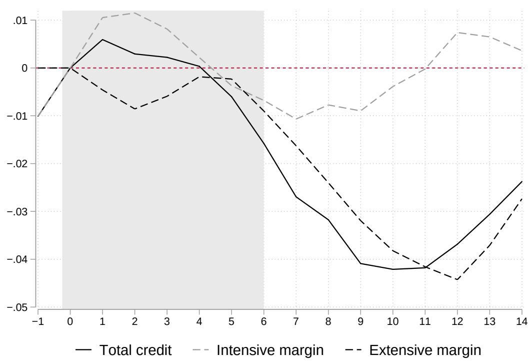
Figure 14: Anatomy of a Crisis: Details



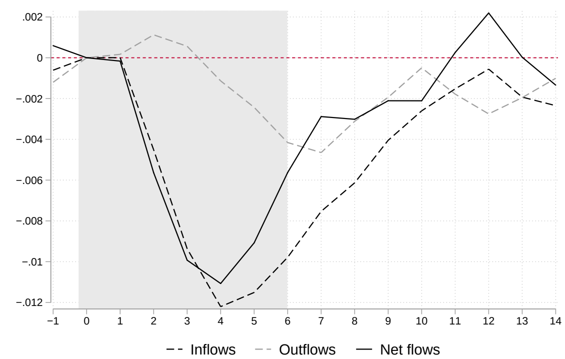
(a) Aggregate variables: 2001-2003



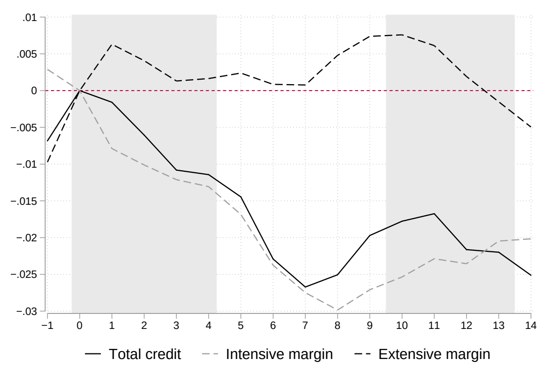
(b) Credit flows: 2001-2003



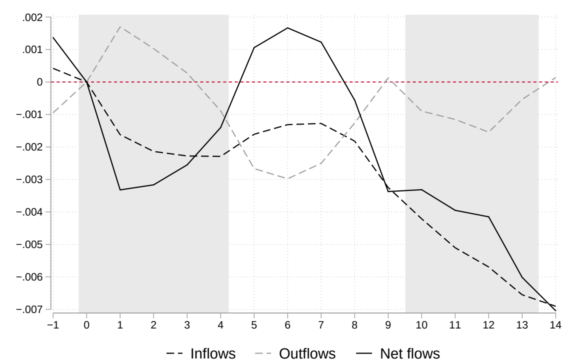
(c) Aggregate variables: 2008-2009



(d) Credit flows: 2008-2009



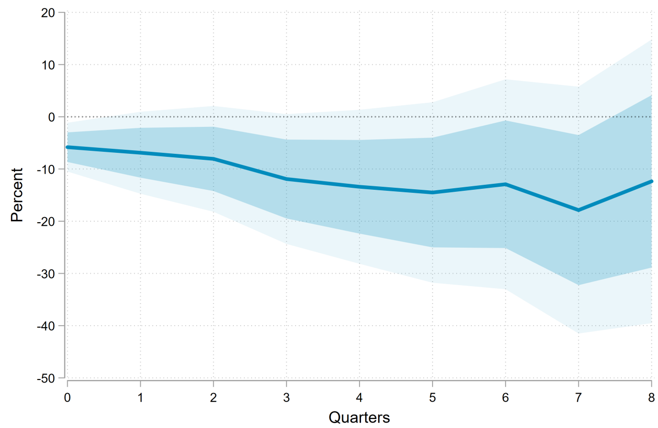
(e) Aggregate variables: 2012-2014



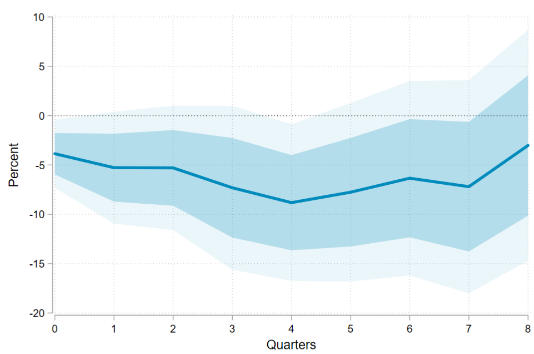
(f) Credit flows: 2012-2014

Notes: These figures report the evolution of (i) aggregate credit, intensive, and extensive margins (left-hand side panels), and (ii) net and gross flows (right-hand side panels) over the fourteen quarters following the onset of each recession. The intensive/extensive margins are constructed based on the refined credit decomposition 2 specified in equation (10). The aggregate credit dynamics reported are based on the sum of the intensive and extensive margins. 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 of 1600. Gray-shaded areas correspond to recession periods.

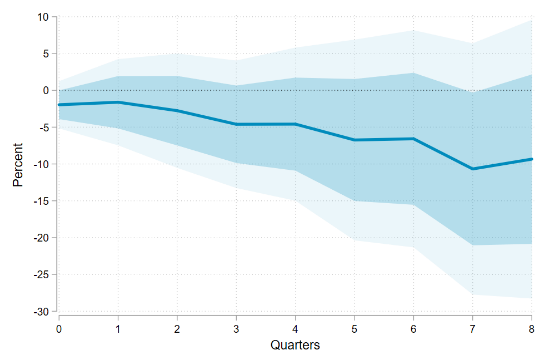
Figure 15: Monetary Policy Transmission and Credit



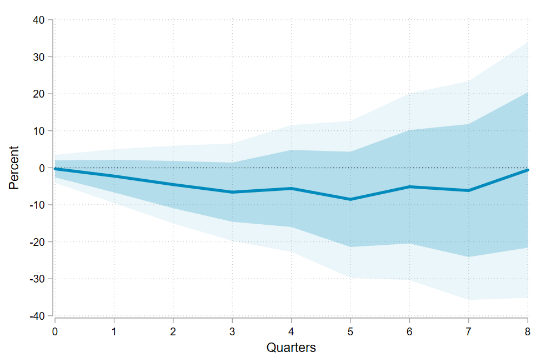
(a) Aggregate credit



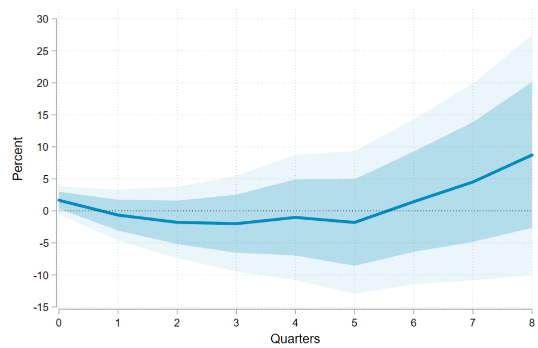
(b) Intensive margin



(c) Extensive margin



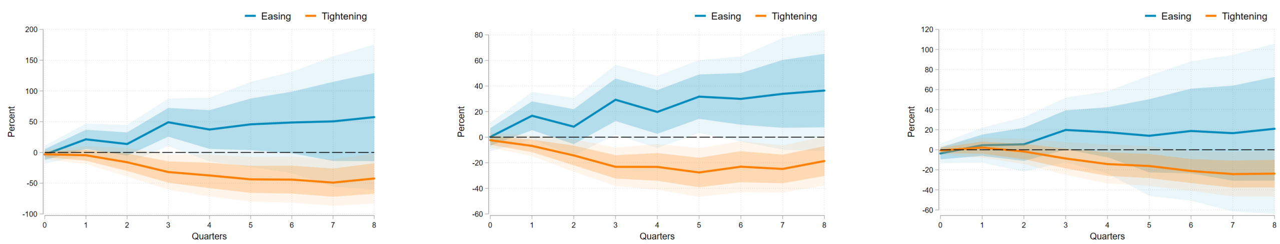
(d) Creation



(e) Destruction

Notes: These figures illustrate impulse responses to a one percentage point contractionary monetary policy shock for (a) aggregate credit, (b) intensive margin, (c) extensive margin, and the corresponding (d) creation and (e) destruction components. The results rely on the refined credit decomposition 2 with the local projection specification described in equation (15) and the "purified" monetary policy surprises from Jarociński and Karadi (2020). The sample period is 2002-2018. The x-axis represents the number of quarters after the shock, and the y-axis is in percent. The blue-shaded areas correspond to the 68% (dark blue) and 90% (light blue) confidence intervals constructed using Newey and West (1987) standard errors.

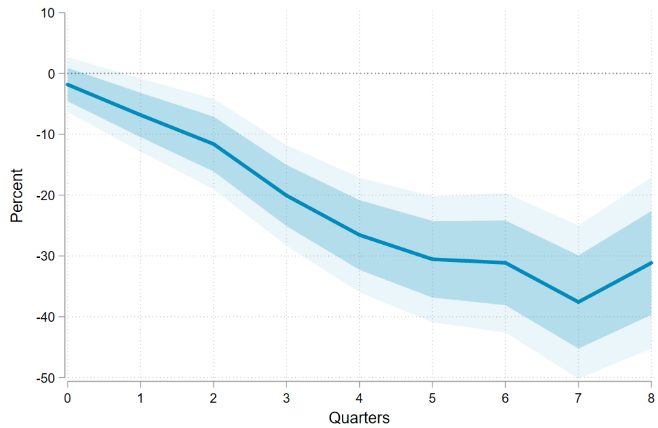
Figure 16: Monetary Policy Transmission and Credit – Easing vs. Tightening



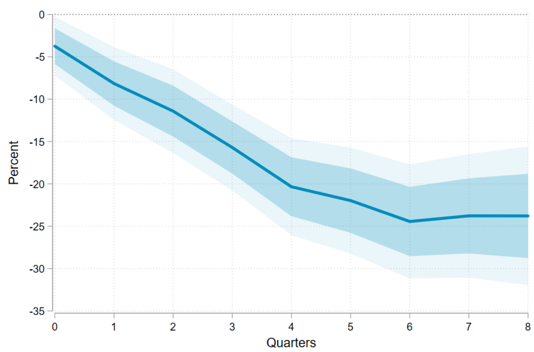
(a) Aggregate credit **(b) Intensive margin** **(c) Extensive margin**

Notes: These figures illustrate impulse responses to a one percentage point contractionary (orange) and expansionary (blue) monetary policy shock for (a) aggregate credit, (b) intensive margin, and (c) extensive margin. The results rely on the refined credit decomposition 2 with the local projection specification described in equation (15) and the "purified" monetary policy surprises from Jarociński and Karadi (2020). The local projections are estimated following the specification described in equation (16). The sample period is 2002-2018. The x-axis represents the number of quarters after the shock, and the y-axis is in percent. The shaded areas correspond to the 68% (dark color) and 90% (light color) confidence intervals constructed using Newey and West (1987) standard errors.

