International Financial Flows and Misallocation: Evidence from Micro Data

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Abstract

Using detailed bank-firm matched data, we examine the impact of international financial flows on resource misallocation. We leverage a capital inflow boom in Italy to identify credit allocation patterns by banks with varying levels of exposure. Our findings indicate that banks with greater exposure to the capital inflows shift credit supply toward high-MRPK (marginal revenue product of capital) firms, which in turn reduces the dispersion of MRPK. We quantify the effects on aggregate total factor productivity (TFP), incorporating general equilibrium effects, and find significant positive gains.

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1 Introduction

This paper examines the effects of international financial flows on the real economy, particularly focusing on misallocation and aggregate productivity. Previous studies on capital inflow booms in Southern Europe and the United States suggest that these inflows slowed productivity by increasing misallocation both across and within sectors (Reis, 2013; Benigno and Fornaro, 2014; Gopinath et al., 2017; Benigno, Fornaro and Wolf, 2023). In contrast, financial liberalization in emerging markets is often associated with positive impacts on productivity growth (Larrain and Stumpner, 2017; Varela, 2018; Bau and Matray, 2023).

This paper revisits the early 2000s capital inflow boom in Southern Europe and provides new micro-level estimates of its effects on misallocation by employing a novel bank-firm matching approach. While studies such as Gopinath et al. (2017), Larrain and Stumpner (2017), Varela (2018), and Bau and Matray (2023) analyze firm-level data, they do not capture the direct link between firms, banks, and capital inflows.[1] By integrating credit registry data with balance sheets information for all Italian banks and the entire population of incorporated firms, we identify the causal impact of international financial flows on misallocation, offering new insights into the productivity implications of capital inflows in Southern Europe.

Challenging the conventional view, our findings suggest that international financial flows did not exacerbate misallocation. Instead, banks exposed to capital inflows disproportionately increased lending to firms with high marginal revenue product of capital (high-MRPK), promoting their growth and reducing productivity dispersion across the economy. This shift in lending behavior appears to be driven by a 'portfolio channel,' whereby more exposed banks redirected their portfolios toward high-MRPK firms following the inflow boom. Importantly, we find no evidence that these banks were previously associated with high-MRPK firms, making a 'sorting channel' an unlikely explanation

We then aggregate the firm-level results to quantify the effects of capital inflows on total factor productivity (TFP) while accounting for general equilibrium effects. Using the framework of Sraer and Thesmar (2023), we estimate the impact of capital flows through a set of sufficient statistics that align with many macro-finance models. Our results indicate that international financial flows raised aggregate TFP by 0.9% annually from the early 2000s until the global financial crisis. These gains occurred despite a marked decline in allocative efficiency during this period.

[1] Papers like Baskaya et al. (2017) and di Giovanni et al. (2021) link capital flows to credit supply in Turkey using bank-firm data, but do not observe firm-level characteristics such as productivity.

Estimates from Calligaris et al. (2018) indicate that rising misallocation, reflected in the increased dispersion of the marginal revenue product of capital (MRPK) among Italian firms, reduced TFP growth by 1.3% annually during this time. Similar patterns were observed in other Southern European economies, such as Spain. These trends coincided with a surge in cross-border financial flows toward Southern Europe, which motivated several theoretical studies exploring the relationship between capital flows and misallocation (Reis 2013, Benigno and Fornaro 2014, and Gopinath et al. 2017). A key contribution of this paper is to empirically test this link by leveraging micro-level data on firms, banks, and their credit relationships to explore the bank lending channel

Our identification strategy exploits the variation in bank exposure to the capital inflow boom, measured by the ex-ante foreign-liability ratio (foreign liabilities as a share of total liabilities). This approach, similar to Paravisini et al. (2015) and Mian and Sufi (2021), rests on the idea that capital inflows disproportionately benefit banks with pre-existing reliance on foreign market funding due to some stickiness of bank funding structures.[2]

To estimate the causal effect of bank exposure on credit supply, we apply the within-firm specification introduced by Khwaja and Mian (2008). This approach allows us to account for firm-specific factors that affect credit demand across all lenders, including changes in credit demand driven by the capital inflow boom. We evaluate credit allocation patterns through the lens of standard misallocation models, such as Restuccia and Rogerson (2008), Hsieh and Klenow (2009), and Baqaee and Farhi (2020). These models suggest that high-MRPK firms, which are sub-optimally small relative to their physical productivity, should attract more credit and absorb additional resources. By testing whether firms with higher or lower ex-ante MRPK benefit most from the increase in credit supply, we aim to capture the relationship between capital flows and misallocation.

We also examine the role of collateral constraints, using firms' fixed assets as a proxy. This analysis connects our findings to other studies like Gopinath et al. (2017), which emphasize size-dependent borrowing constraints as a key mechanism connecting capital inflows to increased misallocation.

Our findings reveal that the increase in credit supply from capital inflows is more pronounced for firms with higher ex-ante MRPK. Exposed banks also extend more credit to firms with higher collateral, but this is tied to productivity rather than collateral alone. Firms with low fixed assets but high MRPK benefit significantly from the credit-supply

[2]We show that the ex-ante ratio of foreign liabilities to total liabilities accurately predicts the subsequent share of total inflows across banks. Additionally, we use two alternative measures to isolate the push component of international capital flows: a time-varying measure of exposure, following Cesa-Bianchi et al. (2018), and a shift-share indicator, which is constructed using bank-level information about the geographical composition of foreign funding.

shock, whereas the firms with both low MRPK and low collateral are the ones that receive no additional credit from exposed banks. These results suggest that banks benefiting from capital inflows allocate credit in a manner that reduces misallocation. Furthermore, the credit-supply shock leads to higher investments and employment for high-MRPK firms, particularly those that were previously more credit-constrained.

To quantify the broader impact of these results on aggregate TFP, we apply the methodology developed by Sraer and Thesmar (2023). Unlike Hsieh and Klenow (2009) and Baqaee and Farhi (2020), this approach endogenizes the capital wedges responsible for MRPK dispersion in the economy. This allows wedges to adjust in response to concurrent shocks beyond capital flows and other equilibrium factors. Such flexibility enables us to account for general equilibrium forces that may offset the credit allocation patterns observed at the firm level. Our analysis shows that capital inflows reduced misallocation and boosted aggregate TFP, even after accounting for general equilibrium effects.

Although productivity declined and credit expanded in Italy and other Southern European countries - consistent with the findings of Muller and Verner (2023) - our analysis shows that capital inflows were not the primary source of bank funding driving this trend. In the conclusion, we suggest avenues for future research on the relationship between credit growth and misallocation. Specifically, we highlight the need to explore the interaction between banks' funding structures (beyond capital inflows), banking competition, and credit allocation.

Finally, our results hold under a wide range of robustness checks. We also test for potential indirect effects of capital inflows on misallocation. For example, exposed banks could increase the liquidity of non-exposed banks through interbank lending, bond purchases, or equity acquisitions, potentially leading to additional credit for less productive firms. However, we find no evidence of such spillover effects. Interbank lending between exposed and non-exposed banks did not rise, nor did bond or equity financing from exposed to non-exposed banks. Additionally, we test whether capital inflows made banks more fragile after 2008, as foreign funding rapidly declined, but we find no evidence of this effect.

The paper is structured as follows: section 2 describes the historical context; section 3 presents the data; section 4 discusses the empirical strategy; section 5 presents the results; section 6 looks at the aggregate implication on TFP; section 7 analyzes the robustness of our results along several dimensions; finally, section 8 concludes discussing potential avenues for further research.

Related literature

The paper contributes to the literature about the impact of international financial flows on productivity such as Buera et al. (2011), Reis (2013), Benigno and Fornaro (2014), Benigno et al. (2015), Larrain and Stumpner (2017), Buera and Shin (2017), Gopinath et al. (2017), Varela (2018), Castillo-Martínez (2019), Bau and Matray (2023), Saffie et al. (2020), and Benigno et al. (2023). These studies present varying theoretical predictions on how capital inflows affect resource allocation and aggregate TFP. Differences arise primarily from the types of shocks they examine—some focus on transitional dynamics following declines in real interest rates in developed economies (Gopinath et al., 2017; Reis, 2013; Benigno and Fornaro, 2014), while others explore episodes of financial liberalization in emerging markets (Buera and Shin, 2017; Varela, 2018). Relative to this literature, we can empirically identify the causal impact of capital inflows on misallocation in a way that these other papers could not. This contribution leads us to assess a beneficial effect of capital inflows in Southern Europe on productivity.

More broadly, our paper contributes to the literature on the effects of foreign capital flows on the real economy, such as Gourinchas and Jeanne (2006), Prasad et al. (2007), Bonfiglioli (2008), Rodrik and Subramanian (2009), Levchenko et al. (2009), Bekaert et al. (2011); Chari et al. (2012), Gourinchas and Jeanne (2013), Broner and Ventura (2016), Baskaya et al. (2017), di Giovanni et al. (2021), Bau and Matray (2023). Most of these works examine episodes of financial account liberalization in emerging markets from a macroeconomic perspective. Baskaya et al. (2017), di Giovanni et al. (2021) and Bau and Matray (2023) are notable exceptions. Nevertheless, the former two papers use micro data on banks and credit in Turkey, but do not have data on firm characteristics. Whereas, Bau and Matray (2023) identify the impact of foreign direct investment (FDI) liberalization in India on misallocation, leveraging its staggered implementation across industries. However, their study cannot directly observe the firms benefiting from these inflows. In our analysis we are able to identify the banks exposed to capital inflows as well as the firms associated with these banks. Furthermore, we complement their work by focusing on banking flows into an advanced economy, rather than FDI flows into an emerging market, while arriving at similar conclusions regarding the positive effects of capital inflows.

Finally, the current paper speaks to the literature analyzing capital flows and the EMU such as, Lane and Milesi-Ferretti (2007*a*), Spiegel (2009), Kalemli-Ozcan et al. (2010), Giavazzi and Spaventa (2011), Lane (2013), and Hale and Obstfeld (2016). Our contribution is to look into the effect of these flows on local banking and productivity. Our paper relates also to the extensive literature on the so-called bank-lending channel as in Khwaja and Mian (2008), Paravisini (2008), Amiti and Weinstein (2011), Schnabl (2012), Jiménez et al. (2014), Chodorow-Reich (2014), Paravisini et al. (2015), Cingano et al. (2016), Mian et al. (2020), and Amiti and Weinstein (2018).

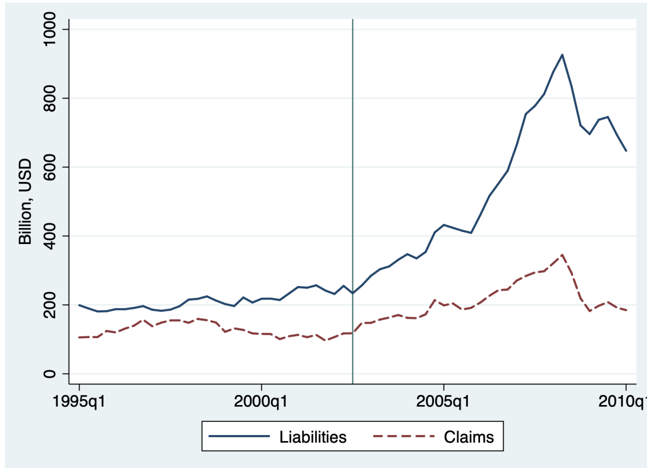
2 Capital inflows boom and misallocation trend

Several studies have examined the surge of capital inflows into Southern Europe during the early 2000s. Lane and Milesi-Ferretti (2007*b*) and Lane (2013) argue that this rise in cross-border flows was part of a broader global trend driven by changes in international banking practices—particularly the growth of securitization—which increased bank liquidity. This period also coincided with a reduction in global uncertainty, as reflected in the decline of the VIX. In the euro area, cross-border flows were particularly significant, with the introduction of the common currency promoting greater financial integration (Kalemli-Ozcan et al., 2010). European banks played a key role in the securitization surge (Lane and Milesi-Ferretti, 2008). Hale and Obstfeld (2016) further illustrate how banks from core eurozone countries used foreign capital to increase lending to peripheral eurozone banks.

Figure 1 shows the trajectory of foreign liabilities and claims for Italian banks from 1995 to 2010. Foreign liabilities remained stable until 2002, after which they increased nearly fourfold, peaking before the global financial crisis. This increase in liabilities was not accompanied by a corresponding rise in foreign assets, leading to greater liquidity in the domestic economy. As a result, the net international investment position of Italian banks declined from -5% to -25% of GDP between 2002 and 2008. Most of the foreign funding came in the form of euro-denominated loans, minimizing currency risk, with an average maturity of 12 months.

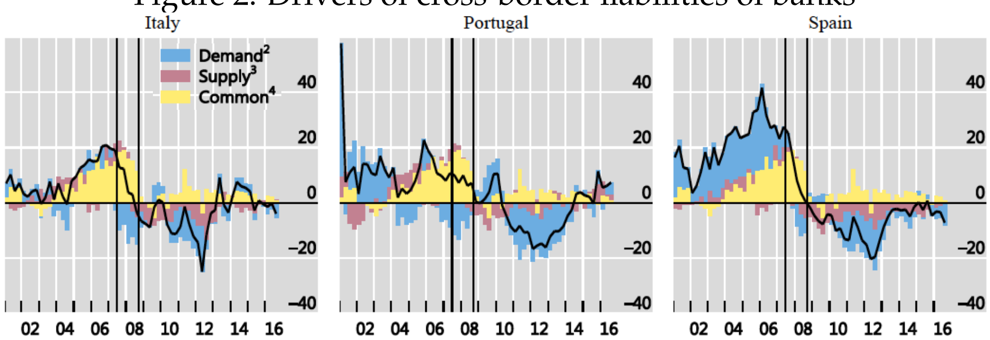
The pattern of cross-border banking flows in Italy mirrored trends seen in other European countries like Spain, although Italy's current account imbalance was less pronounced. More importantly, Amiti et al. (2017) show that capital inflows to Italy were primarily driven by global push factors, while domestic pull factors dominated in Spain (see Figure 2). This distinction is significant for both policy implications and identification strategies. If misallocation were caused by push factors, it would support the case for capital controls, while pull-factor-driven misallocation would suggest the need for stronger macro-prudential measures. When it comes to identification, in Italy's case, where global factors were predominant, the risk of endogenous bias in estimating the effects of cross-border flows from domestic drivers is minimized.

Figure 1: Foreign liabilities and claims of banks operating in Italy



Source: BIS, locational banking statistics. Vertical line is at 2002-Q3.

