Capital Allocation and Firm Dynamics in Small Open Economies

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Abstract

In this paper, I study the consequences of large capital inflows for aggregate output, aggregate productivity, and resource allocation across firms. Using balance of payment data, I identify capital inflow booms across 85 countries between 1975 and 2019. I show that in the aftermath of such episodes, countries typically experience a large and persistent increase in private credit accompanied by transitory booms in aggregate output, while aggregate productivity (TFP) undergoes a persistent bust. Using firm-level data for 30 countries, I analyze the micro dynamics behind the macro results. I show that, on average, firms experience strong but transitory booms, and that there is a substantial reallocation of capital and debt toward high marginal revenue product of capital (MRPK) firms. Finally, I interpret these findings using a small open economy firm dynamics model with heterogeneity and financial frictions. After matching key moments from the micro data, I simulate a capital inflow boom in the model by feeding a sequence of credit supply increases. Through this experiment, I show that considering general equilibrium adjustments, which affect the entry and exit decisions of firms, is critical for matching the sign of the aggregate TFP response.

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1 Introduction

Financial integration has increased substantially over the past 45 years, and at the same time capital inflows have become more volatile across countries (Figure 1). These facts have spurred a growing literature (Miranda-Agrippino and Rey, 2022; Florez-Orrego et al., 2023), but there is still plenty of debate about the allocative effects of these trends. In this paper, I study how large capital inflow episodes affect aggregate output, aggregate productivity, and resource allocation across firms.

Figure 1: De Facto Financial Integration and Volatility in Capital Inflows: 1975-2019

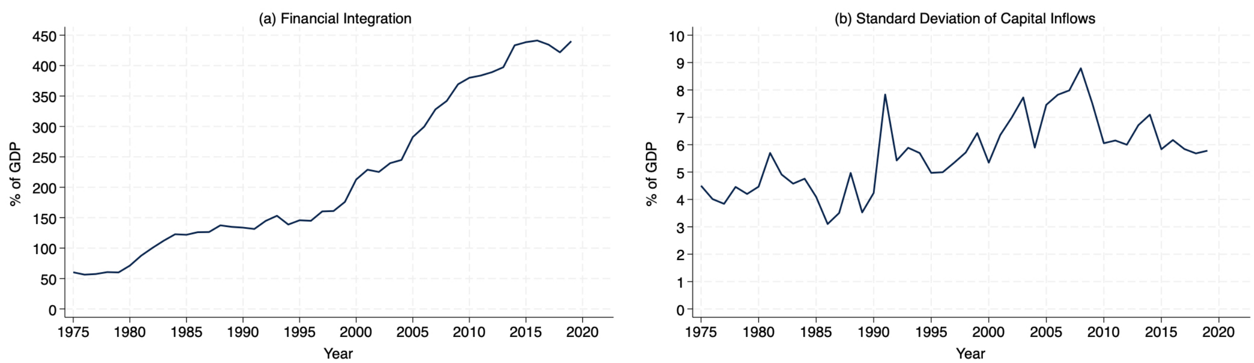

Figure 1. Panel (a). De facto financial integration is defined as the ratio between the sum of net foreign assets and net foreign liabilities over GDP following Lane and Milesi-Ferretti (2003). The line represents the yearly average of this measure across 85 countries. Panel (b). The line represents the yearly standard deviation of the capital inflows to GDP ratio across 85 countries. Data on net foreign assets and net foreign liabilities are obtained from the International Financial Statistics produced by the International Monetary Fund. GDP data and exchange rate data are obtained from the World Development Indicators produced by the World Bank.

Recent work has focused on two channels. The empirical literature on unexpected policy changes argues that access to foreign resources leads to a relaxation of financial frictions for firms, which allows them to invest more and generates a decrease in resource misallocation (Varela, 2018; Bau and Matray, 2023). On the other hand, the quantitative literature on the effects of the relaxation of financial constraints through either capital market integration or decreases in real interest rates argues that these events can lead to a decrease in aggregate productivity—measured as total factor productivity (TFP)—when the new abundant credit is misallocated (Benigno and Fornaro, 2014; Gopinath et al., 2017).

I explore an alternative explanation that considers both positive direct effects from the relaxation of financial frictions and negative indirect effects due to general equilibrium forces. I argue that large capital inflows can be interpreted as large positive credit supply shocks. An increase in the availability of credit allows incumbent firms to grow and generates substantial factor reallocation, but it also leads to strong general equilibrium effects that shape the response of macroeconomic aggregates. This argument is based on three empirical facts I observe in the data. First, in the aftermath of large capital inflow episodes, the economy typically undergoes a large and sustained increase in private credit. Second, in tandem with these credit supply shocks, there is a transitory boom in economic activity—caused mostly by aggregate investment—during which a substantial increase in wages occurs, as well as a persistent bust in measured TFP. Third, incumbent firms experience strong but transitory booms, during which a strong reallocation of capital and debt toward constrained firms takes place.

I rationalize this set of results using a simple heterogeneous-firms model that reproduces key empirical moments from the micro data. I use the model to study the allocative effects of a large capital inflow boom episode by simulating, within the model, the average private credit dynamics observed in the data. I then solve for two different paths of this model economy: a partial equilibrium (PE) one, in which wages are kept at the initial steady-state level, and a general equilibrium (GE) one, in which wages are allowed to adjust as credit expands. These model-implied paths show that taking GE adjustments into account is key for matching the sign of the aggregate TFP response in the data, while also allowing for an increase in the average firm size and substantial reallocation of resources. The intuition for these results is that the increase in average firm size and the boom in economic activity lead to an increase in wages. This increase in wages changes entry and exit decisions for firms, which results in a smaller number of operating firms. Under the assumption of decreasing returns to scale in production, a smaller number of operating firms causes a reduction in aggregate productivity despite the increase in average firm size and the reallocation of factors.

In the first part of this paper, I revisit the macroeconomic and microeconomic evidence on the effects of large capital inflow booms. I start by identifying the years in which capital inflow booms happen across a sample of 85 countries—26 advanced economies (AEs) and 59 emerging market and developing economies (EMEs)—between 1975 and 2019 using balance of payment data. I identify a total of 346 episodes during this period. These episodes are markedly stronger, longer, and more frequent in EMEs than in AEs.

Next, I combine these identified episodes with a panel of countries that contains a combination of activity, productivity, and credit market data from various sources. Using a local projections approach in the spirit of Dube et al. (2023), I estimate the average dynamics of a series of macroeconomic variables around these boom years relative to normal times and notice three empirical regularities. First, I show that large capital inflows lead to large and sustained private credit expansions. Second, I show that these are typically accompanied by a transitory boom in economic activity, driven mostly by investment. Third, I show that these episodes are typically followed by a persistent bust in aggregate productivity (TFP).

I inspect these results further by combining the dataset described in the previous paragraph with balance sheet and income statement firm-level data for 30 countries (18 AEs and 12 EMEs) between 1995 and 2019, covering all sectors and the entire firm-size distribution. Using a local projections approach akin to the framework established by Jordà (2005), I estimate the average response of firm-level variables in the aftermath of capital inflow booms. I show that firms undergo strong but transitory increases in output, wage bill, capital, and total debt. I also show that this leads, on average, to a reduction of firms' marginal revenue products of capital (MRPK) and labor (MRPL), which are broadly used as proxies for the presence of constraints to firm growth. Given this reduction in MRPs, I use a binary classification between high- and low-MRPK firms to test for possible distributional effects of capital inflows. I find evidence of substantial capital and debt reallocation toward high-MRPK firms away from low-MRPK firms, which causes a compression in the distribution of MRPKs, even though there is not much reallocation of labor or output. Overall, the evidence suggests that constrained firms, who are typically young and small, become less constrained at the expense of unconstrained firms.

A natural question arises: How is it possible to observe, simultaneously, a decrease in TFP and the reallocation of factors toward constrained firms? In the remainder of the paper, I rationalize these seemingly contradictory empirical facts through a model in the spirit of the recent firm dynamics literature. More precisely, I develop and solve a general equilibrium small open economy firm dynamics model with heterogeneity and financial frictions in the spirit of Khan and Thomas (2013) and Jo and Senga (2019).

The model economy is populated by a representative household and an endogenously determined mass of heterogeneous firms. The representative household has preferences over the consumption of a single homogeneous good and leisure, and owns all firms in this economy. Firms face idiosyncratic shocks to their productivity and possess a decreasing returns to scale technology that requires capital and labor for production. At every period, incumbent firms face the possibility of exit through an exogenous shock or through an endogenous decision, given that they must pay an operating cost and that their profitability fluctuates over time due to the presence of idiosyncratic productivity shocks. Also, there is a mass of prospective entrants that decide whether to enter upon drawing their initial levels of productivity, capital, and debt.

One of the key building blocks of the model is the presence of financial frictions. First, firms are not allowed to issue equity. Second, firms face forward-looking collateral constraints. The combination of firm heterogeneity and financial frictions ensures that not only does the distribution of factors shape aggregate productivity, but also that aggregate productivity can be affected by an external shock that changes the availability of credit. Also, allowing for an endogenously determined mass of producing firms means that the model encompasses a relevant feedback channel arising from general equilibrium adjustments, especially given the decreasing returns to scale.

After parameterizing the model to match the firm size distribution and key additional moments from the micro data—specifically, the investment rate, leverage ratio across firms, capital to output ratio, total exit rate, and employment share of entrants—I study the impact of a capital inflow boom in the parametrized model economy. More precisely, I posit that a capital inflow boom in this economy can be interpreted as a credit supply shock generated by a lowering of lending standards. Through a sequence of shocks to the tightness of the borrowing constraint, I match the dynamics of the firm credit to GDP ratio observed in the data and study the aggregate response of this economy to those shocks in both a PE setting, in which wages are not allowed to readjust, and a GE setting, in which wages are allowed to adjust.[1]

The main quantitative finding is that allowing for GE adjustments is crucial for matching the decline in aggregate productivity. While the PE setting is informative about the relevance of the direct effect of large capital inflow booms to incumbent firms, only by allowing wage adjustments can we match aggregate dynamics as the ones observed in the data. Interestingly, even in the GE setting, the average effect is positive for incumbent firms. Therefore, the main driving force for the aggregate decline in productivity is the decline in the number of operating firms, given the changes in entry and exit thresholds prompted by the increase in wages.

Related Literature

I contribute to several strands of the literature. First, I bridge a significant gap between the empirical and quantitative literatures that study the relationship between financial integration and misallocation. The empirical literature has focused on how firms—and, in particular, the resource allocation across them—have responded to financial liberalization episodes: Larrain and Stumpner (2017) study a set of Eastern European economies in the post-1990s period; Varela (2018) and Saffie et al. (2020) study the 2001 relaxation of capital controls in Hungary; Bau and Matray (2023) study two waves of reforms in 2001 and 2006 in India. These papers have a common message despite the heterogeneity in contexts:

[1]Given the small open economy assumption and the presence of borrowing constraints, the only price that can adjust in equilibrium is the wage rate that clears the labor market.

(incumbent) firms accrue substantial benefits from liberalizations and posterior influxes of capital, because financial frictions are eased and they are more readily able to grow toward their efficient scales. In other words, there is substantial evidence that financial liberalizations lead to positive direct effects at the firm level and reduce misallocation. I add to this branch of the literature through a systematic review of the effects of capital inflow booms on firms in a broader set of countries and episodes: large capital inflows, because they significantly expand the availability of private credit, allow incumbent firms to get closer to their efficient scales.

However, the empirical literature is at odds with the evidence on aggregate trends: Increases in financial integration have been associated with a slowdown in aggregate productivity growth—the financial resource curse, as in Benigno and Fornaro (2014). This has been the focus of the quantitative literature; in particular, Reis (2013) and Gopinath et al. (2017), who study the experience of different southern European countries after the implementation of the euro, and examine the role of resource reallocation across sectors and within sectors, respectively. In this paper, I focus on the within-sector channel using a simple small open economy model with endogenous firm dynamics and financial frictions. More precisely, I contribute by providing a framework in which, unlike previous work, capital inflows have positive direct effects on firms and lead to a "positive" reallocation of resources across firms—but at the same time there are general equilibrium effects that can attenuate or even reverse the gains from the direct effects.

Second, this paper is closely related to the literature that studies the effects of aggregate shocks and the response of firms in the context of heterogeneity; in particular, Buera and Moll (2015) and Ottonello and Winberry (2020). I contribute to this literature by revealing the extent of heterogeneity in firms' responses to a large capital inflow episode, using the interpretation whereby these events work primarily as large private credit supply expansions.

Third, this paper intersects with two distinct bodies of literature: one that analyzes the effects of credit booms and another that examines the consequences of capital inflow booms. I use their established definitions of a boom and framework for empirical analysis. Some notable examples in the credit literature are Gourinchas et al. (2001) and Mendoza and Terrones (2008); while, in the international literature, I highlight Reinhart and Reinhart (2009), Cardarelli et al. (2010), Benigno et al. (2015), and Caballero (2016). Methodologically, this paper is closest to Müller and Verner (2023), who use the Hamilton filter to identify periods in which the credit to GDP ratio increases rapidly relative to its trend. I follow this detrending approach in my identification of changes in the capital inflows measure relative to its long-term trend.

Fourth, I build on the large literature that studies the connections between financial frictions and misallocation such as Buera and Shin (2013) and Midrigan and Xu (2014). This paper is closest to the literature that employs these concepts in a heterogenous firm dynamics framework. More precisely, I build on the quantitative framework developed by Khan and Thomas (2013) and Jo and Senga (2019), in which heterogeneous firms face financial frictions: a borrowing constraint and a no-equity issuance constraint. I build on this work by solving a small open economy version of the model and simulating a capital inflow boom in the model, using it as a laboratory to test the relative strength of direct effects, due to the relaxation of financial constraints, and indirect effects, due to general equilibrium forces.

Road Map

The paper is organized as follows. Section 2 describes the data and the methodology used to identify capital inflow boom episodes. Section 3 provides empirical evidence that large capital inflow episodes lead to sustained private credit expansions, transitory activity booms and a persistent bust in aggregate productivity. Section 4 expands on the macroeconomic evidence by examining the effects of the identified episodes on firms, and shows that firms experience strong but transitory booms, and there is substantial capital and debt reallocation. Section 5 develops and solves a small open economy firm dynamics model with heterogeneity and financial frictions. Section 6 uses the model to study how a large capital inflow boom affects the economy, and demonstrates how the interplay between PE and GE forces determine the aggregate response of productivity. Finally, Section 7 provides concluding remarks.

2 Detecting Capital Inflow Booms in the Data

In this section, I document how I identify large capital inflow episodes —or capital inflow booms— using balance of payment data. To this end, I combine data for 85 countries—26 AEs and 59 EMEs—between 1975 and 2019 from the International Financial Statistics provided by the International Monetary Fund with GDP and exchange rate data from the World Development Indicators provided by the World Bank.[2]

The selection of countries is guided by the usual set of criteria in this literature. I start by excluding countries with population below 1 million and countries for which average GDP across sample years is below 10 billion 2015 USD. Then, I exclude countries

[2] The complete list of countries can be found in Appendix A.1.1.

for which oil rents are either above 50% of GDP for any year included in the sample or above 10% for all years included in the sample. Lastly, I remove countries for which the sample mean of GDP per capita measured in 2017 parity of purchasing power units is below 1,700, which would render these countries eligible to receive foreign aid from international development institutions, and in particular the World Bank. These three steps presumably exclude countries for which the relationships between capital flows and the real economy differ from the typical economy.

I follow Reinhart and Reinhart (2009) and Benigno et al. (2015) in defining capital inflows as the sum of the current account deficit and the change in holdings of official reserves. This choice allows me to measure the resources acquired (or spent) through the issuance (or repayment) of home country liabilities while expanding the timespan of analysis, since it is available for a longer time span and for more countries than information from balance of payment detailed financial accounts. I scale this measure by taking the ratio with regard to GDP to capture the relative size of these flows with regard to the economy.

I then identify booms as periods when the capital inflow measure rises rapidly relative to its trend. This notion builds on two strands of the literature: first, the literature that studies credit booms, such as the work of Gourinchas et al. (2001) and Mendoza and Terrones (2008); second, the literature that has applied credit boom methods to international capital inflows, such as Cardarelli et al. (2010), Benigno et al. (2015), and Caballero (2016).

Procedurally, I obtain the trend of capital inflows and their fluctuation around the trend for each country through an application of the Hamilton (2018) filter with a horizon of 4 years, as Müller and Verner (2023) do for the identification of credit booms. Importantly, using the Hamilton filter avoids the pitfalls of the usual detrending approach based on the Hodrick-Prescott (HP) filter.[3]

I define a capital inflow boom as the first year when the detrended capital inflow measure exceeds the country-specific long-term standard deviation—i.e. the standard deviation of the detrended series. In Figure 2, I provide two examples by plotting the cases of Spain in Panel (a) and India in Panel (b). Using this approach, I obtain 346 episodes, of which 94 occur in AEs and 252 in EMEs, between 1975 and 2019.[4]

[3]See Hamilton (2018) for a complete discussion of these pitfalls. In this context, the crucial concern is that the HP filter can produce filtered series that exhibit spurious dynamic relations that do not reflect the underlying data-generating process.

[4]The complete list of episodes can be found in Appendix A.1.2.

Figure 2: Hamilton Filter-Based Identification of Capital Inflow Booms – Spain and India

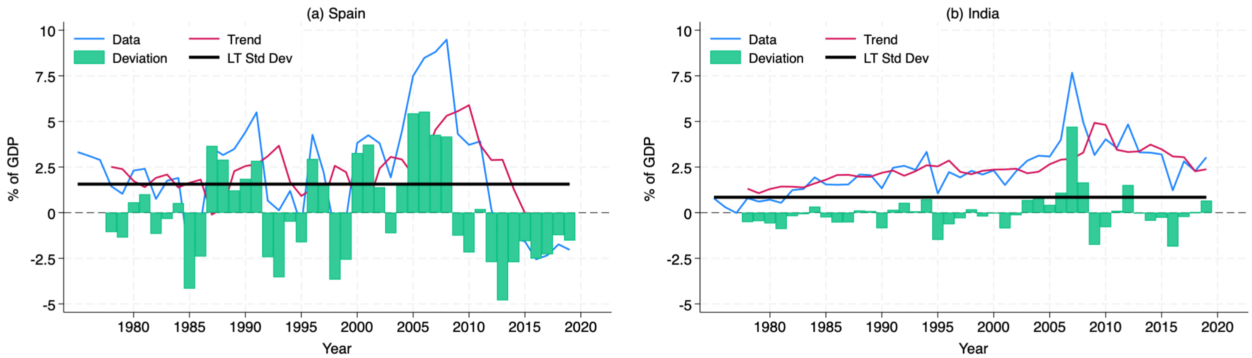

Figure 2. Panels (a) and (b) plot the experience of Spain and India, respectively. The blue line represents the capital inflow measure in its raw format. The red line represents the trend of this measure obtained through an application of the Hamilton filter. The black solid line represents the country-specific standard deviation based on the trend measure. Green bars represent the difference between the raw data and the trend measure. Visually, a capital inflow boom episode starts when the green bar first crosses above the black line and ends when it crosses back below for at least two periods.

In Figure 3, I plot the evolution of the number of countries undergoing episodes within a year across these two groups. It is clear that there is substantial fluctuation over time, with two noticeable peaks: one in the early 1980s and another in the late 2000s. Interestingly, the aftermath of both these periods are marked by two well-known and studied economic crises: the 1980s Debt Crisis and the Great Recession, respectively.

Figure 3: Capital Inflow Booms between 1975 and 2019 – Evolution

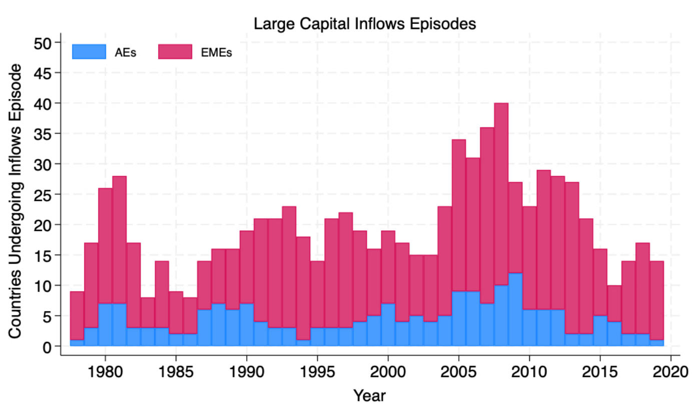

Figure 3. This figure plots the evolution of the number of countries, split into two groups, that experienced a capital inflow boom episode between 1975 and 2019. The plot is based on a sample of 85 countries.

In Table 1, I provide descriptive statistics pooled over countries and years. Overall, these episodes last a bit longer than a year and represent capital inflows of about 8% of GDP. Also, episodes are markedly stronger in EMEs than in AEs, and also last longer. In the Appendix A.1.3, I provide additional details on the classification of these episodes based on the nature of the flows using the IMF definitions.

Table 1: Capital Inflow Booms between 1975 and 2020 – Summary Stats

Moment	All	AEs	EMEs
Average Capital Inflows (% of GDP)	7.85	5.88	8.60
Average Current Account Deficit (% of GDP)	5.18	3.30	5.90
Average Duration (Years)	1.39	1.32	1.42
Number of Episodes	346	94	252

Table 1. Summary statistics of capital inflow booms for the period 1975 to 2019. Statistics are generated by pooling countries over time.

3 Macro Evidence: Transitory Booms and a Persistent Bust

I document that capital inflow booms are associated with large increases in credit supply, transitory booms in economic activity, and a persistent decline in aggregate productivity.

Data Sources

My sample combines capital inflow boom episodes with annual macroeconomic and financial data from several sources. Apart from GDP and exchange rate data, as outlined in the previous section, other economic activity series are drawn from the World Development Indicators produced by the World Bank. Labor market series are drawn from a combination of the International Financial Statistics, International Labor Organization, and national Censuses. Credit market series are constructed through a combination of data from the Bank of International Settlements, national Censuses and the Global Credit Project (Müller and Verner, 2023). Finally, in the baseline estimates, aggregate productivity is measured following the procedure proposed by Imbs (1999) using the implementation proposed by Levchenko and Pandalai-Nayar (2020). Details on each of the series can be found in Appendix A.2.1.

Baseline Specification

I estimate the following empirical specification:

$$y_{c,t+h} - y_{c,t-1} = \alpha_c^h + \lambda_t^h + \beta^h \textbf{Boom}_{c,t} + \sum_{j=1}^{5} \gamma_j^h y_{c,t-j} + \Gamma' X_{c,t-1} + \varepsilon_{c,t+h}, \; h = -5, \ldots, 5 \quad (1)$$

where y denotes a macroeconomic variable of interest, α_c^h is a country c fixed effect, λ_t^h is a time fixed effect, $\textbf{Boom}_{c,t}$ is an indicator of the occurrence of a large capital inflow episode in period t in country c, $X_{c,t-1}$ is a vector of country- and time-specific controls, and $\varepsilon_{c,t+h}$ is the residual at horizon h.

The main coefficient of interest is β^h, which is informative about how the average behavior of the dependent variable y changes during periods when there is a surge in capital inflows compared with normal periods. To be more specific, this coefficient measures the average change, expressed as a percentage, in our variable of interest that occurs in conjunction with episodes of large capital inflows.

