Trade, Technology Adoption, and Inequality in Distorted Economies

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Abstract

This paper examines how labor market imperfections distort firm-level technology choices and alter the distribution of the gains from trade in developing countries. We begin our analysis by documenting that firms using modern technologies are disproportionately exposed to labor market distortions in low-income countries. We introduce this feature into a quantitative trade model with technology adoption, providing formulas for the welfare cost of misallocation and the gains from productivity growth in distorted economies. We find that labor market distortions provide a possible explanation for the inefficiently low levels of modern technology adoption in developing countries. Further trade integration can, in theory, remedy this type of inefficiency, but it comes with distributional consequences. Counterfactual simulations reveal that labor market distortions reduce the gains from trade integration for workers, with the benefits accruing primarily to the owners of distortion rents.

Keywords: Trade, Technology Adoption, Labor Market Distortions, Inequality, Developing Economies

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1 Introduction

In the past four decades, developing countries have become significantly more integrated into global supply chains. This process has spurred the emergence of modern manufacturing firms operating with advanced technologies that make intensive use of imported intermediate inputs.

There has been much debate, however, about the extent to which trade integration has been successful. Critics typically emphasize two points: The rate of modern technology adoption in many low-income countries remains unusually low despite recent episodes of trade liberalization (Hsieh and Klenow, 2014; Buera, Hopenhayn, Shin, and Trachter, 2021). Moreover, the adoption of modern technologies has coincided with a stagnation of aggregate labor productivity in many countries (Diao, Ellis, McMillan, and Rodrik, 2021).

The existing literature provides a few possible explanations for these so-called anomalies. The big-push theories of economic development identify fixed production costs and inadequate market size as the main barrier to modern technology adoption in low-income countries (Murphy, Shleifer, and Vishny, 1989). Another body of literature on (in)appropriate technologies attributes the above patterns to a possible mismatch between modern technologies and the resource endowment of low-income countries (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001).

Appealing to economic theory and detailed firm-level data, we argue that labor market distortions provide another explanation for these anomalies. We, specifically, estimate that modern firms are disproportionately exposed to labor market distortions in low-income countries. Embedding this feature into a quantitative trade model with technology adoption, we show that labor market distortions lead to inefficiently low adoption of modern technologies and a weak relationship between trade-led modern manufacturing growth and aggregate labor productivity in low-income countries.

Our analysis begins by documenting empirical patterns using firm-level data from the World Bank Enterprise Survey (WBES). To do so, we classify firms in our sample according to two technological types, modern and traditional, based on firms' total sales, and estimate firms' labor intensity—i.e., elasticity of output relative to labor input—for each technology type. Based on these estimates and classifications, we report three empirical findings. First, relative to traditional firms, modern firms have substantially lower labor intensity. Second, labor market distortions are larger for modern firms, and substantially more so in low-income countries.[1] Third, low-income countries have a substantially larger share of traditional firms.

[1]Consistent with this second pattern, we additionally document that modern firms, relative to traditional ones, face lower market distortions in richer economies according to direct measures of distortions reported by firms to WBES, such as losses due to theft, labor market regulations, and time spent with bureaucracy.

Motivated by these empirical patterns, we develop a multi-country, multi-industry general equilibrium framework in which firms self-select into traditional and modern types of technologies in the presence of labor market distortions. Each country, in addition to its labor force, is endowed with a continuum of heterogenous firms, each corresponding to a unit of managerial capital. In every industry, each firm sorts into the technology type that maximizes the returns to managerial capital. Technologies are characterized by their differences in total factor productivity and how intensive they use managerial capital, labor, and intermediate inputs. In the empirically relevant case, modern technologies exhibit higher total factor productivity, and they are labor-saving and intermediate-input intensive. Consequently, a reduction in trade barriers that provides cheaper access to foreign intermediate inputs raises relative returns to modern technologies. We model this mechanism parsimoniously using distributional assumptions, akin to Farrokhi and Pellegrina (2022), which introduce a "technology elasticity" that controls the extent to which the aggregate share of modern firms responds to shocks that incentivize the adoption of modern technologies. Labor market distortions, meanwhile, vary across countries and across firm types within each country. We model these distortions as labor market wedges that create a gap between what firms pay and what the workers receive. This gap generates revenues that accrue to third parties such as rent-seekers and bureaucrats.[2]

We derive two analytical results to dissect the main mechanisms in our model. First, we show that in a stylized closed economy version of our model, the welfare cost of misallocation depends on the cross-technology dispersion in labor wedges and the technology elasticity—with a higher technology elasticity amplifying the welfare cost of misallocation.[3] Second, in the spirit of Baqaee and Farhi (2019) and Atkin and Donaldson (2021), we decompose the first-order welfare effects of productivity growth into three components: *(i)* the mechanical effect of productivity growth on consumer prices and the terms of trade—which collapses to Hulten's theorem for a closed economy,—*(ii)* the change to allocative efficiency, and *(iii)* the change to the factoral terms of trade—i.e., changes to workers' wages and managerial rents relative to the rest of world.

Having established these analytical formulas, we take our model to data. In doing so, we bring in country-level data from the GTAP database, which provides input-output trade flows for a large set of countries at different levels of development. We combine these country-level data with the technology-level statistics obtained from WBES, consisting of our estimates of labor intensity and labor market wedges and the share of firms in modern and traditional

[2]In the language of Baqaee and Farhi (2019), this third class of agents can be considered as a "fictitious" input in the production function.

[3]An immediate implication of this result is that misallocation does not occur if labor wedges are large but the same for modern and traditional firms.

technology across countries. We simulate our model equilibrium based on the method of hat algebra, which helps us sidestep the need to calibrate productivity shifters and trade costs.

We start our quantitative analyses by putting numbers on our analytical formulas. First, we quantify the welfare cost of misallocation as the distance to the efficient frontier for closed economies. Our results indicate that the welfare cost of misallocation is considerably higher in low-income countries, reflecting their higher cross-technology dispersion of labor wedges. Second, we decompose the welfare impact of productivity growth in modern technologies for each economy. The relative contributions from the three aforementioned channels differ vastly between low and high-income countries. In low-income countries, the welfare improvement through the allocative efficiency channel is notably larger, and it is comparable to the contribution from the mechanical channel, and in contrast to high-income countries, the factoral terms-of-trade effects are welfare-reducing. In other words, growth in modern technologies improves allocative efficiency in low-income countries by reallocating resources to where distortions are higher. Yet, the reduction in factor rewards (relative to the rest of the world) erodes a fraction of these allocative efficiency gains.

Lastly, we design an experiment to evaluate how labor market distortions, and their interaction with technology adoption, alter the gains from trade for workers in low-income countries. To do so, we consider three counterfactuals: *(i)* a twenty percent reduction in trade costs of low-income countries, which we refer to as the "trade shock;" *(ii)* a reduction in labor wedges of low-income countries to the level of middle-income countries, which we refer to as the "development shock;" *(iii)* a combination of both the trade and development shocks. We then compare the impact of the trade shock when there is a development shock—i.e., case *(iii)* net of *(ii)*—to when there is not—i.e., case *(i)*.

Our results highlight that the interplay between the trade and development shocks is crucial to understanding the impact on technology adoption and real income distribution. Specifically, we find that averaging across low-income countries, the impact of the trade shock on real wages is 24% larger with the development shock than without. In other words, the pass-through of the trade shock onto workers' real wages is decreasing in the level of misallocation. This result is driven by two channels: *(i)* For a given increase in the rate of technology adoption, demand for workers falls relatively more at a higher level of distortions because, in that case, modern firms pay a higher fraction of their total sales to wedges and a lower fraction to workers. *(ii)* A higher level of distortions prompts a higher adoption rate of modern (labor-saving) technologies in response to trade, which results in lower aggregate demand for workers. On the flip side, we find that the pass-through of the trade shock onto managerial rents and, particularly, distortion revenues is increasing in the level of misallocation. This finding underscores the distributional bias of trade in distorted economies: If labor market distortions were smaller in developing countries, the gains from trade integration would be larger for workers and smaller for managers and bureaucrats.

Related Literature. This paper contributes to research evaluating how misallocation interacts with international trade, including studies on the role of firm-level distortions (Bai, Jin, and Lu, 2019; Scottini, 2018; Ding, Lashkaripour, and Lugovskyy, 2022), the impact of distortions on the world's input-output structure (Caliendo, Parro, and Tsyvinski, 2017), the decomposition of the welfare gains from trade shocks (Baqaee and Farhi, 2019), and the interactions of distortions with trade policy (Lashkaripour and Lugovskyy, 2022; Bartelme, Costinot, Donaldson, and Rodriguez-Clare, 2019)—see Atkin and Donaldson (2021) and Atkin and Khandelwal (2020) for reviews of recent research.[4] Relative to this literature, we examine the effects of factor market distortions on firms' technology choice, where technologies are different in their factor intensity. We highlight the implications for distributional gains from trade, particularly between workers that earn wages versus managers and bureaucrats that receive rents on managerial capital and distortion revenues.[5] We find that labor market distortions tend to reduce the gains from trade accruing to workers, which can help explain why some developing countries have been relatively reluctant to trade openness.

By studying the role of technology choices, our paper speaks to rich research on technology adoption. Closer to our work, this front of research has examined the interactions between trade and technology upgrading (Yeaple, 2005; Bustos, 2011; Davidson, Matusz, and Shevchenko, 2008), finance and misallocation (Midrigan and Xu, 2014), economic shocks and capital intensity (Oberfield, 2013), and technology adoption in developing economics (Verhoogen, 2021).[6] To the best of our knowledge, we are the first to study technology choices in a framework with open economies and distorted labor markets. In our analysis, labor market distortions lead to distorted technology choices—specifically, firms' adoption of modern technologies is low relative to an efficient economy.[7]

[4]See Hsieh and Klenow (2009) for seminal work on the impact of misallocation on aggregate output.

[5]In a recent paper, Guner and Ruggieri (2022) study the impact of misallocation across heterogeneous workers. They find that, because misallocation reduces firm size and larger firms tend to pay more for skilled workers, it tends to reduce worker inequality. Here, we examine instead on inequality between workers and owners of managerial capital and distortion reveneus.

[6]There is also a rich literature analyzing the effects of trade on firms' technology choices in developing economies, see De Loecker, Goldberg, Khandelwal, and Pavcnik (2016) and Goldberg, Khandelwal, Pavcnik, and Topalova (2010) for India, Bustos (2011) for Argentina, Medina (2020) for Peru, Pavcnik (2017) and Oberfield (2013) for Chile, and Fieler, Eslava, and Xu (2018) for Colombia. We complement these studies by examining the interaction between technology adoption and technology-specific misallocation.

[7]Our distributional results can be understood more broadly in comparison to Stolper and Samuelson (1941). In our paper, a trade liberalization shock, that increases the return to modern, labor-saving technologies, attenuates the gains from trade accruing to workers. In the Stolper-Samuelson theorem, an increase in the price of labor-saving industries reduces worker's real wages.

More broadly, this paper contributes to a large literature that formulates quantitative equilibrium models to evaluate the welfare gains from trade, following the seminal work of Eaton and Kortum (2002) and as reviewed by Costinot and Rodríguez-Clare (2014). In the past two decades, this literature has developed an abundance of new tools and significantly expanded its scope of analysis, covering topics such as workers' mobility (Caliendo, Dvorkin, and Parro, 2019; Artuç, Chaudhuri, and McLaren, 2010), input-output structures of trade (Caliendo, Parro, and Tsyvinski, 2017), agricultural trade (Sotelo, 2020; Farrokhi and Pellegrina, 2022), optimal industrial and trade policy (Bartelme, Costinot, Donaldson, and Rodriguez-Clare, 2019; Lashkaripour and Lugovskyy, 2022), non-homothetic preferences (Fieler, 2011), multinational firms (Ramondo and Rodríguez-Clare, 2013), among many others. Our contribution to this broader literature is to endogenize technology choices in manufacturing and examine its interactions with domestic market distortions.

2 Data and Empirical Patterns

This section presents our data and three empirical patterns about technology choices, distortions, and economic development that motivate the building blocks of our model. In addition, it describes the method that we use to estimate production functions and labor market distortions.

2.1 Data

Our final dataset combines firm-level with country-level information. This section uses our firm-level data to estimate production functions and labor-market distortions and discusses empirical regularities. Section 5 brings in our country-level information to take our model to data.

The firm-level data come from the World Bank Enterprise Survey (WBES). These data contain rich firm-level information which we use to construct total sales and payments to labor, capital and intermediate inputs. for the manufacturing sector. The WBES data include a wide set of countries in different levels of economic development—specifically, they include cross-sectional data for approximately 90,000 firms operating between 2006-2020 across 140 countries. They are based on surveys that are designed to provide a nationally representative sample of firms. We exploit these data to estimate production technologies and distortions across firm clusters distinguished by their technology status. In addition to data on sales and costs, WBES reports multiple measures of distortions that individual firms face in their businesses, related to corruption, bribery, theft, red tape, bureaucracy, labor market regulations, among many measures. We use these measures to discuss complementary empirical patterns.

At the country-level, we collect global Input-Output data from the Global Trade Analysis Project (hereafter, GTAP) for the year of 2014. The GTAP database reports country-industry-level data on flows of trade, input-output, and value added, among other records. An attractive feature of GTAP data relative to other input-output datasets is its coverage: it includes around 140 countries, spanning countries in largely different levels of economic development. When we take our model to data in Section 5, we harmonize the data from GTAP into a sample of 100 countries, including 99 countries with the largest GDP and another that provides an aggregate representation of the rest of the world.

2.2 Empirical Patterns

We exploit our firm-level data to document three empirical patterns about the relationship between technology, labor market distortions, and economic development. Before reporting the main regularities in our data, we overview the methodology which we employ to estimate production functions and labor market distortions, and the method by which we classify firms into modern and traditional types.

2.2.1 Production Technologies and Labor Wedges

Classification of Firms to Traditional and Modern. We mean to adopt a simple, transparent method of classification that is free from any particular model assumptions. In line with the literature on firm heterogeneity, our presumption is that firms that use modern technologies tend to have greater sales.[8] We, therefore, base our classification on firms' total sales in terms of adjusted USD.[9]

Consider the distribution of sales for our sample of manufacturing firms around the world. We classify a firm as modern if the value of its sales lies above a threshold on the sales distribution. To determine this threshold, we adopt an approach inspired by the clustering analysis in Asturias and Rossbach (2019). Let $Y(\omega)$ be the value of total sales for firm ω,

[8] In addition, we observe that firms that have larger sales also have higher cost share of intermediate inputs (Appendix Figure A.2). This regularity is consistent with research on firm heterogeneity, which has documented that larger firms tend to be more capital-intensive (Bernard and Jensen, 1999; Bernard, Jensen, Redding, and Schott, 2007). See Oberfield (2013) for an analysis of the relationship between firm-heterogeneity, capital-intensity, and misallocation.

[9] Several papers have shown that larger firms use more advanced technologies, including Foster, Haltiwanger, and Krizan (2006), Bernard and Jensen (1999), and Bernard, Jensen, Redding, and Schott (2007). A few papers have previously classified firms by their use of modern and traditional technologies, including Lagakos (2016), Diao, Ellis, McMillan, and Rodrik (2021), and Midrigan and Xu (2014), who use measures such as firm-size and formality to construct their classification.

which we intend to classify into traditional technology ($t = 0$) or modern technology ($t = 1$). We use $Y_t(\omega)$ to denote the total sales of the firm ω conditional on it being classified into technology t. The cutoff point $\omega^\star$ minimizes the distance between $Y_t(\omega)$ and its cluster-level average, $\overline{Y_t}$. Namely,

$$\omega^\star = \arg\min \left[\sum_{t\in\{0,1\}} \sum_{\omega\in\Omega_t} \left(Y_t(\omega) - \overline{Y_t}\right)^2 \right],$$

where $\Omega_0 = \{\omega | Y(\omega) < Y(\omega^\star)\}$ is the set of traditional firms, and $\Omega_1 = \{\omega | Y(\omega) \geq Y(\omega^\star)\}$ is the set of modern firms.[10]

Labor Output Elasticities and Wedges. To estimate production functions and wedges, we assume Cobb-Douglas technologies. Specifically, the production function of firm ω that employs inputs $\{L^f\}$ under technology t is given by:

$$Q(\omega) = A_t(\omega) \times \prod_f \left(L^f(\omega)\right)^{\gamma_t^f},$$

where f indexes production inputs and t denotes technology type. Modern and traditional technologies are, thus, different in terms of their factor intensities—i.e., $\{\gamma_0^f\}$ vs $\{\gamma_1^f\}$—and in terms of their productivities—the distribution of $A_0(\omega)$ vs the distribution of $A_1(\omega)$.

In principle, there can be distortions in markets for inputs and outputs. Let $\tau_t^f(\omega)$ and $\tau_t^Y(\omega)$ respectively denote input and output-side wedges—where a wedge is the difference between the amount paid by buyers and received by sellers. We are, in particular, interested in labor market distortions due to labor wedges. These wedges represent the difference between the amount a firm pays to employ workers and what the workers receive. Cost minimization in the presence of distortions implies (see Appendix **??**),

$$\tau_t^f(\omega)\,\tau_t^Y(\omega) = \frac{\gamma_t^f}{\lambda_t^f(\omega)},$$

where $\lambda_t^f(\omega)$ is the ratio of payments to input f relative to total sales, and γ_t^f is the output elasticity with respect to input f. In the absence of distortions, the output elasticity of input f equals the cost share of that input. In the general case, however, knowledge of $\{\gamma_t^f\}_f$ is not sufficient to disentangle the input wedge from the output wedge. Given our focus on labor market distortions, we overcome this issue by normalizing the wedge on non-labor inputs and on outputs. Under this normalization, it is straightforward to recover labor wedges,

[10] We find that the cutoff $\omega^\star$ which breaks down firms into modern and traditional locates at the 46% percentile of the distribution of total sales.

τ_t^L, given labor cost shares in total revenues, $\lambda_t^L(\omega)$, and labor output elasticities, γ_t^L. We observe $\lambda_t^L(\omega)$ in our data, and estimate γ_t^L as explained below.

We estimate the elasticity of output with respect to labor, γ_t^L, for each technology class, using the control function approach (Levinsohn and Petrin, 2003; Olley and Pakes, 1996).[11] Specifically, we run regressions of total sales against total payments to labor, including a flexible polynomial function of the payments to intermediate inputs and capital. Given our estimates of γ_t^L for each technology, we use data on $\lambda_t^f(\omega)$ to recover $\tau_t^L(\omega)$.[12] To examine robustness, we also estimate and discuss the empirical patterns in the next section by disaggregating the manufacturing sector into more narrowly-defined industries.

Next, we present three empirical patterns that emerge from our classification of firms into modern and traditional and our estimates of labor wedges.

2.2.2 Three Empirical Patterns

Pattern 1. Modern firms use labor less intensively than traditional firms.

Figure 1 reports our estimates of the output elasticity of labor (or alternatively the labor intensity) for modern and traditional technologies. For the manufacturing sector as a whole, the output elasticity of labor is notably smaller for the modern technology than the traditional technology. For the modern technology, the elasticity is 0.40, whereas it is 0.29 for the in the traditional technology. If we disaggregate the manufacturing sector into multiple industries and estimate these elasticities separately for each industry,[13] we continue to find a strikingly stable gap between the labor intensity of modern and traditional technologies.[14] This estimated gap is consistent with previous findings in the firm heterogeneity literature,

[11] We notice that our estimation of γ_t^f is based on revenue data, in practice, we therefore recover the *revenue* elasticity of labor instead of the *output* elasticity. As discussed in Hashemi, Kirov, and Traina (2022), when one uses revenue data, the ratio of the revenue elasticity to input cost share in total revenue already recovers the labor wedge, without any normalization on output wedge.