Figure 2: Drivers of cross-border liabilities of banks

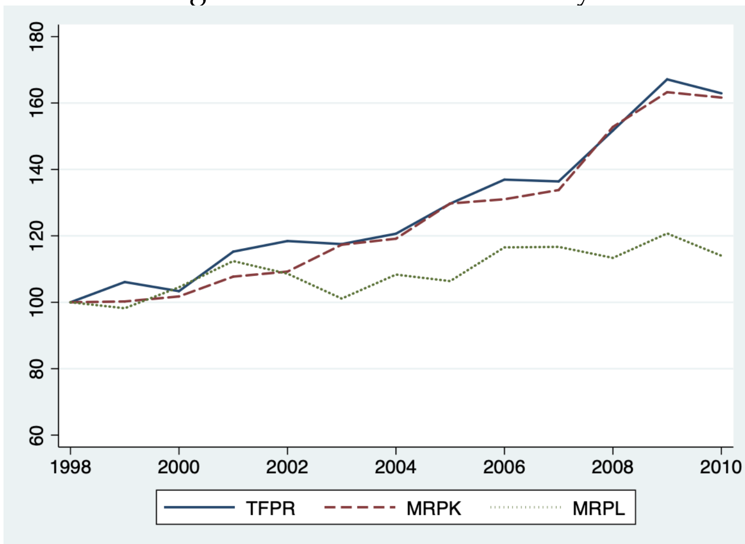


Source: Amiti et al. (2017) on BIS data. Year-on-year growth of cross-border liabilities (adjusted for breaks in series and exchange-rate movements) of banks located in Italy, Portugal and Spain. 2 Demand (pull factors): estimated demand shocks in each borrowing country. 3 Supply (country-specific push factors): estimated net supply shocks to the banking system in that country. 4 Common (push factors): estimated shocks that are common to all banking systems across countries.

During the capital inflow boom, several countries, including Italy, experienced heightened misallocation (Gopinath et al. 2017; Calligaris et al. 2018; García-Santana et al. 2020). Building on the work of Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), misallocation can be measured through the dispersion of total factor productivity revenue (TFPR), the marginal revenue product of capital (MRPK), and the marginal revenue product of labor (MRPL). In Figure 3 we replicate Calligaris et al. (2018) to illustrate the misallocation trend during the period under study. The data reveal a significant rise in the dispersion of TFPR and MRPK, while MRPL dispersion remains relatively stable.

Motivated by the patterns shown in Figures 1 and 3, several models have been developed to explain the rise in misallocation as a consequence of the capital inflow boom (Reis,

Figure 3: Misallocation in Italy



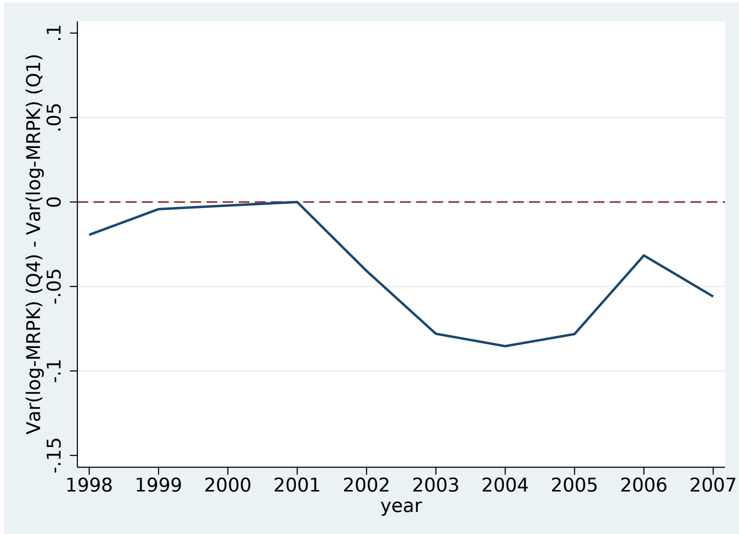
Note: Variance of TFPR, MRPK and MRPL in Italian industries as in Calligaris et al. (2018).

2013; Benigno and Fornaro, 2014; Gopinath et al., 2017; Benigno, Fornaro and Wolf, 2023). Using detailed micro-level data from Italy, we empirically test this link, concentrating on the bank-lending channel, and arrive at markedly different conclusions

As preliminary evidence, we rank 3-digit industries by their exposure to capital flows, using cross-border inflows to the banks lending to firms in these industries (details on this measure are provided in the next section). Although most firms do not borrow directly from abroad, they are indirectly exposed to capital inflows through their lending banks. We then calculate the variance of log-MRPK for each 3-digit industry and aggregate it by quartile based on exposure to capital flows, weighted by credit shares. Figure 4 tracks the evolution of misallocation between industries in the top quartile of capital flow exposure and those in the bottom quartile. While there was no significant difference in misallocation trends during the early years of the sample, MRPK dispersion in the most exposed industries decreases substantially following the surge in capital inflows.

Thus, Figure 4 provides preliminary evidence suggesting that capital inflows are linked to a reduction in misallocation, rather than an increase. The next steps involve identifying the specific impact of capital inflows on credit allocation across firms and quantifying the effects on misallocation and aggregate productivity, while accounting for general equilibrium forces.

Figure 4: Variance of MRPK and sector exposure to capital inflows



Note: The graph shows the difference of the variance of log-MRPK between sectors that are in the top quartile of exposure to capital inflows and those that are in the bottom quartile (the difference is normalized to zero in 2001). For each 3-digit sector in the economy, we compute exposure to capital inflows as the average exposure of the banks lending to the firms in that sector (credit-weighted). We then aggregate this measure for sectors in the top and bottom quartile of exposure, using credit shares as weights.

3 Data and measurment

3.1 Data sources

Our analysis relies on a matched dataset that contains detailed information on bank credit extended to a large sample of Italian companies. This dataset is constructed by integrating three key sources: the Italian Credit Register, banks' balance-sheet data, and firms' balance-sheet data.

The primary source is the Italian Credit Register, administered by the Bank of Italy, which provides a monthly panel of the outstanding debt of every borrower (whether firm or individual) with loans exceeding EUR 75,000 from any bank operating in Italy. For our purposes, we focus exclusively on non-financial corporations and build an annual bank-firm panel. In this panel, loans are measured as the total outstanding credit granted at the end of each year, including both committed credit lines and fixed-term loans.

Banks' balance-sheet data come from the Bank of Italy's Supervisory reports, which offer detailed information on banks' assets and liabilities, including specifics about foreign funding sources. Firms' balance-sheet data, covering variables such as revenues, investments, employment, and wage bills, are obtained from the CERVED database, which captures the universe of incorporated firms in Italy.[3] We match the bank-firm loan data with banks' and firms' balance-sheet data using unique identifiers for both banks and firms.

Since funding structures and lending policies are determined at the banking group level, we consolidate the balance sheets at this level, making it the relevant unit of observation for our analysis of the bank lending channel. If a firm borrows from two banks within the same group, we treat this as a single relationship, aggregating the two loans. We also account for mergers and acquisitions among banks. When a firm's bank is acquired or merged, we track whether a new relationship forms with the newly created or acquiring bank, ensuring that no gaps appear in our dataset due to mergers.

Table A1 in the Appendix provides summary statistics for the characteristics of the banks and firms in our sample. The unit of observation for our empirical analysis is at the bank-firm-year level. On average, the dataset includes approximately 620 banks and 170,000 firms in manufacturing and services per year. The simple average of the share of banks' foreign liabilities is 3.7%, with a standard deviation of 13.1%. The distribution of banks' foreign funding reveals that many smaller banks are not exposed to international financial markets. As a robustness check, we exclude banks with no foreign exposure or exposure below 1%, as well as cooperative banks, which are often localized in their funding sources for institutional and historical reasons. The results remain robust to this exclusion.

Finally, it is important to note that Italian firms typically borrow from multiple banks, including small firms. Approximately 68% of the firms in our sample have credit relationships with two or more banks, and these firms account for 90% of total corporate credit. Firms with multiple lenders have an average of 4.5 banking relationships. This widespread use of multiple banking relationships is a key feature of our identification strategy.

3.2 Bank-level exposure to foreign capital

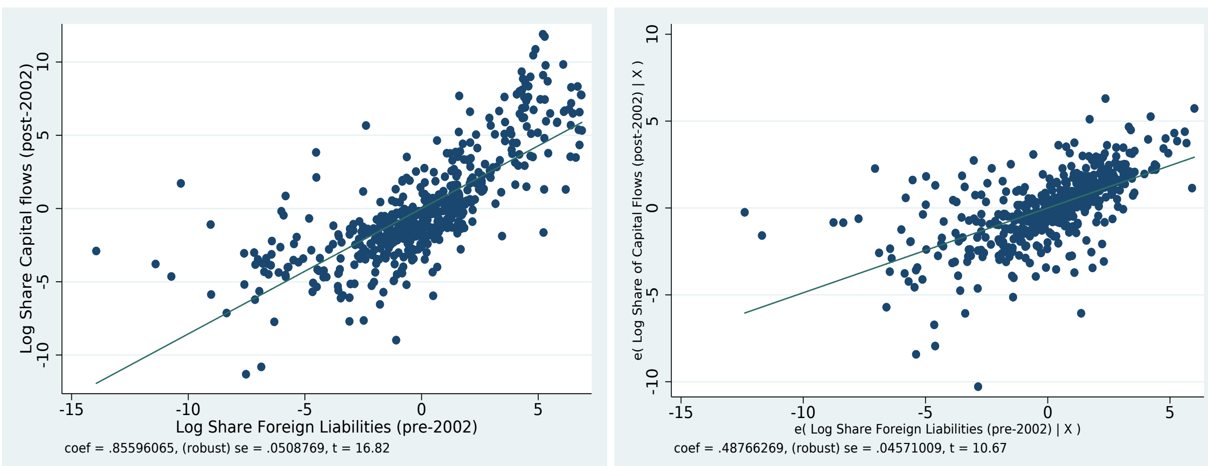
Financial institutions draw on various funding sources when issuing loans. Our measure of bank exposure to international financial flows is based on the premise that the surge in capital flows after 2002 provided greater funding opportunities to banks that already had a higher share of foreign liabilities before the shock. This approach assumes

[3] Incorporated firms from CERVED account for 70% of value added in manufacturing and 60% in services from national accounts and their aggregate trend follows very closely the national one.

some degree of persistence in the liability structure of banks over time.[4]

Figure 5 illustrates a strong correlation between a bank's average share of foreign liabilities in 1998-2001 (horizontal axis) and the share of total capital inflows to the Italian banking system received by each bank after 2002. Panel A presents this correlation without controls, while Panel B adjusts for key bank characteristics measured ex-ante.[5] In both panels, we observe a positive and significant correlation between the two variables. This finding suggests that the level of foreign financing before the capital inflow surge is a reliable proxy for measuring banks' exposure to international financial flows during 2002-2007.

Figure 5: Share of foreign funding (pre-2002) and share of total capital inflows (post-2002)



(a) Unconditional correlation

(b) Controlling for bank characteristics

Table 1 provides additional evidence supporting the use of this proxy. Column (1) reports the regression coefficient from Figure 5, while Column (2) shows that banks with a higher pre-boom share of foreign liabilities experienced greater growth in foreign funding after the inflow surge. Column (3) examines the persistence of banks' liability structure by analyzing the stability of their foreign-liability rankings. A cross-ranking regression of foreign funding in 2002-2007 on the rankings from 1998-2001 yields a coefficient of 0.75. While we abstract from the reasons for this persistence—such as potential fixed costs associated with foreign funding—these findings confirm that a bank's pre-2002 for-

[4]The source of variation that we exploit is conceptually similar to the one employed by Paravisini et al. (2015), di Giovanni et al. (2021) and Mian and Sufi (2021) in the context of other banking shocks.

[5]These controls include log-assets, as a proxy for bank size; the share of core liabilities, to capture the relevance of deposit funding in the liability structure; capital ratio, as a proxy for leverage; and the share of NPLs, to control for bank vulnerability.

eign liability share is a useful instrument for capturing differences in exposure to capital flows.[6]

Table 1: The foreign-liability ratio predicts exposure to capital inflows and is sticky

	Share of total inflows (02-07) (1)	Growth of foreign liabilities (post vs. pre) (2)	Rank foreign liability ratio (02-07) (3)
Foreign liability ratio (98-00)	0.49***	0.51***	
	(0.05)	(0.04)	
Rank foreign liability ratio (98-00)			0.75***
			(0.03)
Bank Chars. $*$ Post	✓	✓	✓
Observations	494	494	494
$Adj.R^2$	0.80	0.63	0.71

Note: All regressions include bank controls measured in 1998-2000 (log-assets, NPL ratio, capital ratio and core funding ratio). Standard errors are clustered at the bank level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

As a robustness check, we employ two alternative measures (see Section 7.2 for details). First, we construct a time-varying measure of bank exposure that isolates the ”push factors” component of capital inflows, following the approach of Cesa-Bianchi et al. (2018) to capture supply shocks. Second, we use a shift-share approach, leveraging bank-level data on the country of origin for foreign funding. This method predicts an Italian bank's exposure as the weighted average of capital outflows from foreign countries (the “shift”), with weights based on the initial composition of the bank's inflows by country of origin (the “shares”). Our results remain robust using these alternative measures.

4 Empirical strategy

4.1 Conceptual framework

Figure 4 shows a reduction in misallocation in industries that borrow from banks exposed to capital inflows. Our aim is to determine whether this decline in misallocation can be explained by changes in credit allocation resulting from these inflows. A useful framework for connecting credit allocation to misallocation is found in traditional heterogeneous firm

[6]This proxy captures the *direct* exposure of Italian banks to capital flows. In the robustness section 7.1 we show that there are no relevant spillover effects through interbank lending or other channels. This suggests that our main variable is a good proxy for the *overall* exposure of banks.

models, where misallocation is measured by the dispersion of the marginal revenue product of inputs (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Baqaee and Farhi, 2020).

In these models, firms differ based on their physical total factor productivity (TFP)—their ability to generate output from a given set of inputs. Ideally, in a frictionless market, the marginal revenue product of inputs (both MRPK and MRPL) should be equal across firms. In such a scenario, firms with higher MRPK would attract more credit and grow, while firms with lower MRPK would contract. However, due to market frictions, there is a gap between the marginal product of inputs and their cost, resulting in MRPK (or MRPL) and TFPR dispersion, which is interpreted as inefficient resource allocation.[7]

In this context, if capital inflows reduce misallocation through increased bank credit, we would expect banks exposed to these inflows to increase credit supply disproportionately to firms with higher MRPK compared to those with lower MRPK, thus encouraging MRPK equalization within industries. Evidence to the contrary would suggest that capital inflows lead to greater misallocation. To explore this, in our baseline estimate, we split firms into those with MRPK above and below the median within their 3-digit sector at the onset of the shock.[8]

Gopinath et al. (2017) highlight that size-dependent borrowing constraints are a significant driver of misallocation in this type of framework. These constraints limit borrowing to a fraction of a firm's assets, and such fraction is increasing in assets size. Consequently, larger firms, though receiving more credit, tend to have lower MRPK, as they are already capital abundant.

