Essays on factor misallocation

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Abstract

This thesis studies different implications of micro-level factor misallocation across heterogeneous agents. It consists of three chapters.

The first chapter examines the impact of firm-level factor misallocation on an open economy’s comparative advantage. After providing empirical evidence on how Colombian metrics of firm-level misallocation are related to measures of its revealed comparative advantage, I explore the general equilibrium effects of such misallocation and its impact on industries’ export capabilities. I compute a counterfactual equilibrium in which the misallocation is removed in Colombia. The reallocation of factors leads to an important change in the country’s industrial structure and a rise in the exports-to-GDP ratio of 18 p.p. This industrial composition effect is absent in the workhorse models of firm-level factor misallocation under closed economies.

Based on a co-authored paper with Tomasz Święcki, the second chapter studies the origin of the income gaps between agricultural and non-agricultural workers in developing countries. We use Indonesian data to document a robust premium for workers who move out of agriculture and a loss for those who move into agriculture, even if they do not migrate. We argue that to generate simultaneously these within-worker premia and the main moments of the joint sector-income distribution over time, self-selection needs to take place under barriers to sectoral mobility that misallocate workers across sectors. We find that removing such barriers prompt 30% of the workforce to reallocate and aggregate output to increase by 17%.

The third chapter extends the standard model of firm-level factor misallocation in a closed economy in two dimensions. First, I introduce idiosyncratic demand shocks. This allows me to evaluate whether metrics of misallocation predict plants’ survival, a test used to claim that misallocation metrics are empirically swamped by demand shocks. I argue that unconditional estimates in this test are biased in the presence of firms’ selection, which would explain the puzzling empirical findings. Second, I compute the TFP gains of removing misallocation both within and across industries. I quantify the importance of inter-industry misallocation and explore its potential role in explaining TFP gaps across countries.
Lay Summary

This thesis studies different aspects related to resource misallocation across heterogeneous agents. The first chapter examines how firm-level factor misallocation can affect the comparative advantage of an open economy. After documenting how standard metrics of factor misallocation are related to measures of comparative advantage, I explore the channels throughout factor misallocation shapes industries’ export capabilities, using a model of international trade. The second chapter studies the origin of the income gaps between agricultural and non-agricultural workers in developing countries. I evaluate whether those gaps are explained by barriers to labor mobility across sectors or efficient sorting of workers. The third chapter extends the standard framework of firm-level factor misallocation in a closed economy in two dimensions: to account for idiosyncratic demand shocks and for misallocation both within and across industries.
Preface

Chapter 2 “Barriers to Mobility or Sorting? Sources and Aggregate Implications of Income Gaps across Sectors and Locations in Indonesia” is a joint work with Professor Tomasz Święcki from the Vancouver School of Economics, at the University of British Columbia. I participated in all stages of the research: collection and statistical analysis of the data; estimation and robustness checks of the reduced form regressions; identification and estimation of the structural model; computation of the counterfactual exercises; and writing several sections of the manuscript.
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Dedication

To Ximena, Eugenio, Myriam and Andrés.
Introduction

In recent years, a growing body of research has strived to understand how resource misallocation across heterogeneous agents can account for differences in aggregate outcomes across countries. This thesis studies some implications of micro-level resource misallocation across heterogeneous agents. For the empirical applications, the study uses data from different developing countries, where extensive evidence shows the problem is more relevant. Besides the introduction, this thesis comprises of three main chapters.

The first chapter examines how firm-level factor misallocation can affect an open economy’s comparative advantage. In an economy with heterogeneous firms in terms of their physical productivity, an efficient allocation of resources implies that more productive firms demand larger amounts of production factors, up to the point where each factor’s marginal revenue product is the same across all firms. Once we take into account measurement error, dispersions in the factors’ marginal revenue product across firms suggest the presence of firm-level factor misallocation. First, I present empirical evidence on how those factor misallocation metrics are related to the observed patterns of Colombia’s comparative advantage, a country whose manufacturing survey allows to separate out components of efficiency and demand from the usual physical productivity measures. As a comparative advantage measure, I use the estimates from an export-industry fixed effect derived from a gravity equation. I find that the factor misallocation metrics have a quantitative importance similar to the “natural” sources of comparative advantage (Ricardian and Heckscher-Ohlin sources) in explaining comparative advantage. Next, I explore the general equilibrium effects of firm-level misallocation in an open economy and their role in shaping industry export capabilities. To do this, I introduce an international trade general equilibrium model with endogenous selection of heterogeneous firms in which the factor allocation is inefficient. I compute a counterfactual in which factor misallocation is removed in Colombia. The factor reallocation allows Colombia to specialize in industries with “natural” comparative advantage and generates a substantial change in the country’s industrial composition, which leads to a rise in the exports-to-GDP ratio of 18 pp. This industrial composition effect is absent in the workhorse models of firm-level factor misallocation under closed economies.

