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ESSAYS IN APPLIED INTERNATIONAL MACROECONOMICS

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Contents

Thesis summary

This thesis consists of three chapters on different topics in applied international macroeconomics. The topics are related to important issues such as globalization, debt, and misallocation.

Chapter 1 investigates the short- and medium-run dynamic effects of debt-based and equity-based capital inflows on real GDP growth in a sample of 28 emerging and developing countries. I use a panel vector autoregressive analysis based on quarterly data for the period 1995Q1 to 2015Q4. My results show asymmetric effects of gross inflows of debt and equity and a potentially destabilizing role of debt inflows. A debt inflow shock has a positive impact effect on GDP growth by raising consumption and investment in the same quarter, and a negative effect on investment and GDP growth in later periods for several quarters. Equity inflows, however, do not tend to have a significant effect on consumption, investment and GDP growth on average across the countries in my sample. By splitting the sample into two groups of emerging and developing countries based on (i) real GDP per capita and (ii) the quality of governance, I find a particularly destabilizing effect of debt inflows in countries with lower governance quality, and a slightly destabilizing effect of equity inflows in countries with higher average income.

Chapter 2 studies the effects of private and public debt accumulation on capital misallocation. I define capital misallocation, similarly to Hsieh and Klenow (2009), as the dispersion in marginal revenue product of capital across firms, and apply the difference-in-differences estimation approach to a novel dataset containing industry-level panel data for 18 European countries. My results indicate that an increase in private debt to GDP ratio exacerbates capital misallocation, particularly in sectors with higher dependence on external finance, higher technological intensity, a larger share of credit-constrained firms and a lower level of competition. These findings suggest that private debt accumulation tends to act as a factor amplifying the negative impact of financial frictions and market imperfections on macroeconomic outcomes. I do not find, however, any significant and robust effect of public debt on capital misallocation.

Chapter 3 proposes a new factor that mediates the effect of trade openness on within-country income inequality. Using the panel of 18 European countries over the period 1999–2016, I show that the effect of trade openness on income distribution is conditioned by the level of efficiency of resource allocation. Here I use the measure of allocative efficiency proposed by Olley and Pakes (1996), based on the decomposition of an industry-level aggregate productivity into the unweighted average and the covariance between firm size and productivity, to create a normalized misallocation index for each country-year. I find that, in case of an efficient allocation of resources within a country, more trade reduces income inequality. Deviations from allocative efficiency, however, significantly influence the distributional effect of openness: higher misallocation impedes—or may even reverse in case of severe misallocation—the inequality-reducing effect of trade. At the same time, I find that countries with a higher level of misallocation are, other things held constant, more equal in terms of income distribution.

Chapter 1

The dynamic effects of debt and equity inflows: evidence from emerging and developing countries

Abstract

This chapter shows that inflows of foreign debt and equity have different (asymmetric) effects on consumption, investment, and GDP growth in emerging and developing economies. By using panel VAR analysis based on quarterly macroeconomic data from 1995Q1 to 2015Q4, my results indicate that debt inflows increase consumption, investment and GDP growth on impact, but decrease investment and GDP growth in later periods (i.e., after around a year) for several quarters. Equity inflows, on the other hand, do not have a significant impact on consumption, investment, and GDP growth in emerging and developing countries on average. I also account for cross-country heterogeneity by splitting my sample into two groups based on their (i) real GDP per capita and (ii) governance quality. I find that countries with lower governance quality benefit from debt inflows in terms of increased consumption, investment and GDP growth in the short run, but are hurt by reduction in all of these indicators in the medium run. My findings regarding equity inflows indicate that, although their effects are not so much destabilizing as those of debt inflows, policymakers in higher income emerging countries might still need to be attentive, since an equity inflow shock in these countries seems to have a somewhat negative effect on investment and GDP growth in later periods following a positive impact effect on consumption and GDP growth.

I thank participants at the 5th International Conference on Applied Theory, Macro and Empirical Finance (Thessaloniki) and the XX Conference on International Economics (Granada) for their comments.

1.1. Introduction

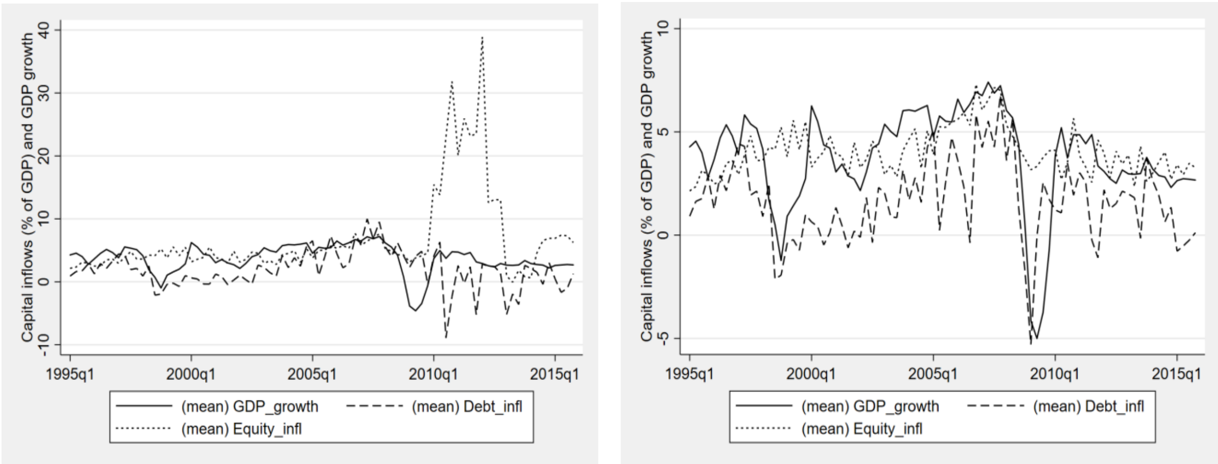
The real effects of cross-border capital flows have recently become one of the most active areas of research in international macroeconomics and finance. While the consequences of overall capital flows (both in net and in gross terms) have been studied a great deal—albeit with conflicting results—there is a shortage of studies investigating the dynamic effects of different components of capital flows (i.e., debt and equity flows) on growth and stability of emerging and developing countries. Over the last decade there have appeared several studies finding different effects of equity flows (i.e., foreign direct investment and portfolio equity) and debt flows (short-term and long-term debt, private and public debt etc.) on countries' growth and macroeconomic stability. It should be noted, however, that the research in this area is inconclusive about whether these capital flows are good or bad for the economic performance of recipient countries.

This chapter intends to add to the empirical literature on the growth effects—for developing and emerging countries—of capital inflows by disaggregating them into debt-based and equity-based inflows. Thus, it presents further evidence on the debate whether different categories of capital inflows have different dynamic effects on countries' output growth. I use a panel vector autoregressive (panel VAR) approach on quarterly data from 1995Q1 to 2015Q4 for a sample of 28 emerging and developing countries.[1] I also investigate the channels through which debt and equity inflows affect the GDP growth. Since there is a shortage of studies using the panel VAR approach to analyze the growth effects of debt and equity inflows in developing countries, I have decided to fill this gap with the current study.

I define the sum of capital inflows in the form of portfolio debt and bank lending as debt inflows, and the sum of capital inflows in the form of foreign direct investment (FDI) and portfolio equity as equity inflows. Figure 1.1 shows time series of real GDP growth, debt inflows and equity inflows averaged for the countries in my sample: panel (a) plots the time series mean for all the 28 emerging and developing countries, while panel (b) excludes two countries, namely Cyprus and Mauritius, since they had extraordinarily large variability in the amount of capital inflows as compared to other countries in the sample.[2] From Figure 1.1, especially in panel (b), we can see that real GDP growth seems to move more together with debt inflows, and not so much with equity inflows. This can make sense if we consider that

[1] The countries are: Argentina, Bolivia, Brazil, Bulgaria, Chile, Colombia, Croatia, Cyprus, Czech Republic, Estonia, Georgia, Indonesia, Kyrgyz Republic, Lithuania, Mauritius, Mexico, Peru, Philippines, Poland, Romania, Russia, Slovak Republic, Slovenia, South Africa, South Korea, Sri Lanka, Thailand, Ukraine.

[2] The ratio of debt inflows to GDP in Cyprus ranges from -356% to 221%, while the ratio of equity inflows to GDP ranges from -57% to 705%. In Mauritius, the ratio of equity inflows to GDP ranges from -47% to 712%.



a) 28 emerging and developing countries

b) 26 emerging and developing countries (Cyprus and Mauritius excluded)

Figure 1.1. Average time series of debt and equity inflows and real GDP growth

debt inflows are more likely to raise consumption in the short run, while equity inflows—even if likely to increase investment—may simply bring with them imports of intermediate goods, hence not having any short-run impact on real GDP growth. My aim is to investigate deeper how debt and equity inflows to emerging and developing countries affect their consumption, investment and GDP growth over time.

The remaining part of this chapter proceeds as follows. Section 1.2 reviews the related literature. Section 1.3 discusses the data, empirical methodology, and identification issues. Section 1.4 discusses the results of the empirical analysis. Finally, Section 1.5 concludes.

1.2. Literature review

There are a lot of studies finding a positive, while some finding a negative, association between inflows of foreign equity capital—in particular of FDI—on economic growth of countries in the medium to long run. I will review only some of the more recent contributions here. Bussiere and Fratzscher (2008) find that countries tend to benefit from FDI inflows only in the medium to long run but not in the short run after financial liberalization. Kose, Prasad and Terrones (2009) find that both FDI and portfolio equity flows boost the growth of total factor productivity (TFP). Aizenman, Jinjarak and Park (2013) show that lagged FDI flows are associated with higher growth, including in the periods of crisis, while the association between growth and lagged portfolio equity flows is smaller and much less stable than that between growth and FDI flows. MacDonald (2015) shows that FDI inflows to developing and emerging countries are directed towards those with the highest growth rates, but that portfolio investment outflows exceed these inflows, thus driving the negative correlation between net capital inflows and productivity growth—the so-called "allocation puzzle"—found by Gourinchas and Jeanne (2013). In a recent study, Beckmann and Czudaj (2017) use the Bayesian panel VAR approach to investigate the relationship between capital flows and GDP in a sample of 24 countries (18 OECD and 6 emerging market economies); by decomposing the capital flows into FDI and portfolio flows, the authors find a robust positive effect of these flows (both in gross and in net terms) on GDP.

Not all studies, however, find positive growth effects of equity inflows. Baharumshah, Slesman and Devadason (2017) show that only countries achieving better financial market development beyond a certain threshold level can facilitate positive growth effects of FDI and portfolio equity inflows, whereas those below that threshold experience negative growth effects. Agbloyor et al. (2014) find that private capital flows (including FDI, portfolio equity and private debt flows) have an overall detrimental effect on economic growth in African countries; after interacting the capital flows variables with financial market indicators, however, the authors show that this negative growth effect decreases—or even turns positive for FDI—with financial market development. Some other authors, such as Ostry et al. (2010) and Davis (2015), fail to find a statistically significant effect of equity inflows on GDP growth.

Previous research also finds contradictory evidence on the relationship between debt inflows and growth. Bussiere and Fratzscher (2008) find that the total debt and short-term debt ratios hurt growth in financially open economies but not in closed ones. Kose, Prasad and Terrones (2009) show that debt flows are negatively correlated with TFP growth. Ostry et al. (2010) find that debt liabilities have a significantly negative effect on GDP growth. Aizenman, Jinjarak and Park (2013) find that the association of growth and lagged short-term debt was nil before the global financial crisis, and negative and large during the crisis. Rocha and Oreiro (2013) find in a sample of 55 emerging countries that any positive level of external debt is harmful for economic growth of these countries. Baharumshah, Slesman and Devadason (2017) show that portfolio debt inflows have a negative impact on growth in countries with low financial development, and no impact in those with high financial development. On the other hand, Davis (2015) shows in a panel of 30 developed and emerging countries that debt inflows affect output gap positively, but also increase inflation, asset prices, credit growth, and exchange rate appreciation, hence posing a greater threat to financial stability. Using industrial data for 22 emerging market economies, Igan, Kutan and Mirzaei (2016) find that (net) private debt inflows are associated with stronger growth in industries that are more dependent on external finance.

Studies also find different results concerning the association of capital flows with output volatility and macroeconomic stability. Aizenman, Chinn and Ito (2010) show that net FDI inflows tend to dampen output volatility; they also find that countries with a higher share of non-financial FDI were less vulnerable to output growth decline during the global financial crisis. Federico, Végh and Vuletin (2013) find that the volatility of gross FDI inflows is positively associated with output volatility if the correlation between FDI and other flows is positive. Broner et al. (2013) show that gross capital flows (both inflows and outflows) expand during 'good times' (booms) and decline during 'bad times' (recessions), thus speaking to the procyclicality of capital flows first documented by Kaminsky, Reinhart and Végh (2004). Blanchard, Faruqee and Das (2010) find a strong correlation between short-term debt and unexpected growth decline in emerging market countries. Lane and Milesi-Ferretti (2011) find that countries with higher short-term debt as a ratio of reserves experienced sharper output and demand declines during the last crisis. Powell and Tavella (2015) show in a panel of 41 emerging countries that portfolio debt inflows and banking inflows increase the probability of a banking crisis while equity inflows do not.

As we can see from the review of studies above, the existing literature is inconclusive as to whether different components of capital flows, such as equity flows (including FDI and portfolio equity) and debt flows (including bank loans and portfolio debt), have a positive or negative effect on growth performance of emerging and developing countries. The lack of tractable theoretical models also makes it difficult to explain the conflicting empirical findings regarding the macroeconomic effects of capital inflows. On the empirical front, there is a shortage of studies using multivariate time series methods, such as vector autoregressions, applied to panels of countries in addressing the question of capital flows and growth nexus. Among the studies mentioned above, only Davis (2015) and Beckmann and Czudaj (2017) use panel vector autoregressions; neither of these two, however, focus on a panel of developing countries, which may have experienced a different kind of outcome from debt and equity inflows as compared to developed countries. This chapter aims to fill this gap by using the structural panel VAR methodology on a sample of 28 emerging and developing countries to analyze the dynamic effects of debt and equity inflows on real GDP growth.

1.3. Empirical methodology

1.3.1. The data

For testing the short- and medium-run dynamic effects of debt and equity inflows on domestic consumption, investment and output, I use quarterly data from 1995Q1 to 2015Q4 on a sample of 28 emerging and developing countries.[3] I obtain the data on disaggregated gross capital inflows (i.e., inflows of FDI, portfolio equity, portfolio debt, and bank lending by foreigners net of disinvestment), real GDP growth, CPI inflation, and the growth of real domestic private credit from the dataset of Cerutti, Claessens and Rose (2017)[4]. The data on gross fixed capital formation, final consumption expenditures of the private and public sectors, and money market (nominal) interest rates come from the IMF's International Financial Statistics (IFS) database.

The data on disaggregated capital inflows, final consumption expenditure and gross fixed capital formation are normalized by nominal GDP. As in Forbes and Warnock (2014) and Davis (2015), I sum the liabilities of FDI and portfolio equity to get the gross equity inflows, and sum the liabilities of portfolio debt and bank lending to get the gross debt inflows. Besides, I use the growth rates (in percentage) of consumption, gross fixed capital formation and real credit to the private sector to make them comparable across countries.[5] My data set is unbalanced and all the data I use in my baseline model are of quarterly frequency. The summary statistics for my data are given in Appendix 1.B.

1.3.2. Empirical model

To investigate the macroeconomic effects of different forms of capital inflows I estimate a panel VAR model and calculate orthogonalized impulse-response functions (IRFs) of the variables of interest. One of the main advantages of the panel VAR approach is that it allows studying the dynamic relationships between variables, while not requiring any of the variables to be strictly exogenous for estimating their effects.

My empirical model looks as follows:

[3] I chose countries based on availability of quarterly data on variables I use in my baseline panel VAR model. For the list of the countries, see Footnote 1.

[4] The authors get these data from the IMF's Balance of Payments Statistics (BOPS) and International Financial Statistics (IFS) databases.

[5] In order to dampen observed seasonal fluctuations, I smooth the data on consumption and fixed capital formation using 8-quarter centered moving average before calculating their growth rates. The data on real credit growth is already seasonally adjusted.

$$y_{i,t} = \mu_i + \sum_{j=1}^{p} A_j y_{i,t-j} + e_{i,t} \tag{1.1}$$

where $i = 1, \dots, N$ are the cross-sectional (i.e., country) indices, $t = 1, \dots, T$ are the time period indices, $y_{i,t}$ is a 7×1 vector of (endogenous) variables for each country, A_j is a 7×7 matrix of coefficients (for each lag order) that are assumed to be common across the sample countries, p is the lag length of the endogenous variables, μ_i is a vector of country-specific fixed effects, and $e_{i,t}$ is a vector of random errors (i.e., the VAR residuals). $y_{i,t}$ includes seven variables: gross equity inflows, gross debt inflows,[6] real GDP growth[7], short-term real interest rate (calculated as one-year money market nominal interest rate minus CPI inflation, and taken as deviation from country-specific mean), the growth rate of real credit to the private sector, the growth rate of total (private and general government) final consumption expenditure, and the growth rate of gross fixed capital formation.

I estimate my model using the Least Squares Dummy Variable (LSDV) estimator, as per Bun and Kiviet (2006), which was shown to have better finite sample properties as compared to GMM estimators when the time dimension is significantly larger than the cross-sectional dimension. The LSDV estimator accounts for country-specific fixed effects but generates a bias due to the inclusion, in dynamic panel models, of the lagged dependent variable (Nickell, 1981). This bias, however, is likely to be of no major concern since the time dimension of my data is sufficiently large. To choose the number of lags for my model specification, I use the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).[8] Both the AIC and the BIC suggest that I include four lags of the endogenous variables for estimating my panel VAR model. The confidence intervals of the IRFs are computed by using 200 Monte Carlo draws from the estimated model. To account for time-specific common factors such as the effects of global crises and the changes in global risk conditions, I remove the cross-sectional means of each variable in each quarter before estimating the model.

1.3.3. Identification

In order to recover the structural parameters from my panel VAR model given by Eq. (1.1), I should orthogonalize the shocks in my model, i.e., decompose the reduced-form residuals into mutually uncorrelated shocks. I can write my reduced-form panel VAR in companion form as follows:

[6] Both gross equity inflows and gross debt inflows are taken as deviations from country-specific linear trends.
[7] I use the Hodrick-Prescott filtered component of the growth rate of real GDP.
[8] I am grateful to Ulrich Glogowsky for sharing his own Stata program to determine the lag length in panel VAR models. I also use the Stata module *xtvar*, developed by Cagala and Glogowsky (2014), to estimate my model.

$$Y_t = \mu + AY_{t-1} + e_t \tag{1.2}$$

To obtain a structural representation of the above model, I should then find a lower triangular matrix B, such that $E(e_t e_t') \equiv \Omega = BB'$:

$$B^{-1}Y_t = \kappa + B^{-1}AY_{t-1} + \varepsilon_t \tag{1.3}$$

By construction ε_t is orthogonal because $E(\varepsilon_t \varepsilon_t') = B^{-1}\Omega(B^{-1})' = B^{-1}BB'(B^{-1})' = I$.

This is the recursive identification scheme, which is based on the Cholesky decomposition of reduced-form VAR residuals. The vector moving average representation of my model can be written as follows:

$$Y_t = \nu + B\varepsilon_t + AB\varepsilon_{t-1} + A^2B\varepsilon_{t-2} + A^3B\varepsilon_{t-3} + \cdots \tag{1.4}$$

or

$$Y_t = \nu + C(L)\varepsilon_t \equiv \nu + C_0\varepsilon_t + C_1\varepsilon_{t-1} + C_2\varepsilon_{t-2} + \cdots \tag{1.5}$$

Then, the impulse responses at horizon h to structural shocks ε_t are given by:

$$\frac{\partial Y_{t+h}}{\partial \varepsilon_t} = C_h = A^h B$$

To justify the recursive ordering of the variables, I need identifying assumptions that are based on some theoretical considerations. As far as I know, there is no established theoretical model explaining the effects of different forms of capital inflows on economic growth. Therefore, here I consider a basic analytical framework to think about the short-run effects of debt and equity inflows.

Let's see how debt and equity inflows could affect the GDP growth in the short-run period. Suppose that a small open developing economy finances its consumption and investment in any period from a combination of domestic (output) and external (foreign debt and equity) sources:

$$C_t + I_t = Y_t + DI_t^* + EI_t^* \tag{1.6}$$

where C is domestic (private + public) consumption, I is domestic investment (i.e., gross capital formation), Y is domestic real GDP, DI^* and EI^* are the levels (in real terms) of financing obtained from foreign lenders (i.e., debt inflows) and from equity investors (i.e., equity inflows), respectively.[9]

[9] One can notice that Eq. (1.6) is solely a rearrangement of the standard GDP identity ($Y = C + I + G + NX$), where I merge private consumption (C) and government consumption (G) into a single term, C, and identify capital inflows ($DI^* + EI^*$) as the negative of net exports (NX). For simplicity, here I assume full capital inflow mobility but rule out any capital outflow mobility to make gross and net inflows equal.

By rearranging Eq. (1.6) we get:

$$Y_t = C_t + I_t - (DI_t^* + EI_t^*) \tag{1.7}$$

If we take the growth rate of GDP, we have:

$$\ddot{y}_{t+1} = \frac{Y_{t+1}-Y_t}{Y_t} = \frac{C_{t+1}-C_t+I_{t+1}-I_t-(DI_{t+1}^*-DI_t^*)-(EI_{t+1}^*-EI_t^*)}{Y_t} = \ddot{c}_{t+1} + \ddot{\imath}_{t+1} - \ddot{d\imath}_{t+1}^* - \ddot{e\imath}_{t+1}^* \tag{1.8}$$

where $\ddot{x}_{t+1} = \Delta X_{t+1}/Y_t$ for every variable on the right-hand side.

Eq. (1.8) implies that any shock to either debt or equity inflows (as a share of GDP) will lead to an increase in current GDP growth *only* on the condition that the resulting rise in consumption or investment spending (as a share of GDP) is greater than that capital inflow shock. This is possible for fixed investment if, for instance, an additional capital inflow induces a domestic entrepreneur to spend on a piece of machinery, of which she could not afford the full cost—but only a fraction—without external borrowing. In the case of consumption, this additional growth can materialize if an extra unit of capital inflow—by raising consumers' demand—encourages domestic producers to increase their supply of goods and services. So based on this basic and intuitive framework, it is appropriate to order the inflows of debt and equity before the growth rates of investment, GDP and final consumption.

In fact, in support of the ordering of debt- and equity-based capital inflows before GDP growth, recent empirical studies find that the main drivers of emerging market capital inflows are factors exogenous to recipient countries, such as the U.S. interest rates, global commodity prices, growth in advanced economies (Byrne and Fiess, 2016), and changes in global risk and uncertainty (Forbes and Warnock, 2012). Domestic factors, instead, are found to be less important, with country-specific characteristics driving capital inflows to emerging markets being financial openness and the quality of institutions, rather than domestic output and interest rates (Byrne and Fiess, 2016). Eventually, ordering capital inflows before GDP growth makes complete sense even in the case that foreign investors make their investment decisions on the basis of *expected* growth in recipient countries: since growth expectations are typically based on past/recent growth performance, capital inflows can react to GDP growth only with a time lag.

In Appendix 1.A, I also provide a conceptual framework based on demand and supply of foreign debt and equity funds to rationalize the occurrence of the inflows of foreign capital. Based on this framework, I expect a change in debt inflows to have a contemporaneous effect on equity inflows through the real interest rate (and hence via the credit channel), while a change in equity inflows to not have any *immediate* effect on debt inflows. Therefore, my baseline panel VAR estimation is based on the following ordering: debt inflows, short-term real interest rate, real credit growth, equity inflows, growth of fixed capital formation, real GDP growth, and growth of consumption spending.[10] However, albeit not explicitly stated in my conceptual framework (Appendix 1.A), it is probably more appropriate to think about the *long-term interest rate*—rather than the short-term money market interest rate—as a factor modulating the effect of debt inflows on equity inflows, while the short-term rates may themselves be possibly affected by the equity inflows. Moreover, in the short run, capital inflows may simply raise consumption, while investment growth may be the result of GDP growth rather than vice versa. For this reason, I also use an alternative ordering where I place the short-term interest rate and real credit growth after the equity inflows, and switch the places of fixed capital formation and consumption growth.

1.4. Empirical analysis

1.4.1. Baseline model results

In this section I present the impulse-response functions of my variables of interest to one-standard-deviation shocks identified in the previous section. I am particularly interested in the response of real GDP growth to the debt and equity inflow shocks.

As we can see from Figure 1.2, a positive shock to debt inflows has a positive effect on real GDP growth on impact, while a shock to equity inflows has no effect. The impact effect of debt inflows seems to operate both through the channel of fixed capital formation and that of demand for consumption. However, interestingly, this positive shock to debt inflows does not have any significant impact on real credit growth to the private sector, which, as such, has a positive impact effect on the growth rates of both consumption and fixed capital formation. This suggests that banks may not necessarily increase their credit to the private sector in response to a debt inflow shock. Another noteworthy observation is that a positive debt inflow shock starts to exert a negative effect on fixed capital formation after two quarters and on GDP growth after five quarters, which is probably due to the fact that the rise in external borrowing increases the debt burden to the country.

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[10] Because I use panel data with countries of different size and characteristics, I normalize both equity inflows and debt inflows by GDP. This, however, creates an artificial downward bias in the relationship between these inflows and GDP growth, my main variables of interest. To adjust for this negative bias, I multiply these "equity inflows to GDP" and "debt inflows to GDP" ratios by "one plus the growth rate of GDP" in each period. I do the same with gross fixed capital formation and final consumption expenditure before calculating their growth rates, since they are also normalized by GDP.

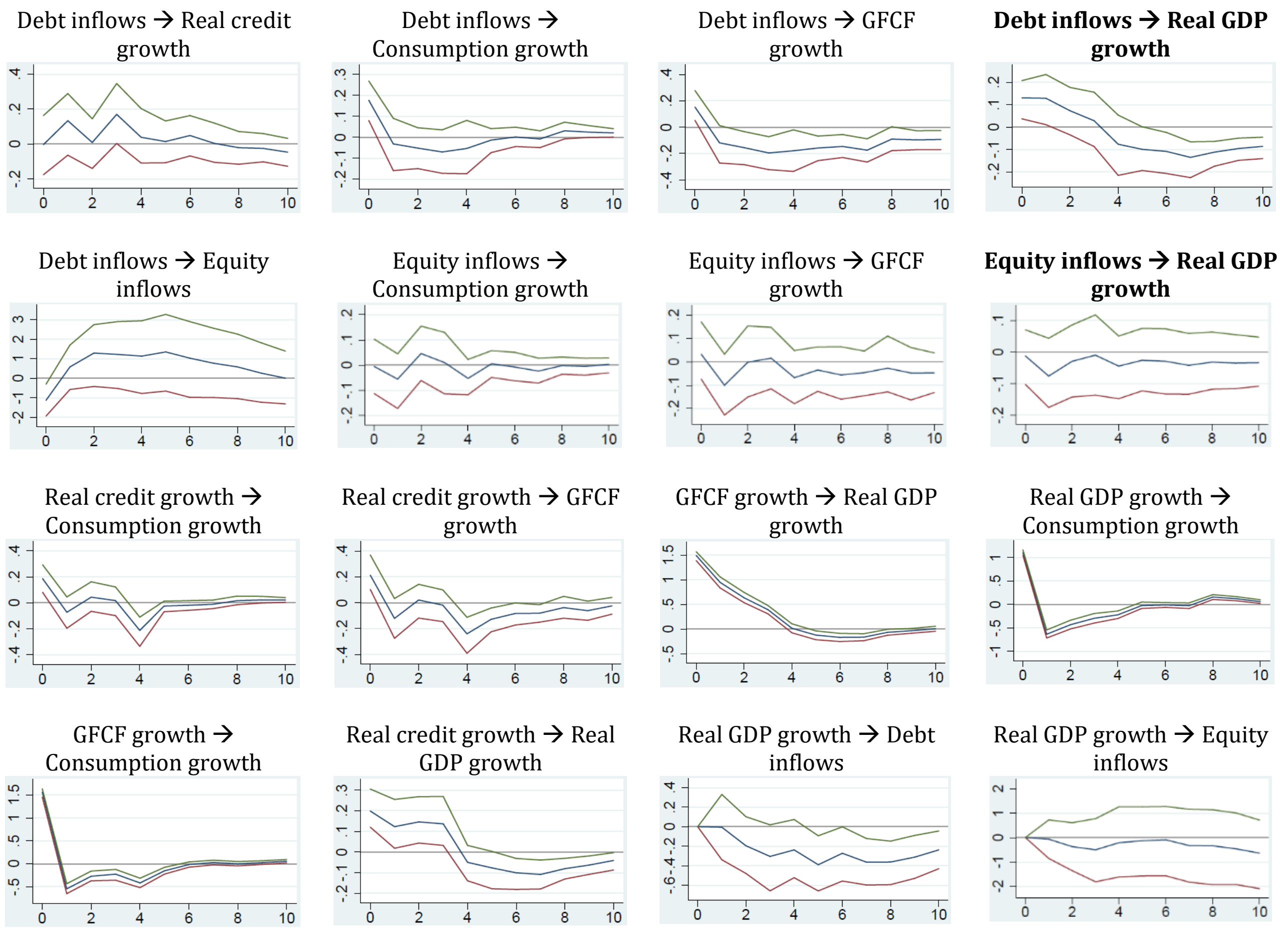


Figure 1.2. Impulse-response functions (to one-standard-deviation shocks) computed from estimated baseline panel VAR for 28 countries over the period 1995Q1 to 2015Q4. 95% confidence bands are based on 200 Monte Carlo draws from the estimated model.

We can also see from Figure 1.2 that a debt inflow shock has a negative effect on equity inflows on impact, which probably suggests, according to my conceptual framework (see Figure 1.A3 in the Appendix), that the debt inflows to emerging countries in my sample are driven *mostly* by supply-side factors (i.e., by the actions of global suppliers of debt investment rather than those of domestic borrowers). Equity inflows increase neither investment nor consumption. From Eq. (1.8) we see that it is impossible for equity inflows to have a zero impact on consumption, investment and GDP growth at the same time. One should note, however, that the debt and equity inflows in Equations (1.2) and (1.3) represent *net* inflows, as opposed to gross inflows, the distinction I have disregarded in my analytical framework by ruling out capital outflows. Then, the observed result—that gross equity inflows have no impact on consumption, capital formation, and real GDP growth—can only be true if foreign equity inflows to a country are associated with an equal amount of outflows by domestic agents. I test this by adding gross equity and debt outflows (i.e., outflows of FDI and portfolio equity, and outflows of portfolio debt and bank lending, from domestic agents to the rest of

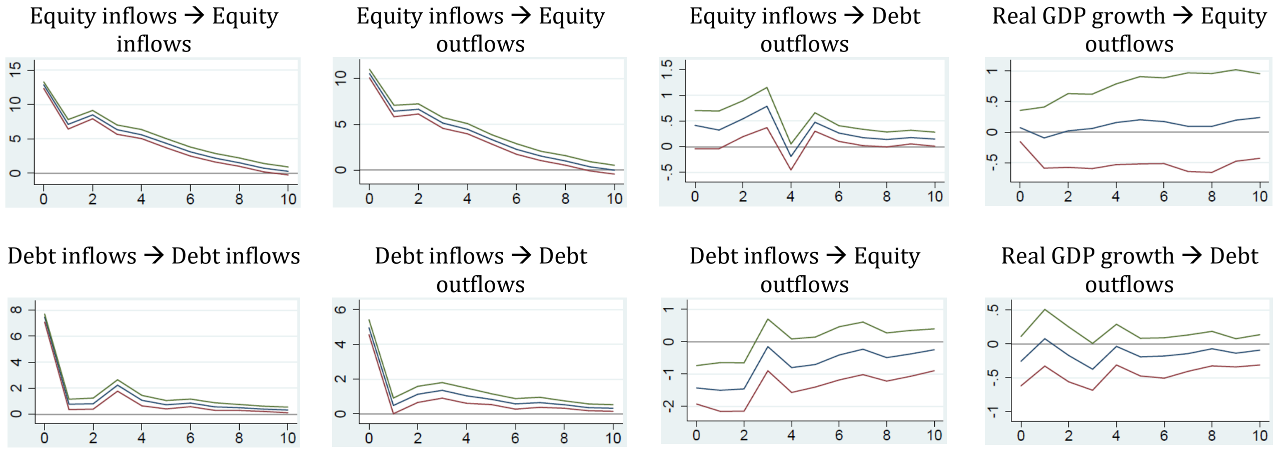


Figure 1.3. Impulse-response functions (to one-standard-deviation shocks) computed from estimated panel VAR for 28 countries over the period 1995Q1 to 2015Q4. 95% confidence bands are based on 200 Monte Carlo draws from the estimated model.

the world)[11] into my panel VAR and placing these outflows as the last two variables in my recursive ordering.

Figure 1.3 shows that gross equity inflows have an extremely strong positive (close to one-to-one) association with gross equity outflows—both contemporaneously and over several subsequent quarters,—hence leading to a small change in *net* equity inflows. Gross debt inflows, likewise, have a very strong positive association with gross debt outflows.[12] However, equity inflows also seem to have a positive effect on debt outflows, while debt inflows have a negative impact on equity outflows. Thus, overall, a shock to gross debt inflows seems to result in the rise of net capital inflows (including debt and equity inflows), while a shock to gross equity inflows seems to have no significant impact on net capital inflows. These results explain the observed lack of impact of gross equity inflows on investment, consumption and GDP growth.