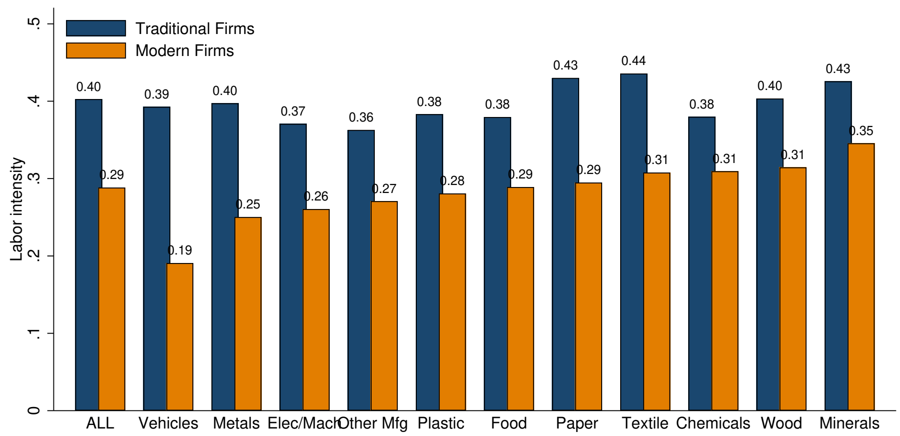
[12] Following the control function approach, we assume that labor is the flexible input and that capital is a state variable for the firm. As such, we can consistently estimate the output elasticity of labor by controlling for a flexible polynomial of capital and intermediate inputs, which will absorb the effect of the unobserved firm-level productivity. Since we do not have a panel-data, we are unable to fully implement the production function estimation approach in the literature (Levinsohn and Petrin, 2003; Olley and Pakes, 1996) to estimate the output elasticity of the remaining inputs. Later, when we take the model to data, we calibrate the remaining factor intensity parameters of the production functions using aggregate moments and our assumption that production functions are constant-returns-to-scale. This approach is also more consistent with our static framework, where "intermediate inputs" include tradeable durables such as machinery and equipments that in the WBES data might be counted as "capital."

[13] In that case, we apply the procedure described in Section 2.2.1 for each industry separately to classify firms into modern and traditional technology types.

[14] Appendix Table A.1 examines alternative specifications to Figure 1. We experiment with different control functions in the estimation of the production function, employ different definitions of modern and traditional firms, and split the firms into three technology types instead of two.

showing a strong correlation between firm-size and technology choices even within narrowly-defined product categories (Bernard, Jensen, Redding, and Schott, 2007).

Figure 1: Labor Intensity by Modern and Traditional Firm across Sectors



Notes: This figure shows our estimates of output elasticity of labor by firm status in terms of modern and traditional technology, for the manufacturing industry as a whole, and disaggregated by sector, using firm-level data from WBES. Section 2.2.1 provides for details about the methodology that we apply to estimate technologies and assign firms into modern and traditional technological regimes.

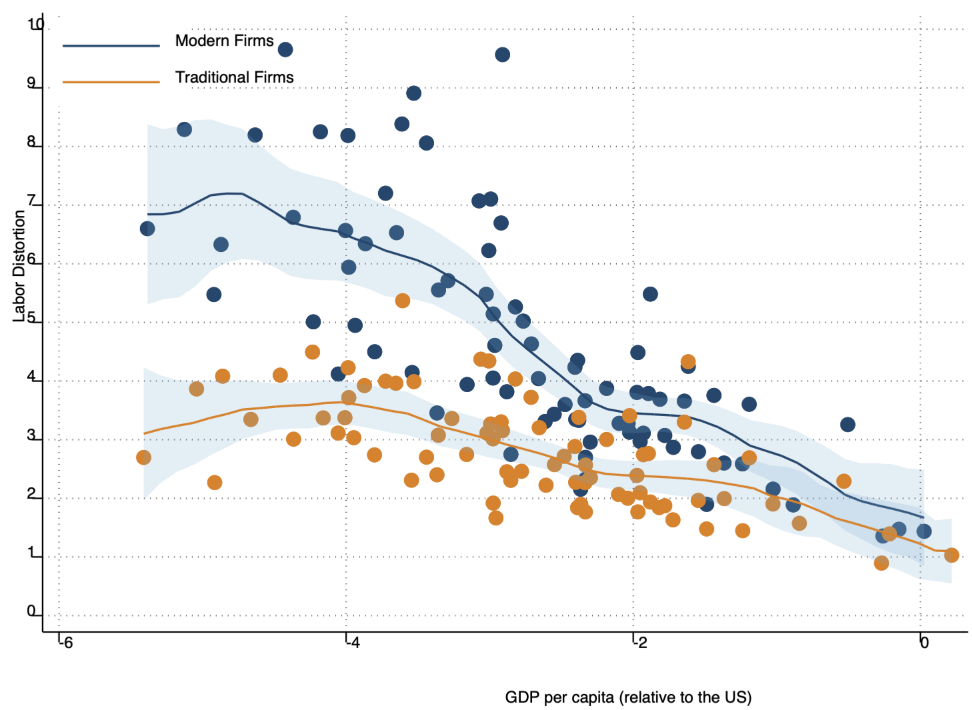
Appendix B provides a complementary discussion about the relationship between the cost share of labor and the cost share of intermediate inputs across firms of different size, corroborating the evidence presented here. Specifically, we document a strong negative relationship between the size of firms and the cost share of payments to labor, but a positive relationship between size and the cost share of intermediate inputs. Overall, the results that we find across these additional analyses are largely consistent with the results reported here.

In our theoretical model that follows, we allow firms to self-select into traditional or modern technologies, characterized by different productivity and input intensity levels. As such, different from the previous trade literature, the aggregate cost share of labor (or intermediate inputs) is an *endogenous* feature of the economy, which depend on firms' selection into traditional and modern technologies.

Pattern 2. Labor wedges are larger for modern firms, and significantly more so in less developed economies.

We now examine how our estimated labor wedges vary across traditional and modern firms, and how those wedges differ between countries with different GDP per capita levels (Figure 2). Two observations stand out. First, regardless of whether firms are modern or traditional, labor wedges are larger in lower-income countries: Firms within countries in the bottom quartile of the GDP per capita distribution face a labor wedge of 5-7, whereas firms in the upper quartile of that distribution face a labor wedge of 2-3.[15] Second, labor wedges are larger for modern firms, and more so in low-income countries. For the median country, the modern-to-traditional labor wedge ratio is 1.60. This ratio, however, declines with GDP per capita—to the point that the difference in the labor wedge faced by modern and traditional firms is minimal for higher-income countries, compared to the 60 percent difference in low-income countries.

Figure 2: Relationship between Labor Wedges and GDP per capita by Type of Firm



Notes: This figure shows the distribution of firm-specific labor wedges across countries in different levels of GDP per capita. Section 2.2.1 describes the procedure that we use to recover labor wedges.

The key takeaway from Figure 2 is that modern firms face substantially larger labor distortions in low-income countries, relative to high-income counterparts. To provide complementary evidence on this result, we take advantage of the direct measures of distortions reported by firms in the WBES. These measures record the difficulty of running businesses, including the proportion of total sales lost due to crime and bribery, the share of a manager's time spent dealing with bureaucracy. Table 1 reports the results from regressions in which we run each of these direct measures of market distortion against firms' technology type

[15]This result is consistent with Donovan, Lu, Schoellman, et al. (2020), who show evidence that labor market frictions, implied by labor market flows such as job-finding rates and employment-exit rates, are systematically larger in developing economies.

Table 1: Direct Evidence on the relationship between Market Distortions and Modern Firms across countries in Different Levels of Economic Development

	Sales loss to Theft (1)	Time with Bureaucracy (2)	Taxes Barrier (3)	Labor Regulation (4)	Informal Sector (5)
Modern	1.029***	0.533	1.035***	0.647***	0.756
	(0.215)	(0.850)	(0.226)	(0.196)	(0.469)
Modern $\times$ log(GDP per capita)	-0.108***	-0.081	-0.111***	-0.062***	-0.103*
	(0.024)	(0.102)	(0.024)	(0.022)	(0.056)
pseudo-R2	0.255	0.217	0.073	0.110	0.062
Obs	71848	61484	77574	76364	73420
Country FE	Y	Y	Y	Y	Y

Notes: * / ** / *** denotes significance at the 10 / 5 / 1 percent level. Robust standard errors are clustered at the country level. All regressions are estimated via poisson pseudo-likelihood regression and weighted according to firms sampling weights. The dependent variables in each column are: (1) the percentage of total sales losss related to criminal activities (theft, bribery, and security), (2) the percentage of the time spent by senior managers dealing with government regulation, (3) an indicator variable for whether taxes are a large obstacle for their activities, (4) an indicator variable for whether labor market regulations are a large barrier for their activities, and (5) an indicator variable whether the practices of competitors in the informal sector are a large barrier for their activities.

and its interaction with log of GDP per capita, while controlling for country fixed effects to remove the influence of any differences in average market distortions between countries. Across different measures of market distortions, we find the interaction term to be consistently negative—that is, compared to traditional firms, modern firms face systematically lower distortions in countries with a higher GDP per capita. We find it reassuring that the results from Table 1, which are based on *direct* measures of distortions in the data, are qualitatively consistent with those in Figure 2, which is based on our *indirect* measures of distortions.

Motivated by this empirical pattern, our forthcoming model allows labor wedges to be different across countries and across modern and traditional technologies. These differences, in turn, affect firms' choice of technology, and consequently, the aggregate exposure of an economy to labor market distortions will depend on the equilibrium mix of traditional and modern firms.

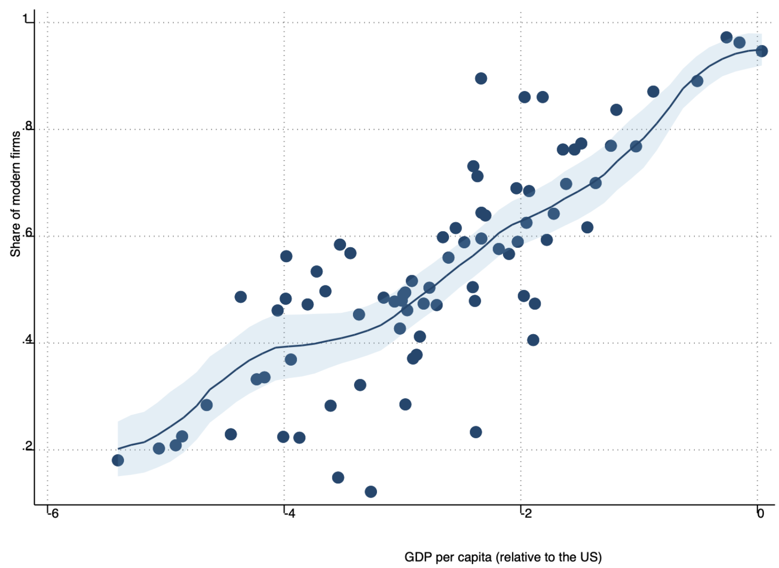
Pattern 3. The share of modern firms increases with economic development.

Given our classification of modern and traditional firms, we conclude this section by reporting the implied share of firms operating with a modern technology for countries across different levels of economic development. Figure 3 shows that the share of modern firms rises substantially with GDP per capita: In the bottom quartile, about 26 percent of firms are classified as modern, whereas in the upper quartile, 73 percent of firms are modern.

In our forthcoming model, the share of firms using modern versus traditional technologies is endogenously determined. Two channels incentivize the greater adoption of modern technologies in high- versus low-income countries. First, the higher wage rate in high-income countries motivates the adoption of modern, labor-saving technologies. Second, the higher modern-to-traditional labor wedge ratio in low-income countries acts as a barrier to modern technology adoption.

To take stock, this section paints the following picture. First, there are systematic differences in labor intensity between modern and traditional firms (empirical pattern 1): modern firms tend to be less intensive in the use of labor and more integrated into global-value chains, as measured by their higher cost share of intermediate inputs. Second, modern firms are disproportionately exposed to labor market distortions in low-income countries (empirical pattern 2). Third, the share of modern firms is larger in high-income countries. (empirical pattern 3). In what follows, we develop a theoretical model that can accommodate these empirical patterns.

Figure 3: Share of Modern and Traditional Firms across countries in Different Levels of Economics Development



Notes: This figure shows the share of firms classified as modern versus traditional across countries in different levels of economic development of the distribution of GDP per capita. The classification of firms into modern technology is based on their size. See details in Section 2.2.1.

3 The Model

Environment. The global economy consists of multiple countries indexed by $i,\ j \in \mathbb{I}$ and multiple industries indexed by $s \in \mathbb{S}$. Production in country $i-$industry s can take place under two types of technology indexed by $t \in \mathbb{T} \equiv \{0, 1\}$; namely, "traditional" ($t = 0$) and "modern" ($t = 1$). Country i is endowed with $\bar{L}_i$ units of labor and is populated by a fixed number of firms in each industry, each of which operates with a fixed amount of managerial capital. Markets are perfectly competitive.

Labor Market Wedges. Each economy is subject to wedges in the labor market. We denote these wedges by $\tau^L_{i,st}$ as the difference between the amount a firm pays to employ a worker and the amount the worker receives. These wedges vary not only across countries and industries, but also between modern and traditional technologies.

3.1 Production

Industry s in country i is populated by an exogenously given continuum of firms, indexed by $\omega \in \Omega_{i,s}$. Each firm is endowed by one unit of managerial capital. The production function for firm $\omega \in \Omega_{i,s}$ under technology t is given by:

$$Q_{i,st}(\omega) = A_{i,st}\Big(Z_{i,st}(\omega)\,\frac{\mathcal{K}_{i,st}(\omega)}{\gamma^Z_{st}}\Big)^{\gamma^Z_{st}}\Big(\frac{L_{i,st}(\omega)}{\gamma^L_{st}}\Big)^{\gamma^L_{st}}\Big(\frac{M_{i,kt}(\omega)}{\gamma^M_{st}}\Big)^{\gamma^M_{st}},$$

where $A_{i,st}$ is total factor productivity under technology t, $\mathcal{K}_{i,st}\left(\omega\right) \leq 1$ is managerial input, $Z_{i,st}(\omega)$ is the idiosyncratic managerial productivity, $L_{i,st}(\omega)$ is labor employment, and $M_{i,st}(\omega)$ is a composite intermediate input that aggregates over inputs sourced from various industries and origins. More formally, $M_{i,st}(\omega) = \prod_{s' \in \mathbb{S}} M_{i,s'st}(\omega)^{\phi_{i,s'st}}$, where $M_{i,s'st}(\omega)$ is a bundle of goods from industry s' sourced from various origin countries, and $\sum_{s' \in \mathbb{S}} \phi_{i,s'st} = 1$. Production technologies are constant-returns to scale, amounting to $\gamma^Z_{st} + \gamma^L_{st} + \gamma^M_{st} = 1$.

Firms' Choices of Technology. Traditional ($t = 0$) and modern technologies ($t = 1$) differ in their input intensity parameters, $\boldsymbol{\gamma}_0 \equiv \{\gamma^Z_{s0}, \gamma^L_{s0}, \gamma^M_{s0}\}_s$ versus $\boldsymbol{\gamma}_1 \equiv \{\gamma^Z_{s1}, \gamma^L_{s1}, \gamma^M_{s1}\}_s$, and total factor productivity levels, $A_{i,s0}$ versus $A_{i,s1}$. Each firm $\omega \in \Omega_{i,s}$ draws a vector of managerial productivity levels, $[Z_{i,s0}(\omega), Z_{i,s1}(\omega)]$, and chooses its desired type of technology. Per cost minimization, the marginal cost of production for a firm $\omega \in \Omega_{i,s}$ that sorts to technology t equals:

$$c_{i,st}(\omega) \equiv \frac{1}{A_{i,st}}\left(\frac{r_{i,st}(\omega)}{Z_{i,st}(\omega)}\right)^{\gamma^Z_{st}}\left(\tau^L_{i,st} w_i\right)^{\gamma^L_{st}}\left(m_{i,st}\right)^{\gamma^M_{st}}$$

where $r_{i,st}(\omega)$ denotes the return to managerial capital, $\tau^L_{i,st} w_i$ is the wage rate in country i inclusive of labor market wedges, and $m_{i,st}$, is the price of the intermediate input bundle. All firms within a country-industry, regardless of their technology type, supply products that are perfectly substitutable. Let $p_{i,s}$ denote the competitive price supplied by country $i-$industry s. The zero profit condition—which requires the equalization of price and marginal cost, $p_{i,s} = c_{i,st}(\omega)$—pins down the return to each firm ω if it sorts to technology t:

$$r_{i,st}(\omega) = Z_{i,st}(\omega) \times \left(a_{i,st} p_{i,s} h_{i,st} / \dot{\tau}^L_{i,st}\right)$$

The return, $r_{i,st}(\omega)$, depends on output price, $p_{i,s}$, the technology-specific impact from input prices,

$$h_{i,st} \equiv \left(\frac{w_i}{p_{i,s}}\right)^{-\gamma^L_{st}/\gamma^Z_{st}} \left(\frac{m_{i,st}}{p_{i,s}}\right)^{-\gamma^M_{st}/\gamma^Z_{st}},$$

the effective labor market wedge, $\dot{\tau}^L_{i,st} \equiv \left(\tau^L_{i,st}\right)^{\gamma^L_{st}/\gamma^Z_{st}}$, the impact of technology-specific productivity, $a_{i,st} \equiv \left(A_{i,st}\right)^{1/\gamma^Z_{st}}$, and the firm-level productivity draw, $Z_{i,st}(\omega)$.[16] Firm ω faces a discrete choice problem wherein it chooses technology $t \in \mathbb{T}$ that maximizes returns, $r_{i,st}(\omega)$. Namely,

$$\max\left\{Z_{i,st}(\omega) \times \left(a_{i,st} p_{i,s} h_{i,st} / \dot{\tau}^L_{i,st}\right), \quad \text{for } t \in \mathbb{T}\right\}.$$

We assume that the vector of firm-level productivities, $\mathbf{Z}_{i,st}(\omega) \equiv [Z_{i,st}(\omega) \quad \text{for } t \in \mathbb{T}]$, is drawn independently by firms from a Fréchet distribution, $\Pr\left(\mathbf{Z}_{i,st}(\omega) \le \mathbf{z}_{i,st}\right) = \exp\left(-\bar{\phi} \sum_{t \in \mathbb{T}} z^{-\theta}_{i,st}\right)$, where $\bar{\phi} \equiv \left[\Gamma\left(1 - 1/\theta\right)\right]^{-\theta}$ is a normalization which ensures that $\mathbb{E}\left[Z_{i,st}(\omega)\right] = 1$, with parameter $\theta > 1$ governing the dispersion in productivity draws. Under this distributional assumption, the share of firms that select technology t in country $i-$industry s, denoted by $\alpha_{i,st}$, is given by:

$$\alpha_{i,st} = \left(\frac{a_{i,st} h_{i,st} / \dot{\tau}^L_{i,st}}{H_{i,s}}\right)^{\theta}, \quad \text{with} \quad H_{i,s} \equiv \left[\sum_{t' \in \mathbb{T}} \left(a_{i,st'} h_{i,st'} / \dot{\tau}^L_{i,st'}\right)^{\theta}\right]^{1/\theta}; \tag{1}$$

where $H_{i,s}$ is the industry-level return to managerial capital relative to the output price. Intuitively, a greater share of firms select technology t if it exhibits (i) a higher average productivity, $a_{i,st}$; (ii) more favorable impact from wages and intermediate input prices, as summarized by $h_{i,st}$; and, (iii) lower exposure to labor market distortions, $\dot{\tau}^L_{i,st}$. The extent

[16] To provide intuition for how these relative input prices matter, consider the empirically-relevant case in which the traditional technology is intensive in the use of labor, and the modern technology is intensive in the use of intermediate inputs. In that case, within each industry the return to the traditional technology falls when the relative wage $(w_{i,st}/p_{i,s})$ increases, and the return to the modern technology rises if the relative intermediate input price $(m_{i,st}/p_{i,s})$ decreases.

of these relationships is governed by parameter θ, which we accordingly call the "technology elasticity."