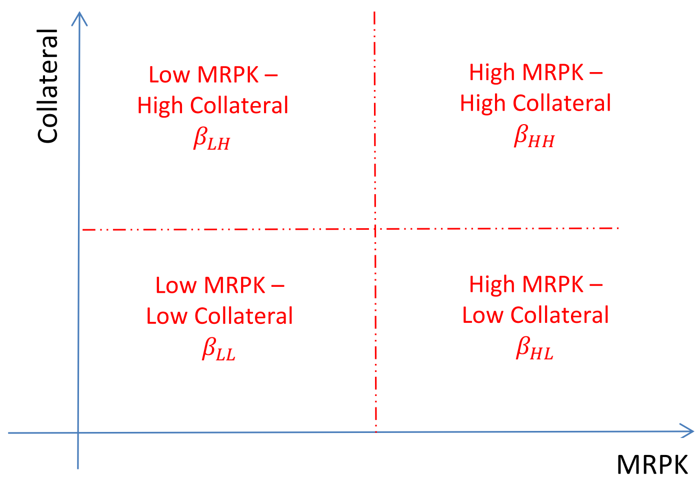
To account for this dynamic, we differentiate borrowers also based on their collateral,

[7]This approach has several caveats, as the literature highlights that dispersion in marginal products may not always indicate resource misallocation. Asker et al. (2014) argue that, in the presence of adjustment costs in investment, transitory idiosyncratic TFP shocks across firms can naturally create dispersion in productivity without implying inefficiency. Similarly, De Loecker and Goldberg (2014) and Haltiwanger (2016) suggest that much of the variation in revenue-based TFP reflects demand shifts and market power, rather than allocative inefficiency.Bils et al. (2021) emphasize the role of mismeasurement in calculating the marginal product of factors, which can lead to errors in assessing misallocation. Additionally, Haltiwanger et al. (2018) show that the Hsieh-Klenow model only maps observed production behaviors to inefficient wedges or distortions under strict theoretical assumptions, which may not always hold. David and Venkateswaran (2019) further demonstrate that in the U.S., firms' adjustment costs explain only a small portion of productivity dispersion, while markups account for about 28% of the overall dispersion.

[8]We compute MRPK following the production function estimation methodologies of Levinsohn and Petrin (2003), Wooldridge (2009), and Gandhi et al. (2020). Detailed information on these estimates is provided in Appendix section A.3. We would like to thank Simone Lenzu and Francesco Manaresi for sharing their data and code for estimating MRPK using the CERVED sample. The results remain consistent when applying the methodologies of De Loecker and Warzynski (2012) or of Hsieh and Klenow (2009). Additionally, estimating the median threshold across the full sample of firms, rather than by industry, does not alter our findings. In the Appendix, we also present results by splitting firms into quintiles based on the MRPK distribution.

as measured by fixed assets. Figure 6 provides a simple illustration of this partition. It is important to note that our approach does not strictly link asset size to MRPK. A firm with high MRPK indicates that its size is suboptimal relative to its physical productivity, though the firm may still be large in absolute terms.[9]

Figure 6: Portfolio allocation by MRPK and collateral



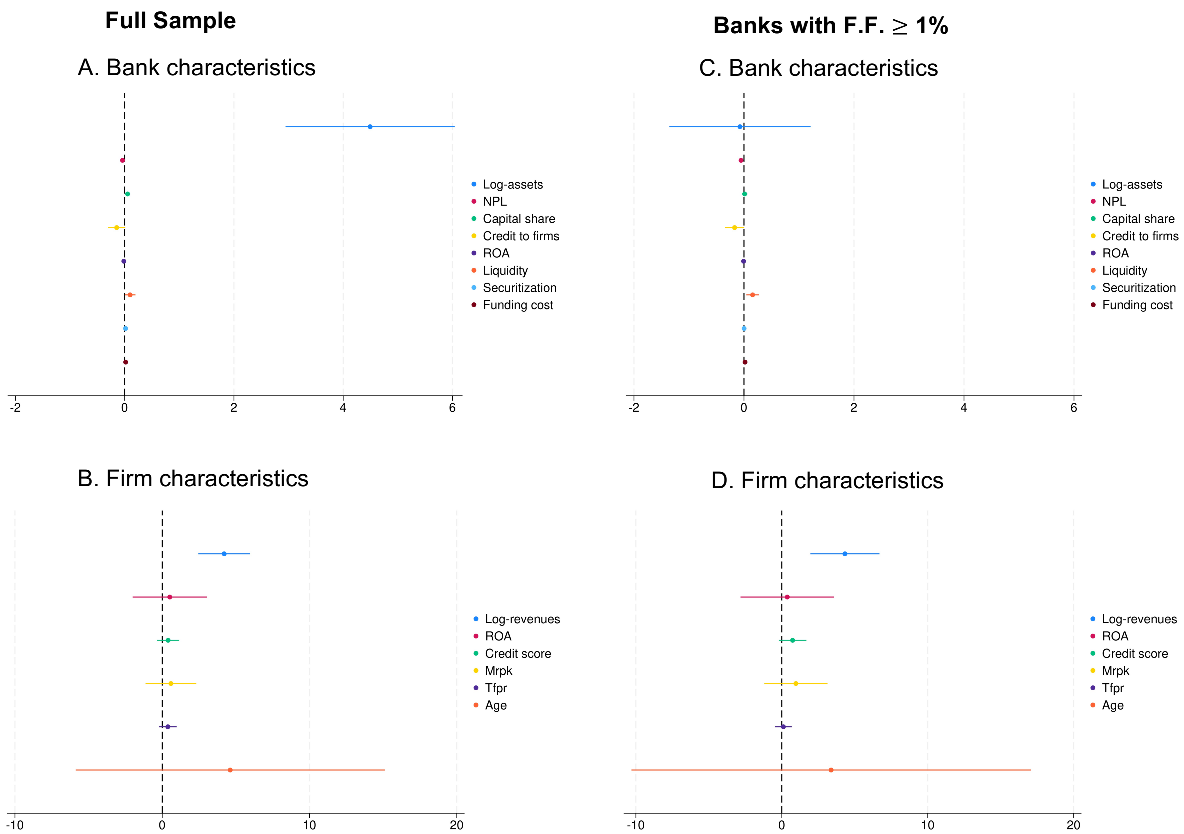
We also examine the channels through which capital inflows might affect misallocation via bank lending. One possibility is the "sorting channel," where credit misallocation is a byproduct of pre-existing patterns between bank exposure and firm characteristics. In this case, if high-MRPK firms were already borrowing more from exposed banks before the capital inflows, these firms would naturally receive a larger share of new resources. Alternatively, exposed banks could actively adjust their portfolio, targeting high-MRPK firms, which we refer to as the "portfolio channel."

Figure 7 illustrates the correlation between bank exposure to capital inflows and both bank characteristics (panel A) and borrower characteristics (panel B). We find that banks exposed to capital inflows tend to be larger and lend to larger firms. However, other bank and firm characteristics are well balanced. Exposed banks are not necessarily more profitable or better capitalized, nor they tend to match with high-MRPK or high-profitability firms. Our empirical approach controls for the possible confounding role of these other bank characteristics, to ensure the findings do not overstate the impact of bank exposure.

The positive correlation between bank size and foreign borrowing is driven by the presence of many small banks that do not engage in foreign borrowing. Panel C shows

[9]Empirically the correlation between MRPK and total fixed assets is -0.27, which is sufficiently weak to ensure that firms with a high-MRPK are not necessarily also the ones with low collateral.

Figure 7: Correlation of bank exposure with bank and firm characteristics



Note: Regression coefficients of bank exposure on bank and firm characteristics (1998-2000 averages), at 95% confidence intervals. Full sample in panels A and C; banks with at least 1% foreign funding in panels C and D.

that, among banks with minimal foreign funding, there is no relationship between bank size and exposure to capital inflows, supporting the notion that foreign borrowing involves fixed costs. Many of the banks that do not rely on foreign funding are cooperative banks, which, due to their history, tend to have localized sources of funding and operations.[10] Our findings remain consistent when these banks are excluded, indicating that the results are not merely a comparison between banks exposed to foreign funding and small cooperative banks. Finally, while larger firms tend to be linked to banks with greater exposure to capital inflows, Figure A1 in the Appendix shows that the size distribution of firms borrowing from banks with above- or below-average exposure is quite similar. These results suggest that ex-ante sorting is unlikely to be the primary driver of the paper's findings.

[10]Until the banking reform of 1993, cooperative banks were geographically restricted to their areas of operation and could engage in a more limited range of activities compared to standard banks. Although these banks are numerous (around 400), they account for only 5% of total credit.

4.2 Foreign capital flows and the bank-lending channel

As a next step, we aim to identify how exposure to international financial flows influences credit allocation. Specifically, we test whether banks with greater exposure tilt their credit supply towards high-MRPK firms. Our empirical approach follows the within-estimator methodology of Khwaja and Mian (2008), exploiting the fact that most firms borrow from multiple banks, each of which have varying levels of exposure to capital inflows:

$$\ln C_{ibt} = \beta_1\ Exposure_b \times Post_t + \beta_2\ Spec_{ibt} + \boldsymbol{X_b'}\boldsymbol{\delta} \times Post_t + \alpha_{it} + \gamma_{ib} + \epsilon_{ibt} \tag{1}$$

In this baseline specification the dependent variable is the logarithm of outstanding credit granted by bank b to firm i at the end of year t. The variable $Exposure_b$ measures the ex-ante share of foreign funding in 1998-2001 period, and it is interacted with a dummy equal to 1 for the years after the boom in capital inflows (2002-2007), and 0 for the earlier years ($Post_t$). The specification includes a full set of firm-year fixed effects (α_{it}) controlling for any firm-specific shocks that could influence credit demand, assuming these shocks affect all banks equally.

Given that demand shocks may not be uniformly distributed across banks, but can be tilted towards lenders specialized in the sector of the firm, we include the variable $Spec_{ibt}$, a dummy equal to 1 if a firm operates in a sector into which a bank is specialized (Paravisini et al., 2023).[11] To account for potential non-random matching between firms and banks, we include firm-bank fixed effects γ_{ib}, which capture time-invariant factors affecting credit, such as relational banking or firm-bank sorting mechanisms. Additionally, we control for other possible determinants of lending decisions, allowing for a potentially concurrent effect on credit of a set of bank characteristics other than exposure.[12] Given that our source of variation is at the bank level and that firms' demand for specific banks can vary according to the sector of specialization of the bank, we cluster the standard errors at the bank and sector (3-digits) level.

The coefficient β_1 captures the marginal effect of bank exposure on credit supply, following the surge in capital inflows. Since firm-year fixed effects are included, our identification strategy relies on within-firm variation in credit allocation across multiple lenders

[11] A bank is considered specialized in a particular sector (3-digit) if its share of loans in that sector exceeds the interquartile range of all other banks in the economy.

[12] These characteristics include the following: log assets, serving as a proxy for bank size; the share of non-performing loans (NPLs), reflecting bank performance and management quality; bank core liabilities, controlling for the bank's funding structure; the capital ratio, which accounts for the degree of bank leverage; and the share of domestic interbank funding, to control for potential spillovers between domestic banks. These variables represent average values from 1998-2000 and are interacted with the $Post_t$ dummy.

with differing levels of exposure. The firm-year fixed effects and the bank specialization dummy help absorb firm-level shocks affecting credit demand, enabling β_1 to identify the bank lending channel driven by exposure to international capital inflows.

To account for potential pre-trends among banks that could affect our results, we also employ a dynamic difference-in-difference approach. This method allows us to examine the full dynamics of credit supply from 1998 to 2007 and assess how credit allocation varies before and after the capital inflows boom. Specifically, we run:

$$\ln C_{ibt} = \sum_{q=1998}^{2007} \beta_q \; Exposure_b \times \mathbb{1}_{t=q} + \beta_2 \; Spec_{ibt} + \sum_{q=1998}^{2007} \boldsymbol{X_b'\delta_q} \times \mathbb{1}_{t=q} + \alpha_{it} + \gamma_{ib} + \epsilon_{ibt}$$

where β_q captures the year-by-year effect of bank exposure.

Equation 1 captures the bank lending channel for the average firm in the economy. However, we are interested in the allocation of credit across different types of firms along the lines discussed in Section 4.1. For each 3-digit industry in our sample, we characterize firms as high- or low-MRPK and high- or low-fixed assets, based on the median within their industry. We then estimate the effect of bank exposure to capital inflows on credit supply across these firm groups, as outlined in Figure 6:

$$\ln C_{ibt} = \sum_{d} \beta_d \; D_i^d \; (Exposure_b \times Post_t) + \beta_2 \; Spec_{ibt} + \boldsymbol{X_b'\delta} \times Post_t + \alpha_{it} + \gamma_{ib} + \epsilon_{ibt} \quad (2)$$

where D_i^d is an indicator variable representing different firm groups, with *d*= *HH*,*LH*, *HL*, *LL*. For example, HH refers to High-MRPK & High-Fixed asset borrows and LL to Low-MRPK & Low-Fixed asset borrowers. We also estimate this specification by dividing firms into simpler groups, with $d = H, L$, such as high-MRPK and low-MRPK.

If capital inflows help reduce misallocation, we would expect $\beta_{High-MRPK} > \beta_{Low-MRPK}$. Moreover, if credit allocation is constrained by pledgeable collateral, the effect should be strongest for $\beta_{H,H}$ (High-MRPK and High-Fixed assets firms) and weakest for $\beta_{L,L}$(Low-MRPK and Low-Fixed assets). In the intermediate cases, banks face a risk-return trade-off, and comparing $\beta_{H,L}$ to $\beta_{L,H}$ allow us to assess which factor - productivity or collateral - prevails. We discuss several robustness checks for this analysis in Section 7.

4.3 Extensive margin and total firm-level effects

While equations (1) and (2) we are also interested in examining the effects on the extensive margin. To do this, we estimate the following specification:

$$Entry_{ib\tau}\ (Exit_{ib\tau}) = \sum_{d} \beta_d\, D_i^d\, (Exposure_b \times Post_\tau) + \beta_2\, Spec_{ib\tau} + \boldsymbol{X_b'}\boldsymbol{\delta} \times Post_\tau + \alpha_{i\tau} + \gamma_b + \epsilon_{ib\tau} \tag{3}$$

In this specification, the dependent variable takes a value of 1 if bank b and firm i either start or end a lending relation after the capital inflows boom, with the years before and after 2002 collapsed into two periods panel ($\tau = 1, 2$). As with the previous specifications, we control for whether the bank specializes in the sector in which the firm operates, as well as for bank pre-characteristics, firm-period fixed effects, and bank fixed effects.