The question that may arise is: why do gross equity inflows fail to affect fixed capital formation, whereas they are supposed to finance the unmet investment needs in emerging markets? One possible answer is that, if an equity inflow shock is driven by the actions of foreign investors, thus shifting up the *FE* curve in Figure 1.A2 (in the Appendix), then the resulting fall in marginal profitability of equity-financed domestic firms—which connotes the reduction in the amount of profitable investment opportunities for domestic investors—may induce domestic agents to pursue investment opportunities abroad. This, then, would amount

[11] The data are obtained from Cerutti, Claessens and Rose (2017), the same data set I used for obtaining the data on inflows.
[12] Overall, these results strongly support the co-movement of gross capital inflows and outflows documented by Broner et al. (2013).

to a crowding-out effect of equity inflows on domestic investment. Mody and Murshid (2005), indeed, argued that agents' portfolio optimizing behaviour under financial integration may not involve increasing domestic investment, but rather achieving diversification objectives. Nevertheless, to make better sense of the possible mechanism of the crowding-out effect of equity inflows, we should review the components of these inflows.

Equity inflows are composed of inflows of FDI and portfolio equity. Portfolio equity inflows involve acquisition of shares in domestic stock markets, where the foreign investors do not usually have a lasting interest. Because these inflows typically imply a purchase of existing assets from domestic shareholders, they do not finance new capital formation per se. Instead, they can simply be used to increase the consumption of previous shareholders or to acquire foreign assets. On the other hand, an FDI inflow is more likely to increase capital formation since it relates to the purchase of domestic shares where the foreign investor has a lasting interest (10 percent or more of voting stock according to the IMF definition). However, the definition of FDI still incorporates two different forms of foreign investment: "greenfield" investment, where foreign entrepreneurs build their operations in a country from the ground up, and cross-border mergers and acquisitions (M&A), where foreign investors acquire already existing assets. While M&A sales—by generating a rent to the firms' previous domestic owners (see Harms and Méon, 2017)—may have an effect similar to that of portfolio equity, "greenfield" investment does increase capital formation (but not necessarily contemporaneous GDP)[13]. The IRFs in Figures 1.2 and 1.3, therefore, suggest that the equity inflow shocks that I have identified in my panel VAR probably capture the shocks to inflows of portfolio equity and M&A-type FDI, rather than "greenfield" FDI. In fact, Calderón, Loayza and Servén (2004) argue that, in the 1990s, FDI in the form of M&A grew much more rapidly than "greenfield" FDI in developing countries. In addition, Mody and Murshid (2005) also find that capital inflows to developing countries in the last two decades of the last century were "channelled increasingly through portfolio flows"—including FDI in the form of M&A— "resulting in weak investment stimulus".[14]

The observed lack of real impact of gross equity inflows in emerging and developing countries makes sense if we take into consideration the possible crowding-out effects of these inflows that may be, for example, contingent on the absorptive capacity of these economies,

[13] While capital formation resulting from "greenfield" investment has a positive effect on GDP, the initial fixed cost associated with this type of investment usually reflects the imports of foreign machinery (see Harms and Méon, 2017), thus having a negative impact on current net exports.

[14] Some other studies finding a short-run crowding-out effect of, in particular, FDI inflows on domestic investment include Wang (2010) and Jude (2018).

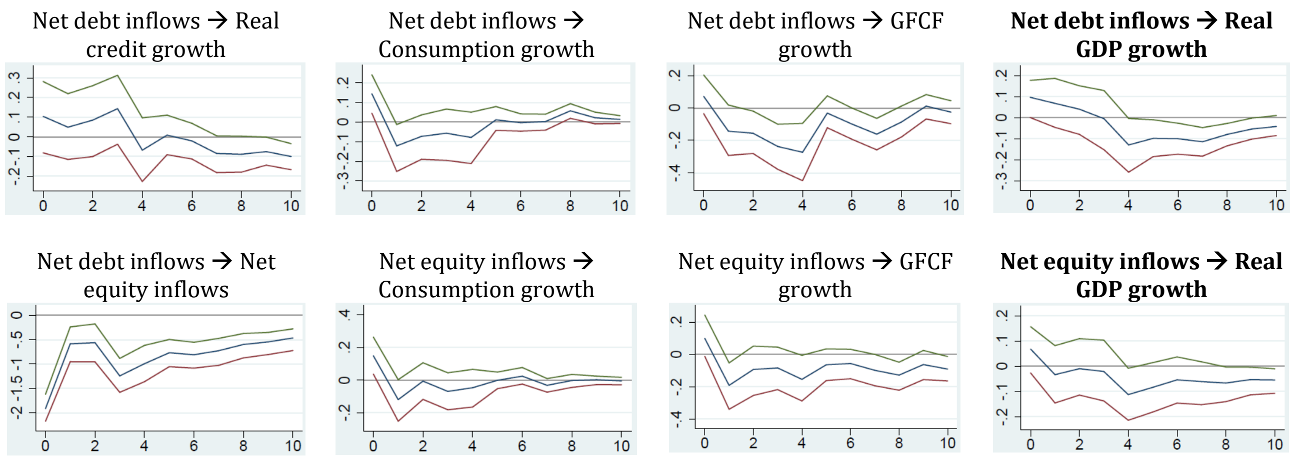


Figure 1.4. Impulse-response functions (to one-standard-deviation shocks) computed from estimated panel VAR for 28 countries over the period 1995Q1 to 2015Q4. 95% confidence bands are based on 200 Monte Carlo draws from the estimated model.

which in turn depends on the level of their financial and institutional development (see, e.g., Durham, 2004). I can check this by splitting my sample countries in two groups based on their different economic and institutional characteristics. Before this, however, to check the correctness of my reasoning about the crowding-out effects of gross equity inflows, I estimate my baseline panel VAR model using net—rather than gross—inflows of debt and equity capital, which I measure as the difference between gross inflows and gross outflows. Figure 1.4 above shows, indeed, that net equity inflows do have a positive impact on domestic consumption growth, even though they do not seem to have a significant impact effect on fixed capital formation and GDP growth. Thus, the fact that net equity inflows raise contemporaneous consumption growth, despite their lack of significant contemporaneous impact on domestic investment and GDP growth, is consistent with my basic analytical framework summarized in Eq. (1.8). What is somewhat surprising, however, is that net equity inflows seem to have a negative effect on fixed capital formation in later periods, albeit this effect is not stable.

1.4.2. Results of robustness checks

As a robustness check, I estimate my panel VAR: (i) with an alternative ordering as mentioned in Section 1.3.3; (ii) with three lags instead of four; and (iii) excluding Cyprus and Mauritius. The IRFs from these robustness exercises are given in Appendix 1.C. In Figures 1.C1 (IRFs with an alternative ordering), 1.C2 (IRFs with three lags) and 1.C3 (IRFs excluding Cyprus and Mauritius), the impulse responses of growth rates of consumption, investment and GDP to a debt inflow shock are generally similar to those in Figure 1.2: debt inflows are found to have a positive effect on impact and a negative effect after some quarters on investment and GDP growth. The impulse responses to an equity inflow shock in Figures 1.C1 and 1.C2 are also similar to those in Figure 1.2 (i.e., no significant effect of equity inflows); in Figure 1.C3, however, we see that a shock to equity inflows has a significantly positive short-run impact on growth of consumption, investment and real GDP, and a somewhat negative effect after several quarters, although this negative effect is much less pronounced (and smaller in magnitude) than that of debt inflows.

These general results notwithstanding, we can be interested to see whether the effects of foreign debt and equity inflows on consumption and investment can differ depending on certain economic and institutional characteristics of emerging and developing countries. To test this, I estimate my panel VAR model by splitting my sample into two groups of countries based on (i) average income (i.e., per capita real GDP) and (ii) institutional quality (proxied by the average of three governance indicators: control of corruption, rule of law, and regulatory quality)[15].

Figures 1.5 and 1.6 show, respectively, the panel IRFs for samples of 14 emerging and developing countries with above-median and below-median average GDP per capita over the period 1995Q1-2015Q4. We see that debt inflows are more likely to reduce investment (after 2 quarters) and GDP growth (after 5 quarters) in lower-income developing countries, while equity inflows seem to have significant effects on consumption (a positive impact effect), investment (a somewhat negative effect after 4 quarters) and GDP growth (a positive impact effect and a somewhat negative effect after 6 quarters) in higher-income emerging countries. We can also observe that debt inflows are more likely to have a positive effect—albeit not very strong—on private credit growth in lower-income countries; this might be partly, as argued by Igan and Tan (2017), due to a lower level of domestic banking sector development in these countries, whereby foreign inflows relieve credit constraints and boost credit growth.

Figures 1.7 and 1.8 show, respectively, the panel IRFs for samples of 14 emerging and developing countries with above-median and below-median quality of governance over the period 1995Q1-2015Q4. We see that debt inflows seem to have a short-run positive effect on consumption, investment and GDP growth, and are much more likely to reduce consumption (after 3 quarters), investment (after 3 quarters) and GDP growth (after 4 quarters) in developing countries with lower governance quality, but they have no similar effects in those with higher governance quality (though they only have a small negative effect on GDP growth

[15] I obtain the data from The Worldwide Governance Indicators (WGI) by Kaufmann and Kraay: http://info.worldbank.org/governance/wgi/#home

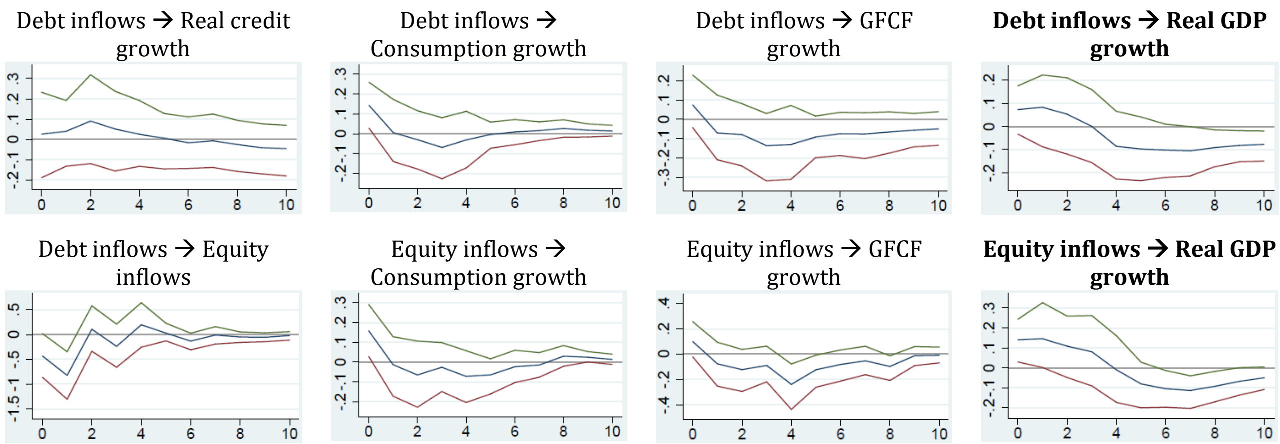


Figure 1.5. Impulse-response functions (to one-standard-deviation shocks) computed from estimated panel VAR for 14 countries with *above-median average GDP per capita* over the period 1995Q1 to 2015Q4. 95% confidence bands are based on 200 Monte Carlo draws from the estimated model.

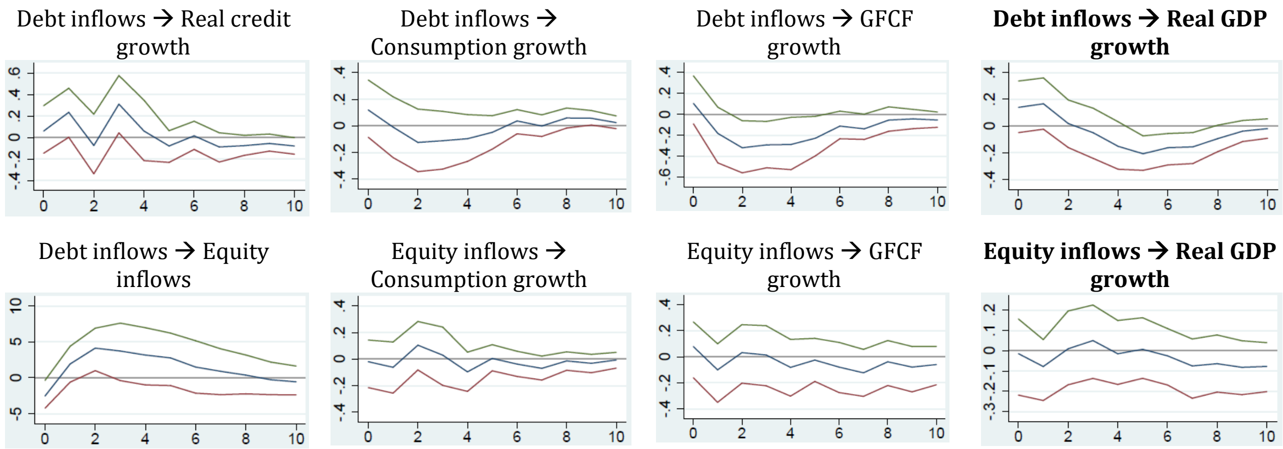


Figure 1.6. Impulse-response functions (to one-standard-deviation shocks) computed from estimated panel VAR for 14 countries with *below-median average GDP per capita* over the period 1995Q1 to 2015Q4. 95% confidence bands are based on 200 Monte Carlo draws from the estimated model.

after around 6 quarters). By contrast, equity inflows tend to have no strong effect on these variables in countries of either a higher or lower governance quality, albeit they seem to have some short-lasting negative effect on investment growth (after 4 quarters) in countries with lower-quality governance. Also note that debt inflows are much more likely to increase private credit growth (after 2 quarters) in countries with a lower governance quality, probably due to higher importance of credit constraints, as argued by Igan and Tan (2017).

Overall, Figures 1.5 to 1.8 suggest that debt inflows are more likely to have a negative medium-run effect on capital formation and GDP growth in countries with lower income per capita and lower governance quality. Also, equity inflows do not seem to be completely “harmless” for higher-income emerging and developing countries. The observed effects of debt and equity inflows only partly support an earlier finding by Davis (2015), which suggests

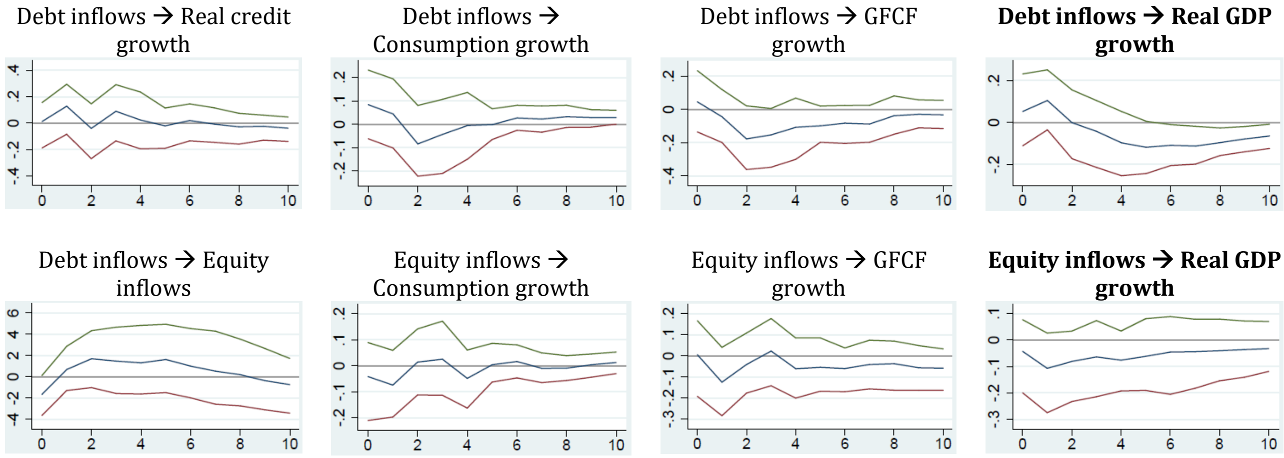


Figure 1.7. Impulse-response functions (to one-standard-deviation shocks) computed from estimated panel VAR for 14 countries with *above-median governance quality* over the period 1995Q1 to 2015Q4. 95% confidence bands are based on 200 Monte Carlo draws from the estimated model.

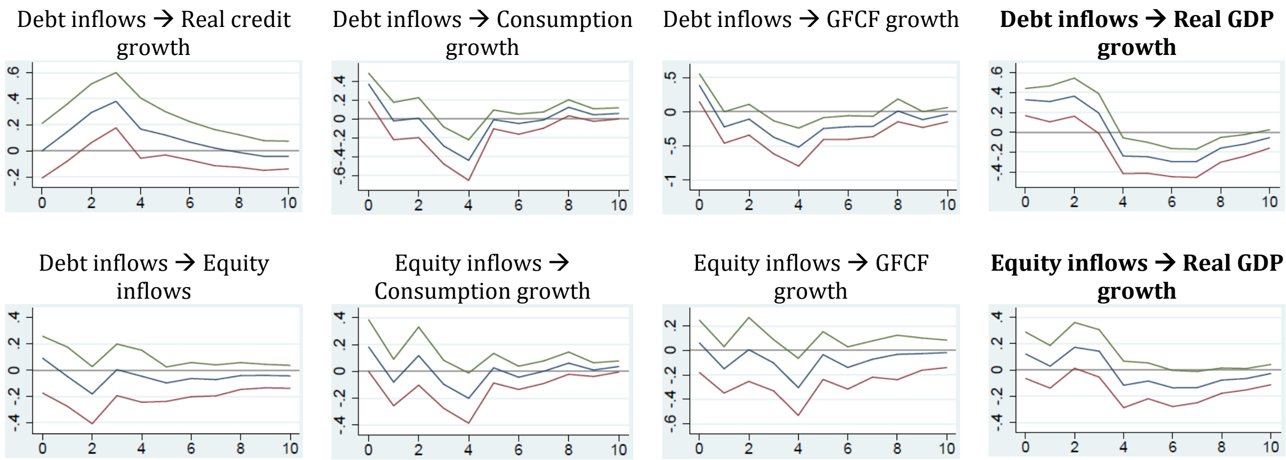


Figure 1.8. Impulse-response functions (to one-standard-deviation shocks) computed from estimated panel VAR for 14 countries with *below-median governance quality* over the period 1995Q1 to 2015Q4. 95% confidence bands are based on 200 Monte Carlo draws from the estimated model.

that only debt inflows are responsible for destabilizing macroeconomic effects of capital inflows: my findings imply that equity inflows to higher-income developing countries may have a positive impact effect on consumption and GDP growth and a short-lasting negative effect on the growth of fixed investment and GDP in later periods, although the overall effect of equity inflows may be insignificant. In general, however, debt inflows seem to be much more destabilizing for emerging and developing countries. Continued debt inflow surges to emerging and developing countries may generate several problems in the medium to long run by leading to the real exchange rate appreciation, hurting exports, and making these economies more susceptible to crises associated with sudden stops and capital flow reversals. This is also supported by Kalemli-Özcan (2015), who finds that both debt and equity inflows have a positive initial impact on output growth, while the effect of debt inflows becomes negative afterwards; she explains this with debt inflows crowding out private investment (as my results suggest as well), leading to an appreciation and hurting exports.

In addition, in Appendix 1.C, I present the IRFs from the panel VARs estimated for three groups of developing and emerging countries divided by geographical regions: Asia (6 countries), Central and Eastern Europe (13 countries), and Latin America (7 countries). I find that, in Asia and Latin America, the initial positive impact of gross debt inflows on real GDP growth lasts up to three quarters; these inflows start having a negative growth effect after five quarters in Asia and after seven quarters in Latin America, though this negative effect is short lasting in Latin America. In Central and Eastern Europe, the effect of debt inflows is positive only on impact and turns slightly negative after approx. two years. On the other hand, the lack of any effect of gross equity inflows that I found in my baseline model only applies to countries of Central and Eastern Europe. In Asian countries equity inflows are found to have a positive effect on GDP growth that lasts for up to three quarters, while in Latin America equity inflows have a short-run positive effect on GDP growth after two quarters and a negative effect after seven quarters. These results show that, even though debt inflows have destabilizing (i.e., positive short-run and negative medium- to long-run) growth effects and equity inflows lack any effect on GDP growth in my overall sample of developing and emerging countries, these effects are not necessarily homogeneous across different geographical regions.

Generally speaking, however, my results indicate that surges in foreign debt inflows to emerging and developing countries increase contemporaneous GDP growth by raising current consumption and investment, but decrease GDP growth by reducing investment in later periods. On the other hand, surges in foreign equity inflows seem to have either insignificant or minor medium-run effect on consumption, investment and GDP growth. The lack of real impact of foreign equity inflows seem to be mostly due to their crowding-out effect on domestic equity holdings and partly on domestic debt holdings (as mentioned in Section 1.4.1).

1.5. Conclusion

This chapter shows that inflows of foreign debt and equity have different (asymmetric) effects on consumption, investment, and GDP growth in emerging and developing economies. By using panel VAR analysis based on quarterly macroeconomic data from 1995Q1 to

2015Q4, my results indicate that debt inflows increase consumption, investment and GDP growth on impact, but decrease investment and GDP growth in later periods (i.e., after around a year) for several quarters. Equity inflows, on the other hand, do not seem to have a significant impact on consumption, investment, and GDP growth of emerging and developing countries on average. This lack of impact of equity inflows might be primarily due to their crowding-out effect on domestic holdings of debt and equity, which results in equity and debt outflows by domestic agents.

In order to account for cross-country heterogeneity among the emerging and developing countries, I carry out my analysis by splitting my sample into two groups based on their (i) real GDP per capita and (ii) governance quality. When I do this, I find that countries with higher income per capita may only benefit from debt inflows in the form of a positive impact effect on consumption, but are harmed by them in the form of a negative medium-run effect (after around 2 years) on GDP growth; also, countries with lower per capita income are harmed by debt inflows in the form of reduced investment (after 2 quarters) and reduced GDP growth (after 5 quarters) in the medium run. On the other hand, countries with lower governance quality benefit from debt inflows in terms of increased consumption, investment and GDP growth in the short run, but are hurt by reduction in all of these indicators in the medium run. My findings regarding equity inflows indicate that, although their effects are not so much destabilizing as those of debt inflows, higher income emerging countries might still need to be attentive, since an equity inflow shock in these countries seems to have a somewhat negative effect on investment and GDP growth in later periods following a positive impact effect on consumption and GDP growth.

Overall, my results suggest that debt inflows have more destabilizing effects on the economies of emerging and developing countries, in the sense of "short-run gain, long-run pain" (see Bussiere and Fratzscher, 2008), and this is mostly true for those countries with lower quality of governance. On the contrary, equity inflows are not found to have such destabilizing effects on the economies of emerging and developing countries in general. This implies that lower-income emerging and developing countries would be relatively better off by trying to attract capital inflows in the form of equity rather than debt; at the same time, developing countries should focus on improving their governance quality (in such areas as control of corruption, regulatory quality, and the rule of law) so that they could avoid potential harms caused by capital inflows, particularly, in the form of debt.

One of the limitations of my analysis consists in the availability of quarterly data only for limited number of developing and emerging countries. Since my robustness analyses by splitting the countries on the basis of certain characteristics (such as average income, governance quality, and geographical location) show that results may sometimes differ due to these heterogeneities, having a large number of countries would probably make my findings more robust and externally valid. Another limitation is the lack of a fully-fledged theoretical model that could possibly provide a more thorough explanation for the observed differential effects of debt and equity inflows on macroeconomic performance. Hence, a deeper theoretical investigation into the interrelationships and macroeconomic effects of debt-based and equity-based capital flows would be beneficial both for economists to better understand the effects of financial globalization and for policymakers to design more appropriate policies regarding capital controls.

Appendix 1.A: A conceptual framework for the determination of debt and equity inflows

In order to rationalize the occurrence of debt and equity inflows in developing countries, I try to illustrate—in a simplified supply-and-demand framework—what may drive these inflows in the first place. In a manner slightly similar to Razin, Sadka and Yuen (2001), I assume that low-productivity domestic firms seek equity finance, and those with a productivity level above a certain threshold no longer raise equity (i.e., they either use internal funds or borrow). However, because only firms themselves can observe their true productivity—hence creating an informational asymmetry between the parties—I assume that firms' observed *profitability* is the mechanism bringing together seekers and providers of equity capital. Moreover, higher availability of equity markets—and hence lower costs of equity issuance—increases firms' willingness to obtain equity (including foreign equity). Thus, demand for equity finance depends negatively on profitability and positively on market interest rates[1] and stock market development. So, on the demand side, desired levels of external borrowing and external equity issuance of a representative domestic firm can be written as:

$$B = b_0 - b_1 r \tag{1.A.1}$$

$$Q = q(d) \cdot (r^e + \Delta - \pi) \tag{1.A.2}$$

where B and Q denote, respectively, the desired levels of foreign borrowing and foreign equity issuance, b_0 is the base level of desired external borrowing unrelated to interest rates, r captures all the possible real interest rates and r^e is the equilibrium real interest rate, Δ is an add-on term such that firms have a non-zero demand for foreign equity finance up to the point $(r^e + \Delta)$, π is the level of profitability[2], and $q(d)$ is a parameter directly proportional to the level of stock market development (d). Equations (1.A.1) and (1.A.2) are also consistent with the "pecking order" of corporate capital structure, where firms prefer internal funds to debt and debt to outside equity when financing their investment (see, e.g., Katagiri, 2014).

On the supply side, we have desired levels of lending (FL) and equity investment (FE) by foreign agents, where FL depends positively on the country's "creditworthiness" (c) and domestic interest rate premium ($r - r^*$, where r^* is the "world" interest rate), and FE depends

[1] High interest rates make it less likely for a firm to take a loan and more likely to seek equity instead.

[2] I assume that demand for equity finance is proportional to the term $(r^e + \Delta)$ and that $\pi_{max} \gg r^e + \Delta$. I also assume that the form of the distribution of domestic firms' profitability levels does not change over time.

positively on domestic firms' profitability (π) relative to the "world" profitability (π^*) and on domestic stock market development:[3]

$$FL = \lambda(c) \cdot (r - r^*) \tag{1.A.3}$$

$$FE = \varphi_0 + \frac{\pi}{\pi^*}\varphi_1(d) \tag{1.A.4}$$

We can show the relationship between demand for and supply of foreign loans and domestic interest rate, and the relationship between demand for and supply of foreign equity finance and profitability, with the help of graphs as in Figures 1.A1 and 1.A2. Figure 1.A1 shows debt inflows as an effective level of foreign borrowing determined by the equilibrium interest rate. Figure 1.A2 shows equity inflows as an effective level of equity sales to foreigners determined by the marginal profitability (or equilibrium level of profitability, π^e) below which domestic firms cannot obtain foreign equity financing.

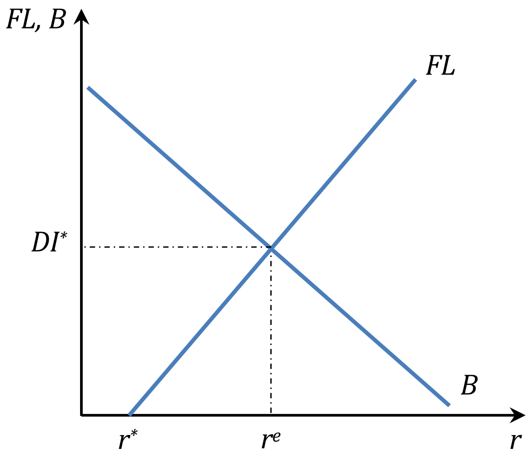


Figure 1.A1. Equilibrium level of debt inflows (DI^*) for given r^* and c.

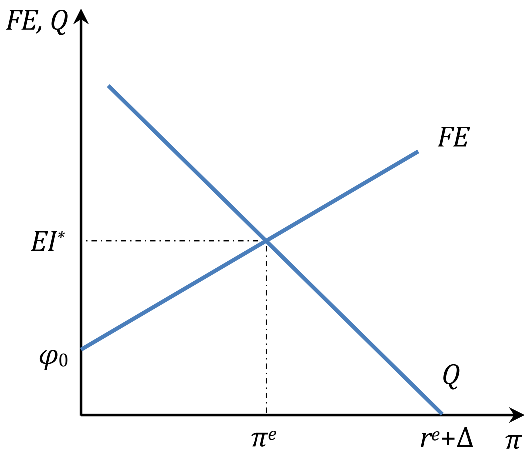


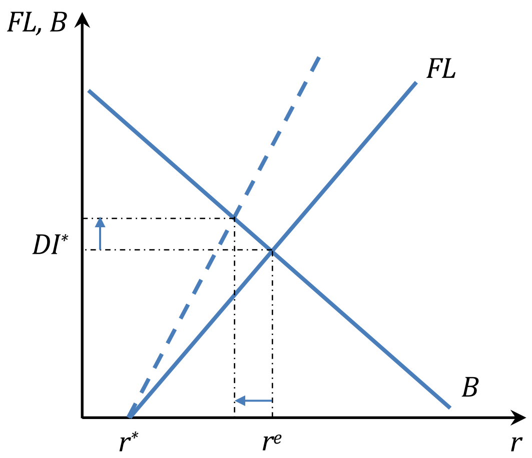
Figure 1.A2. Equilibrium level of equity inflows (EI^*) for given r^e, π^*, and d.

Now I attempt to briefly analyze how domestic investment could change in response to shocks to debt and equity inflows. The capital inflow shocks can arise from factors associated with the supply side (FL, FE) or the demand side (B, Q). In my simplified model, pure FL-related supply shocks can arise either from a shock to the country's "creditworthiness" (we can call it a "solvency" shock) or from a shock to the "world" interest rate. Pure FE-related shocks, on the other hand, can arise either from a shock to the "world" profitability (that

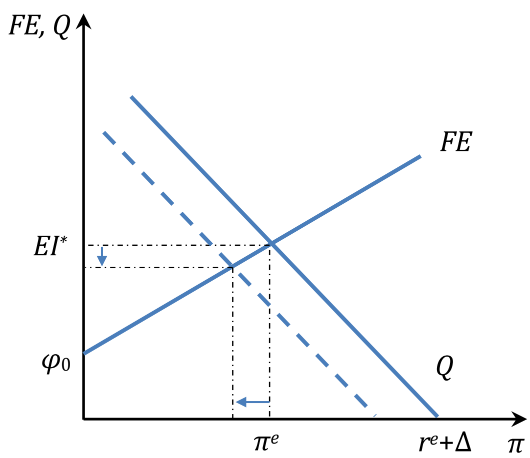
[3] Since global direct equity investors are often concerned with unit labour costs when choosing which country to invest in, I reasonably assume that firms' profitability is, for the most part, a function of both productivity and unit labour costs. I also assume that FE includes a part (φ_0) that is unrelated to relative profitability and stock market development; this may capture, for example, direct investors' interest in a foreign country purely motivated by availability of natural resources or raw materials. For simplicity, I abstract from other possible factors such as political stability and institutional quality, which may affect the supply of all types of foreign investment funds simultaneously.

captures the "world" productivity) or from a shock to φ_0, the autonomous component of FE (which could capture a country's "attractiveness" to investors that is unrelated to its relative productivity and stock market development). Moreover, a shock to the domestic stock market development would affect both the supply of and the demand for foreign equity finance.

Figure 1.A3, a–b, shows, as an example, the effect of a shock to a country's creditworthiness on debt and equity inflows. A positive "solvency" shock increases the supply of foreign loans to the country, thus reducing the interest rate at which the country borrows from foreigners and increasing the debt inflows.[4] The fall in the foreign borrowing rate decreases the demand for foreign equity finance and—by making some of the regular suppliers of equity exit the market—reduces the equity inflows into the country. Since this decrease in demand for equity capital induces foreign investors who intend to keep their share in the economy to finance firms with lower profitability, the marginal profitability of those financed by foreign equity (π^e) decreases. Because, as can be seen from Figure 1.A3, the short-term changes in debt and equity inflows are in opposite directions, the impact of this debt-inflow shock on the recipient country's level of investment will depend on the relative magnitudes of these changes, which in turn depend on the model parameters b_1, $q(d)$, $\lambda(c)$, and $\frac{\varphi_1(d)}{\pi^*}$.



a) The direct effect on debt inflows



b) The indirect effect on equity inflows

Figure 1.A3. The effect of a "solvency" shock on debt and equity inflows

[4] Of course, a country's creditworthiness is probably endogenous to its level of external debt accumulation, which I disregard here for simplicity. In this case, given the country has reached a certain threshold, additional debt inflows might increase its credit risk, hence decreasing debt inflows in the following period. This could partly explain the higher volatility and negative growth effects of debt inflows in the medium to long run, which was found in the literature.