Industry Aggregates. We can now specify aggregate sales in country i–industry s given firms' choices of technology. Let $R_{i,st}(\omega) \equiv p_{i,s} Q_{i,st}(\omega)$ denote sales of firm $\omega \in \Omega_{i,st}$ where $\Omega_{i,st}$ is the set of firms in country $i-$industry s that choose technology t; and by aggregation, $R_{i,st} = \sum_{\omega \in \Omega_{i,st}} R_{i,st}(\omega)$. Recall that the return to managerial capital of firm ω is given by $r_{i,st}(\omega) = Z_{i,st}(\omega) \times \left(a_{i,st} p_{i,s} h_{i,st} / \grave{\tau}^L_{i,st}\right)$. Since the return, $r_{i,st}(\omega)$, is a fraction γ^Z_{st} of firm ω's sales, i.e., $R_{i,st}(\omega) = \left(\gamma^Z_{st}\right)^{-1} r_{i,st}(\omega)$, we can express the industry-level sales as:

$$R_{i,s} = \sum_{t \in \mathbb{T}} R_{i,st} = \sum_{t \in \mathbb{T}} \left[\alpha_{i,st} \times |\Omega_{i,s}| \times \mathbb{E}\left[Z_{i,st}(\omega) \mid \omega \in \Omega_{is,t}\right] \times \left(\gamma^Z_{st}\right)^{-1} \left(a_{i,st} p_{i,s} h_{i,st} / \grave{\tau}^L_{i,st}\right)\right] \tag{2}$$

Since the expected value of productivity draws conditional on firms' selections equals $\mathbb{E}\left[Z_{i,st}(\omega) \mid \omega \in \Omega_{is,t}\right] = \alpha_{i,st}^{-\frac{1}{\theta}}$, by normalizing $|\Omega_{i,s}| = 1$ (without of loss of generality), we can derive the industry-level sales as

$$R_{i,s} = p_{i,s} \Gamma^Z_{i,s} H_{i,s}, \qquad \text{with} \quad \Gamma^Z_{i,s} \equiv \left[\sum_{t \in \mathbb{T}} \alpha_{i,st} \left(\gamma^Z_{st}\right)^{-1}\right]^{-1}; \tag{3}$$

The aggregate sales from each type of technology, in turn, can be obtained according to:

$$R_{i,st} = \alpha_{i,st} \left(\frac{\Gamma^Z_{i,s}}{\gamma^Z_{st}}\right) R_{i,s}, \tag{4}$$

where $\alpha_{is,t}$, $R_{i,s}$, and $\Gamma^Z_{i,s}$ are given by Equations (1)-(3).

3.2 Trade and Consumption

The representative consumer in each country j receives utility C_j according to the following two-tier preference system:

$$C_j = \prod_{s \in \mathbb{S}} \left(C_{j,s}\right)^{e_{j,s}}, \qquad C_{j,s} = \left[\sum_{i \in \mathbb{I}} \left(b_{ij,s}\right)^{1/\sigma_s} \left(C_{ij,s}\right)^{\frac{\sigma_s - 1}{\sigma_s}}\right]^{\frac{\sigma_s}{\sigma_s - 1}}$$

In the upper tier, the final consumption, C_j, is a Cobb-Douglas aggregation over industry-level bundles, $\{C_{j,s}\}_{s \in \mathbb{S}}$, with constant expenditure shares $e_{j,s}$. In the lower tier, $C_{j,s}$ is a CES aggregation over within-industry varieties that are differentiated by their origin country, $\{C_{ij,s}\}_{i \in \mathbb{I}}$, where $b_{ij,s}$ is a demand shifter and σ_s is the elasticity of substitution between varieties within industry s.

Country i's variety of industry s can be delivered to country j at price $d_{ij,s} p_{i,s}$, where

$p_{i,s}$ is the price at the location of production, origin country $i-$industry s, and $d_{ij,s}$ is the iceberg trade costs corresponding to origin $i-$destination $j-$industry s.[17] We make the assumption that final consumption and intermediate input demand are characterized by the same CES function, as given by $C_{j,s}$ in the above equation. Accordingly, country j's share of expenditure on goods originating from country i within industry s is:

$$\pi_{ij,s} = \frac{b_{ij,s}\left(d_{ij,s}p_{i,s}\right)^{1-\sigma_s}}{\left(P_{j,s}\right)^{1-\sigma_s}}, \qquad \text{with} \quad P_{j,s} = \left[\sum_{i\in\mathbb{I}} b_{ij,s}\left(d_{ij,s}p_{i,s}\right)^{1-\sigma_s}\right]^{\frac{1}{1-\sigma_s}}; \tag{5}$$

where $P_{j,s}$ denotes the CES price index of industry s in location j.

3.3 General Equilibrium

Market Clearing and Equilibrium. The labor market in each country i clears by ensuring the supply of labor equals the global demand for for that country's labor:

$$w_i L_i = \sum_{s\in\mathbb{S}}\sum_{t\in\mathbb{T}}\left(\frac{1}{\tau_{i,st}}\right)\gamma_{st}^{L} Y_{i,st}. \tag{6}$$

For each dollar that is paid to employ workers, only a fraction $1/\tau_{i,st}$ is the payment to workers, and the remainder, $\left(\tau_{i,st}-1\right)/\tau_{i,st}$, is the payment associated with labor wedges. Hence, all else equal, higher labor wedges lower the demand for workers. In turn, labor-wedge payments amount to

$$T_i = \sum_{s\in\mathbb{S}}\sum_{t\in\mathbb{T}}\left(\frac{\tau_{i,st}-1}{\tau_{i,st}}\right)\gamma_{st}^{L} Y_{i,st}. \tag{7}$$

The labor wedge represents a range of costs that firms incur due to labor market distortions, e.g., bribery, theft, bureaucratic berries, labor market regulations, and search frictions. Our model takes $\tau_{i,st}$ as a reduced-form representation of these distortions without taking a stance on their specific nature.

The goods market for each country $i-$industry s clears by ensuring that total sales, $R_{i,s}$, equal the corresponding global demand. Namely,

$$R_{i,s} = \sum_{j\in\mathbb{I}} \pi_{ij,s} E_{j,s}, \tag{8}$$

where country i's gross expenditure on industry s, $E_{i,s}$, is the sum of final good and inter-

[17] As is standard in the literature, we assume that $d_{ii,s} = 1$ and $d_{ij',s}d_{j'j,s} > d_{ij,s}$.

mediate input expenditure:

$$E_{i,s}=e_{i,s}Y_i+\sum_{s'\in\mathbb{S}}\sum_{t\in\mathbb{T}}\left[\phi_{i,s'st}\gamma^M_{s't}R_{i,s't}\right]. \tag{9}$$

Lastly, Y_i denotes national income or GDP, and is given by

$$\begin{aligned} Y_i &= w_i L_i + T_i + \Pi_i \\ &= \textstyle\sum_{s\in\mathbb{S}}\sum_{t\in\mathbb{T}}\left(1-\gamma^M_{i,st}\right)R_{i,st} \end{aligned} \tag{10}$$

where $\Pi_i \equiv \sum_{s\in\mathbb{S}}\sum_{t\in\mathbb{T}}\gamma^Z_{st}R_{i,st}$ is the aggregate rents that accrue to managerial capital in country i. The above equations ensure that trade is balanced and the national expenditure net of labor-wedge payments, $E_i - T_i$, equals the sum of factor rewards (labor wages and managerial rents).

Throughout the analysis that follows, we refer to w_iL_i/P_i as workers' real wages, and similarly to T_i/P_i and Π_i/P_i respectively as real managerial rents and real distortion revenues, and we call Y_i/P_i as country i's welfare.

4 Misallocation and Growth Accounting

This section discusses how labor market wedges undermine allocative efficiency, emphasizing the crucial role of technology adoption. First, we examine a closed-economy version of our model, allowing us to transparently characterize the cost of misallocation under technology adoption. Then, we return to our general setup and decompose the welfare impacts of productivity growth into (i) mechanical welfare gains that materialize regardless of misallocation or openness, (ii) the change to allocative efficiency, and (iii) factoral terms-of-trade effects.

Employments and Output Shares. To set the stage for our welfare analysis, we define additional share variables. We use $\rho_{i,st}$ to denote the share of technology t from total output (sales) of country i–industry s; $r_{i,s}$ to denote the share of industry s from output in country i; and $\ell_{i,s}$ to denote the share of labor employed by industry s–technology t in country i. Stated formally,

$$\rho_{i,st} \equiv \frac{R_{i,st}}{\sum_{t'}R_{i,st'}}; \qquad r_{i,s} = \frac{\sum_t R_{i,st}}{\sum_{s'}\sum_t R_{i,s't}}; \qquad \ell_{i,st} \equiv \frac{L_{i,st}}{L_i}.$$

As demonstrated in Appendix C.1, $\rho_{i,st}$ and $\ell_{i,st}$ can be inferred from the vector of firm-technology shares, $\{\alpha_{i,st}\}_{s,t}$, as follows

$$\rho_{i,st} = \frac{\Gamma_{is}^{Z}}{\gamma_{st}^{Z}}\alpha_{i,st}; \qquad \ell_{i,st} = \frac{\left(\gamma_{st}^{L}/\tau_{i,st}^{L}\gamma_{st}^{Z}\right)\alpha_{i,st}}{\sum_{t'}\left(\gamma_{st}^{L}/\tau_{i,st}^{L}\gamma_{st}^{Z}\right)\alpha_{i,st'}}\ell_{i,s},$$

where $\ell_{i,s} \equiv \sum \ell_{i,st}$ is the total employments share of industry s in country i, and recall that $\Gamma_{is}^{Z} = \sum_t \frac{1}{\gamma_{st}^{Z}}\alpha_{i,st}$ denote average managerial capital intensity.

4.1 The Cost of Misallocation under Technology Adoption

In our model, labor market wedges ($\tau_{i,st}^{L}$) create misallocation for two reasons. First, given technology choices, employment shares are inefficiently low in firms using high-τ^L technologies. Second, labor wedges distort firm-level technology choices, leading to inefficiently low adoption of high-τ^L technologies. Since modern technologies are subject to higher labor market wedges empirically (see Section 2), misallocation will manifest as inefficiently low adoption of and employment by modern technologies.

To communicate this point transparently, we provide an exact formula for the cost of misallocation in a special case of our model. We consider a closed economy to disentangle the cost of misallocation from terms of trade-related effects. We also assume that firms employ only primary factors of production (i.e., no intermediate inputs), and factor intensities are symmetric across technologies. The two technologies available to firms, nevertheless, differ in their total factor productivity and labor wedges. Finally, in the interest of exposition, we focus our discussion here on a single-sector economy, noting that the same discussions and formulas apply to the multi-sector case with little modification (see Appendix D).

Following the literature, we define the welfare cost of misallocation, $\mathcal{D}_i$, as the (log) welfare distance to the Pareto-efficient frontier. We, moreover, define

$$\tilde{\tau}_{i,st} \equiv \tau_{i,st}/\mathbb{E}_{\ell}\left[\tau_{i,st}\right]$$

as the normalized wedge associated with technology t, with $\mathbb{E}_{\ell}\left[\tau_{i,st}\right] \equiv \sum_{s,t}\left[\ell_{i,st}\tau_{i,st}\right]$ denoting the employment-weighted average wedge in country i. As shown in Appendix D, the welfare cost of misallocation from labor wedges is

$$\mathcal{D}_i = \frac{\Gamma_i^Z}{\theta}\log\mathbb{E}_{\ell}\left[\left(\tilde{\tau}_{i,st}^{L}\right)^{1+\frac{\Gamma_i^L}{\Gamma_i^Z}\theta}\right],$$

where Γ_i^L and Γ_i^Z (as defined earlier) denote aggregate labor and managerial capital intensity in economy i, with $\mathbb{E}_\ell[.]$ denoting the employment-weighted mean.

The above formula reveals that misallocation occurs only if labor market wedges exhibit dispersion from the mean. In particular, a common wedge $\tau_{i,st} = \tau_i$ that applies equally to all technologies will amount to $\tilde{\tau}_{i,st} = 1$ and zero misallocation. To communicate this point more clearly and underscore the role of technology adoption, we can examine the second-order approximation of $\mathcal{D}_i$ for small departures from a common wedge. This approximation takes the following form,

$$\mathcal{D}_i \approx \frac{\Gamma_i^L}{2}\left(1 + \frac{\Gamma_i^L}{\Gamma_i^Z}\theta\right)\mathrm{Var}_\ell\left[\widetilde{\tau}_{i,st}^L\right], \tag{11}$$

where $\mathrm{Var}_\ell\left[\widetilde{\tau}_{i,st}^L\right]$ is the variance of normalized labor wedges or the coefficient of variation of actual wedges. The above approximation reveals that dispersion from the mean (rather than the mean level of wedges) determines the cost of misallocation from labor market wedges. This observation is crucial, considering our earlier finding that labor wedges exhibit greater dispersion across traditional and modern technologies in low-income countries.

The above approximation also highlights the misallocation-magnifying effects of technology adoption. Misallocation without endogenous technology adoption would simply amount to $\frac{\Gamma_i^L}{2}\mathrm{Var}_\ell\left[\widetilde{\tau}_{i,st}^L\right]$. However, when firms' endogenous technology choices are distorted by labor wedges, misallocation is amplified by an additional amount $\frac{\Gamma_i^L}{2} \times \frac{\Gamma_i^L}{\Gamma_i^Z}\theta\mathrm{Var}_\ell\left[\widetilde{\tau}_{i,st}^L\right]$. In other words, misallocation occurs because, first, there is insufficient adoption of modern, high-τ^L technologies and, second, there is insufficient labor employment by firms that adopt modern, high-τ^L technologies.

4.2 Growth Accounting under Trade and Technology Adoption

We now elucidate the welfare consequences of productivity growth in the general specification of our framework. Specifically, we derive formulas for the change in welfare ($d\ln W_i$) in response to a vector of technological shocks $\{d\ln a_{i,st}\}_{s,t}$ in country i. Since preferences are homothetic, the welfare impact of a small productivity shock can be written as the change in (log) national income minus the change in the (log) consumer price index. For economy i, the corresponding welfare decomposition is given by

$$d\ln W_i = d\ln Y_i - \sum_s \sum_n \left[e_{i,s} \times \pi_{ni,s} \times d\ln p_{ni,s}\right], \tag{12}$$

where the change in prices can be expressed as $d\ln p_{ni,s} = d\ln p_{n,s}$, since our focus is on exogenous shocks to productivity holding trade costs constant—i.e., $d\ln d_{ni,s} = 0$.

Following the derivations provided in Appendix (E), the change in (log) welfare in response to a change in productivity can be specified as follows, in terms of observable shares and the general equilibrium change in wages, employments shares, and intermediate input use per worker,

$$
\begin{aligned}
d\ln W_i \;=\; & \overbrace{\sum_s \sum_t \left[e_{i,s}\pi_{ii,}\rho_{i,st} d\ln \widetilde{a}_{i,st}\right]}^{\Delta\text{Mechanical}} \;+\; \overbrace{\frac{\Gamma_i^L}{1-\Gamma_i^M} \times \mathrm{Cov}_\ell\left(\widetilde{\tau}_{i,st}^L, d\ln \ell_{i,st}\right)}^{\Delta\text{Allocative Efficiency}} \\
& + \underbrace{(1-\pi_{ii})\, d\ln w_i \;+\; \sum_{s,t}\left[\rho_{i,st}\left(\frac{1}{1-\Gamma_i^M} r_{i,s} - \pi_{ii,s} e_{i,s}\right)\gamma_{st}^Z d\ln \ell_{i,st}\right]}_{\Delta\text{Factoral Terms of Trade}},
\end{aligned}
\tag{13}
$$

where $d\ln \widetilde{a}_{i,st} \equiv d\ln a_{i,st} + \gamma_{st}^M d\ln\left(M_{i,st}/L_{i,st}\right)$ combines the direct productivity growth with the indirect effect of changing intermediate inputs per worker, and $\pi_{ii} \equiv \sum_s e_{i,s}\pi_{ii,s}$ is the aggregate domestic expenditure share.[18]

The first sum encompasses the mechanical effects of productivity growth on consumer prices and the terms of trade. As we demonstrate shortly, this term reduces to Hulten's formula in the closed economy case where mechanical terms of trade effects are absent.

The second term represents the changes in allocative efficiency in response to productivity growth. This term expectedly collapses to zero when the economy is efficient, wherein $\widetilde{\tau}_{i,st}^L = 1$ for all s and t. Otherwise, allocative efficiency improves if productivity growth relocates workers toward high-τ^L technologies and industries, i.e., $\mathrm{Cov}_\ell\left(\widetilde{\tau}_{i,st}^L, d\ln \ell_{i,st}\right) > 0$. The intuition echoes our earlier arguments that high-τ^L technologies exhibit inefficiently low employment shares. Misallocation is, therefore, mitigated if more workers are relocated to these firms, which is the case when growth is biased toward modern (high-$\widetilde{\tau}^L$) technologies. It is also worth highlighting that technology adoption typically amplifies the impact of technology growth on $d\ln \ell_{i,st}$ and, thus, misallocation.

The last two terms account for factoral terms of trade effects. The term $(1-\pi_{ii})\, d\ln w_i$ accounts for terms of trade effects that channel through general equilibrium wage adjustments. The last sum accounts for terms of trade effects that channel through adjustments to managerial rents. Intuitively, productivity growth often inflates domestic factor prices. The terms accounting for factoral terms of trade effects measure the extent to which factor price inflation is passed onto foreign versus domestic consumers. Indeed, terms of trade effects are zero in a closed economy where factor price inflation is borne entirely by domestic

[18] In the final step of deriving Equation (13), we have assumed that each country i is a small open economy, meaning that prices in the rest of the world do not respond to productivity adjustments in country i. Specifically, $d\ln p_{n,s} \approx 0$, $\forall n \neq i$. We make this assumption merely for a clearer exposition. In Section 6.1.2 where we put numbers on the components of growth account, we use the complete version of this equation which relaxes the small-open-economy assumption.

consumers——i.e., if $\pi_{ii} = 1$ and $r_{i,s}/\left(1 - \Gamma_i^M\right) = \pi_{ii,s} e_{i,s}$.