For the $Exit$ specification, the dependent variable equals 1 if an existing credit relation between firm i and bank b ends in period τ, and 0 if the relationship continues. The $Entry$ specification runs on a larger sample as it considers all potential firm-bank relations in a given province, which, from a regulatory point of view, identifies the relevant market for bank lending. In this case, the dependent variable equals 1 if bank b starts a credit relation with firm i during period τ, and 0 if no relationship is initiated

Next, we analyze the impact of bank exposure on the total credit a firm receives, as well as on the firms' investments and employment. It is possible that high-MRPK firms increase their borrowing from more exposed banks while decreasing it from less exposed ones. If this happens, capital inflows may simply trigger a substitution of credit across lenders, without significantly changing the total credit available to high-MRPK firms. Moreover, if there were no stickiness in lending, firms — including low-MRPK firms — could rapidly form or deepen relationships with banks benefiting from the inflows, which would weaken or negate the within-firm effects observed on the intensive margin.

To assess the overall firm-level impact of the bank-lending channel driven by capital inflows, we aggregate the bank-firm regressions from Equations (1) and (2) to the firm level, using the bank shares in firms' borrowing as weights. Our primary variable of interest is the firm-level measure of exposure to capital flows, which is calculated as the weighted average of the firm's lenders' exposure:

$$Exposure\ Firm_i = \sum_b Exposure_b\ \frac{Credit_{ib}}{Total\ Credit_i} \tag{4}$$

Using this firm-level exposure as the main dependent variable, we run the following specification at the firm-year level:

$$\ln Y_{it} = \sum_{d} \beta_d \, D_i^d \; Exposure \; Firm_i \times Post_t + \boldsymbol{X_i'}\boldsymbol{\delta} \times Post_t + \hat{\alpha_{it}} + \gamma_i + \epsilon_{it} \tag{5}$$

In this specification, Y_{it} represents total credit, investment, or employment, while X_i is a weighted average of firm lenders' characteristics measured in 1998-2000. The firm fixed effects γ_i are derived from the aggregation of the firm-bank fixed effects and $\hat{\alpha_{it}}$ represents the firm-time fixed effects estimated in equation (2). This latter variable allows us to control for credit demand at the firm level, consistent with the approaches of Alfaro et al. (2021) and Bofondi et al. (2018). We present results both with and without the estimated firm-time fixed effects.

Our set of specifications offers a comprehensive picture of the credit effect of a trade shock. Equation (1) allows us to distinguish neatly between supply and demand effects; equation (3) accounts for the extensive margin of credit; and equation (5) looks into the effect on the aggregate credit that a firm receives and the real effects on investments and employment.

5 Results

Average effects on credit supply. We begin by confirming that the surge in capital inflows significantly expanded bank credit availability for the average firm in the economy. Tables A2, A3 and A4 in the Appendix analyze the intensive margin, extensive margin, and aggregate credit, respectively. Using within-firm variation (equation 1) and various empirical specifications, we estimate that a 10-percentage-point (pp) increase in bank exposure results in a 3% increase in lending along the intensive margin and a 17% lower probability of forming new credit relationships. Regarding aggregate firm credit, a 10pp increase in exposure to capital flows corresponds to a 3% rise in credit following the capital inflow boom. These findings suggest that firms borrowing from highly exposed banks primarily benefit from increased credit supply along the intensive margin, while those borrowing from banks with lower exposure are unable to switch to banks with high exposure.

In the Appendix, we further explore the variation in credit-supply shocks across industries (Tables A5, A6, A7). Our results indicate that banks with higher exposure increase lending to manufacturing firms but not to firms in the construction or wholesale and retail sectors. Despite the overall credit boom in services and construction in Italy, we find no evidence of differential effects based on banks' exposure to capital flows. These findings align with Gopinath et al. (2017), who focused on capital flows and misallocation within manufacturing.

Heterogeneous effects by firm characteristics: intensive margin. Next, we examine how capital inflows influence credit allocation across firms with different characteristics. The results in Table 2, which correspond to the specification in equation (2), allow for heterogeneity in credit-supply shocks based on firms' marginal revenue product of capital (MRPK) and collateral.

Column (1) shows that highly exposed banks disproportionately allocate loans to high-MRPK firms, with a 10pp increase in exposure leading to a 4% rise in credit for these firms. Low-MRPK firms also receive more credit, but the effect is significantly smaller. Column (2) reveals that high-collateral firms benefit more from credit expansion compared to low-collateral firms, consistent with the findings of Gopinath et al. (2017). However, column (3) shows that the role of collateral is not independent of MRPK: firms with high MRPK and low collateral (High MRPK-Low FA) receive a similar amount of extra credit as low-MRPK, high-collateral firms (Low MRPK-High FA), with no significant difference between the two groups. This suggests that banks balance their credit portfolios in a balanced way when it comes to a productivity-risk trade-off. Firms with both low collateral and low MRPK are the only ones that do not benefit from the credit supply expansion. At the other end of the spectrum, firms with both high MRPK and high collateral gain the most from the expansion.

These results remain robust across a wide range of alternative specifications and checks, as detailed in the Appendix. These robustness checks include identifying constrained firms based on credit scores, adjusting the identification strategy, changing explanatory variables, and modifying the sample. These additional analyses are discussed in detail in Section 7.

While these results do not imply optimal lending behavior, they suggest that the shift in credit allocation is consistent with reduced misallocation rather than increased inefficiency.

One concern is whether this shift in credit allocation is directly caused by the surge in foreign capital inflows and does not follow some pre-trend. Support for this view comes from Figure 8, which illustrates the year-by-year marginal effects of bank exposure on credit supply throughout the study period. In Chart 8(a), which represents the full sample of firms, the effect of bank exposure is statistically insignificant in the years preceding the capital inflow surge and becomes significant only afterward, alleviating concerns about pre-trends. This pattern is further confirmed when we examine high-MRPK firms

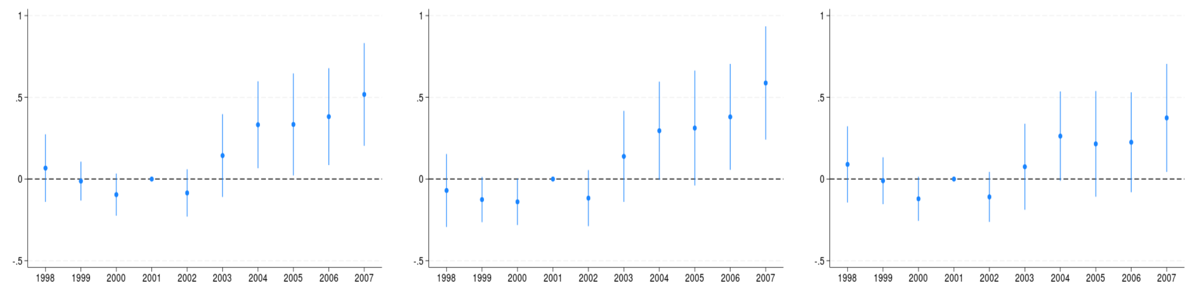
Table 2: Capital inflows and credit allocation by firm characteristics, intensive margin

	Dependent variable: ln $Credit_{ibt}$		
Firm characteristic D_i: Ind. var.: $Exposure_b * Post_t * D_i$	MRPK (1)	Fixed Assets (2)	MRPK / Fixed Assets (3)
High	0.353*** (0.076)	0.310*** (0.068)	
Low	0.218*** (0.072)	0.162*** (0.074)	
High MRPK - High FA			0.504*** (0.074)
High MRPK - Low FA			0.265** (0.078)
Low MRPK - High FA			0.321*** (0.068)
Low MRPK - Low FA			0.046 (0.17)
P-value test High=Low	0.00	0.00	
P-value test HMP-LFA=LMP-HFA			0.24
Firm-time F.E.	✓	✓	✓
Firm-bank F.E.	✓	✓	✓
Specialization	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓
Observations	3,048,308	4,026,717	3,040,766
$Adj.R^2$	0.827	0.827	0.827

Note: The table reports the coefficients of the specification in equation 2 and it captures the effects of capital inflows on the intensive margin of credit allocation by type of firm. Firms are divided according to their level of MRPK (column 1), fixed assets (column 2), and the combination of the two (column 3) measured in 1998-2000. Standard errors are clustered at the bank-sector (3-digit) level.***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

in Chart 8(b), which experience a more pronounced credit shock, and low-MRPK firms in Chart 8(c), where the effect is less pronounced

Figure 8: Dynamic difference-in-differences



(a) Full sample (b) High-MRPK (c) Low-MRPK

Note: The figure plots the coefficients estimated from a dynamic difference-in-differences version of specifications 1 (panel a) and 2 (panels b and c), in which the dummy $Post_t$ is replaced by a set of year dummies (95% confidence intervals).

Extensive margin. Table 3 analyzes the effects of capital inflows on the extensive margin of credit. On the exit side, the results show that highly exposed banks are more likely to terminate relationships with low-collateral firms, regardless of their MRPK level. On the entry side, the findings are more mixed. While the probability of establishing new credit relationships declines across all firms, the effect is more pronounced for low-MRPK firms. Overall, banks with higher exposure are reducing their activity on the extensive margin, with particularly significant effects for firms with low MRPK and low fixed assets (both higher exit and lower entry) and firms with low MRPK and high fixed assets (strong negative effect on entry). In contrast, the results are more nuanced for high-MRPK, low-fixed-asset firms (higher exit but the smallest effect on entry) and high-MRPK, high-fixed-asset firms (negative effects on both exit and entry). Taken together, these findings suggest that foreign capital inflows are unlikely to have increased misallocation through the extensive margin in any meaningful way.

Total credit and real effects. Finally, we examine the aggregate effects of capital inflows on credit and real outcomes in Table 4. Columns (1) and (2) show that high-MRPK firms benefited from increased credit following the capital inflow boom, while low-MRPK firms did not. The difference between the two columns lies in the inclusion of firm-time fixed effects estimated in equation 2, which are used as proxies for firm credit demand. Comparing the two suggests a declining trend in credit demand from low-MRPK firms at more exposed banks. Therefore, the estimated firm-time fixed effects are included in the remainder of this baseline analysis. The results of this table without including the estimated firm-time fixed effect are reported in the Appendix (Table A8).

Table 3: Capital inflows and bank-firm relation by firm characteristics, extensive margin

	Dependent variable:					
	$Exit_{ib\tau}$			$Entry_{ib\tau}$		
$Exposure_b * Post_\tau * D_i$	MRPK	Fixed Assets	MRPK/ Fixed Assets	MRPK	Fixed Assets	MRPK / Fixed Assets
Firm characteristic D_i:	(1)	(2)	(3)	(4)	(5)	(6)
High	-0.001	-0.043		-1.76***	-1.972***	
	(0.047)	(0.041)		(0.323)	(0.294)	
Low	0.018	0.245***		-2.08***	-1.490***	
	(0.045)	(0.046)		(0.318)	(0.439)	
High MRPK - High FA			-0.181***			-1.906***
			(0.051)			(0.292)
High MRPK - Low FA			0.156***			-1.539***
			(0.056)			(0.426)
Low MRPK - High FA			-0.082*			-2.122***
			(0.048)			(0.303)
Low MRPK - Low FA			0.222**			-1.758***
			(0.080)			(0.505)
Firm-period F.E.	✓	✓	✓	✓	✓	✓
Bank F.E.	✓	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓	✓	✓	✓
Observations	556,008	722,635	553,806	63,053,274	95,413,649	62,881,519
$Adj.R^2$	0.48	0.48	0.27	0.10	0.10	0.09

Note: The table reports the coefficients of the specification in equation 3 and it captures the effect of capital inflows on the extensive margin of credit by firm type. Standard errors are clustered at the bank-sector (3-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

The bank-lending channel spurred by capital inflows favored credit expansion for high-MRPK firms, regardless of their collateral levels (column 3). This credit expansion prompted high-MRPK firms to increase both investment and employment (columns 4 and 6), particularly those with low fixed assets, which aligns with the notion that constrained firms exhibit higher elasticity in investment and employment responses to credit (column 5). In contrast, the effect on employment for high-MRPK, high-fixed-asset firms was marginal, indicating that labor constraints were less of an issue for these firms (column 7). Lastly, columns (8) and (9) show that the bank-lending channel contributed to a lower dispersion of MRPK, as high-MRPK firms exposed to capital inflows saw their MRPK decline, while low-MRPK firms experienced an increase.

Table 4: Capital inflows, firm-level credit and real effects

	Dependent variable:								
Ind. var.: $Exposure_i * Post_t * D_i$	Credit			Investment		Employment		MRPK	
Firm characteristic D_i:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High MRPK	0.565***	0.595***		0.857***		0.225***		-2.72***	
	(0.113)	(0.065)		(0.170)		(0.079)		(0.36)	
Low MRPK	-0.405***	0.121*		-0.744***		-0.290***		2.21***	
	(0.112)	(0.067)		(0.177)		(0.078)		(0.32)	
High MRPK - High FA			0.614***		0.421**		0.136*		-1.36***
			(0.067)		(0.169)		(0.079)		(0.37)
High MRPK - Low FA			0.515***		1.726***		0.427***		- 5.61***
			(0.068)		(0.199)		(0.086)		(0.52)
Low MRPK - High FA			0.131**		-0.837***		-0.284***		2.23***
			(0.065)		(0.176)		(0.077)		(0.32)
Low MRPK - Low FA			-0.017		0.452*		-0.227***		1.50***
			(0.084)		(0.240)		(0.093)		(0.33)
Est. Firm-time F.E.		✓	✓	✓	✓	✓	✓	✓	✓
Firm F.E.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector-time F.E.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	852,418	852,418	850,351	852,418	850,351	852,418	850,351	783,419	781,317
$Adj.R^2$	0.89	0.95	0.95	0.54	0.54	0.93	0.93	0.72	0.72

Note: The table reports the coefficients of the specification in equation 5 and it captures the effects of capital inflows on total credit, investment, employment and MRPK by firm type. Standard errors are clustered at the sector (3-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

6 Effects on aggregate misallocation and TFP

In the previous sections, we showed that exposure to capital inflows induced banks to allocate credit in a way consistent with reducing misallocation. In this section, we quantify its aggregate impact on allocative efficiency, using the methodology developed by Sraer and Thesmar (2023).