Appendix 1.B: Data summary

Descriptive statistics of the raw data for the variables used in the empirical analysis

Variable		Mean	Std. Dev.	Min.	Max.	Observations
Gross debt inflows (% of GDP)	overall		15.155	-356.377	221.257	2264
	between	1.936	2.022	-0.422	10.267	
	within		15.046	-364.708	212.926	$\bar{T}$ = 80.86
Gross equity inflows (% of GDP)	overall		37.404	-57.186	712.129	2232
	between	6.866	15.722	0.899	85.286	
	within		34.716	-125.800	690.173	$\bar{T}$ = 79.71
Nominal money market interest rate (%)	overall		16.865	-0.148	433.167	2053
	between	9.850	5.674	4.078	27.522	
	within		15.865	-17.265	422.790	$\bar{T}$ = 73.32
Consumer price inflation (%)	overall		69.912	-4.591	1786.515	2343
	between	12.139	15.161	2.150	72.536	
	within		68.302	-62.777	1762.609	$\bar{T}$ = 83.68
Growth rate of real credit to the private sector (%)	overall		4.423	-31.679	29.394	2299
	between	2.001	1.139	0.102	4.771	
	within		4.283	-33.663	28.480	$\bar{T}$ = 82.11
Total (private + public) consumption (% of GDP)	overall		9.032	61.912	125.400	2064
	between	78.967	7.980	65.197	102.303	
	within		4.331	60.708	108.888	$\bar{T}$ = 76.44
Gross fixed capital formation (% of GDP)	overall		5.079	7.548	41.243	2092
	between	22.735	3.834	15.678	31.393	
	within		3.406	10.255	37.535	$\bar{T}$ = 74.71
Real GDP growth rate (%)	overall		4.378	-20.060	21.550	2119
	between	3.731	1.076	1.865	6.917	
	within		4.271	-21.026	21.779	$\bar{T}$ = 75.68
Gross debt outflows (% of GDP)	overall		17.316	-375.034	264.996	2153
	between	1.266	2.665	-0.047	13.986	
	within		17.200	-379.341	260.690	$\bar{T}$ = 76.89
Gross equity outflows (% of GDP)	overall		34.736	-71.601	692.724	2003
	between	4.150	14.059	-0.555	70.428	
	within		32.363	-119.765	674.962	$\bar{T}$ = 77.04

Appendix 1.C: Robustness checks

1. IRFs for the four-lag panel VAR with the *alternative* Cholesky ordering: debt inflows, equity inflows, short-term real interest rate, real credit growth, growth of consumption spending, real GDP growth, growth of fixed capital formation.

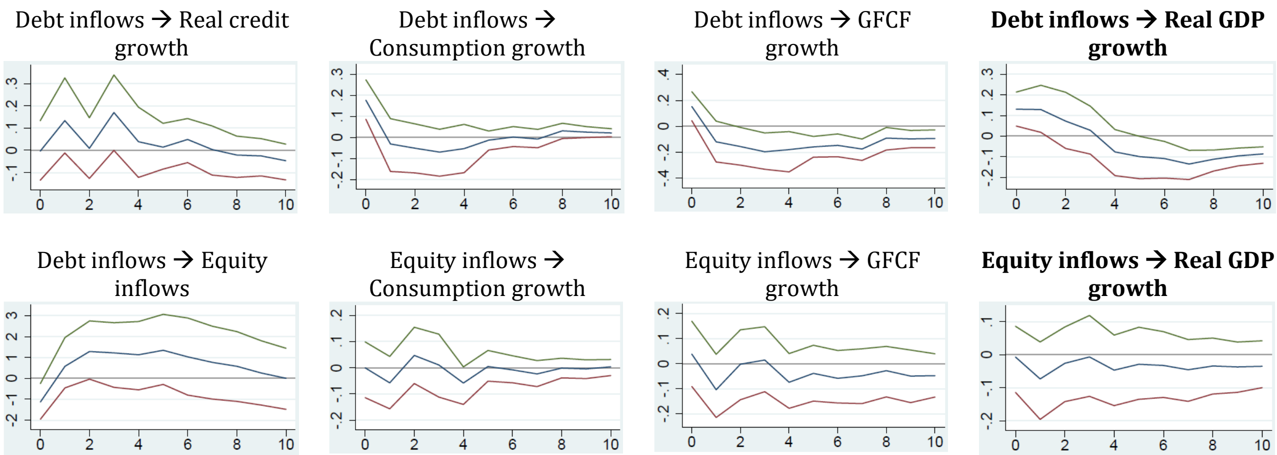


Figure 1.C1. Impulse-response functions (to one-standard-deviation shocks) computed from estimated panel VAR for 28 countries over the period 1995Q1 to 2015Q4. 95% confidence bands are based on 200 Monte Carlo draws from the estimated model.

2. IRFs for the *three-lag* panel VAR with the baseline Cholesky ordering: debt inflows, short-term real interest rate, real credit growth, equity inflows, growth of fixed capital formation, real GDP growth, growth of consumption spending.

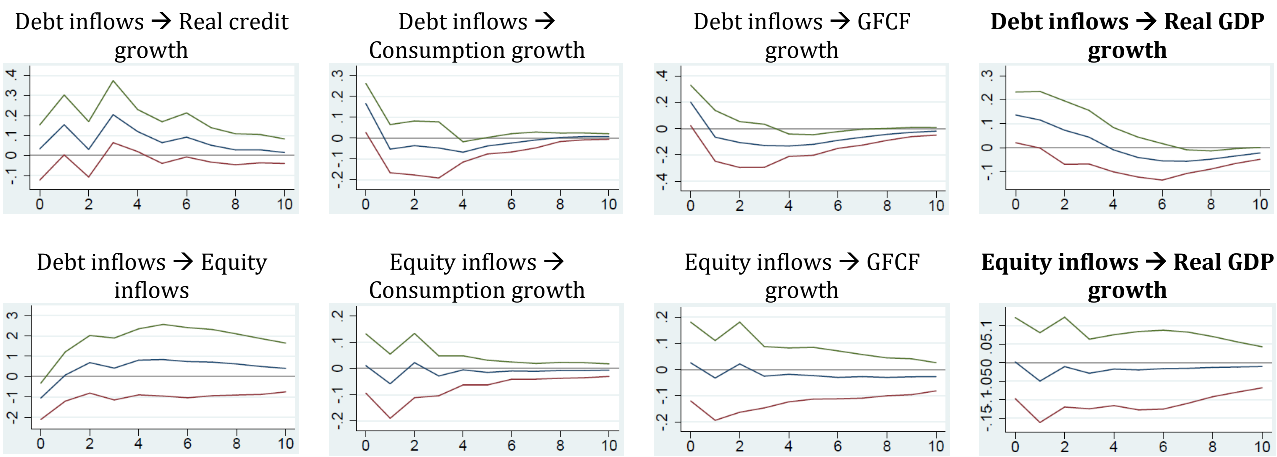


Figure 1.C2. Impulse-response functions (to one-standard-deviation shocks) computed from estimated panel VAR for 28 countries over the period 1995Q1 to 2015Q4. 95% confidence bands are based on 200 Monte Carlo draws from the estimated model.

3. IRFs for the four-lag panel VAR with the baseline Cholesky ordering for 26 countries (*Cyprus* and *Mauritius* are excluded).

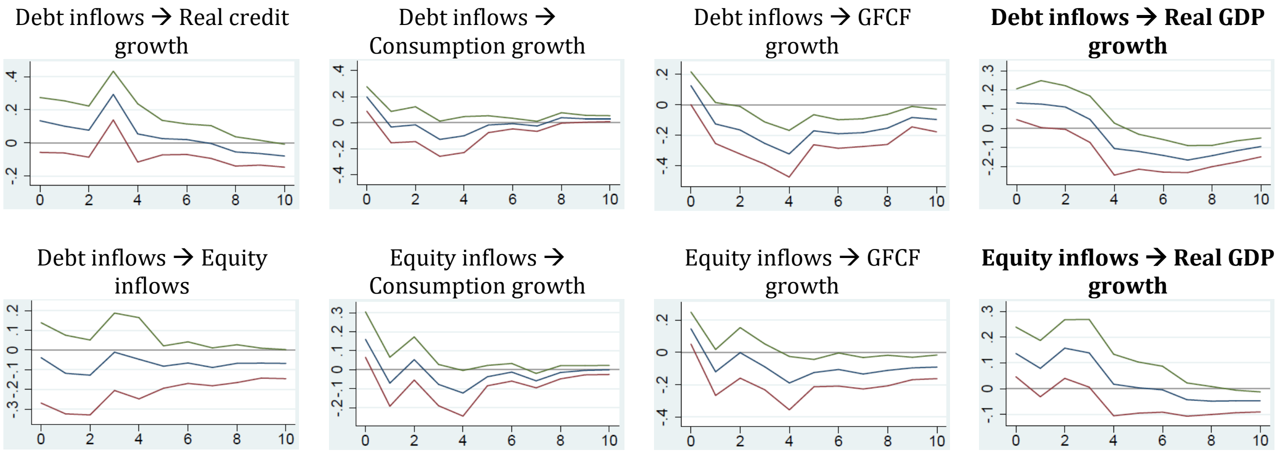


Figure 1.C3. Impulse-response functions (to one-standard-deviation shocks) computed from estimated panel VAR for 26 countries over the period 1995Q1 to 2015Q4. 95% confidence bands are based on 200 Monte Carlo draws from the estimated model.

4. Region-specific IRFs for the four-lag panel VAR with the baseline Cholesky ordering.

    a) Asia (*Indonesia, Kyrgyz Republic, Philippines, South Korea, Sri Lanka, Thailand*)

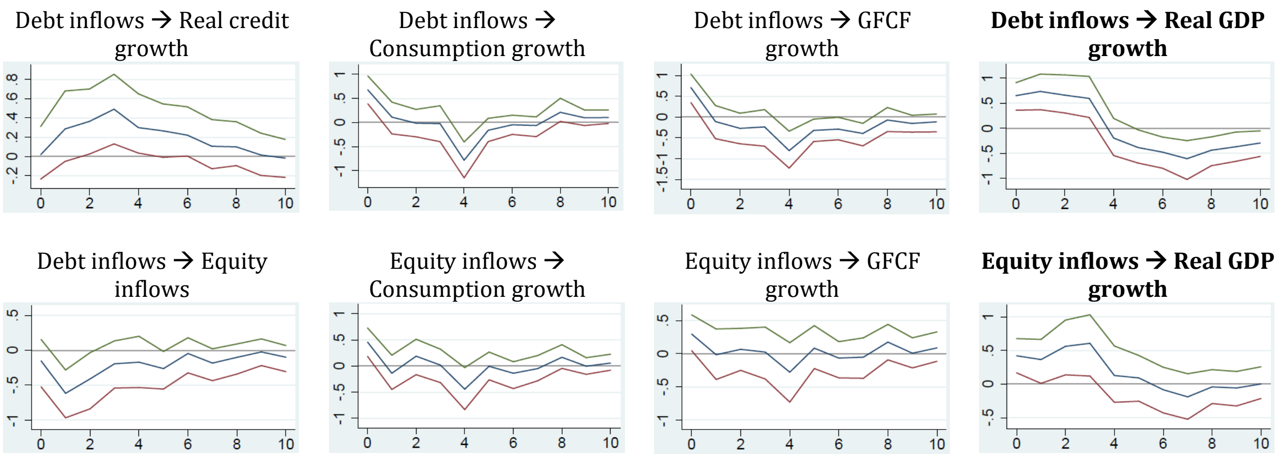


Figure 1.C4. Impulse-response functions (to one-standard-deviation shocks) computed from estimated panel VAR for 6 emerging and developing Asian countries over the period 1995Q1 to 2015Q4. 95% confidence bands are based on 200 Monte Carlo draws from the estimated model.

b) Central & Eastern Europe (*Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Georgia, Lithuania, Poland, Romania, Russia, Slovak Republic, Slovenia, Ukraine*)

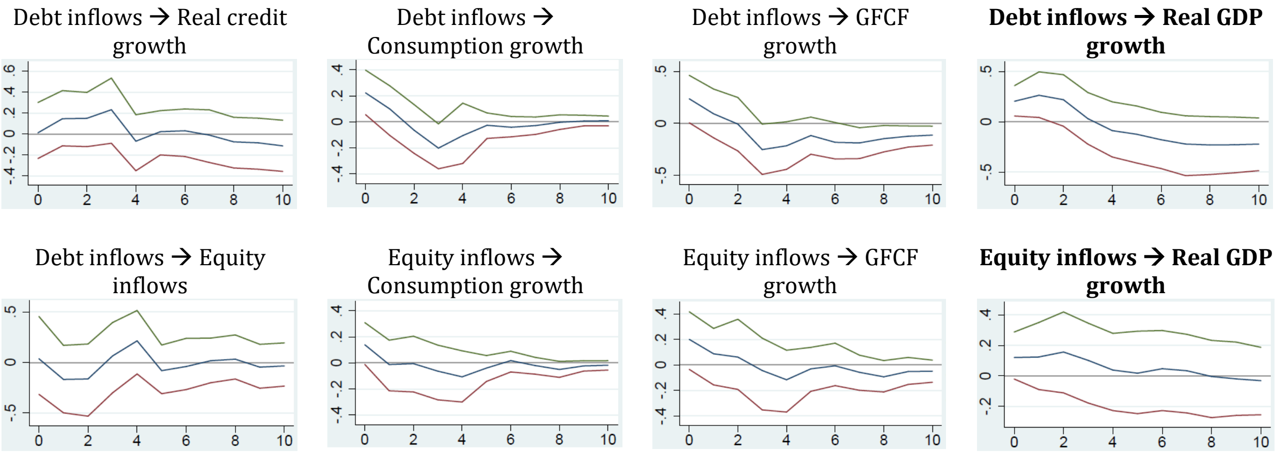


Figure 1.C5. Impulse-response functions (to one-standard-deviation shocks) computed from estimated panel VAR for 13 emerging and developing European countries over the period 1995Q1 to 2015Q4. 95% confidence bands are based on 200 Monte Carlo draws from the estimated model.

c) Latin America (*Argentina, Bolivia, Brazil, Chile, Colombia, Mexico, Peru*)

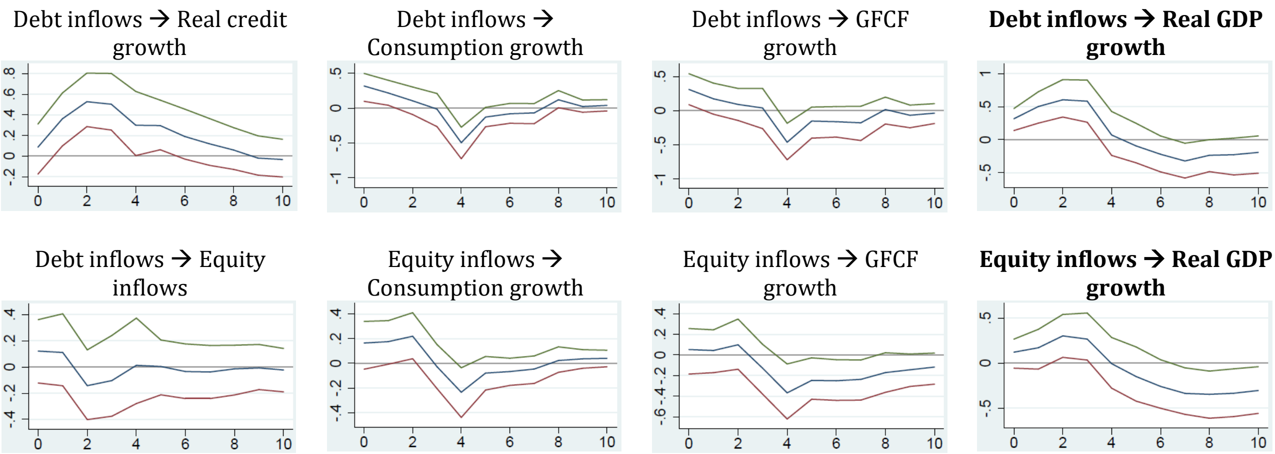


Figure 1.C6. Impulse-response functions (to one-standard-deviation shocks) computed from estimated panel VAR for 7 emerging and developing Latin American countries over the period 1995Q1 to 2015Q4. 95% confidence bands are based on 200 Monte Carlo draws from the estimated model.

Chapter 2

Private debt, public debt, and capital misallocation

Abstract

Does finance facilitate efficient allocation of resources? My aim in this chapter is to find out whether increases in private and public indebtedness affect capital misallocation, which is measured as the dispersion in the return to capital across firms in different industries. For this, I use a novel dataset containing industry-level data for 18 European countries and control for different macroeconomic indicators as potential determinants of capital misallocation. I exploit the within-country variation across industries in such indicators as external finance dependence, technological intensity, credit constraints and competitive structure, and find that private debt accumulation disproportionately increases capital misallocation in industries with higher financial dependence, higher R&D intensity, a larger share of credit-constrained firms and a lower level of competition. On the other hand, I fail to find any significant and robust effect of public debt on capital misallocation within the country-sector pairs in my sample. I believe that the distortionary effects of private debt found in my analysis needs a deeper theoretical investigation.

I thank Mathilde Viennot from France Stratégie and an anonymous reviewer from the Program Committee of the 25th Spring Meeting of Young Economists for their valuable suggestions and comments. I also thank the organizers of and participants at the 1st CompNet Data User Conference in Paris.

2.1. Introduction

Finance, and especially debt finance, is an extremely important part of modern economies. On the one hand, it is indisputable that debt allows firms to realize important investment projects and governments to finance necessary expenditures. On the other hand, persistent debt build-ups can make financial markets—and with them the real economy—vulnerable to crises and may lead governments to default on their liabilities. Economists are now well aware that the likelihood and severity of financial crises tend to increase beyond a certain level of indebtedness (see Reinhart and Rogoff, 2009). While considerable research has been conducted on the nonlinear effects of debt on economic growth, some recent research suggests that high levels of private and public debt can undermine aggregate productivity (Salotti and Trecroci, 2016; Cecchetti and Kharroubi, 2018; Anderson and Raissi, 2018) and impair efficient reallocation of resources (Borio et al., 2015; Pannella, 2018).

The presence of distortions or financial frictions is argued to prevent the equalization of marginal returns to capital and labour across firms, thus leading to resource misallocation (Hsieh and Klenow, 2009; Gilchrist et al., 2013; Moll, 2014; Restuccia and Rogerson, 2017). While the literature has identified many different sources of these distortions and frictions, I argue that increased credit expansion and debt accumulation in the economy may exacerbate existing capital misallocation. The intuition is that benefits of credit growth may accrue disproportionately to large and/or well-established firms that own real estate assets as collateral or have long-term relationships with banks, and hence have stronger bargaining power. This intuition is particularly supported by findings of research regarding financial constraints of small- and medium-size enterprises (SMEs).

Research in this area suggests that SMEs are more dependent on external finance but face greater financing constraints and credit rationing (Kay et al., 2014). Even though SMEs account for nearly 60% of value added and 70% of employment in the euro area (Bremus, 2015), supply-side constraints to SME finance are prevalent: many SMEs have difficulties obtaining bank loans not because they lack creditworthiness, but either because they do not have enough immovable collateral that banks prefer to movable assets such as machinery and receivables, or because of their opaque nature leading to information asymmetry between them and banks (Bremus, 2015; Abraham and Schmukler, 2017). In addition, while large firms are much more likely to be long-established in the market, SMEs are more heterogeneous in terms of age, size, ownership, lending relationships with banks, and industries and regions in which they operate (Banerjee, 2014; Casey and O'Toole, 2014;

Kumar, 2017; Jackowicz and Kozłowski, 2019; D'Ignazio and Menon, 2020). These arguments imply that, other things being equal, industries with a larger number of SMEs and a few very large firms should see a higher increase in the spread of marginal productivity of capital across firms when banks extend more credit to the economy (assuming this credit is used for investment).

My goal in this chapter is to investigate how private debt and public debt at the aggregate level influence capital misallocation across firms in different industries over time. I use an unbalanced panel of 18 European countries from 1999 to 2015 for my analysis. The data come from the Competitiveness Research Network (CompNet) database, which is compiled by a number of institutions including, inter alia, the European Central Bank, the European Bank for Reconstruction and Development, the Halle Institute for Economic Research, and the Tinbergen Institute. This dataset provides micro-based data at the country and country-sector level, but not at the firm level, so I do not have information on size, age and other firm-level characteristics. Therefore, as proxies for industry-level variation in demand for credit and competitive structure, I use the Rajan and Zingales' (1998) measure of sectoral financial dependence based on Compustat data and the indicator of technological intensity obtained from Eurostat, as well as other sector-level indicators provided by CompNet, such as average credit constraints, dispersion of credit constraints, average markups, and the skewness of industry TFP distribution.

To my knowledge, this is the first study to investigate the effects of aggregate leverage on industry-level input misallocation. Few recent studies have analyzed either the role of financial frictions (Buera et al., 2011; Midrigan and Xu, 2014) or the overall financial development (Marconi and Upper, 2017) in generating capital misallocation, or the impacts of firm-level and aggregate leverage on within-firm productivity (Gomis and Khatiwada, 2017). An interesting finding by Gomis and Khatiwada (2017) is that firm leverage is positively associated with total factor productivity (TFP), whereas aggregate leverage (at the country level) has a negative effect on firm-level TFP. My work differs from these studies in that I am interested in how aggregate leverage of private and public sectors affect capital misallocation across firms in different industries in an economy.

The remaining part of this chapter proceeds as follows. Section 2.2 summarizes the literature on the relationship between private and public debt, growth, and aggregate productivity, on the basis of which I then develop my hypothesis. Section 2.3 gives a theoretical insight into capital misallocation and briefly discusses its empirical measurement. Section 2.4 presents data and the empirical methodology. Section 2.5 presents the results of the empirical analysis regarding the effects of private and public debt on capital misallocation. Finally, Section 2.6 concludes.

2.2. Literature review and hypothesis development

2.2.1. Private and public debt, growth, and aggregate productivity

Over the past few decades, extensive research has been carried out on the relationship between private sector debt and economic growth. Earlier studies found positive effects of finance on growth (King and Levine, 1993; Rajan and Zingales, 1998; Levine et al., 2000; Beck et al., 2000). Huang and Lin (2009) find that financial intermediation has much stronger growth-enhancing effects in low-income countries than in high-income countries. More recently, however, several studies have indicated that the effect of finance on growth is unlikely to be strictly positive. Shen and Lee (2006) show that the relationship between bank development and growth has an inverse U-shape in middle-income countries. Rousseau and Wachtel (2011) find that positive finance–growth relationship that was estimated with data from the 1960s to the 1980s has disappeared over the subsequent decades. Law and Singh (2014) estimate a threshold value of around 90-95% of GDP beyond which financial development indicators (i.e., private sector credit and liquid liabilities) affect growth negatively. Arcand et al. (2015) find that financial depth has a negative effect on output growth when private sector credit reaches 100% of GDP. Mian et al. (2017) show that an increase in the household debt to GDP ratio predicts a lower subsequent GDP growth. Other studies document the detrimental effects of private credit growth on financial stability and intensity of subsequent recessions (Mian and Sufi, 2010; Jordà et al., 2011; Schularick and Taylor, 2012; Jordà et al., 2013; Jordà et al., 2015a).

In addition to the growth effects of private sector debt, a number of studies have analyzed the relationship between public debt and economic growth since the publication of Reinhart and Rogoff's (2009) seminal book. Reinhart and Rogoff (2010) find in a sample of both advanced and emerging economies that public debt to GDP ratios as high as 90% and above are associated with significantly lower growth outcomes. These findings are also supported by Cecchetti et al. (2011), whose results suggest that increases in public debt beyond 85 percent of GDP have a negative effect on growth in a sample of 18 OECD countries. Other papers confirming the nonlinear effects of public debt on growth include Checherita-Westphal and Rother (2012), Baum et al. (2013), Woo and Kumar (2015), Karadam (2018), and Yang and Su (2018). Chudik et al. (2017) find significant negative effects of public debt build-up on economic growth in the long run, although they find no evidence for a universally applicable threshold effect of public debt on growth. Panizza and Presbitero (2014), however, fail to find any evidence for a *causal* effect of public debt on growth once corrected for endogeneity.

Another strand of literature—albeit to a limited extent—has focused on the joint dynamics of public and private debt. Reinhart and Rogoff (2011) document numerous episodes where there are surges in private debt before crises and surges in public debt after crises across advanced and emerging market economies. Reinhart et al. (2012) argue that the interaction between the different types of debt overhang is extremely complex and the lines between public and private debt often become blurred in a crisis. Jordà et al. (2015b), after examining the co-evolution of public and private sector debt in 17 advanced countries over a 140-year period (1870–2011), show that financial stability risks originate primarily in the private sector rather than in the public sector; high public debt only exacerbates the effects of private sector deleveraging after financial crises and hence contributes to deepening of the recessions following a credit bust. Indeed, the earlier research by Reinhart and Rogoff (2009) confirms these findings by showing that, in many crisis episodes over the past century, corporate defaults were precursors to government defaults or reschedulings as governments tended to shoulder private sector debts. It can also be seen in Figure 2.1 that private debt in 18 EU countries had been rising dramatically for years preceding the 2007–2008 global financial crisis, while public debt has risen following the crisis. In a recent study that uses data from 29 OECD countries over 1995–2014, Caner et al. (2019) find that the interaction between public and private debt stimulates economic growth at low levels of indebtedness but decreases growth when the private-public debt interaction reaches the threshold level of 137%.

Besides the many studies investigating the effects of debt on output growth, more recent research focuses on how debt accumulation impacts on productivity and allocative efficiency. In one of the early papers, Kim and Maksimovic (1990) apply an econometric methodology for estimating agency costs of debt to the air transport industry to show that high debt levels are associated with firm-level inefficiency and the fall in industry-wide productivity growth. Borio et al. (2015) study a sample of 21 OECD countries over 30 years and find that credit booms tend to undermine aggregate productivity growth mainly through labour reallocations towards sectors with lower productivity growth. Salotti and Trecroci (2016) show for a group of 20 OECD countries over the 1970–2009 period that rising public debt levels are associated with lower rates of aggregate productivity growth. Cecchetti and Kharroubi (2018) argue, using data on 20 advanced economies over 25 years, that a country's credit growth is a drag

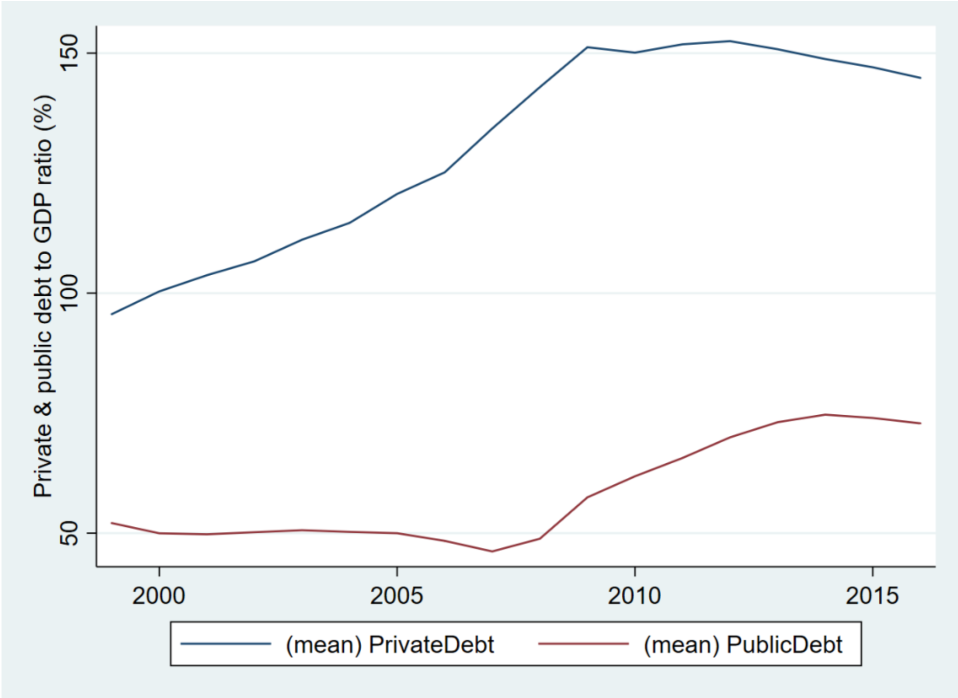


Figure 2.1. Time series of private and public debt (as % of GDP), average for 18 European countries (*Source: Author's calculations based on IMF data*)

on its productivity growth since credit booms slow down the growth in those industries that have either lower asset tangibility or high research and development (R&D) intensity, i.e., in what are usually thought of as the engines for growth. Anderson and Raissi (2018) find significant negative effects of persistent corporate debt accumulation on the growth of TFP within Italian firms over the period 1999–2015.

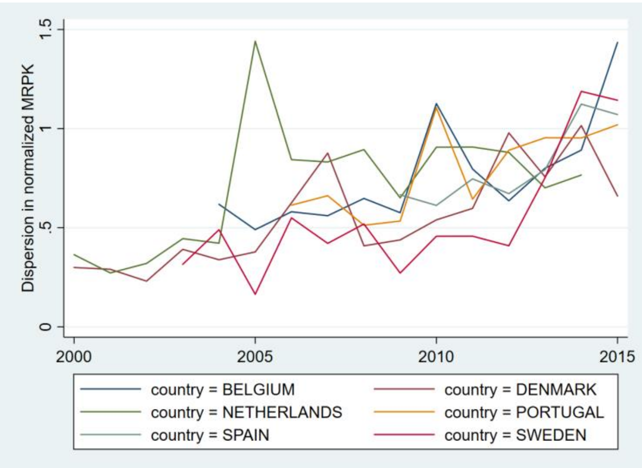
It is widely known that TFP growth is the most important determinant of output growth in the long run (Klenow and Rodriguez-Clare, 1997; Hall and Jones, 1999; Caselli, 2005; Hsieh and Klenow, 2010). This suggests that the observed differences in per capita income across countries are primarily due to the differences in their aggregate productivity. One of the key factors in understanding measured TFP differences is input misallocation—an inefficient allocation of resources across firms and sectors. A baseline paper in this area is by Restuccia and Rogerson (2008), who show that policies that distort the prices faced by different producers lead to reallocation of resources across productive units, thus having important effects on aggregate TFP. In another seminal paper, Hsieh and Klenow (2009) use microdata on manufacturing firms to document much higher dispersion of marginal products of capital and labour (i.e., measures of input misallocation) across plants in China and India as compared to the United States. The authors also estimate large gains from reallocation: had the levels of dispersion of marginal products in China and India been counterfactually equalized to those in the U.S., TFP levels would be increased by 30%–50% in China and by 40%–60% in India.

These studies suggest that aggregate productivity does not consist only of firm-level productive efficiency and industry-level technological advancement, but also of allocative efficiency across firms and industries. While excessive leverage may affect firms' productivity, it seems more plausible that the negative effect of high and growing debt on aggregate productivity comes through the channel of misallocation rather than productive and technical efficiency. Although the exact mechanism through which debt affects misallocation is more of a theoretical issue, we can check how increases in private and public debt change capital misallocation depending on differences in industry characteristics.

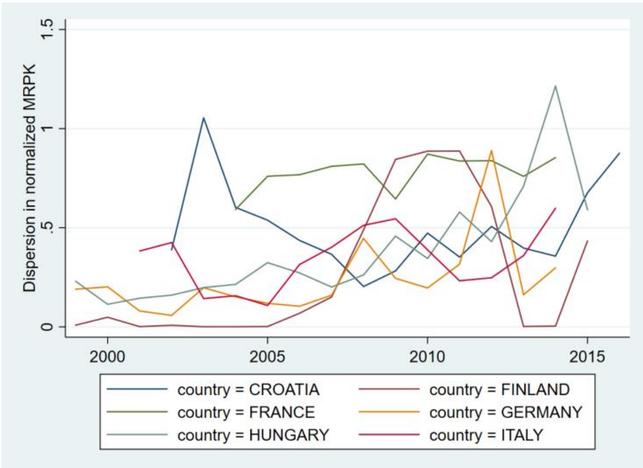
2.2.2. Possible relationship between debt and misallocation

There is no generally accepted theory of how increases in private and public debt affect allocative efficiency or aggregate productivity growth. A few existing studies suggest that debt accumulation may influence aggregate productivity either through intra-firm efficiency channel or through inter-firm reallocation channel. Kobayashi and Shirai (2018) construct a theoretical model to show that excessive debt build-up in the private sector can depress economic growth through persistent productive inefficiency of debt-ridden firms. Pannella (2018) shows in a model of rational bubbles in the credit market that the periods of high credit allow larger but unproductive firms to increase their leverage relative to smaller and productive firms, thus generating a misallocation of capital. Basco et al. (2018), by using matched firm- and bank-level data for Spain, document that housing bubbles generate misallocation of capital within industries and across municipalities by raising the value of the collateral disproportionately more for firms and municipalities that have larger amounts of real estate assets. In a recent paper, Aghion et al. (2019) develop a simple theoretical model to show that there is an inverted-U relationship between credit access and aggregate productivity growth that is generated by two counteracting effects: (i) a positive investment effect of credit access on incumbent firms' productivity growth working through facilitation of innovation, and (ii) a negative *reallocation* effect of credit access working through the exit rate of incumbent firms and its influence on the entry cost for new—potentially more efficient—innovators. Regarding public debt, Kaas (2016) develops a dynamic general equilibrium model with credit market frictions to show that, apart from a stable "no-bubble" steady state, there may exist an unstable “bubble” steady state with a higher interest rate, higher public debt, and higher TFP and output coupled with lower levels of credit and private capital stock.