The inclusion of country fixed effects controls for permanent differences across countries, while the inclusion of a time fixed effect captures common shocks across different countries. The inclusion of lags of y follows the approach of Dube et al. (2023), which allows me to control for possible selection effects generated by the dynamics of the variable y before the capital inflow boom episode happens. The vector $X_{c,t-1}$ includes a measure of financial deepening for a country (aggregate credit to GDP ratio), GDP growth, and a measure of trade openness (the sum of exports and imports to GDP ratio) in the year prior to the episode. Lastly, I cluster standard errors two ways to account for correlation within countries and within time.

Results

#1 Capital Inflow Booms Lead to Large and Sustained Private Credit Expansions

Figure 4 shows the evolution of credit to the non-financial sector relative to GDP around a capital inflow boom episode. Solid dots report the coefficient of interest β^h and capped spikes denote 90% confidence intervals. The response is modest on impact, with an increase of about 1%, but it slowly rises in the aftermath, with credit over GDP rising by about 5% five years after the episode.

Figure 4: Dynamics of Credit to the Non-financial Sector

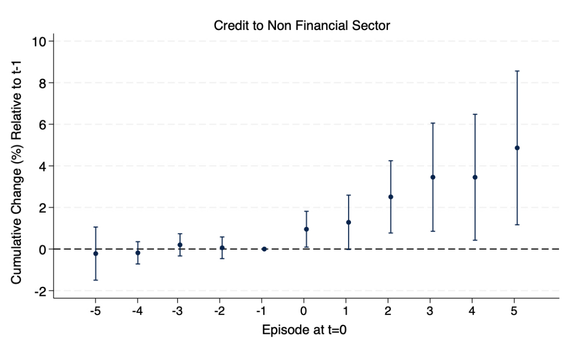

Figure 4. This figure reports the evolution of the coefficient β^h over years $t + h$ around the episode at time t from estimating (1). Capped spikes represent the 90% confidence intervals around the point estimates.

An important question arises: Which sector is driving this response in the dynamics of credit? The first part of the answer is provided in the top row of Figure 5: The increase observed in the aggregate measure is entirely driven by the private sector, while there is no discernible significant effect on credit to the government, with negative point estimates in almost all periods. Notably, the response on impact is large—about 4%—but it accelerates further until it reaches a plateau around 3 years after.

The second part of the answer is shown in the bottom row of Figure 5, which breaks down the response of private credit between firms and households. The increase in private credit is driven mostly by firms, since the response of firm credit is stronger even if the difference between the point estimates is not significant. However, since the share of firm credit relative to total credit is about twice as large as the share of household credit relative to total credit, I will focus on the dynamics of this variable as the key driving force of the aggregate dynamics for the rest of this paper.[5]

Figure 5: Dynamics of Credit to the Non-financial Sector: Private NFS vs Government

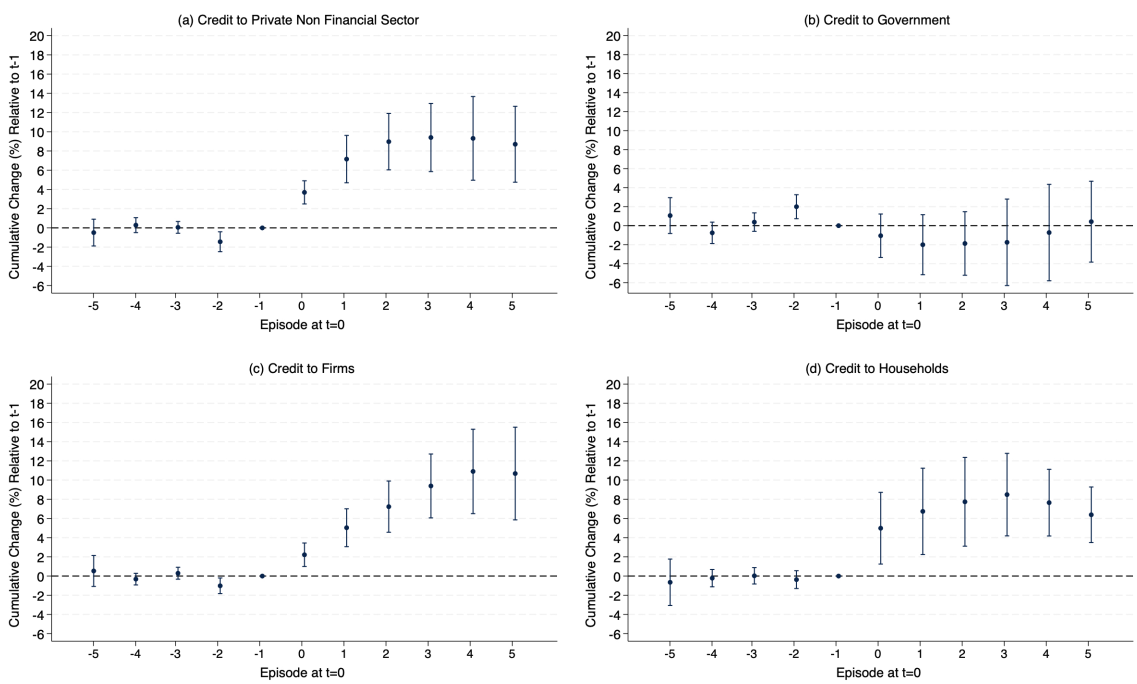

Figure 5. This figure reports the evolution of the coefficient β^h over years $t+h$ around the episode at time t from estimating (1). In the top row, I report the response of credit to private non-financial sector in Panel (a) and credit to government in Panel (b). In the bottom row, I report the response of credit to firms in Panel (c) and credit to households in Panel (d). Capped spikes represent 90% confidence intervals around the point estimates.

[5] In the data, the average share of firm credit over total credit is about 45%, while the average share of household credit over total credit is about 23%.

#2 Capital Inflows Booms Lead to Transitory Booms in Economic Activity

Figure 6 illustrates how GDP and its components behave around a large capital inflow episode. After the episode, all components of GDP—in particular investment—increase slightly, with a peak about one year after followed by a continuous decline. Whereas consumption and government expenditures eventually return to pre-episode levels, investment keeps falling, and ends up at a lower level than before. The headline response of GDP seems, therefore, to be driven by investment. Overall, these responses suggest that large capital inflow episodes lead to short-lived booms that fade as investment decelerates.

Figure 6: Dynamics of GDP

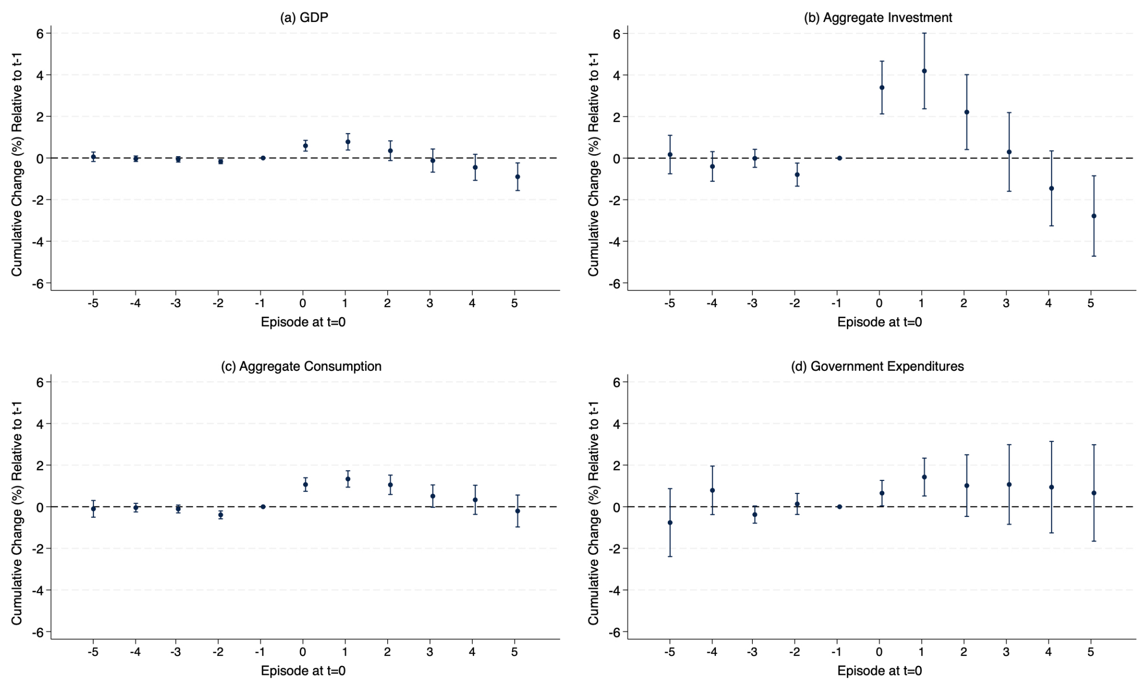

Figure 6. This figure reports the evolution of the coefficient β^h over years $t+h$ around the episode at time t from estimating (1). In the top row, I report the response of GDP in Panel (a) and aggregate investment in Panel (b). In the bottom row, I report the response of aggregate consumption in Panel (c) and government expenditures in Panel (d). Capped spikes represent 90% confidence intervals around the point estimates.

I also analyze the response of real wages in Figure 7. There is a modest increase on impact, but wages continue to increase until they stabilize around a level 1.5% higher than prior to the shock. The increase in real wages is a key element of the analysis in Section 6. In Appendix A.2.2, I analyze the responses of the unemployment rate, which reinforces the evidence of transitory booms, with a sharp decline on impact that is undone in the following periods.

Figure 7: Real Wages

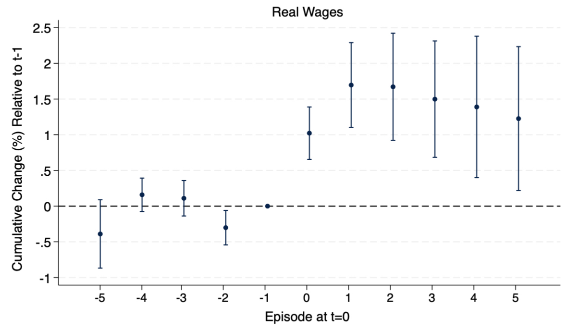

Figure 7. This figure reports the evolution of the coefficient β^h over years $t+h$ around the episode at time t from estimating (1). Capped spikes represent 90% confidence intervals around the point estimates.

#3 Capital Inflow Booms Lead to Persistent Busts in Aggregate Productivity

Figure 8 exhibits the response of aggregate productivity (TFP). After an initial modest and statistically insignificant increase, productivity starts to fall and continues to do so at every subsequent period until it ends up at a level about 1.5% lower than prior to the episode. To put this number into perspective, it is reasonably close to the number referenced as the decline in TFP observed in Spain between 1999 and 2007 (Benigno and Fornaro, 2014; Gopinath et al., 2017). As a measurement robustness check in Appendix A.2.3, I redo this exercise using aggregate productivity data from the Penn World Table (Feenstra et al., 2015), which yields very similar dynamics.

Figure 8: Dynamics of Productivity

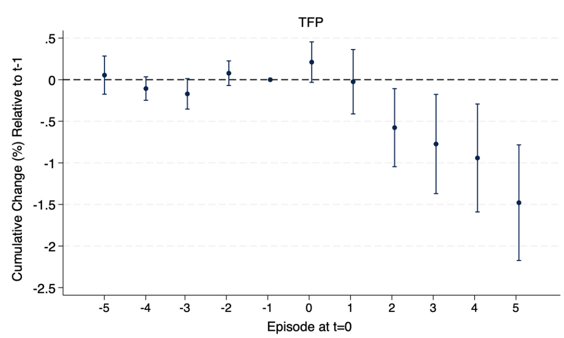

Figure 8. This figure reports the evolution of the coefficient β^h over years $t+h$ around the episode at time t from estimating $t+h$ around the episode at time t from estimating (1). Capped spikes represent 90% confidence intervals around the point estimates.

Additional Results and Validation

In Appendix A.2.4, I report an extensive collection of additional results and alternative specifications for robustness. Of these, I highlight three. First, I show that the dynamics I documented in this section are largely the same for AEs and EMEs. Second, I show that the nature of the flows—i.e. whether the episodes are mostly led by equity or by debt—is largely irrelevant for the results. Finally, as validation that these identified episodes happen at times of large capital inflows, I display the response of net exports—a proxy for the response of current account deficits—and of actual inflows around an episode.

Interpretation of Results

The evidence in Sections 3 and 4 describes how capital inflow booms affect the economy, but there are competing interpretations of the results. First, capital inflow booms could be a response to changes in fundamentals; in particular, an increase in productivity. An increase in productivity triggers an increase in consumption and investment but is likely to deteriorate the trade balance. In turn, this imbalance causes a capital inflow episode, since capital will not increase fast enough to fully offset the increase in demand. This is the standard mechanism proposed in the small open economy real-business-cycle model. However, this interpretation is at odds with the evidence. After controlling for pre-trends and time-varying country fundamentals, the observed dynamics are markedly inconsistent with a shock of this nature, since aggregate investment more than reverts the initial boom and aggregate productivity falls sharply after a boom.

A different interpretation is that these episodes happen in response to changes in global financial conditions, and particularly changes in the appetite for risk or changes in the US monetary policy stance as suggested by Miranda-Agrippino and Rey (2020). In Appendix A.2.5, I show that the number of episodes in a year is highly positively correlated with the global factor in risky asset prices in Miranda-Agrippino et al. (2020) and highly negatively correlated with the VIX index, which is commonly used as a measure of risk appetite.

To support this alternative explanation, I refine the sample of capital inflow booms by excluding any episode that can be associated with a financial liberalization event, since such liberalizations are typically associated with other productivity-enhancing structural reforms. I use a narrative classification based on changes in the Chinn-Ito index (Chinn and Ito, 2006) and the FKRSU index (Fernández et al., 2016) to identify and exclude capital inflow episodes solely associated with liberalization events in specific countries. The results of this exercise, detailed in Appendix A.2.6, reinforce the findings from the baseline sample and analysis. Specifically, I note even weaker peaks in economic activity during these still transitory booms, while productivity dynamics closely mirror the baseline results. Consequently, the evidence presented in Appendices A.2.4 and A.2.5 supports the interpretation that the second hypothesis is more likely to be correct.

4 Micro Evidence: Transitory Booms and Permanent Reallocation

I now combine the capital inflow boom episodes and macroeconomic data with firm-level data from the historical product of Orbis. [6] This data set is produced by Moody's Bureau van Dijk (BvD) by the collecting and harmonizing balance-sheet and income statement information from a variety of sources and providers.

Sample Details

This dataset is uniquely suited for my study: it contains rich firm-level annual balance sheet, income statement and sectoral information, which allows me to measure the main variables of interest; it covers a sizable number of countries, which allows me to use cross-country variation; it is a relatively long panel, which allows me to use within-firm variation and explore the variation in the timing of the capital inflow episodes across countries; it covers a significant share of economic activity both in terms of output and employment in most countries,[7] which means that the data are suitable for capturing aggregate trends stemming from firm-level behavior; it covers the entire distribution of firms, both in terms of size and sectors—in Figure 9, I plot the distribution of size (employment) and sectors in the full sample— which means that it is a representative sample of the firm population.

Figure 9: Size Distribution and Sectoral Distribution – Full Sample (1995-2019)

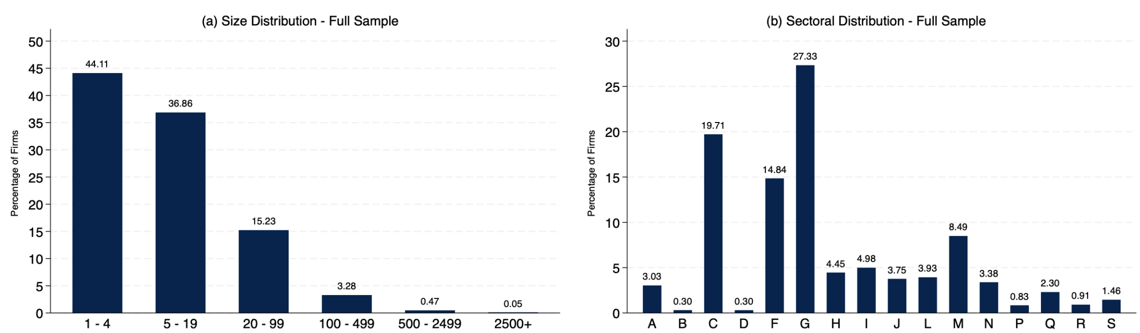

Figure 9. This figure reports details on the size distribution in Panel (a) and the sectoral distribution using 2-digit NACE codes in Panel (b) for the period 1995 to 2019. Statistics are generated by pooling firms over time and countries. Details on sectors are available at nacev2.com.

[6]The empirical work in this section is part of a broader project using Orbis data in collaboration with Alessandra Peter and Simon Gilchrist (Camêlo et al., 2023).

[7]In the final sample, output coverage across countries is about 40% and employment coverage is around 30%.

There are two main disadvantages of using the Orbis data. First, coverage in the period prior to 1995 is substantially worse than in the years after which restricts the period of analysis. Second, it has been argued, such as by Castillo-Martınez (2020), that this data set does a poor job of capturing the extensive margins of production, and particularly the exits of firms. While there are not many alternatives with regard to the first point, the second can be addressed through a combination of modeling and cross-country aggregate data on exit rates, such as in Kochen (2022). In Section 5, I build on Kochen's work, using information on the firm size distribution to calibrate a model that can match key moments from the micro data and the aggregate exit rate.

The final sample contains data from 30 countries across different continents between 1995 and 2019.[8] Construction of this sample follows the steps in Kalemli-Özcan et al. (2023); details on the process can be found in Appendix A.3.2. Nominal variables are transformed into constant price at a constant exchange rate—more precisely, into 2015 USD using GDP deflators and nominal exchange rate data from the World Development Indicators produced by the World Bank. Table 2 presents simple summary statistics of the final sample used in the analysis. The final sample includes about 42.6 million firm-year observations, of which 32.3 million come from AEs and 10.3 million from EMEs.

Table 2: Summary Statistics of Firm-level Variables

Variable	Mean	Standard Deviation	p1	Median	p99
Total Assets	316.41	4,903.02	0.01	0.65	6,155.88
Capital	113.05	2,291.07	0.00	0.12	2,137.23
Revenue	422.12	4,200.27	0.02	0.88	8,609.35
Value Added	71.87	847.30	0.01	0.29	1,424.82
Wage Bill	30.85	430.48	0.00	0.17	602.61
Employment	24.49	222.08	1.00	5.00	306.00
Age	14.03	12.19	1.00	11.00	58.00

Table 2. Summary statistics for firm-level variables for the period 1995 to 2019. Statistics are generated by pooling firms over time and countries. Values are displayed in 2015 USD millions. Total assets are the sum of all assets in a firm's balance sheet; capital is the sum of tangible and intangible fixed assets, as in Gopinath et al. (2017); revenue is the sum of operating revenue/turnover and other operating income; value added is the difference between revenue and material costs; wage bill is the sum of wages/salaries paid and taxes on salaries; employment is the number of employees; the age of a firm in a year t is computed as the difference between t and the year of incorporation plus one.

[8] The full list of countries is in Appendix A.3.1.

Baseline Specification

I estimate the following local projection (Jordà, 2005) specification:

$$y_{i,s,c,t+h} - y_{i,s,c,t-1} = \gamma_i^h + \zeta_s^h + \alpha_c^h + \lambda_t^h + \beta^h \mathbf{Boom}_{c,t} \\ + \Gamma' X_{i,s,c,t-1} + \varepsilon_{i,s,c,t+h}, \; h = 0, \ldots, 5 \quad (2)$$

where γ_i^h is a firm i fixed effect; ζ_s^h is a 4-digit-sector s fixed effect; α_c^h is a country c fixed effect; λ_t^h is a time fixed effect; $\mathbf{Boom}_{c,t}$ is an indicator of the occurrence of a large capital inflow episode in period t in country c; $X_{i,s,c,t-1}$ is a vector of firm, sector, country and time specific controls; and $\varepsilon_{i,s,c,t+h}$ is the residual at horizon h.

In the baseline specification, the main coefficient of interest is β^h, which provides information on the dynamics of variable y after a large capital inflow episode. The interpretation is similar to the one in the previous section: It captures the average percentage change that can be associated with the boom in the variable of interest across firms. Importantly, since the results reported below are obtained through regressions in which observations have equal weights and firm size is relatively small, the magnitudes of the coefficients in this section should not be directly compared to the ones in Section 3, in which the analysis is run at country level.

Besides time and country fixed effects, I also include firm fixed effects, which capture permanent differences across firms and sector fixed effects, which capture permanent differences across sectors. Finally, $X_{i,s,c,t-1}$ includes, besides the aggregate controls from the previous section, controls for time-varying characteristics of firms: revenue growth, current assets as share of total assets, and size. This choice of controls follows the usual approach in the literature; for instance, in Ottonello and Winberry (2020). Lastly, in this section, I cluster standard errors two ways to account for correlation within firms and within time, following Kalemli-Özcan et al. (2022).

In the baseline results, I winsorize the sample at the top and bottom 1% of the observations of variables of interest in order to ensure that results are not driven by outliers. In Appendix A.3.4, I report the results for the untrimmed sample and show that the overall message remains the same.

Baseline Results

#1 Firms experience strong, but transitory booms

Figure 10 shows how firms evolve in the aftermath of a large capital inflow episode. The top row depicts the response of capital in Panel (a) and debt in Panel (b). Whereas capital responds strongly on impact and peaks about 2 years after the onset of the shock, debt responds more weakly initially but then rises at a substantially faster pace, peaking about 3 years after. Although firms return to their initial level of capital, they are more indebted than before. This suggests a more levered-up economy than prior to the shock, in line with the aggregate evidence of a strong and sustained increase in private credit.