Based on a co-authored paper with Tomasz Święcki, in the second chapter we inquire about the source and aggregate implications of the large income gaps between agricultural and non-agricultural workers in developing countries. We use panel data from the Indonesia Family Life Survey to conclude that workers who move out of agriculture see an income gain of around 20% while those who move into agriculture see a similar income loss, even if they stay in the same location. Without controlling for individual heterogeneity, the income premia are even larger, suggesting that sorting of
Introduction

workers occurs and is important. We explore whether those premia can be reconciled with an efficient sorting of workers based on comparative advantage alone. We conclude that, in principle, it can. The reason is that the industry premium on its own has little empirical content. We show this by extending a standard self-selection model based on both permanent and transitory components of comparative advantage to include different types of barriers to sectoral mobility, in particular utility costs of switching sectors and frictions preventing individuals from working in their preferred sectors. We demonstrate that the same cross-sectional and within-worker non-agriculture premia can be rationalized by different combinations of comparative advantage shock processes and barriers to mobility, and hence, the premia alone cannot tell us if there is a misallocation or not. However, we argue that the comparative advantage process and barriers to mobility can be separately identified once we impose some parametric structure and exploit a richer set of moments of the joint sector-income distribution over time. We use indirect inference for our model’s structural estimation, where the selected auxiliary models are the main reduced-form regressions that characterize the moments we are interested in. Our findings suggest that, although both types of sectoral mobility barriers significantly improve the overall fit of the model compared to the frictionless specification, the model that recognizes that not all sectoral transitions are voluntary fits the data considerably better. We conduct a counterfactual in which frictions are removed entirely in this latter specification. Removing all intersectoral mobility barriers would prompt 30% of the workforce to reallocate across sectors. Since the initially misallocated workers reap large income gains from the reallocation (their income doubles on average), the adjustment has a sizable effect on aggregate output, raising it by 17%.

The third chapter extends the usual framework to compute the total factor productivity (TFP) gains from removing factor misallocation in a closed economy (Hsieh and Klenow (2009)) in two dimensions. First, I account for idiosyncratic demand shocks. This extension is useful to test the usual factor misallocation metrics’ ability to explain plants’ survival, a test that has been used recently to claim that misallocation measures are empirically swamped by other profitability determinants, mainly demand shocks (Haltiwanger et al. (2018)). I obtain similar empirical findings using Colombian data with which I can recover demand shock measures due to firm-level price indices availability. However, I argue that explaining plants’ survival with only one profitability determinant produces biased estimates and that including endogenous selection in the model can rationalize the signs of the bias and the data findings addressing those objections. Second, I account for the possibility that production factors are misallocated both within and across industries. I provide closed-form solutions to evaluate the aggregate TFP gains from removing each type of misallocation, offering a simpler computation relative to the methods proposed in the literature. Using data from Colombia and China, I show that the inter-industry misallocation contribution can be as high as 35% of the total gains from removing factor misallocation. Moreover, given the relevance of the inter-industry type for the total gains from removing misallocation, I use cross-country data to document that including this type of misallocation can amplify the usual TFP gaps attributed to factor misallocation based exclusively on intra-industry reforms.
Related literature

The literature on the sources and implications of resource misallocation across heterogeneous agents has grown exponentially in recent years. It is out of scope to offer an extensive review on the topic; see Restuccia and Rogerson (2013) or Hopenhayn (2014a) for this purpose. Instead, I focus my attention on the most relevant papers to the specific topics studied in each chapter of this thesis.

The first chapter is mainly related to the literature that evaluates the effects of trade in open economies with resource misallocation, particularly Ho (2012), Tombe (2015), Święcki (2017), Caliendo et al. (2017) and Costa-Scottini (2018). My focus is different with respect to those papers. Instead of analyzing the effect of trade liberalization in a distorted economy, my objective is to evaluate the impact of the observed resource misallocation on the patterns of a country’s comparative advantage obtained from bilateral trade flows. Ho (2012), who evaluates India’s trade liberalization in a two-country multi-sector setting with firm-level wedges, and Costa-Scottini (2018), who studies the gains from trade and from removing intra-industry misallocation in a multi-country setting with size-dependent factor distortions, are the papers with the closest models to the one used in this chapter. Although my multi-country, multi-sector, and multi-factor framework shares some features with those models, it differs in several aspects. The empirical implementation is also different, since it does not rely on the calibration of large sets of parameters to obtain counterfactuals. In turn, Tombe (2015), Caliendo et al. (2017), and Święcki (2017) use multi-sector and multi-country models to study welfare and the gains from trade under the presence of sectoral frictions, and thus, only inter-industry misallocation. Instead of using a Eaton and Kortum’s (2002) type of model, my framework relies on Melitz’s (2003) type. It generates endogenous ex-post misallocation across industries as the consequence of differences in the moments of the distributions of factor distortions across sectors, which allows for interactions between intra- and inter-industry misallocations.