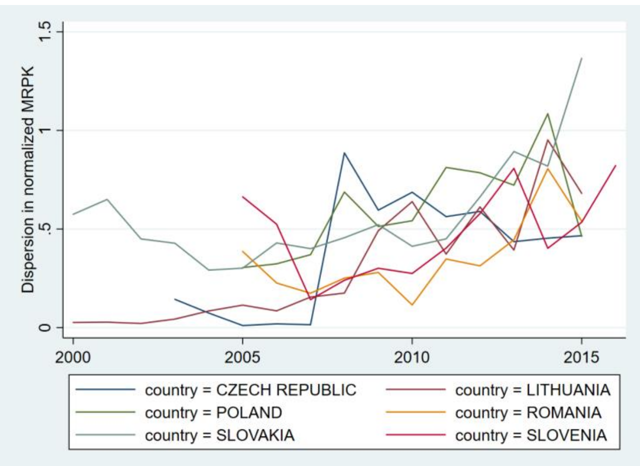
As the above studies suggest, it is reasonable to expect that growing leverage in the financial sector has an impact on the efficiency of resource allocation in the economy. Figure 2.2, a-c, shows the weighted-average dispersion[1] of marginal revenue product of capital for 18 European countries by splitting them equally into those with high, medium and low private debt to GDP ratio over the sample period of my dataset. We can see that, while capital misallocation has an overall upward trend, countries with higher private debt to GDP ratio appear to have a higher level of capital misallocation in general. This association is even more evident in Figure 2.3, where both private debt and public debt seem to have a positive correlation with capital misallocation.



a) Six European countries with high private debt to GDP ratio



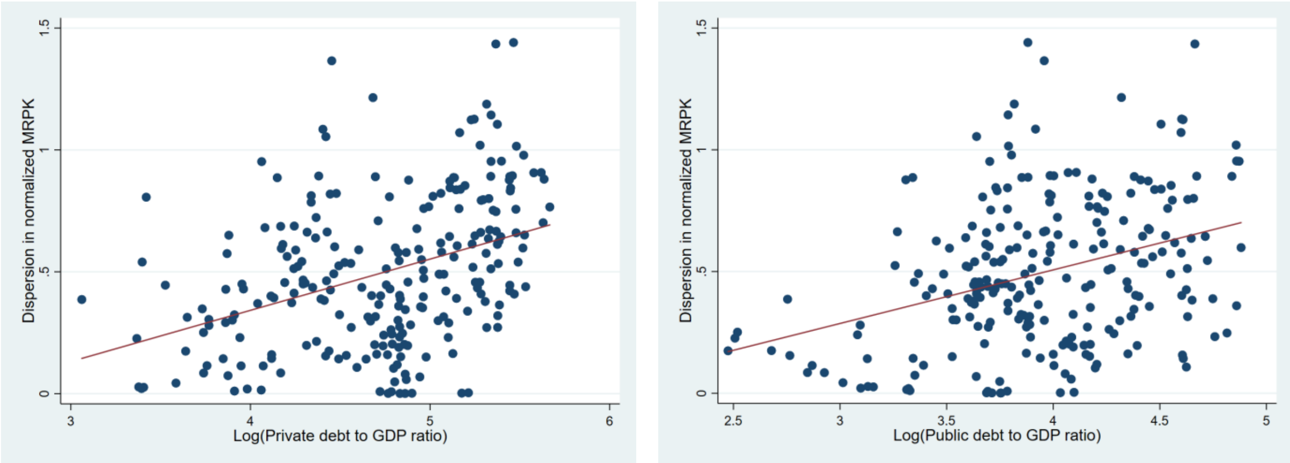
b) Six European countries with medium private debt to GDP ratio



c) Six European countries with low private debt to GDP ratio

Figure 2.2. Time series of capital misallocation (*Source: Author’s calculations based on CompNet data. Values are weighted averages, where the weights are country-specific time-varying sectoral value added shares*)

[1] These dispersion measures are detrended and normalized by sector-specific standard deviations.



a) Private debt and capital misallocation **b)** Public debt and capital misallocation

Figure 2.3. Scatterplot of private/public debt and capital misallocation

(*Source: Author's estimations based on the IMF and CompNet data. The estimations are at the country-year level, and MRPK dispersions are weighted averages, where the weights are country-specific time-varying sectoral value added shares*)

Based on the findings of some recent studies, I can think of at least *two main channels* through which debt accumulation at the aggregate level may affect capital misallocation across firms in a country or an industry. The *first* is the existence of financial frictions and imperfections associated with pledgeable collateral or borrowing constraints. As argued by Moll (2014) in a general equilibrium framework, with the borrowing constraints resulting from credit market imperfections, the equilibrium allocation implies that the marginal product of capital in highly productive firms exceeds that in less productive firms unless idiosyncratic productivity shocks are persistent. Similarly, Doerr (2018) finds that rising property prices reduce aggregate productivity by reallocating capital and labour towards unproductive real estate owning firms. The *second* channel is bubbles arising from excessive debt accumulation. Miao and Wang (2014) construct a two-sector endogenous growth model with credit-driven stock price bubbles to show that bubbles impact on economic growth by easing access to credit and improving investment efficiency on the one side, and by reallocating capital across sectors on the other side. As mentioned earlier in this section, Basco et al. (2018) and Pannella (2018) also find distortionary effects of bubbles in the housing and the credit markets on capital allocation.

So, I hypothesize that an increase in supply of bank credit and other private debt instruments may exacerbate capital misallocation by disproportionately benefiting those firms that have better collateral (e.g., in the form of real estate assets) or easier access to credit (e.g., due to long-term relationships with banks). If this is the case, then an expansion of private lending should exacerbate capital misallocation disproportionately more in industries that have higher inherent demand for external finance and, at the same time, higher average credit constraints or larger differences in credit constraints across firms. As regarding public debt, although I do not have a clear theoretical mechanism in mind, it is possible that an increase in public debt potentially alters the allocation of capital by crowding out private credit or subsidizing certain producers at the expense of others. Based on the findings of the studies discussed above, however, I expect the increases in private debt to have a larger and stronger effect on capital misallocation as compared to the increases in public debt. In addition, I also consider whether other differences across firms (e.g., technological intensity or the level of exposure to competition) could be the basis for disproportionate effects of debt accumulation leading to increased capital misallocation.

2.3. Capital misallocation

2.3.1. A theoretical basis for misallocation

To measure capital misallocation, I adopt the framework developed by Hsieh and Klenow (2009). They consider an economy consisting of S sectors characterized by monopolistic competition. Each sector's output is a constant-elasticity-of-substitution (CES) aggregate of M_s differentiated products:

$$Y_s = \left(\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{2.1}$$

where Y_{si} is the firm i's real value added and σ indicates the elasticity of substitution across varieties of goods.

Each firm's production function is given by a Cobb-Douglas technology of the following form:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}, \tag{2.2}$$

where A_{si}, K_{si} and L_{si} are the firm-level TFP, capital input and labour input, respectively, and α_s is the sector-specific share of capital. In addition to the level of TFP, A_{si}, firms also differ in terms of output and input constraints they face. Hsieh and Klenow (2009) define distortions that simultaneously affect both capital and labour—thus increasing the marginal products of these inputs by the same proportion—as an output distortion, denoted by τ_Y, and those that raise the marginal product of capital relative to labour as the capital distortion, denoted by τ_K. Examples given by the authors for output distortions include government restrictions on size and differences in transportation costs, while an example for capital distortions includes differences in access to credit. Firms maximize profits given by:

$$\pi_{si} = (1 - \tau_{Ysi})P_{si}Y_{si} - wL_{si} - (1 + \tau_{Ksi})RK_{si}, \tag{2.3}$$

where $P_{si}Y_{si}$ stands for the nominal value added, w is the cost of labour (wage rate), and R is the cost of capital (rental rate). By solving the firms' profit maximization problem we can get the standard result that the output price of a monopolistically competitive firm is a markup over its marginal cost:

$$P_{si} = \frac{\sigma}{\sigma-1}\left(\frac{R}{\alpha_s}\right)^{\alpha_s}\left(\frac{w}{1-\alpha_s}\right)^{1-\alpha_s}\frac{(1+\tau_{Ksi})^{\alpha_s}}{A_{si}(1-\tau_{Ysi})} \tag{2.4}$$

The capital-labour ratio is given by:

$$\frac{K_{si}}{L_{si}} = \frac{\alpha_s}{1-\alpha_s} \cdot \frac{w}{R} \cdot \frac{1}{1+\tau_{Ksi}} \tag{2.5}$$

Given the definition of marginal products of capital and labour (MPK and MPL), we obtain the following results for marginal revenue products of these inputs:

$$MRPK_{si} \equiv MR_{si} \cdot MPK_{si} = \alpha_s \frac{\sigma-1}{\sigma}\frac{P_{si}Y_{si}}{K_{si}} = R\,\frac{1+\tau_{Ksi}}{1-\tau_{Ysi}} \tag{2.6}$$

$$MRPL_{si} \equiv MR_{si} \cdot MPL_{si} = (1-\alpha_s)\frac{\sigma-1}{\sigma}\frac{P_{si}Y_{si}}{L_{si}} = w\,\frac{1}{1-\tau_{Ysi}} \tag{2.7}$$

where $MR_{si} \equiv \frac{\sigma-1}{\sigma}P_{si}$ is the marginal revenue from selling an additional unit of output.

It can be seen from (2.6) and (2.7) that, in the absence of distortions, marginal returns to capital and labour would be equalized across firms in a given sector. When there are firm-specific output and capital distortions, however, marginal revenue products differ across these firms.

The "revenue productivity" of the firm—as opposed to its "physical productivity" given by A_{si}—is defined as follows:[2]

$$TFPR_{si} \equiv P_{si}A_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}} \tag{2.8}$$

In the absence of distortions, differences in firms' physical productivity (A_{si}) would lead to the allocation of capital and labour in such a way that all firms within an industry would have the same TFPR, since firms with higher A_{si}—and hence higher output—would charge a correspondingly lower price for their product. Using (2.6) and (2.7), a firm's TFPR is given by:

[2] This *is* the productivity that we observe in the data—and not the physical productivity—as we do not observe the prices of individual firms.

$$TFPR_{si} = \frac{\sigma}{\sigma-1}\left(\frac{MRPK_{si}}{\alpha_s}\right)^{\alpha_s}\left(\frac{MRPL_{si}}{1-\alpha_s}\right)^{1-\alpha_s} = \frac{\sigma}{\sigma-1}\left(\frac{R}{\alpha_s}\right)^{\alpha_s}\left(\frac{w}{1-\alpha_s}\right)^{1-\alpha_s}\frac{(1+\tau_{Ksi})^{\alpha_s}}{1-\tau_{Ysi}} \tag{2.9}$$

By using simple algebra, the industry TFP can then be expressed as:

$$TFP_s = \left[\sum_{i=1}^{M_s}\left(A_{si}\cdot\frac{\overline{TFPR_s}}{TFPR_{si}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}, \tag{2.10}$$

where $\overline{TFPR_s}$ is the weighted average of $TFPR_{si}$ across all firms in the industry. It can be seen from (2.10) that, given the firm-specific physical productivities (A_{si}), the industry TFP would be maximized if all firms in the industry had identical TFPR, i.e., if there were no dispersion in firm-level revenue productivities. Any heterogeneity in TFPR across firms, as can be seen from (2.9), should be driven by differences in capital and output distortions faced by individual firms.[3]

Thus, the dispersion of marginal revenue products of capital and labour can serve as an indirect measure of input misallocation, which in turn is one of the main determinants of aggregate TFP. Then, my hypothesis about the impact of aggregate debt on capital misallocation would be justified if an increase in debt interacts with financial market frictions (e.g., differences in possession of real estate assets or in access to credit) in affecting the dispersion of the marginal revenue product of capital across firms.

2.3.2. Empirical measurement of capital misallocation

As I mentioned earlier, I take the Hsieh and Klenow (2009) approach to defining the misallocation of capital as the dispersion of its marginal revenue products. While CompNet database provides several different measures of sectoral allocative efficiency, the measure of *capital* misallocation in the database is essentially based on the Hsieh and Klenow (2009) methodology.[4] Here I briefly discuss the measurement of this misallocation as explained in the CompNet User Guide.

Taking Eq. (2.2) in logs gives the empirical version of the firm-level (time-varying) production function:

$$rva_{i,t} = \theta^k k_{i,t} + \theta^l l_{i,t} + a_{i,t} + \varepsilon_{i,t}, \tag{2.11}$$

where $rva_{i,t}$ is real value added, $k_{i,t}$ is the real book value of net capital, $l_{i,t}$ is total employment, $a_{i,t}$ is the (Hicks-neutral) TFP indicator, and $\varepsilon_{i,t}$ is an i.i.d. error term. θ^k and θ^l

[3] An important concern here is that, as shown by Haltiwanger et al. (2018), a significant part of the variation in TFPR may reflect the influence of demand shifts rather than true distortions. In order to account for this issue, I control for sectoral demand proxied by sectoral average real turnover as in Gamberoni et al. (2016).
[4] For details, see CompNet User Guide and Cross-Country Report available at https://www.comp-net.org/data/.

denote the output elasticity of capital and labour, respectively. To control for potential endogeneity issues arising from the firm-observed productivity component, a control function approach as in Olley and Pakes (1996) and Levinsohn and Petrin (2003) is applied. Assuming that TFP evolves according to a Markov process and using the control function for productivity, Eq. (2.11) can be rewritten as:

$$rva_{i,t} = \theta^k k_{i,t} + \theta^l l_{i,t} + g_{i,t-1}\left(k_{i,t-1}, l_{i,t-1}\right) + \nu_{i,t} + \varepsilon_{i,t}, \tag{2.12}$$

where $\nu_{i,t}$ denotes the innovation in productivity (TFP). The term $g_{i,t-1}\left(k_{i,t-1}, l_{i,t-1}\right)$ is approximated with a third-order polynomial in all of its variables. Eq. (2.12) is estimated via GMM following Wooldridge (2009), using lagged values of labour as instruments for its contemporaneous values (since labour and TFP are simultaneously determined while capital takes time to build), and controlling for a full set of time dummies. In order to obtain consistent estimates with sufficient degrees of freedom, a cut-off of a minimum of 100 observations per sector and year is introduced.

Having estimated the capital output elasticity, θ^k, from the production function, marginal revenue product of capital is computed as:

$$MRPK_{i,t} = \frac{\theta^k rva_{i,t}}{k_{i,t}} \tag{2.13}$$

The above estimate is then used to calculate the measure of within-sector time-series dispersion of the marginal productivity of capital for each 2-digit industry. In order to control for potential bias driven by sector-specific price dynamics or technology improvements, the marginal productivity of capital at the firm level is detrended and rescaled by the sectoral standard deviation (at the 2-digit level).[5] Then, the macro-sector level of capital misallocation is computed as the median standard deviation of the resulting series across all 2-digit industries belonging to the corresponding 1-digit industry. Hence, the resulting measure of capital misallocation for each macro sector can be formulated as:

$$Capital\_Misallocation_t \equiv Median_t\left[STDEV_{s,t}\left(\frac{MRPK_{si,t} - \overline{MRPK}_s}{\sigma_s}\right)\right] \tag{2.14}$$

where s stands for sector (i.e., 2-digit industry), i stands for firm, $MRPK_{si,t}$ denotes the deviation of $MRPK_{i,t}$ around its 2-digit industry's long-run growth trend, $\overline{MRPK}_s$ is the long-run average level of $MRPK_{si,t}$, and σ_s is the long-run standard deviation of $MRPK_{si,t}$.

[5] This measure was proposed by Kehrig (2015), and it also accounts for Asker et al.'s (2014) critique that cross-industry variability in MRPK could be (partly) due to "uncertainty" and associated adjustment costs faced by different industries.

2.4. Empirical methodology

2.4.1. The data

For capital misallocation I employ the 6th Vintage of CompNet database, which provides micro-based data on a wide range of indicators constructed on firm-level information as described in Lopez-Garcia et al. (2015). The 6th Vintage of CompNet dataset represents an annual unbalanced panel covering 18 EU countries[6] for the period 1999–2015, although actual data availability reduces this time span to 2003–2015 for the majority of these countries. Indicators in the dataset were collected considering two different samples of firms: those with at least one employee (the "full" sample) and those with at least 20 employees (the "20E" sample). In my analysis I use the 20E sample, since it is far more homogenous and comparable across countries than the full sample due to the exclusion rules in some countries such as Poland and Slovakia, where only firms with more than 10 employees and 20 employees, respectively, have to report their accountings. The dataset reports indicators aggregated at macro-sector (1-digit sectors corresponding to NACE Rev.2 sections) and sector (2-digit NACE Rev.2 sectors) levels. For each indicator in the 20E sample, firms are weighted according to their relative presence in the sample, so they are representative of the population of firms in terms of sectoral distribution. I use the macro-sector level data that include nine sectors of the economy at the one-digit industry level: manufacturing, construction, and seven service sectors (wholesale and retail trade; information and communication; transportation and storage; accommodation and food services; professional, scientific and technical services; administrative and support services; real estate services).[7]

The data on private debt and public debt come from the International Monetary Fund's Global Debt Database. Private debt comprises the total stock of loans and debt securities issued by households and nonfinancial corporations (as a share of GDP), and public debt consists of the total stock of debt liabilities issued by the general government (as a share of GDP). I use control variables such as Chinn and Ito (2006) capital account openness index, long-term interest rates[8] (OECD), general government final consumption expenditure (World

[6] The countries are: Belgium, Croatia, Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Lithuania, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden.

[7] The reader must be aware that data collection rules and procedures across countries are different, and out of CompNet's control. Hence, despite all efforts made to improve sample comparability across countries (including the use of population weights), some country samples might still suffer from biases. For a more detailed account of raw data characteristics and sample biases, please refer to the Cross-Country Comparability Report available at https://www.comp-net.org/data/.

[8] The data on long-term interest rates are not available for Croatia and Romania.

Bank), taxes on income, profits and capital gains (ICTD Government Revenue Dataset[9]), trade (sum of exports and imports as a share of GDP, World Bank), sectoral average real turnover (CompNet), and an index of institutional quality measured as the sum of political risk rating indicators such as bureaucracy quality, investment profile, rule of law, and control of corruption (ICRG Researchers Dataset[10]). The variables such as private and public debt, government consumption, taxes on income, profits and capital gains, and trade are all in percent of GDP. The choice of my control variables as possible determinants of capital misallocation is based on different studies including Larrain and Stumpner (2017), Gopinath et al. (2017), Monacelli and Sala (2018), Ramey and Shapiro (1998), McNabb (2018), Edmond et al. (2015), Bai et al. (2019), Gamberoni et al. (2016), Durnev (2010), and Hassan et al. (2019). My explanatory variables are constructed as an interaction term between a time-varying country-level component and a time-invariant sectoral-level component (except for the average real turnover, which is available at the sectoral level from CompNet database). As sector-specific interacting variables I use: (i) an indicator of external finance dependence as in Rajan and Zingales (1998)—based on Compustat data on U.S. listed firms—that I obtained from Franco (2018); (ii) an indicator of credit constraints (ICC) available from CompNet database (i.e., share of credit constrained firms based on the methodology used in the Survey on Access to Finance of Enterprises, SAFE)[11]; (iii) an indicator of sectoral technological intensity obtained from Eurostat (namely, Eurostat indicators on high-tech industry and knowledge-intensive services). More details on these three indicators are given in Appendix 2.B at the end of this chapter.

My decision to use sector-specific interacting variables is motivated by the unavailability of industry-level data on credit or debt ratios as well as the attractiveness of the difference-in-differences approach, where one can exploit the variation across industries to assess the impact of country-level variables on industry-level variables. Rajan and Zingales' (1998) indicator is a commonly used measure of industries' technological dependence on external finance. Since the U.S. capital markets are "among the most advanced in the world, and large publicly traded firms typically face the least frictions in accessing finance" (Rajan and Zingales, 1998), the industry median of external finance dependence of large firms in the U.S. is arguably a good measure of that industry's inherent demand for external finance elsewhere.

[9] ICTD/UNU-WIDER, 'Government Revenue Dataset', 2018, https://www.wider.unu.edu/project/government-revenue-dataset.

[10] PRS Group, 'International Country Risk Guide (ICRG) Researchers Dataset', 2018, https://hdl.handle.net/10864/10120.

[11] I take the average of the indicator for every country-sector over the entire period of available data to make it time-invariant. Note that these data are not available for Hungary and Slovakia.

As for the indicator of technological intensity, Calligaris et al. (2018) show that an increase in misallocation is positively correlated to R&D intensity at the sector level, and argue that relative specialization in sectors where technology has been changing faster helps to explain the patterns of misallocation across geographical areas and firm size classes. Cecchetti and Kharroubi (2018) also find negative effects of credit growth on TFP growth in sectors with high R&D intensity.

2.4.2. The empirical model

In order to study the effects of private and public debt on capital misallocation, I employ a difference-in-differences-type empirical methodology whereby I interact the aggregate debt-to-GDP ratios with various sector-specific[12] indicators, in a manner similar to Rajan and Zingales (1998) and Larrain and Stumpner (2017). The general form of my empirical model looks as follows:

$$
\begin{aligned}
&Capital\_Misallocation_{cj,t} = \\
&\qquad = \beta_0 + \beta_1\left(PrivateDebt_{c,t-1} \times Z_j\right) + \beta_2\left(PublicDebt_{c,t-1} \times Z_j\right) + \gamma\left(X_{c,t} \times Z_j\right) \\
&\qquad + \varepsilon_{cj,t}
\end{aligned}
$$

where $Capital\_Misallocation_{cj,t}$ denotes the level of capital misallocation for sector j in country c at time t, $X_{c,t}$ is a vector of time-varying country-level controls, and Z_j is a sector-specific (time-invariant) interacting variable.

I estimate my empirical model using the fixed-effects (within) regression, since my explanatory variables of interest may be correlated with country and sector-specific unobserved factors. I cluster standard errors at the country level. Additionally, I use heteroscedasticity- and autocorrelation-consistent (HAC) standard errors as per Driscoll and Kraay (1998). For robustness, I test my model using the generalized method of moments (GMM) system estimator as proposed and developed by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998).

[12] Henceforth, I will be referring to the 1-digit NACE Rev.2 sectors whenever I use the terms “sector” or “industry”, unless specified otherwise.

2.5. Results

2.5.1. Baseline regressions

In this section I discuss the results of my panel regressions. As explanatory variables, I use the *natural logarithms* of private debt, public debt, government consumption, taxes on income, profits and capital gains, trade, and sectoral average real turnover across firms; I also control for the long-term interest rate and the indices for capital account openness[13] and the quality of political institutions. I use the *lagged* values of the (logs of) private and public debt in order to account for potential endogeneity concerns, and also the lagged value of the capital account openness index—as in Larrain and Stumpner (2017)—since it is unlikely to have an immediate effect on capital misallocation.

Table 2.1 reports the results of fixed effects regressions where the explanatory variables are interacted with the sectoral-level indicator of external finance dependence. The results strongly suggest that an increase in private debt exacerbates capital misallocation and more so in sectors with higher financial dependence. In other words, those sectors that depend more on external finance—and are hence more likely to benefit from higher credit availability—experience a larger increase in dispersion of marginal revenue products of capital following a rise in private sector indebtedness. Public debt, on the other hand, does not seem to affect capital misallocation after controlling for other potential determinants. The effect of capital account openness is found to be negative, meaning that financial liberalization reduces capital misallocation, supporting the findings of Larrain and Stumpner (2017). The coefficient on the long-term interest rate also has a negative sign, suggesting that declining interest rates tend to increase the dispersion of returns to capital—a finding that is supported by some recent studies including Cette et al. (2016), Gopinath et al. (2017), and Caggese and Pérez-Orive (2019). I do not find any significant effect on capital misallocation of other control variables.

Table 2.2 reports the regression estimates where I interact the explanatory variables with the indicator of average credit constraints. The estimates of the coefficients of private debt are similar in sign to those in Table 2.1: in sectors with a higher share of credit constrained firms, a rise in private debt increases capital misallocation significantly more as compared to sectors with a lower share of credit constrained firms. Although the coefficient of public debt is significantly positive in several columns that exclude most of the controls, it loses any

[13] This index is normalized to take values between 0 and 1.

significance when all controls are included. The long-term interest rate is found to improve capital allocation, as in Table 2.1, when the Driscoll-Kraay standard errors are used.

Table 2.3 shows the results of regressions where the explanatory variables are interacted with sectoral R&D intensity. The strong amplification effect of private debt is again confirmed: a rise in private debt increases capital misallocation particularly in sectors that are more technologically intensive. A potential explanation for this is that R&D-intensive sectors are more likely to be credit constrained due to higher informational asymmetries, lower collateral value of firms (because of the higher usage of intangible assets such as human capital and specialized machinery), and highly uncertain and skewed investment returns (Carpenter and Petersen, 2002; Fauceglia, 2015). Public debt, again, does not seem to have any significant capital misallocation effect. While I find the sign of the effect of financial openness to be similar to that in Table 2.1, meaning that capital account liberalization improves capital allocation (more in highly R&D-intensive sectors), I fail to find any significant effect of interest rates in the current estimation.

I also regress capital misallocation on the two components of private debt separately: non-financial corporations' debt and household debt. The results are given in Table 2.4. In these regressions, I omit public debt since I find that (i) its effect is insignificant anyway and (ii) it does not add noticeably to the explanatory power of the regression model. We can see from the table that both corporate debt and household debt have significant amplifying effects on capital misallocation, but the effect of corporate debt is much larger than—almost three times as large as—that of household debt. This is both an intuitive and important finding, since (i) capital misallocation is mainly the problem of the corporate sector, and (ii) this suggests that excessive corporate debt could be an important factor in reallocating resources toward unproductive firms, hence negatively affecting countries' TFP and long-run growth, as opposed to medium-run (negative) growth effects of household debt (Mian et al., 2017).

2.5.2. Robustness tests

As a robustness check of my baseline specification, I estimate my regression model using the system GMM procedure as proposed by Blundell and Bond (1998)—though without the autoregressive term[14]—by instrumenting the explanatory variables with their lags as described in Holtz-Eakin et al. (1988). In order to avoid the overfitting of endogenous

[14] Since my baseline specification is static and assumes no autocorrelation in the error term, I do not include the lagged dependent variable in my GMM regressions. The results of the Arellano-Bond tests for AR(1) and AR(2) in first differences (given in Table 2.C1) indeed imply no serial autocorrelation in the error terms.

variables and the associated bias caused by too many instruments, I collapse the instrument matrix as recommended by Roodman (2009). Since my data are unbalanced and include gaps, instead of first differencing, I employ forward orthogonal deviations to transform my variables as proposed by Arellano and Bover (1995). Standard errors are clustered at the country level.

Table 2.C1 in the Appendix reports the one-step system GMM estimates using two different instrument sets: all the lags of the explanatory variables dated $t-2$ and earlier, and those dated from $t-2$ to $t-10$. The results strongly support my earlier finding that private debt accumulation increases capital misallocation given the sectoral-level indicators such as financial dependence, average credit constraints, and R&D intensity, albeit the coefficients are not significant at the 1% level in the case of the interaction with average credit constraints. Public debt, on the other hand, is found to have a somewhat negative effect on capital misallocation when the explanatory variables are interacted with financial dependence and technological intensity. We can see that the coefficients on private debt estimated with the GMM are smaller in magnitude than those estimated with the fixed effects estimator when the explanatory variables are interacted with the indicators of financial dependence and credit constraints, while the GMM-estimated coefficients are larger in magnitude when the explanatory variables are interacted with the indicator of technological intensity. All of the private debt coefficients estimated with the GMM, however, lie within the 95% confidence interval of those estimated with the fixed effects estimator. As before, I find negative coefficients for capital account openness and the long-term interest rate (where the coefficients on capital account openness are statistically significant only when I use financial dependence and technological intensity as interacting variables), suggesting that financial openness and higher interest rates tend to improve capital allocation. Moreover, demand conditions (proxied by average real turnover) are found to be positively correlated with capital misallocation in some of the regressions, while the quality of political institutions seems to reduce capital misallocation in all the interactions.

In Table 2.C2 in the Appendix, I present the results of the robustness checks—using both the fixed effects and the GMM estimators—where I exclude four countries: Croatia and Romania due to the lack of data on the long-term interest rate, and Germany and Spain due to the small number of observations for the MRPK dispersion (Germany has 16 observations due to the data availability for the manufacturing sector only, and Spain has 56 observations since the data are available only starting from 2009). In addition, the data on credit constraints are not available for Hungary and Slovak Republic for the regressions using the indicator of credit constraints as an interacting (sectoral-level) variable. The results in Table 2.C2 show that my findings regarding the effect of private debt are robust to excluding certain countries from regressions.

In Table 2.C3 in the Appendix, I use alternative sectoral-level indicators for interaction with the country-level explanatory variables. All of these indicators are available from CompNet database at the sectoral level; I average them over the available time period for each country-sector. In columns (1)-(3), I use the industry standard deviation of credit constraints (instead of the industry mean as I did earlier) to interact with my country-level variables. Here, I hypothesize that private debt may disproportionately increase capital misallocation in sectors with more heterogeneity in credit constraints. In columns (4)-(9), I use as my interacting variable two different measures of sectoral competitive structure: average markups (calculated as per De Loecker and Warzynski, 2012) and the skewness of sectoral TFP distribution.[15] My conjecture here is that market imperfections such as the lack of competition could be the source of capital misallocation, whereby private debt may exacerbate this misallocation particularly in sectors with a low level of competition (or a high level of concentration). The results in Table 2.C3 strongly support my hypotheses that private debt disproportionately increases capital misallocation in sectors with more heterogeneous credit constraints, higher average markups, and more skewed TFP distribution. Public debt is found to have no significant effect except in one regression, column (5), where it is found to increase capital misallocation when the Driscoll-Kraay standard errors are used. Capital account liberalization is found to have a significantly negative effect on capital misallocation when interacted with the skewness of TFP distribution, and the interest rate is found to have a negative significant effect when interacted with the dispersion of credit constraints.

Overall, my results suggest that excessive private debt accumulation is much more detrimental to the efficiency of capital allocation across firms than public debt, since the latter has no robust capital misallocation effect in my sample of European countries. I find that a rise in private debt disproportionately increases the dispersion of returns to capital in sectors that are, on average, more dependent on external finance, more credit constrained, more technologically intensive, and less competitive. This confirms my intuition that continuous debt build-up in the private sector exacerbates capital misallocation by feeding on financial frictions, market imperfections and existing differences across firms. My finding that higher long-term interest rates may sometimes reduce capital misallocation—particularly in sectors

[15] Dias et al. (2019) suggest the skewness of an industry TFP distribution as an inverse measure of the sectoral competitive structure.

with higher financial dependence and credit constraints—strengthens this case because excessive debt accumulation goes hand in hand with low interest rates. To a certain extent, I also confirm the earlier finding of Larrain and Stumpner (2017) that capital account liberalization improves capital allocation, probably because this allows financially constrained domestic firms to access global capital markets, including foreign equity capital. An important message of this chapter, however, is that private debt has turned out to be the most significant and robust determinant of capital misallocation among all its potential macroeconomic determinants that I have used as explanatory variables in my panel regressions. Thus I believe that this fact needs further and deeper exploration, since it pertains to real economic effects of the financial sector that has the potential to destabilize entire economies.

Although the aggregate productivity effects of private debt accumulation is beyond the scope of this chapter, I take seriously Aghion et al. (2019), who find a two-sided effect of credit access on productivity growth resulting in an inverted-U relationship. Thus I conjecture that private debt may increase aggregate TFP at low levels of debt-to-GDP ratio by enabling firms to invest in new technologies, while high levels of private debt may reduce aggregate TFP growth due to its capital misallocation effect dominating the investment effect. Testing this conjecture, however, is left for future research.

2.6. Conclusion

The past two decades of research in international macroeconomics has seen a number of studies finding nonlinear effects of private and public debt on economic growth. In addition, findings of some very recent studies have suggested that there might be an inverted-U relationship between debt accumulation and aggregate productivity growth. At the same time, another active strand of research has shown that misallocation of capital and labour across firms is responsible for a significant part of the differences in total factor productivity across countries. These developments have led me to ask the question about the possible role of debt build-up in partially generating those productivity differences.

In this study I aim to find out whether increases in private and public indebtedness affect capital misallocation, which is measured as the dispersion in the return to capital across firms in different industries. For this, I use a novel dataset containing industry-level data for 18 European countries and control for different macroeconomic indicators as potential determinants of capital misallocation. I exploit the within-country variation across industries in such indicators as external finance dependence, credit constraints, technological intensity, and the degree of competition. My results show that private debt accumulation significantly increases capital misallocation, particularly in industries with high financial dependence, high R&D intensity, a larger share of credit-constrained firms and a lower level of competition among firms. In other words, private debt accumulation seems to act as a factor amplifying the negative impact of financial frictions and market imperfections on macroeconomic outcomes. When considering the two components of private debt, I find that corporate debt has a much larger amplifying effect on capital misallocation as compared to household debt, although the coefficients of both corporate debt and household debt are significant. On the other hand, I fail to find any significant and robust effect of public debt on capital misallocation within industries in my sample.

One of the extensions of my empirical analysis in this chapter would be to develop a theoretical model that accounts for the observed amplification effect of private debt on capital misallocation. Another extension would be to quantitatively analyze the implications of the misallocation-aggravating effects of private debt accumulation for the long-run aggregate productivity growth. A further extension still would be to test the relationship between private and public debt and misallocation for a wide range of developing countries, since the structural differences between advanced and developing economies might give rise to a different finance-productivity nexus. I leave these and other extensions of my analysis for future research.

