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Monday 23 – Friday 27 August

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The Role of Misallocation in the Relationship Between Trade and Income Inequality

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Paper prepared for the 36th IARIW Virtual General Conference
August 23-27, 2021
Theme 4: Globalization and Inequality

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

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Latest update: January 18, 2021

Abstract

Earlier studies suggest that the effect of trade openness on income inequality is not the same across countries. This paper introduces a new factor that moderates 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-reducing 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.

Keywords: Trade openness; Globalization; Income inequality; Misallocation
JEL classification: D33, D61, F14, F62

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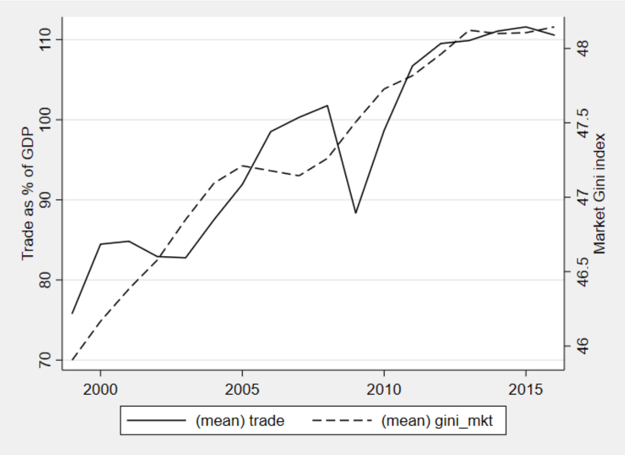
1. Introduction

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 2). Figure 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 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;



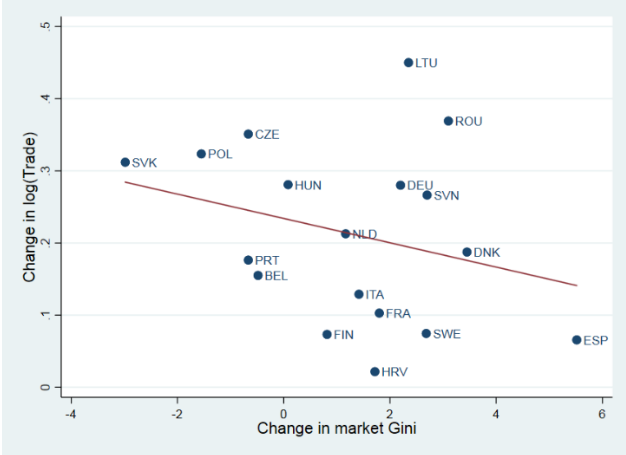


Figure 1. Mean time series of trade and market Gini index for 18 European countries

Figure 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 paper, 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 in a sample of 18 European countries.

The remaining part of this paper proceeds as follows. Section 2 reviews the literature on the relationship between trade and income inequality. Section 3 discusses the theoretical motivation behind the current study of the possible distributional effects of trade openness conditional on existing resource misallocation. Section 4 presents the sources of data and the empirical methodology used in this study. Section 5 presents and briefly discusses the results of the empirical analysis, and Section 6 concludes.

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.

Feenstra and Hanson (2003) show theoretically that trade in *intermediate inputs* has the effect of increasing the relative demand for and the wages of skilled workers—the same effect that skill-biased technical change has on labour demand. Thus, they argue, "distinguishing whether the change in wages is due to international trade, or technological change, is fundamentally an empirical rather than a theoretical question." 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)

[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.

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 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. Theoretical motivation

In this paper, 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:

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

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:

$$r = \alpha(\alpha + (1-\alpha)x^{\rho})^{-\frac{1+\rho}{\rho}}, \tag{2}$$

$$w_h = \beta(1-\alpha)(\alpha + (1-\alpha)x^{\rho})^{-\frac{1+\rho}{\rho}} x^{\rho}\frac{k}{h}, \tag{3}$$

$$w_l = (1-\beta)(1-\alpha)(\alpha + (1-\alpha)x^{\rho})^{-\frac{1+\rho}{\rho}} x^{\rho}\frac{k}{l}, \tag{4}$$