Since the seminal works of Foster et al. (2008), Restuccia and Rogerson (2008), and Hsieh and Klenow (2009), misallocation has been measured by examining the cross-sectional dispersion of marginal products across firms. As discussed in Section 4.1, the underlying principle is straightforward: in the absence of frictions, the marginal revenue product of inputs should be equal across firms, as resources flow from low- to high-marginal-revenue-product firms.

Hsieh and Klenow (2009) show how to calculate aggregate total factor productivity (TFP) losses due to misallocation, assuming that distortions—creating a wedge between marginal products and production costs—are primitive in their model. Sraer and Thesmar (2023) take a different approach, treating capital wedges as endogenous and demonstrating that, under certain assumptions, the distribution of these wedges remains invariant to macroeconomic equilibrium conditions. This implies that shocks altering the distribution of the marginal revenue product of capital (MRPK), such as a boom in capital inflows, have a uniform effect on misallocation, regardless of the economy's equilibrium state or other concurrent shocks. Consequently, a quasi-experimental shock's impact on misallocation can be estimated using a sufficient-statistics approach.

This approach rests on two key assumptions: (1) firm-level production follows a Cobb-Douglas technology, and (2) firm-level distortions are homogeneous of degree one, meaning distortions grow proportionally with the economy. Sraer and Thesmar (2023) show that these assumptions are largely satisfied in the structural macro-finance literature, making their sufficient-statistics approach a valid alternative to structural estimation in the context of many class of models.[13]

In this framework, the effect of international financial flows on aggregate TFP depends on three sufficient statistics that can be directly estimated in a quasi-experimental setting. These statistics include difference-in-differences estimates of the effect of capital inflows on (i) changes in the variance of log-MRPK within industries, (ii) changes in the average log-MRPK by industry, and (iii) changes in the covariance between log-MRPK and log-sales by industry. The aggregate change in TFP can then be expressed with the following formula:

$$\begin{aligned}\Delta \ln TFP = &-\frac{\alpha}{2}\left(1+\frac{\alpha\theta}{1-\theta}\right)\sum_{s=1}^{S}\kappa_s \widehat{\Delta\Delta\sigma^2(s)} \\ &-\frac{\alpha}{2}\left(1+\frac{\alpha\theta}{1-\theta}\right)\sum_{s=1}^{S}(\phi_s-\kappa_s)\left(\widehat{\Delta\Delta\mu^2(s)}+\widehat{\Delta\Delta\sigma_{mrpk,py}}(s)+\frac{1}{2}\frac{\alpha\theta}{1-\theta}\widehat{\Delta\Delta\sigma^2(s)}\right)\end{aligned} \tag{6}$$

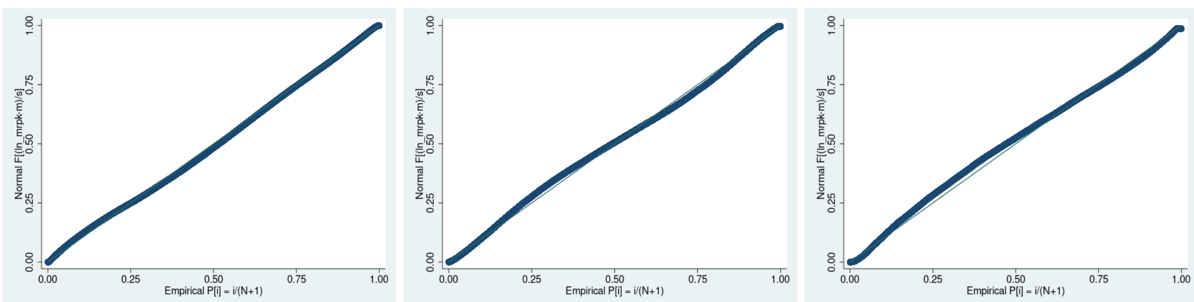
The three statistics are: (i) the estimated change in the log-MRPK variance in industry s, $\widehat{\Delta\Delta\sigma^2(s)}$; (ii) the estimated change in average log-MRPK average, $\widehat{\Delta\Delta\mu^2(s)}$; and (iii) the estimated change in the covariance between log-MRPK and log-sales, $\widehat{\Delta\Delta\sigma_{mrpk,py}}(s)$. Additionally, ϕ_s and κ_s represent the shares of industry s in total sales and capital before the shock; while α is the share of capital in firms' production functions, and θ denotes the elasticity of substitution across varieties. The first term in the formula captures the effect

[13] Among the papers they review, 98% assume that the production function is Cobb-Douglas, and 93% assume the borrowing constraint is homogeneous. A notable exception is Gopinath et al. (2017), which introduces a size-dependent borrowing constraint: firms can borrow up to a fraction of their assets, with this fraction increasing with firm size, implying a non-linear relationship between credit and size. To test for this non-linearity in our data, we run a quadratic regression between firm credit and assets. The results (Table A9 in the Appendix) show a positive and significant coefficient for the linear term, while the quadratic term is slightly negative and not statistically different from zero.

of capital inflows on misallocation *within* sectors, whereas the second term captures the effect *between* sectors.

Two specific assumptions apply to this equation, though they can be relaxed by using a different aggregation formula: log-MRPK must follow a normal distribution, and no labor market frictions should be present. Figure 8 shows the cumulative distribution function (c.d.f.) of log-MRPK for broad industries closely follows a normal distribution, while Figure 3 shows that while the dispersion of log-MRPK has increased over time, whereas the dispersion of log-MRPL remained relatively stable. Both pieces of evidence suggest the assumptions needed for this aggregation formula are reasonable in our setting.

Figure 8: Log-normality of MRPK in broad industries



(a) Manufacturing

(b) Services

(c) Construction

For each of the three moments in equation (6) we estimate the following difference-in-differences specification:

$$M_{st} = \beta_1 \; Exposure \; Sector_s \times Post_t + \boldsymbol{X_s'\delta} \times Post_t + \gamma_s + \delta_t + \mu_s \times t + \epsilon_{st} \tag{7}$$

Here, M_{st} represents either the industry variance of log-MRPK, the average of log-MRPK, or the covariance between log-MRPK and sales in year t. X_s is the usual vector of sector lenders' characteristics measured in 1998-2000, while γ_s and δ_t are industry and year fixed effects. Industry specific trends $\mu_s \times t$ are included, and the errors are clustered at the industry level.

Columns 1 and 2 of Table 5 confirm that exposure to capital inflows has a negative impact on the variance of log-MRPK. Specifically, a 10% increase in industry exposure leads to a 7% reduction in log-MRPK dispersion, following the boom in capital inflows. This result holds with and without industry trends. The effect on average log-MRPK is negative, suggesting that the more constrained firms benefit disproportionately from industry exposure, although this result is not statistically significant. Similarly, the impact of capital inflows on the covariance between MRPK and sales is positive but not significant.

Table 5: Moments of log-MRPK distribution and sector exposure to capital inflows

	Var(log-MRPK)		Mean(log-MRPK)		Cov(log-MRPK, log-Sales)	
	(1)	(2)	(3)	(4)	(5)	(6)
$Exposure_s \times Post_t$	-1.027***	-0.812**	-0.905	-0.173	0.248	0.235
	(0.359)	(0.402)	(0.600)	(0.446)	(0.350)	(0.421)
Industry -trend		✓		✓		✓
Sector F.E.	✓	✓	✓	✓	✓	✓
Year F.E.	✓	✓	✓	✓	✓	✓
Sector Controls	✓	✓	✓	✓	✓	✓
Observations	2,397	2,397	2,397	2,397	2,397	2,397
$Adj.R^2$	0.54	0.65	0.87	0.92	0.44	0.55

Note: Coefficients of the regression in equation 7. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. Standard errors are clustered at the sector (3-digit) level.

These results point to a positive impact of capital inflows on resource allocation. To quantify this effect, we use the coefficients in Columns (2), (4) and (6) of Table 5 to compute the statistics for the variance and average of log-MRPK, and the covariance term in equation (7). For instance, the statistics on the variance of log-MRPK is given by $\sum_{s=1}^{S} \Delta\widehat{\Delta\sigma^2}(s) = \sum_{s=1}^{S} \beta_{VarMRPK}(-0.812) \times Sector\ Exposure_s$. We calibrate the parameters of equation (6) using the values provided by Sraer and Thesmar (2023), which are standard in the literature: $\alpha = 0.33$ and $\theta = 0.83$, corresponding to a price elasticity of demand of 6.

We find the reallocation gains from international financial flows lead to a 0.9% increase of aggregate TFP per year between 2002 and 2007, concentrated mainly in the within-sector component of Equation (6). By comparison, Calligaris et al. (2018) estimate that increased misallocation in the Italian economy caused a 1.3% annual TFP loss during this periods, meaning that capital inflows substantially mitigated this negative trend.

7 Robustness checks

In this section, we conduct several robustness checks and address potential identification challenges that could bias the estimates presented in Section 5. Specifically, we examine five key areas: (1) the possibility of spillovers from exposed to non-exposed banks, (2) alternative measures of bank exposure to capital inflows, (3) the impact of the global financial crisis on exposed banks' fragility, (4) the role of capital flows in household lending as an additional channel for misallocation, and (5) alternative empirical specifications. These include controlling for confounding factors, using different measures of firms' productivity and financial constraints, analyzing the results along the distribution of firms' MRPK, restricting the sample to a balanced panel, and excluding cooperative banks.

7.1 Potential spillovers across banks

One potential threat to our identification strategy is the possibility of spillovers from exposed to non-exposed banks. Non-exposed banks could indirectly benefit from international capital inflows through interbank linkages or market effects, such as bond or equity purchases. Additionally, exposed banks might adjust their retail strategies by focusing less on deposits or by competing more aggressively for them. In these scenarios, capital inflows could influence the funds available to non-exposed banks, complicating the analysis.

Interbank lending is a particular concern, as the interbank market in Italy expanded significantly during the same period as the surge in capital inflows. However, we do not expect this to be a major confounding factor because the increase in interbank transactions was driven by intra-group lending (loans between banks within the same banking group), which is consolidated in our dataset (Figure A2). Lending across groups—between exposed and non-exposed banks—remained flat during this period. Nevertheless, we formally test this potential channel using the following bank-level specification:

$$Y_{bt} = \beta_1 \, Exp_b \times Post_t + \boldsymbol{X_b'\delta} \times Post_t + \gamma_b + \alpha_t + \epsilon_{bt} \tag{8}$$

Here, Y_{bt} represents alternatively (i) interbank lending of bank b in year t, (ii) holding of bonds and equity of financial institutions, (iii) share of deposit on banks' liabilities, or (iv) the bank's share of the total deposits in the economy. The coefficient β_1 captures how these variables change after 2002 for banks more exposed to capital inflows, controlling for our standard vector of pre-2002 bank characteristics, bank fixed effects, and year dummies. Errors are clustered at the bank level.

The results in Table A10 show that bank exposure is not correlated with holdings of bonds or equities of other financial institutions, nor with the share of deposits. Moreover, interbank lending by exposed banks decreased after 2002. These findings suggest that indirect effects of capital inflows are unlikely to weaken our conclusions regarding misallocation.

7.2 Alternative measures of bank exposure to capital flows

We also explore two alternative measures of the impact of foreign capital inflows on banks' balance sheets. The first measure isolates the supply-side component of capital flows and leverage the time-series dimension of the data. Following Cesa-Bianchi et al. (2018), we first project the log-change of Italian banks' foreign liabilities on their world counterpart from 1998 to 2007, using BIS data on changes in outstanding cross-border liabilities:

$$\Delta \ln KF_t^{IT} = \lambda_0 + \lambda_1 \Delta \ln KF_t^{World} + \epsilon_t^{IT} \tag{9}$$

Where KF_t^{IT} represents the outstanding foreign liabilities of the Italian banking sector in year t and KF_t^{World} represents the foreign liabilities of the other countries (excluding Italy).

Assuming that country-specific pull shocks to Italy do not affect global capital flows (i.e. Italy is too small to drive global flows), the fitted values $\hat{\lambda}_1 \Delta \ln KF_t^{World}$ can be interpreted as the supply-side component of capital inflows into the Italian banking sector. Using this measure, we estimate the following specification:

$$\ln C_{ibt} = \sum_{d=1}^{4} \beta_d \, D_{di} \times Exposure_b \times \hat{\lambda}_1 \Delta \ln \; KF_t^{World} + \beta_2 \, Spec_{ibt} + \boldsymbol{X_b'\delta} \times Post_t + \alpha_{it} + \gamma_{ib} + \epsilon_{ibt} \tag{10}$$

Where $Exposure_b$ is the share of foreign funding for each bank before the shock, and it is interacted with the yearly changes in capital inflows driven by push factors. The results in Table A11 confirm the baseline findings. As global flows increase, more exposed banks allocate credit in a manner consistent with reduced misallocation.

The second measure employs a shift-share Bartik instrument, combining (i) the bank composition of foreign liabilities by sourcing country before the shock and (ii) data on capital outflows from those countries to the rest of the world after the shock. We focus on the top 15 sourcing countries, which account for more than 90% of foreign liabilities, and measure the change in their capital outflows to the rest of the world (excluding Italy) between 1998-2001 and 2002-2007. Figure A3 show foreign claims of banks in Germany and Luxembourg. These patterns are similar in the 1980s and in the 1990s but diverge after 2002, with cross-border lending from Germany sharply. The new bank-level exposure indicator captures that Italian banks borrowing from Germany before 2002 are disproportionately more exposed to financial flows than banks borrowing from Luxembourg. Bank exposure is computed as: $Exposure_b^{Geo} = \sum_c \omega_{bc} \, \Delta World\ Outflows_c^{post-pre}$, where ω_{bc} is the share of foreign liability that bank b sources from country c in 1998-2000, and $\Delta World\ Outflows_c^{post-pre}$ represents the increase in country c lending to the rest of the world. Table A12 shows that this alternative exposure measure does not affect our core findings.

7.3 Fragility of exposed banks after the global financial crisis

Our baseline analysis focuses on the surge in capital inflows leading up to the global financial crisis. In 2008, the Italian economy was severely impacted by the Great Recession, followed by a second downturn in 2011 during the sovereign debt crisis. As a result, the banking sector faced a disproportionate rise in non-performing loans (NPLs).

In this context, it is relevant to explore whether banks' reliance on foreign funds made them more vulnerable, resulting in a higher incidence of NPLs during the subsequent double-dip recession. The global financial crisis also triggered a reversal of international capital flows, raising the question of whether borrowers of exposed banks became more vulnerable due to credit contraction.

To investigate these possibilities, we extend our analysis to 2013, evaluating the differential impact of bank exposure across three periods: 1998-2001, 2002-2007, and 2008-2013.[14] We focus on (i) the effect of exposure on NPL ratios at the bank level, and (ii) the impact on the intensive margin of credit supply in bank-firm-level regressions.