Table 2.1. Debt to GDP ratios and capital misallocation: fixed effects regressions (interaction with financial dependence)

Dependent variable: *Capital misallocation*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln(Private\ Debt) \times Fin.Dep.$ (lagged)	0.739*** (0.232)	0.901*** (0.229)	0.856*** (0.211)	0.747*** (0.206)	0.731*** (0.246)	0.608** (0.243)	0.787*** (0.220)	0.668** (0.295)	0.994*** (0.173)	0.994*** (0.262)
$\ln(Public\ Debt) \times Fin.Dep.$ (lagged)	0.391** (0.171)	0.294 (0.185)	0.327 (0.250)	0.385** (0.169)	0.285 (0.212)	0.300 (0.189)	0.360* (0.180)	0.303* (0.172)	0.017 (0.306)	0.017 (0.256)
$Capital\ Acc.Openness \times Fin.Dep.$ (lagged)		-0.878** (0.380)							-1.104** (0.474)	-1.104*** (0.316)
$LT\ Interest\ Rate \times Fin.Dep.$			-0.038 (0.026)						-0.054** (0.023)	-0.054*** (0.017)
$\ln(Govt.Consump.) \times Fin.Dep.$				-0.130 (0.732)					0.076 (0.962)	0.076 (1.177)
$\ln(Taxes\ on\ IPC) \times Fin.Dep.$					-0.273 (0.490)				-0.026 (0.386)	-0.026 (0.356)
$\ln(Trade) \times Fin.Dep.$						0.573 (0.375)			-0.141 (0.686)	-0.141 (0.587)
$\ln(Avg.Real\ Turnover)$							0.158* (0.080)		0.068 (0.088)	0.068 (0.110)
$Institut.Quality \times Fin.Dep.$								-0.031 (0.053)	-0.034 (0.052)	-0.034 (0.041)
Constant	-1.515*** (0.435)	-1.350*** (0.421)	-1.582*** (0.424)	-1.356 (1.196)	-1.072 (0.901)	-2.209*** (0.584)	-3.000*** (0.796)	-0.946 (1.076)	-1.009 (2.581)	-1.009 (2.684)
Standard errors	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	HAC (Driscoll-Kraay)
Observations	1,806	1,806	1,600	1,806	1,782	1,806	1,786	1,806	1,596	1,596
R-squared	0.172	0.176	0.190	0.172	0.180	0.173	0.174	0.172	0.196	0.196

Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 2.2. Debt to GDP ratios and capital misallocation: fixed effects regressions (interaction with average credit constraints)

Dependent variable: *Capital misallocation*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln(Private\ Debt) \times Cred.Constr.$ (lagged)	3.364*** (0.709)	3.310*** (0.733)	3.901*** (0.687)	3.405*** (0.705)	3.478*** (0.709)	2.625*** (0.780)	3.281*** (0.735)	3.428*** (0.674)	3.431*** (1.010)	3.431*** (1.054)
$\ln(Public\ Debt) \times Cred.Constr.$ (lagged)	1.386*** (0.368)	1.148* (0.611)	0.814 (0.465)	1.343*** (0.354)	1.316** (0.515)	0.685 (0.533)	1.430*** (0.375)	1.477** (0.666)	0.472 (1.982)	0.472 (1.030)
$Capital\ Acc.Openness \times Cred.Constr.$ (lagged)		-1.830 (1.822)							-2.010 (5.965)	-2.010 (2.923)
$LT\ Interest\ Rate \times Cred.Constr.$			-0.220** (0.086)						-0.190 (0.116)	-0.190** (0.067)
$\ln(Govt.Consump.) \times Cred.Constr.$				-0.800 (1.901)					1.296 (2.981)	1.296 (3.773)
$\ln(Taxes\ on\ IPC) \times Cred.Constr.$					0.232 (1.183)				0.815 (1.319)	0.815 (0.980)
$\ln(Trade) \times Cred.Constr.$						3.346* (1.850)			1.455 (2.418)	1.455 (1.844)
$\ln(Avg.Real\ Turnover)$							0.153 (0.088)		0.071 (0.097)	0.071 (0.134)
$Institut.Quality \times Cred.Constr.$								0.029 (0.133)	0.004 (0.230)	0.004 (0.135)
Constant	-1.995*** (0.354)	-1.648** (0.618)	-2.010*** (0.347)	-1.709* (0.814)	-2.089*** (0.663)	-3.041*** (0.688)	-3.368*** (0.837)	-2.149** (0.739)	-3.538 (2.981)	-3.538 (2.034)
Standard errors	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	HAC (Driscoll-Kraay)
Observations	1,482	1,482	1,326	1,482	1,473	1,482	1,473	1,482	1,322	1,322
R-squared	0.178	0.179	0.197	0.179	0.178	0.181	0.181	0.179	0.197	0.197

Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 2.3. Debt to GDP ratios and capital misallocation: fixed effects regressions (interaction with technological intensity)

Dependent variable: *Capital misallocation*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln(Private\ Debt) \times$ $Tech.Intensity$ (lagged)	0.566** (0.204)	0.639** (0.245)	0.711*** (0.181)	0.587*** (0.194)	0.533** (0.202)	0.360** (0.171)	0.625*** (0.197)	0.553** (0.213)	0.588** (0.232)	0.588*** (0.179)
$\ln(Public\ Debt) \times$ $Tech.Intensity$ (lagged)	0.354* (0.192)	0.311 (0.218)	0.251 (0.208)	0.339* (0.183)	0.177 (0.191)	0.213 (0.210)	0.328* (0.184)	0.339 (0.228)	0.094 (0.310)	0.094 (0.166)
$Capital\ Acc.Openness \times$ $Tech.Intensity$ (lagged)		-0.390 (0.247)							-0.555* (0.307)	-0.555*** (0.172)
$LT\ Interest\ Rate$ $\times Tech.Intensity$			-0.025 (0.018)						-0.020 (0.019)	-0.020 (0.025)
$\ln(Govt.Consump.)$ $\times Tech.Intensity$				-0.347 (0.526)					0.621 (0.518)	0.621 (0.731)
$\ln(Taxes\ on\ IPC) \times$ $Tech.Intensity$					-0.465 (0.343)				-0.126 (0.287)	-0.126 (0.272)
$\ln(Trade) \times Tech.Intensity$						0.891* (0.424)			0.734 (0.659)	0.734 (0.437)
$\ln(Avg.Real\ Turnover)$							0.176* (0.092)		0.106 (0.094)	0.106 (0.102)
$Institut.Quality$ $\times Tech.Intensity$								-0.005 (0.038)	0.012 (0.037)	0.012 (0.014)
Constant	-0.822*** (0.278)	-0.762** (0.289)	-0.884*** (0.245)	-0.471 (0.709)	-0.167 (0.605)	-1.716*** (0.476)	-2.486*** (0.801)	-0.740 (0.634)	-3.099** (1.208)	-3.099*** (0.876)
Standard errors	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	Clustered (country)	HAC (Driscoll-Kraay)
Observations	1,806	1,806	1,600	1,806	1,782	1,806	1,786	1,806	1,596	1,596
R-squared	0.164	0.165	0.178	0.164	0.171	0.167	0.166	0.164	0.182	0.182

Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 2.4. Private debt to GDP ratios and capital misallocation: fixed effects regressions

Interacting variable	Financial Dependence		Financial Dependence		Avg. Credit Constraints		Avg. Credit Constraints		Technological Intensity		Technological Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\ln(Corporate\ Debt) \times$ *Interaction* (lagged)	0.996*** (0.275)	0.996*** (0.295)			3.347*** (1.012)	3.347** (1.320)			0.597** (0.228)	0.597*** (0.195)		
$\ln(Household\ Debt) \times$ *Interaction* (lagged)			0.359*** (0.090)	0.359** (0.163)			1.159** (0.453)	1.159** (0.481)			0.191** (0.089)	0.191** (0.084)
$Capit.Acc.Openness \times$ *Interaction* (lagged)	-0.852** (0.358)	-0.852*** (0.183)	-1.213* (0.604)	-1.213*** (0.360)	-2.695 (3.800)	-2.695 (2.520)	-1.297 (3.457)	-1.297 (2.259)	-0.465** (0.178)	-0.465*** (0.117)	-0.646* (0.339)	-0.646*** (0.165)
$LT\ Interest\ Rate \times Interaction$	-0.052** (0.020)	-0.052** (0.019)	-0.048* (0.023)	-0.048** (0.018)	-0.198* (0.093)	-0.198** (0.081)	-0.181* (0.097)	-0.181** (0.083)	-0.021 (0.020)	-0.021 (0.028)	-0.019 (0.020)	-0.019 (0.028)
$\ln(Govt.Consump.) \times Interaction$	0.139 (0.925)	0.139 (1.158)	0.884 (1.041)	0.884 (1.035)	0.922 (2.551)	0.922 (3.769)	3.915 (3.075)	3.915 (3.224)	0.624 (0.536)	0.624 (0.732)	1.094** (0.492)	1.094* (0.617)
$\ln(Taxes\ on\ IPC) \times Interaction$	-0.261 (0.391)	-0.261 (0.261)	-0.067 (0.426)	-0.067 (0.372)	-0.072 (1.929)	-0.072 (0.998)	0.251 (1.430)	0.251 (1.191)	-0.298 (0.247)	-0.298 (0.199)	-0.207 (0.279)	-0.207 (0.183)
$\ln(Trade) \times Interaction$	0.261 (0.641)	0.261 (0.613)	0.008 (0.644)	0.008 (0.565)	2.554 (2.366)	2.554 (1.897)	2.400 (2.642)	2.400 (1.919)	0.961 (0.579)	0.961** (0.378)	0.879 (0.658)	0.879** (0.387)
$\ln(Avg.Real\ Turnover)$	0.063 (0.088)	0.063 (0.112)	0.068 (0.086)	0.068 (0.116)	0.077 (0.095)	0.077 (0.133)	0.070 (0.097)	0.070 (0.134)	0.104 (0.094)	0.104 (0.103)	0.095 (0.096)	0.095 (0.102)
$Institut.Quality \times Interaction$	-0.027 (0.055)	-0.027 (0.020)	-0.059 (0.054)	-0.059** (0.025)	-0.019 (0.122)	-0.019 (0.097)	-0.108 (0.136)	-0.108 (0.073)	0.009 (0.039)	0.009 (0.011)	-0.010 (0.040)	-0.010 (0.016)
Constant	-1.545 (2.561)	-1.545 (1.941)	-0.560 (2.726)	-0.560 (2.102)	-3.190* (1.692)	-3.190* (1.959)	-2.921 (2.156)	-2.921 (2.011)	-3.101** (1.328)	-3.101*** (0.749)	-2.602 (1.571)	-2.602*** (0.892)
Standard errors	Clustered (country)	Driscoll-Kraay	Clustered (country)	Driscoll-Kraay	Clustered (country)	Driscoll-Kraay	Clustered (country)	Driscoll-Kraay	Clustered (country)	Driscoll-Kraay	Clustered (country)	Driscoll-Kraay
Observations	1,596	1,596	1,596	1,596	1,322	1,322	1,322	1,322	1,596	1,596	1,596	1,596
R-squared	0.194	0.194	0.192	0.192	0.194	0.194	0.194	0.194	0.182	0.182	0.181	0.181

Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Appendix 2.A: Summary statistics of variables by country

Belgium	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	108	0.777	0.493	0.109	2.902
Private debt (% of GDP)	108	188.12	20.98	156.11	214.07
Public debt (% of GDP)	108	98.88	6.30	87.03	107.02
Chinn-Ito capital account openness index	108	1	0	1	1
Long-term interest rate	108	3.31	1.09	0.84	4.42
Government consumption (% of GDP)	108	23.21	1.05	21.59	24.49
Taxes on income, prof. & cap. gains (% of GDP)	108	15.49	0.59	14.37	16.40
Trade (% of GDP)	108	153.21	10.12	136.04	164.71
Average real turnover	108	21597.94	13216.95	4116.01	48124.33
Index of political institutions quality	108	23.38	1.13	21.5	24.5
Indicator of credit constraints	108	0.104	0.024	0.035	0.234

Croatia	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	135	0.494	0.628	0.019	3.579
Private debt (% of GDP)	135	119.47	23.62	80.85	143.37
Public debt (% of GDP)	135	56.68	19.18	36.60	85.71
Chinn-Ito capital account openness index	135	0.68	0.07	0.42	0.70
Government consumption (% of GDP)	135	19.38	0.85	18.28	20.57
Taxes on income, prof. & cap. gains (% of GDP)	135	5.30	0.42	4.76	6.13
Trade (% of GDP)	135	84.59	5.49	72.67	94.69
Average real turnover	129	9578.41	6383.44	2365.07	34374.34
Index of political institutions quality	135	19.34	0.90	17.58	20.13
Indicator of credit constraints	135	0.055	0.019	0.033	0.147

Czech Republic	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	104	0.406	0.434	0.002	2.754
Private debt (% of GDP)	117	62.40	9.88	46.91	77.20
Public debt (% of GDP)	117	34.64	6.74	27.46	44.91
Chinn-Ito capital account openness index	117	0.995	0.016	0.940	1
Long-term interest rate	117	3.44	1.27	0.58	4.84
Government consumption (% of GDP)	117	20.30	0.82	19.22	22.26
Taxes on income, prof. & cap. gains (% of GDP)	117	7.59	0.79	6.57	8.74
Trade (% of GDP)	117	131.14	17.74	95.02	158.73
Average real turnover	117	12822.01	8550.6	2827.49	33897.22
Index of political institutions quality	117	21.11	1.52	18.5	22.5
Indicator of credit constraints	117	0.102	0.023	0.082	0.205

Denmark	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	142	0.572	0.647	0.038	3.838
Private debt (% of GDP)	142	215.75	34.05	155.26	252.71
Public debt (% of GDP)	142	41.87	6.53	27.35	52.35
Chinn-Ito capital account openness index	142	1	0	1	1
Long-term interest rate	142	3.39	1.44	0.69	5.66
Government consumption (% of GDP)	142	25.45	1.14	23.87	27.94
Taxes on income, prof. & cap. gains (% of GDP)	142	28.35	1.10	27.20	31.69
Trade (% of GDP)	142	94.15	8.72	80.88	104.83
Average real turnover	140	13684.37	10802.48	3483.41	59120.53
Index of political institutions quality	142	26.00	1.35	23	27.04
Indicator of credit constraints	142	0.074	0.025	0.043	0.169

Finland	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	133	0.290	0.637	0.000	3.870
Private debt (% of GDP)	133	149.77	25.21	112.33	193.20
Public debt (% of GDP)	133	45.30	8.58	32.65	63.54
Chinn-Ito capital account openness index	133	1	0	1	1
Long-term interest rate	133	3.49	1.32	0.72	5.48

Finland	Obs.	Mean	Std. Dev.	Min.	Max.
Government consumption (% of GDP)	133	22.32	1.75	19.81	24.74
Taxes on income, prof. & cap. gains (% of GDP)	133	16.05	1.29	14.49	19.75
Trade (% of GDP)	133	75.51	5.59	66.24	86.51
Average real turnover	133	15062.96	10180.06	4699.8	43220.58
Index of political institutions quality	133	27.21	1.00	25.17	28
Indicator of credit constraints	133	0.034	0.011	0.020	0.056

France	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	99	0.775	0.301	0.262	1.850
Private debt (% of GDP)	99	161.05	13.57	139.32	180.29
Public debt (% of GDP)	99	78.75	11.95	64.54	94.89
Chinn-Ito capital account openness index	99	1	0	1	1
Long-term interest rate	99	3.30	0.82	1.67	4.30
Government consumption (% of GDP)	99	23.44	0.64	22.43	24.13
Taxes on income, prof. & cap. gains (% of GDP)	99	10.12	0.65	8.56	11.07
Trade (% of GDP)	99	56.35	3.17	50.46	60.48
Average real turnover	99	13667.51	7324.34	2808.91	27885.09
Index of political institutions quality	99	22.67	1.84	19.54	24.83
Indicator of credit constraints	99	0.094	0.033	0.041	0.149

Germany	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	16	0.241	0.206	0.058	0.890
Private debt (% of GDP)	16	119.88	8.20	106.54	131.00
Public debt (% of GDP)	16	68.14	8.03	57.74	80.95
Chinn-Ito capital account openness index	16	1	0	1	1
Long-term interest rate	16	3.47	1.25	1.16	5.26
Government consumption (% of GDP)	16	18.67	0.54	17.50	19.56
Taxes on income, prof. & cap. gains (% of GDP)	16	10.43	0.70	9.26	11.38
Trade (% of GDP)	16	72.66	10.71	53.37	85.87
Average real turnover	16	12810.33	5394.52	5997.89	19980.77
Index of political institutions quality	16	25.09	0.77	23.25	26
Indicator of credit constraints	16	0.218	0	0.218	0.218

Hungary	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	150	0.416	0.487	0.011	3.934
Private debt (% of GDP)	150	96.57	25.99	51.49	131.24
Public debt (% of GDP)	150	67.04	9.70	51.38	79.91
Chinn-Ito capital account openness index	150	0.90	0.18	0.42	1
Long-term interest rate	150	7.07	1.40	3.43	9.12
Government consumption (% of GDP)	150	21.15	0.91	19.67	22.92
Taxes on income, prof. & cap. gains (% of GDP)	150	8.50	1.26	6.25	10.22
Trade (% of GDP)	150	145.66	19.84	113.73	171.57
Average real turnover	150	10089.5	7825.75	1996	44800.15
Index of political institutions quality	150	20.82	2.03	17.5	25

Italy	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	125	0.347	0.467	0.007	3.815
Private debt (% of GDP)	125	109.73	16.12	82.37	127.32
Public debt (% of GDP)	125	110.23	10.95	99.79	131.78
Chinn-Ito capital account openness index	125	1	0	1	1
Long-term interest rate	125	4.42	0.69	2.89	5.49
Government consumption (% of GDP)	125	19.41	0.59	18.41	20.63
Taxes on income, prof. & cap. gains (% of GDP)	125	13.49	0.72	12.36	14.54
Trade (% of GDP)	125	51.86	3.75	45.61	56.18
Average real turnover	125	13638.83	8401.96	3213.24	34477.21
Index of political institutions quality	125	19.80	1.75	16.5	22.54
Indicator of credit constraints	125	0.153	0.042	0.103	0.265

Lithuania	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	142	0.355	0.594	0.002	4.121
Private debt (% of GDP)	142	58.54	19.24	29.32	86.83
Public debt (% of GDP)	142	27.37	9.92	14.56	42.59
Chinn-Ito capital account openness index	142	0.889	0.125	0.699	1
Long-term interest rate	142	5.28	2.77	1.38	14.00
Government consumption (% of GDP)	142	18.96	1.65	16.61	22.40
Taxes on income, prof. & cap. gains (% of GDP)	142	6.95	1.87	4.30	9.52
Trade (% of GDP)	142	124.59	26.32	83.27	166.87
Average real turnover	140	5261.64	3590.16	1070.82	14293.98
Index of political institutions quality	142	18.87	1.06	16	20
Indicator of credit constraints	142	0.116	0.034	0.069	0.297

Netherlands	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	118	0.727	0.472	0.135	2.969
Private debt (% of GDP)	120	245.97	24.34	216.25	289.12
Public debt (% of GDP)	120	53.82	8.02	41.97	67.10
Chinn-Ito capital account openness index	120	1	0	1	1
Long-term interest rate	120	3.60	1.12	1.45	5.40
Government consumption (% of GDP)	120	23.94	2.04	20.44	26.48
Taxes on income, prof. & cap. gains (% of GDP)	120	9.63	0.43	8.80	10.26
Trade (% of GDP)	120	131.76	13.97	112.65	154.29
Average real turnover	118	18433.11	12158.96	3141.16	48785.33
Index of political institutions quality	120	26.35	1.01	24.08	27.63
Indicator of credit constraints	118	0.118	0.041	0.072	0.211

Poland	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	99	0.619	0.374	0.120	2.820
Private debt (% of GDP)	99	69.00	12.73	43.31	83.40
Public debt (% of GDP)	99	50.12	3.64	44.16	55.69
Chinn-Ito capital account openness index	99	0.472	0.072	0.449	0.699
Long-term interest rate	99	5.01	1.08	2.70	6.12
Government consumption (% of GDP)	99	18.33	0.34	17.93	19.12
Taxes on income, prof. & cap. gains (% of GDP)	99	6.77	0.61	6.25	8.03
Trade (% of GDP)	99	83.97	7.73	70.27	96.01
Average real turnover	99	12606.06	8421.89	2658.92	44081.69
Index of political institutions quality	99	20.74	0.67	19.5	21.5
Indicator of credit constraints	99	0.100	0.014	0.036	0.129

Portugal	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	80	0.782	0.420	0.058	3.028
Private debt (% of GDP)	90	210.24	12.86	187.60	231.38
Public debt (% of GDP)	90	100.94	25.68	68.44	130.59
Chinn-Ito capital account openness index	90	1	0	1	1
Long-term interest rate	90	5.57	2.61	2.42	10.55
Government consumption (% of GDP)	90	19.65	1.01	18.12	21.43
Taxes on income, prof. & cap. gains (% of GDP)	90	9.19	1.03	7.98	10.96
Trade (% of GDP)	90	72.51	5.89	61.08	80.22
Average real turnover	90	10581.47	7279.18	2502.71	35129.67
Index of political institutions quality	90	21.11	2.54	18	24
Indicator of credit constraints	90	0.116	0.040	0.076	0.303

Romania	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	88	0.380	0.451	0.005	2.849
Private debt (% of GDP)	88	35.57	6.87	21.35	43.34
Public debt (% of GDP)	88	26.32	11.09	11.88	39.22
Chinn-Ito capital account openness index	88	0.984	0.037	0.879	1
Government consumption (% of GDP)	88	15.33	1.23	13.74	17.54
Taxes on income, prof. & cap. gains (% of GDP)	64	5.71	0.43	5.03	6.33
Trade (% of GDP)	88	74.95	7.24	59.32	82.77

Romania	Obs.	Mean	Std. Dev.	Min.	Max.
Average real turnover	76	4670.08	2494.13	1187.32	9987.25
Index of political institutions quality	88	15.60	1.02	14	16.5
Indicator of credit constraints	33	0.196	0.049	0.103	0.243

Slovak Republic	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	142	0.608	0.516	0.006	3.588
Private debt (% of GDP)	142	63.49	13.70	47.54	85.86
Public debt (% of GDP)	142	42.45	8.52	28.46	54.74
Chinn-Ito capital account openness index	142	0.571	0.216	0.166	0.750
Long-term interest rate	134	4.36	1.63	0.89	8.04
Government consumption (% of GDP)	142	18.91	0.82	17.22	20.16
Taxes on income, prof. & cap. gains (% of GDP)	142	6.16	0.54	5.33	7.04
Trade (% of GDP)	142	154.09	23.42	110.70	184.33
Average real turnover	141	14859.03	12263.76	1799.03	52769.78
Index of political institutions quality	142	20.05	1.00	18.5	21.5

Slovenia	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	106	0.469	0.512	0.000	2.957
Private debt (% of GDP)	106	108.73	15.15	83.67	125.33
Public debt (% of GDP)	106	48.94	22.95	21.80	82.62
Chinn-Ito capital account openness index	106	0.807	0.110	0.699	1
Long-term interest rate	106	3.98	1.38	1.15	5.81
Government consumption (% of GDP)	106	19.08	0.98	17.29	20.43
Taxes on income, prof. & cap. gains (% of GDP)	106	7.39	0.80	6.31	8.65
Trade (% of GDP)	106	135.18	10.36	112.62	146.15
Average real turnover	104	12114.46	8315.7	2844.98	32399.69
Index of political institutions quality	106	20.01	1.52	18.04	21.5
Indicator of credit constraints	106	0.157	0.022	0.122	0.263

Spain	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	56	0.803	0.355	0.081	2.418
Private debt (% of GDP)	63	201.51	14.81	175.03	215.98
Public debt (% of GDP)	63	80.46	18.34	52.70	100.37
Chinn-Ito capital account openness index	63	1	0	1	1
Long-term interest rate	63	4.08	1.35	1.74	5.85
Government consumption (% of GDP)	63	19.97	0.49	19.34	20.52
Taxes on income, prof. & cap. gains (% of GDP)	63	9.30	0.37	8.77	9.64
Trade (% of GDP)	63	57.81	5.83	46.50	63.61
Average real turnover	63	14619.31	9587	3329.71	39990.55
Index of political institutions quality	63	20.79	1.55	18.71	23.08
Indicator of credit constraints	63	0.199	0.056	0.150	0.316

Sweden	Obs.	Mean	Std. Dev.	Min.	Max.
Dispersion in normalized MRPK	111	0.560	0.597	0.000	2.736
Private debt (% of GDP)	111	184.86	21.47	141.57	210.90
Public debt (% of GDP)	111	42.00	4.17	36.71	48.88
Chinn-Ito capital account openness index	111	1	0	1	1
Long-term interest rate	111	2.98	1.14	0.72	4.64
Government consumption (% of GDP)	111	25.38	0.70	24.07	26.33
Taxes on income, prof. & cap. gains (% of GDP)	111	16.02	1.26	14.50	18.22
Trade (% of GDP)	111	85.71	4.31	76.15	93.36
Average real turnover	111	9849.17	5358.48	3189.28	22889.56
Index of political institutions quality	111	27.18	0.23	27	27.5
Indicator of credit constraints	111	0.068	0.018	0.055	0.141

Appendix 2.B: More details on sector-specific interacting variables

(i) Rajan and Zingales' (1998) indicator of external finance dependence

I obtain the industry-level data on the external finance dependence indicator from Franco (2018). External finance dependence, as defined by Rajan and Zingales (1998), is the amount of a firm's desired investment that cannot be financed through the internal cash flows the firm generates. Franco (2018) uses Compustat data on U.S. listed firms to calculate the external finance dependence (*EFD*) for each firm *i* in sector *s* as follows:

$$EFD_{si} = \frac{\sum_{t=1995}^{2006}(Capital\ expenditures_{sit} - Cash\ flow\ from\ operations_{sit})}{\sum_{t=1995}^{2006} Capital\ expenditures_{sit}}$$

The time period 1995–2006 is deliberately chosen to ensure (i) the comparability of sectoral production structures and financing needs over time and (ii) the cleanness of the measures from potentially distortionary effects of the global financial crisis.

The sector-level measure of *EFD* is then obtained as:

$$EFD_s = Median_s(EFD_{si})$$

Finally, in order to alleviate the problems associated with the U.S. industries' technological characteristics differing from those of other countries, each sector (2-digit level) is assigned 0 (low) or 1 (high) depending on whether EFD_s is below or above the median sectoral value.

Since I use interactions at the 1-digit level, for each macro sector (1-digit), I then calculate the average of the binary EFD_s across all 2-digit industries to obtain my financial dependence indicator.

(ii) CompNet indicator of credit constraints (ICC)

The detailed explanation below is taken from the *User Guide for the 6th Vintage of the CompNet Dataset*:

> CompNet has constructed a firm-level "indicator of credit constraints" (ICC), defining firms that can be considered credit-constrained based on their financial situation.
>
> The first step to construct the ICC indicator is to match firms' responses about binding credit constraints from the Survey on Access to Finance of Enterprises (SAFE) with their financial characteristics available in the AMADEUS database from Bureau van Dijk.
>
> The SAFE is conducted by the ECB jointly with the European Commission twice per year. The survey intends to assess the financial conditions of firms in the Euro area (the survey is also conducted for some countries outside the Euro zone). It defines a firm as credit constrained if:
>
> - The firm reports loan applications which were rejected;
> - The firm reports loan applications for which only a limited amount was granted;

- The firm reports loan applications which were rejected by the firms because the borrowing costs were too high;
- The firm did not apply for a loan for fear of rejection (i.e. discouraged borrowers).

After matching the firms' responses to survey with their financial statements available in the AMADEUS database from Bureau van Dijk, the second stage of the process is to estimate the impact of several indicators of the financial position of a firm on its probability to be credit constrained. More specifically, the regression equation is the following:

$$Prob\ (credit\_constraint) = \\ = \alpha + \beta_1 \cdot finlev + \beta_2 \cdot ifp + \beta_3 \cdot pm + \beta_4 \cdot coll + \beta_5 \cdot cashH + \beta_6 \cdot lnT \\ + \gamma \cdot control\ var + \varepsilon$$

where $finlev$ is the financial leverage, ifp is the index of financial pressure, pm is profit margin, $coll$ is collateral, $cashH$ is cash holding and TA are the total assets. The control variables are time, sector, firm size and country-specific effects. For a more detailed explanation of the variables used in the regression, see Ferrando et al. (2015).

The third step is to use the coefficients of the estimated probit regression to compute a predicted constrained score for the firms in the CompNet dataset, depending on the value of their financial position indicators. This is what we call the "SAFE score", which is computed for each firm i as:

$$SAFE\_score_i = -1.88 + 0.71 \cdot finlev_i + 0.28 \cdot ifp_i - 0.51 \cdot pm_i - 0.21 \cdot coll_i - 1.2 \cdot cashH_i \\ - 0.05 \cdot \ln(TA_i)$$

Once the firms are ranked according to the SAFE score, the next step is to set a threshold value of the SAFE score above which we can define firms in a given level of aggregation as being credit constrained. The value of the threshold is time-varying and country-specific and is set so that the share of firms above this threshold at the country level is the same as the share of credit constrained firms for a given country-year reported in the SAFE survey.

Last, we set $ICC_i = 1$ if the estimated SAFE score index is above the threshold we obtained from the before mentioned exercise, and $ICC_i = 0$ otherwise. The SAFE dummy variable in the CompNet database reflects the ICC values and the mean of the SAFE dummy consequently reports the share of credit constrained firms in any given level of aggregation.

(iii) Eurostat indicators on high-tech industry and knowledge-intensive services

I obtain the industry-level data on the technological intensity indicator from Eurostat. The following explanation is taken from the Eurostat website:

'Statistics on high-tech industry and knowledge-intensive services' (sometimes referred to as simply **'high-tech statistics'**) comprise economic, employment and science, technology and innovation (STI) data describing manufacturing and services industries or products traded broken down by technological intensity... Two main approaches are used in the domain to identify technology-intensity: the sectoral approach and the product approach.

The sectoral approach:

The sectoral approach is an aggregation of the manufacturing industries according to technological intensity (R&D expenditure/value added) and based on the Statistical classification of economic activities in the European Community (NACE) at 2-digit level. The level of R&D intensity served as a criterion of classification of economic sectors into high-technology, medium high-technology, medium low-technology and low-technology industries.

Services are mainly aggregated into knowledge-intensive services (KIS) and less knowledge-intensive services (LKIS) based on the share of tertiary educated persons at NACE 2-digit level.

Source: *https://ec.europa.eu/eurostat/cache/metadata/en/htec_esms.htm*

For each 2-digit industry, I assign 1 if it belongs to either a high-technology or medium-high-technology manufacturing or a knowledge-intensive services (KIS) sector, and assign 0 if it belongs to either a medium-low-technology or low-technology manufacturing or a less knowledge-intensive services (LKIS) sector. Then, for each macro sector (1-digit level), I calculate the average of this indicator across all 2-digit industries.

The binary categorical values of the indicators of external finance dependence and technological intensity for each 2-digit industry are given in Table 2.B1 starting from the next page. Low means the value of 0 and high means the value of 1.

Table 2.B1. Binary values of external finance dependence and technological intensity by sectors.