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:

$$\omega \equiv \frac{w_h}{w_l} = \frac{\beta}{1-\beta}\frac{1}{\eta}, \tag{5}$$

$$\frac{r}{w} = \frac{\alpha}{1-\alpha}\frac{\left(h^{\beta}l^{1-\beta}\right)^{\rho}}{k^{1+\rho}}, \tag{6}$$

$$\frac{r}{w_l} = \frac{\alpha}{(1-\beta)(1-\alpha)}\left(\frac{h^{\beta}l^{1-\beta}}{k}\right)^{\rho}\frac{l}{k}, \tag{7}$$

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. (5)–(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]

$$l = \begin{cases} 0 & \text{if} \quad w_l < 1 \\ \ln w_l & \text{if} \quad 1 \leq w_l < e \\ 1 & \text{if} \quad w_l \geq e \end{cases}, \tag{8}$$

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

$$h = \begin{cases} 0 & \text{if} \quad w_h \le w_l \\ \ln \frac{w_h}{w_l} & \text{if } w_l < w_h \le e \\ 1 - \ln w_l & \text{if} \quad w_h > e \end{cases} \tag{9}$$

where e is the Euler's number.

Assume without loss of generality that $1 < w_l < e$ and $w_l < w_h \le e$. Then it follows from Eqs. (8) and (9) that the relative supply of skilled labour, $\eta \equiv h/l$, is increasing in the skill premium, $\omega \equiv w_h/w_l$:

$$\frac{h}{l} \equiv \eta = \frac{\ln \omega}{\ln w_l} \tag{10}$$

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:

$$w_l = \exp(l) \quad \text{and} \quad w_h = \exp(h + l) \tag{11}$$

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

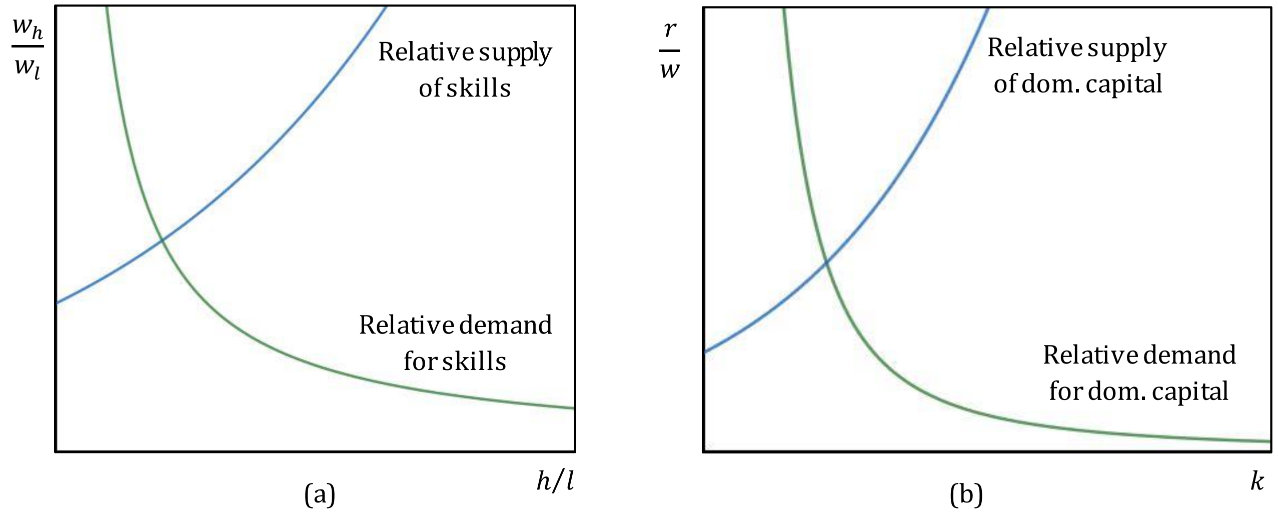
$$\frac{w_h}{w_l} = \exp(h) = \exp(\eta l) \tag{12}$$

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:

$$\frac{r}{w} = \frac{r}{w_h h + w_l l} = \frac{\psi(y,k)}{\exp(l)(\exp(h)h + l)}, \tag{13}$$

$$\frac{r}{w_l} = \frac{\psi(y,k)}{\exp(l)} \tag{14}$$

Figure 3 plots the relative demand and relative supply functions for inputs given by Eqs. (5)–(7) and (12)–(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.