Connection to Hulten (1978). Before concluding this section, it is useful to connect our growth accounting formula to Hulten (1978), which concerns an efficient closed economy. As shown in Appendix Section (E), the mechanical term in our growth accounting formula reduces to Hulten for a closed economy. Setting $\pi_{ii,s} = 1$ for all s, Equation 13 becomes

$$d \ln W_i^{\text{Closed}} = \overbrace{\sum_s \sum_t \left[\frac{1}{1 - \Gamma_i^M} e_{i,s} \rho_{i,st} d \ln a_{i,st} \right]}^{\text{Hulten}} + \overbrace{\frac{\Gamma_i^L}{1 - \Gamma_i^M} \times \text{Cov}_\ell \left(\tilde{\tau}_{i,st}^L, d \ln \ell_{i,st} \right)}^{\Delta\text{Allocative Efficiency}},$$

where $\frac{1}{1-\Gamma_i^M} e_{i,s} \rho_{i,st} = \frac{p_{i,s} C_{i,st}}{\sum_{s',t'} p_{i,s'} Q_{i,s't'}}$ is the Domar weight associated with industry s–technology t. Putting aside misallocation, our formula provides a generalization of Hulten (1978), as our model explicitly accommodates endogenous technology choices. The allocative efficiency term in our formula is, accordingly, different than Baqaee and Farhi (2020) as the change in employment shares reflects both mechanical labor reallocation effects and reallocation via technology adoption—the extent of which depends on θ.

5 Bringing the Model to Data

This section describes how we map our model to data. To run counterfactual analyses, we simulate the general equilibrium of our model in changes based on the exact hat algebra method.[19] For this, we require only a set of sufficient statistics without needing to fully parameterize our model. Table 2 reports these sufficient statistics and their corresponding data sources. Our calibration employs these data to construct the baseline general equilibrium of our model. Below, we briefly explain our calibration strategy, relegating a more detailed discussion to Appendix .

We combine country-level data from the GTAP database with firm-level statistics and estimates obtained from the WBES data. From the GTAP database, we take global flows from each origin country-industry to each destination country-industry (including domestic flows), as well as value added shares, in the year 2014. From the WBES, we use our estimates of technology-specific labor wedges and elasticities of output with respect to labor (as reported in Section 2), and the share of modern firms in each country.[20] Our final sample consists

[19] Appendix F.3 describes our model equilibrium in changes, and the numerical algorithm that we employ to simulate it.

[20] By and large, our focus is on manufacturing. The WBES data, also, inform us only about manufacturing industries. Consequently, we collapse each of our non-manufacturing industries (agriculture, mining, and services) into only one technology type. To set labor wedges in non-manufacturing, we use their averages across the two manufacturing technologies. We take all other information for the non-manufacturing industries

of 99 countries, covering a wide range of geographical locations and national income levels, plus an aggregate of the rest-of-the-world; and 14 industries consisting of 11 manufacturing and 3 non-manufacturing industries.

Table 2: Sufficient Statistics

Parameter	Value / Source
Trade elasticity, $(\sigma_s - 1)$	3.0 (Simonovska-Waugh, 2014)
Technology elasticity, θ	4.5 (Farrokhi-Pellegrina, 2022)
Share of modern firms	Clustering, based on WBES
Labor wedges	Estimates, based on WBES
Labor intensity parameters	Estimates, based on WBES
Other intensity parameters	Based on GTAP and WBES
Expenditures, sales, trade, input-output flows	Based on GTAP

Notes: This table reports the set of sufficient statistics, and their data sources, that we employ to calculate counterfactual changes in our general equilibrium model.

We set the trade elasticity, $(\sigma - 1)$, to 3 in line with available estimates in the literature (Simonovska and Waugh (2014), Imbs and Mejean (2015)). We borrow the value assigned to the technology elasticity, θ, from Farrokhi and Pellegrina (2022) who estimate a comparable elasticity parameter for the agriculture sector.

6 Quantitative Analyses

This section presents two sets of quantitative exercises that shed light on the interplay between labor market distortions, technology adoption, and trade. First, we put numbers on the welfare cost of misallocation and perform growth accounting based on the formulas in Section 4. Second, we run set of counterfactual exercises to study how labor market distortions, and their interaction with technology adoption, alter the gains from trade for workers in developing countries.

6.1 Quantifying Misallocation and Growth Accounting

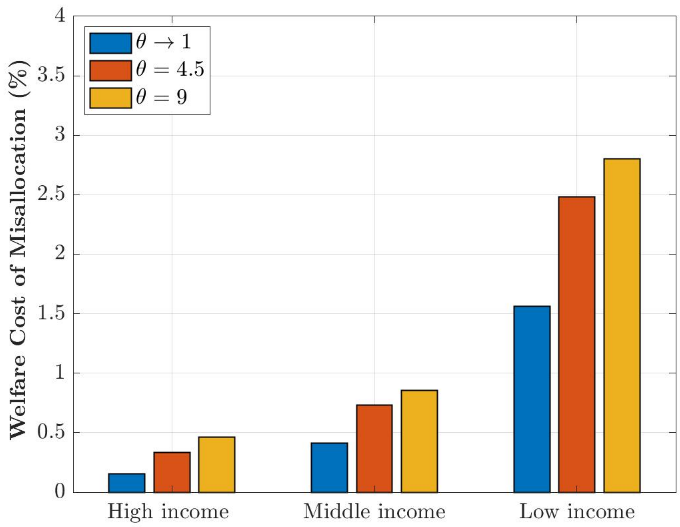
6.1.1 Misallocation

Following Section 4.1, the welfare cost of labor market distortions can be characterized as the distance to the Pareto-efficient frontier for a closed economy. To quantify an economy's distance to the efficient frontier (if it was hypothetically a closed economy), requires two

from the GTAP database, with no need for more disaggregated data.

counterfactuals. First, we move economies to autarky by raising trade costs to infinity. Second, in addition to moving economies to autarky, we eliminate their labor market wedges. The difference between these two counterfactual outcomes maps to the welfare cost of misallocation *if* countries were operating as closed economies.

Figure 4: Welfare Costs of Misallocation—Closed Economies



Notes: This figure shows the welfare cost of misallocation as the percentage change to welfare of nations when they are counterfactually moved to autarky. It reports the outcomes by taking the averages across countries of the high-, middle-, and low-income groups of countries, and it shows them for alternative values of the trade elasticity, θ, below and above the baseline value of 4.5. For a detailed analytical discussion, see Section 4.1.

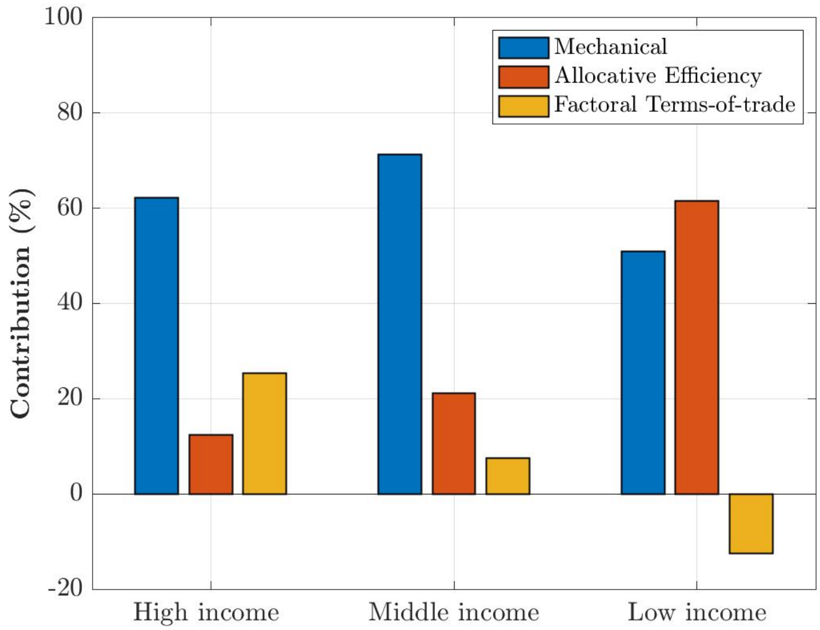
Figure 4 shows the results by averaging across countries in the high, middle, and low-income groups.[21] We find that the welfare cost of misallocation is around ten-times larger in low-income countries relative to their high-income counterparts, reflecting the fact the cross-technology dispersion in labor market wedges is higher in low-income countries. The same figure reveals that a higher technology elasticity, θ, magnifies the welfare cost of misallocation, underscoring the crucial role of technology adoption as in Equation (11).[22,23]

[21] Specifically, high-, middle-, and low-income groups of countries correspond to the top, middle, and bottom one-third of the distribution of countries sorted in terms of their GDP per capita.

[22] Note that our baseline value is 4.5, and $\theta \to 1$ corresponds to the lowest admissible value at which the aggregate supply of managerial capital would become fixed across the technologies.

[23] In addition, Appendix Figure A.3 reports the percentage change to welfare of nations when we counterfactually eliminate their labor market wedges starting from our baseline equilibrium—in which economies are open to trade. Because of terms-of-trade effects these results do not necessarily correspond to an economy's distance to the Pareto frontier. However, we find that also in the case of open economies the welfare gains from the elimination of labor market wedges remain to be comparably larger for low-income countries.

Figure 5: Growth Accounting—Open Economies



Notes: This figure shows the decomposition of growth in modern manufacturing industries into the three components of mechanical, allocative efficiency, and factoral terms of trade effects. We shock each country with one percent change increase in the TFP of modern manufacturing industries, one at a time, and report results by taking averages across countries of the high-, middle-, and low-income groups of countries.

6.1.2 Growth Accounting

As shown in Section 4, the welfare implications of productivity growth can be decomposed into mechanical, allocative efficiency, and factoral terms-of-trade effects. Our growth accounting formula (Equation 13) allows us to measure these components with information on baseline shares (for which we have data) and general equilibrium changes to factor rewards and allocations (which we can numerically solve for). Here, we are interested in measuring the impacts of productivity growth in only modern technologies. Accordingly, we simulate changes in general equilibrium variables in response to a country-specific modern technology TFP growth within manufacturing industries, keeping productivity levels in the rest of the world unchanged. We perform this exercise separately for each of the 99 countries in our sample. Since our formula is a first-order approximation, we consider the shock to be small—namely, one percentage increase in the TFP of modern manufacturing industries. We then calculate and report the average effects for countries in the high, middle, and low-income groups.

Figure 5 shows our decomposition results. We draw two key takeaways. First, the contribution of (improved) allocative efficiency is particularly large in low-income countries,

Table 3: Design of Counterfactual Experiment

		Trade Barriers High	*Trade Barriers* Low
Labor Wedges	High	E_0	E_1
	Low	E_0'	E_1'

amounting to more than 60% of their welfare gains from modern manufacturing growth. In comparison, the corresponding contributions in middle and high-income countries are 21% and 12%. Intuitively, modern firms face relatively larger labor market wedges in low-income countries, leading to inefficiently low shares of modern firms. A productivity growth that applies to modern technologies improves allocative efficiency as it increases modern technology adoption and relocates more workers to modern firms—with the impact being more pronounced, the more distorted the baseline economy.

Second, factoral terms-of-trade effects tend to fall with countries' income levels and even contribute negatively to welfare in low-income countries. These impacts are driven mainly by changes to relative wages in response to modern productivity growth. First, an expansion of modern firms can contract the demand for labor since modern technologies are labor-saving and subject to larger labor wedges—particularly in low-income countries. Second, there is more scope for modernization in low-income countries, given their initial technology profile. As a result, modernization often deflates a low-income country's wage rate relative to the rest of the world, deteriorating its terms of trade.

6.2 Counterfactual Exercises

We now return to one of the key questions motivating our research: How do labor market distortions shape the gains from trade integration for workers in low-income countries?

We begin by designing counterfactual experiments that address to this question. Consider a *trade shock* that corresponds to a uniform 20% reduction in manufacturing trade costs in low-income countries, for imports and exports. In addition, consider a *development shock* that corresponds to lowering labor market wedges in low-income countries to the average levels observed in middle-income countries. Based on our estimates from Section 2, the development shock reduces labor wedge by (on average) 24% and 43% for traditional and modern firms in low-income countries.

With these shocks in mind, consider Table 3. Case E_0 refers to the baseline equilibrium, calibrated to actual data. The other three cases correspond to counterfactual equilibria, which we quantitatively simulate. E_1 denotes the counterfactual equilibrium under the *trade* *shock*, E_0' denotes the counterfactual equilibrium under the *development shock*, and E_1' denotes the counterfactual equilibrium under the *trade shock* and *development shock*. We are interested in comparing the outcomes between:

$$(\text{Scenario } \mathbf{I} : E_0 \to E_1) \quad \text{vs} \quad (\text{Scenario } \mathbf{II} : E_0' \to E_1')\,.$$

Scenario **I** measures the impact of the trade shock on low-income countries at their status-quo level of distortion, and Scenario **II** measures the impact of the trade shock when distortion in these economies is counterfactually lowered to mirror middle-income countries. We are primarily interested in the impact of trade cost reductions on the real wage of workers and how the effects would differ if low-income countries were less-distorted.

Table 4: Percentage Changes to Selected Variables in Response to Trade and/or Development Shocks in Low-income Countries

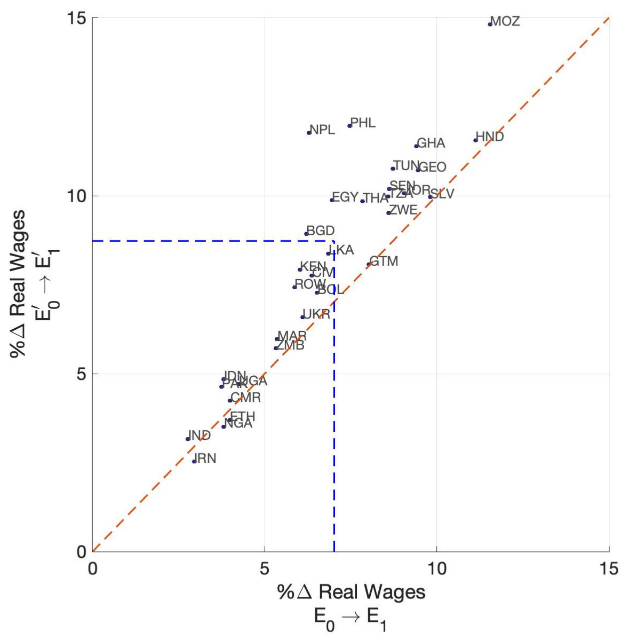
	Scenario **I**			Scenario **II**
	Trade Shock	Development Shock	Trade and Development Shock	Column (3) minus Column (2)
	(1)	(2)	(3)	(4)
Real Wages	7.0	19.3	28.0	8.7
Real Rents and Distortion Revenues	7.7	-2.2	4.8	7.0
Share of Manuf. Modern Firms	8.7	59.8	64.9	5.1
Manuf. Employment	-5.2	-6.0	-11.0	-5.1
Manuf. Avg. Labor Intensity	-1.8	-4.3	-5.3	-1.0

Notes: This table shows the average percentage change to selected variables in low-income countries in response to the trade shock and/or development shock in line with our design of counterfactual Scenarios I and II. For details, see the text.

Table 4 reports the average change to key variables under scenarios **I** and **II**. Column (A) reports the impact of the trade shock, which corresponds to scenario **I**. Column (B) reports the impact of the development shock. Column (C) reports the impact of a trade shock in conjunction with a development shock. By calculating the difference between Columns (C) and (B), Column (D) maps to scenario **II**—which is the impact of the trade shock when labor wedges in low-income countries are counterfactually lowered to the average levels observed in middle-income countries.

The first row of Table 4 reveals that average real wage gains are 7.0% at the currently-high levels of distortion (Scenario **I**) and 8.7% at the counterfactually-low levels of distortion (Scenario **II**). That is, if labor wedges in low-income countries were similar to a typical middle-income country, their workers would (on average) experience 1.7 percentage points larger gains from trade or, equivalently, 24% more. In other words, the excessive labor market distortions in low-income countries are eroding one-fourth of the potential real wage gains.

Figure 6: Real Wages—Impact of Trade in Low-income Countries: High- vs Low-Wedge

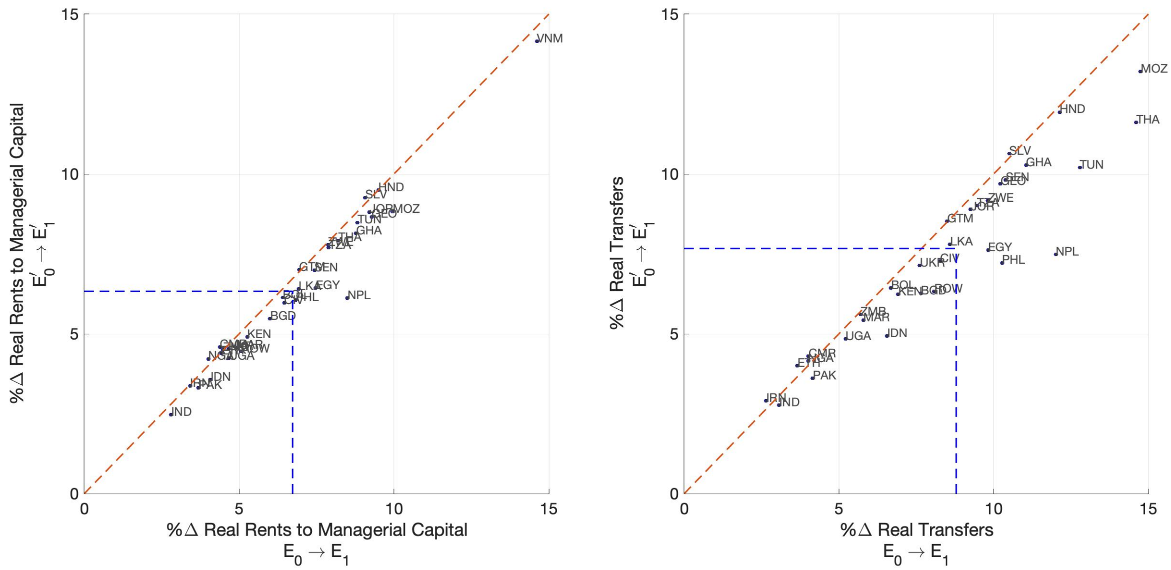


Notes: This figure shows the percentage change to real wages across low-income countries in Scenario I (x-axis) that corresponds to status quo labor wedges in low-income countries, and in Scenario II (y-axis) that corresponds to counterfactually less-distorted labor markets in low-income countries.

This result is driven by two main factors. First, trade integration favors modern (high-wedge) technologies that make intensive use of imported intermediate inputs. So, absent adjustments to technology adoption, demand for workers falls relatively more in response to trade integration in distorted economies. The reason is that, in these economies, modern firms pay a higher fraction of their sales to wedges and a lower fraction to workers. This effect is also manifested in the larger increase in managerial rents and distortion revenues under Scenario **I** than in Scenario **II** (2nd row of Table 4). Second, the rate of modern technology adoption is larger under Scenario **I** than in Scenario **II**. And a greater rate of modern technology adoption attenuates real wage gains since modern technologies are both labor-saving and have greater exposure to labor wedges. To provide numbers, the impact on manufacturing employment is virtually the same between the two scenarios (4th row), but when economies are more distorted, the same trade shock prompts a greater extent of manufacturing modernization: The share of modern firms rises by 8.7% in Scenario **I** and by 5.1% in Scenario **II** (3rd row)—which, in turn, attenuates real wage gains (last row).

Figure 7: Real Rents and Distortion Revenues—Impact of Trade in Low-income Countries: High- vs Low-Wedge

(a) Real Rents to Managerial Capital (b) Real Distortion Revenues



Notes: This figure shows the percentage change to real rents to managerial capital and distortion revenues across low-income countries in Scenario I (x-axis) that corresponds to status quo labor wedges in low-income countries, and in Scenario II (y-axis) that corresponds to counterfactually less-distorted labor markets in low-income countries.

We additionally report our results for individual (low-income) countries in Figure 6. The horizontal axis shows the percentage change to real wages in each low-income country in response to the trade shock at the currently-high labor wedges, which maps to (Scenario $\mathbf{I} : E_0 \rightarrow E_1$). The vertical axis shows the outcome at the counterfactually-low labor wedges, which maps to (Scenario $\mathbf{II} : E'_0 \rightarrow E'_1$). For virtually all low-income countries, the real wage gains from trade integration are higher when there are lower labor market distortions.