NACE Rev.2 Section	1-digit Sector	Description	2-digit Sector	Description	Ext. Finance Dependence	Technological Intensity
C	1	Manufacturing	10	Manufacture of food products	Low	Low
			11	Manufacture of beverages	Low	Low
			12	Manufacture of tobacco products	Low	Low
			13	Manufacture of textiles	High	Low
			14	Manufacture of wearing apparel	Low	Low
			15	Manufacture of leather and related products	Low	Low
			16	Manufacture of wood and of products of wood and cork, except furniture	Low	Low
			17	Manufacture of paper and paper products	Low	Low
			18	Printing and reproduction of recorded media	Low	Low
			19	Manufacture of coke and refined petroleum products	High	Low
			20	Manufacture of chemicals and chemical products	High	High
			21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	High	High
			22	Manufacture of rubber and plastic products	Low	Low
			23	Manufacture of other non-metallic mineral products	Low	Low
			24	Manufacture of basic metals	Low	Low
			25	Manufacture of fabricated metal products, except machinery and equipment	Low	Low
			26	Manufacture of computer, electronic and optical products	High	High
			27	Manufacture of electrical equipment	High	High
			28	Manufacture of	Low	High

NACE Rev.2 Section	1-digit Sector	Description	2-digit Sector	Description	Ext. Finance Dependence	Technological Intensity
				machinery and equipment n.e.c.		
			29	Manufacture of motor vehicles, trailers and semitrailers	Low	High
			30	Manufacture of other transport equipment	Low	High
			31	Manufacture of furniture	Low	Low
			32	Other manufacturing	High	Low
			33	Repair and installation of machinery and equipment	Low	Low
F	2	Construction	41	Construction of buildings	Low	Low
			42	Civil engineering	Low	Low
			43	Specialised construction activities	High	Low
G	3	Wholesale and retail trade; repair of motor vehicles and motorcycles	45	Wholesale and retail trade and repair of motor vehicles and motorcycles	Low	Low
			46	Wholesale trade, except of motor vehicles and motorcycles	Low	Low
			47	Retail trade, except of motor vehicles and motorcycles	High	Low
H	4	Transportation and storage	49	Land transport and transport via pipelines	Low	Low
			50	Water transport	High	High
			51	Air transport	High	High
			52	Warehousing and support activities for transportation	Low	Low
			53	Postal and courier activities	Low	Low
I	5	Accommodation and food service activities	55	Accommodation	High	Low
			56	Food and beverage service activities	High	Low
J	6	Information and communication	58	Publishing activities	High	High
			59	Motion picture, video and television program production, sound recording and music publishing	High	High
			60	Programming and broadcasting	Low	High

NACE Rev.2 Section	1-digit Sector	Description	2-digit Sector	Description	Ext. Finance Dependence	Technological Intensity
				activities		
			61	Telecommunications	High	High
			62	Computer programming, consultancy and related activities	High	High
			63	Information service activities	High	High
L	7	Real Estate activities	68	Real estate activities	Low	Low
M	8	Professional, scientific and technical activities	69	Legal and accounting activities	Low	High
			70	Activities of head offices; management consultancy activities	Low	High
			71	Architectural and engineering activities; technical testing and analysis	Low	High
			72	Scientific research and development	High	High
			73	Advertising and market research	Low	High
			74	Other professional, scientific and technical activities	Low	High
			75	Veterinary activities	Low	High
N	9	Administrative and support service activities	77	Rental and leasing activities	High	Low
			78	Employment activities	Low	High
			79	Travel agency, tour operator and other reservation service and related activities	High	Low
			80	Security and investigation activities	Low	High
			81	Services to buildings and landscape activities	Low	Low
			82	Office administrative, office support and other business support activities	Low	Low

Appendix 2.C: Robustness checks

Table 2.C1. Debt to GDP ratios and capital misallocation: One-step system GMM regressions

Interacting variable	Financial Dependence		Average Credit Constraints		Technological Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(Private\ Debt) \times Interaction$ (lagged)	0.763***	0.694***	2.156**	1.961*	0.640***	0.642***
	(0.208)	(0.201)	(0.911)	(1.038)	(0.210)	(0.212)
$\ln(Public\ Debt) \times Interaction$ (lagged)	-0.463*	-0.507**	-1.408	-1.422	-0.378*	-0.424*
	(0.234)	(0.235)	(1.030)	(1.042)	(0.208)	(0.242)
$Capit.Acc.Openness \times Interaction$ (lagged)	-1.473**	-1.485**	-5.444	-6.521	-1.021*	-1.169**
	(0.540)	(0.552)	(4.046)	(4.330)	(0.505)	(0.496)
$LT\ Interest\ Rate \times Interaction$	-0.055**	-0.055*	-0.251**	-0.221*	-0.057***	-0.061***
	(0.023)	(0.030)	(0.112)	(0.125)	(0.018)	(0.018)
$\ln(Govt.Consump.) \times Interaction$	0.205	0.559	1.071	2.000	0.092	0.302
	(0.627)	(0.737)	(2.824)	(3.289)	(0.358)	(0.416)
$\ln(Taxes\ on\ IPC) \times Interaction$	0.102	0.044	1.028	1.108	-0.149	-0.149
	(0.322)	(0.338)	(1.326)	(1.462)	(0.251)	(0.242)
$\ln(Trade) \times Interaction$	0.276	0.260	0.831	0.705	0.159	0.135
	(0.245)	(0.236)	(0.990)	(1.079)	(0.185)	(0.194)
$\ln(Avg.Real\ Turnover)$	0.306***	0.290	0.345*	0.364*	0.183	0.151
	(0.102)	(0.180)	(0.165)	(0.202)	(0.160)	(0.157)
$Institut.Quality \times Interaction$	-0.107***	-0.127***	-0.340**	-0.366**	-0.058**	-0.068**
	(0.023)	(0.026)	(0.119)	(0.137)	(0.025)	(0.026)
Constant	-2.212**	-2.029	-2.656	-2.832	-0.997	-0.695
	(0.949)	(1.668)	(1.644)	(2.007)	(1.432)	(1.410)
Observations	1,596	1,596	1,322	1,322	1,596	1,596
Instrument count	*133*	*91*	*128*	*91*	*133*	*91*
AR(1) test p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test p-value	0.274	0.274	0.415	0.404	0.236	0.230
Hansen test p-value	1.000	1.000	1.000	1.000	1.000	1.000

Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 2.C2. Debt to GDP ratios and capital misallocation: excluding Croatia, Germany, Romania, and Spain

Interacting variable	Financial Dependence			Average Credit Constraints			Technological Intensity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimation	*FE*	*FE*	*Sys-GMM*	*FE*	*FE*	*Sys-GMM*	*FE*	*FE*	*Sys-GMM*
$\ln(Private\ Debt) \times$ *Interaction* (lagged)	1.046*** (0.178)	1.046*** (0.266)	0.800*** (0.191)	3.506** (1.189)	3.506*** (1.173)	2.473** (0.857)	0.620** (0.250)	0.620*** (0.195)	0.621** (0.208)
$\ln(Public\ Debt) \times$ *Interaction* (lagged)	-0.085 (0.305)	-0.085 (0.280)	-0.470* (0.219)	-0.895 (1.968)	-0.895 (1.487)	-1.291 (0.856)	0.016 (0.310)	0.016 (0.160)	-0.335 (0.201)
$Capit.Acc.Openness \times$ *Interaction* (lagged)	-1.173** (0.464)	-1.173*** (0.347)	-1.423** (0.509)	-5.859 (6.088)	-5.859 (4.315)	-5.994 (4.786)	-0.610* (0.304)	-0.610*** (0.191)	-0.832* (0.407)
$LT\ Interest\ Rate \times Interaction$	-0.053** (0.022)	-0.053*** (0.016)	-0.049** (0.022)	-0.208 (0.123)	-0.208*** (0.069)	-0.208* (0.101)	-0.016 (0.020)	-0.016 (0.023)	-0.045** (0.020)
$\ln(Govt.Consump.) \times Interaction$	0.042 (0.960)	0.042 (1.196)	0.330 (0.556)	1.194 (3.302)	1.194 (4.207)	1.468 (2.630)	0.594 (0.526)	0.594 (0.743)	0.190 (0.259)
$\ln(Taxes\ on\ IPC) \times Interaction$	-0.108 (0.373)	-0.108 (0.373)	0.079 (0.345)	0.475 (1.494)	0.475 (0.886)	1.230 (1.646)	-0.178 (0.294)	-0.178 (0.271)	-0.142 (0.248)
$\ln(Trade) \times Interaction$	-0.266 (0.688)	-0.266 (0.624)	0.161 (0.216)	0.145 (3.122)	0.145 (2.596)	-0.006 (0.792)	0.640 (0.653)	0.640 (0.467)	0.070 (0.138)
$\ln(Avg.Real\ Turnover)$	0.075 (0.094)	0.075 (0.123)	0.255*** (0.082)	0.088 (0.100)	0.088 (0.158)	0.201 (0.123)	0.119 (0.101)	0.119 (0.114)	0.170 (0.140)
$Institut.Quality \times Interaction$	-0.042 (0.053)	-0.042 (0.046)	-0.107*** (0.022)	-0.130 (0.272)	-0.130 (0.200)	-0.314** (0.120)	0.000 (0.037)	0.000 (0.016)	-0.066** (0.027)
Constant	-0.536 (2.548)	-0.536 (2.802)	-1.747** (0.763)	-1.339 (3.446)	-1.339 (2.856)	-1.343 (1.216)	-2.848** (1.188)	-2.848*** (0.916)	-0.892 (1.250)
Standard errors	Clustered (country)	HAC (Driscoll-Kraay)	Clustered (country)	Clustered (country)	HAC (Driscoll-Kraay)	Clustered (country)	Clustered (country)	HAC (Driscoll-Kraay)	Clustered (country)
Observations	1,533	1,533	1,533	1,259	1,259	1,259	1,533	1,533	1,533

Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 2.C3. Debt to GDP ratios and capital misallocation: interaction with alternative sectoral indicators

Interacting variable	Dispersion of Credit Constraints			De Loecker & Warzynski (2012) Markups			Skewness of TFP distribution		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimation	*FE*	*FE*	*Sys-GMM*	*FE*	*FE*	*Sys-GMM*	*FE*	*FE*	*Sys-GMM*
$\ln(Private\ Debt) \times$ $Interaction$ (lagged)	1.534** (0.515)	1.534*** (0.452)	1.370*** (0.315)	0.268*** (0.089)	0.268*** (0.061)	0.163** (0.069)	0.063*** (0.018)	0.063*** (0.008)	0.076*** (0.020)
$\ln(Public\ Debt) \times$ $Interaction$ (lagged)	0.136 (0.915)	0.136 (0.532)	-0.600 (0.387)	0.139 (0.091)	0.139*** (0.046)	0.028 (0.030)	-0.007 (0.025)	-0.007 (0.011)	0.002 (0.018)
$Capit. Acc. Openness \times$ $Interaction$ (lagged)	-1.680 (2.559)	-1.680 (1.634)	-2.356 (1.431)	-0.217 (0.145)	-0.217* (0.116)	-0.216 (0.257)	-0.105** (0.047)	-0.105*** (0.024)	-0.134** (0.052)
$LT\ Interest\ Rate$ $\times Interaction$	-0.082* (0.039)	-0.082** (0.033)	-0.124** (0.042)	-0.003 (0.006)	-0.003 (0.004)	-0.014 (0.009)	-0.003 (0.002)	-0.003 (0.002)	-0.004*** (0.001)
$\ln(Govt. Consump.)$ $\times Interaction$	1.136 (1.731)	1.136 (1.816)	0.251 (1.048)	-0.308 (0.267)	-0.308* (0.172)	-0.466** (0.194)	-0.017 (0.077)	-0.017 (0.061)	-0.099** (0.035)
$\ln(Taxes\ on\ IPC)$ $\times Interaction$	0.031 (0.610)	0.031 (0.463)	-0.110 (0.602)	-0.088 (0.101)	-0.088 (0.091)	-0.075 (0.062)	-0.033 (0.021)	-0.033** (0.014)	-0.014 (0.018)
$\ln(Trade)$ $\times Interaction$	1.004 (1.234)	1.004 (0.917)	0.091 (0.381)	0.137 (0.186)	0.137 (0.118)	0.210** (0.085)	0.040 (0.031)	0.040 (0.024)	0.010 (0.017)
$\ln(Avg. Real\ Turnover)$	0.020 (0.105)	0.020 (0.119)	0.196 (0.150)	0.075 (0.097)	0.075 (0.079)	0.565** (0.202)	0.045 (0.091)	0.045 (0.093)	0.321 (0.213)
$Institut. Quality$ $\times Interaction$	0.009 (0.102)	0.009 (0.055)	-0.140*** (0.043)	0.006 (0.012)	0.006 (0.006)	0.003 (0.008)	0.001 (0.002)	0.001 (0.001)	0.002 (0.001)
Constant	-3.965 (3.551)	-3.965 (2.794)	-1.004 (1.601)	-1.780 (2.416)	-1.780 (1.581)	-4.671** (1.880)	-1.253 (1.536)	-1.253 (1.296)	-2.253 (1.941)
Standard errors	Clustered (country)	HAC (Driscoll-Kraay)	Clustered (country)	Clustered (country)	HAC (Driscoll-Kraay)	Clustered (country)	Clustered (country)	HAC (Driscoll-Kraay)	Clustered (country)
Observations	1,322	1,322	1,322	1,398	1,398	1,398	1,596	1,596	1,596

Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Note: All of the sectoral-level interacting variables are averaged over the available time period for each country-sector to make them time-invariant. I take the natural logarithm of the De Loecker and Warzynski (2012) measure of average markup before interacting it with the country-level variables.

Chapter 3

The role of misallocation in the relationship between trade and income inequality

Abstract

Earlier studies suggest that the effect of trade openness on income inequality is not the same across countries. This chapter introduces a new factor that mediates the impact of trade on income inequality within countries. In a sample of 18 European countries over the period 1999-2016, I find that the effect of trade openness on income distribution is conditional on the existing patterns of resource allocation. In case of an efficient allocation of resources within a country, more trade reduces income inequality. Deviations from allocative efficiency, however, considerably alter the distributional effect of openness: under conditions of misallocation, the inequality-increasing effect of trade is weakened—and may even be reversed when misallocation is sufficiently high—albeit such countries tend to have lower income inequality, other things being equal.

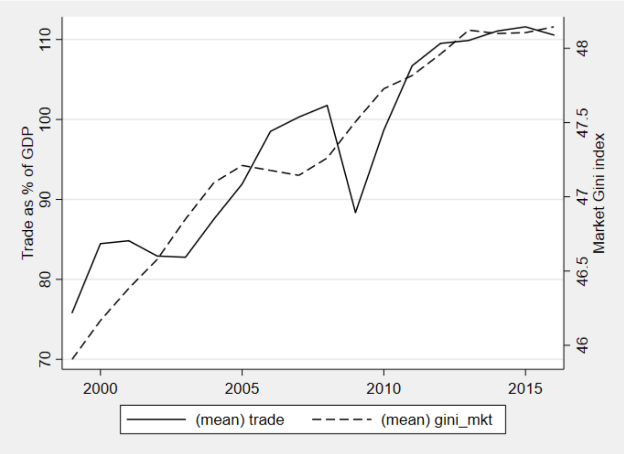
3.1. Introduction

Income inequality and top income shares have been rising all over the world for the last three decades, albeit at different speeds (see the *World Inequality Report 2018*). Noticeably, this has been accompanied by increased globalization for the last half century, both in trade (see Ortiz-Ospina et al., 2019) and in finance (Furceri and Loungani, 2018; Furceri et al., 2019). Findings in the literature generally suggest that the effect of financial liberalization on income inequality mostly depends on the level of financial development and institutional quality (Ni and Liu, 2019, and references cited therein). Studies about the effect on income distribution of trade openness, however, provide quite mixed results.

Most of the relevant theoretical work and some empirical work show that trade increases the skilled-unskilled wage ratio, while other empirical studies suggest that trade reduces income inequality, at least beyond a certain point (see the literature review in Section 3.2). Figure 3.1 shows the mean time series of trade (exports and imports as percentage of GDP) and market Gini index for the period 1999–2016 averaged across 18 European countries. From the figure, it appears as if there is a positive relationship between these two variables. Figure 3.2, on the other hand, shows the scatter plot of the change in log(trade) and the change in market Gini index from the period average of 2000–2005 to that of 2010–2015 for the same 18 countries. From this figure, it looks like there is a negative correlation between these two variables. What this suggests is that the relationship between trade and income inequality is probably not unequivocal.

While the distributional effect of trade openness is, most probably, conditional on countries' economic and institutional characteristics, a common corollary of the moderating factors identified in the literature—i.e., economic development and political regimes—seems to be the degree of *misallocation* stemming from different statutory and discretionary provisions and market imperfections (Restuccia and Rogerson, 2017) associated with those factors. Whereas trade openness can raise average incomes in an economy, the existing patterns of resource allocation, or misallocation, may determine which groups in the country gain—and which groups lose—from this openness, hence affecting the distribution of incomes and wealth in the economy. So, I ask the question: does the effect of trade on income inequality depend on within-country allocative efficiency?

Misallocation of production factors such as labour and capital has been shown to be an important determinant of aggregate productivity differences across countries and across similar industries in different countries (Olley and Pakes, 1996; Banerjee and Duflo, 2005;



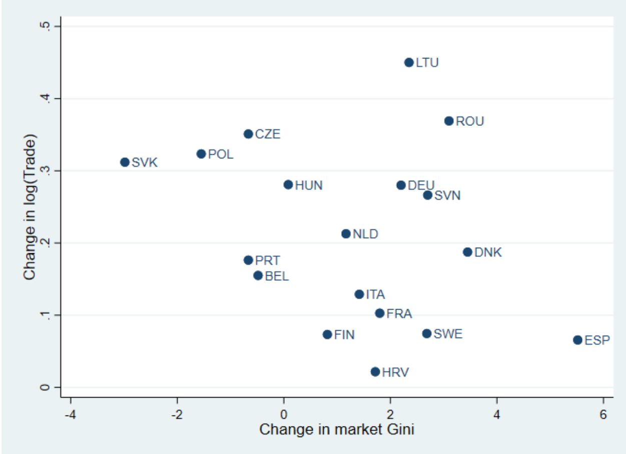


Figure 3.1. Mean time series of trade and market Gini index for 18 European countries

Figure 3.2. Scatter plot of changes in log(trade) and market Gini index from 2000–2005 to 2010–2015

(*Source: Author's own estimations based on World Bank and SWIID data*)

Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Bartelsman et al., 2013; Restuccia and Rogerson, 2013; Hopenhayn, 2014; Inklaar et al., 2016; Restuccia, 2019). In this chapter, I hypothesize that the cross-country heterogeneity in existing misallocation—reflecting distortions and market imperfections that prevent efficient allocation of resources—can also determine the extent to which countries experience a rise or fall in income disparity of its residents as a result of international trade. In a nutshell, my aim is to investigate how trade openness affects income inequality in the presence of differences in allocative efficiency across countries. I address this question by interacting trade openness with a country-level measure of misallocation obtained from a micro-based dataset constructed on firm-level information. My analysis documents an important role played by misallocation.

The remaining part of this chapter proceeds as follows. Section 3.2 reviews the literature on the relationship between trade and income inequality. Section 3.3 discusses the theoretical motivation behind the current study of the possible distributional effects of trade openness conditional on existing resource misallocation. Section 3.4 presents the sources of data and the empirical methodology used in this study. Section 3.5 presents and briefly discusses the results of the empirical analysis, and Section 3.6 concludes.

3.2. Trade and income inequality: the literature review

Earlier empirical work—before 2003—regarding the distributional effects of trade mainly focused on testing the implications of the Heckscher-Ohlin framework, in particular the

Stolper-Samuelson theorem[1]; after the introduction of the seminal Melitz (2003) model to the trade theory, researchers started to more actively analyze the consequences of trade—also for income inequality—under conditions of firm heterogeneity and monopolistic competition (Harrison et al., 2011). Other more recent models incorporate bargaining, trade in tasks, and labour-market frictions into the analysis of trade and inequality (Harrison et al., 2011). Most of the theoretical studies in this area, however, focus on the effect of trade on *wage* inequality, rather than overall income inequality. Moreover, empirical work on the implications of firm heterogeneity and market imperfections for the relationship between trade and income inequality is scarce, not least due to the paucity of data available at the firm level.

Epifani and Gancia (2008) show in a model of trade in differentiated products that international trade can increase the relative demand for skilled labour, and hence the skill premium, by raising the output share of skill-intensive sectors. Meschi and Vivarelli (2009) find in a sample of 65 developing countries that *only* trade with high-income countries increases income inequality, through both imports and exports. Egger and Kreickemeier (2012) show in a model with heterogeneous individuals and firms that trade liberalization amplifies both inter-group and intra-group inequality between managers and production workers. Sampson (2014) shows in a model of intra-industry trade and assortative matching between workers and firms that trade liberalization increases the demand for skilled labour and raises wage inequality. Burstein and Vogel (2017) incorporate heterogeneity in skill-intensity across firms and sectors into a standard international trade model to show that trade affects the skill premium through three mechanisms: (i) the Heckscher-Ohlin (H-O) mechanism that reallocates factors toward a country's comparative advantage sectors; (ii) the within-sector *skill-biased productivity* (SBP) mechanism that reallocates factors toward skill-intensive producers; and (iii) the *between-sector* SBP mechanism that reallocates factors toward skill-intensive sectors. They find that, for most countries, trade tends to increase the skill premium, suggesting that the within-sector and between-sector SBP mechanisms dominate the H-O mechanism. Stijepic (2017) uses a heterogeneous-firm model of intra-industry trade integrated with frictional labour markets and on-the-job search to show that trade magnifies the variations in profitability between small and large firms, and it also raises the relative wages of high-skill workers due to their higher inter-firm mobility. Di Comite et al. (2018) develop and empirically test a monopolistic competition model featuring vertical

[1] The Stolper-Samuelson theorem implies that trade increases the return to capital and reduces the return to labour in developed, capital-abundant countries, while it increases the return to labour and reduces the return to capital in developing, capital-scarce countries.

linkages and fixed costs to show that trade liberalization increases the wage gap by benefiting skilled workers more than the unskilled. Artuc et al. (2019) find evidence of a trade-off between the income gains and the inequality costs of removing import tariffs in a sample of 54 developing countries: while trade liberalization raises average incomes, this comes at the expense of increased income disparity. Other, mainly theoretical, studies showing that trade liberalization raises the skilled-unskilled wage ratio by raising the relative demand for skills include Yeaple (2005), Zhu and Trefler (2005), and Parro (2013).

As compared to the literature on skill-biased trade liberalization, theoretical studies explaining how trade can *reduce* income inequality in developed, or capital-abundant and skill-abundant, countries are rare. One relevant study by Grossman and Rossi-Hansberg (2008) implies that countries whose trade mainly involves the *offshoring* of low-skill tasks may experience the reduction in wage disparity between skilled and unskilled workers. The argument given by the authors is that, when low-skill tasks are easily offshored, the *productivity effect* coming from the cost savings disproportionately benefits low-skill-intensive sectors, thus leading to an increase in the economy-wide demand for low-skilled labour. Lopez-Gonzalez et al. (2015) find evidence for the predictions of Grossman and Rossi-Hansberg (2008)—that countries having a higher *backward participation* (i.e., foreign value added share of gross exports) in global value chains tend to have lower wage inequality. Another study by Helpman et al. (2010) uses a theoretical framework that integrates firm heterogeneity, search and matching frictions, and ex-post heterogeneity in worker ability to show that wage inequality first *increases* and later *decreases* in the degree of trade openness. The intuition for this result is such: when trade is too costly and no firm exports, trade liberalization initially increases wage inequality by inducing most productive firms to export and raise wages of their employees relative to non-exporters; when all firms are exporters, however, a *rise* in trade costs increases wage inequality by inducing least productive firms to exit export markets and reduce wages of their employees relative to exporters. Using detailed firm-level data for Brazil, Helpman et al. (2017) find evidence for the hump-shaped relationship between wage inequality and trade openness, thus confirming the prediction of Helpman et al. (2010).

By studying the effects of economic openness and democracy together in a sample of 69 countries (both developed and developing) over the period 1960–1996, Reuveny and Li (2003) find that trade reduces income inequality. Bensidoun et al. (2011) provide evidence that the effect of trade on income inequality depends on the factor content of trade and the national income level: an increase in the share of labour-intensive exports raises income inequality in poor countries, but reduces income inequality in rich countries. Jaumotte et al. (2013) identify, in a panel of 51 advanced and developing countries over 1981–2003, two offsetting distributional effects of globalization: while foreign direct investment (FDI) tends to exacerbate income inequality, trade openness tends to reduce it. Lin and Fu (2016) find in a sample of small developing countries that trade increases income inequality in democracies and reduces it in autocracies. Cerdeiro and Komaromi (2017) show in a large sample of countries that trade openness increases countries' real income per capita but not income inequality—if anything, higher openness tends to reduce income inequality—in the long run. In a recent study, Dorn et al. (2018) document that overall globalization increases income inequality in transition countries (especially in Eastern Europe and China), while it has no significant effect in advanced economies. Using different sub-indicators of globalization, however, the authors find that the amplifying effect of globalization on income inequality is predominantly driven by FDI and social globalization (migration and tourism, the spread of ideas, information and culture) rather than trade.

3.3. Theoretical motivation

In this chapter, I aim to empirically investigate the effect of trade on income inequality conditional on misallocation. However, in order to justify why I think misallocation might be an important factor affecting the relationship between trade and inequality, I present a very simple theoretical framework based on the relative demand and supply of factor inputs.

Relative input demands. Suppose that firms produce a single output (y) using three inputs—capital (k), skilled labour (h), and unskilled labour (l)—according to a CES production function, as in Checchi and García-Peñalosa (2010), of the form:

$$y = \left[\alpha k^{-\rho} + (1-\alpha)\left(h^{\beta} l^{1-\beta}\right)^{-\rho}\right]^{-\frac{1}{\rho}}, \tag{3.1}$$

where $\rho > 0$, $0 < \alpha < 1$, and $0 < \beta < 1$.

In the absence of distortions, maximization of the profit function $\pi = y - w_l l - w_h h - rk$ gives rise to the following first-order conditions:

$$r = \alpha(\alpha + (1-\alpha)x^{\rho})^{-\frac{1+\rho}{\rho}}, \tag{3.2}$$

$$w_h = \beta(1-\alpha)(\alpha + (1-\alpha)x^{\rho})^{-\frac{1+\rho}{\rho}} x^{\rho} \frac{k}{h}, \tag{3.3}$$

$$w_l = (1-\beta)(1-\alpha)(\alpha+(1-\alpha)x^{\rho})^{-\frac{1+\rho}{\rho}} x^{\rho}\frac{k}{l}, \tag{3.4}$$

where r is the rate of return on capital, w_h and w_l are, respectively, the wage rates of skilled and unskilled workers, and $x \equiv k/h^{\beta} l^{\beta}$.

I assume, as in Checchi and García-Peñalosa (2010), that the economy of size one consists of four types of agents: l unskilled workers, h skilled workers, u unemployed, and κ skilled worker-capitalists (the last are part of h owning capital, so $h > \kappa$). This assumption implies, by definition, that $h + l + u = 1$. Here I can think of three different ratios that can be associated with factor income inequality: the (inverse) relative demand for skilled labour, or the skill premium, ($w_h/w_l \equiv \omega$), the (inverse) demand for domestic capital relative to labour (r/w, where $w \equiv w_h h + w_l l$ is the average wage), and the (inverse) demand for domestic capital relative to unskilled labour (r/w_l). In my case of the efficient allocation of resources, these ratios would look as follows:

$$\omega \equiv \frac{w_h}{w_l} = \frac{\beta}{1-\beta}\frac{1}{\eta}, \tag{3.5}$$

$$\frac{r}{w} = \frac{\alpha}{1-\alpha}\frac{(h^{\beta} l^{1-\beta})^{\rho}}{k^{1+\rho}}, \tag{3.6}$$

$$\frac{r}{w_l} = \frac{\alpha}{(1-\beta)(1-\alpha)}\left(\frac{h^{\beta} l^{1-\beta}}{k}\right)^{\rho}\frac{l}{k}, \tag{3.7}$$

where $\eta \equiv h/l$. In order to be consistent with the reality, I assume that $w_h > w_l$, which implies that $\beta > \eta/(\eta+1) \equiv h/(h+l)$.

We can see from Eqs. (3.5)–(3.7) that the distribution parameter α is positively associated with the relative demand for domestic capital, and the skill-intensity parameter β is negatively associated with the relative demand for unskilled labour. Moreover, the skill premium is increasing in the relative supply of unskilled labour, and the relative return to capital is increasing in the supply of labour relative to capital.

Relative input supplies. I assume, for simplicity, that the supply functions of unskilled and skilled workers are given by:[2]

$$l = \begin{cases} 0 & \text{if } \; w_l < 1 \\ \ln w_l & \text{if } \; 1 \leq w_l < e \\ 1 & \text{if } \; w_l \geq e \end{cases}, \tag{3.8}$$

$$h = \begin{cases} 0 & \text{if } \; w_h \leq w_l \\ \ln \frac{w_h}{w_l} & \text{if } \; w_l < w_h \leq e \\ 1 - \ln w_l & \text{if } \; w_h > e \end{cases} \tag{3.9}$$

where e is the Euler's number.

[2] Note that because $h + l + u = 1$, l and h must each satisfy $0 \leq l \leq 1$ and $0 \leq h \leq 1$.

Assume without loss of generality that $1 < w_l < e$ and $w_l < w_h \leq e$. Then it follows from Eqs. (3.8) and (3.9) that the relative supply of skilled labour, $\eta \equiv h/l$, is increasing in the skill premium, $\omega \equiv w_h/w_l$:

$$\frac{h}{l} \equiv \eta = \frac{\ln \omega}{\ln w_l} \tag{3.10}$$

This conjecture (that $\frac{\partial \eta}{\partial \omega} > 0$) is compatible, for instance, with the North-South trade model developed by Beaulie et al. (2004), and its plausibility is confirmed empirically by He (2012). The intuition is that skilled workers can also work in unskilled jobs, while unskilled workers may obtain skills in the medium run in response to an increase in the skill premium.

We can also write the (inverse) supply functions of unskilled and skilled labour as:

$$w_l = \exp(l) \quad \text{and} \quad w_h = \exp(h + l) \tag{3.11}$$

Then, the (inverse) relative supply of skilled labour will be given by:

$$\frac{w_h}{w_l} = \exp(h) = \exp(\eta l) \tag{3.12}$$

As for the supply of domestic capital, I assume that it is simply an increasing function of income (y) and savings (s): $k = k(y, s(r))$, with $\frac{\partial k}{\partial r} = \frac{\partial k}{\partial s}\frac{\partial s}{\partial r} > 0$. We can formulate the capital supply in terms of the return to capital, so that $r = \psi(y, k)$. Then, the (inverse) supply of capital relative to labour and that relative to unskilled labour, respectively, would be:

$$\frac{r}{w} = \frac{r}{w_h h + w_l l} = \frac{\psi(y,k)}{\exp(l)(\exp(h)h + l)}, \tag{3.13}$$

$$\frac{r}{w_l} = \frac{\psi(y,k)}{\exp(l)} \tag{3.14}$$

Figure 3.3 plots the relative demand and relative supply functions for inputs given by Eqs. (3.5)–(3.7) and (3.12)–(3.14). A rise in the relative demand for skilled labour or domestic capital will increase income inequality by raising, respectively, the skill premium or the relative return to capital, while an increase in the relative supply of these factors will have an opposite effect.

I do not model the relationship between trade and income inequality here but, as we have seen in the literature review, a great deal of studies suggest that trade openness does matter for income distribution. Theoretical literature discusses many different mechanisms through which trade affects *wage inequality*; what they have in common, however, is that this effect occurs by changing the relative *demand* for skilled workers (Goldberg and Pavcnik, 2007). Furthermore, thinking within the Heckscher-Ohlin framework, trade liberalization should

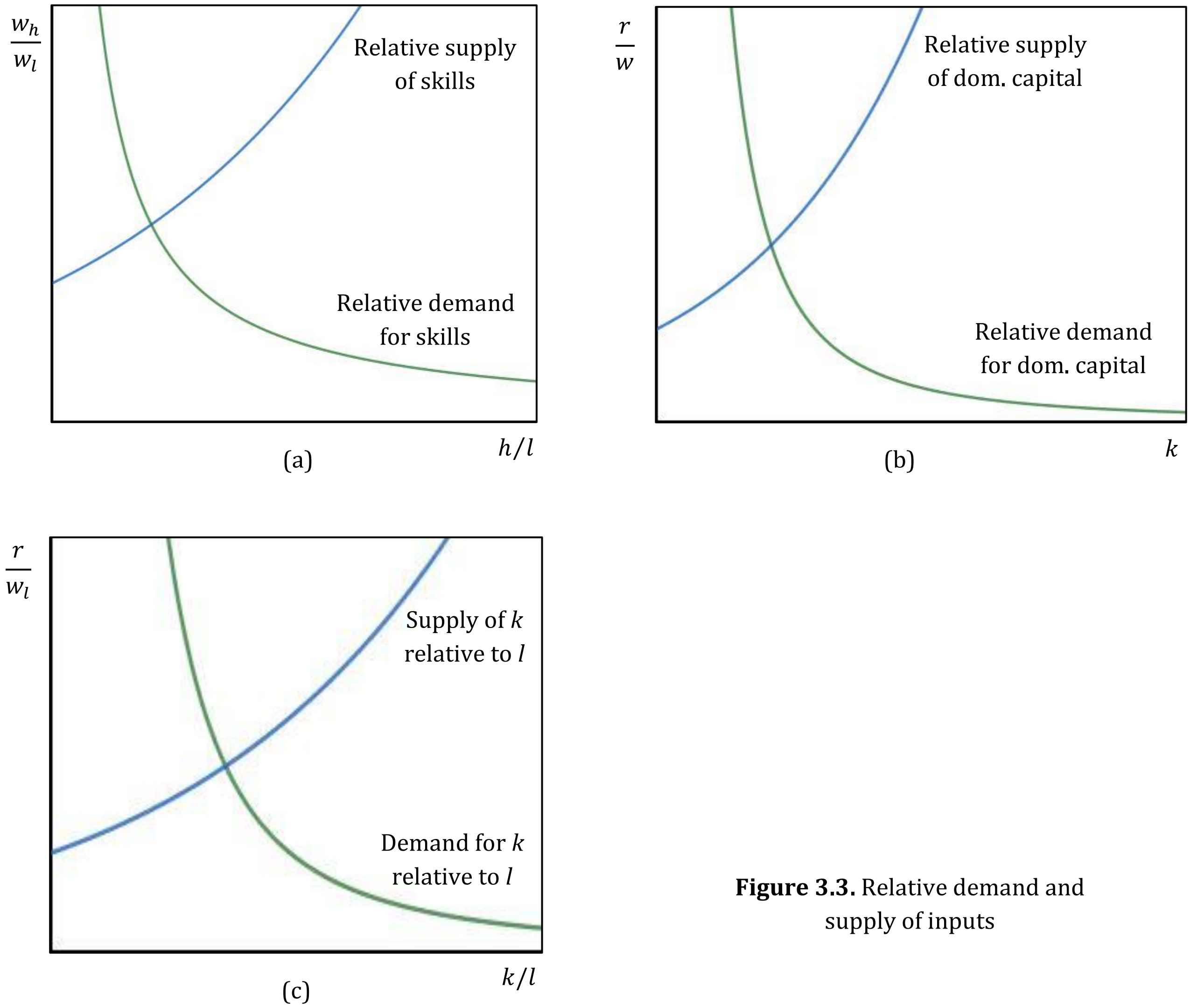


Figure 3.3. Relative demand and supply of inputs

increase the relative demand for capital in a capital-abundant country and the relative demand for labour in a labour-abundant country. On the other hand, by accelerating skill-biased technological change as suggested by Acemoglu (2003), trade liberalization may increase both demand for skilled workers and imports of skill-complementary capital goods. In such a case, to the extent that the imports of foreign capital goods reduce *demand* for domestic capital, the resulting fall in the relative return to domestic capital could offset the positive effect of the increased skill premium on income inequality.