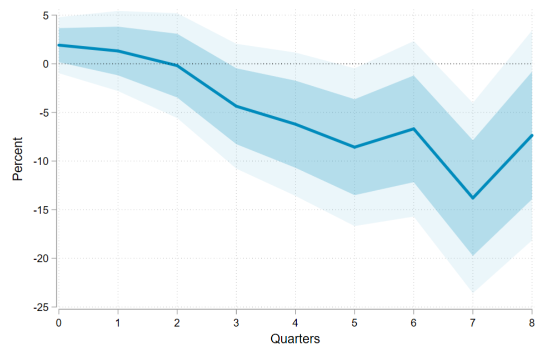
Figure 17: Monetary Policy Transmission and Credit - Bank-level Responses



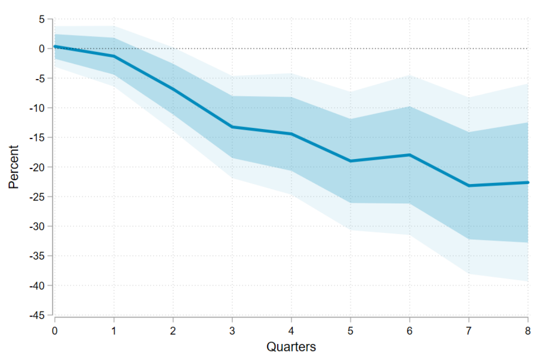
(a) Aggregate credit



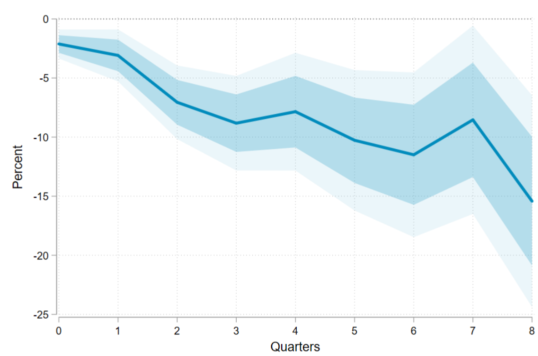
(b) Intensive margin



(c) Extensive margin



(d) Creation

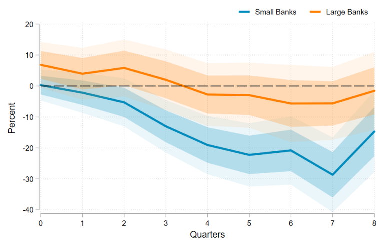


(e) Destruction

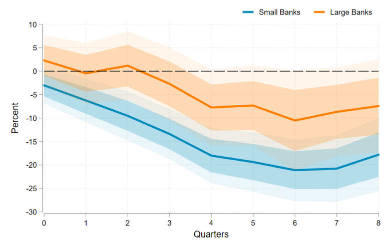
Notes: These figures illustrate impulse responses to a one percentage point contractionary monetary policy shock for (a) aggregate credit, (b) intensive margin, and (c) extensive margin. The results rely on the refined credit decomposition 2 with the local projection specification described in equation (17) and the "purified" monetary policy surprises from Jarociński and Karadi (2020). The sample period is 2002-2018. The x-axis represents the number of quarters after the shock and the y-axis is in percent. The blue-shaded areas correspond to the 68% (dark blue) and 90% (light blue) confidence intervals constructed using Newey and West (1987) standard errors.

Figure 18: Monetary Policy Transmission and Credit – Bank Characteristics

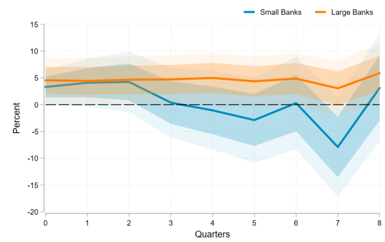
A. Small vs. Large Banks



(a) Aggregate credit

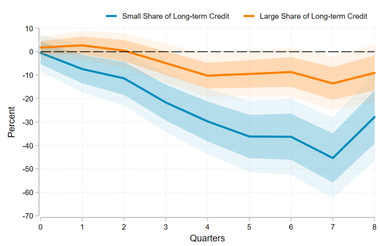


(b) Intensive margin

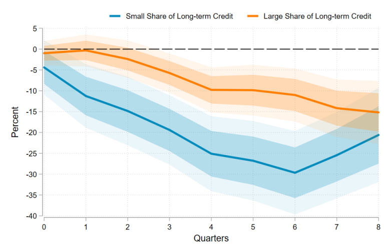


(c) Extensive margin

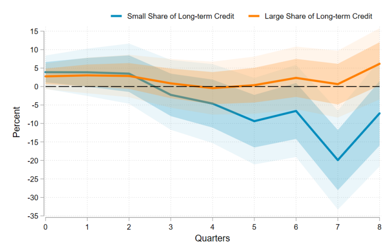
B. Small vs. Large Share of Long-term Credit



(a) Aggregate credit

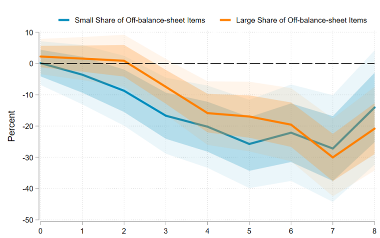


(b) Intensive margin

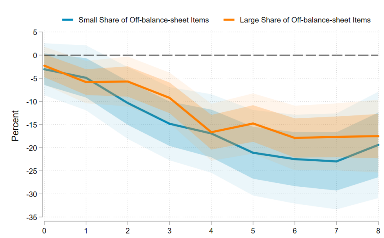


(c) Extensive margin

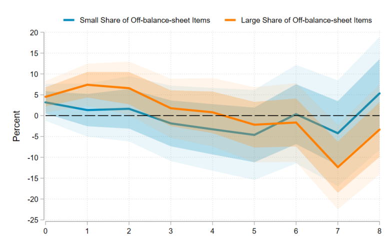
C. Small vs. Large Share of Off-Balance-Sheet Items



(a) Aggregate credit



(b) Intensive margin



(c) Extensive margin

Notes: These figures illustrate impulse responses to a one percentage point contractionary monetary policy shock for (a) aggregate credit, (b) intensive margin, and (c) extensive margin. The results rely on the refined credit decomposition 2 with the local projection specification described in equation (17) and the "purified" monetary policy shocks from Jarociński and Karadi (2020). The local projections are estimated separately for small vs. large banks (Panel A), banks with small vs. large share of long-term credit (Panel B) and banks with small vs. large share of off-balance-sheet credit items (Panel C). Banks are classified into small (large) groups if they are below (above) the median threshold for (i) total credit exposure, (ii) share of long-term credit, and (iii) share of off-balance-sheet items. The sample period is 2002-2018. The x-axis represents the number of quarters after the shock, and the y-axis is in percent. The shaded areas correspond to the 68% (dark color) and 90% (light color) confidence intervals constructed using Newey and West (1987) standard errors.

Online Appendix – Not For Publication

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 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 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 data to be merged with the SCR. Second, the BRN (*Benefices Industriels et Commerciaux - Regime Normal*) dataset is produced by the INSEE (*Institut National de la Statistique et des Etudes Economiques*) and gathers the 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 through 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, 13880, 14138, 18710, 19510, and 18359)
- *Groupe CDC* (Bank identifiers: 23930, 40031, 60030, and 60070)
- *Groupe credit logement* (Bank identifier: 19230)

A.5 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 2003Q3, 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 2012Q1, 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.

B Credit Relationship Flows – Additional Descriptive Results and Robustness Checks

Cross-section. Table B.1 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 extensive and intensive margins of credit.[43] 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.

Table B.1: 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

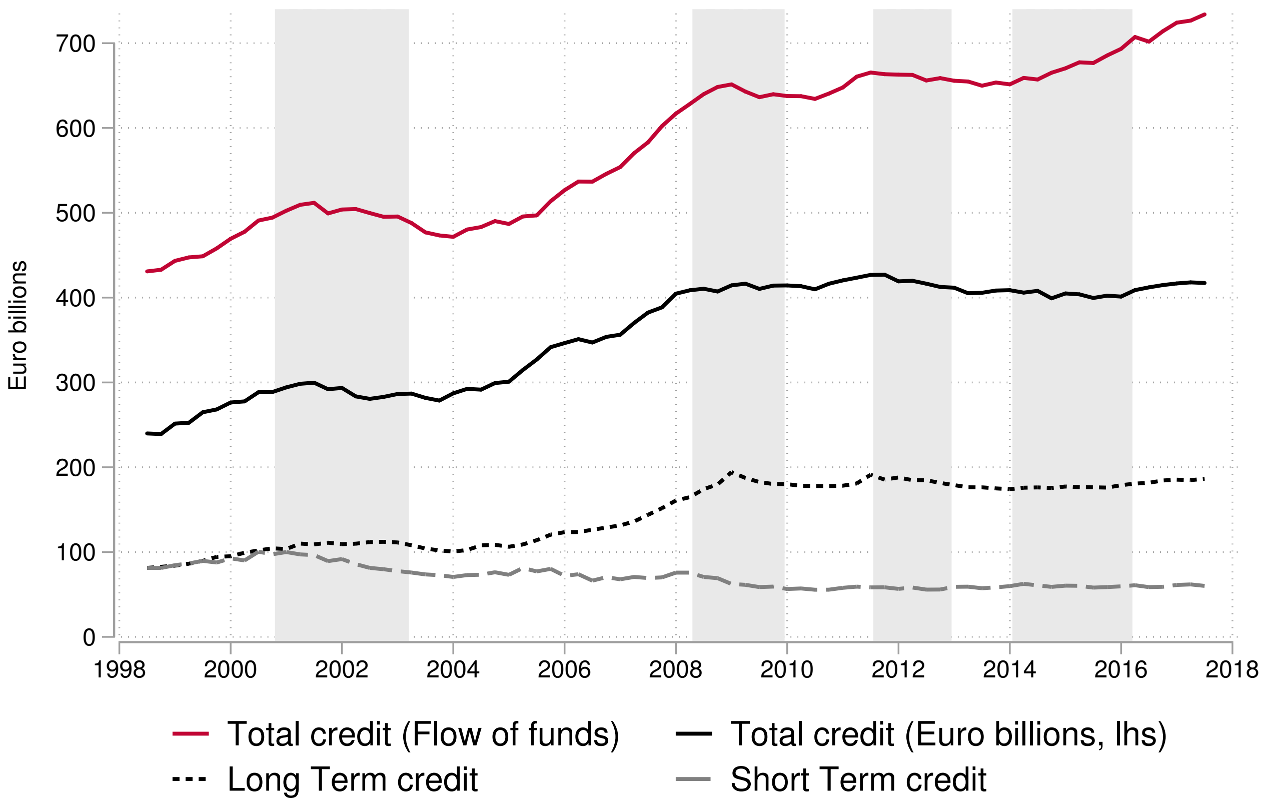
[43] On the one hand, if bank-firm matches were all identical and financial contracts were rigid (i.e., credit per match is constant throughout the relationship), then we should care only about counting the number of credit relationships in the economy (i.e., extensive margin would be a sufficient statistic 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 the relationship portable, then only the intensive margin would matter.