We next report, for each of the low-income countries, the implications for real rents to managerial capital and distortion revenues (Figure 7). In both cases—and, in contrast to real wages—, the impact of the trade shock becomes milder when labor wedges are low. Notice that, at counterfactually-low labor wedges, a higher share of firms use modern technologies. In turn, modern technologies have a higher span-of-control reflected by their lower cost share of managerial capital. When the reduction in the cost share of managerial capital is stronger than the increase in total sales, the rents to managerial capital will tend to decline. Similarly, real distortion revenues rise to a lower extent in less distorted economies where there are less payments associated with labor wedges. The figure shows that the averages that we reported earlier are not driven by a subset of observations, and the impacts which we discussed hold virtually across all low-income countries.

In sum, we find that real wage gains from globalization would be notably larger in low-income countries if labor markets were less distorted there. These results, in addition, highlight that the interaction between labor wedge corrections and trade cost reductions raises real wages by reducing rents to managerial capital and particularly by reducing distortion revenues. For welfare—as the sum of real wages, real managerial rents, and real distortion revenues—, we find the impact to be slightly larger in the case of currently-high wedges versus counterfactually-low wedges (Appendix Figure A.4).

Overall, our findings underscore the distributional implications of trade in developing countries. Specifically, trade would reduce inequality between workers and managers/bureaucrats if developing countries featured less distortions in their labor markets.

7 Conclusion

In this paper, we studied how labor market imperfections distort firm-level technology choices and alter the distribution of the gains from trade. We began our analysis by compiling detailed firm-level data from many countries, classifying firms into modern and traditional technologies. We estimated labor intensity parameters and labor market distortions for firms using traditional and modern technologies. Our estimation revealed that labor market distortions are larger for firms employing modern technologies and substantially more so in low-income countries. Motivated by this empirical pattern, we introduced labor market distortions and technology choices into a multi-country, quantitative trade model. We provided analytical expressions highlighting how the cost of misallocation is shaped by distorted technology choices and the broad mechanisms that drive the welfare impact of productivity growth. Using counterfactual simulations, we studied the distributional implications of trade liberalization on workers and non-labor inputs.

There are two key takeaways from our findings. First, the low adoption of modern technologies, a topic of much debate among researchers and policymakers, can be partly attributed to labor-market distortions. Our results indicate that firms employing modern technologies face significantly larger labor market distortions in low-income countries. Our approach is agnostic about the specific institutional mechanisms that generate such large distortions. Future research could shed light on how specific mechanisms interact with technology adoption, for example, by studying the impact of search frictions in labor markets or the costs of moving firms out of informality.

Second, labor market distortions can substantially reduce the gains from trade accruing to workers. This is an important result for several reasons. First, recent research has studied how the gains from trade are amplified or attenuated by misallocation. We find that these results depend substantially on which group in the economy we are analyzing. At another level, researchers have been particularly concerned about the implications of technology upgrading for workers, given the stagnation of aggregate labor productivity in many countries. Our results suggest that reductions in labor market distortions, a ubiquitous feature of developing economies, can substantially increase how much workers benefit from trade-led growth in modern technologies.

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A Data

Firm-level data. The World Bank Enterprise Survey is a firm-level survey, conducted in more than 150 countries since 2005 and 2006, that covers topics about the business environment, including questions about corruption, competition, bribery, and bureaucracy. There is a global methodology that has been developed to make questions comparable across countries.

The World Bank provides a unified data set, containing information on the total cost of labor—including measures such as wages, salaries, and bonuses—, the total cost for the firm to re-purchasing all of its machinery, and the cost of all raw materials and intermediate inputs used in production.[24] In addition, this data set provides firm-level information on total sales. All of these variables are deflated according to US dollars as of 2009. Using these data, we construct the ratio of the cost of labor, capital, and intermediate inputs with respect to total sales.

The unified data set provided by WBES, however, does not include the questions about business environment, which we use to construct Table 1 in the main body of the paper. We have therefore collected and harmonized all the surveys available from WBES, country by country, to construct a unified data with information on the business environment of firms in countries at different levels of economic development. Specifically, we construct five measures of market distortions at the firm level. First, a measure of percentage of total sales that is lost due to theft. We add to this measure: (i) the percentage of total sales that are paid in informal payments; (ii) the percentage of losses due to bribery, robbery, and vandalism; and (iii) the percentage of total sales that are paid for security. Second, a measure of the percentage of time that managers spent dealing with government regulation. Third, an indicator variable as to whether labor market regulations are a large obstacle for the firm's business. Fourth, an indicator variable as to whether tax rates are a large obstacle for the firms' business. Fifth, whether the practice of competitors in the informal market is a large obstacle for the firms' business.[25]

B Complementary Empirical Patterns

Complementary Pattern 1. Larger firms have a lower cost share of labor and a higher cost share of materials.

Panel (a) in Appendix Figure A.2 paper presents a statistically strong and positive relationship between firm size and the cost share of labor. Panel (b) shows a negative relationship instead between the cost share of intermediate inputs and the size of the firms. These patterns are consistent with the hypothesis that more productive firms tend to adopt more advanced technologies, which are both labor-saving and more intensive in the use of intermediate inputs—which raises their exposure to trade via imports of intermediate goods.

Complementary Pattern 2. Modern firms use labor less intensively than traditional firms. Alternative approaches.

Table A.1 presents a series of alternative estimates of the elasticity of output with respect to labor, which we interchangeably call labor intensity. We experiment with different control functions, different criteria to classify firms into modern and traditional, and also with using total costs instead of total sales for the classification. Results show that, irrespective of the approach that we use for estimation, we systematically find a substantially lower labor intensity for modern firms, relative to traditional firms. Additionally, Figure A.1 presents the case in which we split firms

[24]We construct the total payment to capital by multiplying the total cost for the firm to re-purchase all of its machinery by an interest rate of 10%.

[25]Each of these indicator variables are provided in five categories in the original data, scaled in terms of how much the firm consider that issue a large obstacle for business. We convert this categorical variable into an indicator variable whether firms consider that issue a moderate or larger obstacle for the firm.

into three technological types, instead of two. Across different approaches for the classification of firms' technology and specifications for the estimation of the labor intensity, we systematically find a notably lower labor intensity in modern, larger firms, relative to the traditional, smaller ones.

Complementary Pattern 3. Labor wedges are larger for modern firms, and significantly more so in less developed economies. Alternative approaches.

Table A.2 reports results for alternative estimates of labor market wedges, following the specifications used in Table A.1. Based on Figure 2 in the main body of the paper, for each alternative specification in the estimation of labor intensity, we run a regression of the labor wedge against an indicator variable for modern technology classification, an interaction term between the log of GDP per capita of the country and the modern technology indicator, and country and industry fixed effects. The regressions show that, across different specifications, the labor market wedge is systematically larger for modern firms. In addition, the richer the country is, the smaller the labor market wedge of modern firms.

C Details of the Analytical Results

C.1 Relationship between α, ρ, and ℓ

This appendix derives expressions for revenue shares ($\rho_{i,st}$) and labor shares ($\ell_{i,st}$) as a function of $\alpha_{i,st}$, which is the share of firms that chose technology t in country i–industry s. To fix idea, we formally define the aforementioned share variables. The labor shares are defined as follows for various tiers of production (i.e., firm, technology, and industry)

$$\ell_{i,st}(\omega) = \frac{L_{i,st}(\omega)}{L_i}; \qquad \ell_{i,st} = \sum_{\omega \in \Omega_{i,st}} \ell_{i,st}(\omega); \qquad \ell_{i,s} = \sum_t \ell_{i,st}.$$

We use ρ to denote *within-industry* revenue shares and r to denote industry-level revenue share. In particular,

$$\rho_{i,st}(\omega) = \frac{R_{i,s}(\omega)}{R_{i,s}}; \qquad \rho_{i,st} = \int \rho_{i,st}(\omega)\, dF(\omega | \omega \in \Omega_{st}); \qquad r_{i,s} = \sum_t \rho_{i,st}$$

where $R_{i,st}(\omega) \equiv p_{i,s} Q_{i,st}(\omega)$, recall, denotes total revenues collected by firm ω, with $R_{i,s} \equiv \sum_t \int_\omega R_{i,st}(\omega)\, dF(\omega|\omega \in \Omega_{st})$ denoting industry-level revenues. Appealing to Equations 2 and 3 we can derive the following relationship between firm and sales shares:

$$\begin{cases} \alpha_{i,st} = \left(a_{i,st} h_{i,st} / \tilde{\tau}^L_{i,st}\right)^\theta H_{i,s}^{-\theta} \\ p_{i,s} = \left(\frac{\tilde{\tau}_{i,st}}{a_{i,st} h_{i,st}}\right) \alpha_{i,st}^{\frac{1-\theta}{\theta}} \gamma^Z_{st} \rho_{i,st} R_{i,s} \end{cases} \implies \qquad \frac{\alpha_{i,st}}{\alpha_{i,st'}} = \frac{\gamma^Z_{st} \rho_{i,st}}{\gamma^Z_{st'} \rho_{i,st'}}$$

Combining the above equation with the adding up constraints, $\sum_t \rho_{i,st} = \sum_t \alpha_{i,st} = 1$, yields

$$\rho_{i,st} = \frac{\frac{1}{\gamma^Z_{st}} \alpha_{i,st}}{\sum_{t'} \frac{1}{\gamma^Z_{st'}} \alpha_{i,st'}} = \frac{\Gamma^Z_{is}}{\gamma^Z_{st}} \alpha_{i,st}, \qquad \text{where} \qquad \frac{1}{\Gamma^Z_{is}} = \sum_t \frac{1}{\gamma^Z_{i,st}} \alpha_{i,st}.$$

To derive a relationship between labor shares and firm shares, we appeal to the fact that gross labor cost equals a constant fraction, γ_{st}^L, of gross revenues. In particular,

$$\tau_{i,st}^L w_i \times \overbrace{L_{i,st}}^{\ell_{i,st}L_i} = \gamma_{st}^L \times \overbrace{Y_{i,st}}^{\rho_{i,st}Y_{i,s}} \qquad \Longrightarrow \qquad \frac{\ell_{i,st}}{\ell_{i,st'}} = \frac{\frac{\gamma_{st}^L}{\tau_{i,st}^L}\rho_{i,st}}{\frac{\gamma_{st'}^L}{\tau_{i,st'}^L}\rho_{i,st'}} = \frac{\frac{\gamma_{st}^L}{\tau_{i,st}^L\gamma_{st}^Z}\alpha_{i,st}}{\frac{\gamma_{st}^L}{\tau_{i,st}^L\gamma_{st}^Z}\alpha_{i,st'}}.$$

Combining this equation with the adding up constraints, $\sum_t \ell_{i,st} = \ell_{i,s}$ and $\sum_t \alpha_{i,st} = 1$, delivers

$$\ell_{i,st} = \frac{\frac{\gamma_{st}^L}{\tau_{i,st}^L\gamma_{st}^Z}\alpha_{i,st}}{\sum_{t'}\frac{\gamma_{st'}^L}{\tau_{i,st'}^L\gamma_{st'}^Z}\alpha_{i,st'}}\ell_{i,s}; \qquad \qquad \ell_{i,st} = \frac{\frac{\gamma_{st}^L}{\tau_{i,st}^L}\rho_{i,st}}{\sum_{t'}\frac{\gamma_{st'}^L}{\tau_{i,st'}^L}\rho_{i,st'}}.$$

D The Welfare Cost of Misallocation

Consider the closed economy case of our model with one sector and multiple technologies—noting that, with a reinterpretation of indexes, our derivation extends to multiple sectors and technologies. We, accordingly, condense the notation by dropping the industry subscript, s, going forward. To provide closed-form formulas for the degree of misallocation, we make two additional assumptions: First, we assume that production employs only primary factors of production—namely, labor and managerial capital. Second, we assume that the labor intensity parameter, $\gamma_{i,t}^L$, is common across technologies. All in all, we consider a closed economy where production can be conducted under multiple technologies with different labor input wedges, with firms having the ability to choose and adjust their preferred technology.

Intermediate Definitions. The efficient allocation in this stylized version of our model is achieved if labor input wedges and the revenue associated with them are eliminated from the economy—which is akin to analyzing the following shock:

$$\hat{\tau}_{i,t}^L = \frac{1}{\tau_{i,t}^L}; \qquad \qquad \forall t \in \mathbb{T}.$$

Let $\hat{W}_i(\hat{\boldsymbol{\tau}}_i)$ denote the resulting welfare change from the wedge reduction shock, $\hat{\boldsymbol{\tau}}_i \equiv \left\{\tau_{i,t}^L\right\}$. We define the *degree of misallocation* ($\mathcal{D}_i$) as the welfare distance between the decentralized (i.e, misallocated) and the efficient economies. Namely,

$$\mathcal{D}_i \equiv \log \hat{W}_i(\hat{\boldsymbol{\tau}}_i) = \log \hat{Y}_i(\hat{\boldsymbol{\tau}}_i) - \log \hat{P}_i(\hat{\boldsymbol{\tau}}_i).$$

The Change in Technology Composition. Considering our assumption that $\gamma_{i,t}^L = \gamma_{i,t'}^L = \gamma_i^L$ and $\gamma_{i,t}^Z = \gamma_{i,t'}^Z = \gamma_i^Z$ for all t and t', we can specify the change in the share of firms choosing technology t as

$$\hat{\alpha}_{i,t} = \frac{\left(\hat{\tau}_{i,t}^L\right)^{-\frac{\gamma_i^L}{\gamma_i^Z}\theta}}{\sum_{t'}\alpha_{i,t'}\left(\hat{\tau}_{i,t'}^L\right)^{-\frac{\gamma_i^L}{\gamma_i^Z}\theta}} = \frac{\left(\tau_{i,t}^L\right)^{\frac{\gamma_i^L}{\gamma_i^Z}\theta}}{\sum_{t'}\alpha_{i,t'}\left(\tau_{i,t'}^L\right)^{\frac{\gamma_i^L}{\gamma_i^Z}\theta}}.$$

Appealing to the above expression, we can characterize the change in technology-level employment shares. For this, we invoke the relationships derived in Appendix C.1 to arrive at

$$\rho_{i,t} = \alpha_{i,t}; \qquad \ell_{i,t} = \frac{\frac{1}{\tau_{i,t}^L}\alpha_{i,t}}{\sum_{t'}\frac{1}{\tau_{i,t'}^L}\alpha_{i,t'}}; \qquad \alpha_{i,t} = \frac{\tau_{i,t}^L \ell_{i,t}}{\sum_{t'}\tau_{i,t'}^L \ell_{i,t'}}. \tag{D.1}$$

Notice that in the efficient, wedge-free equilibrium, employment and revenue shares exactly coincide with firm shares (i.e., $\ell'_{i,t} = \rho'_{i,t} = \alpha'{}_{i,t}$), yielding the following expression for technology-level employment shares in the counterfactual wedge-free equilibrium:

$$\begin{aligned}\ell'_{i,t} = \alpha'_{i,t} &= \frac{\alpha_{i,t}\left(\tau_{i,t}^L\right)^{\frac{\gamma_i^L}{\gamma_i^Z}\theta}}{\sum_{t'}\alpha_{i,t'}\left(\tau_{i,t'}^L\right)^{\frac{\gamma_i^L}{1-\gamma_i^L}\theta}}.\\ &= \frac{\alpha_{i,t}\left(\tau_{i,t}^L\right)^{\frac{\gamma_i^L}{\gamma_i^Z}\theta}}{\sum_{t'}\alpha_{i,t'}\left(\tau_{i,t'}^L\right)^{\frac{\gamma_i^L}{\gamma_i^Z}\theta}} = \frac{\tau_{i,t}^L\ell_{i,t}\left(\tau_{i,t}^L\right)^{\frac{\gamma_i^L}{\gamma_i^Z}\theta}}{\sum_{t'}\tau_{i,t'}^L\ell_{i,t'}\left(\tau_{i,t'}^L\right)^{\frac{\gamma_i^L}{\gamma_i^Z}\theta}}.\end{aligned}$$

The Change in Nominal Income. In the decentralized (baseline) economy, nominal income in country i is the sum of wage income, managerial rents, and wedge revenues—i.e., $Y_i = w_iL_i + \Pi_i + T_i$. Noting that $w_iL_i + T_i = \sum_t \tau_{i,t}^L w_i L_{i,t}$ and that by cost minimization, $\Pi_i = \sum_t \frac{\gamma_i^Z}{\gamma_i^L}\tau_{i,t}^L w_i L_{i,t}$, we can specify the nominal income in the baseline economy as

$$\begin{aligned}Y_i &= \sum_t \left[\left(\tau_{i,t}^L + \frac{\Pi_{i,t}}{w_iL_{i,t}}\right)\frac{L_{i,t}}{L_i}\right] w_iL_i\\ &= \sum_t \left[\tau_{i,t}^L\left(1+\frac{\gamma_i^Z}{\gamma_i^L}\right)\frac{L_{i,t}}{L_i}\right] w_iL_i = \sum_t\left[\frac{\tau_{i,t}^L}{\gamma_i^L}\ell_{i,t}\right] w_iL_i.\end{aligned}$$

Invoking the same logic, nominal income in the efficient (counterfactual) economy is $Y'_i = \sum_t \left[\frac{1}{\gamma_i^L}\ell'_{i,t}\right] w'_iL_i$. Combining the expressions for Y_i and Y'_i and assigning labor in country i as the numeraire ($w'_i = w_i = 1$) deliver the following expression for the change in nominal income in country i:

$$\hat{Y}_i = \frac{\frac{1}{\gamma_i^L}\sum_t\left[\ell'_{i,t}\right] w'_iL_i}{\frac{1}{\gamma_i^L}\sum_t\left[\tau_{i,t}^L\ell_{i,t}\right] w_iL_i} = \frac{1}{\sum_t\left[\tau_{i,t}^L\ell_{i,t}\right]}.$$

Finally, appealing to our short-hand notation for weighted means, $\mathbb{E}_\ell\left[\tau_{i,t}^L\right] = \sum_t\left[\tau_{i,t}^L\ell_{i,t}\right]$, we can express the change in log income as:

$$\hat{Y}_i \equiv \mathbb{E}_\ell\left[\tau_{i,t}^L\right]^{-1} \tag{D.2}$$

The Change in Consumer Prices. Following Equation (3) in Section 3, the change in the competitive price of goods produced via technology t is

$$\hat{p}_i = \hat{Y}_i \times \left(\hat{H}_i\right)^{-1}, \tag{D.3}$$

where the above equation uses two features of our stylized model: First, $\hat{\Gamma}_i^Z = 1$, since factor intensities are the same across technologies. Second, gross output, R_i, equals value added, Y_i, since no intermediate inputs are used in production—and, hence, in a one-sector economy $R_i = Y_i$ delivers national income. By choice of numeraire, $\hat{w}_i = 1$, and using Equation (1), we can express the change in H_i as:

$$\hat{H}_i = \sum_t \left[\alpha_{i,t} \left(\hat{p}_i / \hat{\tau}_{i,t}^L \right)^{\frac{\gamma_i^L}{\gamma_i^Z}\theta} \right]^{\frac{1}{\theta}} = (\hat{p}_i)^{\frac{\gamma_i^L}{\gamma_i^Z}} \sum_t \left[\alpha_{i,t} \left(\tau_{i,t}^L \right)^{\frac{\gamma_i^L}{\gamma_i^Z}\theta} \right]^{\frac{1}{\theta}}$$