The model I use in the first chapter has the same interactions between country, industry, and firm characteristics in general equilibrium as the multi-factor models that exhibit factor reallocations, both within and across industries in response to trade shocks, particularly Bernard et al. (2007) and Balistreri et al. (2011). The introduction of resource misallocation generates a new source of comparative advantage that alters the frictionless trade equilibrium. Instead of a full characterization of the inefficient equilibrium properties, my focus is mostly on the implications of allocative inefficiency for the industrial specialization patterns. Therefore, my primary interest relies on the counterfactual exercise of removing the misallocation. Finally, the first chapter is also related to the trade literature concentrated on gravity equations to derive indirect measures of relative export capability, as in Costinot

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1First, since my main focus is on comparative advantage, I let misallocation arise in any factor market. This can distort industries’ advantages in unit costs based on the relative size of the countries’ factor endowments (Heckscher-Ohlin forces). Second, I do not constrain factor distortions to be size-dependent. With size-dependent distortions, the model behaves exactly as a Melitz model with a unique physical productivities cut-off. Thus, the selection effects of distortions do not generate rank-reversals, which are necessary to obtain the large TFP gaps attributed to factor misallocation (Hopenhayn, 2014a,b). Third, my framework accounts for both intra- and inter-industry misallocations.

2Instead, I use the “exact hat algebra” method proposed by Dekle et al. (2008) that is not demanding in terms of data requirements.
et al. (2012), Hanson et al. (2015), Levchenko and Zhang (2016), and French (2017). I use the same approach to obtain revealed comparative advantage measures, which are the main metric of interest in my counterfactual exercises.

The second chapter is related to the literature that inquires about the origin of income gaps between agricultural and non-agricultural workers in developing countries. Those gaps have been documented for decades (see Lewis (1955) or Rostow (1960) and for more recent evidence Vollrath (2014) or Herrendorf and Schoellman (2018)). There are two main hypotheses in the literature. The first one is that the observed gaps are a manifestation of barriers to mobility, implying labor is misallocated, and hence, there are efficiency gains from reallocating workers. This is the spirit of Restuccia et al. (2008), Adamopoulos et al. (2017) or Bryan and Morten’s (2018). The alternative explanation is that residual income gaps are result of sorting of workers across sectors or locations based on unobservable characteristics. This mechanism is the explanation for the urban premium proposed by Young (2013) or for the non-agriculture premium documented by Alvarez (2018), authors that build on Lagakos and Waugh’s (2013) adaptation of the Roy’s (1951) model. In this view residual gaps across sectors or locations exist despite the efficient allocation of labor.

We document that sorting does occur and is important. However, a frictionless allocation in a sorting model is not able to generate the magnitude of the within-individual sectoral premium and at the same time replicate the main moments of the joint sector-income distribution over time. This is why we have to combine both strands of literature. We evaluate the importance of utility costs related to switching sectors (Dixit and Rob (1994), Cameron et al. (2007), Artuç et al. (2010), Dix-Carneiro (2014)) and frictions preventing individuals from working in their preferred sectors (akin to search costs as outlined in Taber and Vejlin (2016), that can be rationalized by on-the-job searching frictions (Gautier et al. (2010), Gautier and Teulings (2015)), for example), to enable the sorting model to fit the main features of the data.

The third chapter is related to the recent literature on the implications of firm-level factor misallocation for aggregate productivity in more general settings than the one used in the pioneer works of Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). I augment the closed economy model to account for idiosyncratic demand shocks, an extension that does not affect the model’s main logic, but allows me to test the misallocation metrics’ ability to explain plants’ survival while controlling for the full set of profit determinants, as in Haltiwanger et al. (2018). I argue that including endogenous selection in the model, as in Bartelsman et al. (2013), Adamopoulos et al. (2017) or Yang (2017), can rationalize the apparent lack of empirical content of the misallocation measures in predicting plants’ exit. I also incorporate both intra- and inter-industry misallocation, as in Oberfield (2013) or Brandt et al. (2013). I offer simpler closed-form formulas for the gains from removing each type of misallocation, and hence, a more straightforward way to compute each type’s contribution, plus empirical evidence about the importance of inter-industry misallocation and its potential role in explaining TFP gaps across countries.
Chapter 1

Firm-level Factor Misallocation and Comparative Advantage

1.1 Introduction

What are the implications of firm-level factor misallocation in open economies? Most of the literature on the effects of resource misallocation on the aggregate economic performance has focused on closed economies.\(^3\) In open economies, if the extent of factor misallocation varies not only across countries but also across industries, it could also shape comparative advantage.\(^4\) For example, consider the broad range of industrial policies that several East Asian countries introduced during the post-war period, intended to promote some strategic industries. Such policies could have generated not only reallocation of factors towards targeted industries but also an increase in resource misallocation across firms within those sectors given the distortionary nature of some instruments used: selective investment tax credits, public enterprises, depreciation allowances, etc.\(^5\) Thus, the likely improvement in the export capability of targeted sectors due to the reduction in the average cost of the factors, compared to un-targeted industries, could have been countered by decreases in their sectoral TFP, due to their larger extent of within-industry factor misallocation. A relevant question here is then how to assess the role of those policies in shaping comparative advantage through their effect on the allocation of resources. Did those policies accentuate or distort the “frictionless” patterns of industrial specialization?