Table B.2: 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, relationship capital, and average credit, over the period 1999-2016. GDP, total credit, relationship capital, and average credit refer to the log-growth of these variables. Flow variables are detrended using an HP filter with a smoothing parameter of 1600. Nominal credit variables are deflated using the French GDP deflator, deseasonalized using the X-13 adjustment procedure, and smoothed based on MA(-1, 1).

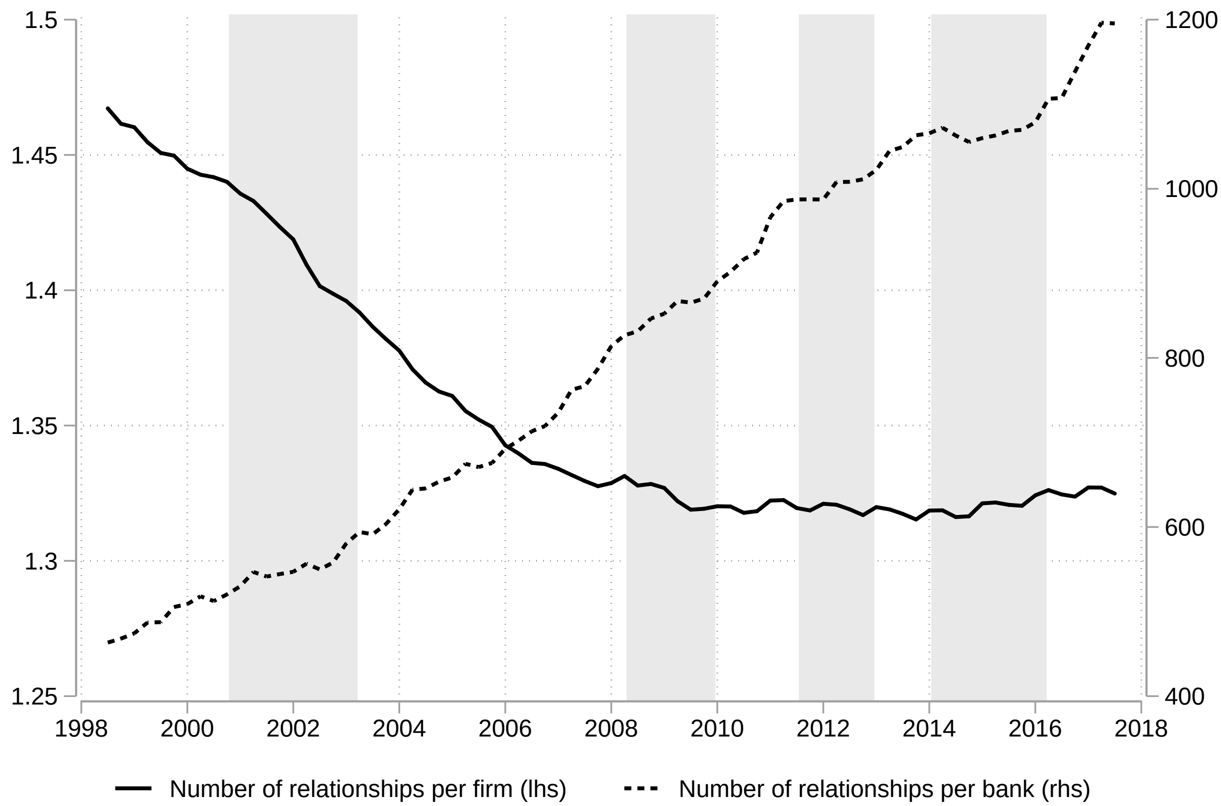
	A. Cross-correlation of GDP with:						
	x(-8)	x(-4)	x(-2)	x	x(+2)	x(+4)	x(+8)
Relationship capital	-0.36	-0.10	0.16	0.44	0.42	0.21	-0.06
Average credit	0.07	-0.04	0.16	0.23	0.32	0.35	-0.04
Creation flows	-0.29	-0.13	0.11	0.43	0.44	0.18	-0.28
Destruction flows	0.06	-0.26	-0.37	-0.26	0.14	0.40	0.21
Net flows	-0.30	-0.02	0.24	0.50	0.34	0.00	-0.34
	B. 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
	C. 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
	D. 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

Figure B.1: Aggregate Credit: French Credit Register (SCR) vs. Flow of Funds



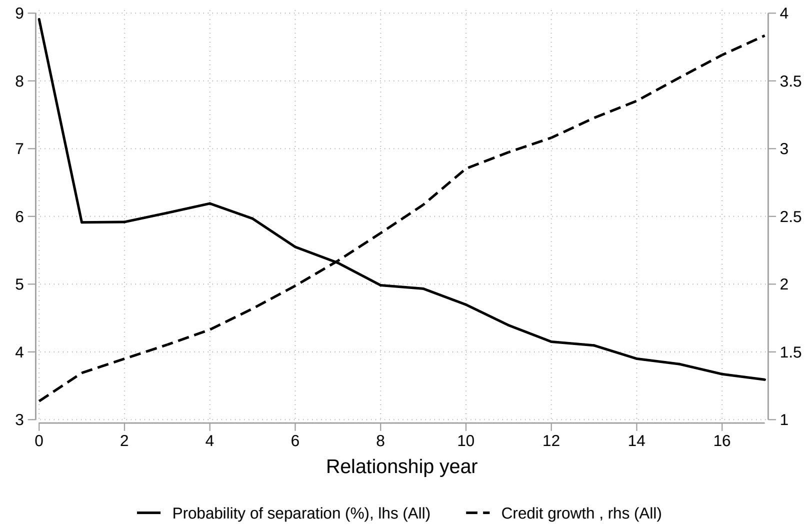
Notes: This figure compares the time series of aggregate bank credit obtained from the national balance sheet items (solid red line) and aggregate credit obtained from the SCR after filters (solid black line). The black dashed curve presents the time series of aggregate long-term credit (initial maturity ≥ 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 B.2: Number of Credit Partners per Bank and per Firm

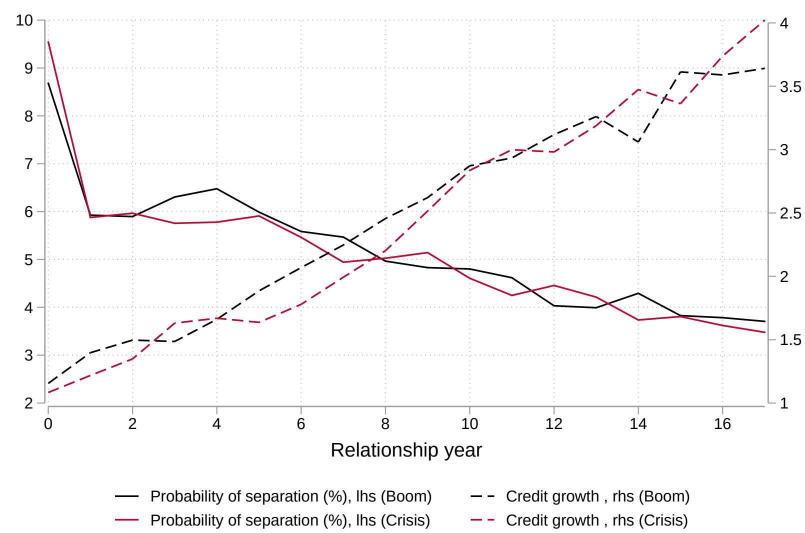


Notes: This figure reports the evolution of the number of relationships per firm (solid line) and the number of relationships per bank (dashed line) over the period 1999-2016. The sample accounts for only those relationships that are above the reporting threshold. Gray-shaded areas correspond to recession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