Our results, presented in Table A13, suggest that while exposed banks supplied more credit during the capital inflow boom, this did not lead to a higher incidence of NPLs in the subsequent years (columns 1 and 2). Additionally, we find no evidence of a significant decline in credit supply from exposed banks in the post-2008 period (columns 3 and 4).

[14] We consolidate the data based on groups' composition in 2013, and we recompute all bank-specific variables accordingly.

7.4 A focus on household lending

Foreign capital inflows can also lead to increased lending to households, particularly through mortgages, which may fuel the expansion of the real estate sector—a relatively low-productivity sector. To explore this, we adopt an empirical approach similar to that of Greenstone et al. (2014) and Gilchrist et al. (2017). Since most households typically borrow from only one bank, we identify credit supply shocks by analyzing bank lending across multiple provinces:

$$\ln C^{H}_{pbt} = \beta_1 \; Exposure_b \times Post_t + \boldsymbol{X_b'\delta} \times Post_t + \alpha_{pt} + \gamma_{pb} + \epsilon_{pbt} \tag{11}$$

Where, the dependent variable is the log of outstanding credit from bank b to households in province p in year t. The specification includes province-time fixed effects to control for local demand shocks, and province-bank fixed effects to account for bank sorting into specific provinces. The vector $\boldsymbol{X_b}$ contains the same pre-2002 bank controls used in earlier specifications, and β_1 is our coefficient of interest, estimated using weighted least squares (WLS).[15]

The results, shown in Table A14, indicate that exposed banks did not significantly increase household credit supply relative to other banks. While household lending expanded considerably in Italy after 2002, our findings suggest that this expansion was not driven by the surge in foreign capital inflows.

7.5 Extensions to the baseline analysis

Omitted-variable bias and confounding factors. There are potential identification challenges stemming from simultaneous shocks that correlate with bank exposure to foreign capital flows. For instance, during the early 2000s, the rise of securitization increased liquidity for banks, including those in Italy. Additionally, Italy experienced a sharp drop in GDP growth during 2002-03, which could have affected banks differently. Furthermore, as Federico et al. (2020) demonstrate, banks were also exposed to China's entry into the WTO.

To address these potential confounding factors, we extend the baseline specification by including a bank-time fixed effect that controls for bank-specific shocks in a given year. In this regression we cannot estimate the bank-lending channel for all the categories

[15] We take the geometric average of two sets of weights. The first is the share of a bank's credit in a province relative to total lending in that province, capturing the bank's significance within the province. The second is the share of a bank's credit in a province relative to the bank's total lending, capturing the province's importance to the bank.

of firms in the baseline analysis, but only the effects relative to an omitted category, e.g. the effect on High-MRPK firms relative to Low-MRPK firms. The results in Table A15 confirm that our main results hold also in this more restrictive specification.

Alternative measures of firms' characteristics. Our baseline analysis focuses on firms' MRPK, which accounts for the largest increase in misallocation (Figure 3), and on fixed assets, which serve as a proxy for credit constraints due to their role as collateral. As a robustness check, we also examine credit allocation based on firms' TFPR (to account for labor misallocation) and revenues per worker (RLP), which provides a measure independent of the production function's estimation assumptions. Additionally, we use firms' credit scores, as computed by CERVED, as an alternative proxy for financial constraints. The credit score, similar to an Altman score, reflects factors such as profitability, assets, and credit history. Firms with a score above 6 are considered high-risk (Rodano et al., 2018).

Table A16 presents the results of this robustness check. For simplicity, we classify firms with a credit score below 6 (low default risk) as "High-credit score firms" and those with a score above 6 as "Low-credit score firms." The main findings hold: firms with higher TFPR, RLP, and credit scores benefit from a significantly larger increase in credit supply. Additionally, banks appear to expand their portfolios in a balanced manner along a productivity-risk trade-off (e.g., comparing High-RLP & Low-Credit score firms to Low-RLP & High-Credit score firms).

Results along firms' distribution. In our baseline results, we divide firms into High-MRPK and Low-MRPK groups based on the median MRPK distribution by sector. This allows us to examine whether credit allocation promotes convergence in MRPK across firms. We expand this analysis by looking at the effects of capital inflows along the distribution of firms' characteristics.

In Table A17 we characterize firms by quintiles of MRPK and fixed assets within sectors (columns 1 and 2). Additionally, in column 3, we examine firms by MRPK quintiles, maintaining the division into high- and low-fixed asset groups based on the baseline cut-off.

The results in column 1 indicate that firms in the bottom quintile of the MRPK distribution do not experience an increase in credit supply, while those in the top two quintiles benefit the most. Column 2 shows an upward trend in credit supply across firms' asset quintiles. Column 3 demonstrates that collateral's role is not independent of MRPK: among high-fixed asset firms, credit supply increases significantly by MRPK quintile, with firms in the bottom quintile receiving no additional credit despite having high fixed assets. Conversely, firms in the top two MRPK quintiles receive more credit even if they have low collateral.

Balanced panel. We restrict the baseline specification in Equation 2 to a balanced panel, consisting of firm-bank relationships that persist across all years of the dataset. The results in Table A18 confirm our baseline findings, even for the sample of firm-bank ties that are strongest, which can capture the role of relationship lending and informational advantages.

Excluding cooperative banks. Lastly, we exclude cooperative banks from our analysis. These institutions, typically small and localized, do not engage in foreign funding and focus their activities within a limited number of provinces. Although there are around 400 cooperative banks in our dataset, they account for only 5% of total credit to firms.

We want to ensure that our results are not driven by the presence of numerous small cooperative banks acting as a "control group". To that end, we replicate the baseline specifications for both the intensive margin (Equation 2) and on the total effect on credit and real outcomes (Equation 5), excluding cooperative banks from the analysis. The results reported in Table A19 and A20 confirm the robustness of our findings.

8 Concluding remarks and further research

This paper examines the empirical link between international financial flows and misallocation using micro-level data. The results indicate that capital flows have a positive effect on reducing misallocation and enhancing aggregate productivity, while previous papers based on more aggregate data concluded the opposite when analyzing similar episodes.

In these concluding remarks we discuss potential avenues for future research based on the findings of the paper. First, our analysis focuses on the bank lending channel, in a setting where capital flows were driven by global push factors. It would be essential to also examine other types of capital flows and their drivers to gain a fuller understanding of the impact of international financial flows on misallocation. For one thing, capital inflows directed towards government debt may influence resource allocation through the government borrowing channel. These flows could indirectly affect misallocation through increased public expenditure and aggregate demand or directly through public procurement favoring low-MRPK firms. Other forms of capital flows, such as portfolio flows, also warrant further investigation.

Second, the drivers behind capital flows are crucial to consider. While Italy's capital inflows were largely driven by external push factors, their effects could differ if driven by domestic pull factors. Understanding whether different drivers lead to varying outcomes is critical from a policy perspective. If capital flows distort resource allocation when driven by global factors, capital controls could be a necessary tool to mitigate these negative effects. However, if capital flows have a negative impact when primarily driven from domestic pull factors, macro-prudential tools might be more suitable.

Finally, misallocation could also result from credit expansion fueled by other funding sources or shifts in market structure. In the late 1990s and early 2000s, the issuance of bank bonds—mostly sold domestically to households and insurance companies—became a significant funding source in Italy and other Southern European countries. While bond financing grew at a similar pace to foreign capital inflows, it has received less attention in the literature (with Lane, 2013 being a notable exception), and its implications for credit allocation remain understudied. During the same period, the banking sector also faced increased competition, which likely influenced credit allocation. These two factors, which may not be independent, do contribute to credit allocation decisions according to recent works. In fact, funding sources with lower rollover risk, such as bonds compared to foreign capital, tend to exert less discipline on banks' lending decisions (e.g., Jasova et al., 2021). Additionally, heightened competition may drive banks to extend credit to more opaque borrowers (Boyd and Nicoló, 2005).

These findings highlight that the interplay between a bank's funding structure and market competition can significantly influence credit allocation, misallocation, and aggregate productivity. This remains a complex and important area in need of further research.

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A Online Appendix

Figure A1 shows the distribution of borrowers' size, proxied by firm revenues, for banks with a measure of exposure above and below average.

Figure A2 shows the evolution of the Italian interbank lending market discussed in Subsection 7.1.

Figure A3 shows the evolution of cross-border banking flows in Germany and Luxembourg discussed in Subsection 7.2.

Table A1 provides the summary statistics of banks and firms in our sample.

Tables A2-A4 shows the effects of bank exposure to capital inflows on credit supply to the average firm in the economy (intensive margin, extensive margin, and aggregate credit) discussed in Section 5.

Tables A5-A7 shows the effects of bank exposure to capital inflows on credit supply across different industries (intensive margin, extensive margin, and aggregate credit) discussed in Section 5..

Table A8 show the firm-level effects of capital inflows on credit and real variables as in Equation 5, excluding the estimated firm-time fixed effects.

Table A9 tests for a non-linear relationship between firm credit and assets.

Table A10 analyzes the potential spillover across banks discussed in Subsection 7.1.

Tables A11 and A12 show the results on credit allocation using alternative measures of bank exposure to capital inflows, as discussed in Subsection 7.2.

Table A13 looks at the effects of bank exposure to capital inflows on the non-performing loans (NPLs) and on credit, after the global financial crisis when capital inflows revert. This table is discussed in Subsection 7.3.

Table A14 shows the result of bank exposure to capital inflows on household lending, as discussed in Subsection .

Table A15 reports the coefficients of the baseline specification in equation (2) saturated with bank-time fixed effect. Given the presence of bank-time fixed effects, we need to omit a category, namely low-MRPK and low-collateral firms, so the coefficients should be interpreted as the marginal difference with respect to the excluded category.

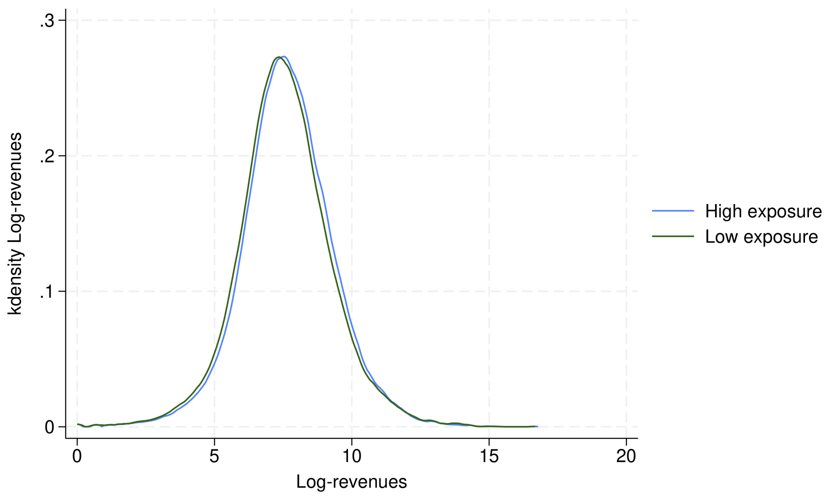
Table A16 replicates the baseline specification in equation (2) using TFPR, revenues per worker, and credit score as alternative measures to MRPK or fixed assets.

Table A17 shows the results of the baseline specification in equation (2) by quintiles of MRPK and fixed assets along the distribution of firms.

Table A18 reports the coefficients of the baseline specification in equation (2) using a balanced panel of firm-bank relations. Subsection A.3 outlines the methodology for computing firm-level MRPK and TFPR.

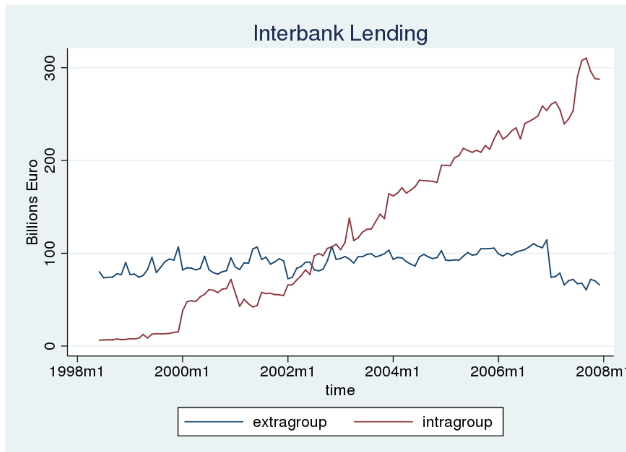
A.1 Appendix figures

Figure A1: Borrower size and bank exposure



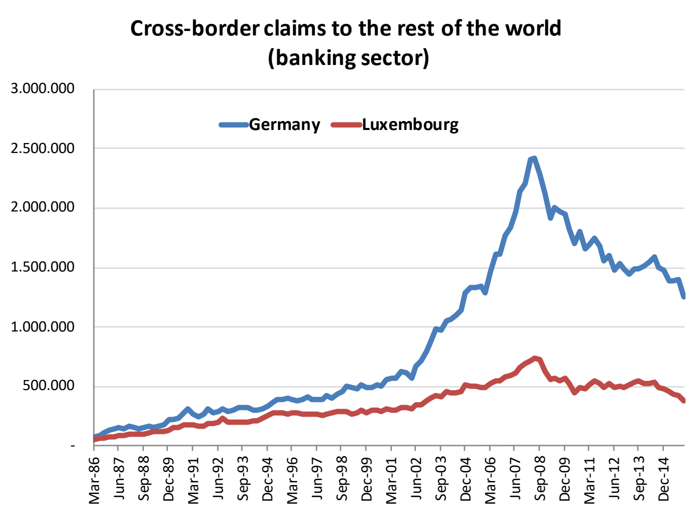
Distribution of firm size (log-revenues) for banks with exposure to capital flows above and below the sample average.

Figure A2: Interbank lending between and within groups



Source: Bank of Italy Supervisory Reports. The figure reports the evolution of the interbank lending at monthly frequency between 1998 and 2007 across and within banking groups. It shows interbank lending increased mainly within banking groups and not much across groups.

Figure A3: Capital outflows by banks operating in Germany and Luxembourg



Source: BIS, locational banking statistics. Foreign claims of banks located in Germany and Luxembourg to the banks located in the rest of the world (nominal USD).