This chapter explores how firm-level factor misallocation can influence the core determinants of industries’ export capabilities in an open economy, and hence, the patterns of industrial specialization. I do this by addressing the following two questions. First, does resource misallocation explain observed industries’ export capabilities once we control for the “frictionless” sources of comparative advantage? Second, if so, what are the implications of removing such misallocation for the compar-

\(^3\)In the trade literature, most of the analysis has been addressed from a different angle: the effect of trade on a metric of firm-level misallocation, such as mark-ups dispersion (Epifani and Gancia (2011), Edmond et al. (2015)) or how much plant survival depend on productivity (Eslava et al. (2013)). Others have studied the effects of trade liberalization for welfare in economies with factor misallocation, papers that are mentioned below.

\(^4\)I use the term comparative advantage to describe the differences in the average unit cost of a good across industries relative to the same differences in a reference country. Hence, the sources of comparative advantage comprise all primitive variables that affect the three determinants of the unit costs in an industry: sectoral average productivities, factors prices and the number of varieties produced. Those sources include not only “natural” differences in technology distributions or factor endowments, but also, in a world with economies to scale, differences in the primitive determinants of industries’ scale (i.e. entry barriers) and, as I show below, the extent of factor misallocation within and across industries in allocative inefficient economies.

\(^5\)For details of East Asian industry policies, see for example Rodrik (1995), Chang (2006) or Lane (2017).
1.1. Introduction

ative advantage of a country and its industrial composition taking into account general equilibrium effects?

To verify the role of firm-level factor misallocation as a determinant of comparative advantage, I first present empirical evidence on how standard metrics of firm-level misallocation are related to the observed patterns of export capability of Colombian industries, once we control for the “natural” determinants of comparative advantage. The choice of Colombia is due to the fact that its manufacturing firm-level data, considered one of the richest in the world (De Loecker and Goldberg (2014)), offers a better understanding of the role of firms’ efficiency in aggregate productivity. A unique feature of the data is the possibility to obtain direct measures of firms’ physical productivity (TFPQ) using plant-level deflators for firms’ inputs and outputs. Those measures of TFPQ allow me to decompose the contribution of efficiency, demand shocks and factor distortions in the sectoral TFP. As my metric of export capability, I use the estimates of the exporter-industry fixed effect derived from a gravity equation, an approach that has gained popularity as a measure of “revealed” comparative advantage, RCA hereafter (Costinot et al. (2012); Levchenko and Zhang (2016), Hanson et al. (2015), French (2017)). I regress the Colombian RCA measure relative to the United States on indicators of both intra- and inter-industry misallocation, exploiting their variation over time. I control for the “natural” sources of comparative advantage using total endowments interacted with factor intensities and efficient sectoral productivities, which capture Heckscher-Ohlin and Ricardian forces respectively. I find that firm-level misallocation have a quantitative relevance for shaping Colombian RCA with a magnitude similar to the one observed for the “natural” determinants.

Next, I examine the general equilibrium channels with which firm-level factor misallocation can shape relative industries’ unit costs and hence comparative advantage. This exploration, which is the main contribution of this chapter, takes into account several adjustments that are absent when removing factor misallocation under a closed economy. For example, consider first the impact of firm-level misallocation within industries only. As it is well known, this type of misallocation generates losses in sectoral TFP. In a closed economy setting with a fixed mass of firms, as in Hsieh and Klenow (2009), HK hereafter, the gains in sectoral efficiency from removing intra-industry misallocation do not generate reallocation of factors across sectors under the standard two-tier (Cobb Douglas-CES) demand system. Instead, in an open economy, even with the same demand structure and a fixed mass of firms, sectoral revenue shares are endogenously determined and depend not only on how substitutable goods are across sectors, but also on the gains from industrial specialization. Removing intra-industry misallocation in a country leads to two types of adjustments on factor prices, absent in a closed economy. First, it produces a change in the relative factor prices across countries to restore trade balance equilibrium, a result analogous to the introduction of a set of sectoral-specific productivity shocks in standard Ricardian models. And second, it changes the relative real factor

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6Constant revenue shares across sectors imply that the efficiency gained by each industry, translated into a lower aggregate price index, is automatically followed by an increase in demand, so there are not inter-industry factor reallocations and their relative prices do not adjust. Under a more general demand (two-tier CES) there is reallocation of factors across sectors, but abstracting from inter-industry misallocation, the effect on factor prices is marginal (see HK and Chapter 3).
returns depending on the adjustment of relative prices of goods, as in the standard Heckscher-Ohlin model.