Figure B.3: Trajectories of Credit Growth and Separation Probability



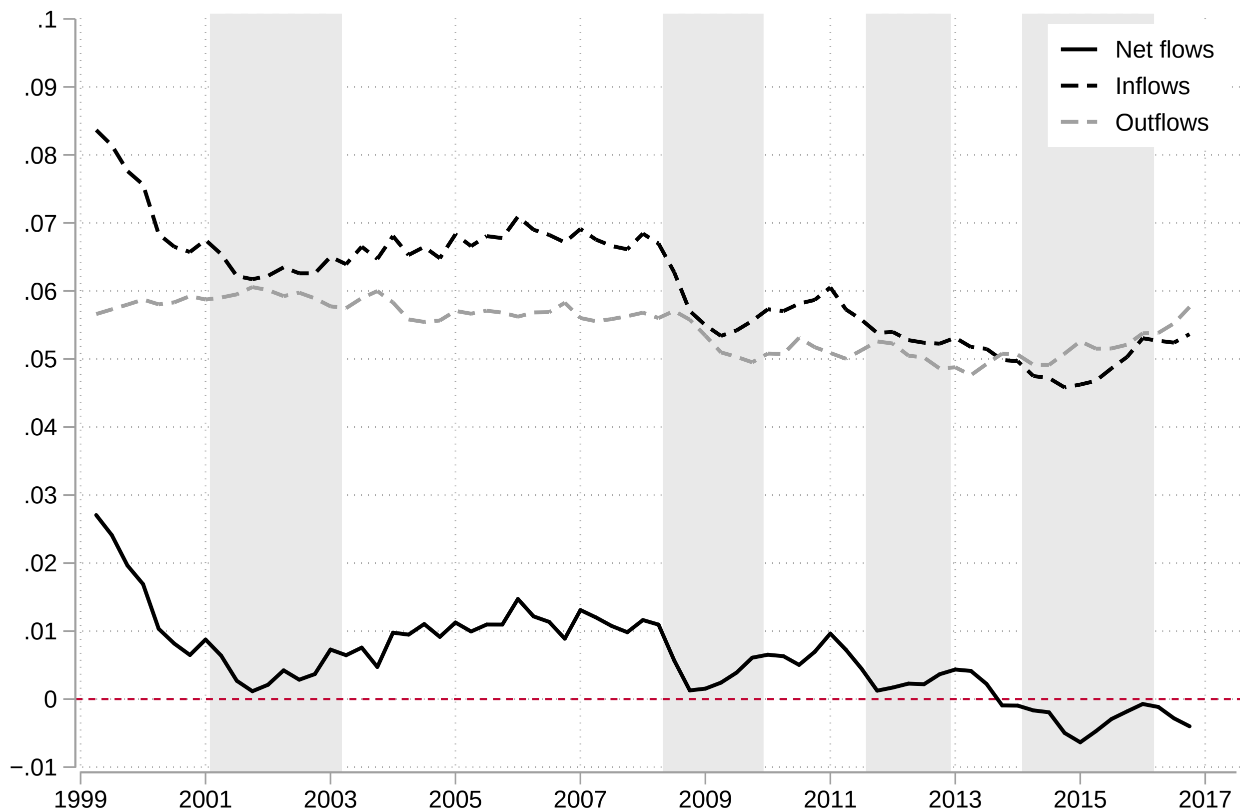
(a) Unconditional results



(b) Boom vs. crisis periods

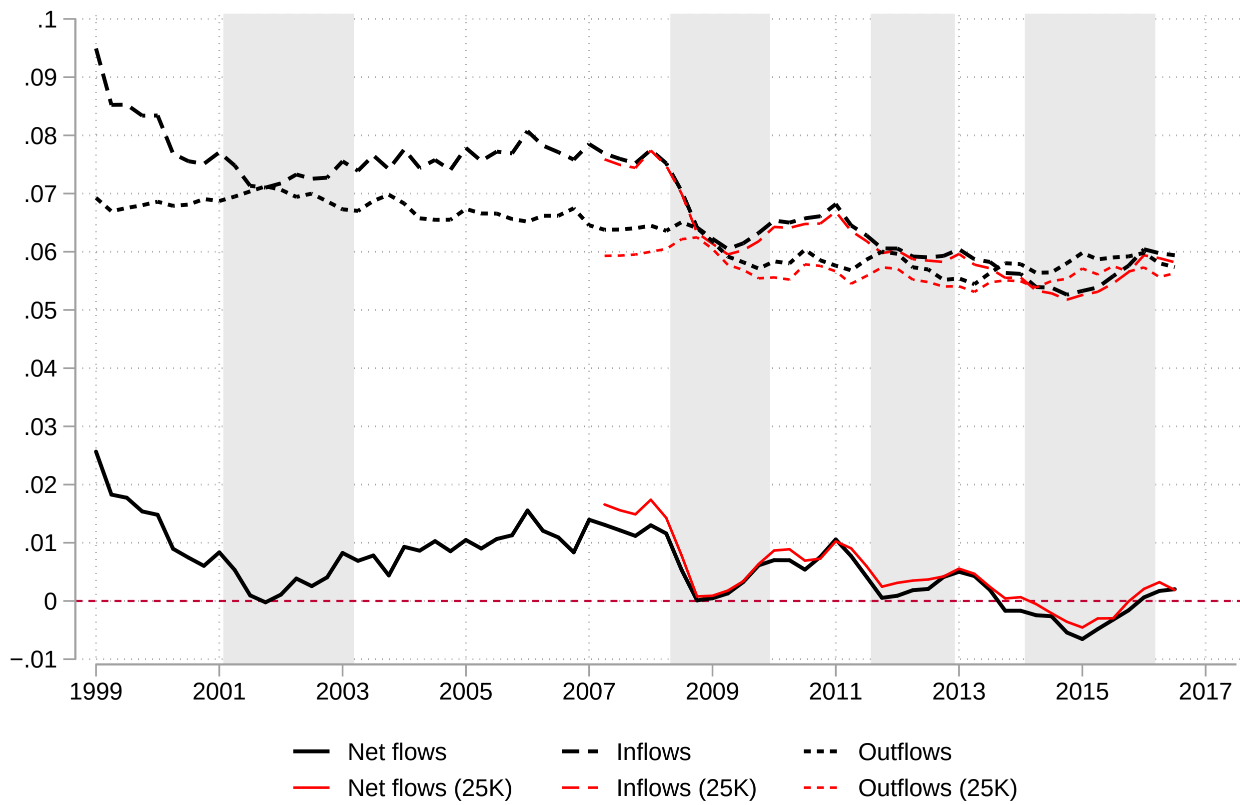
Notes: These figures show the trajectories of cross-sectional averages of credit, normalized to one at time 0 (dashed line) and separation probability (solid line) throughout the duration of a credit relationship. Panel (a) reports unconditional results, while Panel (b) reports the results for boom (in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

Figure B.4: Credit Relationship Flows with 8-Quarter Gaps



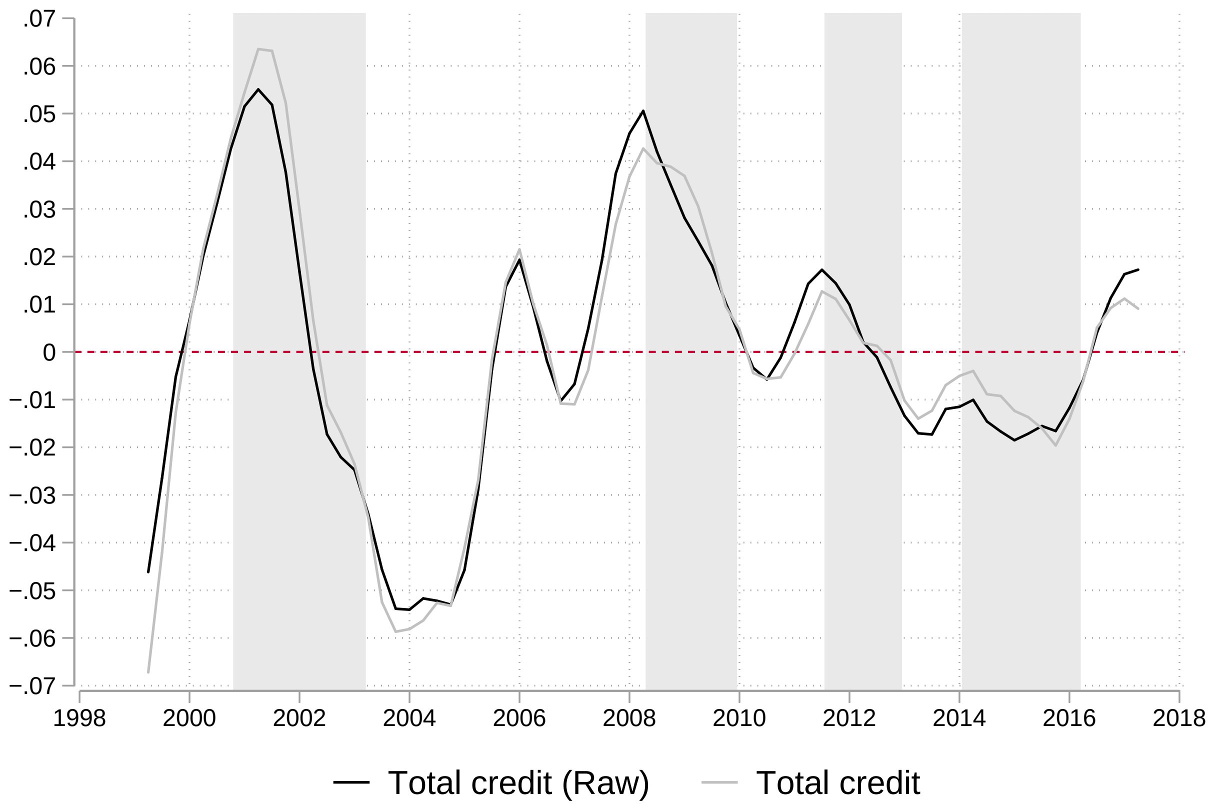
Notes: This figure shows raw net (solid black line) and gross flows of credit relationships, constructed using an 8-quarter gap. Gross creation flows (inflows) are reported in dashed black line, while gross destruction flows (outflows) are reported in dashed gray line. Results are based on relationships above the 75K Euro reporting threshold (adjusted for inflation) for the period 1999-2016. Gray-shaded areas correspond to recession periods.

Figure B.5: Credit Relationship Flows with the 25K Euro Threshold



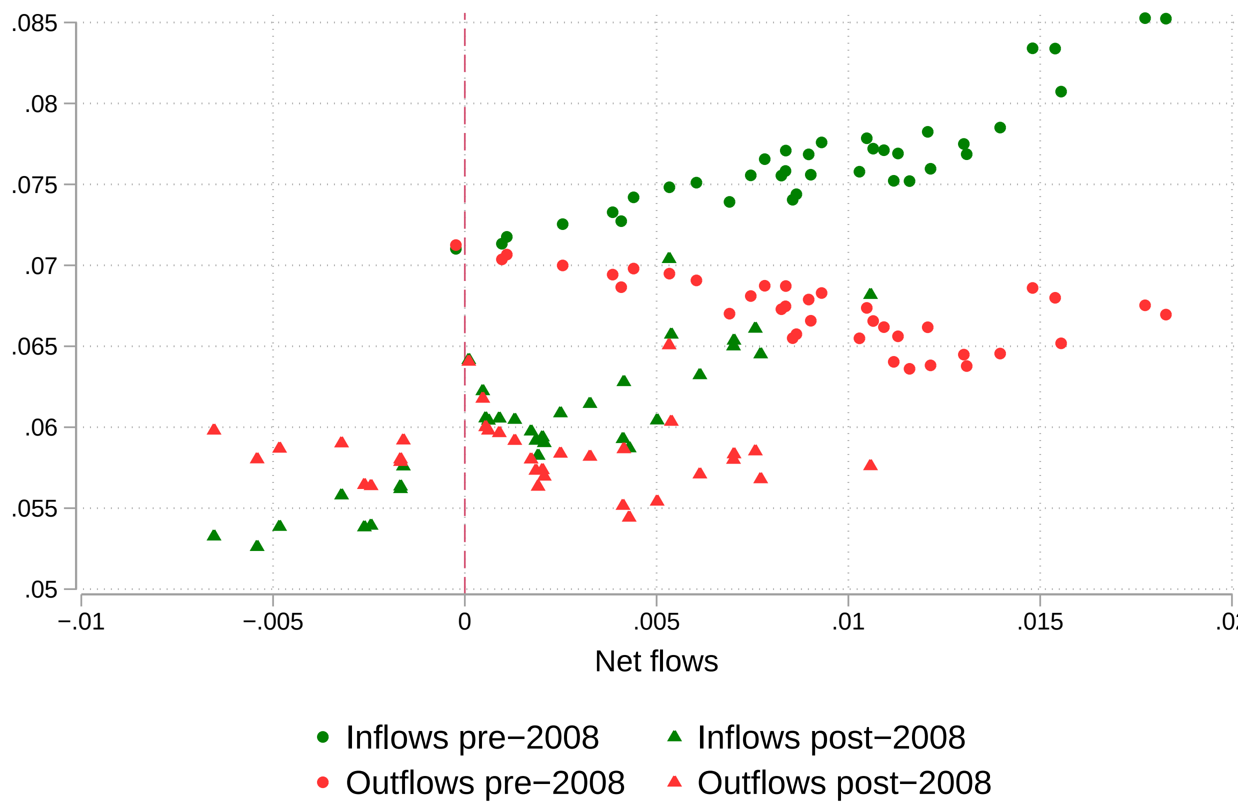
Notes: This figure shows raw net (solid lines) and gross flows (creation flows in dashed lines and destruction flows in dotted lines) of credit relationships. Results are based on relationships above the 75K Euro reporting threshold for the period 1999-2016 (in black), and above the 25K Euro reporting threshold for the period 2007-2016 (in red). Both reporting thresholds are adjusted for inflation. Gray-shaded areas correspond to recession periods.

Figure B.6: Aggregate Credit Variations – Cyclical Components (HP Filter)



Notes: This figure shows the cyclical deviations (in log) of aggregate credit, based on the raw time series (black line), and approximated as the sum of extensive and intensive margin components from the decomposition in equation 10 (gray 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 B.7: Creation vs. Destruction Flows: Pre- and Post-2008



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 a smoothing parameter of 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 1998-2016.