A.2 Appendix tables

Table A1: Summary statistics

	Unit	Mean	S.D.	p25	p50	p75
Bank characteristics						
Total Assets	€Millions	3,230	27,800	79	176	442
Liquid Assets	% Assets	3,605	5,230	626	1,473	3,841
Nonperforming Loans	% Assets	2.6	3.3	0.8	1.7	3.3
Core capital	% Assets	1.8	8.2	0.01	0.2	1.5
Deposits	% Liabilities	54.5	19.1	45	54	68
Bonds	% Liabilities	22.3	16.2	8.4	22.0	34.7
Foreign Funding	% Liabilities	3.7	13.1	0.3	1.0	6.1
Firm characteristics						
Bank Credit	€Thousands	1,642	15,700	155	395	1083
Revenues	€Thousands	4,173	5,673	743	1,751	4,708
Fixed Assets	€Thousands	2,327	72,301	70	240	819
Gross operating margin	% Revenues	6	52	3.3	7.6	13
Credit Score	Units	5.2	1.9	4	5	7

Note: The table reports relevant statistics (1998-2007, average) of banks and firms in the firm-bank matched sample. Bank balance-sheet data are from the Supervisory Reports submitted by banks to the Bank of Italy. Credit data are from the Italian Credit Register. Firm balance-sheet data are from CERVED.

Table A2: Capital inflows and credit supply, intensive margin

	Dependent variable: ln $Credit_{ibt}$				
$Bank\ Exposure$:	Continuous	Dummy 10%	Dummy 15%	Continuous (above 1%)	Continuous (WLS)
	(1)	(2)	(3)	(4)	(5)
$Exposure_b \times Post_t$	0.29***	0.058***	0.056***	0.34***	0.31***
	(0.07)	(0.006)	(0.004)	(0.05)	(0.07)
Firm-time F.E.	✓	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓	✓	✓
Observations	4,138,531	4,138,531	4,138,531	3,542,118	4,029,126
$Adj.R^2$	0.83	0.83	0.83	0.83	0.83

Note: The table reports the coefficients of the specification in equation (1) and it captures the effects of capital inflows on the intensive margin of credit for the average firm in the economy. Column (1) shows the baseline explanatory variable, i.e. the share of foreign liabilities by bank computed over the period 1998-2000 interacted with a post-2002 dummy. The explanatory variable in column (2) and (3) is a dummy that takes the value of 1 if the share of foreign liabilities in 1998-2000 is above 10% and 15% respectively, and 0 otherwise. Column (4) replicates the baseline specification restricting the sample to the banks that have at least 1% share of foreign funding in 1998-2000. Column (5) estimates the baseline specification through weighted least squares, using firms' credit as weight. Standard errors are clustered at the bank-sector (3-digit) level, ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A3: Capital inflows and bank-firm relation, extensive margin

	Dependent variable:			
	$Exit_{ib\tau}$		$Entry_{ib\tau}$	
$Bank\ Exposure$:	Continuous (1)	Dummy 10% (2)	Continuous (3)	Dummy 10% (4)
$Exposure_b * Post_\tau$	-0.067	-0.000	-1.77 ***	-0.45***
	(0.043)	(0.004)	(0.37)	(0.07)
Firm-period F.E.	✓	✓	✓	✓
Bank F.E.	✓	✓	✓	✓
Specialization	✓	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓	✓
Observations	736,136	736,136	120,181,408	120,181,408
$Adj.R^2$	0.48	0.48	0.10	0.10

Note: The table reports the coefficients of the specification in equation (3) and it captures the effect of capital inflows on the extensive margin of credit for the average firm in the economy. In column (1) and (3) we use the baseline explanatory variable, i.e. the share of foreign liabilities by bank computed over the period 1998-2000 interacted with a post-2002 dummy. The explanatory variable in column (2) and (4) is a dummy that takes the value of 1 if the share of foreign liabilities in 1998-2000 is above 10%, and 0 otherwise. Standard errors are clustered at the bank-sector (3-digit) level, ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A4: Capital inflows and credit supply, aggregate credit

	Dependent variable: ln $Credit_{it}$				
$Bank\ Exposure$:	Continuous	Dummy 10%	Dummy 15%	Continuous (above 1%)	Continuous (WLS)
	(1)	(2)	(3)	(4)	(5)
$Exposure_i \times Post_t$	0.29***	0.04***	0.026***	0.32***	0.27***
	(0.06)	(0.003)	(0.004)	(0.08)	(0.06)
Estimated firm-time F.E.	✓	✓	✓	✓	✓
Firm F.E.	✓	✓	✓	✓	✓
Sector-time F.E.	✓	✓	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓	✓	✓
Observations	1,166,743	1,166,743	1,166,743	1,052,506	1,135,706
$Adj.R^2$	0.95	0.95	0.95	0.95	0.95

Note: The table reports the coefficients of the baseline specification in equation (5) and it captures the effect of capital inflows on total credit for the average firm in the economy. Column (1) shows the baseline explanatory variable, i.e. the share of foreign liabilities by bank computed over the period 1998-2000 interacted with a post-2002 dummy. The explanatory variable in column (2) and (3) is a dummy that takes the value of 1 if the share of foreign liabilities in 1998-2000 is above 10% and 15% respectively, and 0 otherwise. Column (4) replicates the baseline specification restricting the sample to the banks that have at least 1% share of foreign funding in 1998-2000. Column (5) estimates the baseline specification through weighted least squares, using firms' credit as weight. Standard errors are clustered at the sector (3-digit) level, ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A5: Capital inflows and credit allocation by industry, intensive margin

	Dependent variable: ln $Credit_{ibt}$			
	Manufacturing (1)	Construction (2)	Trade Service (3)	Other (4)
$Exposure_b \times Post_t$	0.46***	0.04	0.12	0.15
	(0.06)	(0.18)	(0.18)	(0.09)
Firm-time F.E.	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓
Specialization	✓	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓	✓
Observations	1,921,142	427,031	1,100,857	689,501
$Adj.R^2$	0.84	0.76	0.84	0.82

Note: The table shows the coefficients of the specification in equation (1) and it captures the effects of capital inflows on the intensive margin of credit for the average firms in each of the reported industry. The explanatory variable is the baseline measure of bank exposure, i.e. the share of foreign liabilities by bank computed over the period 1998-2000 interacted with a post-2002 dummy. Column (1) shows the results for firms in manufacturing, column (2) for firms in construction, column (3) for firms in wholesale and retail services, and column (4) for other services. Standard errors are clustered at the bank-sector (3-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

Table A6: Capital inflows and firm-bank relations by industry, extensive margin

	Dependent variable:							
	$Exit_{ib\tau}$				$Entry_{ib\tau}$			
	Manuf. (1)	Constr. (2)	Trade Service (3)	Other (4)	Manuf. (5)	Constr. (6)	Trade Service (7)	Other (8)
$Exposure_b * Post_\tau$	-0.17***	0.06	0.07	-0.04	-1.83***	-1.63	-1.79***	-1.71***
	(0.05)	(0.15)	(0.10)	(0.08)	(0.34)	(1.06)	(0.60)	(0.39)
Firm-period F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Bank F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓	✓	✓	✓	✓	✓
Observations	351,553	71,070	193,161	120,194	23,287,508	28,404,780	12,570,715	30,215,028
$Adj.R^2$	0.27	0.27	0.27	0.26	0.10	0.08	0.09	0.08

Note: The table reports the coefficients of the specification in equation (3) and it captures the effect of capital inflows on the extensive margin of credit for the average firm in each of the reported industry. The explanatory variable is the baseline measure of bank exposure, i.e. the share of foreign liabilities by bank computed over the period 1998-2000 interacted with a post-2002 dummy. Column (1) shows the results for firms in manufacturing, column (2) for firms in construction, column (3) for firms in wholesale and retail services, and column (4) for other services. Standard errors are clustered at the bank-sector (3-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A7: Capital inflows and credit allocation by industry, aggregate credit

	Dependent variable: ln $Credit_{it}$			
	Manufacturing (1)	Construction (2)	Trade Service (3)	Other (4)
$Exposure_b \times Post_t$	0.65***	0.04	-0.14	0.14
	(0.08)	(0.17)	(0.09)	(0.09)
Estimated firm-time F.E.	✓	✓	✓	✓
Firm F.E.	✓	✓	✓	✓
Sector-time F.E.	✓	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓	✓
Observations	503,175	129,550	316,508	217,510
$Adj.R^2$	0.96	0.93	0.95	0.94

Note: The table reports the coefficients of the specification in equation (5) and it captures the effect of capital inflows on total credit for the average firm in each of the reported industry. The explanatory variable is the baseline measure of bank exposure, i.e. the share of foreign liabilities by bank computed over the period 1998-2000 interacted with a post-2002 dummy. Column (1) shows the results for firms in manufacturing, column (2) for firms in construction, column (3) for firms in wholesale and retail services, and column (4) for other services. Standard errors are clustered at the sector (3-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A8: Firm-level credit and real effects without the estimated firm-time FE

	Dependent variable:							
Ind. var.: $Exposure_i * Post_t * D_i$	Credit		Investment		Employment		MRPK	
Firm characteristic D_i:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High MRPK	0.282***		0.634***		0.050		-2.63***	
	(0.083)		(0.183)		(0.070)		(0.252)	
Low MRPK	-0.658***		-1.258***		-0.568***		2.20***	
	(0.08)		(0.184)		(0.069)		(0.241)	
High MRPK - High FA		0.323***		0.280		-0.020		-1.397***
		(0.084)		(0.185)		(0.081)		(0.255)
High MRPK - Low FA		0.208***		1.510***		0.247***		- 5.578***
		(0.086)		(0.192)		(0.075)		(0.242)
Low MRPK - High FA		-0.659***		-1.314***		-0.558***		2.13***
		(0.082)		(0.205)		(0.069)		(0.242)
Low MRPK - Low FA		-0.617***		0.064		-0.471***		1.385***
		(0.223)		(0.220)		(0.084)		(0.250)
Est. Firm-time F.E.								
Firm F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Sector-time F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓	✓	✓	✓	✓	✓
Observations	789,679	789,679	789,679	789,679	789,679	789,679	727,110	727,110
$Adj.R^2$	0.89	0.89	0.53	0.53	0.93	0.93	0.72	0.72

Note: The table reports the coefficients of the specification in equation (5) *excluding* the estimated firm-time fixed effects and it mirrors the results presented in Table 4, which includes them. The table captures the effect of capital inflows on total credit, investment, employment and MRPK by firm type. Standard errors are clustered at the sector (3-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.The table reports the coefficients of specification in equation (5) and it captures the effect of capital inflows on total credit for the average firm in each of the reported industry. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. Standard errors are clustered at the bank-sector level.

Table A9: Relationship between firm credit and assets

Dependent variable: C_{it}	Total assets (1)	Total Fixed Assets (2))
$Assets_t$	0.560***	0.630***
	(0.148)	(0.207)
$Assets_t^2$	-0.003	-0.079
	(0.098)	(0.154)
Sector F.E.	✓	✓
Time F.E.	✓	✓
Observations	1,421,218	1,421,218
$Adj.R^2$	0.57	0.57

Note: The table reports the coefficients of the following regression: $\ln C_{ist} = \beta_0 + \beta_1 \ln\ Assets_{it} + \beta_2 \ln\ Assets_{it}^2 + \gamma_s + \delta_t + \epsilon_{ist}$, where $\ln C_{ist}$ is the log of total outstanding credit of firm i operating in sector s in year t, $\ln\ Assets_{it}$ are total assets (column 1) or total fixed assets (column 2), γ_s and δ_t are sector and time fixed effects, and errors are clustered at the firm level. The specification captures the average relation between credit, assets, and squared assets across firms in a given sector and year. All variables are standardized, so the interpretation of the coefficient is such that, for example, a one standard-deviation increase in total assets is associated to 0.56 standard-deviation increase in credit. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A10: Spillover across banks, a balance sheet analysis

Dependent variable Y_{bt}:	Interbank lending (1)	Bonds & equity holdings (2)	Deposits (3)	Share of deposits (4)
$Exposure_b \times Post_t$	-1.92***	-0.36	0.21	-0.0003
	(0.45)	(1.07)	(0.40)	(0.0003)
Bank F.E.	✓	✓	✓	✓
Time F.E.	✓	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓	✓
Observations	4,761	4,761	4,761	4,761
$Adj.R^2$	0.90	0.90	0.93	0.99

Note: The table reports the coefficients of the specification in equation (7.1) and it captures the effects of bank exposure to capital inflows on banks' balance sheet variables, as discussed in Section 7.1 . Column 1 looks at the effects on a bank's lending in the domestic interbank market, column 2 on the holdings of bonds and equities issued by other banks operating in Italy, column 3 on the share of deposits in a bank's funding, column 4 on a bank's share of the total deposits in the economy. Standard errors are clustered at the bank-sector (3-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A11: Capital inflows and credit allocation by firm characteristics, time-varying measure of exposure to capital inflows driven by push-factors

	Dependent variable: ln $Credit_{ibt}$		
Firm characteristic D_i:	MRPK	Fixed Assets	MRPK / Fixed Assets
Ind. var.: $Exposure_b * \hat{\lambda_1} \Delta \ln KF_t^{World} * D_i$	(1)	(2)	(3)
High	0.406***	0.344***	
	(0.040)	(0.033)	
Low	0.27***	0.265***	
	(0.035)	(0.040)	
High MRPK - High FA			0.452***
			(0.042)
High MRPK - Low FA			0.291***
			(0.046)
Low MRPK - High FA			0.280***
			(0.036)
Low MRPK - Low FA			0.056
			(0.062)
P-value test High=Low	0.00	0.00	
P-value test HMP-LFA=LMP-HFA			0.78
Firm-time F.E.	✓	✓	✓
Firm-bank F.E.	✓	✓	✓
Specialization	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓
Observations	3,048,308	4,026,717	3,038,602
$Adj.R^2$	0.828	0.827	0.827

Note: The table reports the coefficients of the specification in equation (10) and it captures the effects of exposure to capital inflows on the allocation of the intensive margin of credit by firm type, using an alternative measure of bank exposure as discussed in Section 7.2. The explanatory variable is the foreign-liability ratio over the period 1998-2000 interacted with a measure of capital inflows to Italy in year t driven by push factors, as estimated in equation (9). Standard errors are clustered at the bank-sector (3-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A12: Capital inflows and credit allocation by firm characteristics, shift-share measure of bank exposure

	Dependent variable: ln $Credit_{ibt}$		
Firm characteristic D_i:	MRPK	Fixed Assets	MRPK / Fixed Assets
Ind. var.: $Exposure^{Geo}_b * Post_t * D_i$	(1)	(2)	(3)
High	0.14***	0.12***	
	(0.013)	(0.013)	
Low	0.10***	0.09***	
	(0.014)	(0.013)	
High MRPK - High FA			0.153***
			(0.014)
High MRPK - Low FA			0.102***
			(0.014)
Low MRPK - High FA			0.105***
			(0.014)
Low MRPK - Low FA			0.048**
			(0.019)
P-value test High=Low	0.00	0.03	
P-value test HMP-LFA=LMP-HFA			0.68
Firm-time F.E.	✓	✓	✓
Firm-bank F.E.	✓	✓	✓
Specialization	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓
Observations	3,048,308	4,026,717	3,038,602
$Adj.R^2$	0.828	0.827	0.827