Figure 10: Responses of Firm Outcomes to Capital Inflow Booms

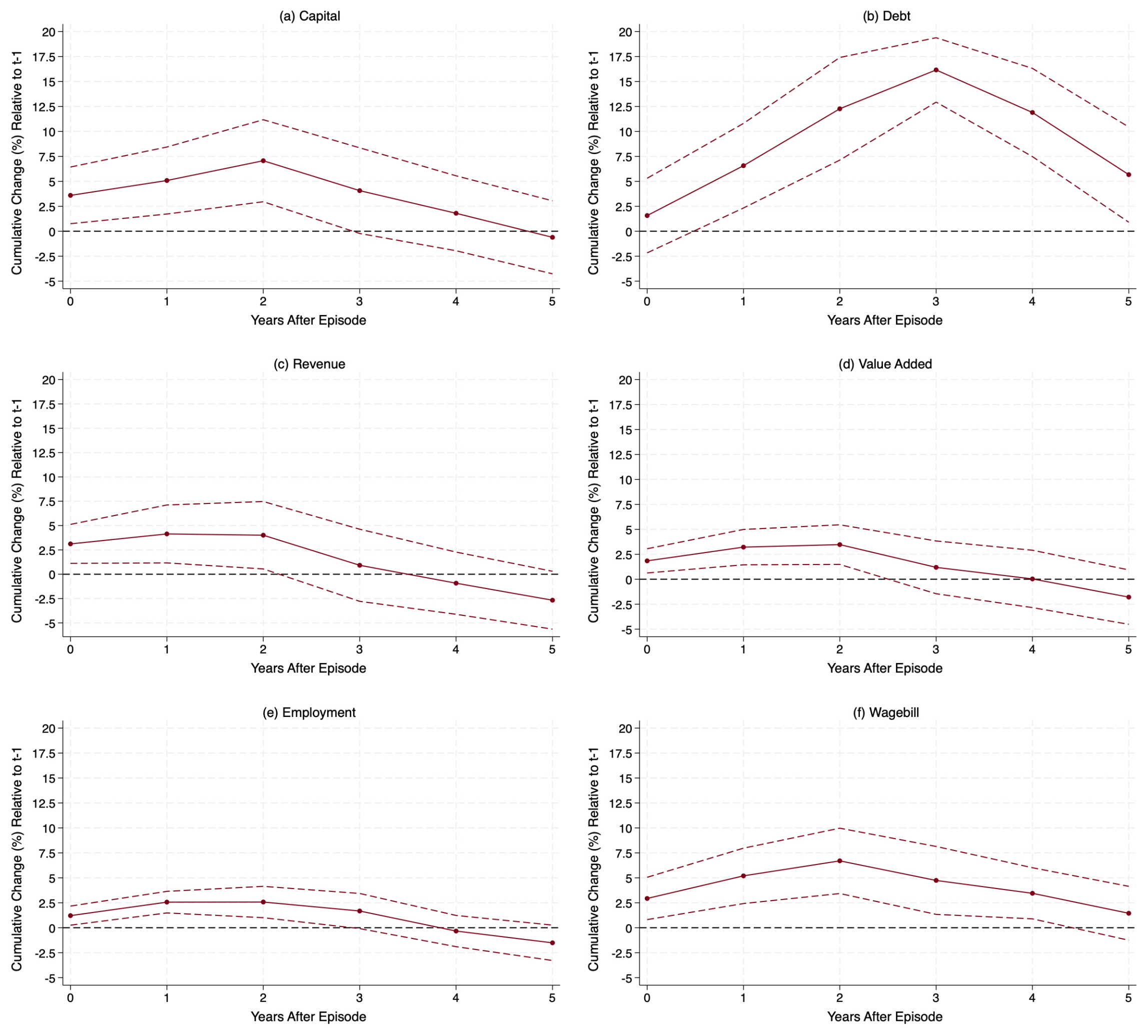

Figure 10. This figure reports the evolution of the coefficient β^h over years $t+h$ after the episode at time t from estimating (2). In the top row, I report the response of capital in Panel (a) and debt in Panel (b). In the middle row, I report the response of revenue in Panel (c) and value added in Panel (d). In the bottom row, I report the response of employment in Panel (e) and wage bill in Panel (f). Dashed lines represent 90% confidence intervals around the point estimates.

The middle and bottom rows show how the main real-firm outcomes respond in the aftermath of capital inflow boom. Panel (c) depicts the response of revenue, which peaks about 1 year after the episode even though it remains elevated 2 years after, when it starts returning to the level prior to the episode. In Panel (d), it is easy to see that value added follows a similar trajectory. The bottom two panels outline the response of employment and the wage bill, respectively. Notably, the effect on the wage bill is stronger—which is most likely a compounding effect due to an increase in the average real wage, as observed in the macro data (Figure 7)—on top of the increase in the number of employees on payroll, since the average number of hours effectively worked has been stable over the past 20 years.

#2 Firms experience strong reductions in their marginal revenue products

In order to investigate how allocative efficiency is affected by large capital inflows, we need to impose a bit more structure. In the spirit of most of the misallocation literature (Restuccia and Rogerson, 2017), I assume that firms have Cobb-Douglas technologies given by

$$y_{i,s,c,t} = z_{i,s,c,t} k_{i,s,c,t}^{\alpha_s^k} l_{i,s,c,t}^{\alpha_s^l} \tag{3}$$

which, as in Hsieh and Klenow (2009), implies that marginal revenue products within an industry are proportional to the ratios between revenue and factor inputs

$$MRPK_{i,s,c,t} \propto \frac{\text{Revenue}_{i,s,c,t}}{k_{i,s,c,t}} \tag{4}$$

$$MRPL_{i,s,c,t} \propto \frac{\text{Revenue}_{i,s,c,t}}{l_{i,s,c,t}} \tag{5}$$

as long as $\alpha_k^l$and α_s^l are the same for all firms within an industry s. Any friction or constraint that prevents firms from achieving their efficient scale will show up as a "wedge" in the relationship between the marginal revenue products and the actual marginal products of firms. This wedge also affects the relationship with factor prices. As such, reductions in marginal products or in frictions can lead to reductions in marginal revenue products.

Figure 11 details the response of marginal revenue products of capital (MRPK) and labor (MRPL) following an episode. Both MRPK and MRPL fall considerably, with further decreases happening over the years after the episode. Considering the evidence in Figure 10, which shows transitory booms at the firm level, it appears that firms experience a reduction in their wedges. This indicates a possible reallocation of factors across firms. I will investigate this issue further in what follows.

Figure 11: Responses of Marginal Revenue Products to Capital Inflow Booms

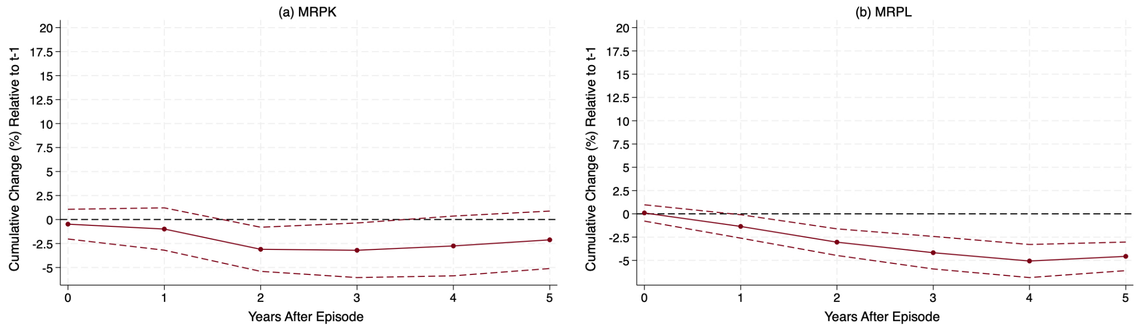

Figure 11. This figure reports the evolution of the coefficient β^h over years $t+h$ after the episode at time t from estimating (2). I report the response of MRPK in Panel (a) and MRPL in Panel (b). Dashed lines represent the 90% confidence intervals around the point estimates.

Distributional Effects

In order to test for possible reallocation across firms within the same sector, I estimate

$$y_{i,s,c,t+h} - y_{i,s,c,t-1} = \gamma_i^h + \zeta_s^h + \alpha_c^h + \lambda_t^h + \beta_1^h \mathbf{Boom}_{c,t} + \beta_2^h \mathbf{Boom}_{c,t} \times \mathbf{HighMRPK}_{i,s,c,t} \quad (6)$$
$$+ \Gamma' X_{i,s,c,t-1} + \varepsilon_{i,s,c,t+h},\ h = 0, \ldots, 5.$$

This specification introduces an interaction term between the boom indicator and a classification that determines whether a firm i in sector s, country c during year t is a high-MRPK firm. This interaction term is designed to capture the differential effects of a capital inflow boom between low- and high-MRPK firms.

There are two main coefficients of interest: β_1^h and β_2^h. The first coefficient, β_1^h, represents the average percentage change associated with the boom for low-MRPK firms. The second and more critical coefficient, β_2^h , measures the differential change for high-MRPK firms. As such, a positive value of β_2^h would indicate that the dependent variable increases more for high-MRPK firms than low-MRPK firms within the same industry, which can be interpreted as suggestive evidence of reallocation within that industry. Evidently, the average percentage change for the high-MRPK firms is given by the sum of coefficients $\beta_1^h + \beta_2^h$.

In classifying firms as low or high MRPK, I follow an approach similar to that of Bau and Matray (2023). A firm is considered to be high-MRPK if its average MRPK in the 3 years preceding year t exceeds the median for its 4-digit industry within the same country during the same time period.

Which are the high-MRPK firms?

Before turning to the results, I provide descriptive evidence on which firms exhibit higher MRPKs by estimating the following saturated specification:

$$MRPK_{i,s,c,t} = \zeta_s^h + \alpha_c^h + \lambda_t^h + \sum_{g \in \mathcal{G}} \phi_g D_{i,s,c,t}^g + \varepsilon_{i,s,c,t} \tag{7}$$

in the spirit of Haltiwanger et al. (2013), where $D_{i,s,c,t}^g$ is an indicator that firm i in sector s, country c, and year t belongs to group g in collection $\mathcal{G}$. I consider two alternatives: In the first alternative, $\mathcal{G}$ is a collection of firm size classes; in the second, $\mathcal{G}$ is a collection of firm age classes. As highlighted by Haltiwanger et al. (2013) and Angrist and Pischke (2009), the coefficients $\{\phi_g\}_{g \in \mathcal{G}}$ obtained through the estimation of the specification in (7) represent the mean values for each group g.

I report the estimates for these coefficients in two panels in Figure 12. The left panel shows the relationship between MRPK and firm size, and the right panel shows the relationship between MRPK and firm age. These pictures indicate that firms that typically exhibit higher MRPKs are often younger and smaller in size. Also, these figures suggest a monotonically decreasing relationship with size and age: As firms become bigger or older, they experience a reduction in MRPKs.

Figure 12: MRPK: Relationship with Size and Age

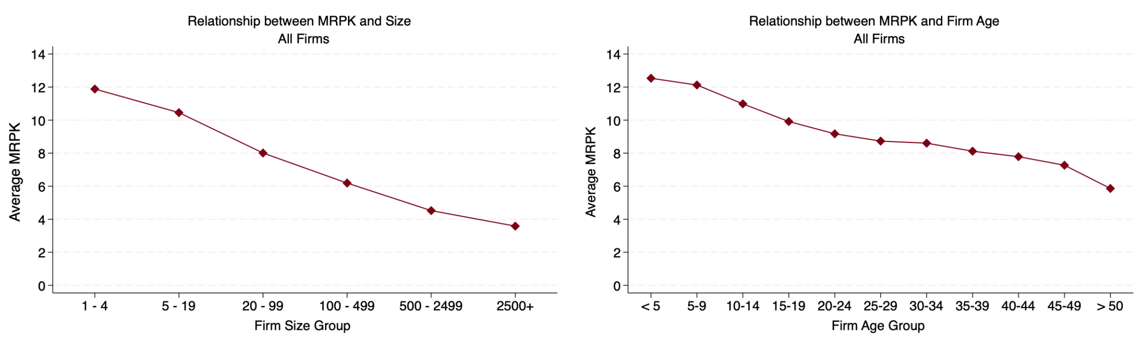

Figure 12. The panels in this figure report coefficients $\{\phi_g\}_{g \in \mathcal{G}}$ from estimating (7). In the left panel, $\mathcal{G}$ is a collection of firm size bins. In the right panel, $\mathcal{G}$ is a collection of firm age bins.

Distributional Results

#3 Capital and debt are reallocated toward high-MRPK firms

In Figure 13, I display the responses of capital (top row) and debt (bottom row) obtained through the estimation of the distributional specification. High-MRPK firms expand their capital stocks and take on more debt relative to low-MRPK firms. The reallocation effect is particularly strong in terms of capital, with high MRPK firms being on average 20% larger than prior to the episode and low-MRPK firms about 20% smaller. Compared with the evidence of Bau and Matray (2023) using the 2001 and 2006 liberalization reforms in India, these point estimates suggest smaller gains for high-MRPK firms, while low-MRPK firms fare substantially worse.

Figure 13: High vs Low MRPK: Heterogeneous Response of Capital and Debt

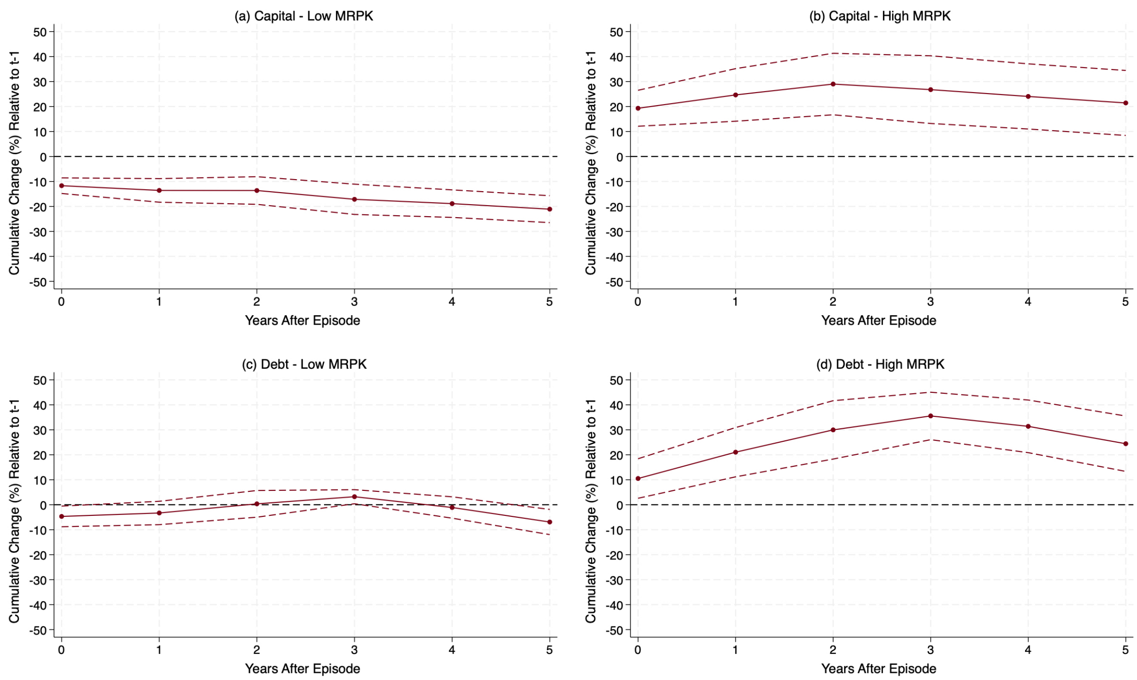

Figure 13. This figure reports the evolution of the coefficient β_1^h in Panel (a) and the sum of coefficients $\beta_1^h + \beta_2^h$ in Panel (b) after the episode at time t from estimating (6). In the top row, I report the response of capital for Low-MRPK firms in Panel (a) and for High-MRPK firms in Panel (b). In the bottom row, I report the response of capital for Low-MRPK firms in Panel (c) and for High-MRPK firms in Panel (d). Dashed lines represent the 90% confidence intervals around the point estimates.

#4 The reallocation of capital benefits high-MRPK firms at the expense of low-MRPK firms

Figure 14 provides further evidence of reallocation. Specifically, high-MRPK firms observe marked decreases in their MRPKs, while low-MRPK firms experience strong increases in their MRPKs. These trends suggest a reduction in MRPK dispersion, which is typically indicative of enhanced allocation efficiency and increases in productivity. However, this pattern at the micro level presents a stark contrast to the trends observed in macro-level data. In Sections 5 and 6, I will explore these seemingly contradictory pieces of evidence through the lens of a model that can generate substantial reallocation at micro level without significant gains in aggregate productivity.

Figure 14: High vs Low MRPK: Heterogeneous Response of MRPK

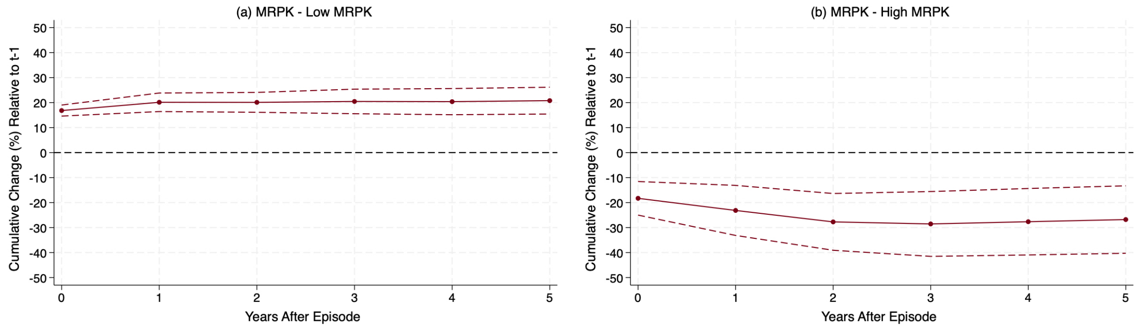

Figure 14. This figure reports the evolution of the coefficient β_1^h in Panel (a) and the sum of coefficients $\beta_1^h + \beta_2^h$ in Panel (b) after the episode at time t from estimating (6). I report the response of capital for Low-MRPK firms in Panel (a) and for High-MRPK firms in Panel (b). Dashed lines represent the 90% confidence intervals around the point estimates.

Additional Results

In Appendix A.3, I present other interesting results. I show that despite the evidence of strong reallocation of capital and also reallocation of debt, there are no signs of reallocation of revenue, labor, or value added. I also present results for different sample selections: a permanent sample—i.e. only firms that are continuously present in the data; entrant sample—i.e. only firms that enter during the period between 1999 and 2015; exiting firms sample,—i.e. only firms that exit at some point during the period between 1999-2015. The results are broadly as expected: Incumbents drive the results in this section; entrants observe stronger effects; and exiting firms see the weakest effects.

5 A Small Open Economy Firm Dynamics Model

Motivated by the conflicting messages from both the macro and micro empirical evidence, in this section I develop a small open economy heterogeneous-firms model with financial frictions and endogenous dynamics in the spirit of Khan and Thomas (2013) and Jo and Senga (2019).

After solving and calibrating the model to match key empirical moments from the micro data, I will use the model to rationalize how, in the aftermath of a large capital inflow episode, it is possible to simultaneously observe a decrease in TFP while there is substantial reallocation toward constrained firms. In particular, this will allow me to answer the following question: How important are indirect general equilibrium forces in shaping the response of aggregate variables?

Environment

I study a discrete time, infinite horizon, small open economy. The economy features two types of agents: (i) a representative household that consumes, saves through a risk-free bond issued by firms, works, and owns all the firms in this economy and (ii) risk-neutral heterogeneous firms that invest in capital, produce, and make capital structure decisions in order to maximize the present discounted value of their dividend stream. Firms produce a homogeneous good with a price normalized to 1 while the wage rate w is determined in general equilibrium and the interest rate r is taken as given. [9] In what follows, I focus on a stationary recursive equilibrium without any aggregate uncertainty or risk.

Household

The representative household has preferences given by

$$\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^{t}U\left(C,1-L\right)\right] \tag{8}$$

with $\beta \in (0,1)$ and $U\left(C,1-L\right) = \ln C + \Psi\left(1-L\right)$ where C denotes the amount of consumption, L denotes the amount of hours worked and Ψ is the parameter that governs the disutility of labor.

The household owns all of the firms in the economy, which means that they determine the stochastic discount factor, [10] and they can also save through a risk-free bond that is issued by firms. As such, we have that the optimal labor leisure choice and the consumption-savings decision—i.e. the Euler Equation, satisfy, respectively,

$$w = -\frac{\partial U\left(C,1-L\right)/\partial L}{\partial U\left(C,1-L\right)/\partial C} \tag{9}$$

$$1 = \mathbb{E}\left[\beta\frac{\partial U\left(C',1-L'\right)/\partial C'}{\partial U\left(C,1-L\right)/\partial C}\left(1+r\right)\right] \tag{10}$$

For simplicity, I assume that $\beta = \frac{1}{1+r}$ for the remainder of the paper.

[9] This is a standard assumption in small open economy models.

[10] Without aggregate uncertainty, this means that the discount factor is simply β.

Firms

Production, in this economy, is carried out by an endogenously determined mass of firms. First, I describe incumbent firms and later consider potential entrants. The objective of a firm is to maximize the discounted value of its dividend stream. Any firm can be described through three state variables (z, k, b), where z denotes their idiosyncratic productivity, k denotes their stock of capital, and b denotes the amount of debt (savings) carried by the firm.

Technology and Input Markets

Firms combine capital k and labor l to produce a single homogeneous consumption good using a Cobb-Douglas production function that exhibits decreasing returns to scale:

$$y = zf(k, l) = z\left(k^{\alpha}l^{1-\alpha}\right)^{\nu}, \tag{11}$$

where $\alpha \in (0, 1)$ denotes the capital share and $\nu \in (0, 1)$ is the "span of control," which governs the strength of decreasing returns to scale. Further, I assume that firms are subject to idiosyncratic productivity shocks and that z follows an AR(1) process

$$\log z' = \rho \log z + \sigma\varepsilon',\ \varepsilon' \sim N(0, 1), \tag{12}$$

where ρ denotes the persistence of the process and σ denotes the volatility of the idiosyncratic shocks. I use $G\left(z^{'}|z\right)$ to denote the distribution of $z^{'}$ conditional on z.

Input markets are assumed to be perfectly competitive. Capital is owned by firms and is supplied infinitely elastically. Firms make their investment decision x ahead of time without any adjustment costs, i.e., $k^{'} = (1-\delta)k + x$, which means that at any period, the capital owned by a firm is predetermined. Labor, on the other hand, is hired on the spot market at rate w, and a firm's labor demand is an entirely static choice. Finally, the earnings of a firm with current productivity z and capital k can be written as

$$e(z, k) = \max_{l} z\left(k^{\alpha}l^{1-\alpha}\right)^{\nu} - wl. \tag{13}$$

Firms' Resources and Financial Frictions

In each period, firms can raise external resources by issuing one-period risk-free debt $b^{'}$ at price q.[11] However, firms are limited to issuing only up to a certain fraction of their

[11] In equilibrium, the absence of aggregate uncertainty ensures that $q = \beta = \frac{1}{1+r}$.

collateral. I assume a slightly modified version of Buera and Shin (2013), in which firms can use their future capital, $k^{'}$, as collateral for their current issuance of debt. Formally, this means that

$$b^{'} \leq \theta k^{'}, \tag{14}$$

where θ is assumed to be the same for every firm, which captures the overall degree of financial frictions in this economy. In the next section, I model a capital inflow boom through an increase in θ that I interpret as a lowering of lending standards that leads to an increase in the supply of credit.

In addition to these external resources, firms carry their internal resources or their cash-on-hand, which is the sum of a firm's earnings and the current value of its productive capital after depreciation net of the maturing debt issued in the previous period. Formally, I define the firm's cash-on-hand n as

$$n\left(z,k,b\right) = e\left(z,k\right) + \left(1-\delta\right)k - b. \tag{15}$$

Firms use their own internal resources and external resources to issue dividends and make investments in new capital $k^{'}$

$$d + k^{'} = n\left(z,k,b\right) + qb^{'}. \tag{16}$$

As is standard in the literature, I assume, on top of the collateral constraint, that firms are not able to issue equity:

$$d \geq 0. \tag{17}$$

These two assumptions together ensure that the capital structure of firms matters for their input choices and, therefore, that there is a tight connection between capital structure and resource allocation in this economy.