Plugging the above expression back into Equation (D.3) yields

$$\hat{p}_i = \left[\sum_t \alpha_{i,t} \left(\tau_{i,t}^L \right)^{\frac{\gamma_i^L}{\gamma_i^Z}\theta} \right]^{-\frac{\gamma_i^Z}{\theta}} \left(\hat{Y}_i \right)^{\gamma_i^Z}.$$

Using our short-hand notation for means, whereby $\mathbb{E}_\alpha \left[\left(\tau_{i,t}^L \right)^{\frac{\gamma_i^L}{\gamma_i^Z}\theta} \right] = \sum_{t'} \left[\alpha_{i,t'} \left(\tau_{i,t'}^L \right)^{\frac{\gamma_i^L \theta}{\gamma_i^Z}} \right]$ and noting that $\hat{Y}_i = \mathbb{E}_\ell \left[\tau_{i,t}^L \right]^{-1}$ (Equation D.2), we get

$$\hat{p}_i = \mathbb{E}_\alpha \left[\left(\tau_{i,t}^L \right)^{\frac{\gamma_i^L}{\gamma_i^Z}\theta} \right]^{-\frac{\gamma_i^Z}{\theta}} \times \mathbb{E}_\ell \left[\tau_{i,t}^L \right]^{-\gamma_i^Z},$$

where the first mean on the right-hand side can be converted from an α-weighted mean to an ℓ-weighted mean by noticing that $\alpha_{i,t} = \tau_{i,t} \ell_{i,t} / \mathbb{E}_\ell [\tau_{i,t}]$. Specifically,

$$\mathbb{E}_\alpha \left[\left(\tau_{i,t}^L \right)^{\frac{\gamma_i^L}{\gamma_i^Z}\theta} \right]^{-\frac{\gamma_i^Z}{\theta}} = \mathbb{E}_\ell \left[\left(\tau_{i,t}^L \right)^{1+\frac{\gamma_i^L}{\gamma_i^Z}\theta} \right]^{-\frac{\gamma_i^Z}{\theta}} \mathbb{E}_\ell \left[\tau_{i,t}^L \right]^{\frac{\gamma_i^Z}{\theta}},$$

which when plugged into our last expression for $\hat{p}_i$, yields

$$\hat{p}_i = \left(\mathbb{E}_\ell \left[\left(\tau_{i,t}^L \right)^{1+\frac{\gamma_i^L}{\gamma_i^Z}\theta} \right] \times \mathbb{E}_\ell \left[\tau_{i,t}^L \right]^{\theta - 1} \right)^{-\frac{\gamma_i^Z}{\theta}}. \tag{D.4}$$

Assembling the Pieces Together. The final step collects the expressions for $\hat{Y}_i$ (Equation D.2) and $\hat{p}_i$ (Equation D.4), to calculate the degree of misallocation, $\mathcal{D}_i = \log \hat{Y}_i - \log \hat{P}_i$. Doing so and rearranging the terms delivers,

$$\begin{aligned}
\frac{\hat{Y}_i}{\hat{p}_i} &= \frac{1}{\mathbb{E}_\ell \left[\tau_{i,t}^L \right]} \left(\mathbb{E}_\ell \left[\left(\tau_{i,t}^L \right)^{1+\frac{\gamma_i^L}{\gamma_i^Z}\theta} \right] \times \mathbb{E}_\ell \left[\tau_{i,t}^L \right]^{\theta - 1} \right)^{\frac{\gamma_i^Z}{\theta}} \\
&= \left(\frac{\mathbb{E}_\ell \left[\left(\tau_{i,t}^L \right)^{1+\frac{\gamma_i^L}{\gamma_i^Z}\theta} \right]}{\mathbb{E}_\ell \left[\tau_{i,t}^L \right]^{1+\frac{\gamma_i^L}{\gamma_i^Z}\theta}} \right)^{\frac{\gamma_i^Z}{\theta}} = \mathbb{E}_\ell \left[\left(\tilde{\tau}_{i,t}^L \right)^{1+\frac{\gamma_i^L}{\gamma_i^Z}\theta} \right]^{\frac{\gamma_i^Z}{\theta}},
\end{aligned}$$

where, recall that, $\tilde{\tau}_{i,t} \equiv \tau_{i,t} / \mathbb{E}_\ell [\tau_{i,t}]$.

Next, we reintroduce the sector subscript, s, for consistency in notation, and substitute γ_i^L and

γ_i^Z with average Γ_i^L and Γ_i^Z, which denote average input intensities—noting that the average input intensity in country i is the same as the technology-level intensity in the simple model we consider. With these amendments to the notation, we get the following expression for the welfare cost of misallocation:

$$\mathcal{D}_i = \mathbb{E}_\ell\left[\left(\tilde{\tau}_{i,st}^L\right)^{1+\frac{\Gamma_i^L}{\Gamma_i^Z}\theta}\right]^{\frac{\Gamma_i^Z}{\theta}}. \tag{D.5}$$

Approximate Formula. Next, we derive a simple approximation for $\mathcal{D}_i$ using Taylor's Theorem. To this end, we construct the Taylor expansion of the following function,

$$f\left(\left\{\tilde{\tau}_{i,st}^L\right\}_t\right) = \mathbb{E}_\ell\left[\left(\tilde{\tau}_{i,st}^L\right)^{1+\frac{\Gamma_i^L}{\Gamma_i^Z}\theta}\right],$$

around $\left\{\tilde{\tau}_{i,st}^L\right\}_t = \left\{\mathbb{E}_\ell\left[\tilde{\tau}_{i,st}^L\right], ..., \mathbb{E}_\ell\left[\tilde{\tau}_{i,st}^L\right]\right\}$, which delivers the following second-order approximation

$$\mathbb{E}_\ell\left[\left(\tilde{\tau}_{i,st}^L\right)^{1+\frac{\Gamma_i^L}{\Gamma_i^Z}\theta}\right] \approx \mathbb{E}_\ell\left[\mathbb{E}_\ell\left[\tilde{\tau}_{i,st}^L\right]^{1+\frac{\Gamma_i^L}{\Gamma_i^Z}\theta}\right] + \left(1+\frac{\Gamma_i^L}{\Gamma_i^Z}\theta\right)\mathbb{E}_\ell\left[\mathbb{E}_\ell\left[\tilde{\tau}_{i,st}^L\right]^{\frac{\Gamma_i^L}{\Gamma_i^Z}\theta}\left(\tilde{\tau}_{i,st}^L - \mathbb{E}_\ell\left[\tilde{\tau}_{i,st}^L\right]\right)\right]$$
$$+\frac{1}{2}\left(1+\frac{\Gamma_i^L}{\Gamma_i^Z}\theta\right)\frac{\Gamma_i^L}{\Gamma_i^Z}\theta\mathbb{E}_\ell\left[\mathbb{E}_\ell\left[\tilde{\tau}_{i,st}^L\right]^{\frac{\Gamma_i^L}{\Gamma_i^Z}\theta-1}\left(\tilde{\tau}_{i,st}^L - \mathbb{E}_\ell\left[\tilde{\tau}_{i,st}^L\right]\right)^2\right].$$

Notice that $\mathbb{E}_\ell\left[\tilde{\tau}_{i,st}^L\right] = 1$ since $\tilde{\tau}_{i,st} \equiv \tau_{i,st}/\mathbb{E}_\ell\left[\tau_{i,st}^L\right]$. Also, the second term on the right-hand is zero by definition of the mean and the last term is simply the variance of $\left\{\tilde{\tau}_{i,st}^L\right\}_t$, which we denote by $\mathrm{Var}_\ell\left[\tilde{\tau}_{i,st}^L\right]$. Considering these points we can simplify the above approximation as

$$\mathbb{E}_\ell\left[\left(\tilde{\tau}_{i,st}^L\right)^{1+\frac{\Gamma_i^L}{\Gamma_i^Z}\theta}\right] \approx 1 + \frac{1}{2}\left(1+\frac{\Gamma_i^L}{\Gamma_i^Z}\theta\right)\frac{\Gamma_i^L}{\Gamma_i^Z}\theta\mathrm{Var}_\ell\left[\tilde{\tau}_{i,st}^L\right]. \tag{D.6}$$

Plugging the above approximation back into Equation D.5 and noting that $\log(1+x) \approx x$ when $x \approx 0$, we get

$$\mathcal{D}_i \approx \frac{\Gamma_i^L}{2}\left(1+\frac{\Gamma_i^L}{\Gamma_i^Z}\theta\right)\mathrm{Var}_\ell\left[\tilde{\tau}_{i,st}^L\right].$$

D.1 Cost of Misallocation with Multiple Sectors

Next, we consider an economy with multiple sectors. The change in nominal income is still given by $\hat{Y}_i = \mathbb{E}_\ell\left[\tau_{i,st}^L\right]^{-1}$. Accordingly, the change in price is given by

$$\hat{p}_{i,s} = \left[\sum_t \alpha_{i,st}\left(\tau_{i,st}^L\right)^{\frac{\gamma_i^L}{\gamma_i^Z}\theta}\right]^{-\frac{\gamma_i^Z}{\theta}}\left(\hat{Y}_i\right)^{\gamma_i^Z},$$

which, considering that $\hat{Y}_i = \mathbb{E}_\ell \left[\tau^L_{i,st}\right]^{-1}$ and our notation for the mean operator, yields

$$\frac{\hat{Y}_i}{\hat{p}_{i,s}} = \mathbb{E}_{\alpha,s}\left[\left(\tau^L_{i,st}\right)^{\frac{\gamma^L_i}{\gamma^Z_i}\theta}\right]^{\frac{\gamma^Z_i}{\theta}} \mathbb{E}_\ell\left[\tau^L_{i,st}\right]^{\gamma^Z_i - 1}.$$

Notice that with multiple sectors $\alpha_{i,st} = \tau_{i,st}\ell_{i,st}/\mathbb{E}_{\ell,s}\left[\tau^L_{i,st}\right]$, where $\mathbb{E}_{\ell,s}[.]$ denotes the within-industry mean weighted by industry s employment shares. Appealing to the point, we can re-write the first mean on the right-hand side of the above equation as

$$\mathbb{E}_{\alpha,s}\left[\left(\tau^L_{i,st}\right)^{\frac{\gamma^L_i}{\gamma^Z_i}\theta}\right]^{\frac{\gamma^Z_i}{\theta}} = \mathbb{E}_\ell\left[\left(\frac{\tau^L_{i,t}}{\mathbb{E}_{\ell,s}\left[\tau^L_{i,st}\right]}\right)^{1+\frac{\gamma^L_i}{\gamma^Z_i}\theta}\right]^{-\frac{\gamma^Z_i}{\theta}} \mathbb{E}_{\ell,s}\left[\tau^L_{i,st}\right]^{-\gamma^L_i}.$$

Combining the above two equations, derivers the following expression for the change in real income with respect to industry s goods:

$$\frac{\hat{Y}_i}{\hat{p}_{i,s}} = \left(\frac{\mathbb{E}_{\ell,s}\left[\tau^L_{i,st}\right]}{\mathbb{E}_\ell\left[\tau^L_{i,st}\right]}\right)^{\gamma^L_i} \mathbb{E}_{\ell,s}\left[\left(\frac{\tau^L_{i,st}}{\mathbb{E}_{\ell,s}\left[\tau^L_{i,st}\right]}\right)^{1+\frac{\gamma^L_i}{\gamma^Z_i}\theta}\right]^{-\frac{\gamma^Z_i}{\theta}}.$$

To make the notation more compact, redefine the normalized wedges at the technology and industry levels as

$$\tilde{\tau}_{i,st} = \frac{\tau_{i,st}}{\mathbb{E}_\ell\left[\tau^L_{i,st}\right]}; \qquad \tilde{\mathcal{T}}^L_{i,s} \equiv \frac{\mathbb{E}_{\ell,s}\left[\tau^L_{i,st}\right]}{\mathbb{E}_\ell\left[\tau^L_{i,st}\right]}.$$

Finally, given that preferences are Cobb-Douglas across industries $\mathcal{D}_i = \sum_s e_{i,s} \log\left(\frac{\hat{Y}_i}{\hat{p}_{i,s}}\right)$, which delivers the following equation for the welfare cost of misallocation in a multi-sector model:

$$\mathcal{D}_i = \log \sum\left[e_{i,s}\left(\Gamma^L_{is}\log\left(\tilde{\mathcal{T}}^L_{i,s}\right) + \frac{\Gamma^Z_{is}}{\theta}\log \mathbb{E}_\ell\left[\left(\tilde{\tau}^L_{i,st}\right)^{1+\frac{\Gamma^L_{is}}{\Gamma^Z_{is}}\theta}\right]\right)\right].$$

E Welfare Impacts of Technology Shocks

Consider a technology shock, $\{d\ln a_{i,st}\}_{s,t}$, that alters productivities in economy i. The welfare impact of this technology shock can be written as the change in log national income minus the log expenditure-weighted change in consumer prices. Namely,

$$d\ln W_i = d\ln Y_i - \sum_s \sum_n \left[e_{i,s} \times \pi_{ni,s} \times d\ln p_{ni,s}\right], \tag{E.1}$$

where $d\ln p_{ni,s} = d\ln p_{n,s}$ since our focus is on a technology shock holding iceberg trade costs constant, i.e., $d\ln d_{ni,s} = 0$. Considering the above decomposition, we next characterize the change in income, $d\ln Y_i$, and prices, $d\ln p_{ni,s}$.

Change in Prices ($d\ln p_{n,s}$). Following Shepherd's lemma, the change in the competitive price of goods supplied by firms in country i and industry s is

$$d\ln p_{i,s}=\gamma_{st}^{L}d\ln w_i+\gamma_{st}^{Z}d\ln r_{i,st}\left(\omega\right)+\gamma_{st}^{M}d\ln m_{i,st}-d\ln a_{i,st},\qquad\forall\omega\in\Omega_{i,st};\tag{E.2}$$

where $r_{i,st}\left(\omega\right)$ is the rental rate paid to firm-specific managerial capital and $m_{i,st}$ is the price of the intermediate input bundle used by firms operating with technology t in industry s. Notice that Equation (E.2) implies that the change to log rental rate of managerial input, $d\ln r_{i,st}\left(\omega\right)$, must be the same for all firms $\omega\in\Omega_{i,st}$ that have selected to use technology t in country $i-$industry s. That is: $d\ln r_{i,st}\left(\omega\right)=d\ln r_{i,st}\left(\omega'\right)=d\ln r_{i,st}$. Cost minimization, meanwhile, entails that

$$r_{i,st}\left(\omega\right)\mathcal{K}_{i,st}\left(\omega\right)=\frac{\gamma_{st}^{L}}{\gamma_{st}^{Z}}\tau_{i,st}^{L}\times w_i\ell_{i,st}\left(\omega\right)L_i,$$

where $w_i\ell_{i,st}\left(\omega\right)L_i$ denotes firm ω's net wage bill, with $\ell_{i,st}=L_{i,st}/L_{i,s}$. Considering that $\mathcal{K}_{i,st}\left(\omega\right)=1$, fully differentiating the above expression yields the following expression for the change in the firm-specific managerial rents: $d\ln r_{i,st}\left(\omega\right)=d\ln\ell_{i,st}\left(\omega\right)+d\ln w_i$. Here again, since $d\ln r_{i,st}\left(\omega\right)=d\ln r_{i,st}\left(\omega^{'}\right)=d\ln r_{i,st}$ across all $\omega,\omega^{'}\in\Omega_{i,st}$, the change to log employment share must be the same across all firms $\omega\in\Omega_{i,st}$, i.e., $d\ln\ell_{i,st}\left(\omega\right)=d\ln\ell_{i,st}\left(\omega^{'}\right)=d\ln\ell_{i,st}$ for all $\omega,\omega^{'}\in\Omega_{i,st}$. Therefore, we can write the change to log managerial rents as:

$$d\ln r_{i,st}=d\ln w_i+d\ln\ell_{i,st}.\tag{E.3}$$

Similarly, cost minimization implies that the following relationship between the intermediate input and labor cost bills:

$$m_{i,st}M_{i,st}\left(\omega\right)=\frac{\gamma_{st}^{L}}{\gamma_{st}^{M}}\tau_{i,st}^{L}\times w_iL_{i,st}\left(\omega\right),$$

where $M_{i,st}\left(\omega\right)$ and $m_{i,st}$ are respectively the quantity and price of the intermediate input bundle used by firm ω. Note that $L_{i,st}\left(\omega\right)=\ell_{i,st}\left(\omega\right)\bar{L}_i$ and (as shown earlier) $d\ln\ell_{i,st}(\omega)=d\ln\ell_{i,st}$. Since aggregate labor supply is inelastic, it immediately follows that $d\ln\ell_{i,st}\left(\omega\right)=d\ln L_{i,st}(\omega)=d\ln L_{i,st}$ for all $\omega\in\Omega_{i,st}$. Invoking this point and fully differentiating the above equation, we obtain $d\ln m_{i,s}=d\ln w_i+d\ln L_{i,st}-d\ln M_{i,st}(\omega)$. This expression, in turn, implies that $d\ln M_{i,st}(\omega)=d\ln M_{i,st}(\omega')=d\ln M_{i,st}$ for all $\omega,\omega^{'}\in\Omega_{i,st}$, yielding the following expression for the (technology-specific) change in intermediate input prices:

$$d\ln m_{i,st}=d\ln w_i-d\ln\left(M_{i,st}/L_{i,st}\right).\tag{E.4}$$

Plugging the expressions for $d\ln r_{i,st}$ and $d\ln m_{i,st}$ back into Equation (E.2) and noting that $\gamma_{st}^{L}+\gamma_{st}^{Z}+\gamma_{st}^{M}=1$, yields the following expression for the change in price of industry s goods:

$$d\ln p_{i,s}=-d\ln\tilde{a}_{i,st}+d\ln w_i+\gamma_{st}^{Z}d\ln\ell_{i,st}.\tag{E.5}$$

where $d\ln\widetilde{a}_{i,st}\equiv d\ln a_{i,st}+\gamma_{st}^{M}d\ln\left(M_{i,st}/L_{i,st}\right)$ denotes the *effective* (or input-output-adjusted) change in productivity—a definition introduced to make the notation more compact.[26] Since the above equation describes the price change for both modern and traditional technologies, we can alternatively formulate $d\ln p_{i,s}$ as the weighted average of contributions from each technology.

[26] In deriving Equation E.5, we appeal to the fact that $d\ln\ell_{i,st}=d\ln L_{i,st}$, since $L_{i,st}=\ell_{i,st}L_i$, with L_i denoting the constant supply of labor.

