Trade, Technology Diffusion and Misallocation: Trade Partner Matters *

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Abstract

This paper suggests that contingent on the productivity level of the trade partner; international trade may create resource misallocation in less productive countries. It theoretically shows how the interaction between technology diffusion induced by trade and cross sectoral heterogeneity in productivity distributions, and technology adoption rates leads to asymmetric pro-competitive effects, which in turn result in misallocation. In this framework trade increases welfare in the long-run due to technology diffusion, even though there is steady-state resource misallocation across industries. Using firm level data from 32 European countries for the period of 1992-2007, it also presents robust empirical evidence supporting the model predictions by showing that trade with more productive regions as a share of purchasing power parity (PPP) GDP (1) increases economy wide markup variation, (2) raises mean sectoral productivity, and (3) decreases productivity dispersion within 4-digit sectors, only in less productive countries.

Keywords: International trade, Technology diffusion, Firm size distribution, Misallocation

JEL codes: F10, F15, L11, O33

1. Introduction

Efficient resource allocation is crucial in utilizing available input factors and technology. When prices reflect true costs or price distortions are uniform, efficient allocation is achieved (Lerner (1934)). However, the link between costs and prices can be tilted due to various factors such as distortionary taxes or limited access to finance which might lead to inefficient use of resources. Recently, there has been an upsurge in the empirical studies documenting the presence and extent of resource misallocation for developing countries (Banerjee and Duflo (2005), Jeong and Townsend (2007), Alfaro et al. (2009), and Hsieh and Klenow (2009)). Hsieh and Klenow (2009) report that there could be large productivity gains, in the magnitude of 40-60 % in India and 30-50 % in China, if allocative efficiency is hypothetically improved to the US level. Similarly,

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using firm level data for 79 countries, Alfaro et al. (2009) find that incorporating allocative efficiency in a neoclassical growth model improves the explained part of the cross country dispersion in income per worker from 42 to 58 %. These substantial figures indicate the importance of allocative efficiency in explaining the formerly unexplained part of the productivity variation across countries. An immediate query growing out of these observations relates international trade and resource misallocation: How does the exchange of goods and ideas interact with the allocative efficiency of trading countries? In this paper, we explicitly focus on this issue and argue that the answer depends on the cross-sectoral variation of monopoly power in autarky and the innovative capacity of the country. If the economy has limited capacity to generate excludable knowledge and is characterized by monopolies facing little competitive pressure in autarky, international trade leads to resource misallocation by affecting competitiveness of different sectors asymmetrically even though it gradually eliminates the absolute level of market power within each sector. This seemingly special case is not only of theoretical interest but also accords well with the experience of transition economies which were dominated by large establishments having considerable market power and very low levels of innovative activity before integrating the world economy. Consistent with our argument, McMillan and Rodrik (2011) document that as a response to trade liberalization, East Asian countries gained more by being able to reallocate resources towards more productive sectors whereas Latin American and African countries experienced the opposite. The mechanics behind this result can be summarized as follows: International trade initiates exchange of goods and knowledge transfers among trading partners. The knowledge transfers are unidirectional from more productive countries (North) to less productive ones (South) in the form of spillovers from which both the active southern firms (incumbents) and their potential competitors (competitive fringe) can benefit.[1] Technology diffusion decreases the relative productivity of the southern incumbents with respect to their fringe over time due to faster catch up of initially less productive firms. As a result, average productivity increases while sectoral productivity dispersion is declining and competition is tougher once the economy moves into a period of trade liberalism. The crucial elements which establish the link between international trade and misallocation are the differences in *initial productivity distributions* and *technology adoption rates* across sectors.[2] In the presence of these differences, trade will have asymmetric pro-competitive effects in the South and inflate markup dispersion. More competitive sectors employ a larger share of the labor force for lower relative output prices; that is, they will be sub-optimally large, and the markup dispersion will create resource misallocation which keeps the laggard economy from its *potential*

[1] Knowledge transfers and technology diffusion are used interchangeably.

[2] While presence of only one factor is enough to create misallocation in the transition, long-run level of allocative efficiency is determined by the cross-sectoral differences in technology adoption rates.

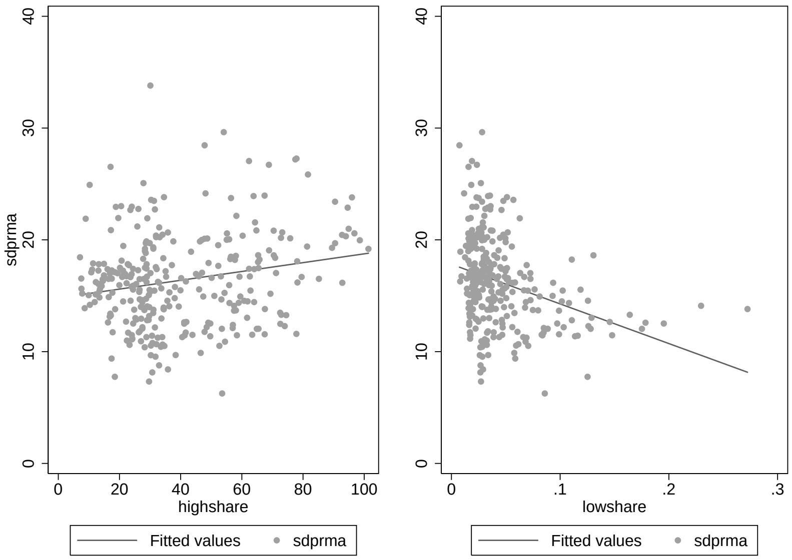

Figure 1: Productivity of the trade partner and variation in profit margins. *highshare* (*lowshare*) is the sum of merchandise imports and exports with the high (low) productivity region as a share PPP GDP. *sdprma* is the standard deviation of profit margins. Each point is a country-year pair. T-statistic for *highshare* (*lowshare*) is 3.91 (-5.43).

output, which is defined as the after-trade output level with no markup dispersion.[3] It should be apparent that the mechanism described above predicts that productivity of the trade partner is operative where openness due to trade with high productivity regions, rather than the average openness, brings about pro-competitive effects and associated welfare losses. As preliminary evidence for our model predictions, Figure 1 shows the relationship between trade openness and variation in profit margins -a commonly used measure for markups- for a large sample of European countries between 1992 and 2007.[4] It is seen that trading more with high productivity regions (US, Canada, Japan and Western Europe) implies higher markup dispersion (left panel) whereas the increased share of trade with low productivity regions (MERCOSUR members, Eastern Europe, North Africa and SACU countries) suggests the opposite (right panel). These patterns are not explicitly investigated so far in the literature and this study suggests a theoretical framework to explain the observed relationship between the relative productivity of trade partners and variation in profitability.

Our work is related to different strands of literature. *First*, this paper is closely related to the recent

[3]There are two alternative ways of determining the *potential output*. First, we can compare the before and after trade values of relative output. In this case, the resultant effect of trade liberalism on the international distribution of wealth is not trivial and determined by the net effect of positive productivity gains and negative allocational effects of higher markup variation. Second, we can define the potential output which is achieved by the laggard economy when there is no markup variation under free trade and evaluate the effects of international trade and markup heterogeneity with respect to this reference. In either case, there is room for intervention and the adverse effects of resource misallocation can be - at least partly- eliminated by careful trade and competition policies. We follow the second alternative and compare the after-trade outcomes with and without markup variation since long-run productivity gains from trade are likely to dominate the losses due to misallocation.

[4]The profit margin data are provided by Bureau van Dijk. Trade data comes from UN Comtrade. Data sources are explained in Section 3 in detail.

literature on resource misallocation and aims to provide a theoretical explanation for the empirical evidence documented especially for developing economies (Banerjee and Duflo (2005), Jeong and Townsend (2007) and Hsieh and Klenow (2009)). There are two regularities which can be distilled from this body of empirical research: To explain the observed deviations from an efficient firm size distribution (which is assumed to be US firm size distribution), firm level distortions should be (1) positively related to firm productivity and (2) negatively correlated with firm size (Restuccia and Rogerson (2008), Hsieh and Klenow (2009) and Banerjee and Moll (2010)). In this respect, we argue that markups are self-created distortions by firms' profit-maximizing behavior, which act as a wedge between marginal costs and prices. Trade creates markup variation due to asymmetric pro-competitive effects across sectors and firms imposing higher markups are observed to have higher revenue productivity while being smaller in size due to higher prices and lower demand for their output. As a result, our model provides a rationale for the positive (negative) relationship between firm level distortions and marginal revenue productivity (size). The prominent theoretical explanation in this literature is the imperfections in financial markets. Buera et al. (2011) report that "a factor-of-two difference in income levels, or almost 80 % of the difference in per-capita income between Mexico and US" can be explained by the differences in financial development. Banerjee and Moll (2010) propose that credit constraints together with a convex-concave production function give rise to misallocation but creating misallocation as a steady-state phenomenon is left as an open question to be answered. Clearly, impediments against resource reallocation may cause misuse of available factors and indeed these frictions are shown to be empirically important. One of our contributions is to show that even when there are no frictions against resource flow; misallocation may emerge due to pro-competitive effects of international trade, heterogeneity in productivity distributions, and technology adoption rates across sectors. Furthermore, our framework generates misallocation in the steady-state due to cross-sectoral variation in technology adoption rates across sectors.

Being close to our argument, Epifani and Gancia (2011) contribute to the discussion by stating that there can be pro-competitive welfare losses associated with increased markup heterogeneity where the distortion is mainly created due to asymmetric exposure to foreign competition. As a result, they use the second moment of the openness distribution to explain the sectoral differences in profitability. Complementary to their argument, we emphasize that productivity distribution is heterogeneous across sectors and thereby there are natural differences across sectors in the way which they react to market integration. Hence, even under complete liberalization, asymmetric effects emerge due to these sectoral differences. Furthermore, we propose a specific mechanism -technology diffusion- through which international trade affects the competition in the laggard economies and provide novel predictions which call for the average openness into the analysis, but this time in a specific manner. Namely, we predict that the productivity gap between trade partners is an important ingredient of the analysis and trading more with more productive regions may create misallocation for relatively backward economies. We also present robust empirical results in support of our model predictions. *Second*, this paper aims to contribute to the understanding of cross-country convergence and international trade literature. We aim to provide useful insight on two main questions of this line of research: How does the technological progress in developed countries affect the productivity in the least developed countries where there is no or limited innovative activity? Does exposure to trade change the observed patterns in income differentials? Several papers (among others Young (1991), Grossman and Helpman (1991), Van de Klundert and Smulders (1996), Coe et al. (1997), Acemoglu and Zilibotti (2001)) have discussed different mechanisms which may foster or prevent cross-country convergence. Apparently, the changes in allocative efficiency introduced by international trade have not been investigated explicitly. In this respect, we propose that observed levels of convergence in real income might understate the convergence in physical productivity levels due to trade induced misallocation. This argument can be helpful in understanding the lack of convergence experienced by transition economies. Another line of related research is on the incapability of CES utility functions to create pro-competitive effects of international trade since the markups are constant over time. Behrens and Murata (2007) show the importance of using CARA (Constant Absolute Risk Aversion) utility functions to generate variable markups. Among others, Melitz and Ottaviano (2008) use a special case of this type of utility functions to model the pro-competitive effects of international trade. Remarkably, our model generates pro-competitive effects of trade with CES utility as a consequence of the interaction between trade and sectoral heterogeneity in productivity distribution. Briefly, considering supply side heterogeneity yields an intuitive relationship between trade and markup distribution even when we abstract from the demand side arguments. The remainder of the paper is organized as follows. In Section-2, the model is presented and the effects of trade on markup dispersion and relative output are discussed. In Section-3, the data are introduced and model predictions are empirically tested. Section-4 concludes.