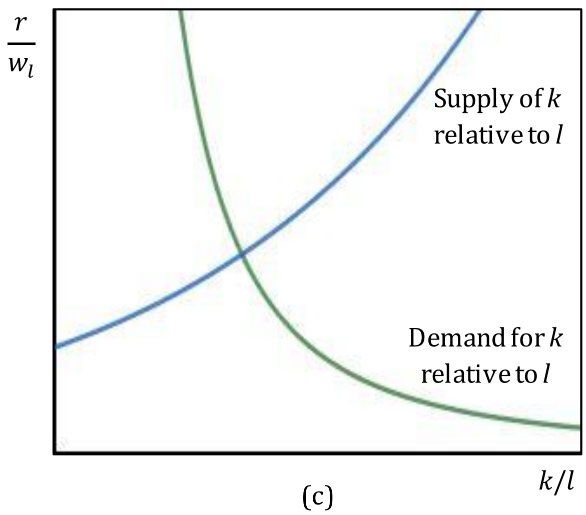


Figure 3. Relative demand and supply of inputs

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 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 paper 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

$$\pi = y - w_l l - (1+\tau_h) w_h h - (1+\tau_k) rk, \tag{15}$$

hence resulting in the following first-order conditions:

$$r = \frac{\alpha}{1+\tau_k}(\alpha + (1-\alpha)x^{\rho})^{-\frac{1+\rho}{\rho}}, \tag{16}$$

$$w_h = \frac{\beta(1-\alpha)}{1+\tau_h}(\alpha + (1-\alpha)x^{\rho})^{-\frac{1+\rho}{\rho}} x^{\rho}\frac{k}{h}, \tag{17}$$

$$w_l = (1-\beta)(1-\alpha)(\alpha + (1-\alpha)x^{\rho})^{-\frac{1+\rho}{\rho}} x^{\rho}\frac{k}{l}, \tag{18}$$

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

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

$$\frac{w_h}{w_l} = \frac{1}{1+\tau_h}\left[\frac{\beta}{1-\beta}\frac{1}{\eta}\right], \tag{19}$$

$$\frac{r}{w} = \frac{1+\tau_h}{(1+\tau_k)(1+(1-\beta)\tau_h)}\left[\frac{\alpha}{1-\alpha}\frac{\left(h^{\beta}l^{1-\beta}\right)^{\rho}}{k^{1+\rho}}\right], \tag{20}$$

$$\frac{r}{w_l} = \frac{1}{1+\tau_k}\left[\frac{\alpha}{(1-\beta)(1-\alpha)}\left(\frac{h^{\beta}l^{1-\beta}}{k}\right)^{\rho}\frac{l}{k}\right] \tag{21}$$

We can see from Eqs. (19)–(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, 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 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.

4. Empirical methodology

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.

[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.

(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 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 A.

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

[4] I use the 6th Vintage of 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. CompNet offers a micro-based dataset with 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 for the period 1999–2016, 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.

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

[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/.

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 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 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.

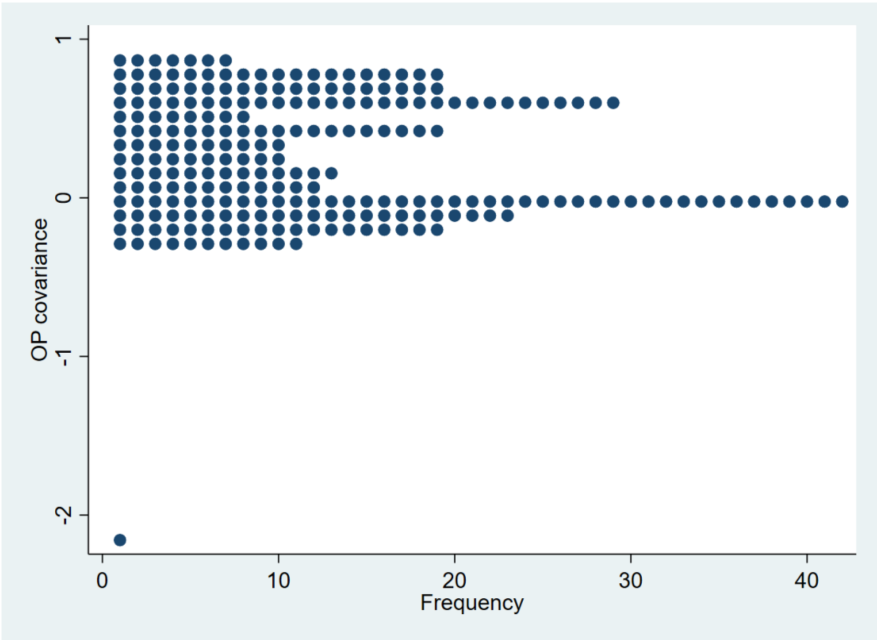


Figure 4. Dot plot of the Olley-Pakes covariances on pooled data for 18 European countries.
(*Source: CompNet*)