Namely,

$$d\ln p_{i,s} = d\ln w_i + \sum_t \left[\rho_{i,st}\left(-d\ln \tilde{a}_{i,st} + \gamma^Z_{st} d\ln \ell_{i,st}\right)\right]. \tag{E.6}$$

Change in National Income ($d\ln Y_i$). Recall that national income is the sum of net wage payments, the revenue associate with wedges, and rents accruing to managerial capital. Namely, $E_i = w_i L_i + T_i + \Pi_i$, where $T_i \equiv \sum\left[\left(\tau^L_{i,st} - 1\right) w_i L_{i,s}\right]$ is the revenue from wedges and $\Pi_i \equiv \sum_{s,t,\omega} \Pi_{i,st}(\omega) = \sum_{s,t,\omega}\left[r_{i,st}(\omega)\mathcal{K}_{i,st}(\omega)\right]$ denotes managerial capital rents. Considering that $L_{i,st} = \ell_{i,st} L_i$, we can simplify the expression for national income as

$$Y_i = \sum_s \sum_t \left[\tau^L_{i,st}\ell_{i,st}\right] w_i L_i + \Pi_i.$$

Taking full derivatives from the above equation, yields the following expression for the change in (log) national income:

$$d\ln Y_i = \frac{w_i L_i + T_i}{Y_i}\left(d\ln w_i + d\ln \sum_s \sum_t \left[\tau^L_{i,st}\ell_{i,st}\right]\right) + \sum_{s,t}\left[\int_\omega \frac{\Pi_{i,st}(\omega)}{Y_i} d\ln \Pi_{i,st}(\omega)\, dF\left(\omega | \omega \in \Omega_{i,st}\right)\right] \tag{E.7}$$

Appealing to the fact that $\Pi_{i,st}(\omega) = r_{i,st}(\omega)\bar{\mathcal{K}}_{i,st}(\omega)$, yields

$$d\ln \Pi_{i,st}(\omega) = d\ln r_{i,st}(\omega) = d\ln \ell_{i,st}(\omega) + d\ln w_i,$$

where the last line follows from Equation E.3. Invoking the above equation simplifies the last sum in Equation E.7 as

$$\begin{aligned}\sum_{s,t,\omega}\left[\frac{\Pi_{i,st}(\omega)}{Y_i} d\ln \Pi_{i,st}(\omega)\right] &= \left(\frac{\Pi_i}{Y_i}\right) d\ln w_i + \sum_{s,t}\left[\int_\omega \left(\frac{\Pi_{i,st}(\omega)}{R_{i,st}(\omega)} \times \frac{R_{i,st}(\omega)}{R_i} \times \frac{R_i}{Y_i} \times d\ln \ell_{i,st}(\omega)\right) dF\left(\omega|\omega \in \Omega_{i,st}\right)\right] \\ &= \left(\frac{\Pi_i}{Y_i}\right) d\ln w_i \ + \sum_{s,t}\left[\int_\omega \left(\gamma^Z_{st} \times r_{i,s}\rho_{i,st}(\omega) \times \left(1 - \Gamma^M_i\right)^{-1} \times d\ln \ell_{i,st}(\omega)\right) dF\left(\omega|\omega \in \Omega_{i,st}\right)\right].\end{aligned}$$

where $(1 - \Gamma^M_i)$ is the national-level value added share—i.e, share of GDP to national-level gross sales:

$$\left(1 - \Gamma^M_i\right) \equiv \frac{Y_i}{\sum_s \sum_t R_{i,st}} = \frac{Y_i}{R_i}.$$

Invoking the within-technology uniformity in employment share changes, i.e., $d\ln \ell_{i,st}(\omega) = d\ln \ell_{i,st}$ and noting that $\sum \rho_{i,st}$

$$\int_\omega \left[\frac{\gamma^Z_{st}}{\left(1 - \Gamma^M_i\right)} r_{i,s}\rho_{i,st}(\omega)\, d\ln \ell_{i,st}(\omega) dF\left(\omega|\omega \in \Omega_{i,st}\right)\right] = \frac{\gamma^Z_{st}}{\left(1 - \Gamma^M_i\right)} r_{i,s}\rho_{i,st} \times d\ln \ell_{i,st},$$

where $\rho_{i,st} \equiv \sum_{\omega \in \Omega_{i,st}} \rho_{i,st}(\omega)$ is the aggregate revenue share of firms $\omega \in \Omega_{i,st}$. It then follows that:

$$\sum_{s,t} \left[\int_{\omega} \frac{\Pi_{i,st}(\omega)}{Y_i} d\ln \Pi_{i,st}(\omega)\, dF(\omega | \omega \in \Omega_{i,st}) \right] = \left(\frac{\Pi_i}{Y_i} \right) d\ln w_i + \frac{1}{1-\Gamma_i^M} \sum_{s,t} \left[\gamma_{st}^Z r_{i,s} \rho_{i,st} \times d\ln \ell_{i,st} \right]. \tag{E.8}$$

Plugging the above expression back into Equation E.7, yields

$$d\ln Y_i = d\ln w_i + \frac{w_i L_i + T_i}{Y_i} d \left(\ln \sum_s \sum_t \left[\tau_{i,st}^L \ell_{i,st} \right] \right) + \frac{1}{1-\Gamma_i^M} \sum_{s,t} \left[\gamma_{st}^Z r_{i,s} \rho_{i,st} \times d\ln \ell_{i,st} \right]. \tag{E.9}$$

We can unpack and simplify the second term on the right-hand side of the above equation by appealing to the fact that

$$d \left(\ln \sum_s \sum_t \left[\tau_{i,st}^L \ell_{i,st} \right] \right) = \sum_s \sum_t \left[\frac{\tau_{i,st}^L}{\mathbb{E}_\ell \left[\tau_{i,st}^L \right]} \ell_{i,st} d\ln \ell_{i,st} \right], \qquad \text{where} \qquad \mathbb{E}_\ell \left[\tau_{i,st}^L \right] \equiv \sum_s \sum_t \tau_{i,st} \ell_{i,st}$$

and the fact that $(w_i L_i + T_i)/R_i$ represents the economy-wide average labor intensity in country i—namely,[27]

$$\frac{w_i L_i + T_i}{Y_i} = \frac{\Gamma_i^L}{1-\Gamma_i^M}, \qquad \text{where} \qquad \Gamma_i^L \equiv \sum_s \left[\Gamma_{is}^L r_{i,s} \right].$$

Consolidating these points, delivers the following expression for the welfare-weighted change in wedge revenues:

$$\frac{w_i L_i + T_i}{Y_i} d \left(\ln \sum_s \sum_t \left[\tau_{i,st}^L \ell_{i,st} \right] \right) = \frac{\Gamma_i^L}{1-\Gamma_i^M} \times \sum_s \sum_t \left[\tilde{\tau}_{i,st}^L \ell_{i,st} d\ln \ell_{i,st} \right], \tag{E.10}$$

where $\tilde{\tau}_{i,st}^L \equiv \tau_{i,st}^L / \mathbb{E}_\ell \left[\tau_{i,st}^L \right]$, recall, denotes the labor wedges normalized by the mean. Plugging Equation E.8 into Equation E.9, delivers the following expression for the change in nominal GDP in response technology shocks:

$$d\ln Y_i = d\ln w_i + \left(\frac{\Gamma_i^L}{1-\Gamma_i^M} \right) \times \sum_s \sum_t \left[\tilde{\tau}_{i,st}^L \ell_{i,st} d\ln \ell_{i,st} \right] + \left(\frac{1}{1-\Gamma_i^M} \right) \sum_{s,t} \left[\gamma_{st}^Z \times r_{i,s} \rho_{i,st} d\ln \ell_{i,st} \right]. \tag{E.11}$$

Consolidating Equations (E.1), (E.6), and (E.11). Suppose country i is a small open economy such that prices in the rest of the world do not respond to productivity adjustments in country i. In particular,

$$d\ln p_{n,s} \approx 0 \qquad \forall n \neq i.$$

[27] Recall that $\bar{\gamma}_{i,s}^L$ denotes the average labor intensity in industry s of country i , which is defined analogously to $\bar{\gamma}_{i,s}^Z$—that is, $\frac{1}{\gamma_{,s}{}_i^L} \equiv \sum_t \left[\frac{1}{\gamma_{st}^L} \alpha_{i,st} \right]$.

Integrating Equations (E.1), (E.6), and (E.11), for a small open economy, yields the following formula describing the welfare impact of a productivity shock, $\{d\ln a_{i,st}\}_{s,t}$:

$$\begin{aligned} d\ln W_i \; = & \overbrace{\sum_s\sum_t\left[e_{i,s}\pi_{ii,}\rho_{i,st}d\ln\widetilde{a}_{i,st}\right]}^{\Delta\text{Mechanical}} + \overbrace{\frac{\Gamma_i^L}{1-\Gamma_i^M}\times\mathrm{Cov}_\ell\left(\widetilde{\tau}_{i,st}^L, d\ln\ell_{i,st}\right)}^{\Delta\text{Allocative Efficiency}} \\ & \underbrace{+\;(1-\pi_{ii})\,d\ln w_i + \sum_{s,t}\left[\rho_{i,st}\left(\frac{1}{1-\Gamma_i^M}r_{i,s}-\pi_{ii,s}e_{i,s}\right)\gamma_{st}^Z d\ln\ell_{i,st}\right]}_{\Delta\text{Terms of Trade}}, \end{aligned}$$

where $d\ln\tilde{a}_{i,st} = d\ln a_{i,st} + \gamma_{st}^M d\ln\left(M_{i,st}/L_{i,st}\right)$ summarizes the exogenous productivity growth and its associated endogenous impact on the use of intermediate inputs per worker and $(1-\pi_{ii})$ is the aggregate imported share of expenditure as a national index of trade openness: $\pi_{ii}\equiv\sum_s e_{i,s}\pi_{ii,s}$. Lastly, $\mathrm{Cov}_\ell\,(.)$ is the covariance operator weighted by labor shares—specifically,

$$\mathrm{Cov}_\ell\left(\widetilde{\tau}_{i,st}^L, d\ln\ell_{i,st}\right) = \sum_{s,t}\left[\ell_{i,st}\left(\widetilde{\tau}_{i,st}^L\times d\ln\ell_{i,st}\right)\right] - \overbrace{\sum_{s,t}\left(\ell_{i,st}d\ln\ell_{i,st}\right)}^{=0}\times\sum_{s,t}\left(\ell_{i,st}\widetilde{\tau}_{i,st}^L\right).$$

E.1 Special Case: *Closed Economy*

Next, we consider the closed economy case of our formula. The goal here is to show that the "mechanical" effect of productivity growth in a closed economy exactly coincides with Hulten's formula. This is different from the open economy case where the "mechanical" effect is contaminated with mechanical terms of trade effects. To set the stage for our forthcoming derivation, it is useful to highlight that in a closed economy (denoted by superscript, CE) welfare changes are given by

$$d\ln W_i^{\mathrm{CE}} = d\ln Y_i - \sum_s e_{i,s}d\ln p_{i,s}. \tag{E.12}$$

To characterize price changes, we can re-invoke Shephard's Lemma but unpack the change in the price of the intermediate input bundle as the sum of individual input price changes. Doing so delivers

$$d\ln p_{i,s} = \gamma_{st}^L d\ln w_i + \gamma_{st}^Z d\ln r_{i,st} + \sum_g \gamma_{i,gst}^M d\ln p_{i,g},$$

where $\gamma_{i,gst}^M$, recall, denotes the share of industry g inputs used by firms using technology t in industry s, with $\sum_g\gamma_{s,t}$. Following the steps outlined above, we can rewrite the above equation as

$$d\ln p_{i,s} = \left(1-\gamma_{st}^M\right)d\ln w_i + \gamma_{st}^Z d\ln\ell_{i,st} + \gamma_{st}^M\sum_g\phi_{i,s'st}d\ln p_{i,g}.$$

Inverting the system of equations describing the change in industry-level prices, yields

$$d\ln p_{i,s} = \sum\widetilde{\gamma}_{i,s'st}\left(d\ln a_{i,st} + \left(1-\gamma_{st}^M\right)d\ln w_i + \gamma_{st}^Z d\ln\ell_{i,st}\right),$$

where $\widetilde{\gamma}_{i,s'st}$ is the element (s', s) of the inverse Leontief matrix, pertaining to technology t. We can re-write the above equation by appealing to two intermediate observations. First, $\sum_{s'}\widetilde{\gamma}_{i,s'st}\left(1-\gamma_{st}^M\right) = 1$, by definition of the inverse Leontief matrix. Second, the above equation describes the price change for all technologies in industry s, so that we can alternatively write the change in price as the weighted average of (uniform) technology-specific price changes. Invoking these observations, we can re-write the above equation as

$$d\ln p_{i,s} = d\ln w_i + \sum_t \left[\rho_{i,st}\left(\frac{\gamma_{st}^Z}{1-\gamma_{st}^M} d\ln \ell_{i,st} + \sum_{s'} \widetilde{\gamma}_{i,s'st} d\ln a_{i,st}\right)\right].$$

Next, we invoke that standard property of the inverse Leontief matrix, whereby $\sum_{s'}\sum_t \left(\tilde{\gamma}_{i,ss't} e_{i,s'} \rho_{i,s't}\right) Y_i = \left(\rho_{i,st} r_{i,s}\right) R_i$, which can be further simplified considering that $Y_i/R_i = 1-\Gamma_i^M$. Also, we make use of the fact that for any generic variable $x_{i,st}$ $\sum_{s,t}\left[e_{i,s}\rho_{i,st}\frac{\gamma_{st}^Z}{1-\gamma_{st}^M} x_{i,st}\right] = \frac{1}{1-\Gamma_i^M}\sum_{s,t}\left[r_{i,s}\rho_{i,st}\gamma_{st}^Z x_{i,st}\right]$. Capitalizing on these relationships. we can write the the sum of price effects in the Equation E.12 as

$$\begin{aligned}\sum_t e_{i,s} d\ln p_{i,s} &= \sum_s \left[e_{i,s}\left(d\ln w_i + \sum_t \rho_{i,st}\left(\frac{\gamma_{st}^Z}{1-\gamma_{st}^M} d\ln \ell_{i,st} + \sum_{s'} \widetilde{\gamma}_{i,s'st} d\ln a_{i,st}\right)\right)\right] \\ &= d\ln w_i + \left(\frac{1}{1-\Gamma_i^M}\right)\sum_s\sum_t \left[\gamma_{st}^Z \rho_{i,st} r_{i,st} d\ln \ell_{i,st} + r_{i,s}\rho_{i,st} \mathrm{dln}\, a_{i,st}\right]. \qquad \text{(E.13)}\end{aligned}$$

The steps leading to Equation E.9 remain the same for a closed economy, so that Equation E.9 still describes the change in nominal GDP, $d\ln Y_i$. Combining the expression for $d\ln Y_i$ and Equation E.13 delivers the Hulten formula

$$d\ln W_i^{\mathrm{CE}} = \sum_s\sum_t\left[\frac{1}{1-\Gamma_i^M} e_{i,s}\rho_{i,st} d\ln a_{i,st}\right] + \frac{\Gamma_i^L}{1-\Gamma_i^M} \times \mathrm{Cov}_\ell\left(\widetilde{\tau}_{i,st}^L, d\ln \ell_{i,st}\right),$$

where $\frac{1}{1-\Gamma_i^M} e_{i,s}\rho_{i,st} = \frac{p_{i,s}C_{i,st}}{\sum_{s',t'} p_{i,s'}Q_{i,s't'}}$ is the Domar weight associated with industry s–technology t.

F Quantification of the Model

This section provides details about the quantification of the model. Section 5 describes how we estimate the elasticity of output intensity with respect to labor and calibrate remaining factor intensity parameters of traditional and modern production technologies. Section F.2 describes the baseline calibration of our model, and Section F.3 presents our general equilibrium model in changes and the numerical algorithm that we use to simulate it.

F.1 Estimation and Calibration of Factor Intensity Parameters

The estimation of the output elasticity of labor is based on the control function approach (Levinsohn and Petrin, 2003; Olley and Pakes, 1996). Specifically, the main insight from this literature is that the output elasticity of transitory inputs can be estimated by controlling for a flexible function of the non-transitory inputs (e.g. capital) and the intermediate inputs. We therefore estimate:

$$y_{st}(\omega) = \alpha_{st} + \tilde{\gamma}_{st}^L l_{st}(\omega) + f_{st}\left(k_{st}(\omega), i_{st}(\omega)\right) + \epsilon_{st}(\omega), \qquad \text{(F.1)}$$

where $y_{st}(\omega)$ is the log of total sales of firm ω in industry s using technology t, $l_{st}(\omega)$ is the log of total payments to labor, $k_{st}(\omega)$ is the log of total payments to capital, $i_{st}(\omega)$ is the log of total payments to intermediate inputs, and α_{st} is a set of fixed effects. We employ a fifth order polynomial of $k_{st}(\omega)$ and $i_{st}(\omega)$ and interaction terms between $k_{st}(\omega)$ and $i_{st}(\omega)$. Here, $\tilde{\gamma}_{st}^L$ is the output elasticity of labor.[28]

In the discussion of our empirical patterns, we use both our estimates of labor intensity $\tilde{\gamma}_{st}^L$ by industry, as well as our estimates of labor intensity when we pool all the manufacturing industries, so that we have one labor-intensity for the modern technology, $\tilde{\gamma}_1^L$, and one for the traditional technology, $\tilde{\gamma}_0^L$. Because we find these labor-intensity parameters to be similar across industries, to simplify matters, in our quantitative analysis of the model we work with the case in which the output elasticity of the modern technology and the traditional one are the same across industries.

Once with estimates of $\tilde{\gamma}_t^L$, as we turn to the calibration of the model, we impose the assumption that the production function is Cobb-Douglas with constant returns to scale. In that case, the output elasticity of labor, given by our estimate of $\tilde{\gamma}_t^L$ from equation (F.1), becomes the share of labor in the Cobb-Douglas function, γ_t^L. To recover the rest of the parameters, we rely on the constant-returns to scale assumption and assume that there are three factors of production: (i) labor (L), (ii) managerial capital (Z), and (iii) intermediate inputs (M). This gives us 6 parameters to be calibrated: $\{\gamma_t^L, \gamma_t^Z, \gamma_t^M\}_{t\in\{0,1\}}$. We already have γ_0^L and γ_1^L from our estimation of equation F.1. We are then left with 4 parameters to be calibrated. Imposing constant returns to scale ($\gamma_t^L + \gamma_t^Z + \gamma_t^M = 1$) gives 2 equations:

$$\gamma_0^L + \gamma_0^Z + \gamma_0^M = 1 \tag{F.2}$$

$$\gamma_1^L + \gamma_1^Z + \gamma_1^M = 1 \tag{F.3}$$

We still need two additional equations. The third equation that we use is:

$$\rho_0\gamma_0^M + \rho_1\gamma_1^M = \bar{\gamma}^M \tag{F.4}$$

where $\bar{\gamma}^M$ is the average cost share of intermediate inputs across firms, ρ_0 is the share of sales under the traditional technology, and ρ_1 is the share of sales under the modern one. We pick ρ_0 and ρ_1 directly from our classification of firms into modern and traditional technologies using the WBES data. For $\bar{\gamma}^M$, we have different potential values to pick, depending on the interpreation of the model and the data. Since we work with a static model, what we refer to as the intermediate input category includes, in part, durable intermediate goods such as various forms of tradeable machinery and equipment. Some of these items, in turn, are likely to be counted under the category of capital in firm-level data such as WBES. On the other hand, input-output databases such as GTAP dataset are likely to have a different definition to distinguish between intermediate inputs and capital. In addition, input-output records largely rely on imputations in the case of missing records and inconsistencies in the accounting of flows. In other words, input-output tables are not observed data, but constructed data subject to the accounting of trade and production flows. For these reasons, the average cost share of intermediate inputs differs between WBES and GTAP. We therefore use a simple rule and pick the average between these two sources of data as the value of $\bar{\gamma}^M$.

To obtain our fourth equation, we impose the assumption that firms select into modern and traditional technologies based on a Fréchet distribution. This gives us the following ratio of average

[28] As discussed in the main body of the paper, since we use revenue data instead of output data, we recover the revenue elasticity of labor (Hashemi, Kirov, and Traina, 2022). We would still recover the relevant object for our purpose in this paper.

employment of workers in the modern, $\overline{L}_1$, and traditional sectors, $\overline{L}_0$:[29]

$$\frac{\overline{L}_1}{\overline{L}_0} = \frac{\gamma_1^L}{\gamma_0^L}\frac{\gamma_0^Z}{\gamma_1^Z}. \tag{F.5}$$

As such, we have four equations (F.2)-(F.4) and four unknowns, which allows us to pin down all the factor shares. Aggregating across manufacturing industries, we obtain the intensity parameters of the manufacturing traditional technology, $(\gamma_0^L, \gamma_0^M, \gamma_0^Z) = (0.404, 0.120, 0.476)$, and modern technology, $(\gamma_1^L, \gamma_1^M, \gamma_1^Z) = (0.281, 0.596, 0.123)$.