Entry and Exit

My modeling choice for entry and exit follows the standard in the firm dynamics literature and is exactly the same as in Jo and Senga (2019). Incumbent firms can exit the economy in two ways at any period. First, before producing, firms are informed, like in Khan and Thomas (2013), whether they were hit by an exit shock which can happen with a fixed probability $\pi \in (0,1)$ that is common across all firms. If it receives the exit shock, the firm produces and leaves the economy after. [12] On the other hand, if a firm has not

[12]The timing of the exit after production follows the seminal approach of Hopenhayn (1992). The inclusion of an exogenous exit shock, on the other hand, is important for matching quantitatively the exit rates

been forced to exit the economy after production, it must decide whether it wants to pay a fixed cost c_f in units of output to keep operating, as in Hopenhayn (1992). If the firm decides not to pay, the business is closed down. For simplicity, the value of an exiting firm upon not paying this fixed cost is normalized to 0. Finally, the remaining firms make their intertemporal decisions: how much to invest k', how much to borrow or save b', and how much dividends to issue $d \geq 0$. As such, the timing of decisions for an incumbent firm within a period can be summarized as in Figure 15.

Figure 15: Timing of Decisions Within a Period — Incumbent Firm

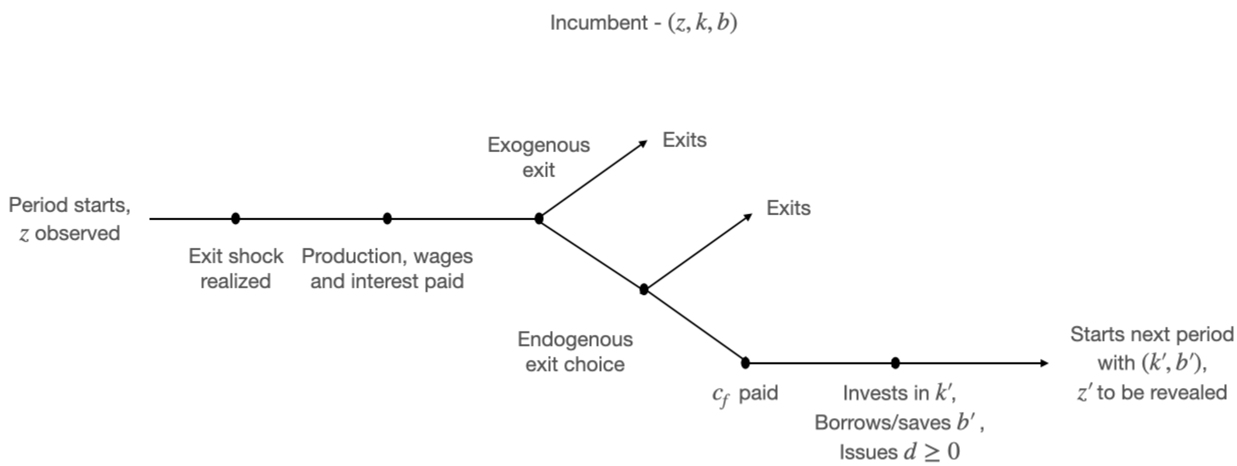

Figure 15. This diagram illustrates the timing of decisions made and information received by an incumbent firm during a period.

The entry decision, on the other hand, can be seen as a simplification of the approach of Clementi and Palazzo (2016). At every point in time, there is a fixed measure M of potential entrants. These potential entrants are uniformly distributed over an initial combination of capital and debt (k_0, b_0) , i.e. $(k_0, b_0) \sim U\left[0, \bar{k}_0\right] \times U\left[0, \bar{b}_0\right]$. I assume that $\bar{k}_0 = \chi_e \bar{k}$, where $\bar{k}$ is the choice of capital that an unconstrained firm with productivity equal to $E[z]$ would choose. I also assume that $\bar{b}_0 = \theta_e \bar{k}_0$, where θ_e is potentially different from the tightness in the borrowing constraint of incumbent firms. [13]

These two assumptions together ensure that entrants are small relative to incumbent firms, and particularly unconstrained incumbent firms. Also, their productivity z_0 is drawn from H, the ergodic distribution of z. Upon observing their draw (z_0, k_0, b_0), en-

observed in the data.

[13] An informal discussion of the definition of constrained and unconstrained firms is presented after the equilibrium definition. In Appendix A.4.1, I present these definitions formally and discuss the implications for firm choices.

trants must decide whether they want to pay a fixed entry cost c_e. If a firm decides to do so, it enters the economy at the end of the period, once production has taken place and all exiting firms have already left. This assumption means that entrants only start operating in the next period, given their initial state. Figure 16 outlines the timing of decisions for a potential entrant.

Figure 16: Timing of Decisions Within a Period — Potential Entrant Firm

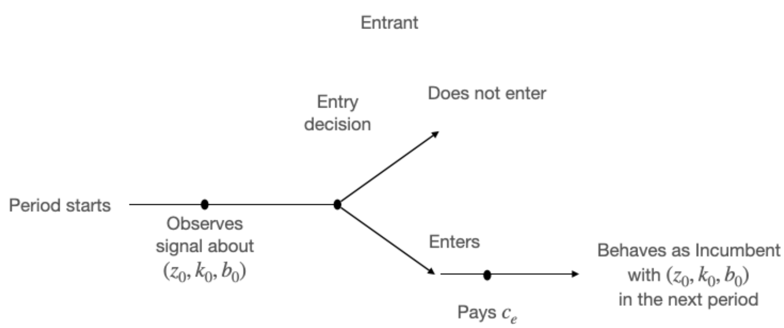

Figure 16. This diagram illustrates the timing of decisions made and information received by a potential entrant firm during a period.

Recursive Formulation of Firms' Problems

Let V^0 denote the value of an incumbent firm at the beginning of a period, before it has received information about the exit shock. Additionally, let V^1 denote the value of a firm that has received information about the exit shock, but has yet to decide whether it will pay the operating cost. Finally, let V denote the value of a firm that decides to continue operating into the next period. As such, we have that

$$V^0 (z,k,b) = (\pi)\, n\, (z,k,b) + (1-\pi)\, V^1 (z,k,b)\,, \tag{18}$$

where

$$V^1 (z,k,b) = \max \left\{ \overbrace{0}^{\text{Exit}}, \overbrace{-c_f + V(z,k,b)}^{\text{Continue}} \right\}. \tag{19}$$

We then have that the value of continuing to operate in the period is given by

$$
\begin{aligned}
V(z,k,b) = \max_{k',b',d} \; & d + \frac{1}{1+r}\mathbb{E}_{z'|z}\left[V^{0}\left(z',k',b'\right)\right] \\
\text{s.t. } & d + k' = n(z,k,b) + qb' \\
& d \geq 0,\; b' \leq \theta k'.
\end{aligned} \tag{20}
$$

With these in hand, we can define the value of a potential entrant V^{e} that has drawn a triple (z_0, k_0, b_0):

$$
V^{e}(z_0,k_0,b_0) = \max\left\{0, -c_e + \frac{1}{1+r}V^{0}(z_0,k_0,b_0)\right\}. \tag{21}
$$

Equilibrium

In this subsection, I define the equilibrium of the model. I focus on the steady-state equilibrium of this model or, in the language of Hopenhayn (1992), on the stationary industrial equilibrium of the model in which the distribution of firms over the states $\Omega(z,k,b)$ is time-invariant. In a steady state, the price of debt is always given by $q = \beta = \frac{1}{1+r}$, so I treat it as a parameter. Also, I assume that $k \in K \subset \mathbb{R}^{+}$, $b \in B \subset \mathbb{R}$ and $z \in Z \subset \mathbb{R}^{++}$ such that the state space can be described by $\mathcal{S} = Z \times K \times B$.

Definition. In this economy, a stationary recursive competitive equilibrium consists of value functions $\left(V^{0}, V^{1}, V, V^{e}\right)$, a price w, firm policies $\left(g_l, g_{k'}, g_{b'}, g_e\right)$, household policies (g_C, g_L), a measure of incumbent firms Ω and a measure of entrants $\mathcal{E}$ such that

1. Given w, $\left(V^{0}, V^{1}, V\right)$ and $\left(g_l, g_{k'}, g_{b'}, g_d\right)$ solve the incumbent's' problem
2. Given V^{0}, V^{e} solves the entrant's problem
3. Given w, g_C and g_L solve the FOCs of the household's problem
4. The labor market clears: $g_L = \int_{\mathcal{S}} g_l(z,k,b) \cdot \Omega(d[z \times k \times b])$
5. The goods market clears:

$$
\begin{aligned}
g_C = \int_{\mathcal{S}^{s}} & \left[zf(k, g_l(z,k,b)) - (1-\pi)\left[g_k(z,k,b) - (1-\delta)k\right]\right. \\
& \left. +\pi(1-\delta)k - c_f\right]\Omega(d[z \times k \times b]) \\
& + \mathcal{E}(k_0 - c_e) - \int_{\mathcal{S}^{e}} [k]\,\Omega(d[z \times k \times b])
\end{aligned} \tag{22}
$$

where $\mathcal{S}^s = \left\{(z,k,b) \in \mathcal{S} \left| V(z,k,b) \geq c_f \right.\right\}$ and $\mathcal{S}^e = \left\{(z,k,b) \in \mathcal{S} \left| V(z,k,b) < c_f \right.\right\}$.

6. For all Borel sets $Z \times K \times B$, the mass of entrants $\mathcal{E}$ satisfies

$$\mathcal{E}(Z \times K \times B) = M \cdot \int_{\mathcal{B}_e} d([k_0 \times b_0])\, dH(z) \tag{23}$$

where $\mathcal{B}_e = \left\{(z_0,k_0,b_0) \in \mathcal{S} \left| v^0(z_0,k_0,b_0) \geq c_e(1+r) \right.\right\}$ and H is the ergodic distribution of z

7. For all Borel sets $Z \times K \times B$, the mass of operating firms Ω satistifies

$$\Omega(Z \times K \times B) = (1-\pi) \int_{\mathcal{B}_c} d\Omega(z,k,b)\, d\left[G\left(z^{'} | z\right)\right] + \mathcal{E} \tag{24}$$

where $\mathcal{B}_c = \left\{(z,k,b) \in \mathcal{S}^s \mid g_{k'}(z,k,b) \in K,\ g_{b'}(z,k,b) \in B\right\}$[14]

In Appendix A.4.1, I discuss in detail how firm-level decisions can be characterized across three different types of firms and what the implications of this characterization are. In short, there are unconstrained firms, which given their current state (z,k,b) will never experience a binding borrowing constraint, and constrained firms, which given their current state (z,k,b) might experience a binding borrowing constraint in a future possible state. Among constrained firms, there are two types of firms: those *currently* experiencing binding constraints and those who are not. The latter group can achieve the unconstrained level of capital, even though it is not able to save—i.e. $b < 0$—as much as the unconstrained firms. As such, the share of firms *currently* experiencing binding constraints is a key object in determining the firms that are unable to achieve their desired scale.

In Appendix A.4.2, I show how the state space can be reduced by writing the firm's problems as a function of productivity z and cash-on-hand n. This simplification of the recursive formulation significantly speeds up the computational procedure, which is detailed in Appendix A.4.5, to solve the model and it renders the model suitable for the experiments that I run in Section 6.

Quantification of the Model

This subsection describes the model's quantification strategy. I solve the model following the approach of Jo (2022), which essentially relies on value function iteration to obtain the values of firms and their policy functions, followed by iterating on the distribution

[14] The bond-market clearing condition is satisfied by Walras's law.

of incumbent firms until it finds a stationary equilibrium in which firms' decisions are consistent with a market-clearing wage. In Appendix A.4.3, I further discuss how a firm's individual state determines its choices. I now proceed to discuss the calibration and fit of the model.

Calibration and Model Fit

The model is calibrated at annual frequency with the goal of matching the firm size distribution and moments—investment rate, capital to output ratio, debt to capital ratio, total exit rate, employment share of entrants—from the Orbis data, which are pooled across firms and countries over time; more precisely, between 1995 and 2019.

Table 3: Parameter Values

Panel (a): Externally Calibrated			Panel (b): Internally Calibrated		
Parameter	Value	Description	Parameter	Value	Description
r	0.040	Real Rate	π	0.080	Exog. Exit Prob.
α	0.300	Capital Share	c_f	0.085	Operating Costs
ν	0.800	Span of Control	c_e	0.084	Entry Costs
δ	0.100	Depreciation Rate	M	0.200	Mass of Entrants
ψ	2.606	Labor Disutility	χ_e	0.450	Rel. Size of Entrants
ρ	0.800	Prod. Persistence	θ	0.800	Collateral Constraint
σ	0.180	Prod. Std Dev	θ_e	$\theta/2$	Entrant's C.C.

Table 3. In Panel (a), I describe the parameters for which values are assigned based on prior work in the literature or on estimations conducted outside of the model solution. In Panel (b), I describe the parameters for which the values are calibrated in order to match a set of empirical moments from the micro data and the size distribution of firms.

The assigned parameters are reported in Panel (a) of Table 3. I set the exogenous interest rate r to 4%, which matches the annual average of the real interest rate for the countries included in the sample between 1995 and 2019. I set the capital share in the production function, α, to be equal to 0.30 and the span of control, ν, to be 0.8, which is within the range of estimates of this parameter in the literature (Clementi and Palazzo, 2016). The depreciation rate δ is set to 10% in order to match the average investment rate in the data. [15]The labor disutility parameter ψ is picked to generate a total of hours worked that is equivalent to 1/3 of the total endowment of hours, as it is observed in the data. Lastly, the parameters related to the idiosyncratic productivity process of firms are obtained by directly estimating the persistence and volatility of the firm-level productivity process in the data in an approach similar to that of Foster et al. (2008).

[15]Given the absence of adjustment costs, the average investment rate in the steady state is exactly equal to the depreciation rate.

In Table 4, I report the model-generated aggregate moments targeted in the calibration. The model fits well the life-cycle of firms, matching the exit rate and the labor share of entrants. It also does well in generating a capital to output ratio similar to that in the data. However, the model falls slightly short of generating the same average leverage ratio as in the data. In Figure 17, I plot the comparison between firm-size distribution in the data and in the model. In Panel (a), employment shares by firm-size are depicted; these shares are a key element of the quantitative strategy. As in Jo (2022) and Jo and Senga (2019), I use the stationary distribution of the model, Ω, obtained in the solution of the model to construct the distribution of employment in the steady state. Then I find, in the model, the thresholds of labor l along the employment distribution that generate 6 bins with the same employment shares as the ones in the data. Then, I obtain the share of incumbent firms in each of these bins and this is what is depicted in Panel (b). The model, even though fairly parsimonious, does a reasonable job in matching the data.

Table 4: Model vs Data — Aggregate Moments

Moment (Source)	Data	Model	Parameters
Average Hours Worked (ILO)	0.333	0.327	ψ
Investment Rate (Orbis)	0.100	0.100	δ
Capital to Output Ratio (Orbis)	1.799	1. 719	α, ν
Debt to Capital Ratio (Orbis)	0.584	0.457	θ
Total Exit Rate (Kochen, 2022)	0.110	0.105	π, c_o
Employment Share of Entrants (Orbis)	0.039	0.025	χ_e, θ_e
Measure of Firms	-	1.000	M, c_e, c_f

Table 4. This table describes the model fit by comparing model generated moments with data generated moments. Data moments are pooled across firms and countries between 1995 and 2019. Model generated moments are obtained directly from the steady state solution of the model using the calibration outlined in Table 3.

Figure 17: Model vs Data — Distribution of Firms

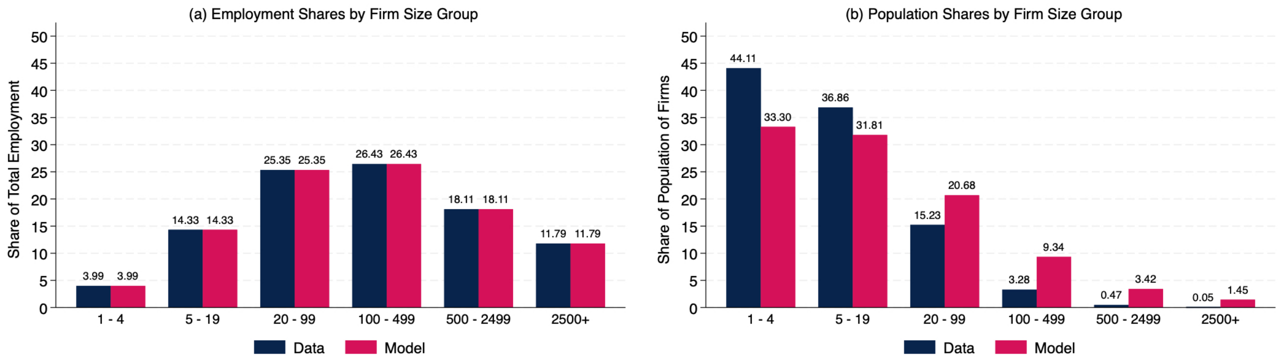

Figure 17. In the two panels, the firm size distribution is compared between the model and the data. In Panel (a), I plot the distribution of employment shares across 6 firm-size bins. In Panel (b), I plot the distribution of population shares across 6 firm-size bins. In both panels, blue bars represent the data and pink bars represent the model.

6 A Model Interpretation of the Evidence: PE vs GE

I now quantitatively analyze the effect of a capital inflow boom through the lens of the model presented in Section 5. Given the evidence from Section 3, I simulate a prototypical episode—i.e. , a large and sustained increase in the ratio of firm credit to GDP—and assess the role of equilibrium forces in determining the response of aggregates by comparing the change in macroeconomic aggregates in an economy in which wages are allowed to readjust across different steady states and in an economy in which wages are kept at the same level as in the initial steady state.

Therefore, in order to run this experiment, I submit the economy to a series of credit supply increases. These increases are modeled as changes in constraint tightness parameter θ, which ensures that the model replicates the observed expansion in debt relative to GDP. The same sequence of changes in θ is applied in the GE and PE versions.[16]

Figure 18 depicts the evolution of the firm credit to GDP ratio in the data and in the two versions of the model. It is important to highlight the fact that the same sequence of changes to θ is used in the two versions of this exercise. While the distribution of firms is substantially different in the two cases, the credit to GDP ratio is pinned down directly by this parameter.

[16] The credit to GDP ratio in the model is an equilibrium object and, of course, it depends on the entire set of parameters but the sensitivity of this moment with regard to changes in θ is substantially higher than to changes in any of the other parameters.

Figure 18: A Capital Inflow Boom in This Model — Fitting the Response of Credit to GDP

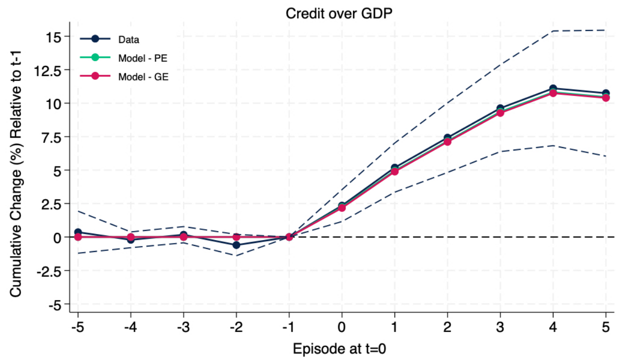

Figure 18. This figure depicts the evolution of the firm credit over GDP ratio in the data and in the two versions of the model. The blue line represents the coefficients depicted in Panel (c) of Figure 5. Dashed blue lines represent the upper and lower bounds of the 90% confidence intervals associated with the coefficient estimates. The green line represents the cumulative change in the firm credit over GDP ratio generated by the model under the PE assumption. The pink line represents the cumulative change in the firm credit over GDP ratio generated by the model under the GE assumption.

Aggregate Response to Capital Inflow Booms: PE vs GE

Figure 19 plots the response of measured TFP to a capital inflow boom in the two versions of the model and in the data. As discussed in Section 3, the evidence points to an insignificant increase in TFP on impact, which is followed by a continued slump in the years after. This is captured by the GE version of the model, which, even if it does not manage to generate the same downturn seen in the data, falls within the 90% confidence intervals for most of these estimates. On the other hand, the PE version of the model generates a large increase in TFP,—about 1.5% higher than prior to the capital inflow boom.

Why is this the case? Before delving into the mechanism, it is important to fix ideas in terms of measurement. In the model, measured TFP is defined as

$$\text{Measured } TFP \equiv \frac{Y}{K^{\alpha\nu}L^{(1-\alpha)\nu}} = \frac{\int_{\mathcal{S}} z\left(\left(g_k\left(z,k,b\right)\right)^{\alpha}\left(g_l\left(z,k,b\right)\right)^{1-\alpha}\right)^{\nu} d\Omega\left(z,k,b\right)}{\left(\left(\int_{\mathcal{S}} g_k\left(z,k,b\right) d\Omega\left(z,k,b\right)\right)^{\alpha}\left(\int_{\mathcal{S}} g_l\left(z,k,b\right) d\Omega\left(z,k,b\right)\right)^{1-\alpha}\right)^{\nu}}. \tag{25}$$

Given this definition, the assumption of decreasing returns to scale, i.e. $\nu \in (0,1)$, implies that, holding aggregate levels of inputs fixed, an economy in which factors of production are distributed across a smaller number of firms, i.e. across a smaller subset of the state space, has lower measured TFP than one in which they are distributed across a larger number of firms, i.e. across a larger subset of the state space. More simply, this means that a smaller number of bigger operating firms leads to a reduction in measured TFP relative to an economy with a bigger number of smaller operating firms given the same levels of aggregate factor inputs.

Figure 19: Model vs Data: TFP

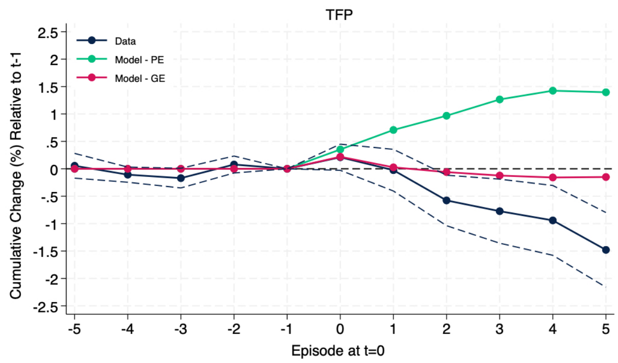

Figure 19. This figure depicts the evolution of TFP in the data and in the two versions of the model. The blue line represents the coefficients depicted in Figure 8. Dashed blue lines represent the upper and lower bounds of the 90% confidence intervals associated with the coefficient estimates. The green line represents the cumulative change in the model measure of TFP under the PE assumption. The pink line represents the cumulative change in the model measure of TFP under the GE assumption.

As such, Figure 19 captures the key tension generated by a large capital inflow, which was also present when faced with the results in Section 3 and Section 4. The increased availability of credit allows firms to invest more and hire more labor, and therefore to get closer to their efficient scale. Importantly, the nature of the shock, which affects θ, means that only constrained firms experiencing binding borrowing constraints at the time of the shock will benefit directly. This is the force captured in the PE scenario: looser constraints leading to a reduction in the dispersion of marginal products as constrained firms become less constrained.

However, the increase in firm size has secondary effects. Larger firms lead to a higher steady-state level of wages in equilibrium, as shown in Figure 20. A higher equilibrium wage decreases the value of the incumbent firms V^0 as it pushes the entire stream of dividends downward. The decrease in the value of incumbent firms, in turn, has two important effects, given that the entry and operating costs are kept constant. First, it will no longer be worthwhile for certain incumbents to stay. Second, it will no longer be worthwhile for certain potential entrants to exert their entry option. These two effects have the same implication: a decrease in the number of operating firms. As such, while the direct effects of the newly available credit are largely positive—which is what we see in the micro data, when analyzing what happened to firms— indirect effects due to GE are negative and, under the parameterization outlined in Section 5, stronger than the GE effects.