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:

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

where c denotes country, t denotes year, γ and δ are the row vectors of coefficients, S_{ct} is the column vector of potential shifters of the relative supply of inputs (share of educated workforce, domestic credit supply, domestic investment)[9], and X_{ct} 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

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

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 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 bias-corrected LSDV (LSDVC) estimator as per Bruno (2005a) and Bruno (2005b).[11]

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

[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.

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.

5. Results

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).

Table 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, a) and the relative supply of capital (Figure 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 Gini index, 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 market Gini, 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 market Gini index, misallocation significantly impairs this

Table 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.

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 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 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

Table 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. $p<0.1$; ** $p<0.05$; *** $p<0.01$.

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 LSDVC estimators. In fact, my theoretical framework (see Eqs. (19)–(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 2 show that misallocation seems to be relevant also for the net income inequality measured by the Palma ratio.

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 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 1. Other control variables are not found to significantly affect the market income inequality measured by the Gini index.

Table 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 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. However, the observed effect of trade may still suffer from

Table 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.

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 B1 and B2

Table 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.

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 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.

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) 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 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 paper 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 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.

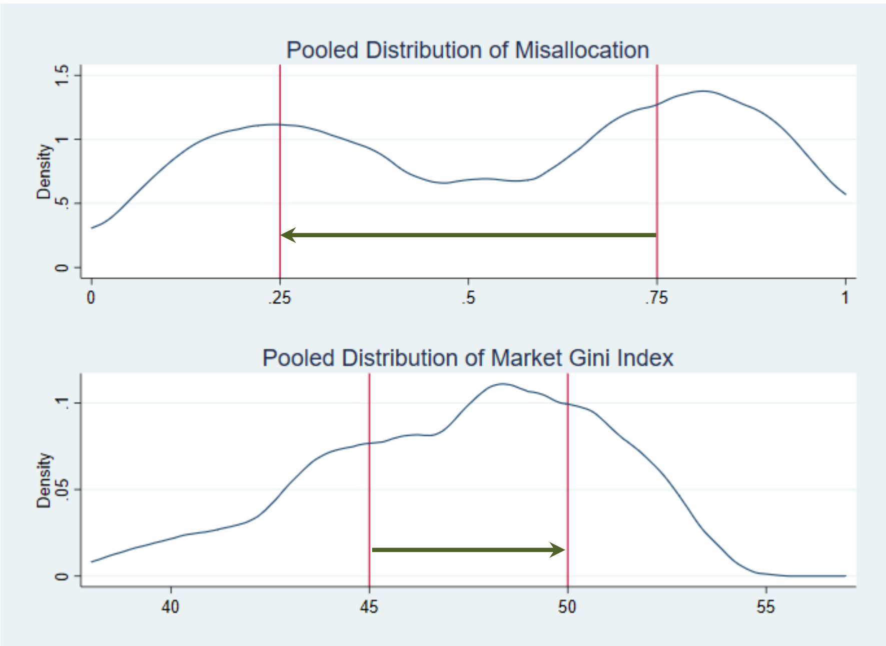


Figure 5. Kernel density functions for the misallocation index and the market Gini index.
Nonparametric densities obtained using the Epanechnikov kernel with the optimal bandwidth.

6. Conclusion

In this paper 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 used the dynamic panel model with fixed-effects estimators corrected for small-sample bias, sufficient caution is still required in generalizing my results.

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Appendix 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	$T = 18$

Notes: The overall summary (std. dev., min., or max.) of a variable $x_{i,t}$ is decomposed into a between ($\bar{x}_i$, the mean of the panel means) summary and a within ($x_{i,t} - \bar{x}_i + \bar{x}$, the global mean $\bar{x}$ being added back in to make results comparable) summary. $\bar{T}$ denotes the average number of time periods (years).

Appendix B: Robustness of results to including contemporary misallocation

Table B1. 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 B2. 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.