2. Theoretical Framework

2.1. Model setup

We study a two country North-South model with fully integrated goods markets and no international factor mobility. There is a continuum of differentiated goods whose measure is normalized to 1 in each country. The southern (northern) goods are indexed by $i, i \in [0,1]$ $(j, j \in [0,1])$. The elasticity of substitution $(\varepsilon > 1)$ is constant among domestic and foreign goods.[5] The individuals' utility function is of the familiar

[5] We use domestic (foreign) country and the South (North) interchangeably.

CES form[6]

$$U = C \equiv \left(\int_0^1 c_i^{\frac{\varepsilon-1}{\varepsilon}} \, \mathrm{d}i + \int_0^1 c_j^{\frac{\varepsilon-1}{\varepsilon}} \, \mathrm{d}j \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{1}$$

where c_i is consumption of good i. Consumers maximize their utility (1) with respect to the following budget constraint

$$\int_0^1 c_i p_i \, \mathrm{d}i + \int_0^1 c_j p_j \, \mathrm{d}j = I, \tag{2}$$

where p_i is the price of the domestic good i and I denotes the income. Given these conditions, domestic demand for the ith good will be

$$c_i = C \left(\frac{p_i}{P} \right)^{-\varepsilon}, \tag{3}$$

where P is the domestic price index. Similarly foreign demand for the domestic good i is given by

$$\bar{c}_i = \bar{C} \left(\frac{p_i}{\bar{P}} \right)^{-\varepsilon}. \tag{4}$$

where bars denote the foreign counterparts. Finally, total domestic and foreign spending are given as follows

$$CP = \int_0^1 c_i p_i \, \mathrm{d}i + \int_0^1 c_j p_j \, \mathrm{d}j, \tag{5}$$

$$\bar{C}\bar{P} = \int_0^1 \bar{c}_i p_i \, \mathrm{d}i + \int_0^1 \bar{c}_j p_j \, \mathrm{d}j. \tag{6}$$

The domestic and foreign price indices are equal ($P = \bar{P}$) since the markets are fully integrated, transportation is costless and there is no pricing to market. The price index will be our numeraire and is equal to 1. Hence, all variables are in real terms.

[6] All variables are functions of time. Time indices are dropped for ease of notation.

2.1.1. Firm behavior and productivity

Southern (Northern) firm i (j) uses a production technology with constant returns to the only mobile resource labor with productivity $h_i, i \in [0,1]$ ($h_j, j \in [0,1]$). Then, the output of firm i is given by

$$x_i = h_i l_i \quad \forall i \in [0,1]. \tag{7}$$

It is assumed that incumbent firms have the same productivity within each region while the North has a higher aggregate productivity ($\int_0^1 h_i d_i = h_i = H < \bar{H} = h_j = \int_0^1 h_j dj$).[7] For each southern sector $i \in [0,1]$, there is a competitive fringe which can produce the same good with a lower productivity ($h_i^f < h_i$) hence at a higher marginal cost. In addition, fringe productivities are allowed to be different across sectors to model the cross-sectoral variation in productivity distributions. Firms within a sector engage in Bertrand competition and incumbent i sets its price p_i given its marginal cost $\frac{w}{h_i}$, the demand schedules (3) and (4) and the fringe productivity in order to maximize the present value of its cash flow stream, where w is the domestic wage rate. The price of good i is equal to a constant markup ($\varepsilon/(\varepsilon-1)$) times the marginal cost as long as the fringe is not able to break even at this price. Otherwise, the incumbent cuts down its price and equates it to the marginal cost of the fringe to prevent entry and make positive profits. Briefly,

$$p_i = \begin{cases} \frac{h_i}{h_i^f}\frac{w}{h_i} & \text{if } \frac{h_i}{h_i^f} \leq \frac{\varepsilon}{\varepsilon-1} \\ \frac{\varepsilon}{\varepsilon-1}\frac{w}{h_i} & \text{otherwise} \end{cases} \tag{8}$$

Northern incumbents always set the monopoly price since they are assumed to be able to innovate to escape from competition:

$$p_j = \frac{\varepsilon}{\varepsilon-1}\frac{\bar{w}}{h_j} \quad \forall j \in [0,1]. \tag{9}$$

2.1.2. Productivity growth: Technology diffusion

A northern firm invests in R&D and has a constant positive productivity growth ($\hat{h}_j = g \ \forall j \in [0,1]$) which is assumed to be exogenous. When the markets are integrated, the South experiences productivity gains in the form of technological knowledge spillovers. In the absence of these spillovers, the South is assumed to have constant productivity. Hence, the innovative activity of southern firms is assumed to be of negligible magnitude which causes their productivity growth to be dependent on the aggregate productivity

[7] Symmetry of incumbent productivity is a simplifying assumption to make the exposition clearer and not crucial for any of the qualitative results. It is used to crystallize that price heterogeneity within a country, if exists, is not justified by the productivity differences of operating firms. The general solution without incumbent symmetry is available upon request from the author.

stock of the trade partner. This mechanism is reflected in the law of motion of the labor productivity for southern firms as follows

$$\dot{h}_i = \gamma_1 (\bar{H}/h_i)^{\delta} h_i^{\theta} \ \ , \ \delta, \theta, \gamma_1 > 0 \ \ \forall i \in [0,1], \tag{10}$$

$$\dot{h}_i^f = \gamma_i^f (\bar{H}/h_i^f)^{\delta} (h_i^f)^{\theta} \ \ , \ \delta, \theta, \gamma_i^f > 0 \ \ \forall i \in [0,1], \tag{11}$$

where the dot indicates the time derivative.[8] The spillover equations (10) and (11) imply that the change in the productivity of the southern firms is increasing in the productivity gap ($\frac{\bar{H}}{h_i}$) and outside sector productivity stock is also effective on the subsequent productivity growth since the frontier is determined by the aggregate foreign productivity ($\bar{H}$). This formulation is based on the empirical evidence on knowledge spillovers which we will present in section 2.3. To find the evolution of relative incumbent productivity we define $m_i(t) \equiv \frac{h_i(t)}{h_i^f(t)}$ and solve it for the endogenous growth case $\theta = 1$ (see Appendix A.1).

$$m_i(t) = \left(\frac{\frac{\gamma_1}{\hat{h}_j} + \left(g_i(0) - \frac{\gamma_1}{\hat{h}_j} \right) e^{-\delta \hat{h}_j t}}{\frac{\gamma_i^f}{\hat{h}_j} + \left(f_i(0) - \frac{\gamma_i^f}{\hat{h}_j} \right) e^{-\delta \hat{h}_j t}} \right)^{1/\delta} \quad \forall i \in [0,1], \tag{12}$$

where

$$g_i(t) = \frac{h_i(t)}{h_j(t)} \ , \ f_i(t) = \frac{h_i^f(t)}{h_j(t)} \ , \ m_i(0) \geq \frac{\varepsilon}{(\varepsilon - 1)} \ \forall i \in [0,1] \tag{13}$$

and

$$\lim_{t \to \infty} m_i(t) = (\frac{\gamma_1}{\gamma_i^f})^{1/\delta} \ \ \forall i \in [0,1]. \tag{14}$$

To avoid higher fringe productivity at the steady state, it is assumed that $1 < (\gamma_1/\gamma_i^f)^{1/\delta} < \varepsilon/(\varepsilon - 1) \leq m_i(0), \ \ \forall i \in [0,1]$. In this case, relative incumbent productivity monotonically decreases over time and converges to its long-run value from above. One key point about equation (14) is that the sectors, where the foreign knowledge can be easily replicated and implemented will be more competitive in the long run. This observation is pertinent to predict which sectoral characteristics influence the economy wide variation

[8] Our formulation assumes that trade is a binary variable and trade volume has no effect on the intensity of technology diffusion. This is a simplifying assumption to make the exposition clearer. The positive relationship between knowledge transfers and trade volume can be easily included in our specification by defining δ as an increasing function of the trade openness, which is defined for positive trade levels, without changing any of the qualitative results of our model. Such a function should take positive values to be consistent with productivity convergence and bounded from above to rule out the possibility of instantaneous catch up with the frontier. In the empirical part, we follow the standard route in the empirical literature and use continuous openness measures based on trade volume.

in trade induced price distortions. Moreover, it is apparent that *your trade partner matters*: the initial productivity level of the trade partner is important in determining how large the pro-competitive effects will be, especially in the short run:

$$\frac{\partial m_i(t)}{\partial h_j(0)} < 0 \ , \ \lim_{t\to\infty} \frac{\partial m_i(t)}{\partial h_j(0)} = 0 \ \ \forall i \in [0,1], \tag{15}$$

since $m_i(0) > (\frac{\gamma_1}{\gamma_i^f})^\delta$ (see Appendix A.2). A larger productivity gap results in stronger spillovers and a faster catch up for the competitive fringe. *Ceteris paribus*, the downward pressure on markups is more pronounced when the trade partner is more productive.