Figure 20: Model vs Data: Wages

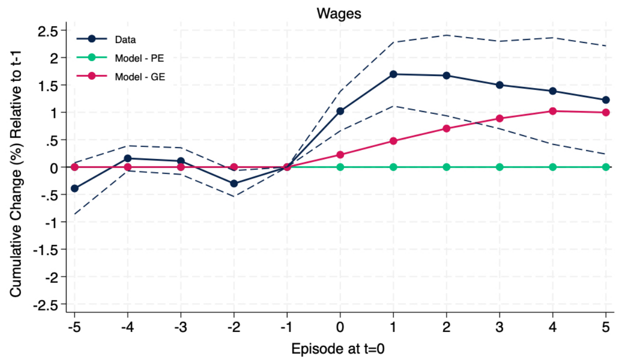

Figure 20. This figure depicts the evolution of the real wage in the data and in the two versions of the model. The blue line represents the coefficients depicted in Figure A.2 in Appendix A.2.2. Dashed blue lines represent the upper and lower bounds of the 90% confidence interval associated with the coefficient estimates. The green line represents the cumulative change in the equilibrium wage under the PE assumption, which is by assumption equal to zero at all times. The pink line represents the cumulative change in the equilibrium wage rate under the GE assumption.

Other moments obtained through this exercise provide further evidence of the competition between these forces. In Table 5, it can be seen how, in GE, the number of active firms falls, with a higher exit rate and a lower participation of entrants in terms of total employment. However, the share of constrained firms falls substantially, which suggest that there is plenty of reallocation going on. Finally, in Figure 21, the attenuation forces of GE are made even clearer, even though the model does a worse job of reproducing the dynamics of output and investment seen in the data.

Table 5: Capital Inflow Episode: PE vs GE Comparison, 5 Years After

	Initial SS	5 Years After Episode	
Moment		PE	GE
Mass of Active Firms	1.000	1.086	0.982
Exit Rate	0.105	0.093	0.131
Share of Constrained Firms	0.251	0.200	0.201
Employment Share of Entrants	0.025	0.024	0.016

Table 5. This table contains moments generated by the model's stationary distribution in three different scenarios: the initial steady state and the steady state 5 years after the capital inflow episode under the PE and GE scenarios.

Figure 21: Model vs Data: Other Aggregates

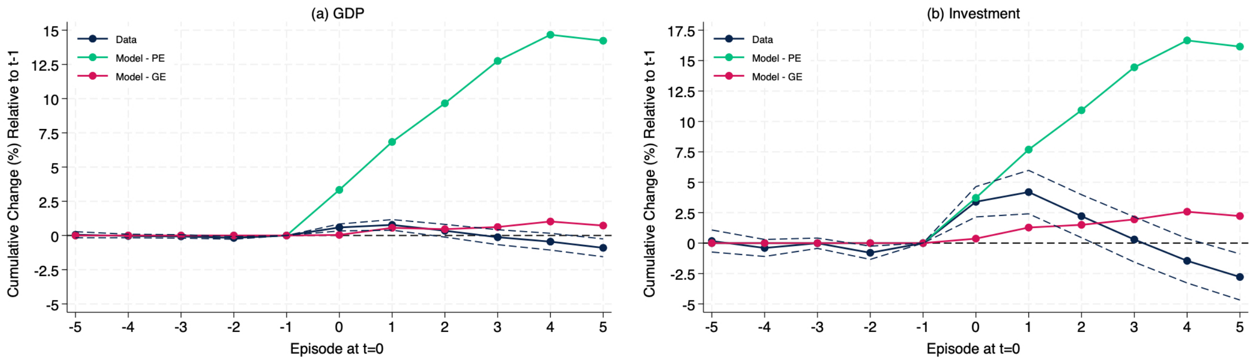

Figure 21. This figure depicts the evolution of output, Panel (a), and investment, Panel (b), in the data and in the two versions of the model. Blue lines represent the coefficients of output and investment in Figure 6. Dashed blue lines represent the upper and lower bounds of the 90% confidence interval associated with the coefficient estimates. Green lines represent the cumulative change in these variables under the PE assumption. Pink lines represent the cumulative change in these variables under the GE assumption.

7 Conclusion

In this paper, I examine how large capital inflows affect aggregate output, aggregate productivity, and the allocation of resources among firms. I offer a novel hypothesis that encompasses both the positive direct effects to firms of relaxed financial constraints and the negative indirect effects due to general equilibrium adjustments. The first contribution of my work is to provide empirical evidence on the consequences of large capital inflows for the macroeconomy and for firms; in particular, in terms of resource allocation. On the macroeconomic level, I show that countries typically experience large and sustained private credit expansions, and at the same time economic activity undergoes a transitory boom and aggregate productivity declines in a persistent manner. On the microeconomic level, I show that firms also experience transitory booms fueled by an expansion in their debt issuance, but I also show evidence that there is substantial reallocation of capital and that marginal revenue products decline, particularly for high-MRPK firms.

My second contribution is to connect these seemingly contradictory pieces of evidence through the lens of a small open economy firm dynamics model with heterogeneity and financial frictions. I start by showing that the model can replicate key characteristics of the firm-level data, and particularly the firm-size distribution. Then, I use the calibrated version of this model to study the effects of a large capital inflow episode. Given the empirical evidence, I do this by submitting the model to a similar increase in the firm credit to GDP ratio by inducing a sequence of credit supply changes. This experiment allows me to weigh the relative forces of direct effects (PE) and indirect effects (GE) in shaping the aggregate response of productivity. GE adjustments, through increases in wages that affect the entry and exit decisions of firms and, therefore, a decrease in the number of operating firms, are critical for matching the sign of the TFP response.

These results suggest an important role for policy in shaping how the economy handles large influxes of capital. A serious quantitative effort that builds on this research and measures the possible gains from designing optimal capital controls is a promising avenue for future research.

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A Appendix

A.1 Section 2 Appendices

A.1.1 List of Countries

Table A.1: Countries included in the Sample of Sections 2 and 3

Country ISO Code	Country Name	Country Status Classification
AR	Argentina	EME
AT	Austria	AE
AU	Australia	AE
BH	Bosnia and Herzegovina	EME
BD	Bangladesh	EME
BE	Belgium	AE
BG	Bulgaria	EME
BO	Bolivia	EME
BR	Brazil	EME
BY	Belarus	EME
CA	Canada	AE
CH	Switzerland	AE
CI	Côte d'Ivoire	EME
CL	Chile	EME
CM	Cameroon	EME
CN	China	EME
CO	Colombia	EME
CR	Costa Rica	EME
CY	Cyprus	AE
CZ	Czechia	EME
DE	Germany	AE
DK	Denmark	AE
DO	Dominican Republic	EME
EE	Estonia	AE
ES	Spain	AE
FI	Finland	AE
FR	France	AE

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Table A.1 – continued from previous page

Country ISO Code	Country Name	Country Status Classification
GB	United Kingdom	AE
GE	Georgia	EME
GH	Ghana	EME
GR	Greece	AE
GT	Guatemala	EME
HK	Hong Kong	AE
HN	Honduras	EME
HR	Croatia	EME
HT	Haiti	EME
HU	Hungary	EME
ID	Indonesia	EME
IE	Ireland	AE
IL	Israel	AE
IN	India	EME
IT	Italy	AE
JM	Jamaica	EME
JO	Jordan	EME
JP	Japan	AE
KE	Kenya	EME
KH	Cambodia	EME
KR	South Korea	AE
LB	Lebanon	EME
LK	Sri Lanka	EME
LT	Lithuania	EME
LV	Latvia	EME
MA	Morocco	EME
MM	Myanmar	EME
MX	Mexico	EME
MY	Malaysia	EME
NL	Netherlands	AE
NO	Norway	AE
NP	Nepal	EME
NZ	New Zealand	AE

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Table A.1 – continued from previous page

Country ISO Code	Country Name	Country Status Classification
PA	Panama	EME
PE	Peru	EME
PG	Papua New Guinea	EME
PH	Philippines	EME
PK	Pakistan	EME
PL	Poland	EME
PT	Portugal	AE
PY	Paraguay	EME
RO	Romania	EME
RU	Russia	EME
SD	Sudan	EME
SE	Sweden	AE
SG	Singapore	AE
SI	Slovenia	EME
SK	Slovakia	EME
SN	Senegal	EME
TH	Thailand	EME
TN	Tunisia	EME
TR	Turkey	EME
TZ	Tanzania	EME
UA	Ukraine	EME
UY	Uruguay	EME
UZ	Uzbekistan	EME
VN	Vietnam	EME
ZA	South Africa	EME

Table. This table details the countries included in the sample utilized in Sections 2 and 3.

A.1.2 List of Episodes

Table A.2: List of Episodes obtained in Section 2

Country	Count	Start	Peak	End	Avg Cap. Inf. (% GDP)	Avg CA Def. (% GDP)
AR	1	1979	1979	1979	4.04	0.43
AR	2	1984	1984	1986	4.39	3.56
AR	3	1988	1988	1988	5.15	2.34
AR	4	1992	1993	1994	4.56	3.39
AR	5	1996	1998	2000	4.56	3.77
AR	6	2015	2018	2018	6.59	4.80
AU	1	1995	1995	1995	5.17	5.06
AU	2	1998	1999	1999	5.69	5.15
AU	3	2003	2005	2006	6.69	5.78
AU	4	2008	2008	2009	5.98	5.37
AU	5	2012	2012	2012	4.30	4.14
AU	6	2015	2015	2015	4.60	4.80
BA	1	2001	2001	2002	20.41	14.48
BA	2	2004	2005	2005	20.12	16.01
BD	1	1979	1981	1982	4.02	4.06
BD	2	1986	1986	1987	2.81	1.97
BD	3	2003	2004	2004	1.37	0.11
BD	4	2013	2013	2014	2.26	-0.89
BE	1	2008	2008	2008	0.61	0.88
BE	2	2011	2011	2012	1.31	1.09
BE	3	2018	2018	2018	1.06	0.90
BG	1	1992	1992	1993	10.74	8.21
BG	2	1997	1997	1997	11.34	-3.98
BG	3	2000	2000	2000	8.31	5.25
BG	4	2004	2007	2008	21.07	16.14
BG	5	2015	2015	2015	8.36	0.25
BO	1	1979	1979	1979	11.68	11.00
BO	2	1984	1984	1984	12.41	8.10
BO	3	1986	1986	1986	15.25	9.83
BO	4	1992	1993	1993	10.72	9.59
BO	5	1996	1996	1998	9.26	6.92

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Table A.2 – continued from previous page

Country	Count	Start	Peak	End	Avg Cap. Inf. (% GDP)	Avg CA Def. (% GDP)
BO	6	2011	2011	2011	6.75	-2.23
BR	1	1978	1978	1982	5.96	6.59
BR	2	1992	1993	1993	6.67	-2.15
BR	3	2000	2001	2001	4.46	4.35
BR	4	2007	2011	2012	4.89	2.60
BR	5	2014	2014	2015	4.93	4.63
BY	1	1998	1998	1998	13.00	13.73
BY	2	2007	2011	2011	14.25	11.15
CA	1	1981	1981	1981	4.22	4.04
CA	2	1986	1988	1989	3.89	3.21
CA	3	1998	1998	1998	2.30	1.48
CA	4	2009	2010	2010	3.57	3.10
CA	5	2015	2015	2016	3.96	3.48
CH	1	2009	2012	2012	7.21	-8.12
CH	2	2015	2015	2017	4.42	-7.33
CI	1	2013	2015	2015	1.44	0.24
CI	2	2017	2018	2019	3.97	2.72
CL	1	1978	1981	1981	11.83	8.37
CL	2	1984	1984	1984	16.09	14.01
CL	3	1990	1990	1990	8.70	1.62
CL	4	1994	1994	1994	7.60	2.68
CL	5	1997	1997	1997	8.54	4.48
CL	6	2008	2008	2008	8.82	4.49
CL	7	2011	2011	2013	6.43	4.41
CM	1	1980	1983	1983	7.32	6.85
CM	2	1985	1985	1985	6.06	5.53
CM	3	1987	1987	1988	5.19	4.82
CM	4	2001	2002	2002	4.59	3.21
CM	5	2009	2009	2010	4.72	3.49
CM	6	2014	2015	2015	5.27	3.96
CM	7	2018	2019	2019	4.89	3.95
CN	1	1985	1985	1986	2.60	3.28
CN	2	1993	1994	1996	2.99	-0.09

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Table A.2 – continued from previous page

Country	Count	Start	Peak	End	Avg Cap. Inf. (% GDP)	Avg CA Def. (% GDP)
CN	3	2001	2004	2005	4.00	-3.11
CN	4	2007	2007	2007	2.91	-9.55
CN	5	2009	2010	2011	3.36	-3.44
CN	6	2013	2013	2013	2.89	-1.51
CO	1	1979	1982	1982	4.94	3.37
CO	2	1985	1985	1985	6.81	6.27
CO	3	1993	1997	1997	5.35	4.76
CO	4	2007	2007	2008	4.68	2.98
CO	5	2010	2014	2015	5.52	4.34
CO	6	2018	2019	2019	5.31	4.60
CR	1	1980	1981	1981	21.03	19.80
CR	2	1989	1989	1989	11.73	9.50
CR	3	2006	2007	2007	9.14	4.78
CR	4	2011	2012	2012	7.67	5.26
CY	1	1979	1984	1984	13.53	10.54
CY	2	1989	1989	1990	8.87	3.95
CY	3	1999	2001	2001	7.35	3.24
CY	4	2005	2006	2006	10.06	5.72
CY	5	2008	2008	2008	13.39	15.20
CZ	1	1998	1998	1998	4.47	1.83
CZ	2	2001	2002	2002	9.65	4.69
CZ	3	2005	2005	2005	5.00	2.10
CZ	4	2015	2017	2017	12.33	-1.18
DE	1	1991	1992	1992	2.01	1.26
DK	1	1983	1983	1983	4.88	2.46
DK	2	1995	1997	1997	1.31	-1.08
DK	3	2002	2002	2002	1.05	-1.74
DK	4	2009	2009	2009	6.70	-3.40
DO	1	1978	1980	1981	7.22	7.10
DO	2	1991	1992	1992	5.93	3.85
DO	3	2000	2001	2001	4.51	3.63
DO	4	2005	2008	2013	6.65	5.63
EE	1	2002	2006	2007	13.36	11.52

Continued on next page

Table A.2 – continued from previous page

Country	Count	Start	Peak	End	Avg Cap. Inf. (% GDP)	Avg CA Def. (% GDP)
EE	2	2012	2012	2012	2.21	1.83
ES	1	1987	1991	1991	4.02	1.97
ES	2	1996	1996	1997	3.24	0.25
ES	3	2000	2001	2002	3.96	4.03
ES	4	2004	2008	2008	7.75	7.87
FI	1	1980	1980	1980	3.30	2.69
FI	2	1987	1987	1988	4.17	2.08
FI	3	1990	1990	1991	5.62	5.06
FI	4	2011	2012	2012	2.28	2.05
FR	1	1980	1983	1983	1.28	1.15
FR	2	1990	1990	1990	1.54	0.73
FR	3	2009	2009	2010	1.12	0.81
FR	4	2018	2018	2018	1.36	0.90
GB	1	1987	1988	1988	4.07	2.65
GB	2	2007	2008	2008	4.37	4.40
GB	3	2013	2016	2016	5.82	5.31
GE	1	2006	2008	2008	24.35	20.97
GE	2	2011	2011	2011	16.62	12.87
GE	3	2015	2016	2016	14.44	13.89
GH	1	1991	1991	1991	7.84	4.06
GH	2	1993	1993	1994	10.56	8.49
GH	3	1998	1999	1999	11.03	11.79
GH	4	2004	2005	2005	11.12	8.51
GR	1	1984	1985	1985	6.19	6.19
GR	2	1994	1994	1994	5.48	0.12
GR	3	1999	2000	2000	8.22	6.37
GR	4	2005	2008	2009	11.47	11.36
GR	5	2011	2011	2011	10.86	10.87
GT	1	1987	1989	1989	5.11	5.66
GT	2	1991	1991	1993	7.22	5.07
GT	3	1997	2001	2001	7.16	5.53
GT	4	2003	2004	2004	7.53	4.99
GT	5	2012	2013	2013	5.21	3.99

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Table A.2 – continued from previous page

Country	Count	Start	Peak	End	Avg Cap. Inf. (% GDP)	Avg CA Def. (% GDP)
HK	1	2009	2009	2009	27.04	-9.89
HK	2	2012	2015	2015	5.52	-1.95
HK	3	2017	2017	2017	4.85	-4.59
HN	1	1984	1984	1984	7.79	7.61
HN	2	1992	1992	1992	8.37	6.40
HN	3	1994	1994	1994	10.05	8.27
HN	4	1997	1999	2000	11.22	7.03
HN	5	2004	2004	2004	13.77	7.88
HN	6	2007	2008	2008	11.46	12.18
HN	7	2010	2010	2011	8.61	6.54
HN	8	2013	2013	2014	10.90	8.38
HR	1	2002	2003	2003	9.88	6.91
HR	2	2006	2006	2006	10.62	7.34
HT	1	1981	1981	1982	7.99	8.37
HT	2	1995	1995	1995	10.42	3.45
HT	3	2005	2008	2008	7.09	5.72
HT	4	2010	2010	2010	23.26	16.20
HU	1	1994	1995	1995	11.72	7.01
HU	2	1998	1999	2000	11.53	8.53
HU	3	2003	2005	2005	11.02	8.78
HU	4	2008	2008	2008	15.15	7.82
HU	5	2018	2018	2018	2.37	-0.27
ID	1	1984	1984	1984	3.50	2.29
ID	2	1987	1987	1987	4.40	2.77
ID	3	1990	1990	1992	4.47	2.94
ID	4	1995	1996	1996	4.71	3.32
ID	5	2010	2010	2010	3.30	-0.67
ID	6	2013	2014	2014	3.90	3.47
IE	1	2008	2008	2009	4.20	3.96
IE	2	2016	2016	2016	4.90	4.40
IE	3	2019	2019	2019	11.33	11.21
IL	1	1998	1998	2003	1.60	1.02
IL	2	2008	2008	2010	3.76	-2.66

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Table A.2 – continued from previous page

Country	Count	Start	Peak	End	Avg Cap. Inf. (% GDP)	Avg CA Def. (% GDP)
IN	1	2003	2007	2008	4.28	0.68
IN	2	2012	2012	2012	4.84	5.06
IT	1	1980	1980	1981	2.50	2.47
IT	2	1984	1984	1984	1.44	0.81
IT	3	1987	1989	1990	1.82	0.92
IT	4	2000	2000	2000	0.55	0.27
IT	5	2005	2010	2011	2.21	2.09
JM	1	1980	1982	1982	9.67	9.01
JM	2	1984	1984	1985	16.90	14.72
JM	3	1990	1990	1991	8.64	8.99
JM	4	2000	2001	2002	12.30	8.13
JM	5	2004	2008	2008	14.01	12.71
JM	6	2011	2011	2011	12.84	14.36
JM	7	2013	2014	2014	12.41	9.16
JO	1	1978	1978	1979	14.93	5.41
JO	2	1990	1991	1992	31.61	10.15
JO	3	2005	2007	2010	17.61	11.23
JO	4	2013	2013	2015	16.63	8.75
JP	1	2003	2003	2003	0.97	-2.84
JP	2	2011	2011	2011	0.60	-2.02
KE	1	1978	1979	1980	10.30	10.68
KE	2	1993	1999	1999	15.40	12.83
KE	3	2012	2014	2014	10.37	8.36
KH	1	2007	2008	2008	11.49	6.40
KH	2	2018	2019	2019	19.18	11.31
KR	1	1979	1980	1981	9.89	8.88
KR	2	1990	1991	1992	1.57	1.46
KR	3	1995	1996	1996	3.78	3.02
KR	4	2000	2000	2000	2.64	-1.98
KR	5	2009	2009	2009	3.42	-3.18
LB	1	2008	2009	2009	41.85	16.57
LB	2	2011	2014	2014	26.80	22.25
LB	3	2016	2016	2017	27.69	21.68

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Table A.2 – continued from previous page

Country	Count	Start	Peak	End	Avg Cap. Inf. (% GDP)	Avg CA Def. (% GDP)
LK	1	1978	1981	1982	10.24	9.63
LK	2	1988	1989	1989	6.72	6.22
LK	3	1991	1993	1994	9.97	5.48
LK	4	2006	2006	2006	6.11	5.84
LK	5	2012	2012	2012	6.76	5.69
LT	1	1998	1998	1999	12.10	11.21
LT	2	2003	2003	2003	8.60	6.08
LT	3	2005	2007	2008	13.57	11.62
LT	4	2011	2011	2011	8.56	3.93
LV	1	1999	1999	1999	10.68	8.69
LV	2	2004	2006	2007	19.85	15.53
MA	1	1981	1982	1982	10.58	10.79
MA	2	1990	1990	1990	5.60	0.63
MA	3	2009	2014	2014	6.58	6.61
MM	1	1979	1979	1980	8.22	6.72
MM	2	2012	2012	2013	9.88	1.46
MM	3	2017	2017	2018	6.78	6.19
MX	1	1989	1991	1994	5.18	5.08
MX	2	1997	1998	1998	3.81	2.43
MX	3	2000	2001	2001	3.36	2.49
MX	4	2008	2008	2008	2.84	1.93
MX	5	2011	2013	2014	3.57	1.83
MY	1	1980	1982	1983	9.08	8.89
MY	2	1989	1993	1993	11.48	3.61
MY	3	1996	1996	1996	6.94	4.44
MY	4	2004	2004	2004	5.59	-12.10
NL	1	1978	1978	1978	0.08	0.53
NL	2	1980	1980	1980	1.24	0.47
NO	1	1985	1987	1988	2.46	2.38
NO	2	1993	1993	1993	4.16	-3.10
NP	1	1987	1991	1992	9.46	7.50
NP	2	1997	1997	1997	12.41	8.76
NP	3	2000	2000	2000	11.55	5.85

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Table A.2 – continued from previous page

Country	Count	Start	Peak	End	Avg Cap. Inf. (% GDP)	Avg CA Def. (% GDP)
NP	4	2017	2018	2019	5.88	5.85
NZ	1	2005	2006	2007	9.34	6.73
PA	1	1981	1981	1981	10.31	10.24
PA	2	1996	1999	1999	8.80	6.28
PA	3	2005	2005	2005	9.47	6.50
PA	4	2007	2008	2008	9.87	7.32
PA	5	2010	2011	2012	11.10	10.95
PA	6	2014	2014	2014	15.82	13.38
PE	1	1982	1982	1982	11.78	10.49
PE	2	1991	1991	1991	8.40	5.40
PE	3	1993	1994	1996	10.87	7.37
PE	4	2007	2007	2008	8.12	1.68
PE	5	2010	2010	2010	9.81	2.40
PE	6	2012	2012	2013	8.30	3.82
PG	1	1980	1981	1984	15.13	15.03
PG	2	1987	1991	1991	6.85	7.51
PG	3	1996	1996	1997	2.74	0.51
PG	4	2002	2002	2002	10.78	9.06
PG	5	2009	2009	2009	5.77	8.01
PG	6	2012	2013	2013	19.60	16.80
PH	1	1980	1980	1980	8.54	5.26
PH	2	1988	1991	1991	4.26	3.02
PH	3	1993	1994	1994	6.05	4.35
PH	4	1996	1996	1996	8.46	4.19
PH	5	1999	1999	2000	5.56	3.23
PH	6	2010	2010	2011	3.12	-2.89
PH	7	2018	2019	2019	2.36	1.67
PK	1	1979	1980	1980	5.11	4.79
PK	2	1988	1989	1989	4.08	3.84
PK	3	1992	1993	1994	6.49	4.68
PK	4	1996	1996	1997	5.33	5.76
PK	5	2005	2007	2009	5.80	5.54
PK	6	2014	2014	2014	4.36	1.46