Note: The table reports the coefficients of the specification in equation (2) with an alternative measure of bank exposure, as discussed in Section 7.2, and it captures the effects of exposure to capital inflows on the allocation of the intensive margin of credit by firm type. Bank exposure is defined as $Exposure^{Geo}_b = \sum_c \omega_{bc}\ \Delta World\ Outflows^{post-pre}_c$, where $\Delta World\ Outflows^{post-pre}_c$ is the change in outstanding claims of the banks of country c towards the rest of the world, excluding Italy, in the period before and after 2002; ω_{bc} is the share of inflows of bank b from country c in the 1998-2000 period. Standard errors are clustered at the bank-sector (3-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A13: Bank exposure to capital inflows and post-2008 fragility

	Bank level regression		Bank-firm level regression	
Dependent variable:	*NPL ratio*$_{bt}$		*Credit*$_{ibt}$	
Bank Exposure:	Continuos (1)	Dummy 15% (2)	Continuos (3)	Dummy 15% (4)
$Exposure_b \times Post_t^{2002}$	0.02	-0.001	0.23***	0.05***
	(0.02)	(0.004)	(0.06)	(0.004)
$Exposure_b \times Post_t^{2008}$	0.03	0.008	0.25***	0.04***
	(0.02)	(0.012)	(0.05)	(0.007)
Bank F.E.	✓	✓		
Year F.E.	✓	✓		
Firm-time F.E.			✓	✓
Firm-bank F.E.			✓	✓
Specialization			✓	✓
Bank Chars. $*$ Post	✓	✓	✓	✓
Observations	5,846	5,846	7,494,518	7,494,518
$Adj.R^2$	0.62	0.62	0.84	0.84

Note: In column 1 and 2 we report the results of the bank-level regression $NPL\ Ratio_{bt} = \beta_1\ Exposure_b \times Post_t^{2002-07} + \beta_2\ Exp_b \times Post_t^{2008-13} + \boldsymbol{X_b'\delta} \times Post_t + \gamma_b + \alpha_t + \epsilon_{bt}$. In column 3 and 4 we report the results of the bank-firm-level regression $\ln C_{ibt} = \beta_1\ Exposure_b \times Post_t^{2002-07} + \beta_2\ Exposure_b \times Post_t^{2008-13} + \beta_3\ Spec_{ibt} + \boldsymbol{X_b'\delta} \times Post_t^{2002-07} + \boldsymbol{X_b'\delta} \times Post_t^{2008-13} + \alpha_{it} + \gamma_{ib} + \epsilon_{ibt}$. Standard errors are clustered at the bank level (column 1 and 2) and at the bank-sector (3-digit) level (column 3 and 4). ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A14: Capital inflows and household lending

	Dependent variable: $\ln Household\ credit_{pbt}$		
$Exposure_b$:	Continuos (1)	Dummy 10% (2)	Dummy 15% (3)
$Exposure_b \times Post_t$	0.086 (0.068)	-0.043* (0.024)	-0.013 (0.021)
Province-Year F.E..	✓	✓	✓
Province-BankF.E.	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓
Observations	128,904	128,904	128,904
$Adj.R^2$	0.97	0.97	0.97

Note: The table reports the coefficients of the specification in equation (11) and it captures the effects of capital inflows on bank lending to households in a given province, as discussed in Section . Standard errors are clustered at the province level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A15: Capital inflows and credit allocation by firm characteristics, adding bank-time FE

	Dependent variable: ln $Credit_{ibt}$		
Firm characteristic D_i:	MRPK	Fixed Assets	MRPK / Fixed Assets
Ind. var.: $Exposure_b * Post_t * D_i$	(1)	(2)	(3)
High	0.535***	0.052**	
	(0.021)	(0.021)	
Low	-	-	
	-	-	
High MRPK - High FA			0.831***
			(0.042)
High MRPK - Low FA			0.513***
			(0.042)
Low MRPK - High FA			0.227***
			(0.040)
Low MRPK - Low FA			-
			-
Bank-time F.E.	✓	✓	✓
Firm-time F.E.	✓	✓	✓
Firm-bank F.E.	✓	✓	✓
Specialization	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓
Observations	2,929,360	3,859,095	2,919,761
$Adj.R^2$	0.82	0.82	0.82

Note: The table reports the coefficients of the specification in equation (2) with the addition of bank-time fixed effects as discussed in Section 7.5; it captures the impact of capital inflows on the intensive margin pf credit allocation by type of firm. Standard errors are clustered at the bank-sector (3-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A16: Capital inflows and credit allocation by alternative definitions of firm characteristics

	Dependent variable: ln $Credit_{ibt}$							
Firm characteristic D_i:	TFPR	RLP	Credit score	A: TFPR / B: Fixed Assets	A: RLP / B: Fixed Assets	A: MRPK / B: Credit score	A: TFPR / B: Credit score	A: RLP B: Credit score
Ind. var.: $Exposure_b * Post_t * D_i$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High	0.36***	0.27***	0.22***					
	(0.07)	(0.03)	(0.03)					
Low	0.126*	-0.004	-0.02					
	(0.07)	(0.03)	(0.04)					
High A - High B				0.39***	0.28***	0.29***	0.29***	0.31***
				(0.07)	(0.03)	(0.04)	(0.03)	(0.03)
High A - Low B				0.19**	0.17***	0.11*	0.07	0.05
				(0.08)	(0.04)	(0.06)	(0.05)	(0.05)
Low A - High B				0.13*	0.02	0.16***	0.08*	0.03
				(0.07)	(0.03)	(0.04)	(0.045)	(0.03)
Low A - Low B				0.11	-0.09*	-0.09	-0.13**	-0.21***
				(0.07)	(0.05)	(0.07)	(0.6)	(0.06)
Firm-time F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3,721,817	3,922,078	4,013,803	3,612,178	3,921,234	3,032,579	3,597,895	3,913,815
$Adj.R^2$	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83

Note: The table reports the coefficients of the specification in equation (2) and it captures the effects of capital inflows on the allocation of the intensive margin of credit by firm type, using alternative firms' characteristics as described is Section 7.5. Specifically, we look at firms' TFPR, revenues per worker (RLP), credit score and their combination. Standard errors are clustered at the bank-sector (3-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A17: Capital inflows and credit allocation by quintiles of firm characteristics, intensive margin

	Dependent variable: ln $Credit_{ibt}$		
Firm characteristic D_i:	MRPK	Fixed Assets	MRPK / Fixed Assets
Ind. var.: $Exposure_b * Post_t * D_i$	(1)	(2)	(3)
Q1	0.07	0.05	
	(0.07)	(0.09)	
Q2	0.29***	0.15*	
	(0.08)	(0.08)	
Q3	0.29***	0.19***	
	(0.08)	(0.07)	
Q4	0.35***	0.27***	
	(0.08)	(0.08)	
Q5	0.39***	0.36***	
	(0.08)	(0.07)	
Q1 MRPK - High FA			0.07
			(0.07)
Q2 MRPK - High FA			0.31***
			(0.08)
Q3 MRPK - High FA			0.33***
			(0.08)
Q4 MRPK - High FA			0.40***
			(0.08)
Q5 MRPK - High FA			0.50***
			(0.09)
Q1 MRPK - Low FA			-0.03
			(0.12)
Q2 MRPK - Low FA			-0.04
			(0.12)
Q3 MRPK - Low FA			-0.06
			(0.13)
Q4 MRPK - Low FA			0.15*
			(0.09)
Q5 MRPK - Low FA			0.23***
			(0.08)
Firm-time F.E.	✓	✓	✓
Firm-bank F.E.	✓	✓	✓
Specialization	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓
Observations	3,048,907	4,027,030	3,039,200
$Adj.R^2$	0.83	0.83	0.83

Note: The table reports the coefficients of the specification equation 2, grouping firms by quintiles of the MRPK and fixed assets distribution in their sectors (column 1 and 2) and by quintiles of MRPK combined with being above or below median of fixed assets in column 3, as described is Section 7.5. Standard errors are clustered at the bank-sector (3-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A18: Capital inflows and credit allocation by firm characteristics, intensive margin, balanced panel

	Dependent variable: ln $Credit_{ibt}$		
Firm characteristic D_i:	MRPK	Fixed Assets	MRPK / Fixed Assets
Ind. var.: $Exposure_b * Post_t * D_i$	(1)	(2)	(3)
High	0.46***	0.35***	
	(0.07)	(0.07)	
Low	0.29***	0.25***	
	(0.07)	(0.07)	
High MRPK - High FA			0.51***
			(0.08)
High MRPK - Low FA			0.31***
			(0.08)
Low MRPK - High FA			0.31***
			(0.07)
Low MRPK - Low FA			0.09
			(0.12)
P-value test High=Low	0.00	0.00	
P-value test HMP-LFA=LMP-HFA			0.93
Firm-time F.E.	✓	✓	✓
Firm-bank F.E.	✓	✓	✓
Specialization	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓
Observations	1,422,499	1,807,475	1,417,431
$Adj.R^2$	0.827	0.827	0.827

Note: The table reports the coefficients of the specification in equation 2 estimated using a balanced panel of bank-firm relations as described in Section 7.5. Standard errors are clustered at the bank-sector (3-digit) level.***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A19: Capital inflows and credit allocation by firm characteristics, intensive margin (excluding cooperative banks)

	Dependent variable: ln $Credit_{ibt}$		
Firm characteristic D_i:	MRPK	Fixed Assets	MRPK / Fixed Assets
Ind. var.: $Exposure_b * Post_t * D_i$	(1)	(2)	(3)
High	0.392***	0.360***	
	(0.079)	(0.072)	
Low	0.264***	0.165***	
	(0.075)	(0.079)	
High MRPK - High FA			0.458***
			(0.081)
High MRPK - Low FA			0.194**
			(0.087)
Low MRPK - High FA			0.285***
			(0.076)
Low MRPK - Low FA			-0.072
			(0.113)
P-value test High=Low	0.00	0.00	
P-value test HMP-LFA=LMP-HFA			0.12
Firm-time F.E.	✓	✓	✓
Firm-bank F.E.	✓	✓	✓
Specialization	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓
Observations	2,759,302	3,632,247	2,749,977
$Adj.R^2$	0.827	0.827	0.827

Note: The table reports the coefficients of the specification in equation 2 excluding cooperative banks from the sample. It captures the effects of capital inflows on the intensive margin of credit allocation by type of firm. Firms are divided according to their level of MRPK (column 1), fixed assets (column 2), and the combination of the two (column 3) measured in 1998-2000. Standard errors are clustered at the bank-sector (3-digit) level.***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A20: Capital inflows, firm-level credit and real effects (excluding cooperative banks)

	Dependent variable:								
Ind. var.: $Exposure_i * Post_t * D_i$	Credit			Investment		Employment		MRPK	
Firm characteristic D_i:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High MRPK	0.282***	0.449***		0.743***		0.090		-2.63***	
	(0.083)	(0.060)		(0.180)		(0.068)		(0.252)	
Low MRPK	-0.658***	-0.009		-0.833***		-0.416***		2.19***	
	(0.08)	(0.059)		(0.181)		(0.067)		(0.241)	
High MRPK - High FA			0.482***		0.384**		0.017		-1.40***
			(0.060)		(0.183)		(0.069)		(0.255)
High MRPK - Low FA			0.353***		1.605***		0.284***		- 5.58***
			(0.061)		(0.189)		(0.073)		(0.242)
Low MRPK - High FA			0.008		-0.876***		-0.401***		2.12***
			(0.059)		(0.181)		(0.068)		(0.242)
Low MRPK - Low FA			-0.194***		0.341		-0.370***		1.38***
			(0.067)		(0.220)		(0.082)		(0.250)
Est. Firm-time F.E.		✓	✓	✓	✓	✓	✓	✓	✓
Firm F.E.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector-time F.E.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bank Chars. $*$ Post	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	789,679	789,679	789,679	789,679	789,679	789,679	789,679	727,110	727,110
$Adj.R^2$	0.89	0.95	0.95	0.54	0.54	0.93	0.93	0.72	0.72

Note: The table reports the coefficients of the specification in equation 5 excluding cooperative banks from the sample. It captures the effects of capital inflows on total credit, investment, employment and MRPK by firm type. Standard errors are clustered at the sector (3-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

A.3 Estimation of MRPK and TFPR

The marginal revenue product of capital (MRPK) and the total factor productivity revenues (TFPR) are obtained through a production function estimation as described in Lenzu and Manaresi (2018), who follow Gandhi et al. (2020). The starting point is a gross output production function of the form:

$$y_{it} = f(k_{it}, l_{it}, m_{it}) + \nu_{it} \tag{A1}$$

where k_{it}, l_{it}, and m_{it} are the production inputs (capital, labor, and material) and ν is a productivity shock that can be decomposed as $\nu_{it} = \omega_{it} + \epsilon_{it}$. ω_{it} is assumed to be known to the firm prior to input decisions, while ϵ_{it} is an ex-post productivity shock.

The production function in A1 is assumed to be a second-oder Tanslog:

$$f(k_{it}, l_{it}, m_{it}) = \beta_K k_{it} + \beta_L l_{it} + \beta_M m_{it} + \beta_{KK} k_{it}^2 + \beta_{LL} l_{it}^2 + \beta_{MM} m_{it}^2 + \beta_{KL} k_{it} l_{it} + \beta_{KM} k_{it} m_{it} + \beta_{ML} m_{it} l_{it} \tag{A2}$$

To estimate the production function, firm-level output is measured by log-revenues; log-capital is recovered through the perpetual inventory method using both tangible and intangible fixed assets (relying on firm-level data starting in 1994); labor is proxied by the log of annual wage bill; and intermediate inputs are measured as the log of total expenditures in raw materials, services, and energy consumption. Revenues and materials variables are deflated using a 2-digit output deflator, capital is deflated with a 2-digit investment deflator, and the wage bill is deflated by the consumer price index.

Equation A2 is estimated through a 2-step estimation routine and allowing the structural technology parameters to vary by 4-digit industry. First, the routine recovers the elasticity of intermediate inputs m from the maximization conditions for flexible inputs. The estimated parameter is then used in a second step to compute the elasticities with respect to capital and labor. Given the elasticity of all inputs, TFPR can be simply obtained as the difference between revenues and the estimated production function:

$$TFPR_{it} = y_{it} - f(\widehat{k_{it}, l_{it}, m_{it}}, \hat{\beta}) \tag{A3}$$

Finally, MRPK is obtained as:

$$MRPK_{it} = \theta_{it}^K \frac{Y_{it}}{K_{it}} \tag{A4}$$

where the first term (θ_{it}^K) is the elasticity of capital, computed from the coefficients estimated in A2, and the second is the average product of capital.