F.2 Calibration of the Baseline Equilibrium

To calibrate the baseline equilibrium of our model, we combine the country-level data from GTAP dataset and statistics and estimates that we have obtained based on the WBES dataset.

From WBES, we obtain the share of firms in traditional and modern technologies across countries, their corresponding share of sales. Since the number of firms covered in WBES are relatively low for some country-industry pairs, we assign the national-level share of modern firms in the aggregate of manufacturing to individual manufacturing industries, $\alpha_{i,st} \equiv \alpha_{i,t}$. In turn, we observe the technology-specific share of sales, $\rho_{i,st}$.

From GTAP, we obtain within-industry share of expenditure (trade shares), $\pi_{ij,s}$, within-intermediate expenditure shares (input-output parameters), $\phi_{i,ss'}$, (here, we assume that within-intermediate-input shares are common to both technologies, $\phi_{i,ss'0} = \phi_{i,ss'1} = \phi_{i,ss'}$) and final expenditure shares, $\beta_{i,s}$. We use the technology-specific intermediate input shares, $\gamma_{i,st}^M$, as explained in Section F.1.

The general equilibrium of our model requires that the following three equations hold (Equations 8, 9, 10),

$$E_{i,s} = \beta_{i,s} Y_i + \sum_{s' \in \mathbb{S}} \sum_{t \in \mathbb{T}} \left[\phi_{i,s'st} \gamma_{s't}^M \rho_{i,s't} R_{i,s'}\right]$$

$$Y_i = \sum_{s \in \mathbb{S}} \sum_{t \in \mathbb{T}} \left(1 - \gamma_{i,st}^M\right) \rho_{i,st} R_{i,s}$$

$$R_{i,s} = \sum_{j \in \mathbb{I}} \pi_{ij,s} E_{j,s}$$

Given $\{\rho_{i,st}, \pi_{ij,s}, \phi_{i,s's}, \gamma_{st}^M, \beta_{i,s}\}$, We solve for $\{E_{i,s}, R_{i,s}, Y_i\}$ consisting of industry-level expenditures, $E_{i,s}$, industry-level sales, $R_{i,s}$, and GDP, Y_i, such that the above system of equations hold.

F.3 General Equilibrium in Changes

Consider a "policy" as a set of exogenous shocks to trade costs, labor wedges, and productivities, $\mathcal{P} = \{\hat{d}_{ij,s}, \hat{\tau}_{i,st}^L, \hat{a}_{i,st}\}$. Let $\mathcal{B} = \{\sigma, \theta, \pi_{ij,s}, \alpha_{i,st}, \gamma_{st}^L, \gamma_{st}^M, \gamma_{st}^Z, \tau_{i,st}^L, \phi_{i,\ell s}, \beta_{i,s}, w_i L_i, R_{i,st}, E_{i,s}, Y_i\}$ denote the "baseline" values of the general equilibrium—i.e., the set of sufficient statistics. For any generic variable x in the baseline equilibrium, let x' be its corresponding value in the counterfactual equilibrium, and $\hat{x} \equiv x'/x$ denote its change from the baseline to the counterfactual

[29] To see that, notice that the average ratio of sales in the modern and traditional technology satisfies $\gamma_1^Z \frac{R_1}{N_1} = \gamma_0^Z \frac{R_0}{N_0}$, where R_τ is total sales and N is the total number of firms. Given our Cobb-Douglas assumption, that expression can be written as $\gamma_1^Z \frac{wL_1/N_1}{\gamma_1^L} = \gamma_0^Z \frac{wL_0/N_0}{\gamma_0^L}$. Assuming that wages equalize across firms give us equation (F.5).

equilibrium. Given policy $\mathscr{P}$ and baseline values $\mathscr{B}$, the following equations define general equilibrium in changes to trade and technology shares, aggregate sales and expenditures, and prices and wages, $\mathscr{E} \equiv \{\hat{\pi}_{ij,s}, \hat{\alpha}_{i,st}, \hat{R}_{i,st}, \hat{E}_{i,s}, \hat{Y}_i, \hat{p}_{i,s}, \hat{P}_{i,s}, \hat{w}_i\}$.

The change to sales in country $i-$industry $s-$technology t is:

$$\widehat{R}_{i,st} = \left(\widehat{a}_{i,st}\widehat{h}_{i,st}/\widehat{p}_{i,s}\right) \times (\widehat{\alpha}_{i,st})^{\frac{\theta-1}{\theta}}, \tag{F.6}$$

where the change to the share of firms in each technology type is given by:

$$\widehat{\alpha}_{i,st} = \frac{\left(\widehat{a}_{i,st}\widehat{h}_{i,st}\right)^{\theta}}{\sum_{t\in\mathbb{T}} \alpha_{i,st}\left(\widehat{a}_{i,st}\widehat{h}_{i,st}\right)^{\theta}}, \quad \text{where} \quad \widehat{a}_{i,st} = \left(\hat{A}_{i,st}\right)^{1/\gamma^Z_{st}}; \tag{F.7}$$

and the change to technology-specific return to managerial capital is:

$$\widehat{h}_{i,st} \equiv \left(\frac{\hat{\tau}^L_{i,st}\widehat{w}_i}{\widehat{p}_{i,s}}\right)^{-\gamma^L_{st}/\gamma^Z_{st}} \left(\frac{\widehat{m}_{i,st}}{\widehat{p}_{i,s}}\right)^{-\gamma^M_{st}/\gamma^Z_{st}}, \quad \text{where} \quad \widehat{m}_{i,st} = \prod_{\ell\in\mathbb{S}} \left(\widehat{P}_{i,\ell}\right)^{\phi_{i,\ell st}}. \tag{F.8}$$

In turn, the change to the industry-level (consumer) price index equals:

$$\widehat{P}_{j,s} = \left[\sum_{i\in\mathbb{I}} \pi_{ij,s}\left(\widehat{d}_{ij,s}\widehat{p}_{i,s}\right)^{1-\sigma_s}\right]^{\frac{1}{1-\sigma_s}}, \tag{F.9}$$

and the change to within-industry share of expenditure (trade share) is:

$$\widehat{\pi}_{ij,s} = \frac{\left(\widehat{d}_{ij,s}\widehat{p}_{i,s}\right)^{1-\sigma_s}}{\left(\widehat{P}_{j,s}\right)^{1-\sigma_s}}. \tag{F.10}$$

Lastly, the following four equations guarantee the market clearing conditions and the accounting of general equilibrium. The labor market clearing condition and the goods market clearing condition in the counterfactual equilibrium must satisfy:

$$\widehat{w}_i w_i L_i = \left[\sum_{s,t} \frac{\gamma^L_{st}}{\hat{\tau}^L_{i,st}\tau^L_{i,st}} \widehat{R}_{i,st}R_{i,st}\right] \tag{F.11}$$

$$\left(\sum_t \hat{R}_{i,st}R_{i,st}\right) = \sum_j \hat{\pi}_{ij,s}\pi_{ij,s}\hat{E}_{j,s}E_{j,s} \tag{F.12}$$

The change to the industry-level gross expenditures and the total national expenditure (nominal GDP) satisfy:

$$\widehat{E}_{i,s}E_{i,s} = \left[\beta_{i,s}\widehat{Y}_iY_i + \sum_{t,\ell} \phi^s_{i,\ell}\gamma^M_{\ell t}\widehat{R}_{i,\ell t}R_{i,\ell t}\right] \tag{F.13}$$

$$\widehat{Y}_iY_i = \sum_{s,t}\left(1-\gamma^M_{i,st}\right)\widehat{R}_{i,st}R_{i,st} \tag{F.14}$$

We now turn to presenting the computational algorithm that we use to simulate the general equilibrium of our model in response to counterfactual policy shocks.

Numerical Algorithm to Simulate the GE in Changes.

1. Guess $\widehat{w}_i$ and $\widehat{p}_{i,s}$. (By the choice of numeraie, here we impose that $\hat{w}_{i_0} = 1$ for a reference country i_0)

2. Calculate the change to industry-level price index, $\widehat{P}_{i,s}$, according to equation (F.9).

3. Calculate the change to technology-level returns to managerial capital according to equation (F.8).

4. Calculate the change to trade shares, $\hat{\pi}_{ij,s}$, based on equation (F.10).

5. Calculate the change to technology shares, $\widehat{\alpha}_{i,st}$, according to equation (F.7).

6. Calculate the change to sales, $\hat{R}_{i,st}$, based on equation (F.6).

7. Calculate the change to national expenditure, $\hat{Y}_i$, based on equation (F.14).

8. Calculate the change to industry-level gross expenditures, $\widehat{E}_{i,s}$, based on equation (F.13).

9. Update the change to wages and prices, based on market clearing conditions (F.11) and (F.12),
$$(\widehat{w}_i)^{new} = \frac{1}{w_i L_i}\left[\sum_{s,t} \frac{\gamma^L_{st}}{\hat{\tau}^L_{i,st}\tau^L_{i,st}} \widehat{R}_{i,st} R_{i,st}\right]$$
$$(\widehat{p}_{i,s})^{new} = \frac{\sum_j \hat{\pi}_{ij,s}\pi_{ij,s}\hat{E}_{j,s}E_{j,s}}{\left(\sum_t \left(\hat{R}_{i,st}/\hat{p}_{i,st}\right) R_{i,st}\right)}$$
If the $|\,(\widehat{w}_i)^{new} - \widehat{w}_i| > \epsilon$ and $|\,(\widehat{p}_{i,s})^{new} - \widehat{p}_{i,s}| > \epsilon$, for a sufficiently small tolerance ϵ, then update: $\widehat{w}_i = (\widehat{w}_i)^{new}$ and $\hat{p}_{i,s} = (\widehat{p}_{i,s})^{new}$, and normalize the updated price and wage changes with respect to the wage change in a reference country (whose labor serves as a numeraire), then go to Step 2. Otherwise, the convergence is achieved.

G Additional Tables and Figures

Table A.1: Labor Intensity by Firm Technological Classification - Alternative Specifications - Complementary Pattern 2

Criterion Variable	Control Function Polynomial	Cutoff Criterion	Traditional Avg (1)	Traditional Min (2)	Traditional Max (3)	Modern Avg (4)	Modern Min (5)	Modern Max (6)	Diff (7)
Total sales	Second	Median	0.409	0.377	0.454	0.280	0.214	0.329	-0.129
Total sales	Fifth	Median	0.407	0.377	0.453	0.268	0.199	0.318	-0.138
Total sales	Second	Top quartile	0.422	0.378	0.473	0.213	0.153	0.262	-0.208
Total sales	Fifth	Top quartile	0.419	0.374	0.471	0.209	0.140	0.261	-0.210
Total costs	Second	Median	0.491	0.443	0.550	0.361	0.301	0.411	-0.129
Total costs	Fifth	Median	0.491	0.443	0.548	0.358	0.293	0.410	-0.133
Total costs	Second	Top quartile	0.463	0.425	0.507	0.318	0.219	0.423	-0.145
Total costs	Fifth	Top quartile	0.462	0.423	0.507	0.313	0.193	0.415	-0.148

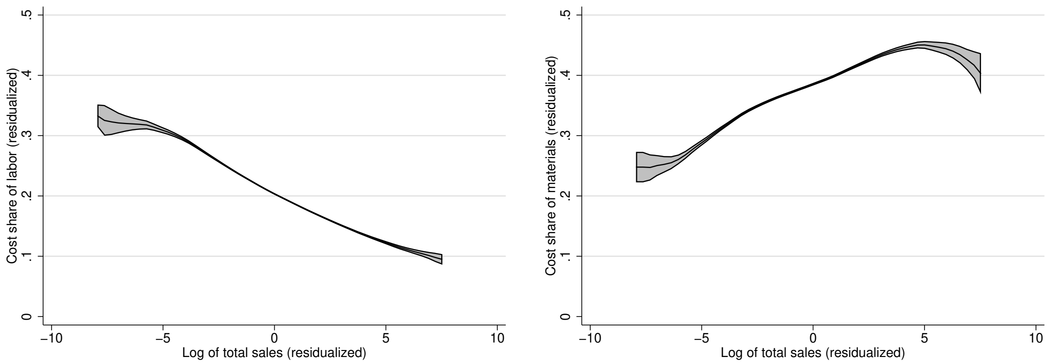
Notes: This table presents the distribution of our estimates of the labor intensity using different specifications. We use two different variables to group firms into modern and traditional: total sales and total costs. We use different flexible polynimals for the control function and the interactions between the inflexible variable and the intermediate inputs in levels. We also split the sample into modern and traditional based on whether the firm is above the median in the grouping variable, or in the top quartile. The final column presents the difference between the average labor intensity among modern and traditional firms.

Table A.2: Wedges, Firms' Technology, and GDP per capita - Alternative Specifications - Complementary Pattern 3

Criterion Variable	Control Function Polynomial	Cutoff Criterion	Modern coef (1)	LGDP × Modern coef (2)	Obs (3)	pseudo-R2 (4)
Total sales	Second	Median	1.279***	-0.102***	63987	0.113
Total sales	Fifth	Median	1.247***	-0.102***	63987	0.110
Total sales	Second	Top quartile	1.040***	-0.112***	63987	0.094
Total sales	Fifth	Top quartile	1.032***	-0.112***	63987	0.094
Total costs	Second	Median	1.305***	-0.136***	63987	0.093
Total costs	Fifth	Median	1.292***	-0.136***	63987	0.093
Total costs	Second	Top quartile	0.732**	-0.082**	63987	0.084
Total costs	Fifth	Top quartile	0.724**	-0.082**	63987	0.084

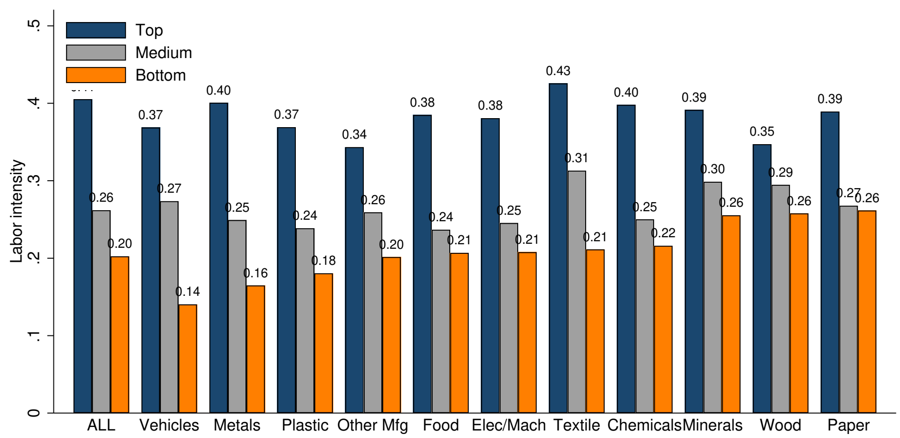
Notes: This table reports results for the relationship between labor market wedges and firms' technological classification across countries in different levels of economic development. Specifically, for each specification. For each alternative specification in the estimation of labor elasticity, we run a regression of the labor wedge against an indicator variable for modern technology classification, an interaction term between the log of GDP per capita of the country, and country and industry fixed effects. Regressions are estimated via PPML, so that coefficients should be interpreted as elasticities. * / ** / *** denotes significance at the 10 / 5 / 1 percent level. Standard errors are clustered at the country level.

Figure A.2: Firm Size and the Cost Share of Labor and Materials (Complementary Pattern 1)



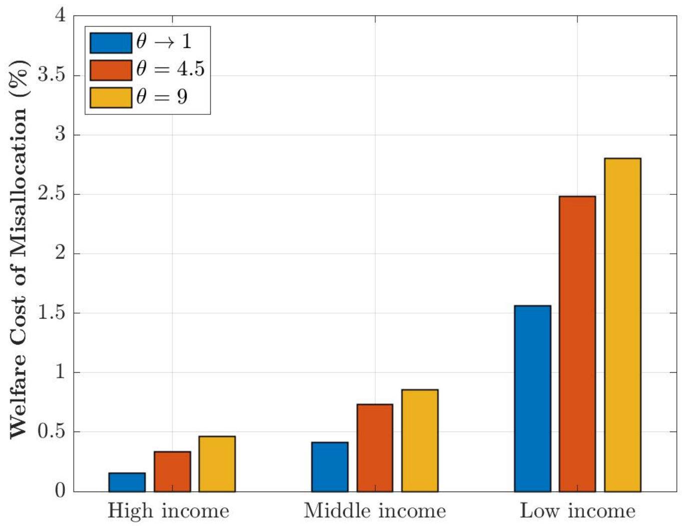
Notes: Panel (a) presents, on the y-axis, the cost share of labor after removing sector fixed effects and adding the average cost share across firms and, on the x-axis, the total sales after removing sector fixed effects. Panel (b) replicates the exercise in Panel (a) using cost share of materials. Both panels present local polynomial regressions.

Figure A.1: Labor Intensity according to Three Technological Regimes - Complementary Pattern 1



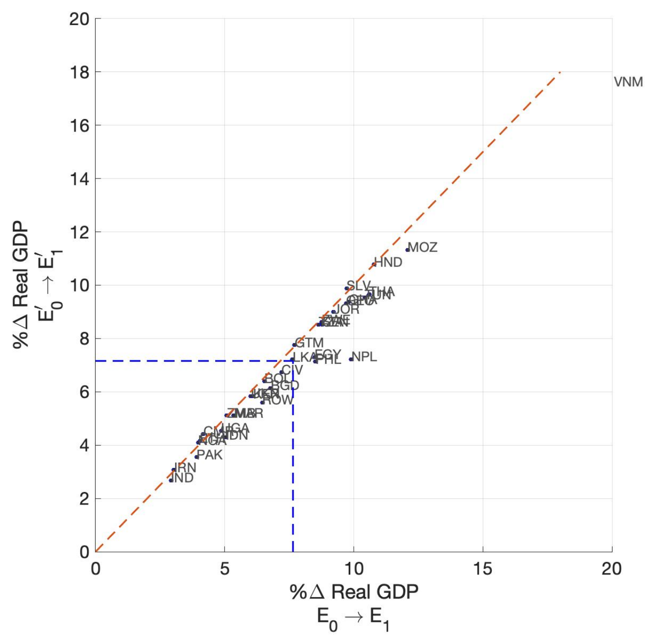
Notes: This figure replicates the exercise in Figure 1 but using three technology regimes rather then two. Here, we split the sample in terms of firm size according to three groups within each sector of the economy: (1) those in the first quartile in the distribution of firm size; (2) those in the bottom quartile in that distribution; and (3) those in the second and third quartile.

Figure A.3: Welfare Costs of Eliminating Labor Wedges — Open Economies



Notes: This figure replicates the exercise from Figure 4, in which we evaluate the impact of removing labor market distortions, but for open economies.

Figure A.4: Welfare—Impact of Trade in Low-income Countries: High- vs Low-Wedge



Notes: This figure shows the percentage change to welfare—as the sum of real wages, real managerial rents, and real distortion revenues—, across low-income countries in Scenario I (x-axis) that corresponds to status quo labor wedges in low-income countries, and in Scenario II (y-axis) that corresponds to counterfactually less-distorted labor markets in low-income countries.