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Table A.2 – continued from previous page

Country	Count	Start	Peak	End	Avg Cap. Inf. (% GDP)	Avg CA Def. (% GDP)
PK	7	2017	2019	2019	4.23	4.91
PL	1	1993	1993	1993	7.21	7.09
PL	2	1996	1996	1996	4.72	2.17
PL	3	1998	1999	1999	7.58	5.82
PL	4	2004	2005	2005	5.61	4.13
PL	5	2007	2007	2008	8.26	7.15
PL	6	2010	2010	2011	7.78	5.53
PL	7	2016	2016	2016	6.20	1.09
PT	1	1981	1981	1982	13.46	13.80
PT	2	1988	1989	1989	4.82	0.84
PT	3	1997	2001	2002	9.02	8.43
PT	4	2004	2008	2010	9.65	9.83
PY	1	1978	1978	1981	9.84	5.83
PY	2	1984	1984	1984	6.64	6.94
PY	3	1986	1987	1987	8.68	10.29
PY	4	1991	1991	1991	3.19	-1.27
PY	5	1994	1994	1995	5.48	2.97
PY	6	2003	2003	2005	2.54	0.17
RO	1	1990	1992	1992	9.68	11.11
RO	2	1996	1997	1997	11.01	7.99
RO	3	2001	2001	2001	9.98	5.99
RO	4	2004	2007	2008	15.30	10.75
RU	1	1997	1997	1997	0.70	0.21
RU	2	2006	2007	2007	3.56	-7.17
RU	3	2019	2019	2019	0.05	-3.73
SD	1	1981	1981	1982	9.45	6.81
SD	2	1992	1992	1992	9.41	9.98
SD	3	1994	1994	1994	6.70	6.50
SD	4	1996	1996	1998	9.47	9.48
SD	5	2002	2002	2003	6.80	4.99
SD	6	2005	2006	2006	10.48	9.98
SD	7	2009	2009	2009	7.62	8.22
SD	8	2012	2012	2013	11.38	11.42

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Table A.2 – continued from previous page

Country	Count	Start	Peak	End	Avg Cap. Inf. (% GDP)	Avg CA Def. (% GDP)
SD	9	2018	2018	2019	13.92	13.94
SE	1	1989	1990	1990	3.48	1.83
SE	2	1992	1992	1993	5.05	2.93
SG	1	1979	1980	1981	15.67	10.02
SI	1	2001	2001	2002	6.13	-0.55
SI	2	2007	2008	2009	3.41	3.51
SK	1	1996	1996	1997	10.35	9.65
SK	2	2001	2002	2002	14.34	7.52
SN	1	1980	1981	1981	10.46	10.55
SN	2	1983	1983	1985	8.60	8.66
SN	3	2007	2008	2009	9.91	8.58
SN	4	2011	2012	2014	7.92	7.69
SN	5	2017	2018	2019	10.25	8.27
TH	1	1978	1981	1981	7.14	6.68
TH	2	1984	1984	1984	7.05	5.79
TH	3	1988	1991	1991	10.15	5.56
TH	4	1994	1995	1996	10.01	7.24
TH	5	2005	2005	2006	5.73	1.57
TH	6	2008	2008	2008	8.50	-0.33
TN	1	1982	1982	1984	9.08	8.71
TN	2	1992	1993	1993	9.59	8.55
TN	3	2006	2006	2006	7.66	1.76
TN	4	2012	2014	2015	9.69	8.62
TN	5	2017	2018	2019	11.94	10.08
TR	1	1980	1980	1981	5.31	4.56
TR	2	1993	1993	1993	4.92	4.70
TR	3	1995	1995	1997	5.04	1.83
TR	4	2004	2005	2008	5.92	4.78
TR	5	2010	2011	2013	8.18	6.93
TZ	1	1991	1993	1993	22.96	20.83
UA	1	2005	2008	2008	8.07	3.03
UA	2	2010	2010	2011	6.38	4.10
UA	3	2013	2013	2013	6.81	8.67

Continued on next page

Table A.2 – continued from previous page

Country	Count	Start	Peak	End	Avg Cap. Inf. (% GDP)	Avg CA Def. (% GDP)
UA	4	2016	2018	2019	5.56	3.19
UY	1	1981	1981	1981	4.83	4.47
UY	2	1985	1985	1987	4.87	1.36
UY	3	1993	1994	1995	3.02	1.95
UY	4	1997	1998	1998	3.52	1.60
UY	5	2000	2001	2001	3.85	2.60
UY	6	2003	2003	2005	6.36	0.20
UY	7	2007	2008	2009	8.27	2.80
UY	8	2011	2012	2014	7.84	3.22
UY	9	2017	2017	2017	3.77	-0.01
UZ	1	2009	2009	2009	1.97	-5.39
UZ	2	2018	2019	2019	6.25	6.52
VN	1	2003	2003	2003	10.28	4.93
VN	2	2005	2007	2008	11.33	5.39
VN	3	2017	2017	2017	5.06	0.59
ZA	1	1981	1982	1982	4.48	4.95
ZA	2	2004	2008	2008	5.51	3.94
ZA	3	2011	2013	2015	4.97	4.66

Table. This table lists all the large capital episodes identified in Section 2.

A.1.3 Details on Episodes

Table A.3: Capital Inflow Booms between 1975 and 2020 - Summary Stats

Moment	All	AEs	EMEs
Average Capital Inflows (% of GDP)	7.85	5.88	8.60
Average Current Account Deficit (% of GDP)	5.18	3.30	5.90
Average Duration (Years)	1.39	1.32	1.42
Number of Episodes	346	94	252
Equity Inflow Episodes (% of Total)	28.0	14.4	32.8
Debt Inflow Episodes (% of Total)	72.2	85.6	67.2

Table. Summary statistics of capital inflow booms for the period 1975 and 2019. Statistics are generated pooling countries over time. Equity episodes and debt episodes denote episodes in which most of the inflows can be attributed to equity inflows and debt inflows respectively, where these classifications follow directly from the IFS (IMF) denomination.

A.2 Section 3 Appendices

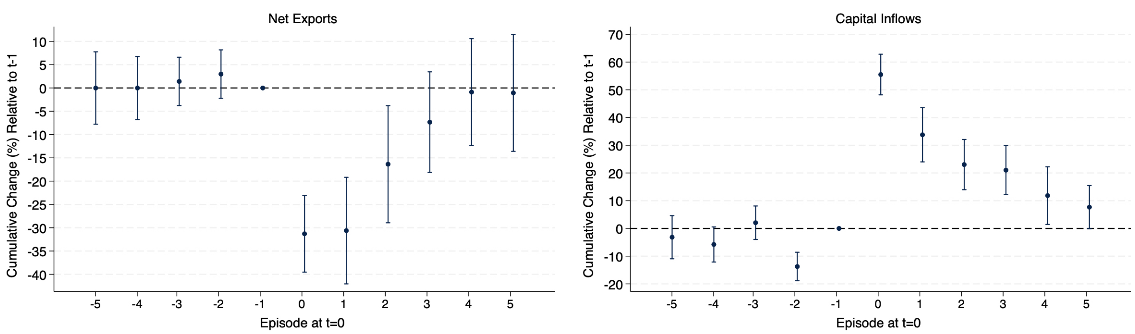
A.2.1 Data Description and Sources

- GDP & Activity: WDI (WB)
- TFP: Penn World Table
- BOP & IIP: IFS (IMF), BIS
- Labor Market: IFS (IMF), ILO, Oxford Economics
- Interest Rate: IFS (IMF), BIS, Oxford Economics, JP Morgan
- Credit Market: BIS, Oxford Economics, Muller & Verner (2023)
- Oil rents: the difference between the value of crude oil production at regional prices and total costs of production

A.2.2 Additional Results on Economic Activity under Baseline Specification

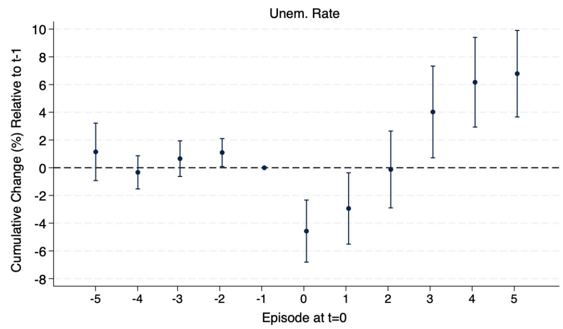
Validation

Figure A.1: Net Exports and Capital Inflows



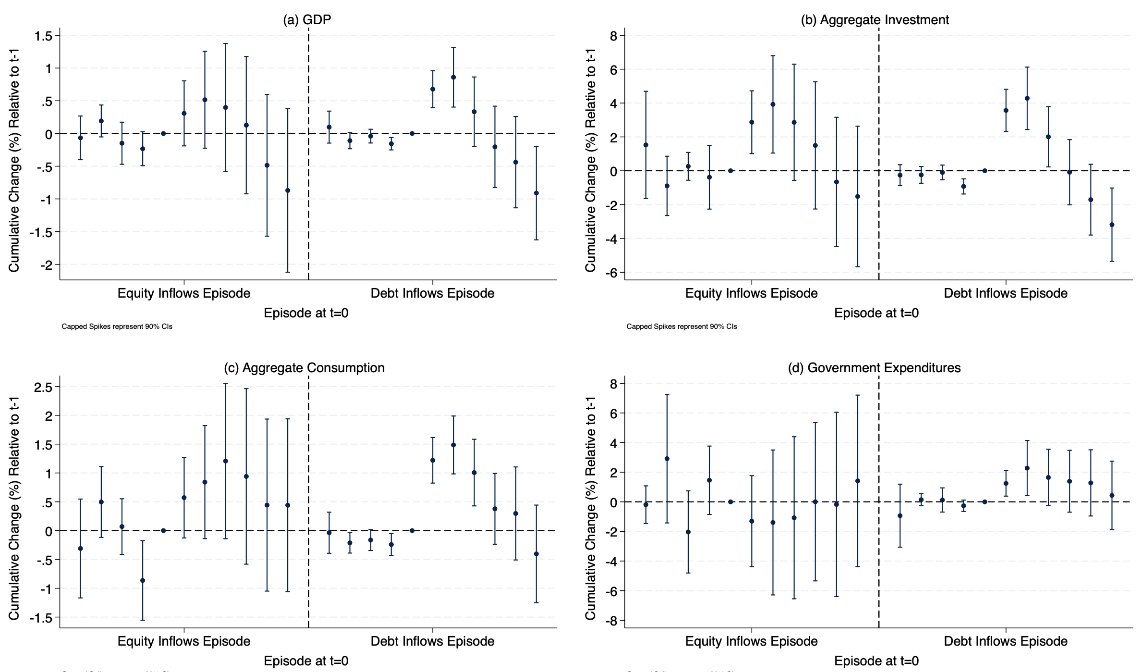
Unemployment Rate

Figure A.2: Unemployment Rate



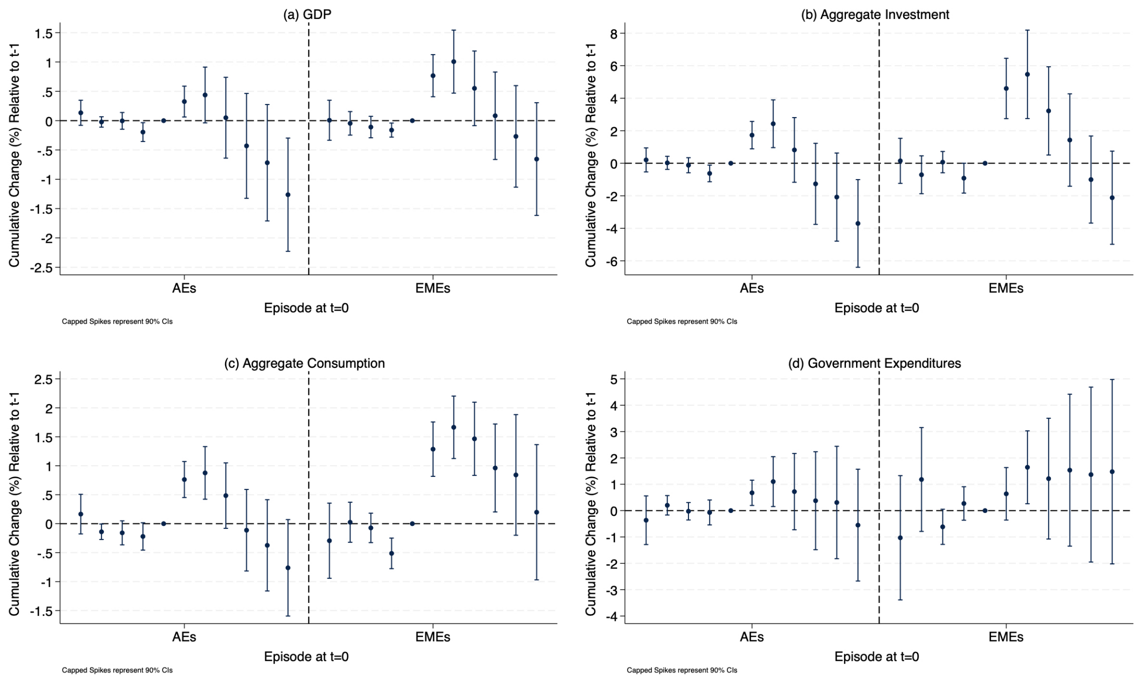
Sample Splits: Equity vs Debt

Figure A.3: Transitory Boom in terms of Economic Activity - Splitting Sample Across Types of Booms



Sample Splits: AE vs EME

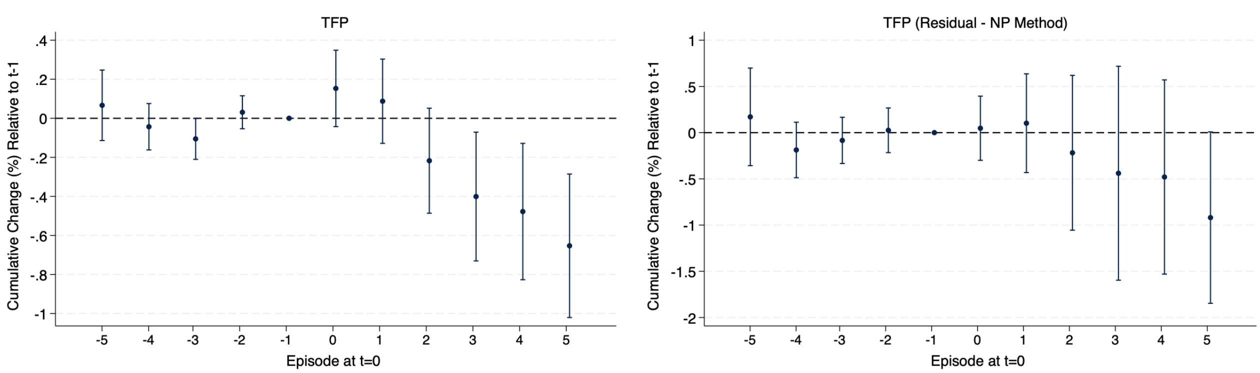
Figure A.4: Transitory Boom in terms of Economic Activity - AE vs EME



A.2.3 Additional Results on TFP under Baseline Specification

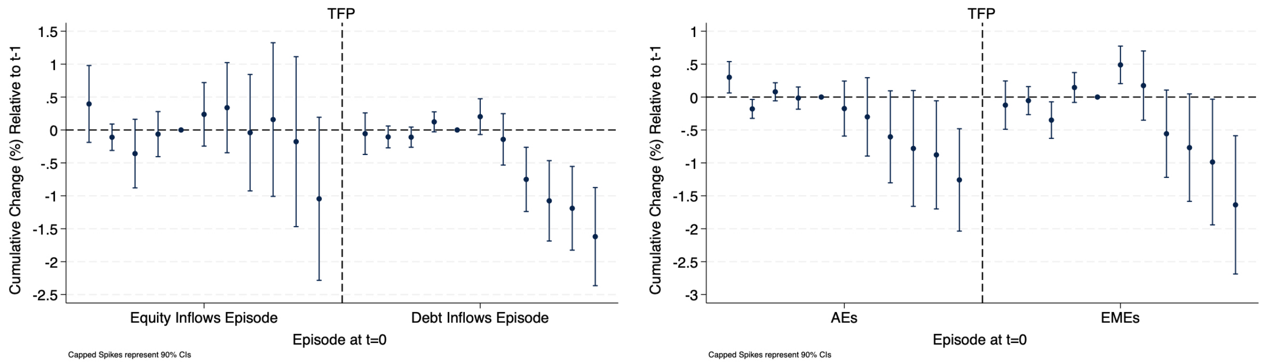
Additional Results on TFP

Figure A.5: Baseline Additional TFP Measures - PWT & Residual NP Measure



Sample Splits: Two Versions

Figure A.6: TFP - Additional Sample Splits



A.2.4 Robustness Exercises under Alternative Specifications

Figure A.7: Economic Activity - No Controls

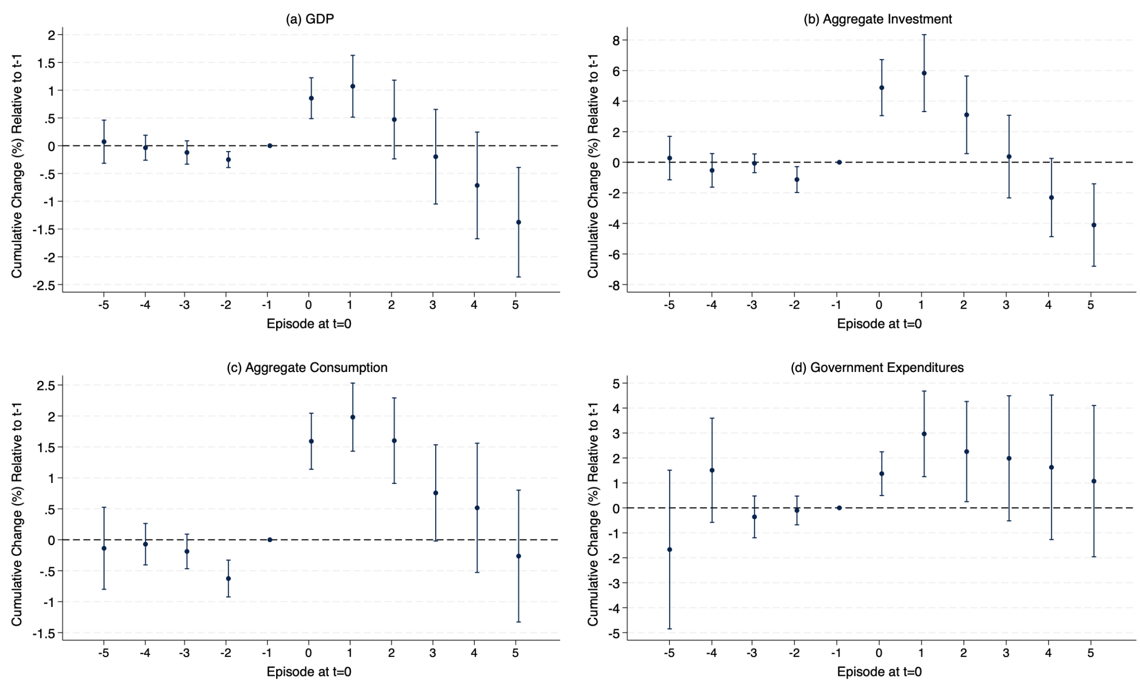


Figure A.8: Wages and Unemployment Rate - No Controls

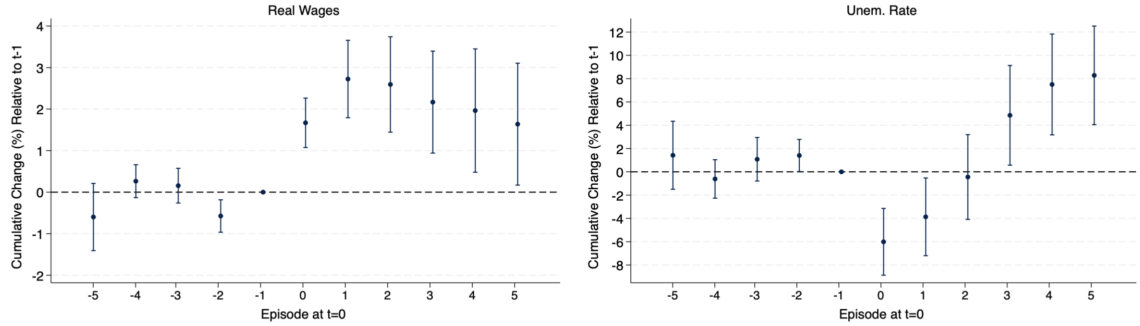
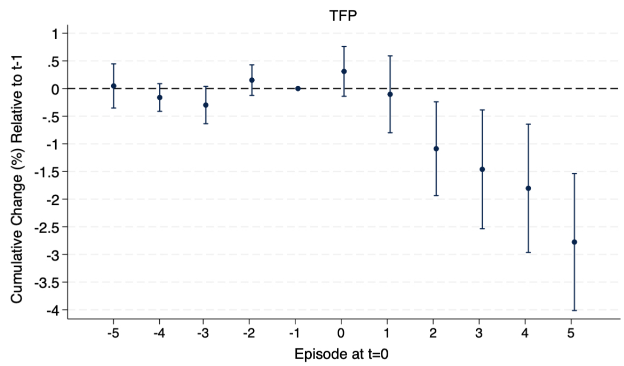
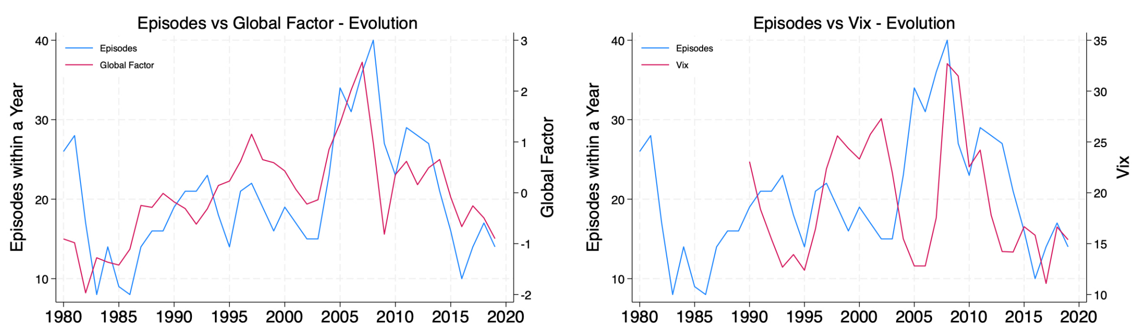