C Extensive/Intensive Margin Decompositions – Additional Derivations and Results

C.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):

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

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

$$\begin{aligned}\Delta\log(N_{t+1}) &= \log(N_t + Pos_{t+1} - Neg_{t+1}) - \log(\tilde{N}_t + \tilde{Pos}_{t+1} - \tilde{Neg}_{t+1}) \\ &= \Delta\log(N_t) + \log(1 + \gamma_{t+1} - \delta_{t+1}) - \log(1 + \tilde{\gamma}_{t+1} - \tilde{\delta}_{t+1}),\end{aligned} \tag{19}$$

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:

$$\begin{aligned}\Delta\log(N_{t+1}) &= \Delta\log(N_0)+\sum_{i=1}^{t+1}\log(1+\gamma_i-\delta_i)-\sum_{i=1}^{t+1}\log(1+\tilde{\gamma}_i-\tilde{\delta}_i)\\ &\simeq \Delta\log(N_0)+\sum_{i=1}^{t+1}(\gamma_i-\tilde{\gamma}_i)-\sum_{i=1}^{t+1}(\delta_i-\tilde{\delta}_i)\\ &\simeq \Delta\log(N_0)+\sum_{i=1}^{t+1}\Delta\gamma_i-\sum_{i=1}^{t+1}\Delta\delta_i, \qquad (20)\end{aligned}$$

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

$$\beta_{Ext} \simeq \underbrace{\frac{\operatorname{cov}(\sum_{i=1}^{t+1}\Delta\gamma_i,\Delta\log(C_t))}{\operatorname{var}(\Delta\log(C_t))}}_{\beta_{Pos}}+\underbrace{\frac{\operatorname{cov}(-\sum_{i=1}^{t+1}\Delta\delta_i,\Delta\log(C_t))}{\operatorname{var}(\Delta\log(C_t))}}_{\beta_{Neg}} \qquad (21)$$

C.2 Alternative Decomposition 2

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

$$C_{t+1}=C_t+\underbrace{n_{t+1}^{\iota}\Delta C_{t+1}^{\iota}}_{T_{1,t+1}}+\underbrace{n_{t+1}^{\nu}\bar{C}_{t+1}^{\nu}}_{T_{2,t+1}}-\underbrace{n_{t+1}^{\sigma}\bar{C}_{t+1}^{\sigma}}_{T_{3,t+1}}. \qquad (22)$$

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,

$$\begin{aligned}\operatorname{var}(\Delta\log(C_t)) &\simeq \operatorname{cov}(\sum_{i=1}^{t}\Delta\frac{T_{1,i}}{C_{i-1}},\Delta\log(C_t))\\ &\quad+\underbrace{\operatorname{cov}(\sum_{i=1}^{t}\Delta\frac{T_{2,i}}{C_{i-1}},\Delta\log(C_t))}_{Entry}+\underbrace{\operatorname{cov}(\sum_{i=1}^{t}\Delta\frac{-T_{3,i}}{C_{i-1}},\Delta\log(C_t))}_{Exit}, \qquad (23)\end{aligned}$$

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

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

C.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:

$$C_{t+1} = C_t + Pos^{\iota}_{t+1} + Pos^{\nu}_{t+1} - Neg^{\iota}_{t+1} - Neg^{\sigma}_{t+1}, \tag{24}$$

where Pos^{ι}_t and Neg^{ι}_t represent positive and negative flows of incumbent credit relationships, while Pos^{ν}_t represents positive flows associated with new relationships, and Neg^{σ}_t represents the negative flows associated with newly severed ones.

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

$$\begin{aligned} \Delta \log(C_{t+1}) &= \log(1 + \frac{Pos^{\iota}_{t+1}}{C_t} + \frac{Pos^{\nu}_{t+1}}{C_t} - \frac{Neg^{\iota}_{t+1}}{C_t} - \frac{Neg^{\sigma}_{t+1}}{C_t}) \\ &\simeq 1 + \frac{Pos^{\iota}_{t+1}}{C_t} + \frac{Pos^{\nu}_{t+1}}{C_t} - \frac{Neg^{\iota}_{t+1}}{C_t} - \frac{Neg^{\sigma}_{t+1}}{C_t}. \end{aligned} \tag{25}$$

And, similar to previous decompositions, we get:

$$1 \simeq \beta_{\text{Pos}^{\iota}} + \beta_{\text{Neg}^{\iota}} + \beta_{\text{Pos}^{\nu}} + \beta_{\text{Neg}^{\sigma}}.$$

For the HP filter approach, we can equivalently write:

$$C_{t+1} = C_t + Pos^{\iota}_{t+1} + Pos^{\nu}_{t+1} - Neg^{\iota}_{t+1} - Neg^{\sigma}_{t+1}. \tag{26}$$

and, assuming small $\frac{Pos^{\iota}_{t+1}}{C_t}$, $\frac{Pos^{\sigma}_{t+1}}{C_t}$, $\frac{Neg^{\iota}_{t+1}}{C_t}$, and $\frac{Neg^{\sigma}_{t+1}}{C_t}$,

$$\begin{aligned}
\Delta\log(C_{t+1}) &= \Delta\log(C_t) + \Delta\log(1 + \frac{Pos^{\iota}_{t+1}}{C_t} + \frac{Pos^{\nu}_{t+1}}{C_t} - \frac{Neg^{\iota}_{t+1}}{C_t} - \frac{Neg^{\sigma}_{t+1}}{C_t}) \\
&\simeq \Delta\log(C_0) + \sum_{i=1}^{t+1}\Delta\frac{Pos^{\iota}_i}{C_{i-1}} + \sum_{i=1}^{t+1}\Delta\frac{Pos^{\nu}_i}{C_{i-1}} - \sum_{i=1}^{t+1}\Delta\frac{Neg^{\iota}_i}{C_{i-1}} - \sum_{i=1}^{t+1}\Delta\frac{Neg^{\sigma}_i}{C_{i-1}}. \qquad (27)
\end{aligned}$$

We can eventually derive the variance decomposition as:

$$\begin{aligned}
\mathrm{var}(\Delta\log(C_t)) &= \mathrm{cov}(\sum_{i=1}^{t}\Delta\frac{Pos^{\iota}_i}{C_{i-1}}, \Delta\log(C_t)) + \mathrm{cov}(-\sum_{i=1}^{t}\Delta\frac{Neg^{\iota}_i}{C_{i-1}}, \Delta\log(C_t)) \\
&\quad + \mathrm{cov}(\sum_{i=1}^{t}\Delta\frac{Pos^{\nu}_i}{C_{i-1}}, \Delta\log(C_t)) + \mathrm{cov}(\sum_{i=1}^{t}-\Delta\frac{Neg^{\sigma}_i}{C_{i-1}}, \Delta\log(C_t)), \qquad (28)
\end{aligned}$$

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

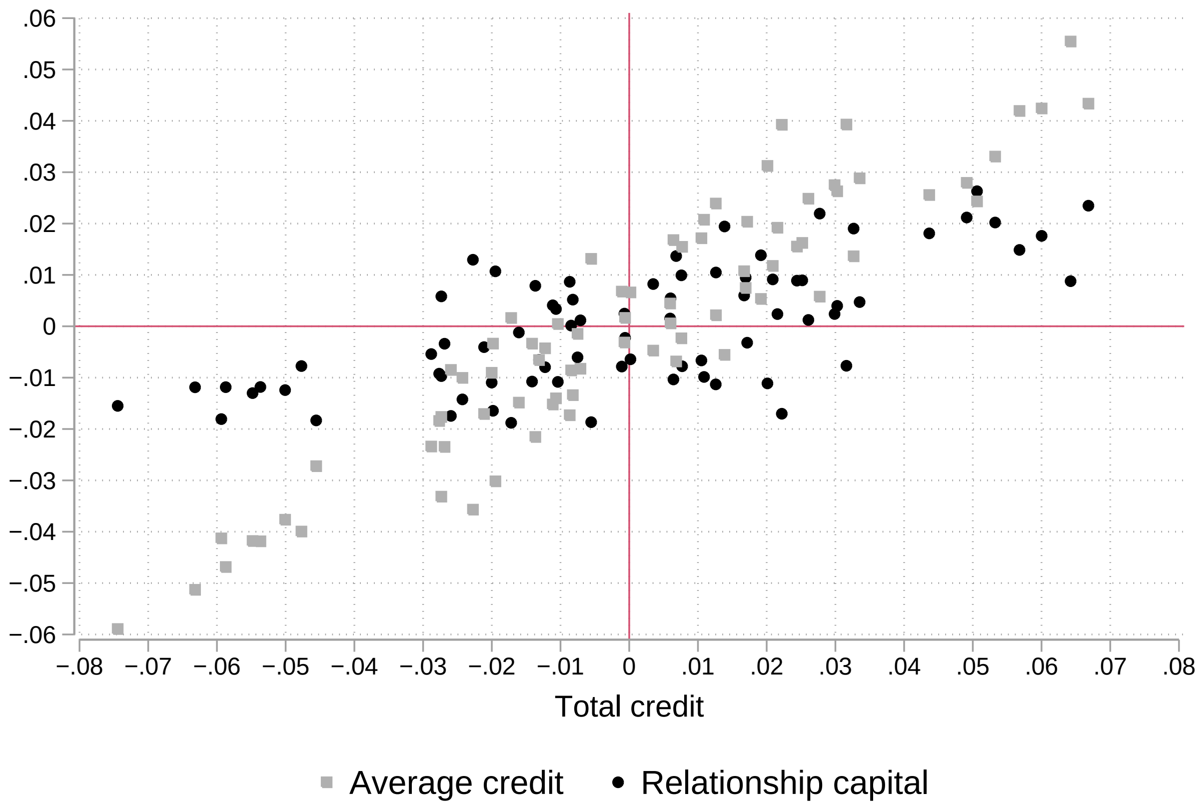
$$1 \simeq \underbrace{\beta_{Pos^{\iota}} + \beta_{Neg^{\iota}}}_{\beta_{Int}} + \underbrace{\beta_{Pos^{\nu}} + \beta_{Neg^{\sigma}}}_{\beta_{Ext}}.$$

Table C.1: Variance Decomposition: Intensive vs. Extensive Margins (Decomposition 3)

This table reports the results for variance decompositions of aggregate credit fluctuations over the period 1999-2016. The intensive/extensive margin decompositions are derived based on first-differences and log-deviations from trend obtained from HP filter with a smoothing parameter of 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 3				
First-Difference	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
HP Filter	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

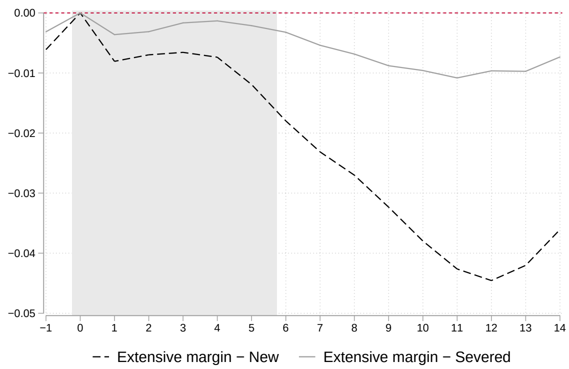
Figure C.1: Extensive vs. Intensive Margins: Cyclical Deviations



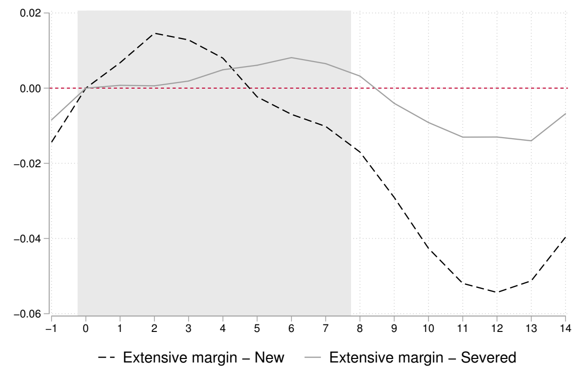
Notes: This figure shows a scatter plot of the cyclical deviations (in log) of average credit and the stock of relationship, as a function of their aggregate credit counterparts. Cyclical deviations are extracted using an HP filter with a smoothing parameter of 1600. Nominal variables are deflated using 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.