2.2. Model Solution

Goods markets and labor market clearing conditions, and balanced trade will determine the prices and wages simultaneously given the initial productivity distributions and spillover equations. Labor market clearing implies

$$\int_0^1 l_i \mathrm{d}i = L. \tag{16}$$

Under balanced trade, the value of southern imports is equal to the exports. Hence,

$$\int_0^1 c_j p_j dj = \int_0^1 \bar{c}_i p_i \mathrm{d}i. \tag{17}$$

The initial productivity gap between the incumbent and its fringe is sufficiently large; hence all incumbents are able to set monopoly prices in autarky. Since the relative incumbent productivity is monotonically decreasing over time, firm i switches from monopoly pricing to limit pricing at a particular point in finite time. We define a non-decreasing function $G(t)$ which captures the fraction of firms which switched to limit pricing up to time t, with the following properties:

$$\lim_{t\to\infty} G(t) \leq 1 \ , \ G(0) = 0 \ , \ \frac{\partial G(t)}{\partial t} \geq 0. \tag{18}$$

In this case, at time t, $100G(t)$ percent of the firms will use limit pricing and their prices will be different due to heterogeneous productivity distributions across sectors. On the other hand, $100(1 - G(t))$ percent of the firms will use monopoly pricing. Given the symmetry among incumbents, the same prices are observed if the fringe productivity is not binding, whereas prices are lower and heterogeneous otherwise. Using the balanced budget condition, goods and labor market clearing, we find relative wage, $w^* \equiv w/\bar{w}$, of southern workers as[9]

$$w^* = \left(\frac{H}{\bar{H}}\right)^{\frac{\varepsilon-1}{\varepsilon}} \left[\int_0^{G(t)} \left(\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon}\right)^{-\varepsilon} \mathrm{d}i + (1-G(t))\right]^{1/\varepsilon} \tag{19}$$

with $(\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{-\varepsilon} > 1$ for the firms whose fringe productivities are binding. So, the integral on right hand side is greater than $G(t)$ and the expression in square brackets is larger than 1. Equation (19) shows that higher competition induced by international trade unambiguously increases relative wages. To link this relationship formally to the moments of the markup distribution, let $\tilde{m}_i(t)$ represent the observed markup relative to monopoly markups:

$$\tilde{m}_i(t) = \begin{cases} 1 & \text{if } i \in (G(t),1] \\ m_i(t)\frac{\varepsilon-1}{\varepsilon} & \text{if } i \in [0,G(t)] \end{cases} \tag{20}$$

Then, (19) can be written in terms of the observed markup levels:

$$w^*(t) = \left(\frac{H}{\bar{H}}\right)^{\frac{\varepsilon-1}{\varepsilon}} \left[\int_0^1 (\tilde{m}_i(t))^{-\varepsilon}\, di\right]^{1/\varepsilon} \tag{21}$$

Equation (21) reveals that relative wage of the southern workers is inversely related to average markup level since the second term on the right hand side is homogenous of degree -1. As a result, higher competition leads to higher relative wages for southern workers. Does the increase in relative wages also translate into an increase in the relative consumption? The answer is not trivial due to allocational effects of markup heterogeneity. Hence, labor allocation should be characterized. The relative demand of incumbent k whose fringe is binding with respect to incumbent m setting monopoly prices will be

$$\frac{c_k + \bar{c}_k}{c_m + \bar{c}_m} = \left(\frac{p_k}{p_m}\right)^{-\varepsilon} = \left(\frac{h_k}{h_k^f}\frac{\varepsilon-1}{\varepsilon}\right)^{-\varepsilon} = \frac{h_k l_k}{h_m l_m} = \frac{l_k}{l_m};\ k \in [0, G(t)]\ ,\ m \in (G(t), 1], \tag{22}$$

where the last two equalities follow from goods market equilibrium and the symmetry among incumbent productivity. Although it is assumed that all active firms in the South are equally productive, international trade reveals underlying institutional or technological differences among southern sectors and there is continuous reallocation of labor, as apparent from (22). In order to evaluate the resultant effect of the increase in relative wages and change in the market structure across sectors, we solve for the labor allocated to each

[9]General equilibrium solution is presented explicitly in Appendix B.

firm using the labor market clearing condition. A firm whose fringe productivity is binding employs

$$l_k = \left(\frac{h_k}{h_k^f}\frac{\varepsilon-1}{\varepsilon}\right)^{-\varepsilon} \frac{L}{\int_0^{G(t)}\left(\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon}\right)^{-\varepsilon}\mathrm{d}i + (1-G(t))}\ ,\ \forall k \in [0, G(t)] \tag{23}$$

$$= (\tilde{m}_k(t))^{-\varepsilon}\frac{L}{\int_0^1 \tilde{m}_i(t)^{-\varepsilon}di}\ ,\ \forall k \in [0, G(t)], \tag{24}$$

while other firms employ

$$l_m = \frac{L}{\int_0^1 \tilde{m}_i(t)^{-\varepsilon}di}\ ,\ \forall m \in (G(t), 1]. \tag{25}$$

Inspection of (24) and (25) shows that $l_k > l_m$. Therefore, southern firms with lower profitability are larger relative to more profitable firms. Using (19), (24), (25) and dividing (5) by (6), relative consumption of the domestic economy is given by

$$\frac{C}{\bar{C}} = \left(\frac{H}{\bar{H}}\right)^{\frac{\varepsilon-1}{\varepsilon}} \frac{\int_0^{G(t)}(\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{1-\varepsilon}\mathrm{d}i + (1-G(t))}{\left(\int_0^{G(t)}(\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{-\varepsilon}\mathrm{d}i + (1-G(t))\right)^{(\varepsilon-1)/\varepsilon}} \tag{26}$$

$$= \left(\frac{H}{\bar{H}}\right)^{\frac{\varepsilon-1}{\varepsilon}} \frac{\int_0^1(\tilde{m}_i(t))^{1-\varepsilon}\mathrm{d}i}{\left(\int_0^1(\tilde{m}_i(t))^{-\varepsilon}\mathrm{d}i\right)^{(\varepsilon-1)/\varepsilon}}. \tag{27}$$

Equation (27) summarizes the effects of trade and markup dispersion on relative output of the South. The last term on the right hand side makes it clear that markup distribution has a first order effect on the relative output. A formal interpretation requires a definition of the efficient benchmark according to which the current state of the economy is compared to.

Definition 1. *The potential output of the South is the maximum relative output level given the relative labor productivity:*

$$\frac{C}{\bar{C}} = \left(\frac{H}{\bar{H}}\right)^{\frac{\varepsilon-1}{\varepsilon}}. \tag{28}$$

Proposition 1. *When markup variation is positive, the relative output of the laggard economy is lower than its potential value:*

$$\frac{\int_0^1(\tilde{m}_i(t))^{1-\varepsilon}\mathrm{d}i}{\left(\int_0^1(\tilde{m}_i(t))^{-\varepsilon}\mathrm{d}i\right)^{(\varepsilon-1)/\varepsilon}} < 1$$

Proof. We define $z_i(t) \equiv \tilde{m}_i(t)^{1-\varepsilon}$. Then the numerator and the denominator are generalized means with exponents 1 and $\frac{\varepsilon}{\varepsilon-1}$, respectively:

$$\frac{C}{\bar{C}} = \left(\frac{H}{\bar{H}}\right)^{\frac{\varepsilon-1}{\varepsilon}} \frac{\int_0^1 (\tilde{m}_i(t))^{1-\varepsilon}\mathrm{d}i}{\left(\int_0^1 (\tilde{m}_i(t))^{-\varepsilon}\mathrm{d}i\right)^{(\varepsilon-1)/\varepsilon}} \tag{29}$$

$$= \left(\frac{H}{\bar{H}}\right)^{\frac{\varepsilon-1}{\varepsilon}} \left(\frac{\int_0^1 z_i(t)\mathrm{d}i}{\left(\int_0^1 z_i(t)^{\frac{\varepsilon}{\varepsilon-1}}\mathrm{d}i\right)^{\frac{\varepsilon-1}{\varepsilon}}}\right) \tag{30}$$

For $\varepsilon > 1$, $\frac{\varepsilon}{\varepsilon-1} > 1$. By Lyapunov's inequality, a generalized mean is increasing in the exponent unless there is no variation in $z_i(t)$. Hence the multiplier is strictly smaller than 1 and the relative output is smaller than the potential value when the variance of the observed markups is positive. □

Unless markups are equalized, firm level price distortions will be different across southern sectors and the ones with lower profitability and marginal revenue productivity will employ more labor. Hence, market allocation results in a lower output level than the best possible case, which we interpret as misallocation. The multiplier of the potential value in (29) measures how far the domestic economy is away from its potential value. Hence, we can define the degree of misallocation -*M(t)*- by making use of this multiplier as follows:

$$M(t) = 1 - \left(\frac{\int_0^1 z_i(t)\mathrm{d}i}{\left(\int_0^1 z_i(t)^{\frac{\varepsilon}{\varepsilon-1}}\mathrm{d}i\right)^{\frac{\varepsilon-1}{\varepsilon}}}\right) \tag{31}$$

Besides having level effects, misallocation induced by international trade has also growth effects. If we log-linearize (29) and use (31), we find that $\hat{C} - \hat{\bar{C}} = (\frac{\varepsilon-1}{\varepsilon})(\hat{H} - \hat{\bar{H}}) - \dot{M}(t)$ for $1 - M(t) \approx 1$. Hence, the difference in the observed growth rates of the frontier and laggard economies might understate the convergence in physical labor productivity due to trade induced misallocation and we may observe a divergent pattern unless productivity gains dominate allocational losses. Using equation (31), it is theoretically possible to quantify misallocation once we have a valid measure for the elasticity of substitution. However, one should propose an empirically sound measure for the elasticity of substitution among all commodities produced in a country to empirically analyze the determinants of misallocation. Finding the empirical counterpart of such a variable requires elaborate solution of obvious conceptual problems. Proposition 2 provides a useful way to deal with this issue for our purposes:

Proposition 2. *A mean-preserving spread on the observed markups; that is, increasing the variation of observed markup distribution while keeping its mean unchanged increases resource misallocation at the country level.*

Proof. See Appendix C. □

Proposition-2 links the observed markup variation and country level resource misallocation. It provides an intuitive way of quantifying misallocation by using a non-parametric estimate of observed markup variation. We will use this result while conducting the empirical tests of our model implications. Namely, we analyze the effects of trade openness and the productivity of trade partners on resource misallocation using the standard deviation of markups as a proxy for resource misallocation.

2.3. Remarks and Discussion

Before presenting the empirical tests of the model predictions, we will discuss the validity of the spillover mechanism employed to model knowledge transfers among trade partners, since it is of particular importance for the theoretical consequences of our model. *First*, it is argued that the followers in terms of productivity can benefit from the knowledge stock of leader firms in the form of technological knowledge spillovers when they operate in integrated markets. There is voluminous empirical work on the relationship between international trade and productivity growth (e.g., Coe and Helpman (1995), Coe et al. (1997), Keller (2002) and Lumenga-Neso et al. (2005)). Although there have been skeptical concerns about positive effects of international trade on productivity (e.g., Keller (2000)), Madsen (2007) shows that when a larger time span relative to the existing studies is used, imports of knowledge constitute 93 percent of the increase in TFP over the period 1870 to 2004 for OECD countries. *Second*, the strength of spillovers is assumed to be an increasing function of the productivity gap - labor productivity of the leader relative to the follower - between the trading partners (e.g., Griffith et al. (2004), Salomon and Jin (2008)). *Third*, the productivity gap which is relevant for international spillovers is defined using aggregate productivity of the trade partner, hence it is argued that both within sector and outside the sector foreign knowledge stock can contribute to technology diffusion (see, Keller (2002)). *Finally*, we assume away other factors which may affect the ability to make use of knowledge spillovers such as firms' own R&D intensity. This modeling choice is not as restrictive as it first seems. The R&D expenditure is only relevant for our purposes if its intensity differs between the incumbent and the fringe. Even in this case, if this difference is explained by the initial differences in productivity or can be captured by a time-invariant multiplicative factor, our formulation is still valid. Also, we allow for differences in the steady-state relative incumbent productivity ($\frac{\gamma_1}{\gamma_i^f}$) across sectors in a general manner. Hence, we account for the possibility that the effects of spillovers may have differential effects on competitive conduct across sectors, be it dependent on the differences in R&D intensity, institutional setting or nature of the production process.