My aim in this chapter is to investigate whether distortions in the labour and capital markets—leading to resource misallocation—influence the relationship between trade and income distribution, assuming realistically that trade affects relative input returns by shifting these inputs' *relative demand* curves. For this, suppose that there are two types of distortions in the economy: skilled labour distortions, τ_h, and capital distortions, τ_k, with $\tau_h > -1$ and

$\tau_k > -1$. A positive value of τ_h or τ_k would correspond to a "tax" on the use of skills or capital, while a negative value of these would correspond to a "subsidy" on their use. Skilled labour distortions may give rise to differences across firms in access to highly educated workforce, while capital distortions may lead to differences in access to credit. The profit function of a typical firm is then given by

$$\pi = y - w_l l - (1+\tau_h) w_h h - (1+\tau_k) r k, \tag{3.15}$$

hence resulting in the following first-order conditions:

$$r = \frac{\alpha}{1+\tau_k}(\alpha + (1-\alpha)x^\rho)^{-\frac{1+\rho}{\rho}}, \tag{3.16}$$

$$w_h = \frac{\beta(1-\alpha)}{1+\tau_h}(\alpha + (1-\alpha)x^\rho)^{-\frac{1+\rho}{\rho}} x^\rho \frac{k}{h}, \tag{3.17}$$

$$w_l = (1-\beta)(1-\alpha)(\alpha + (1-\alpha)x^\rho)^{-\frac{1+\rho}{\rho}} x^\rho \frac{k}{l}, \tag{3.18}$$

where, as before, $x \equiv k/h^\beta l^\beta$.

The relative factor demand functions with distortions would look as follows:

$$\frac{w_h}{w_l} = \frac{1}{1+\tau_h}\left[\frac{\beta}{1-\beta}\frac{1}{\eta}\right], \tag{3.19}$$

$$\frac{r}{w} = \frac{1+\tau_h}{(1+\tau_k)(1+(1-\beta)\tau_h)}\left[\frac{\alpha}{1-\alpha}\frac{\left(h^\beta l^{1-\beta}\right)^\rho}{k^{1+\rho}}\right], \tag{3.20}$$

$$\frac{r}{w_l} = \frac{1}{1+\tau_k}\left[\frac{\alpha}{(1-\beta)(1-\alpha)}\left(\frac{h^\beta l^{1-\beta}}{k}\right)^\rho \frac{l}{k}\right] \tag{3.21}$$

We can see from Eqs. (3.19)–(3.21) that the existence of distortions affects the relative demand for inputs at any given price of those inputs. If τ_h and τ_k both have positive values, then misallocation unambiguously reduces the skill premium, the ratio of capital return to the unskilled wage rate and, for any $\tau_k > \tau_h$, the ratio of capital return to the average wage rate. This, other things being equal, implies lower income inequality. In the opposite case, where τ_h and τ_k both have negative values (and $\tau_h > \tau_k$), misallocation should increase income inequality. In other cases, where one of the distortions has a positive value and the other is negative, the effect of misallocation on income inequality is ambiguous. An important thing here is that the distributional effect of any exogenous shock that shifts the relative demand curves in Figure 3.3, a–c, will depend on the extent of misallocation arising from skilled labour and capital distortions.

Then, if trade shifts the relative demand curves in Figure 3.3 upward, hence *increasing* income inequality, then misallocation would mitigate this adverse distributional effect of trade in case $\tau_h > 0$ and $\tau_k > 0$, and exacerbate this adverse effect in case $-1 < \tau_h < 0$ and $-1 < \tau_k < 0$. If trade, however, shifts these relative demand curves downward, hence *reducing* income inequality, then misallocation would impair this favourable distributional effect of trade in case $\tau_h > 0$ and $\tau_k > 0$, and boost this favourable effect in case $-1 < \tau_h < 0$ and $-1 < \tau_k < 0$. Since I do not model the relationship between trade and income inequality, I cannot make any prediction regarding the distributional effect of trade openness per se. Therefore, I leave the determination of this effect to my empirical analysis.

3.4. Empirical methodology

3.4.1. The data

For the empirical analysis, I use two different measures of income inequality: (i) the market Gini index from Solt's (2019) Standardized World Income Inequality Database (SWIID), Version 8.1; and (ii) the ratio of top 10 percent to bottom 40 percent of population income distribution (also called the *Palma ratio*), with data obtained from the World Income Inequality Database (WIID) provided by the United Nations University World Institute for Development Economics Research (UNU-WIDER). The former index is based on the pre-tax national income, while the latter is based on equivalized household disposable income, i.e., the total income received by households less the current taxes and transfers paid, adjusted for household size with an equivalence scale[3].

For trade openness I use the sum of exports and imports as percentage of GDP (from the World Bank). As a measure of allocative efficiency I use the Olley and Pakes (1996) covariance term (referred to as "the OP covariance" henceforth), which was used as such in many studies including, inter alia, some more recent ones by Bartelsman et al. (2013) and Hagemejer et al. (2017). The (unbalanced) data I employ for the OP covariance are available from the Competitiveness Research Network (CompNet) database[4] for 18 European countries[5] for the period 1999–2016. Because of the limited number of countries in this database (and since I was unable to find any cross-country panel dataset with necessary firm-level data to be able

[3] For more information, see the latest version (17th December, 2019) of the UNU-WIDER World Income Inequality Database (WIID), User Guide and Data Sources. The Palma measure of income inequality was proposed by Cobham and Sumner (2013), and has since received increased attention, including from international organizations such as the World Bank and United Nations.

[4] I use the 6th Vintage of CompNet database. As I did in Chapter 2, I use the "20E" sample for my analysis, since it is far more comparable across countries than the "full" sample.

[5] The countries are: Belgium, Croatia, Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Lithuania, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden.

to calculate allocative efficiency measures for a larger number of countries), I use only these 18 European countries for my analysis. CompNet makes data available at the country-sector (1-digit and 2-digit NACE Rev.2 industries) and country levels, but not at the firm level.

As control variables, I include real GDP per capita (constant 2010 US$), financial openness (sum of assets and liabilities of FDI, portfolio equity and external debt as % of GDP), research and development (R&D) expenditure (as % of GDP), unemployment rate, financial depth (domestic private credit as % of GDP), tertiary enrolment rate, gross fixed capital formation (% of GDP), government size (general government final consumption expenditure as % of GDP), income tax share (taxes on income, profits and capital gains as % of total taxes)[6], age dependency ratio (as % of working-age population), democratic accountability, and the size of population (in millions). The data on all these variables come from the World Bank, except for financial openness, which I take from Lane and Milesi-Ferretti (2018), and the indicator of democratic accountability, which I take from the ICRG Researchers Dataset[7]. The descriptive statistics for the data are given in Appendix 3.A.

3.4.2. Empirical measurement of misallocation

CompNet database provides country-level measures of the OP covariance that are based on firm-level labour productivities and total factor productivities.[8] The OP covariance is a measure of the within-industry covariance between firm productivity and size (firm's share of industrial employment or value added). Olley and Pakes (1996) decompose the industry-level productivity, which is the weighted average of firm-level productivities, as follows:

$$\Phi_t = \sum_i \theta_{it}\varphi_{it} = \bar{\varphi}_t + \sum_i (\theta_{it} - \bar{\theta}_t)(\varphi_{it} - \bar{\varphi}_t)\,,$$

where Φ_t is the index of industry productivity at time t, φ_{it} is the productivity of firm i at time t, θ_{it} is the size of firm i at time t, $\bar{\varphi}_t$ and $\bar{\theta}_t$ are the unweighted industry mean productivity and size at time t, respectively. The second term on the right-hand side of the above equation is the OP covariance that captures the extent to which firms with higher than average productivity have a greater market share, hence reflecting the degree of allocative efficiency. Except for an unlikely scenario where all firms have the same productivity level—in which case firm sizes do not matter at all—a higher value of the OP covariance term reflects more

[6] I include government size as an additional control when my dependent variable is the Gini index of market income, and include income tax share when my dependent variable is the Palma ratio of net income.

[7] PRS Group, 'International Country Risk Guide (ICRG) Researchers Dataset', 2018, https://hdl.handle.net/10864/10120.

[8] For details, see CompNet User Guide and Cross-Country Report available at https://www.comp-net.org/data/.

efficient allocation of resources (or lower misallocation). If it is positive, more productive firms employ a higher share of resources and hence are larger. If it is negative, then small productive firms face higher barriers to growth, while large incumbent firms remain unproductive. In my analysis, for the sake of direct interpretation as the degree of misallocation, I take the opposite of the OP covariance term and normalize it to take the values between 0 and 1. In this case, zero reflects the most efficient allocation within my sample, whereas one reflects the highest misallocation within this sample. I use the measure of misallocation based on the Olley-Pakes decomposition of (the log of) the average *labour* productivity. The OP covariance in this case reflects the covariance between firms' value added per unit of labour employed and their labour share in their industry.

Prior to generating the index of misallocation I inspect the OP covariance data to ensure there are no unlikely observations that could potentially affect my estimations. Figure 3.4 shows the dot plot of the OP covariances on pooled data for the 18 European countries from the CompNet dataset I employ. We can see that almost all data are concentrated in the range between ca. −0.3 and ca. 0.9, while there is a single outlier with the value of ca. −2.2. This outlier is observed for the *Netherlands in 2006*, while the other observations for this country range from −0.16 to 0.01. Because such a large negative covariance seems unlikely given the distribution we observe, this is most probably due to a measurement error. Therefore, I drop this observation before generating my normalized misallocation index.

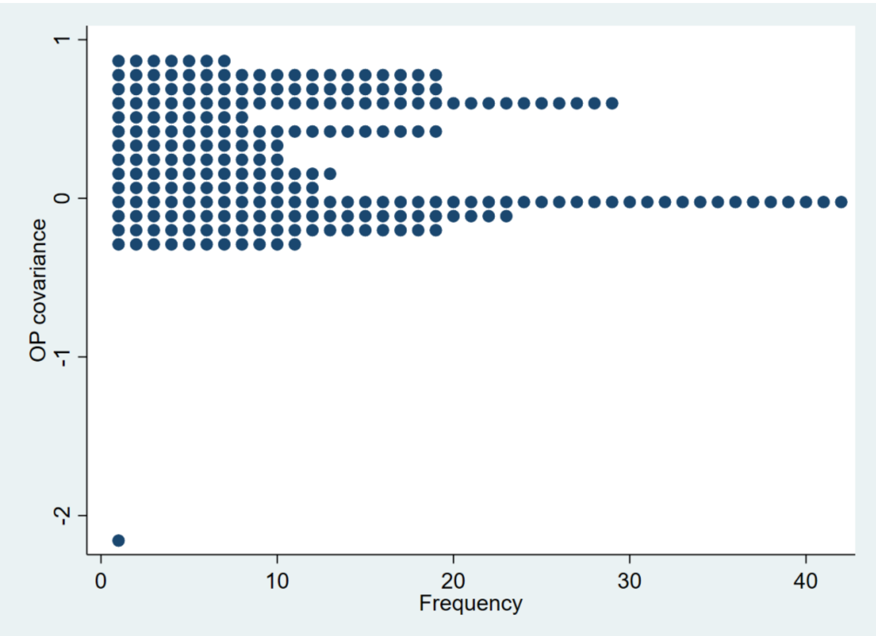


Figure 3.4. Dot plot of the Olley-Pakes covariances on pooled data for 18 European countries. (*Source: CompNet*)

3.4.3. The empirical model

In order to study the effect of trade openness—conditional on misallocation—on within-country income inequality, I estimate the following dynamic panel model:

$$\begin{aligned} Inequality_{c,t} = {} & \alpha_1 Inequality_{c,t-1} + \alpha_2 GDPpc_{c,t} + \alpha_3 GDPpc_{c,t}^2 + \beta_1 Trade_{c,t} \\ & + \beta_2 Misallocation_{c,t-1} + \beta_3 Trade_{c,t} \times Misallocation_{c,t-1} \\ & + \beta_4 FinancialOpenness_{c,t} + \beta_5 R\&DExpenditure_{c,t} + \beta_6 Unemployment_{c,t} \\ & + \gamma S_{c,t} + \delta X_{c,t} + \eta_c + \varepsilon_{c,t} \end{aligned}$$

where c denotes country, t denotes year, γ and δ are the row vectors of coefficients, $S_{c,t}$ is the column vector of potential shifters of the supply of inputs (share of educated workforce, domestic credit supply, domestic investment)[9], and $X_{c,t}$ is the column vector of other control variables. In the interaction term, I use misallocation with a one-period lag in order to avoid potential endogeneity arising from an effect of trade on misallocation. I use the dynamic specification to capture the serial correlation and persistence in income inequality, since the initial conditions leading to different levels of inequality in different countries may otherwise not be accounted for due to data limitations. Moreover, I include both real GDP per capita and its square as regressors to take account of the possible inverted-U relationship between economic development and income inequality as suggested by Kuznets (1955). My main coefficients of interest in the above model are β_1 and β_2, which give, respectively, the effects of trade openness and (lagged) misallocation on income inequality, as well as β_3, which gives the (additional) effect of trade on income inequality that is *conditional* on the level of misallocation prevailing in the country. I also include financial openness, R&D expenditure and unemployment as regressors in order to account for various channels through which globalization may operate and the impact of technological change, as suggested by Jaumotte et al. (2013).

The problem with my data is that I have only 18 unbalanced panels (i.e., countries) observed, on average, over 11-12 years. This makes the use of standard dynamic panel data models questionable in my sample. Moreover, I rule out the use of random effects models because of two reasons: (1) the Hausman test, both when I include and exclude controls, strongly rejects the random effects hypothesis; (2) using the random effects estimation in dynamic panels can severely bias the coefficients of all explanatory variables (Allison, 2015). This together with suspicion that country-specific time-invariant factors may influence

[9] I include these in order to be able to isolate the effect of trade—which is expected to arise from shifts in input demands—from factors shifting the input supply curves.

differences in income distribution across countries leads me to use the fixed effects, or the *least-squares dummy variable* (LSDV), estimator with bias correction for dynamic panels with small *N* and/or small *T*. Therefore, I use three different versions of LSDV-type (within-effects) estimators to test my hypothesis: (1) the LSDV estimator with panel-corrected standard errors (PCSE) as suggested by Beck and Katz (1995)[10]; (2) the fixed effects estimator with bootstrap-based bias correction (BCFE) as proposed by Everaert and Pozzi (2007) and De Vos et al. (2015); (3) the analytical bias-corrected LSDV (LSDVC) estimator as per Bruno (2005a) and Bruno (2005b). [11] More details on these estimators are given in Appendix 3.B.

In the PCSE regressions, parameters are estimated after using the Prais-Winsten transformation that corrects for serial autocorrelation, and the errors are assumed to follow a first-order panel-specific autoregressive process, AR(1). In the BCFE regressions, standard errors are bootstrapped using the parametric error sampling scheme, where I assume cross-sectional independence and temporal heteroscedasticity. In the LSDVC regressions, standard errors are estimated by bootstrapping the covariance matrix assuming normality of errors. In both the BCFE and the LSDVC regressions, 1000 repetitions are used for bootstrapping.

3.5. Results

3.5.1. Baseline regressions

In this section I present and discuss the results of my regressions of two different measures of income inequality on my variables of interest—trade, misallocation, and the interaction between trade and misallocation—as well as other variables that can affect their coefficients. Tables 1 and 2 report the results of my baseline regressions with the Gini index of pre-tax income and the Palma ratio of equivalized disposable income, respectively. The results are presented for coefficient estimates using the standard LSDV (uncorrected), the LSDV with panel-corrected standard errors (PCSE), the bootstrap bias-corrected fixed effects (BCFE) as per Everaert and Pozzi (2007), and the bias-corrected LSDV (LSDVC) as per Bruno (2005a).

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[10] Although the PCSE estimator corrects for heterogeneity and cross-sectional dependence in errors, it does not address the small-sample bias of the parameter estimates arising due to inclusion of the lagged dependent variable. It has been, however, shown to outperform the (feasible) generalized least squares (GLS, FGLS) estimators in small samples like mine (Beck and Katz, 1995; Blackwell, III, 2005).

[11] Both the BCFE and the LSDVC estimators assume strict exogeneity of explanatory variables, which may be argued to be a strong assumption for my model. Unfortunately, I am not aware of bias-corrected fixed effects estimators for small-sample dynamic panel models that allow for weakly exogenous regressors. In addition, the LSDVC estimator makes a more restrictive assumption of homoscedasticity of the error term, whereas the BCFE estimator allows for cross-sectional and temporal heteroscedasticity.

Table 3.1 presents the results of my baseline regressions using the Gini index of market (pre-tax) income as a measure of income inequality. The Kuznets hypothesis seems to be confirmed only when the panel-corrected standard errors (PCSE) estimator is used, and not in the other estimations. The results suggest that tertiary enrolment rate and gross fixed capital formation both significantly reduce the Gini coefficient, supporting my conjecture that an increased share of educated workforce and a higher level of investment, respectively, shift the relative supply of skilled labour (Figure 3.3, a) and the relative supply of capital (Figure 3.3, b-c) to the right, hence reducing relative returns to these inputs. An interesting finding, however, is that domestic private credit tends to significantly increase the Gini coefficient. While this may seem incompatible with persistently low interest rates observed in the euro area and in other developed countries during the last decade (which implies increased supply of credit), higher credit availability may simply have raised the demand for property, financial assets and intangible capital (human capital, software, data and information, brands and reputation etc.), hence increasing the income gap between rich and poor. R&D expenditure also significantly increases the market Gini, which seemingly confirms the skill-biased technological change hypothesis. Regarding my variables of interest, I find that lagged misallocation significantly reduces income inequality based on the Gini index, thus implying that country-specific distortions, on average, act as a "tax" on the use of skills and capital. Most importantly, we see that while trade reduces the Gini coefficient, misallocation significantly impairs this favourable distributional effect of trade. The observed moderating effect of misallocation on the trade–income inequality nexus is thus in line with the predictions of my theoretical framework, where I assume that trade affects the relative demands for factor inputs.

Table 3.2 presents the results of the regressions where I use the Palma ratio of disposable income as a measure of income inequality. The significant inequality-reducing effect of tertiary enrolment rate, as found in Table 3.1, is confirmed here as well, while private credit and gross fixed capital formation are not found to affect the Palma ratio in a significant way. Trade is found to reduce the Palma ratio, though its coefficient is statistically significant only at the 10 percent level when I estimate my model with the bootstrap-based BCFE and the bias-corrected LSDV (LSDVC) estimators. Lagged misallocation is again found to significantly reduce inequality, albeit the significance of its coefficient in the case of the LSDVC estimator is observed only at the 10 percent level. The coefficient on the interaction term between trade and misallocation is significantly positive at the 1 percent level in the case of the LSDV (uncorrected) and PCSE estimators, and at the 5 percent level in the case of the BCFE and

Table 3.1. The effect of trade openness on the *Gini index* of market income

	LSDV	PCSE	BCFE	LSDVC
Gini(t-1)	0.852*** (0.025)	0.820*** (0.033)	0.926*** (0.036)	0.912*** (0.025)
ln(GDP p.c.)	8.027 (6.708)	4.560*** (0.653)	5.681 (5.904)	8.081 (7.806)
ln(GDP p.c.)-squared	-0.422 (0.347)	-0.251*** (0.048)	-0.297 (0.304)	-0.416 (0.406)
ln(Trade)	-2.047*** (0.475)	-2.003*** (0.452)	-1.760*** (0.488)	-1.824*** (0.522)
Misallocation(t-1)	-12.657*** (3.890)	-13.729*** (3.590)	-9.088** (3.774)	-9.571** (4.462)
ln(Trade)×Misallocation(t-1)	2.768*** (0.792)	2.951*** (0.731)	1.992*** (0.766)	2.090** (0.914)
ln(Financial openness)	0.055 (0.111)	0.066 (0.074)	0.075 (0.121)	-0.011 (0.126)
R&D expenditure	0.453*** (0.099)	0.464*** (0.106)	0.434*** (0.097)	0.466*** (0.110)
Unemployment	-0.010 (0.018)	-0.003 (0.017)	-0.016 (0.017)	-0.012 (0.019)
ln(Tertiary enrolment)	-0.807*** (0.216)	-0.957*** (0.223)	-0.693*** (0.190)	-0.710*** (0.247)
ln(Private credit)	0.620*** (0.154)	0.626*** (0.155)	0.572*** (0.161)	0.608*** (0.174)
ln(GFCF)	-0.795*** (0.286)	-0.672*** (0.232)	-0.711** (0.310)	-0.728** (0.328)
Observations	195	195	189	195

Standard errors in parentheses. p<0.1; ** p<0.05; *** p<0.01.

LSDVC estimators. In fact, my theoretical framework (see Eqs. (3.19)–(3.21)) does not imply that trade should have any indirect effect on the skill premium or the relative return to capital conditioned by misallocation *unless* it has a direct (significant) effect on the relative demand for skilled labour or capital. However, my theoretical framework assumes away taxes and transfers, so its implications are only relevant for pre-tax market incomes. Nevertheless, my results from Table 3.2 show that misallocation seems to be relevant also for the net income inequality measured by the Palma ratio.

Table 3.2. The effect of trade openness on the *Palma ratio* of disposable income

	LSDV	PCSE	BCFE	LSDVC
Palma(*t*-1)	0.338*** (0.079)	0.370*** (0.130)	0.532*** (0.104)	0.540*** (0.086)
ln(GDP p.c.)	2.153 (2.583)	0.557*** (0.165)	2.915 (2.786)	3.839 (4.039)
ln(GDP p.c.)-squared	-0.101 (0.133)	-0.013 (0.015)	-0.142 (0.143)	-0.186 (0.209)
ln(Trade)	-0.417** (0.163)	-0.459*** (0.174)	-0.313* (0.177)	-0.373* (0.217)
Misallocation(*t*-1)	-3.487*** (1.281)	-3.404*** (1.082)	-2.875** (1.351)	-3.334* (1.707)
ln(Trade)×Misallocation(*t*-1)	0.724*** (0.262)	0.736*** (0.225)	0.571** (0.279)	0.690** (0.350)
ln(Financial openness)	-0.003 (0.049)	-0.042 (0.030)	-0.016 (0.068)	-0.020 (0.075)
R&D expenditure	0.048 (0.032)	0.049* (0.025)	0.045 (0.036)	0.033 (0.048)
Unemployment	0.004 (0.006)	0.005 (0.006)	0.003 (0.007)	0.003 (0.009)
ln(Tertiary enrolment)	-0.299*** (0.083)	-0.349*** (0.079)	-0.256*** (0.089)	-0.280** (0.117)
ln(Private credit)	-0.045 (0.052)	-0.041 (0.033)	-0.040 (0.063)	-0.016 (0.075)
ln(GFCF)	0.058 (0.115)	-0.003 (0.074)	0.047 (0.113)	0.009 (0.147)
Observations	163	163	159	163

Standard errors in parentheses. p<0.1; ** p<0.05; *** p<0.01.

3.5.2. Robustness checks

Although my baseline regressions show that misallocation significantly matters for income inequality and the relationship between trade and inequality, the coefficients on my variables of interest may still suffer from an omitted variable bias. In order to test the significance of these coefficients for robustness, I run regressions including additional controls that may potentially affect both misallocation and income inequality. Thus, I add government expenditure as a proxy for government intervention to the regressions with the market Gini index, and I add the share of taxes on income, profits and capital gains in total taxes as a proxy for redistributive policies to the regressions with the Palma ratio of disposable income. Moreover, I add other controls such as the age dependency ratio, democratic accountability, population size, as well as a post-2008 dummy in order to account for a possible structural break caused by the global financial crisis.

Table 3.3 shows the results of regressions with the additional controls where the dependent variable is the market Gini index. The coefficients on my main variables of interest—trade, (lagged) misallocation, and the interaction term—remain statistically significant, albeit with an overall increase in their magnitudes. Also the coefficients on R&D expenditure, tertiary enrolment rate, private credit and gross fixed capital formation mostly remain consistent in sign and significance with the findings in Table 3.1. Other control variables are not found to significantly affect the market income inequality measured by the Gini index.

Table 3.4 presents the results of regressions including additional controls where the Palma ratio of net income is used as a dependent variable. As compared to my baseline estimation in Table 3.2, the statistical significances of the coefficients on trade openness and (lagged) misallocation increase in both the bias-corrected (BCFE and LSDVC) regressions, and the significance of the coefficient on the interaction term increases in the BCFE regression. Moreover, all these coefficients increase in magnitude as well. The inequality-reducing effect of education (i.e., tertiary enrolment rate) remains statistically significant, while financial openness and the share of taxes on income, profits and capital gains seem to reduce the Palma ratio when the PCSE estimator is used. The age dependency ratio seems to increase the Palma ratio when the uncorrected LSDV, the PCSE and the BCFE estimators are used.

The results of regressions with additional controls confirm the significance of the role played by misallocation in explaining income inequality. They also suggest that, when resources are efficiently allocated, trade openness reduces income inequality, at least in my sample of European countries. Still, the observed effect of trade openness may suffer from endogeneity if trade has a contemporaneous effect on misallocation that, in turn, affects income inequality in the same period: while I have included lagged misallocation in my regressions, contemporaneous misallocation has not been controlled for. In order to address this potential problem of omitted variable bias, I run my regressions adding contemporaneous misallocation to the series of explanatory variables. The results are given in Tables 3.C1 and 3.C2 in the Appendix. I find that my results for all three variables of interest—trade openness, lagged misallocation, and their interaction—are *mostly* robust, although the levels of significance of the coefficients on all the three variables decrease somewhat when I use the LSDVC estimator in the regression with the market Gini index and the BCFE estimator in the

Table 3.3. The effect of trade openness on the *Gini index* of market income: additional controls

	LSDV	PCSE	BCFE	LSDVC
Gini(t-1)	0.864*** (0.028)	0.838*** (0.035)	0.956*** (0.038)	0.939*** (0.030)
ln(GDP p.c.)	3.876 (7.598)	5.876*** (0.964)	-0.479 (7.005)	4.253 (9.298)
ln(GDP p.c.)-squared	-0.220 (0.393)	-0.333*** (0.058)	0.002 (0.363)	-0.228 (0.482)
ln(Trade)	-2.227*** (0.596)	-2.182*** (0.543)	-1.981*** (0.640)	-1.936*** (0.712)
Misallocation(t-1)	-13.424*** (4.083)	-14.350*** (4.065)	-9.766** (3.878)	-10.276** (4.996)
ln(Trade)×Misallocation(t-1)	2.958*** (0.842)	3.114*** (0.838)	2.149*** (0.813)	2.303** (1.034)
ln(Financial openness)	0.053 (0.114)	0.084 (0.080)	0.101 (0.124)	-0.037 (0.136)
R&D expenditure	0.505*** (0.115)	0.477*** (0.126)	0.505*** (0.116)	0.556*** (0.140)
Unemployment	-0.013 (0020)	-0.014 (0.019)	-0.021 (0.019)	-0.020 (0.023)
ln(Tertiary enrolment)	-0.798*** (0.230)	-0.916*** (0.214)	-0.670*** (0.221)	-0.712** (0.279)
ln(Private credit)	0.663*** (0.195)	0.673*** (0.173)	0.620*** (0.204)	0.749*** (0.243)
ln(GFCF)	-0.855** (0.346)	-0.818*** (0.255)	-0.744** (0.375)	-0.997** (0.427)
ln(Government expenditure)	-0.580 (0.617)	-0.743 (0.536)	-0.865 (0.676)	-0.594 (0.799)
ln(Dependency ratio)	-0.791 (0.829)	-1.029 (0.781)	-1.071 (0.965)	-1.498 (1.039)
Democratic accountability	-0.022 (0.117)	-0.020 (0.072)	0.011 (0.102)	-0.064 (0.140)
ln(Population/Mill.)	-1.006 (1.945)	0.722 (1.678)	-1.490 (1.719)	-0.406 (2.313)
Post-2008 dummy	0.077 (0.065)	0.070* (0.041)	0.110 (0.084)	0.031 (0.082)
Observations	195	195	189	195

Standard errors in parentheses. p<0.1; ** p<0.05; *** p<0.01.

regression with the Palma ratio of net income. The coefficient on contemporaneous misallocation is found to be insignificant in all regressions, suggesting that contemporaneous misallocation does not channel the effect of trade on income inequality.

Table 3.4. The effect of trade openness on the *Palma ratio* of disposable income: additional controls

	LSDV	PCSE	BCFE	LSDVC
Palma(*t*-1)	0.292*** (0.085)	0.325** (0.136)	0.479*** (0.102)	0.487*** (0.090)
ln(GDP p.c.)	1.199 (2.765)	0.513* (0.309)	2.190 (2.887)	2.693 (4.369)
ln(GDP p.c.)-squared	-0.051 (0.142)	-0.009 (0.017)	-0.101 (0.148)	-0.126 (0.225)
ln(Trade)	-0.608*** (0.188)	-0.635*** (0.185)	-0.536*** (0.200)	-0.568** (0.250)
Misallocation(*t*-1)	-4.428*** (1.421)	-4.412*** (1.199)	-4.109*** (1.520)	-4.418** (1.892)
ln(Trade)×Misallocation(*t*-1)	0.915*** (0.293)	0.927*** (0.252)	0.833*** (0.318)	0.910** (0.396)
ln(Financial openness)	-0.046 (0.051)	-0.073** (0.034)	-0.072 (0.068)	-0.047 (0.078)
R&D expenditure	0.031 (0.036)	0.023 (0.029)	0.035 (0.037)	0.021 (0.060)
Unemployment	0.008 (0.007)	0.009 (0.006)	0.008 (0.007)	0.007 (0.009)
ln(Tertiary enrolment)	-0.290*** (0.084)	-0.298*** (0.060)	-0.257*** (0.087)	-0.275** (0.120)
ln(Private credit)	-0.066 (0.061)	-0.055 (0.050)	-0.045 (0.069)	-0.040 (0.094)
ln(GFCF)	0.156 (0.128)	0.112 (0.100)	0.170 (0.124)	0.119 (0.169)
ln(Income tax share)	-0.085 (0.074)	-0.156** (0.065)	-0.084 (0.076)	-0.089 (0.112)
ln(Dependency ratio)	0.580** (0.267)	0.748*** (0.190)	0.567* (0.315)	0.470 (0.430)
Democratic accountability	0.077 (0.078)	0.103 (0.097)	0.051 (0.083)	0.069 (0.109)
ln(Population/Mill.)	-0.595 (0.693)	-0.976 (0.608)	-0.728 (0.677)	-0.816 (0.949)
Post-2008 dummy	0.016 (0.023)	0.012 (0.018)	0.020 (0.027)	0.020 (0.031)
Observations	163	163	159	163

Standard errors in parentheses. $p<0.1$; ** $p<0.05$; *** $p<0.01$.

3.5.3. Brief discussion of results

Overall, my results corroborate the findings of Reuveny and Li (2003) and Jaumotte et al. (2013) that trade openness reduces income inequality. Lim and McNelis (2016) also find that trade openness improves income distribution in economies having reached a sufficient level of capital intensity in production, which seemingly applies to my sample that consists of industrialized European countries. As I do not have a theory to explain the distributional effect of trade openness, I do not know the exact mechanism through which trade reduces income inequality in my sample. Although many theoretical models predict that trade liberalization increases wage inequality, these predictions are the result of the comparison of trade equilibrium relative to the *autarky* outcome, whereas countries in my dataset were already quite open from the beginning of the sample period. Thus, my results may also be supportive of the hump-shaped relationship between trade and income inequality as predicted by Helpman et al. (2010). One possibility for the favourable distributional effect of trade openness—particularly in countries already well integrated into the global value chains—is that the increased trade-to-GDP ratio might mainly reflect increased demand for unskilled workers resulting from an employment-enhancing effect of greater cost efficiency (Grossman and Rossi-Hansberg, 2008; Harrigan et al., 2018).

The more important finding of this study, however, is that income inequality also seems to be a function of the efficiency of resource allocation in the economy: if distortions in the input markets act as a tax on the use of these inputs, then misallocation arising from these distortions moderates the effect of trade on income inequality. My estimation results thus show that the inequality-reducing effect of trade is weakened in the presence of misallocation. At the same time, however, countries with a higher level of misallocation, other things being equal, tend to have lower income inequality, regardless of their degree of trade openness.