D Anatomy of a Crisis – Additional Figures

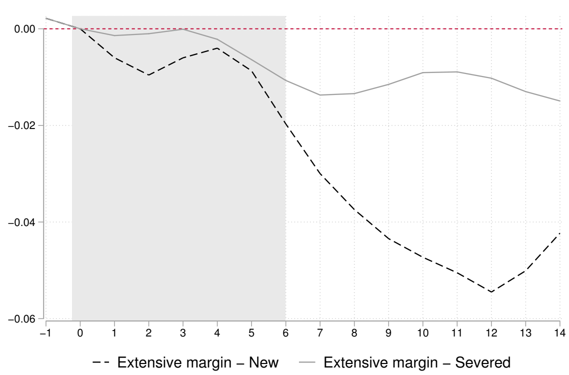
Figure D.1: Anatomy of a Crisis – Decomposition 2 – Creation vs. Destruction



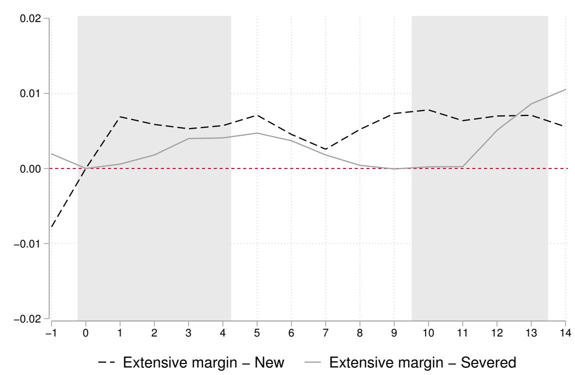
(a) Unconditional



(b) 2001-2003



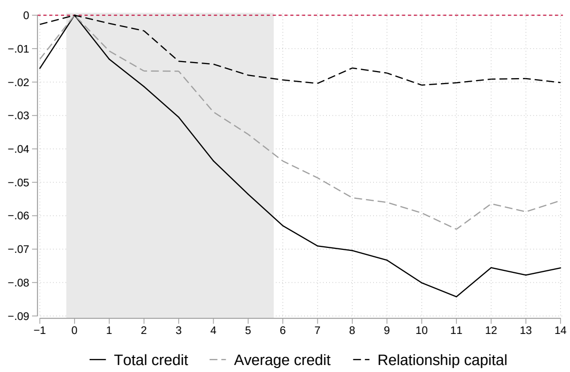
(c) 2008-2009



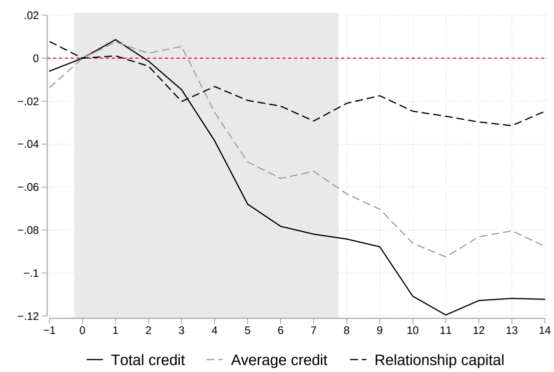
(d) 2012-2014

Notes: These figures report the unconditional and crisis dynamics of the creation (new) and destruction (severed) components of the extensive margin over fourteen quarters following the onset of a recession. The extensive margin is based on decomposition 2, specified in equation (10). 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 of 1600. Gray-shaded areas correspond to the recession period.

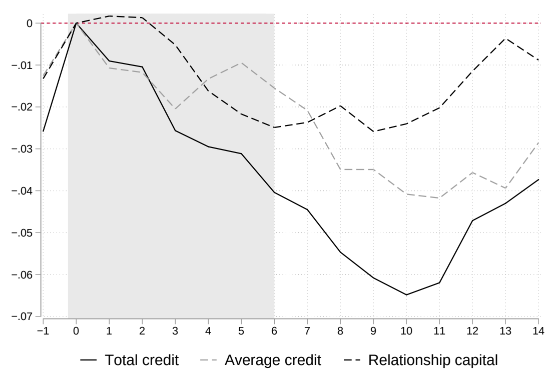
Figure D.2: Anatomy of a Crisis – Decomposition 1



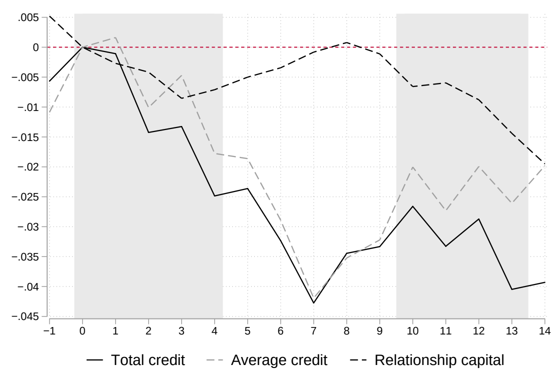
(a) Unconditional



(b) 2001-2003



(c) 2008-2009

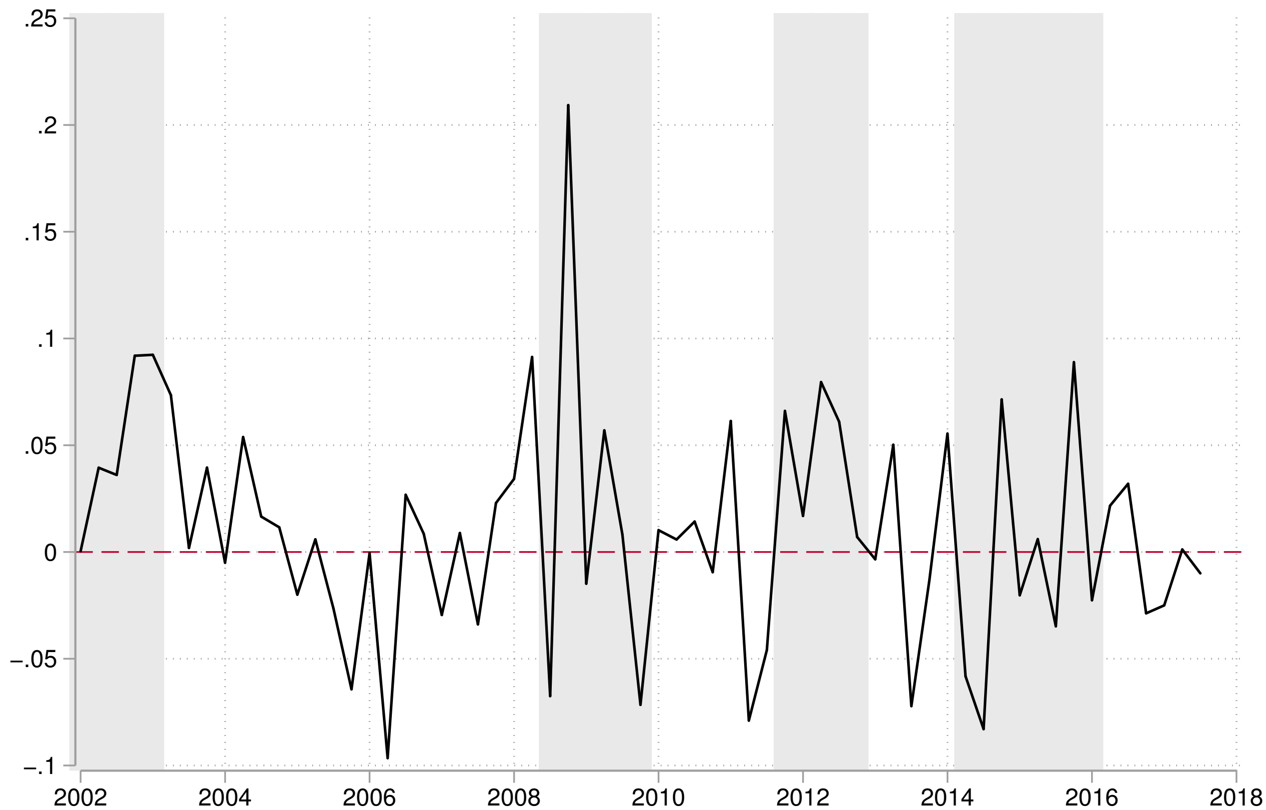


(d) 2012-2014

Notes: These figures report the evolution of aggregate credit, average credit, and relationship capital over the fourteen quarters following the onset of each recession. Panel (a) reports unconditional results, while Panels (b), (c), and (d) report individual recessions. Due to their proximity, the recessions of 2012-2013 and 2014-2016 are shown combined in panels (d). 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.

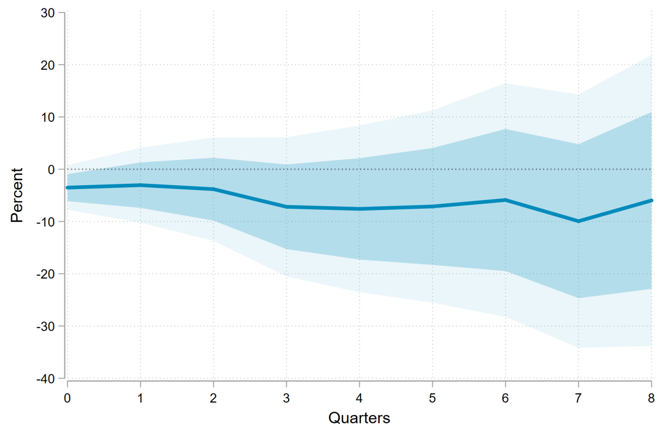
E Local Projections – Additional Figures and Results

Figure E.1: Monetary Policy Shocks – 2002-2018

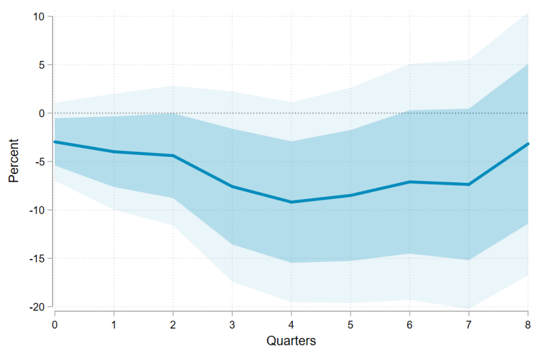


Note: These times series represent the monetary policy shocks based on the "purified" monetary policy surprises from Jarociński and Karadi (2020), aggregated at quarterly frequency over the period 2002-2018.