3. Empirical Analysis

In the empirical part, we test the main prediction of the model regarding the impact of international trade on resource misallocation, present evidence that predicted relationship is present in the data and show that changes in the productivity distribution as a reaction to trade with more productive trade partners are consistent with the mechanism we suggested. The model predicts that trading with more productive regions increases resource misallocation, which is proxied by economy wide markup variation, for less productive countries. Hence, it is expected that trading more with high productivity regions as a share of GDP has a positive effect on country level markup variation for relatively less productive economies and a less positive, if significant, effect for relatively more productive economies since they are on average closer to the frontier. Regarding the relevance of the knowledge transfers, it is tested whether trading more with more productive regions increases average productivity while decreasing the productivity gap at the sectoral level. For empirical purposes, the last prediction is generalized to cases where there are more than two firms within a sector and as a result productivity dispersion within 4-digit sectors is used instead of the productivity gap. To be able to test these predictions, we need three sets of data: (1) firm level markups or profit margins and productivity variables, (2) bilateral trade data at the country level to decompose openness with respect to the productivity of the trade partner and (3) country level macroeconomic indicators to control for other determinants of misallocation and productivity distribution which can bias the estimates if omitted.

3.1. Firm level profitability and productivity

Bureau van Dijk provides detailed firm level financial data (AMADEUS dataset) for a large set of European firms including the ones in relatively less productive countries such as transition economies. Our sample consists of 2.039.139 observations for 351.570 large scale[10] European firms from 1992 to 2007 for which profit margins are available.[11][12] In this dataset, profit margins are computed from the balance sheet entries of firms by computing the before tax profits relative to turnover. We computed the standard deviation of the profit margins (*sdprma*) for each country and year;[13] then constructed a panel and only take the countries for which profit margin is available for at least 50 firms.[14] We end up with 307 observations for 32 countries.

[10]Small or medium scale firms in less productive countries are systematically underrepresented. To mitigate possible biases which can be introduced due to this issue, only large scale firms are considered.

[11]We exclude 2008 and 2009 for which the data are available since there are abrupt changes in the trade patterns due to recent economic downturn.

[12]A financial year starts from the 1st of July and lasts until the 30th of June of the next year. Conventional calendar year is not used since many firms report financial reports after the 1st of January. Alternative choices are not effective on the results presented here.

[13]Apart from the variation of profit margins, mean profit margin (*meanprma*), mean turnover per employee (*meantpe*) and mean capital per employee variables (*meancpe*) are created as relevant variables for the empirical analysis

[14]The results are robust to the choice of this threshold. Table D.8 in Appendix D.1.3 replicates the baseline estimations considering countries for which profit margin data is available for more than 200 large firms.

3.2. Trade Data and Macroeconomic Indicators

The macroeconomic indicators and merchandise trade data are taken from UPenn World Tables 7.0 and UN Comtrade, respectively. Import and export values are compiled by aggregating trade partners at the regional level. North America (US and Canada), Japan and Western Europe are defined as the high productivity region. Alcalá and Ciccone (2004) show that using nominal GDP to evaluate the relative importance of trade with respect to overall economic activity can be misleading in the presence of non-tradables. A decrease in the relative prices of tradables followed by an expansion in trade openness results in an underestimated openness level when the standard nominal openness measures are used. Furthermore, less productive countries have virtually higher levels of openness due to their lower relative price of non-tradables. Hence, they propose *real openness*, which is the sum of imports and exports relative to purchasing power parity (PPP) GDP, as a better measure of trade exposure. We use their insight and construct the variable of interest (*highshare*) by dividing the sum of imports and exports with the high productivity region by PPP GDP. Total real openness (*openr*) including also service trade is constructed by multiplying nominal openness in constant prices by the price level (GDP in exchange rate US$ relative to GDP in PPP US$, which is also the real exchange rate) in UPenn World Table 7.0.

3.3. Specifications and Results

3.3.1. Trade and misallocation

The objective is to test whether higher share of trade with more productive trade partners increases economy wide markup variation only for less productive countries. For this purpose, we estimate reduced-form models relating markup variation (*sdprma*) to trade openness (*openr*) and share of openness with high productivity region (*highshare*) for countries which are above and below the median of PPP adjusted GDP per capita, separately.[15][16] Using PPP adjusted GDP per capita as a proxy for labor productivity, we expect a higher positive impact of *highshare* on variation of the profit margins for below median income countries.[17] In these estimations, we control for mean profit margin (*meanprma*), labor productivity (*meantpe*), real

[15]The threshold is the median PPP adjusted per capita GDP in 2006 in 2005 US$. To prevent transitions from one group to the other, sample average income is computed for all countries and the ones having a mean income level lower than the threshold are labeled as below median income countries. Below median income countries are Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Greece, Hungary, Lithuania, Macedonia, Montenegro, Poland, Romania, Russia, Serbia, Slovakia, Slovenia and Ukraine. Above median income countries are Austria, Denmark, France, Germany, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom.

[16]This grouping of European countries is also consistent with the emphasis on limited R&D intensity of southern economies in the theoretical part. In 2007, the per inhabitant R&D expenditure of the business enterprise sector in below median income countries ranges from 2.5 Euros (Bulgaria) to 29.3 Euros (Czech Republic) whereas it ranges from 67.8 Euros (Italy) to 253.5 Euros (Germany) for above median income countries. The only exception in our sample is Slovenia with a spending of 105.4 Euros per inhabitant on R&D while being below the median income level.

[17]Considering our aim to measure the economy wide markup variation, there can be doubt that the number of firms is not enough to capture the second moment of the profit margin distribution for some country-year pairs. The median numbers of firms which are considered in our analysis are 1431 and 2721 per year, for below and above median income countries, respectively.

and nominal exchange rates (*p* and *xrat*), share of government consumption in PPP GDP (*cg*), capital-labor ratio and a set of country and year fixed effects. The inclusion of the average markup is not to interpret the statistical or economic significance of this variable but to capture the variation in the second moment of the profit margins trivially driven by the changes in the first moment.[18] Real exchange rate is added to control for cross-country differences in the relative price of non-tradable goods on markup variation. Proxies for labor productivity (mean turnover per employee) and capital-labor ratio (capital per employee) are added to our specifications since they might bias the estimates if omitted. Share of government consumption in PPP GDP (*cg*) is controlled for to capture the cross-country variation in profitability driven by the differences in government size. Country and year dummies are also included to control for country specific effects and the common shocks across countries, respectively. Table 1 presents the results for fixed effects (FE) panel estimations, for below and above median income countries in the first and the second column, respectively. It is seen that the joint effect of trade openness is insignificant at sample averages for both groups of countries. On the other hand, redirecting trade from low productivity regions to high productivity ones keeping total openness constant increases economy wide variation of profit margins only for below median income countries, which confirms the model predictions. Labor productivity and capital intensity are both negatively associated with markup variation for below median income countries, which emphasizes the importance of human and physical capital in improving economy wide allocative efficiency for less developed economies. We test the robustness of the observed relationship between trade composition and misallocation to different model specifications by adding the explanatory variables sequentially.[19] Then, the same models are estimated for different time periods by sequentially eliminating the initial year in the sample to check whether the observed relationship is sensitive to the choice of time span.[20] Another issue about our benchmark results is that cross country differences in markup dispersion can be driven by the differences in the degree and/or pattern of specialization across countries. As an example, it can be argued that a more diversified economy should exhibit higher markup dispersion due to different entry costs across industries or an agriculturally oriented economy will exhibit lower levels of markup dispersion due to the relative uniformity of technology inputs across establishments in that sector. We check this possibility by controlling for the share of 2-digit industries such as finance, agriculture, construction, retail trade, protech (professional, scientific, and technical services), administration (administrative and support

[18] All specifications are estimated also without the first moment of the markup distribution. The results are similar, which is not surprising considering the insignificance of this variable in benchmark estimations. The results are not reported here and given in Table D.6 in Appendix D.1.1.

[19] We only report the sequential estimations for below median income countries for the sake of brevity. *highshare* remains to be non-positive in all specifications for above median income countries.

[20] The results are similar until we end up with 2000-2007 sample. After this point, they become weaker in terms of statistical significance due to smaller sample size. We do not report them to save space and they are available upon request.

and waste management and remediation services), and health care in all observations for each country-year pair. Preliminary analysis shows that only the shares of agriculture, protech and health care appear to be significant. Hence, we omit the remaining sectors from our estimations not to lose identifying variation. We also instrument our variable of interest (*highshare*) for possible endogeneity and measurement issues using its first lead and the consumption share of GDP. The consumption share of GDP is expected to be positively related to demand for higher quality foreign products and it is expected that there is a correlation between *highshare* and its first lead. To our knowledge there is no theoretical argument which defines causality from markup variation to future trade with high productivity regions or consumption share of GDP. The formal tests approve the relevance and validity of the instruments. The first stage F-statistic is 17.28 with a partial R^2 of 0.347 and overidentification test yields a J-statistic of 0.492 with a P-value of 0.483 for the least extended specification where the average markup, *openr*, country and year fixed effects are controlled for. The kurtosis of *sdprma* is 5.59. This implies a rather mild effect of outliers on the estimates. Nevertheless, we address the issue of outliers explicitly and estimate all specifications by using robust regression (RR), which downweights the observations with larger residuals in an iterative manner (see Rousseeuw et al. (1987) for a general description of this method).[21] Table 2 presents the results for below median income countries. The first seven columns are the estimates of FE panel models, the eighth column depicts the IV estimation results and the last column presents the RR estimates for the extended specification.[22] The main message of the results in Table 2 and the following robustness checks is that trade with more productive regions has a positive and significant effect on markup variation only for less productive economies and this result is not driven by model specification, measurement errors, endogenous variation, industry composition or outliers in different forms and is robust to the choice of time span. Besides being significant, the influence of *highshare* on markup variation is quantitatively important. Using the figures in Table 2, it is found that one standard deviation increase in *highshare* leads to an increase of 0.30 to 1.32 standard deviations in markup variation for the period of 1992 to 2007. With such a large effect on the markup variation, *highshare* is the most influential factor among the determinants of resource misallocation.

3.3.2. Technology diffusion

In this part, we test whether trade with more productive regions contributes to the mean labor productivity while decreasing the productivity gap among incumbents operating in a given sector. For this purpose, we

[21]The estimator used is readily implemented (*rreg* command) in Stata. It is robust to outliers in the dependent variable and to bad leverage points. However, the estimates can be distorted when there are clusters of outliers (Rousseeuw and Van Zomeren (1990)). To control for this possibility, we use a second estimator (recently implemented by Verardi and Croux (2009)) which is robust even to the existence of outlier clusters. The results are similar and given in Table D.9 in Appendix D.1.4.