Figure A.9: TFP - No Controls



A.2.5 Role of Risk and Global Financial Conditions

Figure A.10: Episodes tied to improvements in global financial conditions



A.2.6 Robustness Exercises under Sample Restrictions

Figure A.11: Dynamics of Credit to the Non-financial Sector

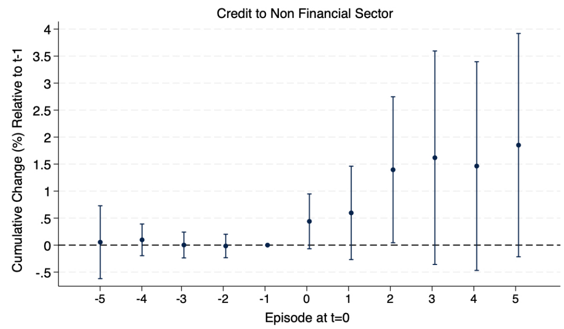


Figure A.12: Dynamics of Credit to the Non-financial Sector: Private NFS vs Government

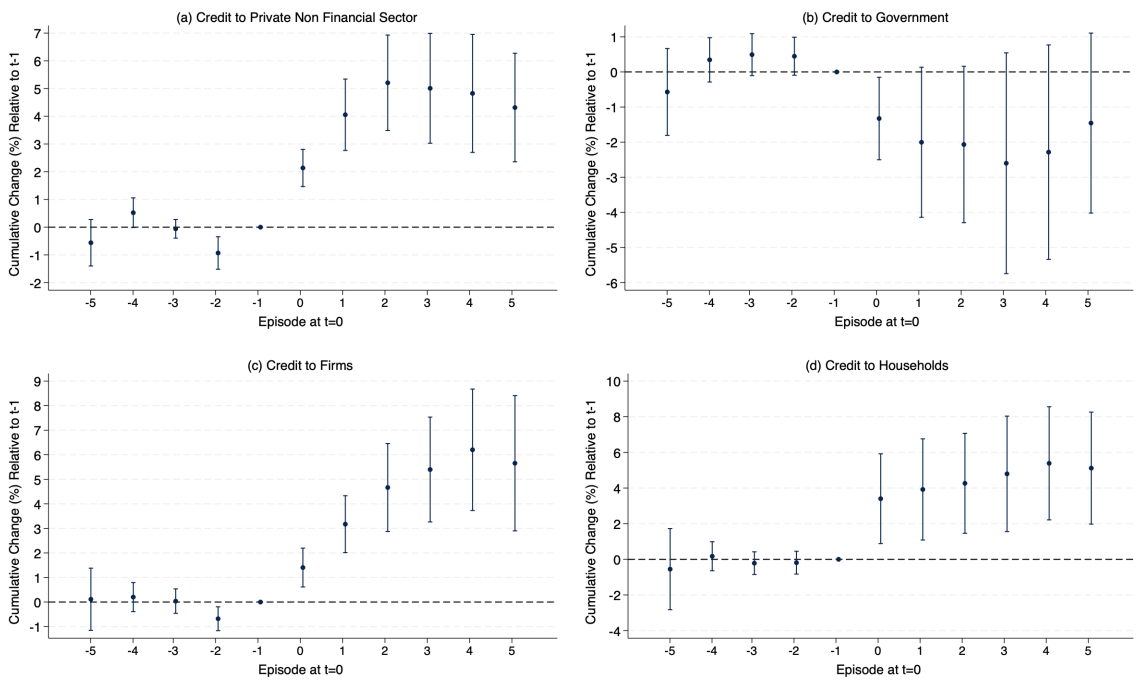


Figure A.13: Dynamics of GDP

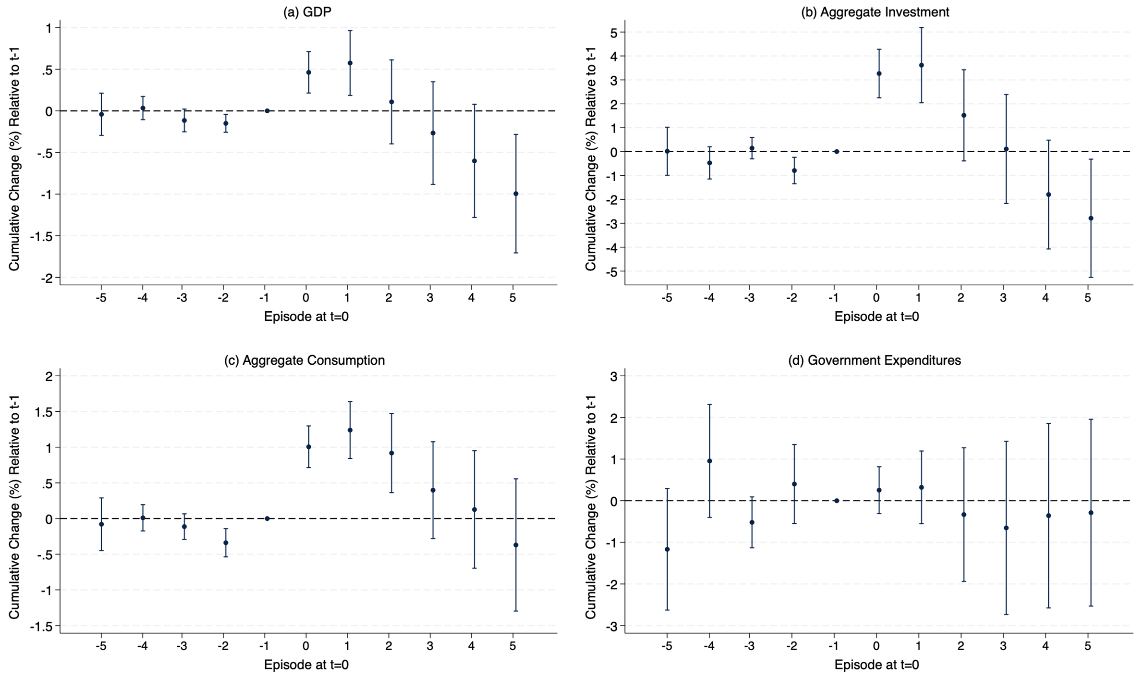


Figure A.14: Real Wages

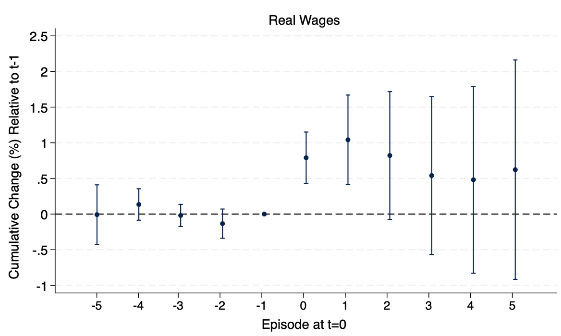
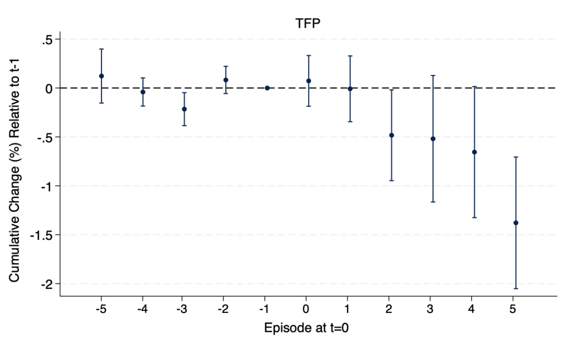


Figure A.15: Dynamics of Productivity



A.3 Section 4 Appendices

A.3.1 List of Countries

Table A.4: Countries included in the Sample of Section 4

Country ISO Code	Country Name	Country Status Classification
AT	Austria	AE
BE	Belgium	AE
BG	Bulgaria	EME
CO	Colombia	EME
CZ	Czechia	EME
DE	Germany	AE
DK	Denmark	AE
EE	Estonia	AE
ES	Spain	AE
FI	Finland	AE
FR	France	AE
GB	United Kingdom	AE
HR	Croatia	EME
HU	Hungary	EME
IT	Italy	AE
JP	Japan	AE
KR	South Korea	AE
LT	Lithuania	EME
LV	Latvia	EME
NL	Netherlands	AE
PL	Poland	EME
RO	Romania	EME
SE	Sweden	AE
SI	Slovenia	EME
SK	Slovakia	EME
UA	Ukraine	EME

Table. This table details the countries included in the sample utilized in Section 4.

A.3.2 Sample Construction

Variable Definitions

Total assets are the sum of all assets in a firm's balance sheet; capital is the sum of tangible and intangible fixed assets, as in Gopinath et al. (2017); revenue is the sum of operating revenue/turnover and other operating income; value added is the difference between revenue and material costs; wage bill is the sum of wages/salaries paid and taxes on salaries; employment is the number of employees; the age of a firm in a year t is computed as the difference between t and the year of incorporation plus one.

Cleaning Steps

1. Companies in several countries report financials in multiple currencies. We always retain the accounts in major currencies, such as, U.S. dollar, Euro, UK Pound, but delete the observations with missing or unreasonable currencies which probably are mistakes (for example South African Rand or Canadian dollar for European companies).

2. I express the financial variables in real dollars 2015 base. To convert from the units of the nominal currency of accounts we i) convert the currency of accounts to the official currency of the country; ii) deflate the series by the national GDP deflator with the 2015 base from the World Bank; and iii) divide by the exchange rate of the official currency to the U.S. dollar in the year 2015. A number of complications arise at this stage

3. Drop company-years with missing information on total assets and operating revenue and sales and employment (simultaneously).

4. Drop the entire company (all years) if total assets is negative in any year.

5. Drop the entire company if employment (in persons) is negative in any year and companies with employment larger than that of Walmart (2 million) in any year.

6. Drop the entire company if sales are negative in any year. Of note, we do not perform this filter in terms of Operating Revenue because this P&L account item is equal to sales + Other operating revenues + Stock variations. While sales cannot be negative, revenue can be negative if a company has a sizable financial loss (say, loss due to hedging, etc.). For countries, like Denmark, whose firms do not report sales but only operating revenue, we cannot use this filter.

7. Drop the entire company when reporting in any year a value of employment per million of total assets larger than the 99.9 percentile of the distribution.

8. Drop the entire company when reporting in any year a value of employment per million of sales larger than the 99.9 percentile of the distribution.

9. Drop the entire company when reporting in any year a value of sales to total assets larger than the 99.9 percentile of the distribution.

10. Drop the entire company if Tangible Fixed Assets (such as buildings, machinery, etc.) is negative in any year.

11. For a given company ID year, we replace missing strings which are unlikely to change over time with values for this company for other years. We complement information on country, company name, city, region, postal code, legal form, and date of incorporation with lagged/lead values in the years where such info is present. This is reasonable because if a company changes the legal form it obtains a new BvD ID and will be treated as a new entity. If information is missing in all years, they remain missing.

A.3.3 Additional Results under Baseline Specification

Figure A.16: High vs Low MRPK: Revenue

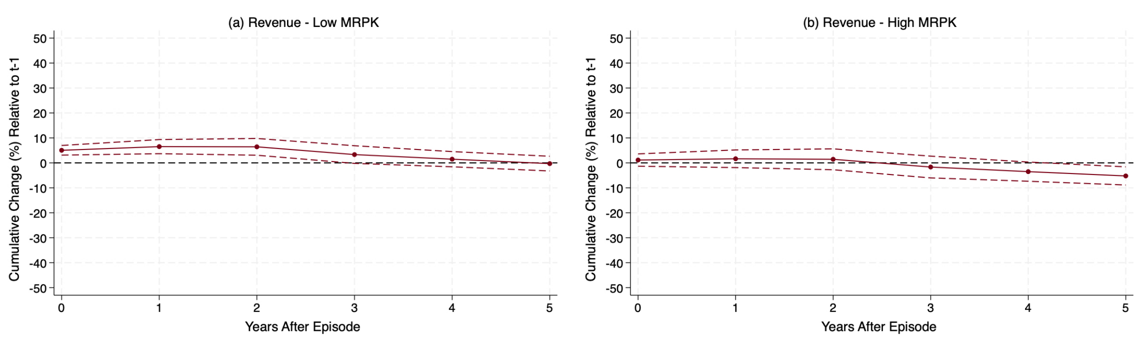


Figure A.18: High vs Low MRPK: Wage Bill

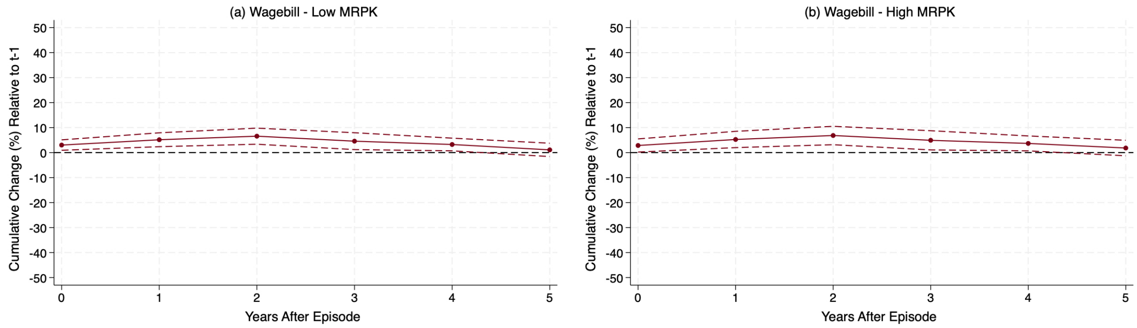


Figure A.17: High vs Low MRPK: Value Added

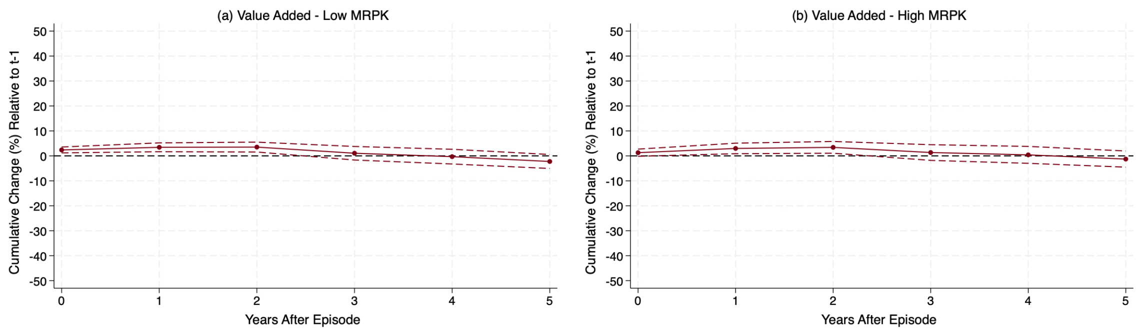
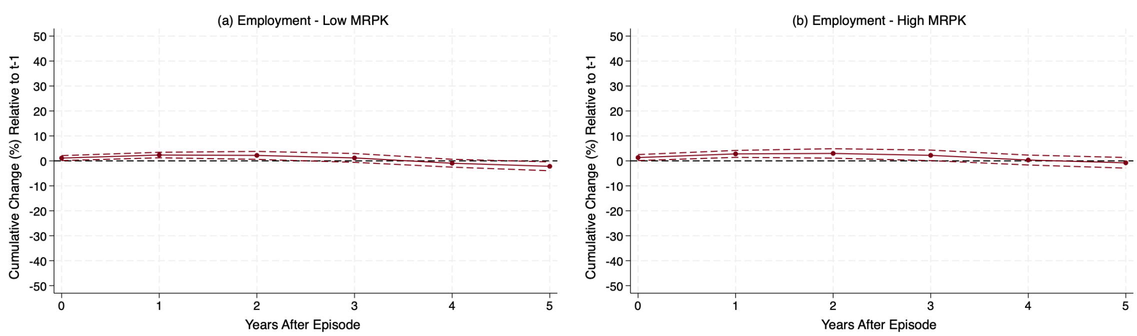


Figure A.19: High vs Low MRPK: Employment



A.3.4 Results without Winsorizing

Figure A.20: Capital and Debt

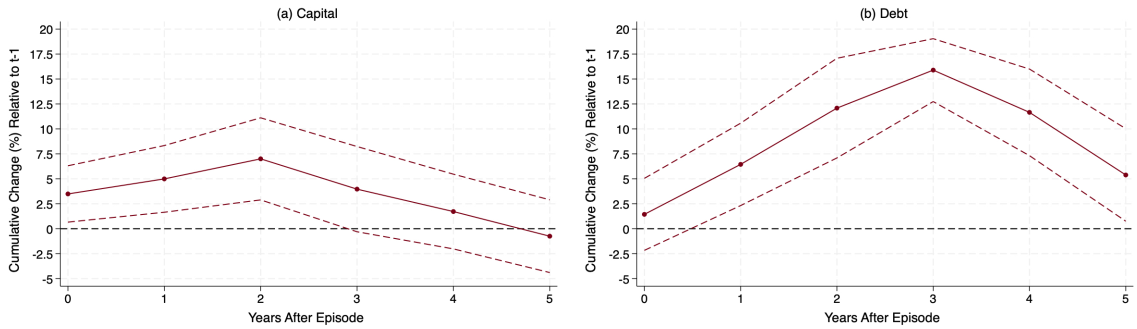


Figure A.21: Real Outcomes

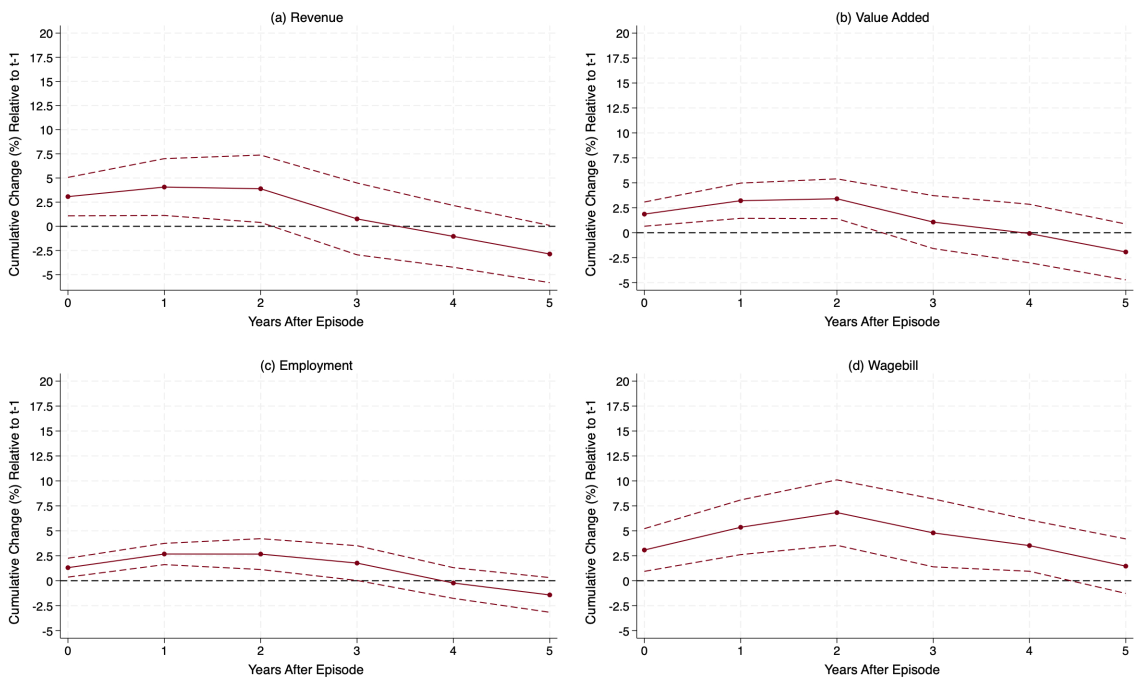


Figure A.22: MRPs

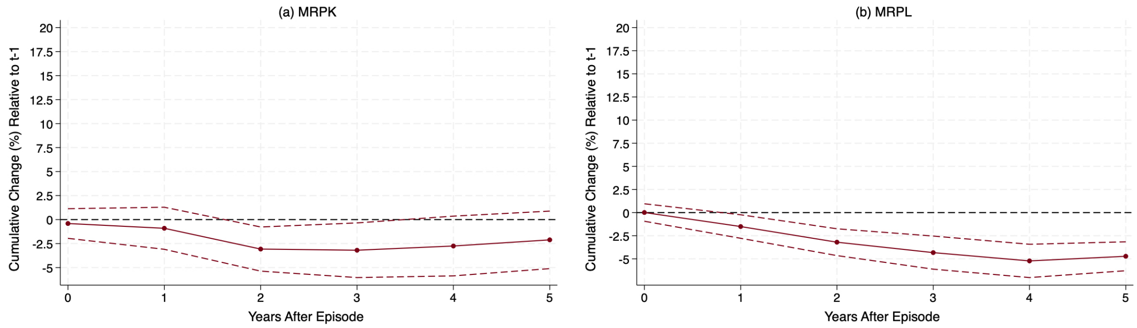


Figure A.23: High vs Low MRPK: Heterogenous Response of Capital

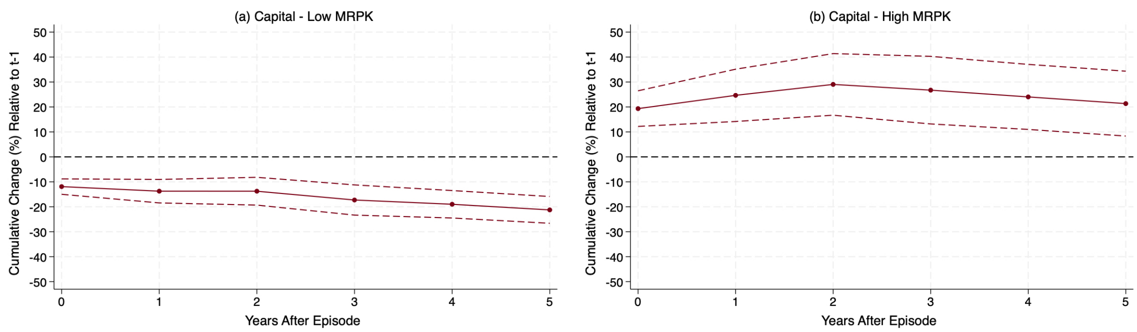


Figure A.24: High vs Low MRPK: Heterogenous Response of Debt

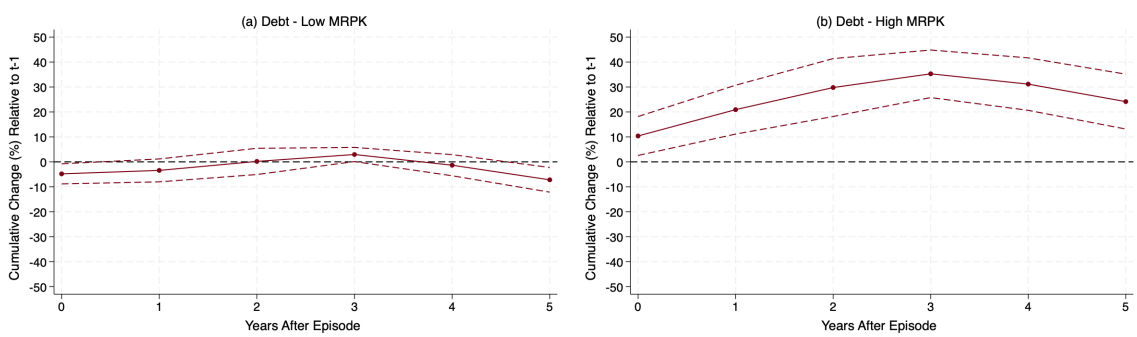
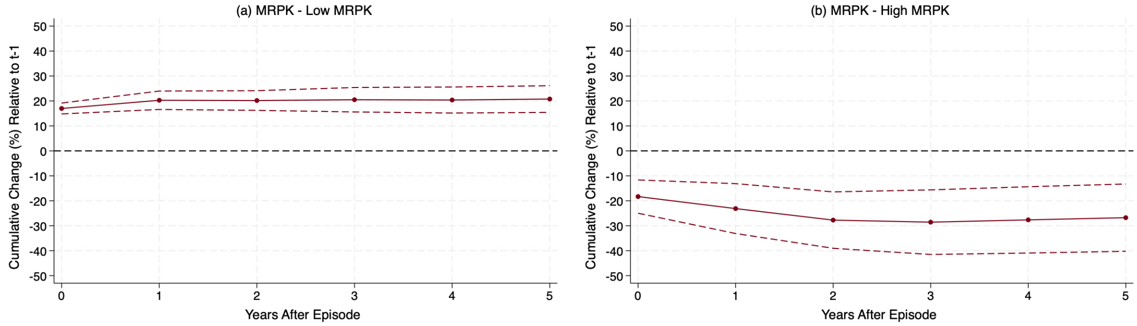