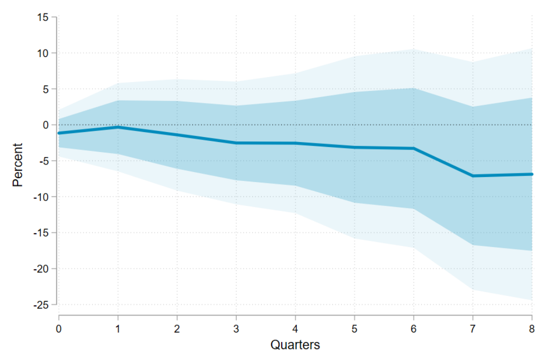
Figure E.2: Monetary Policy Transmission and Credit – Specification with Lags



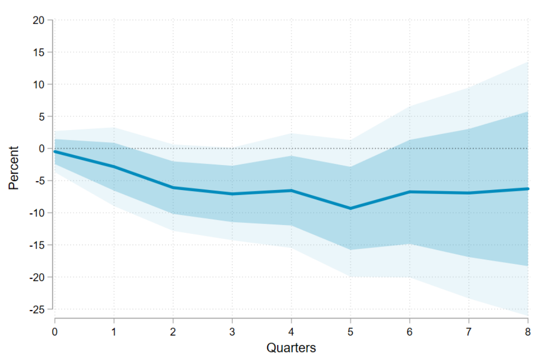
(a) Aggregate credit



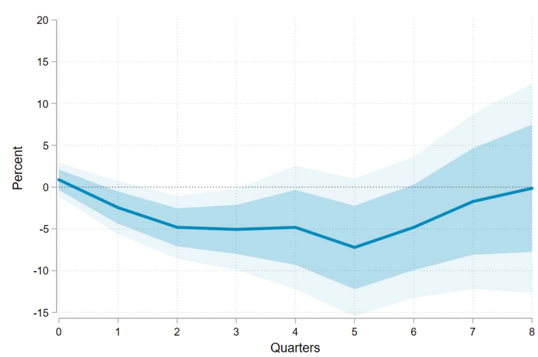
(b) Intensive margin



(c) Extensive margin



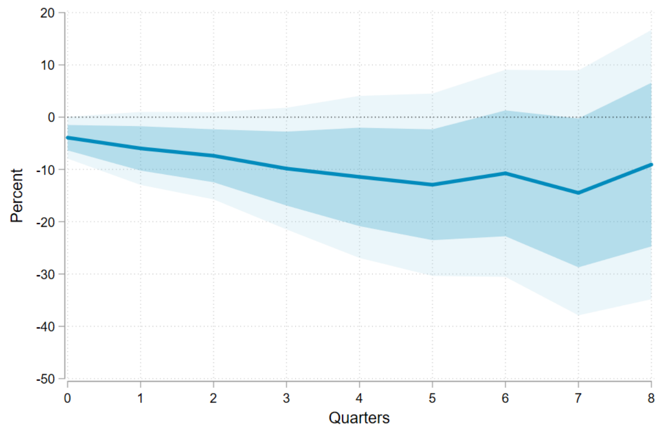
(d) Creation



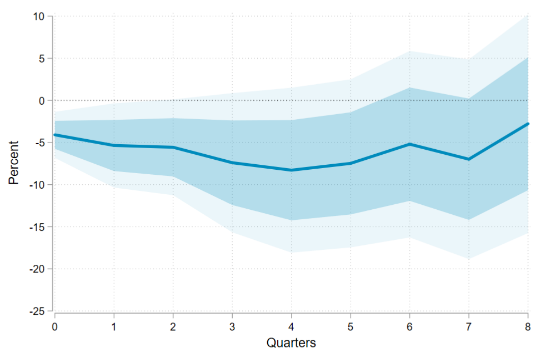
(e) Destruction

Notes: These figures illustrate impulse responses to a one percentage point contractionary monetary policy shock for (a) aggregate credit, (b) intensive margin, (c) extensive margin, and the corresponding (d) creation and (e) destruction components. The results rely on the refined credit decomposition 2 with the local projection specification described in equation (15) and the "purified" monetary policy shocks from Jarociński and Karadi (2020). The sample period is 2002-2018. The x-axis represents the number of quarters after the shock, and the y-axis is in percent. The blue-shaded areas correspond to the68% (dark blue) and 90% (light blue) confidence intervals constructed using Newey and West (1987) standard errors.

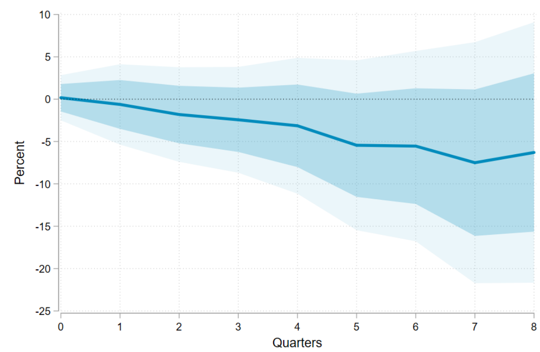
Figure E.3: Monetary Policy Transmission and Credit – Alternative Monetary Shocks



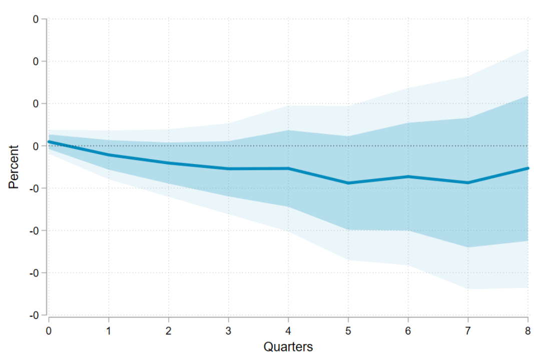
(a) Aggregate credit



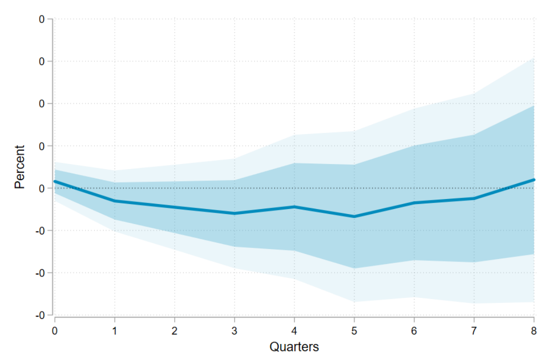
(b) Intensive margin



(c) Extensive margin



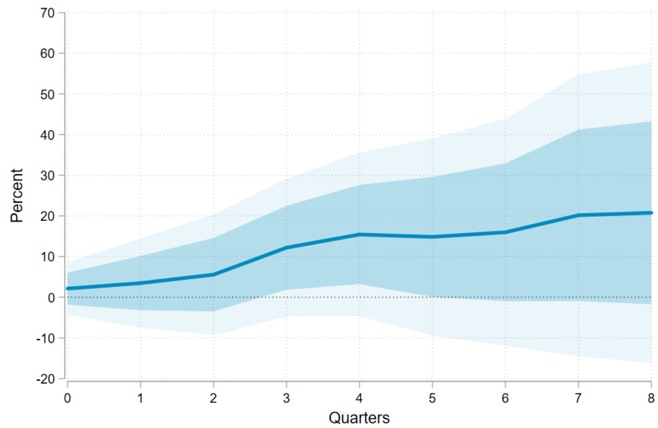
(d) Creation



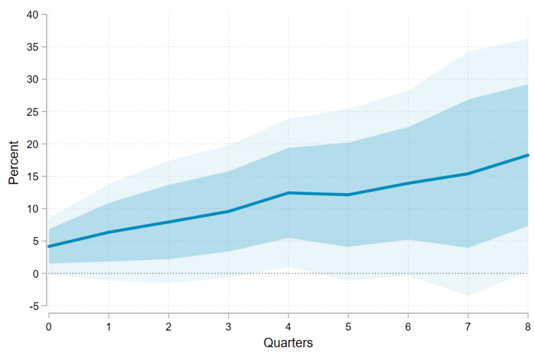
(e) Destruction

Notes: These figures illustrate impulse responses to a one percentage point contractionary monetary policy shock for (a) aggregate credit, (b) intensive margin, (c) extensive margin, and the corresponding decomposition into (d) creation and (e) destruction components. The results rely on the refined credit decomposition 2 with the local projection specification described in equation (15) and the "purified" monetary policy shocks from Kerssenfischer (2019). The sample period is 2002-2018. The x-axis represents the number of quarters after the shock, and the y-axis is in percent. The blue-shaded areas correspond to the 68% (dark blue) and 90% (light blue) confidence intervals constructed using Newey and West (1987) standard errors.

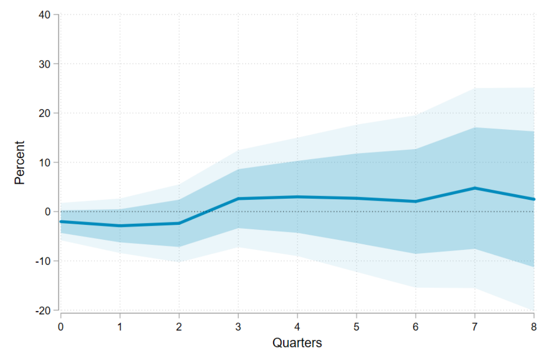
Figure E.4: Monetary Policy Transmission and Credit - ECB Information Shocks