[22]We replicate all estimations by instrumenting *highshare* and the results are in line with baseline findings. They are reported in Table D.7 in Appendix D.1.2

Table 1: Variation in Profit Margins and Trade

	Below Median	Above Median
meanprma	-0.193	0.342
	(0.135)	(0.273)
openr	-0.0813	0.0850*
	(0.0580)	(0.0418)
highshare	0.163**	-0.174**
	(0.0752)	(0.0758)
p	0.0421	-0.0622
	(0.0492)	(0.119)
meantpe	-55.80***	33.11
	(13.56)	(26.50)
meancpe	-0.0809**	0.439
	(0.0287)	(0.300)
xrat	-0.0576***	-0.243***
	(0.0170)	(0.0578)
cg	-0.0333	-0.0637
	(0.242)	(1.131)
Observations	137	143
R^2	0.382	0.499

Robust standard errors clustered at the country level are in parentheses.Dependent variable is the standard deviation of profit margins. Year and country fixed effects are included.
Median income is 23412.07 US Dollars (base year 2005)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Variation in Profit Margins and Trade in Below Median Income Countries

	1	2	3	4	5	6	7	8	9
Variables	FE	FE	FE	FE	FE	FE	FE	IV	RR
meanprma	-0.146	-0.144	-0.189*	-0.158	-0.190	-0.193	-0.132	-0.268*	-0.180**
	(0.0970)	(0.0974)	(0.0970)	(0.136)	(0.130)	(0.135)	(0.131)	(0.150)	(0.0751)
openr	-0.0895***	-0.0942***	-0.0892***	-0.0683	-0.0795	-0.0813	-0.0262	-0.166*	-0.0126
	(0.0205)	(0.0318)	(0.0305)	(0.0414)	(0.0507)	(0.0580)	(0.0392)	(0.0904)	(0.0298)
highshare	0.189***	0.194***	0.186***	0.137**	0.160**	0.163**	0.115**	0.351**	0.0799*
	(0.0434)	(0.0504)	(0.0485)	(0.0565)	(0.0658)	(0.0752)	(0.0508)	(0.164)	(0.0442)
p		0.00952	-0.0107	0.0347	0.0417	0.0421	0.0608	0.129**	0.0189
		(0.0556)	(0.0541)	(0.0459)	(0.0488)	(0.0492)	(0.0423)	(0.0600)	(0.0314)
xrat			-0.00280***	-0.00278***	-0.0573***	-0.0576***	-0.0186	-0.0252*	-0.0309**
			(0.000833)	(0.000906)	(0.0158)	(0.0170)	(0.0151)	(0.0147)	(0.0119)
meantpe				-11.46	-55.99***	-55.80***	-42.33**	-34.52*	-36.66***
				(8.874)	(13.14)	(13.56)	(16.12)	(20.12)	(10.99)
meancpe					-0.0810**	-0.0809**	-0.0905*	-0.0908*	-0.0570**
					(0.0285)	(0.0287)	(0.0442)	(0.0511)	(0.0250)
cg						-0.0333	0.584*	0.448	0.400**
						(0.242)	(0.309)	(0.415)	(0.180)
Industry Composition	No	No	No	No	No	No	Yes	Yes	Yes
Observations	155	155	155	144	137	137	114	100	114
R^2	0.301	0.302	0.321	0.271	0.382	0.382	0.591	-	-

Robust standard errors clustered at the country level are in parentheses. Dependent variable is the standard deviation of profit margins. In IV estimation, *highshare* is instrumented with its first lead and the consumption share of PPP GDP. Kleibergen-Paap LM statistic is 8.85, partial R^2 is 0.277, AP(2) is 19.16 and J-statistic is 0.411. Year and country fixed effects are included in all specifications. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

estimate models relating the mean and the standard deviation of labor productivity at the sectoral level for 4-digit sectors (*meantpeS*, *sdtpeS*) to the openness variables (*openr*, *highshare*), real and nominal exchange rates (*p*,*xrat*), sectoral and country level capital-labor ratios (*meancpeS*,*meancpe*) controlling for year, sector, country fixed effects and industry specific trends. When the outcome variable is *sdtpeS*, *meantpeS* is controlled for to capture the mechanical variation between the first and the second moment of the sectoral productivity distributions. Preliminary analysis shows that the distributions of *meantpeS* and *sdtpeS* are heavy-tailed and quite prone to outliers with substantial kurtoses of 2216.04 and 424.98 for below median countries, respectively. In such cases, ordinary least square methods yield strongly distorted estimates. For that reason, the models are estimated using robust regression method.[23] Table 3 and 4 present the estimation results which support the relationship between trade composition and sectoral productivity distribution predicted by the model. Trade with more productive regions is positively related to average sectoral productivity and negatively associated to the sectoral productivity distribution, for below median income countries. Hence, technology diffusion and productivity convergence provide predictions which are consistent with the

[23]The same models are estimated using OLS where the variables with high kurtosis are logged to check whether the standard OLS estimations yield a similar picture. While taking logs decreases the kurtosis and downweights the outliers, it does so in a specific and rather restrictive manner. Still, they constitute the standard alternatives to our benchmark method and can be useful for comparison purposes. The findings are in line with the benchmark results and reported in Appendix D.2.

observed changes in the moments of sectoral productivity distributions.

Table 3: Average Sectoral Productivity of Below Median Income Countries

	1	2	3	4	5	6
Variables	RR	RR	RR	RR	RR	RR
openr	-1.885***	-3.036***	-3.044***	-3.003***	-2.720***	-2.479***
	(0.258)	(0.325)	(0.326)	(0.359)	(0.503)	(0.493)
highshare	2.705***	4.027***	4.033***	4.009***	5.130***	3.972***
	(0.447)	(0.512)	(0.512)	(0.530)	(0.753)	(0.738)
p		1.708***	1.702***	1.401***	2.132***	2.342***
		(0.399)	(0.399)	(0.406)	(0.589)	(0.578)
xrat			-0.0198	-9.344***	-5.878***	0.847**
			(0.0281)	(0.232)	(0.377)	(0.370)
meancpeS				0.0243	1.810***	2.051***
				(0.139)	(0.186)	(0.187)
Industry Composition	No	No	No	No	Yes	Yes
Industry Trends	No	No	No	No	No	Yes
Observations	19307	19307	19307	19098	17254	17254

Robust standard errors are in parentheses. Dependent variable is the average sectoral turnover per employee at the 4-digit level. Sector, year, and country fixed effects are included in all specifications.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.4. Remarks and Discussion

3.4.1. An alternative explanation: Firm selection

An important alternative explanation which may result in similar changes in the sectoral productivity distributions is the exit of least productive firms as a reaction to higher trade exposure and competition. While theories of firm selection do not underscore the relative productivity of the trade partner, they are still natural alternatives to be evaluated. As a first pass, we observe that only 0.37 percent of the firms did not provide a financial report in the last two years and firm exit seems to be infrequent among large firms. However, in this figure it is possible to miss some firms which are practically inoperative but still presenting financial reports due to legal obligations. For that reason, we count the firms which lose more than 50 percent of their total sales from one year to the next. Only 2.4 percent of the time, firms experience such a large shrinkage in their sales volumes while being operative. It is also likely that measurement errors can account for a significant share of these observed sales losses. These observations do not invalidate the exit hypothesis but may imply that possible shrinkage in the market shares of least productive firms does not translate into exits or sharp declines in sales volumes. Fortunately, in such a case exit and spillover

Table 4: Sectoral Productivity Dispersion of Below Median Income Countries

	1	2	3	4	5	6
Variables	RR	RR	RR	RR	RR	RR
meantpeS	1.333***	1.333***	1.333***	1.333***	1.366***	1.397***
	(0.0000237)	(0.0000237)	(0.0000237)	(0.0000238)	(0.0000295)	(0.0000306)
openr	0.885***	1.013***	1.009***	1.124***	0.976***	0.622**
	(0.160)	(0.205)	(0.205)	(0.223)	(0.300)	(0.309)
highshare	-1.309***	-1.455***	-1.452***	-1.627***	-1.508***	-0.910**
	(0.278)	(0.323)	(0.323)	(0.329)	(0.434)	(0.448)
p		-0.188	-0.187	-0.307	-0.235	0.0934
		(0.243)	(0.243)	(0.245)	(0.341)	(0.353)
xrat			-0.00371	-1.845***	0.0933	3.221***
			(0.0183)	(0.183)	(0.276)	(0.285)
meancpeS				1.436***	1.565***	1.554***
				(0.201)	(0.250)	(0.262)
Industry Composition	No	No	No	No	Yes	Yes
Industry Trends	No	No	No	No	No	Yes
Observations	15919	15919	15919	15855	14535	14535

Robust standard errors are in parentheses. Dependent variable is the sectoral standard deviation of turnover per employee within 4-digit sectors. Sector, year, and country fixed effects are included in all specifications. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

mechanisms can be differentiated because they lead to contrasting patterns in industry concentration. If the least productive firms are not completely driven out of the market but the underlying mechanism is working, exit hypothesis predicts increasing inequality in market shares whereas spillovers and productivity convergence lead to a more homogeneous distribution of sales across operating firms. To be able to observe which prediction is empirically more grounded in our sample, we construct the Herfindahl index for each country, sector, and year to investigate the relationship between *highshare* and industry concentration (Table 5). The first six columns present the results for OLS regressions, the seventh column shows the IV estimation where *highshare* is instrumented with its first lead and the consumption share of PPP GDP, and the last column provides robust regression results to control for the effects of outliers on coefficient estimates. Despite being imprecisely estimated in 1 out of 8 cases, *highshare* has a negative effect on industry concentration in all cases. This finding is in line with the expected effects of technology diffusion on industry structure.

3.4.2. An extension: Endogenous labor supply

A possible extension of our model would be to incorporate labor supply decision of individuals. This point is particularly important since increasing relative wages for southern workers alter the value of employment relative to leisure and labor supply would increase as a result of higher competition induced by trade,

Table 5: Industry Concentration and Trade

	1	2	3	4	5	6	7	8
Variables	OLS	OLS	OLS	OLS	OLS	OLS	IV	RR
openr	1.090**	0.195	0.224	0.328	0.247	0.184	0.296	0.507
	(0.434)	(0.573)	(0.573)	(0.659)	(0.650)	(0.649)	(1.444)	(0.597)
highshare	-4.919***	-3.766***	-3.737***	-2.163**	-2.022**	-2.101**	-2.437	-3.335***
	(0.794)	(0.943)	(0.943)	(0.972)	(0.964)	(0.968)	(2.289)	(0.882)
p		1.801**	1.906***	2.828***	2.897***	2.994***	3.028***	2.642***
		(0.720)	(0.725)	(0.747)	(0.743)	(0.745)	(1.102)	(0.674)
xrat			0.0503***	-0.279	-0.305	-0.306	-0.103	-0.348
			(0.0158)	(0.481)	(0.480)	(0.484)	(0.574)	(0.386)
meancpeS				0.493**	0.506**	0.556**	0.532**	0.742***
				(0.221)	(0.215)	(0.221)	(0.219)	(0.237)
meantpeS					19.17	36.99	65.26	25.69
					(62.62)	(58.21)	(57.80)	(43.50)
Observations	23218	23218	23218	19229	19165	19165	16518	19165
R^2	0.416	0.417	0.417	0.490	0.501	0.513	-	-

Robust standard errors are in parentheses. Dependent variable is the Herfindahl index at the 4-digit level multiplied by 1000 (for demonstrational purposes). Year, sector, and country fixed effects are included in all specifications. Industry specific trends are controlled for in columns (6), (7) and (8). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

assuming that substitution effect dominates the income effect. This increase in effective labor supply would enhance the productive capacity of the South and lead to a higher *potential output value*. Nevertheless, our main proposition would be still valid in the sense that as long as markup variation is inflated by trade, these potential gains would be partly utilized and actual output would be lower than the best possible case.