Furthermore, when allowing for endogenous entry and selection across firms, as in the closed economy models of Bartelsman et al. (2013), Yang (2017) or Adamopoulous et al. (2017), TFP gains and their general equilibrium effects on factor prices are magnified by the adjustment in the extensive margin (the number of operating firms) after removing misallocation. This effect is sizable since it involves a drastic recomposition of incumbent firms: a withdrawal of low-efficiency firms that survived because of factor misallocation plus the addition of potential high-efficiency firms that were not able to operate under allocative inefficiency. In monopolistically competitive industries this recomposition of firms can affect the scale of the sectors, which is a third channel that impacts industries’ relative unit costs. Finally, the marginal returns of the factors might differ on average across sectors, suggesting the presence of inter-industry misallocation as well. Simultaneously removing this type of misallocation affects the direction of sectoral factor reallocations and the magnitude of the adjustments on relative factor prices, which produces further adjustments on average productivities through firms’ selection effects.

To consider all these general equilibrium channels, I use a tractable multi-country, multi-factor and multi-sector model of international trade à la Melitz (2003) in which the allocation of factors across heterogeneous firms is inefficient. I employ wedge analysis to characterize the observed dispersion in the marginal returns of the factors abstracting from the underlying cause of misallocation, an approach introduced by Restuccia et al. (2008) and HK in this context and inspired by the business cycle literature. Under this approach, each firm is represented by a draw of “true” efficiency – physical productivity or TFPQ – and a vector of wedges, whose elements represent the differences between the returns of each primary factor for the firm and the average returns in the economy. I derive a theoretically consistent gravity equation along the lines of Chaney (2008), Arkolakis et al. (2012) and Melitz and Redding (2014) that incorporates the impact of wedges on the determinants of bilateral exports, in particular on the exporter industry fixed effect, my measure of RCA. I then investigate the effect of removing firm-level factor misallocation of a country on its bilateral exports and hence on its RCA.

To this end, I obtain counterfactual equilibria solving the model in relative changes, using the “exact hat algebra” method proposed by Dekle et al. (2008). Each counterfactual incorporates the whole set of general equilibrium effects of reallocating factors to their efficient allocation and is not demanding in terms of data requirements. I perform the exercises using a world composed of 47 countries and an aggregate rest of the world, three production factors and 25 tradable sectors, to evaluate the effect of Colombian firm-level factor misallocation on its comparative advantage schedule. I use Bils et al.’s (2017) method to estimate the dispersion in marginal products in the presence of additive measurement error in revenue and inputs. This methodology exploits the fact that in the absence of measurement

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7Wedge analysis was first developed as accounting methodology in the business-cycle literature by Cole and Ohanian (2002), Mulligan (2005), Chari et al. (2007) and Lahiri and Yi (2009) among others. For recent uses in the literature on factor misallocation, see for example Adamopoulous et al. (2017), Brandt et al. (2013), Bartelsman et al. (2013), Gopinath et al. (2015), Hopenhayn (2014b), Oberfield (2013), Święcki (2017), Tombe (2015) and Yang (2017) among others.
error the elasticity of revenues with respect to inputs should not vary for plants with different average products. Hence, panel data can be used to back out the “true” marginal product dispersion by estimating how such elasticity changes for plants with different average products. Moreover, since overhead factors (necessary to account for endogenous selection) are analogous to an unobservable additive term in measured inputs, this methodology allows me to overcome the problem of measuring the variance of the marginal products of the factors directly from the dispersion of their average products in the presence of fixed costs; a key issue of models with self-selection of heterogeneous firms (Bartelsman et al. (2013)).

The results of the counterfactual exercise suggest that in Colombia resource misallocation plays a major role in shaping comparative advantage. In the case of an extreme reform in which factor misallocation is entirely removed within and across industries, the ratio of exports to manufacturing GDP rises by 18 p.p. and welfare, measured as real expenditure, grows 75%. The large boost in exports is due to the increase in the dispersion of the schedule of comparative advantage, which leads to higher degrees of industrial specialization in the frictionless equilibrium. For instance, the whole chemical sector (both industrial chemicals and other chemicals such as paints, medicines, soaps or cosmetics) climbs to the top of the national export capability ranking, and ends up in the first percentile of the counterfactual RCA world distribution. The opposite case occurs in industries whose comparative advantage in the actual data seems to be due to only factor misallocation, particularly computer, electronic and optical products, transportation equipment, petroleum and machinery and equipment. These four industries shrink and practically disappear, indicating a non-interior solution in the counterfactual equilibrium.