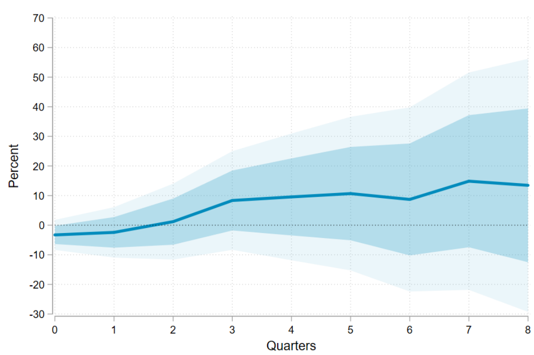
(a) Aggregate credit



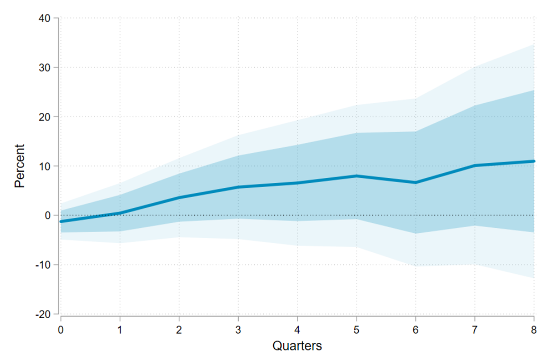
(b) Intensive margin



(c) Extensive margin



(d) Creation



(e) Destruction

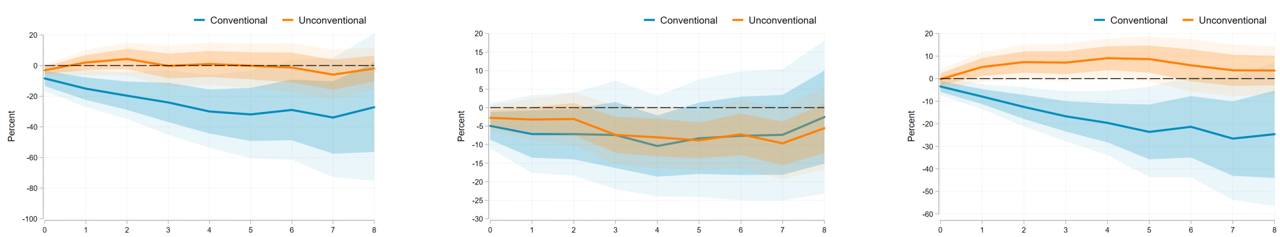
Notes: These figures illustrate impulse responses to a one percentage point contractionary monetary policy shock for (a) aggregate credit, (b) intensive margin, (c) extensive margin, and the corresponding (d) creation and (e) destruction components. The results rely on the refined credit decomposition 2 with the local projection specification described in equation (15) and the central bank information shocks from Jarociński and Karadi (2020). The sample period is 2002-2018. The x-axis represents the number of quarters after the shock, and the y-axis is in percent. The blue-shaded areas correspond to the 68% (dark blue) and 90% (light blue) confidence intervals constructed using Newey and West (1987) standard errors.

E.1 Conventional vs. Unconventional Monetary Policy

Given the significant shift in monetary policy conduct over the past two decades, the information conveyed by policy meetings has also evolved to include details about unconventional monetary policy, with potential implications for both quantities and prices. Among others, Long-Term Refinance Operations (LTRO) have been first announced in August 2007 and used extensively throughout the financial crisis and the European sovereign debt crisis. Here, we focus on the effect of monetary policy surprises when Long-Term LTRO announcements occur simultaneously. We use the event database for the ECB as collected by Cieslak and Schrimpf (2019) to determine whether a policy meeting announcement makes a reference to LTRO. We then run the specification (16), with a dummy variable δ_T, which equals 1 for announcements referring to LTRO and 0 for those that do not.

Our results (Figure E.5) show that monetary policy surprises, when combined with LTRO announcements, do not generate a significant response for aggregate credit. In fact, the extensive and intensive margins appear to react in opposite, as a tightening surprise generates a decline in the intensive margin but an increase in the extensive margin. While a formal investigation of LTRO shocks is outside the scope of this paper, these results would simply argue that (tightening) monetary policy surprises tend to have more significant effects on credit when not confounded with simultaneous LTRO shocks.

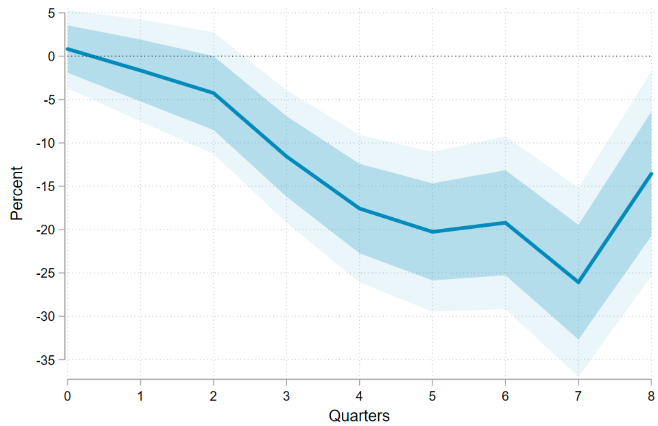
Figure E.5: Monetary Policy Transmission – Conventional vs. Unconventional



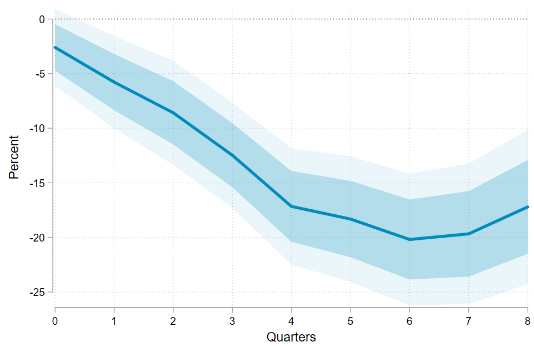
(a) Aggregate credit **(b) Intensive margin** **(c) Extensive margin**

Notes: These figures illustrate impulse responses to a one percentage point contractionary monetary policy shock for (a) aggregate credit, (b) intensive margin, and (c) extensive margin. The results rely on the refined credit decomposition 2 with the local projection specification described in equation (15) and the "purified" monetary policy surprises from Jarociński and Karadi (2020). The sample period is 2002-2018. The local projections are estimated separately for the pre- and post-2008 periods. The x-axis represents the number of quarters after the shock, and the y-axis is in percent. The shaded areas correspond to the 68% (dark color) and 90% (light color) confidence intervals constructed using Newey and West (1987) standard errors.

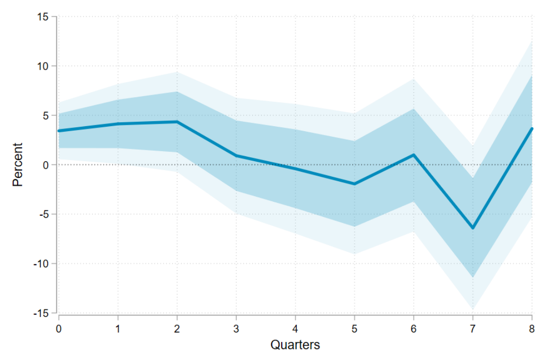
Figure E.6: Monetary Policy Transmission and Credit – Bank-level Responses Specification with Bank-fixed Effects



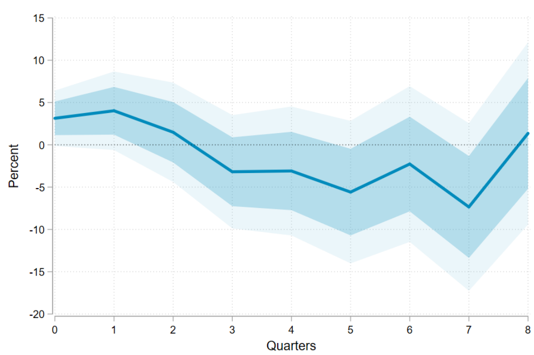
(a) Aggregate credit



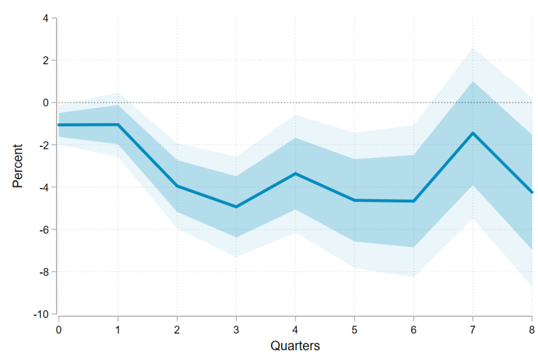
(b) Intensive margin



(c) Extensive margin



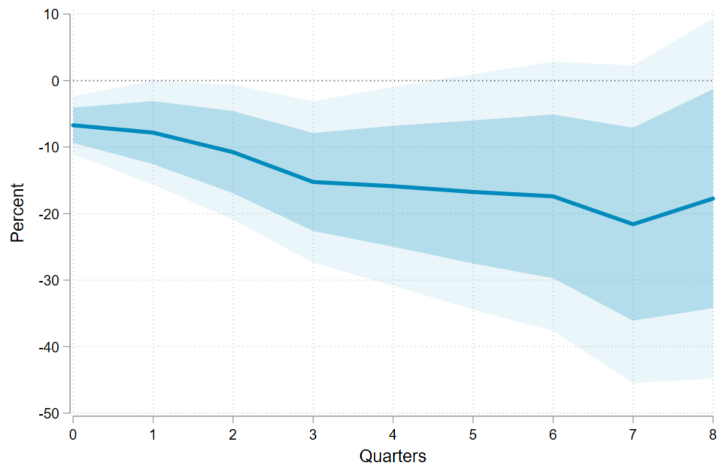
(d) Creation



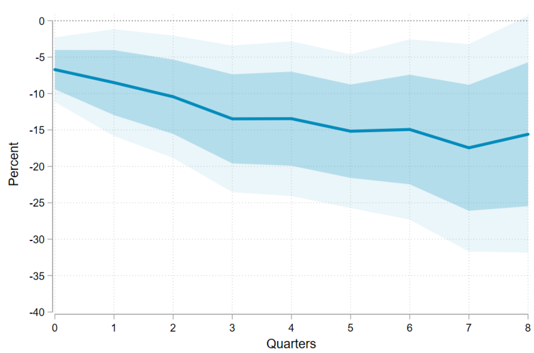
(e) Destruction

Notes: These figures illustrate impulse responses to a one percentage point contractionary monetary policy shock for (a) aggregate credit, (b) intensive margin, (c) extensive margin, and the corresponding (d) creation and (e) destruction components. The results rely on the refined credit decomposition 2 with the local projection specification described in equation (17) with bank-fixed effects and the "purified" monetary policy shocks from Jarociński and Karadi (2020). The sample period is 2002-2018. The x-axis represents the number of quarters after the shock, and the y-axis is in percent. The blue-shaded areas correspond to the 68% (dark blue) and 90% (light blue) confidence intervals constructed using Newey and West (1987) standard errors.

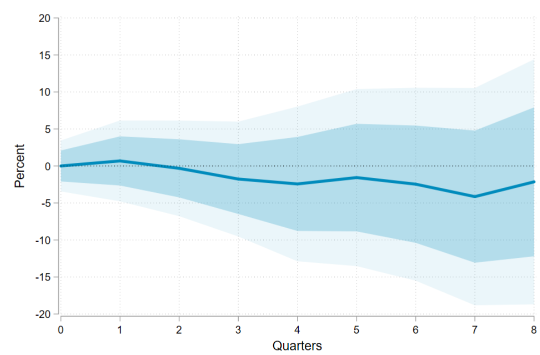
Figure E.7: Monetary Policy Transmission and Credit – Specification with Credit Decomposition 1



(a) Aggregate credit



(b) Intensive margin



(c) Extensive margin

Notes: These figures illustrate impulse responses to a one percentage point contractionary monetary policy shock for (a) aggregate credit, (b) intensive margin, and (c) extensive margin. The results rely on the simple credit decomposition 1 with the local projection specification described in equation (15) and the "pure" monetary policy shocks from Jarociński and Karadi (2020).The sample period is 2002-2018. The x-axis represents the number of quarters after the shock, and the y-axis is in percent. The blue-shaded areas correspond to the 90% (light blue) and 68% (dark blue) confidence intervals constructed using Newey and West (1987) standard errors.