4. Conclusion

The extent of resource misallocation which is recently documented for developing countries is well beyond prior expectations and has created a new avenue of ideas and tools to explain the large income differences across countries. In this paper, we point out the mechanism that trade with more productive countries might lead to resource misallocation for relatively less productive ones using a North-South model of international trade. In this model, southern firms are characterized by lower productivity and limited capacity to generate excludable knowledge. As a result, they rely on knowledge diffusion transmitted through trade with the productive North. This knowledge diffusion expands the common knowledge stock of the South from which both the incumbents and their competitors can benefit. As a reaction to higher trade with more productive regions, mean labor productivity increases whereas the productivity variation diminishes within each sector. The changes in sectoral productivity distribution decrease the market power of sectoral leaders and exert a downward pressure on markups. These pro-competitive effects materialize asymmetrically due to cross sectoral differences in productivity distributions and technology adoption rates. As a consequence, trade with more productive economies inflates markup dispersion across sectors and introduces resource misallocation for the South. These model predictions are tested for a large sample of European countries between 1992 and 2007. The main econometric analysis and following robustness checks show that trading more with more productive partners (1) inflates economy wide markup variation (2) raises mean labor productivity, and (3) decreases productivity dispersion within 4-digit sectors, for less productive countries, which are in line with the model predictions. These findings may shed light on the determinants of resource misallocation in developing countries and provide insight into how to fully utilize the opportunities presented by international trade. Furthermore, they call for careful monitoring of the trade composition and changes in market structure across sectors to device appropriate competition policies, especially during episodes of rapid trade liberalization.

Appendix A. Relative incumbent productivity

Appendix A.1. Main equation

Let $a_i(t) = \frac{h_i^{(1-\theta+\delta)}}{h_j^{\delta}}$ and $b_i(t) = \frac{h_f^{(1-\theta+\delta)}}{h_j^{\delta}}$.[24] Then, the growth of $a_i(t)$ is given by:

$$\hat{a}_i(t) = (1-\theta+\delta)\hat{h}_i(t) - \delta\hat{h}_j$$

$\hat{h}_i(t)$ can be found by dividing both sides of the law of motion for incumbent productivity (10) by $h_i(t)$ and given by $\hat{h}_i(t) = \gamma_1 a_i^{-1}(t)$. The northern productivity is constant and exogenous and we have a differential equation for $a_i(t)$:

$$\dot{a}_i(t) = (1-\theta+\delta)\gamma_1 - \delta\hat{h}_j a_i(t)$$

and

$$a_i(t) = \frac{(1-\theta+\delta)\gamma_1}{\delta\hat{h}_j} + (a_i(0) - \frac{(1-\theta+\delta)\gamma_1}{\delta\hat{h}_j})e^{-\delta\hat{h}_j t} \tag{A.1}$$

Similarly, $b(t)$ is found as:

$$b_i(t) = \frac{(1-\theta+\delta)\gamma_i^f}{\delta\hat{h}_j} + (b_i(0) - \frac{(1-\theta+\delta)\gamma_i^f}{\delta\hat{h}_j})e^{-\delta\hat{h}_j t} \tag{A.2}$$

where $a_i(0)$ and $b_i(0)$ are the initial values of the corresponding functions. Using (A.1) and (A.2),

$$m_i^{(1-\theta+\delta)}(t) = \frac{\frac{(1-\theta+\delta)\gamma_1}{\delta\hat{h}_j} + (a_i(0) - \frac{(1-\theta+\delta)\gamma_1}{\delta\hat{h}_j})e^{-\delta\hat{h}_j t}}{\frac{(1-\theta+\delta)\gamma_i^f}{\delta\hat{h}_j} + (b_i(0) - \frac{(1-\theta+\delta)\gamma_i^f}{\delta\hat{h}_j})e^{-\delta\hat{h}_j t}} \tag{A.3}$$

For endogenous growth case ($\theta = 1$) and using the definitions of $g_i(t)$ and $f_i(t)$ given in the main text, (A.3) becomes:

$$m_i^{\delta}(t) = \frac{\frac{\gamma_1}{\hat{h}_j} + (g_i(0) - \frac{\gamma_1}{\hat{h}_j})e^{-\delta\hat{h}_j t}}{\frac{\gamma_i^f}{\hat{h}_j} + (f_i(0) - \frac{\gamma_i^f}{\hat{h}_j})e^{-\delta\hat{h}_j t}} \tag{A.4}$$

[24] Note that there is a change of notation and h_i^f is denoted by h_f for notational ease.

In the long run, relative incumbent productivity is found as:

$$\lim_{t\to\infty} m_i(t) = (\frac{\gamma_1}{\gamma_i^f})^{1/\delta} \tag{A.5}$$

Appendix A.2. Productivity of the trade partner

In this part, we will show that the sectoral markups are decreasing functions of the initial productivity of the trade partner while this effect approaches to zero in the long-run. Using eq. (12):

$$m_i(t) = \left[\frac{\frac{\gamma_1}{\hat{h}_j} + (g(0) - \frac{\gamma_1}{\hat{h}_j})e^{-\delta\hat{h}_j t}}{\frac{\gamma_i^f}{\hat{h}_j} + (f(0) - \frac{\gamma_i^f}{\hat{h}_j})e^{-\delta\hat{h}_j t}}\right]^{1/\delta}$$

Then, the partial derivative of sectoral markup with respect to the initial productivity of the trade partner is found as:

$$\begin{aligned}
\frac{\partial m_i(t)}{\partial h_j(0)} =& \Big[\frac{-h_i(0)h_j^{-2}(0)e^{-\delta\hat{h}_j t}(\frac{\gamma_i^f}{\hat{h}_j} + (f(0) - \frac{\gamma_i^f}{\hat{h}_j})e^{-\delta\hat{h}_j t})}{(\frac{\gamma_i^f}{\hat{h}_j} + (f(0) - \frac{\gamma_i^f}{\hat{h}_j})e^{-\delta\hat{h}_j t})^2} \\
&+ \frac{(\frac{\gamma_1}{\hat{h}_j} + (g(0) - \frac{\gamma_1}{\hat{h}_j})e^{-\delta\hat{h}_j t})h_i^f(0)h_j^2(0)e^{-\delta\hat{h}_j t}}{(\frac{\gamma_i^f}{\hat{h}_j} + (f(0) - \frac{\gamma_i^f}{\hat{h}_j})e^{-\delta\hat{h}_j t})^2}\Big]\frac{1}{\delta}m_i^{1-\delta}(t) \\
=& \frac{1}{\delta}m_i^{1-\delta}(t)\frac{(1-e^{\delta\hat{h}_j t})(h_i^f(0)\gamma_1 - h_i(0)\gamma_i^f)e^{-\delta\hat{h}_j t}}{h_j^2(0)\hat{h}_j(\frac{\gamma_i^f}{\hat{h}_j} + (f(0) - \frac{\gamma_i^f}{\hat{h}_j})e^{-\delta\hat{h}_j t})^2} < 0 \ \ \forall t \in [0,\infty)
\end{aligned}$$

The last inequality holds since $1 < (\frac{\gamma_1}{\gamma_i^f}) < (\frac{\gamma_1}{\gamma_i^f})^{1/\delta} < \frac{\varepsilon}{\varepsilon-1} \leq \frac{h_i(0)}{h_i^f(0)}$ for $0 < \delta < 1$ and $\lim_{t\to\infty}\frac{\partial m_i(t)}{\partial h_j(0)} = 0$.

Appendix B. General equilibrium

In this part, we will explicitly present the general equilibrium solution of our model. Using (16) and (22), we can find the labor allocated to each firm:

$$\int_0^{G(t)} (\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{-\varepsilon} l_i di + \int_{G(t)}^1 l_i d_i = L \Rightarrow \tag{B.1}$$

$$l_i = (\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{-\varepsilon}\frac{L}{\int_0^{G(t)}(\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{-\varepsilon}di + (1-G(t))} \ , \ \forall i \in [0, G(t)] \tag{B.2}$$

and

$$l_i = \frac{L}{\int_0^{G(t)} (\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{-\varepsilon} di + (1-G(t))} \;, \; \forall i \in (G(t), 1] \tag{B.3}$$

Total expenditure should be equal to total output for each country. Using (B.2) and (B.3), the southern output is found to be:

$$C = h_i \int_0^{G(t)} (\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{-\varepsilon} \frac{L}{\int_0^{G(t)} (\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{-\varepsilon} di + (1-G(t))} \frac{w}{h_i^f} di \tag{B.4}$$

$$+ h_i(1-G(t)) \frac{L}{\int_0^{G(t)} (\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{-\varepsilon} di + (1-G(t))} \frac{\varepsilon}{\varepsilon-1}\frac{w}{h_i} \tag{B.5}$$

The northern output is:

$$\bar{C} = h_j L \frac{\bar{w}}{h_j}\frac{\varepsilon}{\varepsilon-1} \tag{B.6}$$

Dividing (B.4) by (B.6) , multiplying and dividing the numerator with $\frac{\varepsilon}{\varepsilon-1}\frac{h_i}{w}$ and rearranging terms, we get:

$$\frac{C}{\bar{C}} = \frac{(\int_0^1 h_i l_i p_i \; d_i)}{(\int_0^1 h_j l_j p_j \; d_j)} = \frac{h_i L p_i}{h_j L p_j} = w^* \left(\frac{\int_0^{G(t)} (\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{1-\varepsilon} \mathrm{d}i + (1-G(t))}{(1-G(t) + \int_0^{G(t)} (\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{-\varepsilon} \mathrm{d}i} \right) \tag{B.7}$$