In order to have a better idea of economic significance of the estimated coefficients, I will briefly discuss the quantitative implications of my variables of interest. My findings from the regressions with additional controls (Table 3.3) suggest that, in the counterfactual absence of misallocation, a doubling of trade-to-GDP ratio—e.g., from 50% to 100%—will reduce the market Gini index by around 1.34–1.37 points (using the bias-corrected estimators). A reduction in my (lagged) misallocation index, for instance, from 0.75 to 0.25 in a country with the market Gini index of, say, 45—according to my estimations—would increase its market Gini, ceteris paribus, to somewhere around 49.9–50.1. Figure 3.5 illustrates this distributional effect of reduction in misallocation with the help of the kernel density plots for these two variables. This finding is evidently in line with the classical *equity–efficiency trade-off*.

The most important message of this chapter is that previous studies regarding the distributional effect of trade openness may have provided conflicting results for a reason: trade seems to have different effects on income inequality depending on the level of allocative efficiency. My findings indicate that more trade reduces income inequality in open countries where resources are efficiently allocated, whereas these countries tend to have a significantly higher income disparity, other things being equal. In the presence of misallocation, however, the favourable distributional effect of trade openness is impaired, but such countries tend to have, ceteris paribus, a more equal income distribution. For example, my regressions in Table 3.3 suggest that when the level of misallocation changes from 0 to 1—while income distribution will be much more equal—the effect of a doubling of the trade-to-GDP ratio might be to *raise* the market Gini index by around 0.12–0.25 points, in contrast to its inequality-reducing effect in the (counterfactual) absence of misallocation. My regressions using the Palma measure of net income inequality also confirm the findings regarding the direct and conditional effects of trade openness on income distribution.

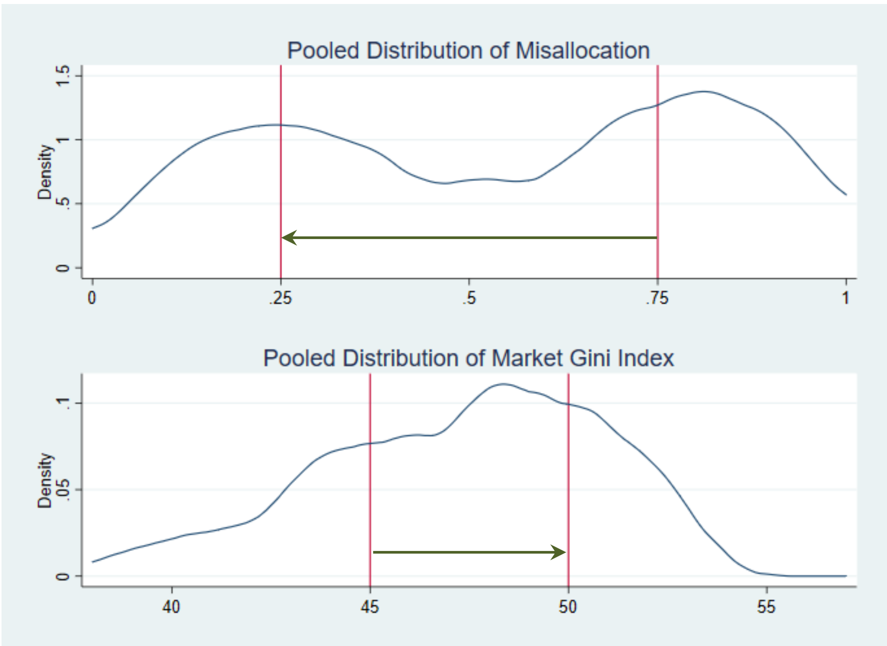

Figure 3.5. Kernel density functions for the misallocation index and the market Gini index.
Nonparametric densities obtained using the Epanechnikov kernel with the optimal bandwidth.

3.6. Conclusion

In this chapter I propose a new factor that shapes the effect of trade openness on within-country income distribution. I show that misallocation—i.e., the level of inefficiency in the allocation of resources—determines the magnitude of the effect of trade on income inequality. Using a panel of 18 European countries, I find that more trade reduces income inequality in the counterfactual absence of misallocation. As misallocation increases, the inequality-reducing effect of trade gradually disappears, and even—as my empirical estimations suggest—it may reverse at sufficiently high levels of misallocation. I find, however, that countries with a higher level of misallocation are, other things held constant, more equal in terms of income distribution.

My findings imply that one of the reasons why previous studies have found conflicting results regarding the effect of trade on income inequality is probably due to this effect being conditional on how efficiently resources, especially labour, are allocated in the economy. Therefore, whenever we speak about the distributional effects of openness to trade, we should expect these effects to be conditional on existing country- and time-specific distortions and market imperfections that manifest themselves in resource misallocation. This, in turn, suggests that policymakers should probably have a better idea of misallocation prevailing in their countries before designing policy measures addressing the distributional consequences of trade openness.

The current study, however, is not without limitations. First, even though I have a basic analytical framework to motivate my empirical part, having a theoretical model that is able to explain the causal effect of trade on income inequality together with its relation to misallocation would much strengthen my arguments. Next, and probably more importantly, my empirical findings are based on a small sample, with both its time dimension and its cross-sectional dimension being smaller than thirty. While I use the dynamic panel model with fixed-effects estimators corrected for small-sample bias, sufficient caution is still required in generalizing my results.

Appendix 3.A: Data summary

Descriptive statistics for the variables used in the empirical analysis

Variable		Mean	Std. Dev.	Min.	Max.	Observations
Gini index (gross income)	overall		3.50	37.9	53.4	324
	between	47.29	3.37	40.25	52.23	
	within		1.21	43.25	50.70	$T = 18$
Palma ratio (net income)	overall		0.22	0.75	1.72	243
	between	1.06	0.22	0.8	1.47	
	within		0.08	0.82	1.43	$\bar{T} = 13.5$
Real GDP per capita (2010 US$)	overall		16,014.08	4,772.89	61,174.55	306
	between	29,199.14	16,300.34	7,386.63	58,138.62	
	within		2,165.21	21,839.52	34,466.13	$T = 17$
Trade (% of GDP)	overall		36.57	44.73	183.99	324
	between	96.51	34.49	51.89	152.19	
	within		14.52	43.67	140.77	$T = 18$
Misallocation index	overall		0.293	0	1	241
	between	0.546	0.293	0.087	0.970	
	within		0.025	0.439	0.660	$\bar{T} = 13.4$
Financial openness (% of GDP)	overall		341.64	59.04	2024.58	306
	between	360.96	317.19	87.49	1404.40	
	within		146.23	-574.02	981.15	$T = 17$
R&D expenditure (% of GDP)	overall		0.91	0.36	3.91	321
	between	1.60	0.91	0.44	3.38	
	within		0.22	1.03	2.39	$\bar{T} = 17.8$
Unemployment rate	overall		4.12	2.12	26.09	306
	between	9.21	3.22	4.35	15.69	
	within		2.68	1.76	19.62	$T = 17$
Tertiary enrolment rate	overall		15.29	21.42	94.92	290
	between	62.77	11.83	44.63	89.57	
	within		9.70	33.98	85.68	$T = 16.1$
Domestic private credit (% of GDP)	overall		42.54	0.19	201.26	285
	between	79.84	39.13	25.33	160.31	
	within		17.16	-46.39	120.79	$\bar{T} = 15.8$
Gross fixed capital formation (% of GDP)	overall		3.35	14.75	37.29	324
	between	22.51	2.12	19.71	27.73	
	within		2.64	15.52	34.76	$T = 18$

Variable		Mean	Std. Dev.	Min.	Max.	Observations
Government expenditure (% of GDP)	overall		2.84	13.74	27.94	306
	between	20.58	2.66	15.34	25.36	
	within		1.15	17.46	24.97	$T = 17$
Age dependency ratio	overall		4.54	38.46	60.08	324
	between	48.78	4.18	40.87	55.21	
	within		2.02	44.64	56.20	$T = 18$
Indicator of democratic accountability	overall		0.45	3	6	306
	between	5.72	0.35	5.03	6	
	within		0.29	3.50	6.16	$T = 17$
Population size (millions)	overall		23.71	1.98	82.53	324
	between	22.28	24.35	2.02	81.86	
	within		0.85	18.22	25.18	$T = 18$

Appendix 3.B: More details on the estimators used in this chapter

(i) OLS with panel-corrected standard errors (Beck and Katz, 1995)

Consider a time-series cross-section model of a general form given by

$$y_{i,t} = \mathbf{x}_{i,t}\boldsymbol{\beta} + \varepsilon_{i,t};\ i = 1, \dots, N;\ t = 1, \dots, T \tag{3.B.1}$$

where $\mathbf{x}_{i,t}$ is a vector of exogenous variables.

Let $\boldsymbol{\Omega}$ denote the $NT \times NT$ covariance matrix of the errors with typical element $E(\varepsilon_{i,t}\varepsilon_{j,s})$. The sampling variability of the OLS estimates will then be:

$$\mathrm{Cov}(\widehat{\boldsymbol{\beta}}) = (\mathbf{X}'\mathbf{X})^{-1}\{\mathbf{X}'\boldsymbol{\Omega}\mathbf{X}\}(\mathbf{X}'\mathbf{X})^{-1} \tag{3.B.2}$$

If the errors are contemporaneously or serially correlated and exhibit "panel heteroscedasticity"[1], then (3.B.2) provides incorrect standard errors.

Let $\boldsymbol{\Sigma}$ be an $N \times N$ matrix of contemporaneous covariances and $e_{i,t}$ be the OLS residual for unit i at time t. We can estimate a typical element of $\boldsymbol{\Sigma}$ by

$$\hat{\Sigma}_{ij} = \frac{\sum_{t=1}^{T} e_{i,t}e_{j,t}}{T}$$

with the estimate $\widehat{\boldsymbol{\Sigma}}$ consisting of all these elements. That is, by denoting the $T \times N$ matrix of the OLS residuals with $\mathbf{E}$, we have

$$\widehat{\boldsymbol{\Sigma}} = \frac{\mathbf{E}'\mathbf{E}}{T}$$

We can then use this to estimate $\boldsymbol{\Omega}$ as

$$\widehat{\boldsymbol{\Omega}} = \frac{\mathbf{E}'\mathbf{E}}{T} \otimes \mathbf{I}_T \tag{3.B.3}$$

where $\otimes$ is the Kronecker product and $\mathbf{I}_T$ is the $T \times T$ identity matrix.

Finally, panel-corrected standard errors (PCSE) are computed by taking the square root of the diagonal elements of

$$(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\left(\frac{\mathbf{E}'\mathbf{E}}{T} \otimes \mathbf{I}_T\right)\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1} \tag{3.B.4}$$

By using Monte Carlo experiments, Beck and Katz (1995) demonstrate that these PCSE outperform both the uncorrected OLS and the feasible generalized least squares (FGLS) correction proposed by Parks (1967).

In estimating my model using the PCSE, I include the lagged dependent variable and the country dummies.

[1] Panel heteroscedasticity means that: $E(\varepsilon_{i,t}^2) \neq E(\varepsilon_{j,t}^2)$, but $E(\varepsilon_{i,t}^2) = E(\varepsilon_{i,t'}^2)$, which implies that $E(\varepsilon_{i,t}^2) = \sigma_i^2$. Contemporaneously correlated errors mean that: $E(\varepsilon_{i,t}\varepsilon_{j,t}) = E(\varepsilon_{i,t'}\varepsilon_{j,t'}) \neq 0$, but $E(\varepsilon_{i,t}\varepsilon_{j,t'}) = 0$, which implies that $E(\varepsilon_{i,t}\varepsilon_{j,t}) = \sigma_{ij}$, with all other covariances being zero.

(ii) Bootstrap-based bias correction for fixed effects (FE) estimator (Everaert and Pozzi, 2007; De Vos et al., 2015)

Consider a dynamic panel-data model of order p given by

$$y_{i,t} = \alpha_i + \sum_{s=1}^{p} \gamma_s y_{i,t-s} + \mathbf{x}_{i,t}\boldsymbol{\beta} + \varepsilon_{i,t};\ i = 1, \dots, N;\ t = 1, \dots, T \tag{3.B.5}$$

where $\mathbf{x}_{i,t}$ is a $1 \times (k-p)$ vector of strictly exogenous explanatory variables (where k is the total number of time-varying regressors) and α_i is an unobserved individual effect. We make the following assumptions regarding the error term $\varepsilon_{i,t}$:

1) $E(\varepsilon_{i,t}\varepsilon_{j,s}) = 0,\qquad \forall i, j$ and $t \neq s$
2) $E(\varepsilon_{i,t}^2) = \sigma_{i,t}^2,\qquad \forall i, t$
3) $E(\varepsilon_{i,t}\varepsilon_{j,t}) = \sigma_{ij,t},\qquad \forall i, j, t$ and $i \neq j$

For notational convenience, it is assumed that the initial values $y_{i,-(p-1)}, \dots, y_{i,0}$ are observed such that T is the actual time-series dimension available for estimation.

By stacking observations over time and cross sections, we get

$$\mathbf{y} = \mathbf{W}\boldsymbol{\delta} + \mathbf{D}\boldsymbol{\alpha} + \boldsymbol{\varepsilon} \tag{3.B.6}$$

where $\mathbf{y}$ is the $NT \times 1$ vector stacking the observations $y_{i,t}$, $\mathbf{W} = (\mathbf{y_{-1}}, \dots, \mathbf{y_{-p}}, \mathbf{X})$ is the $NT \times k$ matrix stacking observations on the lags of the dependent variable $(y_{i,t-1}, \dots, y_{i,t-p})$ and the exogenous explanatory variables $\mathbf{x}_{i,t}$, $\boldsymbol{\delta} = (\boldsymbol{\gamma}', \boldsymbol{\beta}')'$ is the $k \times 1$ vector of parameters of interest, and $\mathbf{D}$ is an $NT \times N$ matrix of dummy variables such that $\mathbf{D} = \mathbf{I}_N \otimes \iota_T$, where ι_T is a $T \times 1$ vector of 1s.

Let $\mathbf{M} = \mathbf{I}_{NT} - \mathbf{D}(\mathbf{D}'\mathbf{D})^{-1}\mathbf{D}'$ denote the symmetric and idempotent matrix that transforms the data into deviations from individual-specific sample means. Since $\mathbf{MD} = 0$, the individual fixed effects $\boldsymbol{\alpha}$ can be eliminated from the model by multiplying (3.B.6) by $\mathbf{M}$:

$$\mathbf{My} = \mathbf{MW}\boldsymbol{\delta} + \mathbf{MD}\boldsymbol{\alpha} + \mathbf{M}\boldsymbol{\varepsilon},$$

$$\tilde{\mathbf{y}} = \widetilde{\mathbf{W}}\boldsymbol{\delta} + \tilde{\boldsymbol{\varepsilon}} \tag{3.B.7}$$

where $\tilde{\mathbf{y}} = \mathbf{My}$ denotes the centered dependent variable and similarly for other variables. The least-squares estimator for $\boldsymbol{\delta}$ in (3.B.7) then defines the FE estimator:

$$\widehat{\boldsymbol{\delta}} = \left(\widetilde{\mathbf{W}}'\widetilde{\mathbf{W}}\right)^{-1}\widetilde{\mathbf{W}}'\tilde{\mathbf{y}} = (\mathbf{W}'\mathbf{MW})^{-1}\mathbf{W}'\mathbf{My}$$

It is known that $\widehat{\boldsymbol{\delta}}$ is a biased estimator for $\boldsymbol{\delta}$ (Nickell, 1981), but the idea of the bootstrap-based correction by Everaert and Pozzi (2007) is that $\widehat{\boldsymbol{\delta}}$ is an unknown function of the true parameter vector:

$$E(\widehat{\boldsymbol{\delta}} \mid \boldsymbol{\delta}, \boldsymbol{\Sigma}, T) = \int_{-\infty}^{+\infty} \widehat{\boldsymbol{\delta}} f(\widehat{\boldsymbol{\delta}} \mid \boldsymbol{\delta}, \boldsymbol{\Sigma}, T)\, d\widehat{\boldsymbol{\delta}} \neq \boldsymbol{\delta} \tag{3.B.8}$$

where $\boldsymbol{\Sigma}$ is the covariance matrix of $\boldsymbol{\varepsilon}$ and $f(\cdot)$ is the probability distribution of $\widehat{\boldsymbol{\delta}}$ for given $\boldsymbol{\delta}, \boldsymbol{\Sigma}$

and T. If we are able to generate a sequence $(\widehat{\boldsymbol{\delta}}_1, \dots, \widehat{\boldsymbol{\delta}}_J)$ of J biased FE estimates $\widehat{\boldsymbol{\delta}}$ through repeated sampling from the data-generating process in (3.B.6), the integral in (3.B.8) can be written as

$$E\left(\widehat{\boldsymbol{\delta}} \middle| \boldsymbol{\delta}, \boldsymbol{\Sigma}, T\right) = \lim_{J\to\infty} \frac{1}{J} \sum_{j=1}^{J} \widehat{\boldsymbol{\delta}}_j | \boldsymbol{\delta}, \boldsymbol{\Sigma}, T \tag{3.B.9}$$

Eq. (3.B.9) shows that $\overline{\boldsymbol{\delta}}$ is an unbiased estimator for $\boldsymbol{\delta}$ if it satisfies

$$\hat{\delta} = \lim_{J\to\infty} \frac{1}{J} \sum_{j=1}^{J} \widehat{\boldsymbol{\delta}}_j | \overline{\boldsymbol{\delta}}, \boldsymbol{\Sigma}, T \tag{3.B.10}$$

i.e., if we would sample repeatedly from a population with parameters $\overline{\boldsymbol{\delta}}$ and calculate the FE estimate $\widehat{\boldsymbol{\delta}}_j(\overline{\boldsymbol{\delta}}, \boldsymbol{\Sigma}, T)$ in each sample, $\overline{\boldsymbol{\delta}}$ is an unbiased estimator for $\boldsymbol{\delta}$ if the average of $\widehat{\boldsymbol{\delta}}_j$ over J samples corresponds to the FE estimate $\widehat{\boldsymbol{\delta}}$ of $\boldsymbol{\delta}$ based on the original data.

Thus, Everaert and Pozzi (2007) suggest that a bias-corrected (BCFE) estimate for $\boldsymbol{\delta}$ can be obtained by searching over the parameter space until a vector of parameters $\overline{\boldsymbol{\delta}}$ is found that satisfies (3.B.10). This search is implemented through an iterative bootstrap algorithm—explained step by step in Everaert and Pozzi (2007) and De Vos et al. (2015)—with which I will not go into detail here.

In my regressions, the small-sample distribution of the BCFE estimator $\overline{\boldsymbol{\delta}}$ is simulated by resampling the original data using the parametric bootstrap[2] and applying the bias-correction to the FE estimates $\widehat{\boldsymbol{\delta}}_j$ obtained in each of the J constructed samples. Confidence intervals are then calculated directly from this bootstrapped distribution. The bootstrap errors are drawn using an independently and identically distributed (i.i.d.) sampling scheme, allowing for unconditional temporal heteroscedasticity.

(iii) Analytical bias approximation for the least-squares dummy-variable (LSDV) estimator (Bruno, 2005a; Bruno, 2005b)

Bruno (2005a) extends the analytical bias approximation in Bun and Kiviet (2003) to accommodate unbalanced panels with a strictly exogenous selection rule.

Consider the standard first-order dynamic panel-data model given by:

$$y_{i,t} = \gamma y_{i,t-1} + \mathbf{x}_{i,t}\boldsymbol{\beta} + \eta_i + \varepsilon_{i,t};\ |\gamma| < 1;\ i = 1, \dots, N;\ t = 1, \dots, T \tag{3.B.11}$$

where $\mathbf{x}_{i,t}$ is a $1 \times (k-1)$ vector of strictly exogenous explanatory variables, η_i is an

[2] The advantage of the parametric approach, as argued by De Vos et al. (2015), is that the resampling of the data used to obtain the small-sample distribution of the BCFE estimator $\overline{\boldsymbol{\delta}}$ is exactly the same as the resampling of the data used to bias-correct the FE estimator $\widehat{\boldsymbol{\delta}}$.

unobserved individual effect, and $\varepsilon_{i,t}$ is an unobserved white-noise disturbance with constant variance σ_ε^2.

Stacking observations over time and across individuals gives

$$\mathbf{y} = \mathbf{W}\boldsymbol{\delta} + \mathbf{D}\boldsymbol{\eta} + \boldsymbol{\varepsilon}$$

where $\mathbf{y}$ and $\mathbf{W} = (\mathbf{y_{-1}}, \mathbf{X})$ are, respectively, the $NT \times 1$ and $NT \times k$ matrices of stacked observations, $\boldsymbol{\delta} = (\gamma, \boldsymbol{\beta}')'$ is the $k \times 1$ vector of coefficients, $\mathbf{D} = \mathbf{I}_N \otimes \iota_T$ is an $NT \times N$ matrix of dummy variables (where ι_T is a $T \times 1$ vector of 1s), and $\boldsymbol{\eta}$ is the $N \times 1$ vector of individual effects.

We already know that the LSDV estimator for model (3.B.11) is inconsistent for finite T. Nickell (1981) derives an expression for this inconsistency as $N \to \infty$, which is $O(T^{-1})$. Bun and Kiviet (2003) provide formulae for more accurate bias approximation that include terms $O(N^{-1}T^{-1})$ and $O(N^{-1}T^{-2})$. Bruno (2005a) extend Bun and Kiviet (2003) formulae to a more general version of model (3.B.11), which allows missing observations in the interval $[0, T]$ for some cross-sectional units. By defining a selection indicator $r_{i,t}$ such that $r_{i,t} = 1$ if $(y_{i,t}, \mathbf{x}_{i,t})$ is observed and $r_{i,t} = 0$ otherwise, we can define the dynamic selection rule $s(r_{i,t}, r_{i,t-1})$ that selects only the observations that are usable for the dynamic model, namely those for which both current values and one-time lagged values are observable:

$$s_{it} = \begin{cases} 1 & \text{if } (r_{i,t}, r_{i,t-1}) = (1,1) \\ 0 & \text{otherwise} \end{cases}$$

Thus, the number of usable observations for any i is given by $T_i = \sum_{t=1}^{T} s_{it}$. The total number of usable observations is $n = \sum_{i=1}^{N} T_i$ and the average group size is $\bar{T} = n/N$. The (potentially) unbalanced dynamic model can then be written as

$$s_{it} y_{i,t} = s_{it}\left(\gamma y_{i,t-1} + \mathbf{x}_{i,t}\boldsymbol{\beta} + \eta_i + \varepsilon_{i,t}\right) \tag{3.B.12}$$

Eq. (3.B.12) can be formulated in matrix form. If we define, for each i, the $T \times T$ diagonal matrix $\mathbf{S}_i = \text{diag}(s_{it})$, and define the $NT \times NT$ block-diagonal matrix $\mathbf{S} = \text{diag}(\mathbf{S}_i)$, then the following is equivalent to model (3.B.12):

$$\mathbf{Sy} = \mathbf{SW}\boldsymbol{\delta} + \mathbf{SD}\boldsymbol{\eta} + \mathbf{S}\boldsymbol{\varepsilon} \tag{3.B.13}$$

Then, the LSDV estimator is equal to

$$\boldsymbol{\delta}_{LSDV} = (\mathbf{W}'\mathbf{M_s}\mathbf{W})^{-1}\mathbf{W}'\mathbf{M_s}\mathbf{y} = \boldsymbol{\delta} + (\mathbf{W}'\mathbf{M_s}\mathbf{W})^{-1}\mathbf{W}'\mathbf{M_s}\boldsymbol{\varepsilon} \tag{3.B.14}$$

where $\mathbf{M_s} = \mathbf{S}(\mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{SD})^{-1}\mathbf{D}')\mathbf{S}$ is the symmetric and idempotent $NT \times NT$ matrix that wipes out individual means and selects usable observations.

Bias approximation terms for unbalanced panels are as follows:

$$c_1(\bar{T}^{-1}) = \sigma_\varepsilon^2 tr(\mathbf{\Pi})\mathbf{q_1};$$

$$c_2(N^{-1}\bar{T}^{-1}) = -\sigma_\varepsilon^2[\mathbf{Q}\bar{\mathbf{W}}'\mathbf{\Pi}\mathbf{M_s}\bar{\mathbf{W}} + tr(\mathbf{Q}\bar{\mathbf{W}}'\mathbf{\Pi}\mathbf{M_s}\bar{\mathbf{W}})\mathbf{I}_{k+1} + 2\sigma_\varepsilon^2 q_{11} tr(\mathbf{\Pi}'\mathbf{\Pi}\mathbf{\Pi})\mathbf{I}_{k+1}]\mathbf{q_1};$$

$c_3(N^{-1}\bar{T}^{-2}) = \sigma_\varepsilon^4 tr(\mathbf{\Pi})\{2q_{11}\mathbf{Q}\bar{\mathbf{W}}'\mathbf{\Pi}\mathbf{\Pi}'\bar{\mathbf{W}}\mathbf{q_1} + [(\mathbf{q_1'}\bar{\mathbf{W}}'\mathbf{\Pi}\mathbf{\Pi}'\bar{\mathbf{W}}\mathbf{q_1}) + q_{11}tr(\mathbf{Q}\bar{\mathbf{W}}'\mathbf{\Pi}\mathbf{\Pi}'\bar{\mathbf{W}}) +$
$+2tr(\mathbf{\Pi}'\mathbf{\Pi}\mathbf{\Pi}'\mathbf{\Pi})q_{11}^2]\mathbf{q_1}\}$

where $\mathbf{Q} = [E(\mathbf{W}'\mathbf{M_s}\mathbf{W})]^{-1} = [\bar{\mathbf{W}}'\mathbf{M_s}\bar{\mathbf{W}} + \sigma_\varepsilon^2 tr(\mathbf{\Pi}'\mathbf{\Pi})\mathbf{e_1}\mathbf{e_1'}]^{-1}$, $\bar{\mathbf{W}} = E(\mathbf{W})$, $\mathbf{e_1} = (1,0,\ldots,0)'$ is a $k \times 1$ vector, $\mathbf{q_1} = \mathbf{Q}\mathbf{e_1}$, $q_{11} = \mathbf{e_1'}\mathbf{q_1}$, $\mathbf{L}_T$ is the $T \times T$ matrix with unit first lower subdiagonal and all other elements equal to zero, $\mathbf{L} = \mathbf{I}_N \otimes \mathbf{L}_T$, $\mathbf{\Gamma}_T = (\mathbf{I}_T - \gamma\mathbf{L}_T)^{-1}$, $\mathbf{\Gamma} = \mathbf{I}_N \otimes \mathbf{\Gamma}_T$, and $\mathbf{\Pi} = \mathbf{M_s}\mathbf{L}\mathbf{\Gamma}$.

The following three possible bias approximations emerge with an increasing level of accuracy:

$$B_1 = c_1(\bar{T}^{-1});\ B_2 = B_1 + c_2(N^{-1}\bar{T}^{-1});\ B_3 = B_2 + c_3(N^{-1}\bar{T}^{-2}) \quad (3.B.15)$$

Since the values of the parameters σ_ε^2 and γ are unknown, consistent bias-corrected estimators can be obtained by first finding consistent estimators for these parameters, plugging them into the bias-approximation formulas, and then subtracting the resulting bias-approximation estimates, $\hat{B}_i$, from LSDV as follows:

$\mathrm{LSDVC}_i = \mathrm{LSDV} - \hat{B}_i,\ i = 1, 2, \text{and } 3.$

Possible consistent estimators for γ include those proposed by Anderson and Hsiao (1982), Arellano and Bond (1991), and Blundell and Bond (1998). Depending on the chosen estimator for γ, say h, a consistent estimator for σ_ε^2 is then given by

$$\hat{\sigma}_h^2 = \frac{\mathbf{e}_h'\mathbf{M_s}\mathbf{e}_h}{N-k-T}$$

where $\mathbf{e}_h = \mathbf{y} - \mathbf{W}\boldsymbol{\delta}_h$, and h denotes the estimator initially chosen for γ.

In my LSDVC regressions, I choose the Blundell and Bond (1998) estimator for initiating the bias correction and approximate the bias up to the term $c_2(N^{-1}\bar{T}^{-1})$.

Appendix 3.C: Robustness of results to including contemporary misallocation

Table 3.C1. The effect of trade openness on the *Gini index* of market income

	LSDV	PCSE	BCFE	LSDVC
Gini(*t*-1)	0.865*** (0.029)	0.839*** (0.036)	0.956*** (0.039)	0.942*** (0.034)
ln(GDP p.c.)	4.503 (7.809)	6.001*** (0.967)	0.682 (7.136)	4.524 (10.159)
ln(GDP p.c.)-squared	-0.255 (0.403)	-0.342*** (0.058)	-0.060 (0.370)	-0.245 (0.527)
ln(Trade)	-2.194*** (0.628)	-2.145*** (0.524)	-2.042*** (0.661)	-1.845** (0.754)
Misallocation(*t*-1)	-12.837*** (4.321)	-13.812*** (3.852)	-9.795** (3.978)	-9.146* (5.210)
ln(Trade)×Misallocation(*t*-1)	2.840*** (0.886)	2.988*** (0.811)	2.207*** (0.821)	2.098* (1.088)
Misallocation	0.175 (1.024)	0.121 (0.786)	0.024 (0.954)	-0.164 (1.258)
ln(Financial openness)	0.043 (0.117)	0.083 (0.079)	0.089 (0.127)	-0.054 (0.143)
R&D expenditure	0.507*** (0.118)	0.475*** (0.125)	0.517*** (0.118)	0.557*** (0.155)
Unemployment	-0.017 (0.021)	-0.019 (0.019)	-0.021 (0.019)	-0.025 (0.026)
ln(Tertiary enrolment)	-0.807*** (0.237)	-0.930*** (0.215)	-0.673*** (0.223)	-0.713** (0.295)
ln(Private credit)	0.693*** (0.203)	0.696*** (0.175)	0.662*** (0.210)	0.774*** (0.276)
ln(GFCF)	-0.963*** (0.368)	-0.933*** (0.296)	-0.763** (0.378)	-1.116** (0.460)
ln(Government expenditure)	-0.692 (0.645)	-0.821 (0.537)	-1.024 (0.706)	-0.689 (0.868)
ln(Dependency ratio)	-0.932 (0.880)	-1.227 (0.846)	-0.986 (0.980)	-1.693 (1.103)
Democratic accountability	-0.022 (0.119)	-0.019 (0.073)	0.009 (0.103)	-0.064 (0.140)
ln(Population/Mill.)	-0.559 (2.028)	1.049 (1.689)	-1.233 (1.746)	0.025 (2.494)
Post-2008 dummy	0.077 (0.067)	0.069 (0.042)	0.108 (0.085)	0.031 (0.085)
Observations	190	190	185	190

Standard errors in parentheses. p<0.1; ** p<0.05; *** p<0.01.

Table 3.C2. The effect of trade openness on the *Palma ratio* of disposable income

	LSDV	PCSE	BCFE	LSDVC
Palma(*t*-1)	0.290*** (0.089)	0.325** (0.140)	0.490*** (0.103)	0.490*** (0.097)
ln(GDP p.c.)	1.574 (2.911)	0.520* (0.309)	2.315 (3.019)	2.914 (4.490)
ln(GDP p.c.)-squared	-0.069 (0.149)	-0.009 (0.017)	-0.108 (0.155)	-0.137 (0.231)
ln(Trade)	-0.644*** (0.206)	-0.657*** (0.205)	-0.522** (0.220)	-0.577** (0.253)
Misallocation(*t*-1)	-4.730*** (1.555)	-4.578*** (1.334)	-4.040** (1.680)	-4.515** (1.992)
ln(Trade)×Misallocation(*t*-1)	0.963*** (0.317)	0.959*** (0.282)	0.820** (0.343)	0.919** (0.410)
Misallocation	0.206 (0.344)	0.137 (0.232)	-0.014 (0.379)	-0.134 (0.464)
ln(Financial openness)	-0.045 (0.054)	-0.076** (0.034)	-0.070 (0.069)	-0.045 (0.080)
R&D expenditure	0.033 (0.037)	0.028 (0.030)	0.036 (0.037)	0.022 (0.061)
Unemployment	0.008 (0.007)	0.009 (0.006)	0.008 (0.007)	0.007 (0.009)
ln(Tertiary enrolment)	-0.299*** (0.088)	-0.310*** (0.064)	-0.258*** (0.090)	-0.283** (0.123)
ln(Private credit)	-0.059 (0.064)	-0.053 (0.051)	-0.046 (0.072)	-0.034 (0.092)
ln(GFCF)	0.159 (0.140)	0.100 (0.115)	0.167 (0.130)	0.108 (0.173)
ln(Income tax share)	-0.088 (0.076)	-0.160** (0.068)	-0.083 (0.079)	-0.089 (0.110)
ln(Dependency ratio)	0.582** (0.287)	0.736*** (0.227)	0.548* (0.324)	0.443 (0.433)
Democratic accountability	0.070 (0.080)	0.103 (0.097)	0.051 (0.086)	0.066 (0.109)
ln(Population/Mill.)	-0.559 (0.723)	-0.929 (0.622)	-0.697 (0.708)	-0.758 (0.995)
Post-2008 dummy	0.013 (0.024)	0.009 (0.018)	0.020 (0.028)	0.018 (0.031)
Observations	158	158	156	158

Standard errors in parentheses. p<0.1; ** p<0.05; *** p<0.01.

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