The model also delivers a decomposition of the change in the RCA measure after removing factor misallocation into three terms, each of which corresponds to a single component of the relative unit cost across industries: the average TFP, factors prices, and the number of produced varieties. I find that the adjustment in the relative number of produced varieties (i.e., in the extensive margin), which is generated by the reallocation of factors across industries, contributes the most to the change in the RCA. This is because in the intensive margin the gains in average TFP relative to the rest of the world are offset in large part by the rise in the relative factor prices, and the remaining effect does not vary much across industries.

The organization of this chapter is as follows. Section 1.2 presents the empirical motivation. I first introduce the empirical measure of RCA derived from a standard gravity equation, and next I propose a strategy to evaluate the impact of different metrics of Colombian factor misallocation on its comparative advantage. Section 1.3 introduces the theoretical model and derives the effect of firms’ wedges on the gravity equation, particularly on exporter-industry fixed effects, the measure of RCA. I also offer an overview of the general equilibrium channels that each type of misallocation can trig-
1.2 Empirical motivation

In this section I present empirical evidence on how factor misallocation is related to the comparative advantage of a country. For this, I first introduce the empirical measure of RCA derived from a standard gravity equation and I explain how this measure is linked to the relative producer price index. Next, I decompose the price index in terms of the “natural” sources of comparative advantage and metrics of factor misallocation. Finally, I propose a strategy to evaluate the relation between the metrics of factor misallocation and the measures of RCA, controlling for the “natural” sources of comparative advantage.

1.2.1 A measure of RCA

A wide range of the new trade models deliver a gravity equation, in which comparative advantage has an important role as a predictor of bilateral trade flows. In the generic formulation of the gravity equation, bilateral exports of country $i$ to country $j$, denoted by $X_{ij}$, can be expressed as the combination of three forces: i) a factor that represents “capabilities” of exporter $i$ as a supplier to all destinations; ii) a factor that characterizes the demand for foreign goods of importer $j$; iii) a factor that captures bilateral accessibility of destination $j$ to exporter $i$, which combines trade costs and other bilateral frictions. The gravity equation can be estimated at the industry level, in order to reduce aggregation bias.\(^{10}\) With cross-sectional data the standard procedure involves taking logs and estimating a regression with fixed effects:

$$\ln x_{ij} = \delta_{is} + \delta_{js} + \delta_{ij} + \epsilon_{ij}$$  \hspace{1cm} (1.1)

where $\delta_{is}$, the exporter-industry fixed effect, characterizes factor i), “capabilities” of exporter $i$ in industry $s$; $\delta_{js}$, the importer-industry fixed effect, captures factor ii), the demand for foreign goods of importer $j$ in industry $s$; and $\delta_{ij} + \epsilon_{ij}$ represent factor iii), bilateral accessibility of $j$ to $i$, a component that involves characteristics of the bilateral relation independent of the sector (distance, common language, etc.), absorbed by the exporter-importer fixed effect $\delta_{ij}$, plus sector-specific bilateral frictions and measurement error, represented by the term $\epsilon_{ij}$.

In this way, the estimate of the industry-exporter fixed effect characterizes the relative country’s productive potential in an industry and, given the structure of the gravity equation, it is “clean” from other determinants that affect bilateral trade flows. Since it is only identified up to a double normalization, that is, it has meaning only when it is compared to a reference country and industry, it

\(^{10}\)For a detailed explanation about the necessary conditions for a trade model to yield a structural gravity equation, see Head and Mayer (2014). On the aggregation bias see Anderson and Yotov (2010, 2016).
1.2. Empirical motivation

can be interpreted as a measure of “revealed” comparative advantage (RCA), an approach that has increasingly gained relevance in the trade literature (Costinot et al. (2012), Hanson et al. (2015), and Levchenko and Zhang (2016)). In contrast to traditional measures of RCA, as Balassa’s (1965) index, the fixed effect estimate is a valid measure of countries’ fundamental patterns of comparative advantage (French (2017)). Moreover, it has better statistical properties than Balassa’s index, especially lower ordinal ranking bias and higher time stationarity (Leromain and Orefice (2014)).

Figure 1.1 displays for Colombia the RCA measures of the 25 manufacturing industries listed in Table A.1 of the Appendix A.1. I rely on the CEPII trade and production database, developed for de Sousa et al. (2012). I use bilateral trade flows among 47 countries plus a rest of the world aggregate for 1995. The set of countries is listed in Table A.2 of Appendix A.1. Similar to Hanson et al. (2015), I use as a reference country and industry the mean over all countries and industries, so the RCA can be interpreted as a measure of Colombian industries’ capabilities relative to a “typical” country and a “typical” sector.\footnote{Therefore, letting $\hat{\delta}_is$ be an estimate of $\delta_is$ in regression (1.1), RCA of country $i$ in sector $s$ is defined as:}

$$RCA_is = \left[ \frac{\exp(\hat{\delta}_is)/\exp(\sum_{s}^{1}S\delta_is)}{\exp(\sum_{i}^{N}N\delta_is)/\exp(\sum_{s}^{S}S\delta_is)} \right]$$

Figure 1.1 compares the estimates obtained by EK-Tobit (vertical axis) and PPML (horizontal axis). Noticeably, the ranking across sectors in the cross section is not strongly affected by the estimation method.