We assume balanced trade to close the model. Using (17), (8) and the definition of $m_i(t)$:

$$\bar{C}\big(\int_0^{G(t)} (\frac{w}{h_i^f})^{1-\varepsilon} \mathrm{d}i + \int_{G(t)}^1 (\frac{\varepsilon}{\varepsilon-1}\frac{w}{h_i})^{1-\varepsilon} \mathrm{d}i \big) = C \int_0^1 (\frac{\varepsilon}{\varepsilon-1}\frac{\bar{w}}{h_j})^{1-\varepsilon} \mathrm{d}j \tag{B.8}$$

$$\Rightarrow \frac{C}{\bar{C}} = (w^* \frac{h_j}{h_i})^{1-\varepsilon} \Big(\int_0^{G(t)} (\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{1-\varepsilon} \mathrm{d}i + (1-G(t)) \Big) \tag{B.9}$$

We equate (B.7) and (B.9) to solve for the relative wage:

$$w^* = (\frac{h_i}{h_j})^{\frac{\varepsilon-1}{\varepsilon}} \Big(\int_0^{G(t)} (\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{-\varepsilon} \mathrm{d}i + (1-G(t)) \Big)^{1/\varepsilon} \tag{B.10}$$

Finally, we find the relative output by plugging (B.10) into (B.7):

$$\frac{C}{\bar{C}} =(\frac{h_i}{h_j})^{\frac{\varepsilon-1}{\varepsilon}} \frac{(\int_0^{G(t)}(\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{1-\varepsilon}\mathrm{d}i+(1-G(t)))}{\left(\int_0^{G(t)}(\frac{h_i}{h_i^f}\frac{\varepsilon-1}{\varepsilon})^{-\varepsilon}\mathrm{d}i+(1-G(t))\right)^{(\varepsilon-1)/\varepsilon}} \tag{B.11}$$

$$=(\frac{h_i}{h_j})^{\frac{\varepsilon-1}{\varepsilon}} \frac{(\int_0^{G(t)}(m_i(t))\frac{\varepsilon-1}{\varepsilon})^{1-\varepsilon}\mathrm{d}i+(1-G(t)))}{\left(\int_0^{G(t)}(m_i(t)\frac{\varepsilon-1}{\varepsilon})^{-\varepsilon}\mathrm{d}i+(1-G(t))\right)^{(\varepsilon-1)/\varepsilon}} \tag{B.12}$$

The second equality follows from the definition of $m_i(t)$. Using the symmetry among incumbents and the definition of $\tilde{m}_i(t)$ yields equation (27) in the main text.

Appendix C. Misallocation and the markup variation

Let $f(x) = x^{1-\varepsilon}$ and $g(x) = x^{-\varepsilon}$.[25] Note that $f''(x) = \varepsilon(\varepsilon-1)x^{(-\varepsilon-1)} > 0$ and $g''(x) = \varepsilon(\varepsilon+1)x^{(-\varepsilon-2)} > 0$. Hence, $f(x)$ and $g(x)$ are strictly convex since $\varepsilon > 1$. Using these two functions, we can rewrite the misallocation function as follows[26]:

$$M = 1 - \frac{E[f(\tilde{m})]}{E[g(\tilde{m})]^{\frac{\varepsilon-1}{\varepsilon}}}$$

Let a be a random variable with mean 0 and uncorrelated to $\tilde{m}$, i.e., $E[a|\tilde{m}] = 0$, $E[\tilde{m}+a] = E[\tilde{m}]$ since $E[a] = 0$. Then, what we want to show is that $\frac{E[f(\tilde{m})]}{E[g(\tilde{m})]^{\frac{\varepsilon-1}{\varepsilon}}} > \frac{E[f(\tilde{m}+a)]}{E[g(\tilde{m}+a)]^{\frac{\varepsilon-1}{\varepsilon}}}$. First, note that

$$\frac{E[f(\tilde{m})]}{E[g(\tilde{m})]^{\frac{\varepsilon-1}{\varepsilon}}} > \frac{E[f(\tilde{m}+a)]}{E[g(\tilde{m}+a)]^{\frac{\varepsilon-1}{\varepsilon}}} \iff \frac{E[f(\tilde{m})]}{E[g(\tilde{m})]} > \frac{E[f(\tilde{m}+a)]}{E[g(\tilde{m}+a)]}$$

since $E[g(\tilde{m})]^{\frac{\varepsilon-1}{\varepsilon}} > 1$ and $\frac{\varepsilon}{\varepsilon-1} > 1$. Now, we approximate the misallocation function by the second order Taylor series approximations of $f(\tilde{m}+a)$ and $g(\tilde{m}+a)$ around the point $\tilde{m}$:

$$f(\tilde{m}+a) \approx f(\tilde{m}) + f'(\tilde{m})a + \frac{f''(\tilde{m})a^2}{2}$$
$$g(\tilde{m}+a) \approx g(\tilde{m}) + g'(\tilde{m})a + \frac{g''(\tilde{m})a^2}{2}$$

[25] In this section, time is dropped for ease of notation.
[26] Recall that observed relative markup for sector i is denoted by $\tilde{m}_i$.

Then,

$$\frac{E[f(\tilde{m}+a)]}{E[g(\tilde{m}+a)]} \approx \frac{E[f(\tilde{m})]+E[f'(\tilde{m})a]+E[\frac{f''(\tilde{m})a^2}{2}]}{E[g(\tilde{m})]+E[g'(\tilde{m})a]+E[\frac{g''(\tilde{m})a^2}{2}]}$$
$$= \frac{E[f(\tilde{m})]+E[f'(\tilde{m})]E[a]+\frac{E[f''(\tilde{m})]E[a^2]}{2}}{E[g(\tilde{m})]+E[g'(\tilde{m})]E[a]+\frac{E[g''(\tilde{m})]E[a^2]}{2}}$$
$$= \frac{E[f(\tilde{m})]+\frac{E[f''(\tilde{m})]\sigma_a^2}{2}}{E[g(\tilde{m})]+\frac{E[g''(\tilde{m})]\sigma_a^2}{2}}$$
$$= \frac{E[f(\tilde{m})]+\frac{((\varepsilon-1)\varepsilon E[\tilde{m}^{(-\varepsilon-1)}]\sigma_a^2}{2}}{E[g(\tilde{m})]+\frac{(\varepsilon(\varepsilon+1)E[\tilde{m}^{(-\varepsilon-2)}]\sigma_a^2}{2}} < \frac{E[f(\tilde{m})]}{E[g(\tilde{m})]}$$

The first equality follows from the zero correlation between a and $\tilde{m}$. The second equality holds because the unconditional mean of a is 0, the third equality uses the explicit values of the second derivatives for $f(x)$ and $g(x)$ evaluated at $\tilde{m}$; finally, the inequality holds because $(\varepsilon+1) > (\varepsilon-1)$ and $E[\tilde{m}^{(-\varepsilon-1)}]/E[\tilde{m}^{(-\varepsilon-2)}] < E[\tilde{m}^{(1-\varepsilon)}]/E[\tilde{m}^{-\varepsilon}] = E[f(\tilde{m})]/E[g(\tilde{m})]$.

Appendix D. Additional Robustness Checks: Not intended for publication

Appendix D.1. Trade and Misallocation

Appendix D.1.1. Without the first moment

In this section, we estimate the same models in section 3.3.1 without controlling for the first moment of the markup distribution. Results are similar, which is not surprising considering the insignificance of the mean markup level in benchmark estimations.

Appendix D.1.2. Full IV estimates

In the main part of the text, we reported only the IV estimates for the most extended specification in section 3.3.1. In this part, we replicate Table 2 of the main text by instrumenting *highshare* with its first lead and the consumption share of PPP GDP (*cc*) in all specifications. Instruments are always exogenous; underidentification is rejected at 1% in all specifications and relatively high F-statistics provide confidence in the strength of the instruments.

Appendix D.1.3. Sensitivity to the threshold

Our benchmark estimations use data on countries with at least 50 large firms per year. In this section, we will show that benchmark results are robust to this choice by replicating Table 2 using the country-year pairs with at least 200 observations. *Highshare* remains to be positive and strongly significant, except the last column where the coefficient estimate of *highshare* misses to be significant at 10% having a P-value of

Table D.6: Variation in Profit Margins and Trade in Below Median Income Countries

	1	2	3	4	5	6	7	8	9
Variables	FE	FE	FE	FE	FE	FE	FE	IV	RR
openr	-0.0753***	-0.0837**	-0.0774**	-0.0641	-0.0736	-0.0719	-0.0210	-0.150*	-0.0477*
	(0.0248)	(0.0362)	(0.0353)	(0.0445)	(0.0547)	(0.0590)	(0.0375)	(0.0845)	(0.0267)
highshare	0.158***	0.167***	0.154***	0.119*	0.136*	0.134*	0.0962**	0.296**	0.113***
	(0.0406)	(0.0512)	(0.0509)	(0.0573)	(0.0679)	(0.0723)	(0.0430)	(0.147)	(0.0386)
p		0.0166	0.00283	0.0541	0.0638	0.0632	0.0671	0.133**	0.0711**
		(0.0564)	(0.0568)	(0.0431)	(0.0446)	(0.0448)	(0.0400)	(0.0587)	(0.0282)
xrat			-0.00213**	-0.00210**	-0.0543***	-0.0540***	-0.0194	-0.0258*	-0.0237**
			(0.000884)	(0.000854)	(0.0138)	(0.0152)	(0.0150)	(0.0148)	(0.0108)
meantpe				-8.519	-50.28***	-50.55***	-41.45**	-35.01	-14.51
				(8.047)	(11.90)	(12.78)	(15.26)	(21.50)	(9.912)
meancpe					-0.0766**	-0.0767**	-0.0919*	-0.0968*	-0.0347
					(0.0274)	(0.0283)	(0.0456)	(0.0559)	(0.0226)
cg						0.0332	0.575*	0.496	0.343**
						(0.218)	(0.286)	(0.421)	(0.162)
Industry Composition	No	No	No	No	No	No	Yes	Yes	Yes
Observations	155	155	155	144	137	137	114	100	114
R^2	0.289	0.290	0.302	0.258	0.364	0.364	0.583	-	-

Robust standard errors in parentheses. Dependent variable is the standard deviation of profit margins. In IV estimation, the instruments are valid with a partial R^2 of 0.296, F-statistic of 9.40, AP(2) of 24.50 and a J-statistic of 0.317. Year and country fixed effects are included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

0.123 with a t-statistic of 1.56. This is probably due to loss of observations as a result of the higher threshold and rapid downweighting of observations with larger residuals and in some cases equating their weight to zero in *Robust Regression* method.

Appendix D.1.4. Cluster of outliers

Our benchmark *Robust Regression* estimator might miss to detect the cluster of outliers. This can be an issue since we have a panel and observe countries over time. To control for this possibility, we use the *mmregress* routine implemented by Verardi and Croux (2009) in Stata. There is a tradeoff between efficiency and the bias of estimates, which is controlled by the efficiency level chosen. To be on the safe side, we use the least efficient estimator which also yields the least biased estimates. It is seen that despite using the least efficient estimator, *highshare* is positively related to markup dispersion and significant at 1% in all cases, except the least extended specification where the effect is still positive.