Figure A.25: High vs Low MRPK: Heterogenous Response of MRPK



A.3.5 Results under Baseline Specification - Entrants

Figure A.26: Capital and Debt

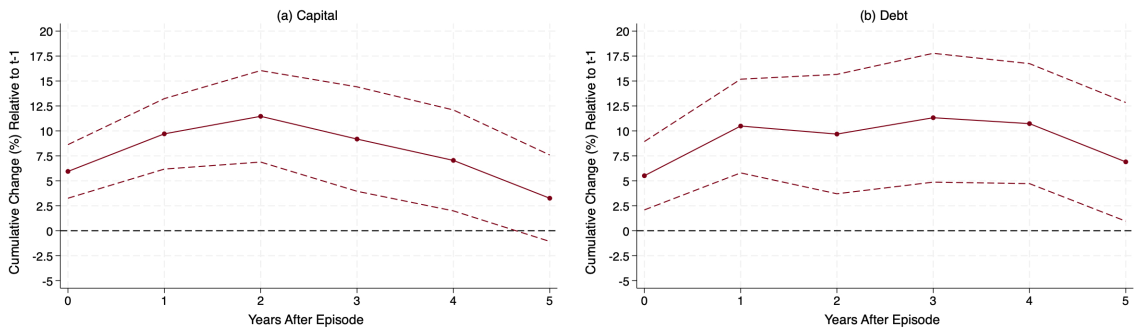


Figure A.27: Real Outcomes

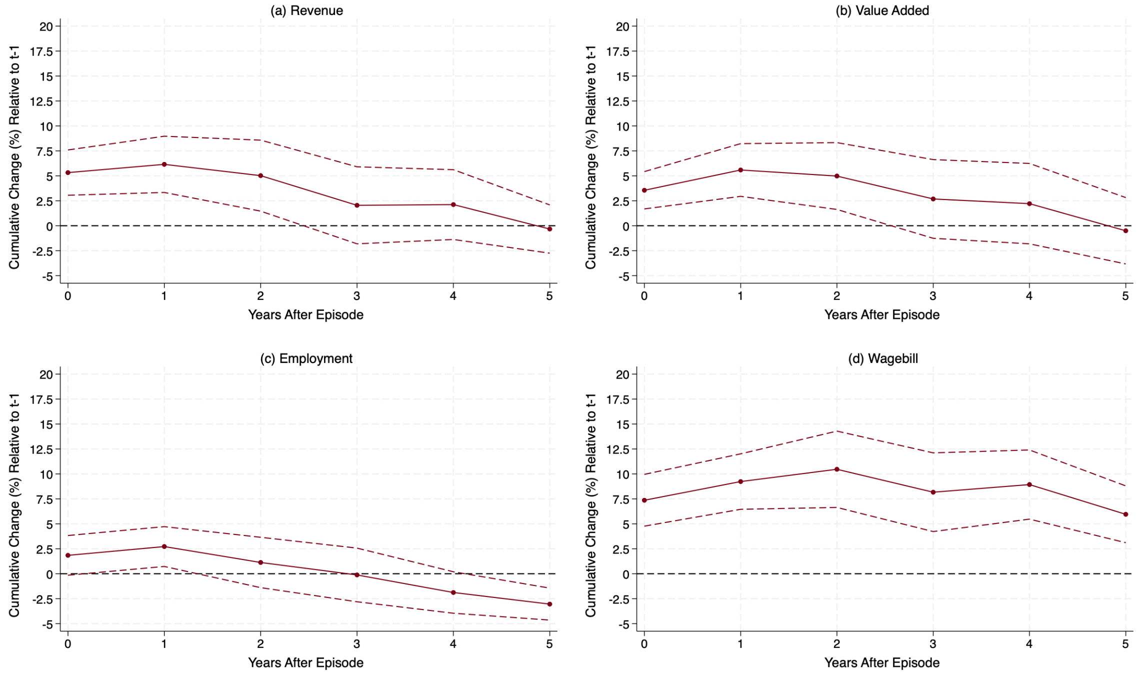
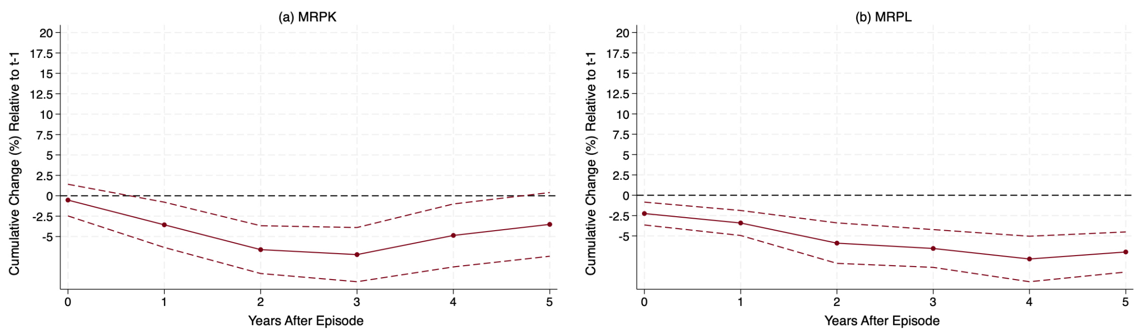


Figure A.28: MRPs



A.3.6 Results under Baseline Specification - Exiting Firms

Figure A.29: Capital and Debt

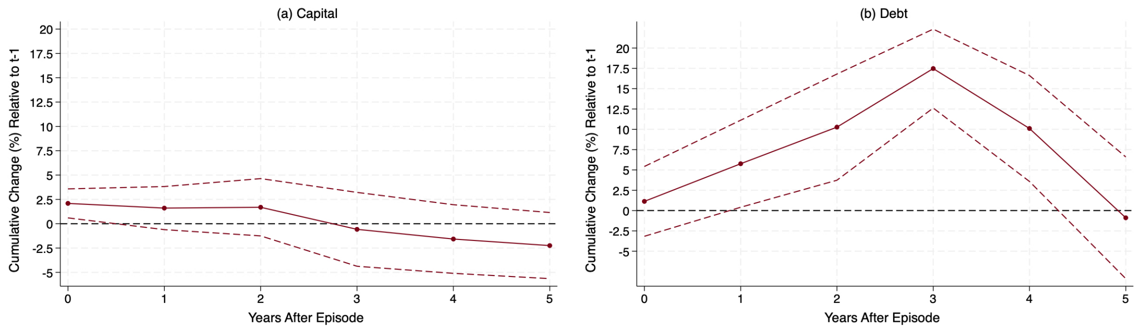


Figure A.30: Real Outcomes

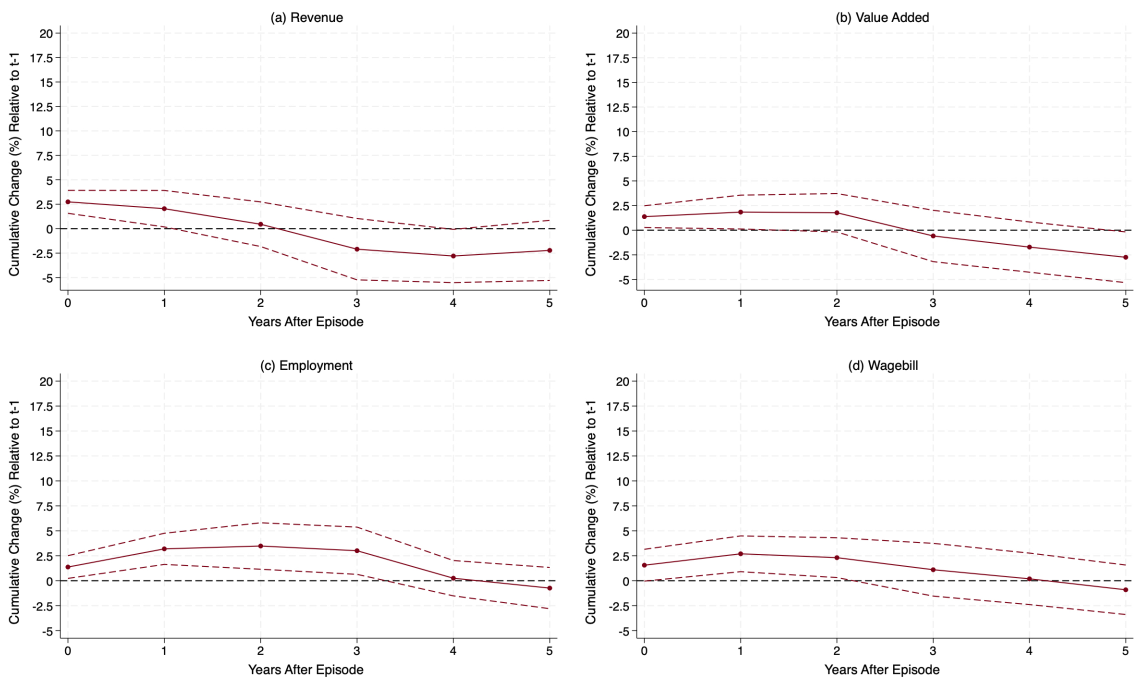
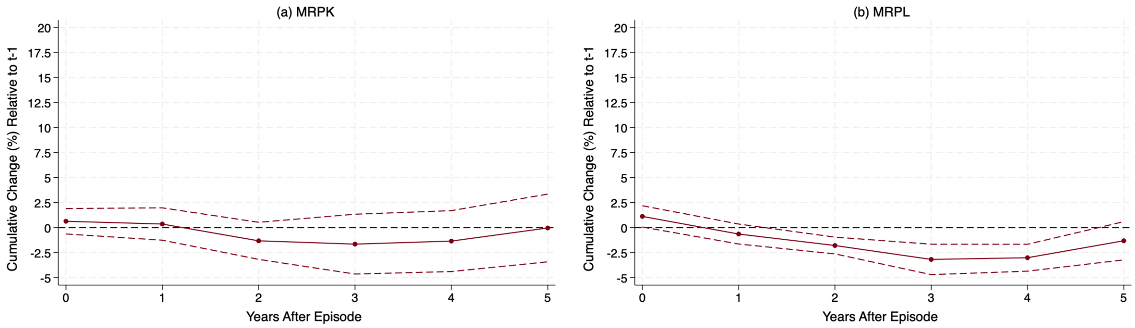


Figure A.31: MRPs



A.4 Section 5 Appendices

A.4.1 Firm Types

A firm is determined to be unconstrained if, given (z, k, b), it does not expect to experience a binding borrowing constraint in any possible future state. Formally, this means that the Lagrange multiplier associated with every borrowing constraint is equal to zero, and that the firm is indifferent between retaining earnings or making dividend payments. Alternatively, if, given (z, k, b), the firm might experience a binding borrowing constraint at any point in time, it is said to be constrained.

Constrained firms can be further divided in terms of whether they face binding borrowing constraints in the current period or not. Firms which do not experience binding borrowing constraints in the current period are said to be Type-1 firms, while firms that do are said to be Type-2 firms.

A.4.2 Reduction of State Space

For the sake of tractability, we can reformulate the problem of the incumbent firm in terms of their cash on hand $n := n(z, k, b) = e(z, k) + (1 - \delta) k - b$.

$$V^0(z, n) = (\pi) n + (1 - \pi) V^1(z, n) \tag{A.1}$$

where

$$V^1(z, n) = \max \left\{ \overbrace{0}^{\text{Exit}}, \overbrace{-c_f + V(z, n)}^{\text{Continue}} \right\} \tag{A.2}$$

We then have that the value of continuing to operate in the period is given by

$$\begin{aligned} V(z, n) = & \max_{k', b', d, n'} d + \frac{1}{1+r} \mathbb{E}_{z'|z} \left[V^0 \left(z', n' \right) \right] \\ \text{s.t. } & d + k' = n + qb' \\ & d \geq 0, \ b' \leq \theta k' \\ & n' = n \left(z', k', b' \right) \end{aligned}$$

A.4.3 Firm Choices

First, note that the labor choice is static and frictionless. As such, we have that a firm with (z, k, b) chooses l that solves

$$w = z\frac{\partial f(k,l)}{\partial l} = (1-\alpha)\nu z\left(k^{\alpha\nu}l^{(1-\alpha)\nu-1}\right)$$

and, therefore, l is such that

$$l = \left[\frac{(1-\alpha)\nu z k^{\alpha\nu}}{w}\right]^{\frac{1}{1-(1-\alpha)\nu}}$$

Unconstrained Firms

An unconstrained firm has accumulated sufficient capital or financial wealth to ensure that collateral constraints will never again affect its investment activities. For any such firm, the multipliers on all future borrowing constraints are zero. Thus it is indifferent between financial savings and dividends; its marginal value of retained earnings equals the household valuation, i.e. a unit of consumption.

An unconstrained firm is such that the borrowing constraint never binds. As such, the Lagrangian multiplier associated with the current constraint and all future constraints is equal to zero. Let W^0 denote the beginning-of-period expected value of an unconstrained firm, W^1 denote the intra-period expected value of an unconstrained firm and W be the firm's value if the firm continues beyond the current period. Then, we have

$$W^0(z,k,b) = (\pi)\, n(z,k,b) + (1-\pi)\, W^1(z,k,b),$$

where

$$W^1(z,k,b) = \max\left\{0, -c_f + W(z,k,b)\right\},$$

and

$$n = n(z,k,b) = e(z,k) + (1-\delta)k - b.$$

As in Khan and Thomas (2013), an unconstrained firm's capital choice $k^{'}$ is independent of their financial positions; it is indifferent about $b^{'}$as it has the same marginal value of savings as the household. Any such firm's $b^{'}$ affects its value only through current earnings, $n(z,k,b)$. Then, we can express the value of a (z,k,b) continuing unconstrained firm as $W(z,k,0)-b$ and I can write the beginning-of-period expected value as $W^0(z,k,0)-b$. Given these observations, we have

$$
\begin{aligned}
W(z,k,b) &= \max_{k',b'} n(z,k,b) + qb' - k' + \frac{1}{1+r}\mathbb{E}_{z'|z}\left[W^0\left(z',k',b'\right)\right] \\
&= \max_{k',b'} n(z,k,b) \cancel{+qb'} - k' + \frac{1}{1+r}\mathbb{E}_{z'|z}\left[W^0\left(z',k',0\right) \cancel{-b'}\right] \\
&= n(z,k,b) + \max_{k'}\left\{-k' + \frac{1}{1+r}\mathbb{E}_{z'|z}\left[W^0\left(z',k',0\right)\right]\right\}
\end{aligned}
$$

and, therefore, we have

$$
\begin{aligned}
W(z,k,b) &= n(z,k,b) \\
&+ \max_{k'}\left\{-k' + \frac{1}{1+r}\mathbb{E}_{z'|z}\left[(\pi)\, n\left(z',k',0\right) + (1-\pi)\, W^1\left(z',k',0\right)\right]\right\}
\end{aligned} \tag{A.3}
$$

Following Clausen and Strub (2020), it is easy to see that this objective function is differentiable at the optimal choice and, thus, a version of the envelope theorem applies[17]. Totally differentiating A.3 with regards to k' and using the envelope condition for W^1, we have that k' solves

$$
1 = \frac{1}{1+r}\mathbb{E}_{z'|z}\left[\frac{\partial e\left(z',k'\right)}{\partial k'} + (1-\delta)\right]
$$

where the left-hand side represents the marginal cost of one extra unit of capital and the right-hand side represents the discounted expected marginal benefit of one extra unit of capital. This implies that for an unconstrained firm

$$
k' = g_{k'}^{unc}(z)
$$

i.e. tomorrow's capital choice is entirely determined by their current productivity draw. Trivially, we can write for an unconstrained firm that $l = g_l^{unc}(z,k)$.

By definition, unconstrained firms are indifferent between financial savings and dividends. To ensure that this indeed the case, I impose that such a firm has a savings rule b' that implies zero probability of a binding borrowing constraint in every possible future date and state. More specifically, I assign a minimum savings policy exactly ensuring that, under all possible paths of z, the firm will have sufficient resources to implement its optimal investment plan without the borrowing constraint. As long as the firm maintains a level of debt that does note exceed the threshold determined by this policy, it will be indifferent to its financial structure. As such, by construction, this savings rule is indeed

[17] See also Bianchi et al. (2018) and Salomao and Varela (2022) for similar applications.

an optimal policy.

To do this, I follow Khan and Thomas (2013). I derive the minimum savings policy, $b^{'} = g_{b'}^{unc}(z)$, recursively as the solution to the following two equations

$$g_{b'}^{unc}(z) = \min_{z'} \left\{ \tilde{B}\left(z^{'}, g_{k'}^{unc}(z)\right) \right\}, \tag{A.4}$$

where

$$\tilde{B}(z,k) = e(z,k) + (1-\delta)k - g_{k'}^{unc}(z) + q \cdot \min\left\{ g_{b'}^{unc}(z), \theta g_{k'}^{unc}(z) \right\}. \tag{A.5}$$

$\tilde{B}\left(z^{'}, g_{k'}^{unc}(z)\right)$ is defined as the largest debt level at which a firm entering next period with capital $g_{k'}^{unc}(z)$ can be unconstrained, given the idiosyncratic state $z^{'}$. By taking the minimum over all possible states $z^{'}$, it is possible to identify the largest debt level a firm can choose at the current period and be sure to remain unconstrained in the following period, $g_{b'}^{unc}(z)$.

Equation A.5 defines the beginning-of-period maximum debt level under which a firm can adopt the unconstrained capital rule and debt not exceeding that identified by the minimum savings policy without paying negative dividends and, hence, satisfy the definition of an unconstrained firm.Notice that $\tilde{B}$ is increasing in the firm's current earnings since these may be used to cover outstanding debt. The minimum operator imposes the borrowing constraint; if the firm does not have sufficient collateral to borrow to $g_{b'}^{unc}(z)$, it can still be unconstrained if it has sufficient savings to finance its investment.

Finally, from the firm's budget constraint, we have that an unconstrained firm pays $d = g_{d}^{unc}(z,k,b)$ such that

$$g_{d}^{unc}(z,k,b) = n(z,k,b) - g_{k'}^{unc}(z) + q g_{b'}^{unc}(z) \geq 0$$

Constrained Firms

From the previous subsection, it follows that a firm will be constrained if it does not possess enough internal resources, i.e. cash-on-hand $n(z,k,b)$, to implement the unconstrained choices $g_{k'}^{unc}(z)$, $g_{b'}^{unc}(z)$. Let $n^{unc}(z) \equiv g_{k'}^{unc}(z) - q g_{b'}^{unc}(z)$. Then, a firm with $n(z,k,b)$ will be constrained if and only if

$$n(z,k,b) < n^{unc}(z)$$

We can further characterize constrained firms between those that are *currently* experiencing binding borrowing constraints (Type-2) and those that are not (Type-1). To do so, notice first that for any constrained firm

$$d = 0$$

Additionally, assume that $b^{'} = \theta k^{'}$. Then, I can define

$$\bar{k}(n) = \frac{n}{1 - q\theta}$$

which is the largest amount of capital that a constrained firm can choose.

A constrained firm solves

$$\begin{aligned} V(z,n) = &\max_{k',b',d,n'} \frac{1}{1+r} \mathbb{E}_{z'|z}\left[V^0\left(z^{'},n^{'}\right)\right] \\ \text{s.t. } & k^{'} = n + qb^{'} \\ & b^{'} \leq \theta k^{'} \\ & n^{'} = n\left(z^{'},k^{'},b^{'}\right). \end{aligned}$$

If the borrowing constraint does not bind, the solution is similar to the one to A.3:

$$k^{'} = g_{k'}^{unc}(z)$$

and

$$b^{'} = \frac{1}{q}\left[g_{k'}^{unc}(z) - n\right]$$

However, if the borrowing constraint binds, the solution is trivially given by

$$k^{'} = \bar{k}(n) = \frac{n}{1 - q\theta}$$

and

$$b^{'} = \frac{1}{q}\left[\bar{k}(n) - n\right] = \frac{\theta n}{1 - q\theta}$$

Therefore, we have that a constrained firm described by (z,n) will be Type-1 if $k^{'} = g_{k'}^{unc}(z) \leq \bar{k}(n)$, implying that $\frac{1}{q}\left[g_{k'}^{unc}(z) - n\right] = b^{'} < \theta k^{'}$. Alternatively, a constrained firm described by (z,n) be Type-2 if $g_{k'}^{unc}(z) > \bar{k}(n) = k^{'}$, implying that $b^{'} = \frac{1}{q}\left[\bar{k}(n) - n\right]$.

Summary

We then have

$$\left(k^{'},b^{'}\right)=\begin{cases}\left(g_{k'}^{unc}\left(z\right),g_{b'}^{unc}\left(z\right)\right), & \text{if } n\geq n^{unc}\left(z\right)\\ \left(g_{k'}^{unc}\left(z\right),\frac{1}{q}\left[g_{k'}^{unc}\left(z\right)-n\right]\right), & \text{if } n<n^{unc}\left(z\right)\ \&\ g_{k'}^{unc}\left(z\right)\leq\bar{k}\left(n\right)\\ \left(\bar{k}\left(n\right),\frac{1}{q}\left[\bar{k}\left(n\right)-n\right]\right), & \text{if } n<n^{unc}\left(z\right)\ \&\ g_{k'}^{unc}\left(z\right)>\bar{k}\left(n\right)\end{cases}$$

A.4.4 Firm Choices - Effect of an increase in θ

A.4.5 Computational Algorithm

Solution Method The solution method follows Jo (2022) & Jo and Senga (2019):

1. Solve for unconstrained policies
2. Then, simplify incumbent's problem with a cash-on-hand formulation
3. Solve the simpler problem with a VFI approach
4. Upon finding policy functions, iterate on distribution until convergence

As for the quantification strategy, the idea is as follows:

- Given the stationary distribution of firms, $\Omega(z, k, b)$, in equilibrium, begin with constructing a cumulative distribution of employment by using $L^w(z, k)$.
- Based on the employment shares across size bins in the Orbis Data, find the employment threshold, $\tilde{l}$, in each firm size group along the above cumulative distribution from the model.
- Then compute the measure of firms specifically located on each firm size bin which is defined from those employment thresholds
- Finally, calibrate parameter values to generate the model population shares as closely as possible to the data.