The determinants of the exporter-industry fixed effect vary according to the sources of comparative advantage in the considered theoretical model. However, a common feature across all standard models is that such determinants are collapsed in the reduced-form of the relative producer price index at the industry level compared to a reference country $\left(\frac{\bar{p}_is}{\bar{p}_i's}^t\right)$, as a measure of the relative unit cost of producing across industries (French (2017)).\footnote{Under heteroskedasticity in the form of a constant variance to mean ratio PPML performs better, whereas under homoskedastic log-normal errors the Tobit proposed by Eaton and Kortum (2001) is preferred.} For example, in Ricardian models, as in Eaton and Kortum (2002), such ratio depends only on sectoral fundamental efficiencies, the source of comparative advantage at the heart of the Ricardian theory.\footnote{Strictly, French (2017) shows that country $i$ has comparative advantage in sector $s$, compared to country $i'$ and industry $s'$, if the relative price of country $i$ in sector $s$ in autarky is smaller than the same price in country $i'$: $\frac{\bar{p}_is}{\bar{p}_i's}^t < 1$ where $\bar{p}_is$ is the counterfactual price index in industry $s$ of country $i$ in autarky.} In a Heckscher-Ohlin model, as in Deardorff (1998), the implicit assumption is that sectors share the same intra-industry heterogeneity in the distribution of varieties’ productivities. If the heterogeneity varies across sectors, the productivity dispersion can be an additional source of comparative advantage.
1.2. Empirical motivation

the ratio depends on the factor prices weighted by sectoral factor intensities, reflecting the balance between the relative sizes of factor endowments and the technology requirements. In the Krugman (1980) model, it depends only on the relative number of varieties produced, reflecting the effect of gains from variety in the aggregate price. In the Pareto version of Melitz (2003), the ratio is analogous to that in Krugman (1980), adjusted by the Pareto lower bound of the productivity distribution. Multi-factor models with heterogenous firms, as in Bernard et al. (2007) or in this chapter, combine all mentioned sources of comparative advantage in the reduced form of the relative price index.

The model with resource misallocation in an open-economy in the next section delivers an analytical expression of the exporter-industry fixed effect taking into account endogenous entry and selection of firms, features that will provide a rich theoretical grounding to the RCA measure. However, at this point we can use the insights from the most well-known misallocation framework, Hsieh and Klenow (2009) (HK hereafter), to decompose the producer price index in its different determinants and empirically test whether the components due to firm-level misallocation are related to the metrics of RCA, once we control for the remaining sources of export capability.

1.2.2 Decomposing the price index under factor misallocation

The starting point in the HK framework to evaluate the implications of firm-level factor misallocation relies on the distinction between physical productivity (TFPQ, defined as the ratio of physical output to inputs) and revenue productivity (TFPR, defined as the ratio of revenues to inputs), first proposed by Foster et al. (2008). Assume a standard monopolistic competition framework in which firms differ in terms of efficiency –i.e. in the TFPQ or Hicks-neutral productivity–, but use the same constant returns to scale technology in each industry. Moreover, assume firms face a CES demand, with the same elasticity of substitution in all industries. In this simple economy if factor markets are frictionless the following two implications emerge: i) TFPR is equalized across firms within industries;\(^\text{15}\) and ii) the sectoral TFP can be computed as a power mean of firms’ TFPQ. Any dispersion in firms’ TFPR within a sector is a signal of within-industry factor misallocation, and leads to a loss in sectoral TFP.

Of course, the reliability of the dispersion of TFPR as a measure of intra-industry factor misallocation depends on the plausibility of the considered assumptions. Some recent papers have tried to quantify the contribution of other possible sources of variation in TFPR, that do not imply factors are misallocated. These include departures from the model specification (heterogeneity in inputs, variable markups, adjustments costs, etc.) and pure measurement error. In Table 1.1 I present a brief survey of those contributions, each one derived from an extended structural model that takes into account the corresponding cause. The main conclusion is that, apart from measurement error, the remaining causes have a relative small contribution to the dispersion in TFPR. In the case of measurement error,

\(^{15}\)This is simply because TFPR is the product of firm’s price and TFPQ. With constant mark-ups, prices vary across firms only due to marginal costs. In turn, with all firms facing the same factor prices and the described technologies, the only source of variation in marginal costs is TFPQ. Hence, differences in TFPQ are perfectly translated into (the inverse of) prices, leaving TFPR invariant.
1.2. Empirical motivation

Bils et al. (2017) propose a method to compute the true dispersion in TFPR in the presence of additive and orthogonal measurement error in revenues and inputs, using panel data. The methodology exploits the fact that in the absence of measurement error the elasticity of revenues with respect to inputs should not vary for plants with different average products; see section 1.4.2 for a detailed explanation. In what follows I use Bils et al.’s (2017) methodology to obtain measures of intra-industry misallocation that correct for measurement error, but, for tractability – and given the evidence cited above – I abstract from other causes of dispersion in TFPR.