Appendix D.2. Sectoral Productivity Distributions

The distributions of average sectoral productivity and sectoral productivity variation are heavy-tailed with substantial kurtoses. In such cases, OLS estimates are distorted. As the benchmark, we use *Robust Regression* to deal with this issue. In this section, we will show that the relationship between average productivity and *highshare* is not driven by this estimation method, which provides further confidence in

Table D.7: Variation in Profit Margins and Trade

Variables	1 IV	2 IV	3 IV	4 IV	5 IV	6 IV	7 IV
meanprma	-0.268**	-0.292**	-0.337**	-0.304*	-0.303*	-0.347**	-0.268*
	(0.131)	(0.141)	(0.139)	(0.161)	(0.170)	(0.160)	(0.150)
openr	-0.237***	-0.345***	-0.342***	-0.396***	-0.296***	-0.320***	-0.166*
	(0.0747)	(0.129)	(0.129)	(0.150)	(0.109)	(0.111)	(0.0904)
highshare	0.475***	0.619***	0.615***	0.646***	0.499***	0.550***	0.351**
	(0.138)	(0.206)	(0.206)	(0.226)	(0.175)	(0.182)	(0.164)
p		0.124	0.107	0.200**	0.145**	0.149**	0.129**
		(0.0867)	(0.0862)	(0.0970)	(0.0724)	(0.0707)	(0.0600)
xrat			-0.00234**	-0.00193*	-0.0649***	-0.0692***	-0.0252*
			(0.000976)	(0.00101)	(0.0181)	(0.0185)	(0.0147)
meantpe				16.05	-47.58**	-47.03**	-34.52*
				(20.17)	(18.61)	(19.36)	(20.12)
meancpe					-0.0930*	-0.0945*	-0.0908*
					(0.0485)	(0.0485)	(0.0511)
cg						-0.426	0.448
						(0.282)	(0.415)
Industry composition	No	No	No	No	No	No	Yes
Underidentification							
Kleibergen-Paap LM	13.22	12.01	12.14	10.99	14.31	13.24	8.85
P-value	0.001	0.003	0.002	0.004	0.000	0.001	0.012
Weak identification							
F-statistic	17.28	10.01	9.87	8.74	14.32	13.44	7.24
Partial R^2	0.347	0.234	0.235	0.227	0.305	0.285	0.277
AP(2)	38.01	21.92	22.48	20.14	34.24	32.50	19.16
Validity							
J-statistic	0.492	0.351	0.206	0.032	0.000	0.003	0.411
Observations	138	138	138	127	120	120	100

Robust standard errors clustered at the country level are in parentheses. Dependent variable is the standard deviation of profit margins. Year dummies and country fixed effects are included. *Highshare* is instrumented by its first lead and the consumption share of PPP GDP. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.8: Variation in Profit Margins and Trade (Threshold=200)

	1	2	3	4	5	6	7	8	9
Variables	FE	FE	FE	FE	FE	FE	FE	IV	RR
meanprma	-0.126	-0.120	-0.183	-0.254**	-0.172*	-0.190**	-0.185**	-0.281***	-0.189**
	(0.0846)	(0.0845)	(0.111)	(0.108)	(0.0844)	(0.0802)	(0.0835)	(0.0859)	(0.0750)
openr	-0.0466**	-0.0558*	-0.0500	-0.0401	-0.0386	-0.0232	-0.0266	-0.0923*	-0.00793
	(0.0212)	(0.0294)	(0.0288)	(0.0248)	(0.0239)	(0.0229)	(0.0264)	(0.0540)	(0.0296)
highshare	0.158***	0.170***	0.160***	0.123***	0.112***	0.0886***	0.0909**	0.210**	0.0688
	(0.0410)	(0.0457)	(0.0417)	(0.0363)	(0.0290)	(0.0289)	(0.0391)	(0.0932)	(0.0441)
p		0.0202	-0.00479	0.0115	0.00912	0.0105	0.0249	0.0588*	0.0222
		(0.0318)	(0.0300)	(0.0332)	(0.0340)	(0.0311)	(0.0329)	(0.0349)	(0.0304)
xrat			-0.00211***	-0.00267***	-0.0465***	-0.0403***	-0.0346***	-0.0405***	-0.0332***
			(0.000523)	(0.000671)	(0.00668)	(0.00637)	(0.00713)	(0.00813)	(0.0113)
meantpe				-13.06*	-61.31***	-62.98***	-44.36***	-36.79***	-39.90***
				(6.103)	(10.17)	(10.81)	(8.579)	(8.953)	(10.67)
meancpe					-0.0939***	-0.0965***	-0.0929***	-0.0845***	-0.0869***
					(0.0163)	(0.0166)	(0.0198)	(0.0225)	(0.0269)
cg						0.320*	0.255	0.117	0.429**
						(0.165)	(0.175)	(0.221)	(0.181)
Industry Composition	No	No	No	No	No	No	Yes	Yes	Yes
Observations	126	126	126	120	113	113	109	95	107
R^2	0.368	0.369	0.395	0.327	0.512	0.528	0.696	-	-

Robust standard errors clustered at the country level are in parentheses. Dependent variable is the standard deviation of profit margins. Year dummies and country fixed effects are included. In IV estimation, *highshare* is instrumented by its first lead and the consumption share of PPP GDP. Kleibergen-Paap LM statistic is 8.009, the partial R^2 is 0.226, AP(2) is 14.10 and the J-statistic is 0.778. The sample consists of the country-year pairs with at least 200 large firms of which profit margin is available. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

our findings. We take the natural logarithm of *meantpeS*, *sdtpeS* and *meancpeS*, which have high kurtosis and estimate the same specifications in section 3.3.2. While taking logarithm decreases the kurtosis and downweights the outliers, it does so in a specific and rather restrictive manner. Still, they constitute the standard alternatives to our benchmark method and can be useful for comparison purposes. Table D.10 and D.11 present the estimation results for average sectoral productivity and sectoral productivity dispersion, respectively, for below median income countries. It is seen that results from the log-log specification are in line with the benchmark results except the fact that the effect of *highshare* on sectoral productivity dispersion becomes significant after controlling for sectoral capital intensity while being negative in all cases as predicted. This finding implies that sectoral capital intensity is positively associated with both trade with high productivity regions, and sectoral productivity dispersion and it should be controlled for to prevent biases in the estimates.

Table D.9: Variation in Profit Margins and Trade (Cluster of Outliers)

	1	2	3	4	5	6	7
Variables	RR	RR	RR	RR	RR	RR	RR
meanprma	0.0180	0.144***	0.0394	-0.000345	0.131***	-0.0580***	-0.154***
	(0.0771)	(0.0428)	(0.0435)	(0.0400)	(0.0243)	(0.0187)	(0.0234)
openr	0.0107	-0.0173**	-0.0121	-0.00665	-0.0240	0.00868	-0.0265**
	(0.00897)	(0.00791)	(0.0183)	(0.0180)	(0.0166)	(0.0178)	(0.0126)
highshare	0.0341	0.0728***	0.0635***	0.0691***	0.0762***	0.0715***	0.0818***
	(0.0223)	(0.0127)	(0.0201)	(0.0213)	(0.0165)	(0.0246)	(0.0147)
p		0.0662***	0.0538***	0.0421**	0.0514***	-0.0180	0.0551***
		(0.0139)	(0.0151)	(0.0174)	(0.0102)	(0.0119)	(0.0130)
xrat			-0.00104***	0.000789**	-0.0453***	-0.0295***	-0.0131***
			(0.000272)	(0.000355)	(0.00180)	(0.00253)	(0.00450)
meantpe				-1.436	-56.49***	-50.39***	-20.10***
				(4.161)	(4.323)	(5.290)	(6.130)
meancpe					-0.109***	-0.122***	-0.331*
					(0.00614)	(0.00546)	(0.167)
cg						-0.446***	0.649***
						(0.0329)	(0.0437)
Industry Composition	No	No	No	No	No	No	Yes
Observations	155	155	155	144	137	137	114

Robust standard errors in parentheses. Dependent variable is the standard deviation of profit margins. Year dummies and country fixed effects are included. The coefficients are estimated by the S-estimator which yields the least biased estimates

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.10: Average Sectoral Productivity of Below Median Income Countries

Variables	1 OLS	2 OLS	3 OLS	4 OLS	5 OLS	6 OLS
openr	-0.0109***	-0.0113***	-0.0114***	-0.0146***	-0.0136***	-0.0141***
	(0.00187)	(0.00216)	(0.00215)	(0.00225)	(0.00241)	(0.00245)
highshare	0.0241***	0.0246***	0.0247***	0.0280***	0.0173***	0.0177***
	(0.00377)	(0.00381)	(0.00379)	(0.00380)	(0.00360)	(0.00365)
p		0.000809	0.000790	0.00385	0.0125***	0.0131***
		(0.00279)	(0.00279)	(0.00283)	(0.00317)	(0.00320)
xrat			-0.000210	-0.00298*	-0.00582**	-0.00605**
			(0.000153)	(0.00161)	(0.00241)	(0.00243)
lnmeancpeS				0.0243***	0.0351***	0.0334***
				(0.00665)	(0.00780)	(0.00800)
Industry Composition	No	No	No	No	Yes	Yes
Industry Trends	No	No	No	No	No	Yes
Observations	19307	19307	19307	19098	17254	17254

Dependent variable is the log of mean turnover per employee within 4-digit industries. Year, country and industry fixed effects are included in all specifications. Heteroskedasticity robust standard errors are in parenthesis and clustered at the industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.11: Sectoral Productivity Dispersion of Below Median Income Countries

Variables	1 OLS	2 OLS	3 OLS	4 OLS	5 OLS	6 OLS
lnmeantpeS	1.094***	1.094***	1.094***	1.093***	1.087***	1.087***
	(0.0161)	(0.0161)	(0.0161)	(0.0159)	(0.0162)	(0.0164)
openr	0.00337**	0.00528***	0.00559***	0.00768***	0.00476**	0.00559***
	(0.00151)	(0.00188)	(0.00189)	(0.00211)	(0.00204)	(0.00207)
highshare	-0.000799	-0.00324	-0.00339	-0.00796***	-0.0138***	-0.0148***
	(0.00263)	(0.00289)	(0.00290)	(0.00295)	(0.00303)	(0.00307)
p		-0.00364*	-0.00354*	-0.00210	0.00694***	0.00646***
		(0.00194)	(0.00194)	(0.00196)	(0.00212)	(0.00217)
xrat			0.000614***	-0.00114	-0.00303*	-0.00295*
			(0.000169)	(0.00177)	(0.00175)	(0.00168)
lnmeancpeS				0.0460***	0.0521***	0.0519***
				(0.00395)	(0.00441)	(0.00441)
Industry Composition	No	No	No	No	Yes	Yes
Industry Trends	No	No	No	No	No	Yes
Observations	15919	15919	15919	15855	14535	14535

Dependent variable is the log of standard deviation of turnover per employee within 4-digit industries. Year, country and industry fixed effects are included in all specifications. Heteroskedasticity robust standard errors are in parenthesis and clustered at the industry level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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