More formally, assume that the production technology is Cobb-Douglas (CD) such that \( q \) units of variety \( m \) in a manufacturing industry \( s \) in country \( i \) are produced using a set of \( L \) homogenous factors \( z_l \) and factor intensities \( \alpha_{ls} \):

\[
q_m = a_m \prod_{l} z_{lm}^{\alpha_{ls}}
\]

(I omit industry and country subscripts for firm-specific variables). Denote firms’ revenue by \( r_m \) and the inverse of the constant mark-up by \( \rho \). The sectoral production function is then:

\[
Q_{is} = A_{is} L \prod_{l} Z_{ils}^{\alpha_{ls}}
\]

(capital letters denote aggregates) where the sectoral TFP \( A_{is} \) depends on the distribution of physical productivities and the extent of intra-industry factor misallocation. In frictionless factor markets the efficient sectoral TFP is the power mean of firms’ TFP \( Q, (A_{is})^{\sigma - 1} = \sum_{m} a_m^{\sigma - 1} \), and all firms face the same price for their homogenous inputs, say \( w_l \) for factor \( z_{lm} \), leading to TFPR equalization across firms within industries, with values equal to

\[
\frac{1}{\rho} \prod_{l} w_{il}^{a_{is}}
\]

Since the sectoral price index can be expressed as the ratio between the sectoral TFPR and the industry TFP, it can be in turn decomposed in terms of “natural” sources of comparative advantage and measures of factor misallocation as:

\[
\ln P_{is} = \ln TFPR_{is} - \ln A_{is} = \sum_{l} \alpha_{ls} \left[ \ln \left( 1 + \tilde{\theta}_{ils} \right) + \ln w_{il} \right] - \ln A_{is}^{e} - \ln AEM_{is}
\]

(1.2)

where \( AEM_{is} \) corresponds to the ratio sectoral TFP to the efficient one, \( AEM_{is} = A_{is} / A_{is}^{e} \), and \( (1 + \tilde{\theta}_{ils}) \) is defined as the ratio between the observed marginal revenue product (MRP) of factor \( l \) at the sector level, \( \frac{\alpha_{ls} R_{ils}}{z_{ils}} \), and its return in the efficient allocation, \( \frac{\alpha_{ls} w_{ils}}{\rho} \), that is: \( (1 + \tilde{\theta}_{ils}) \equiv \frac{\rho \alpha_{ls} R_{ils}}{\alpha_{ls} w_{ils}} \). Those two ratios quantify the extent of resource misallocation. In the first case, \( AEM_{is} \) characterizes the amount of within-industry factor misallocation, with \( 0 \leq AEM_{is} \leq 1 \) and values closer to 1 reflecting less misallocation. According to the implications of the model, this measure is inversely related to the within-industry variance of the TFPR. In the second case, the sectoral wedge \( (1 + \tilde{\theta}_{ils}) \) characterizes the magnitude of inter-industry misallocation in factor \( l \), and thus \( \prod_{l} (1 + \tilde{\theta}_{ils})^{\alpha_{is}} \) is a factor-intensity weighted measure of inter-industry misallocation.

Therefore, the decomposition in equation (1.2) reveals the theoretical determinants of the RCA measure under resource misallocation: i) the efficient TFP, \( A_{is}^{e} \), which depends exclusively on the

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16In the case of a log-normal distribution of factor distortions across firms, the correlation is perfect, see Chen and Irarrazabal (2015) for the proof.

17The sectoral wedge \( (1 + \tilde{\theta}_{ils}) \) can be also computed as the harmonic weighted average of similar wedges at the firm-level, with weights given by firms’ shares in sectoral revenue. See Chapter 3 for more details about the importance of this type of factor misallocation relative to within-industry misallocation in a closed economy.
1.2. Empirical motivation

distribution of physical productivities across firms; ii) the geometric average of factor prices, \( \prod L^{\alpha_{is}} \), which in general equilibrium can be recovered as the interaction between factor endowments and intensities; iii) the geometric average of inter-industry wedges, \( \prod (1 + \bar{\theta}_{is})^{\alpha_{is}} \), a measure of inter-industry misallocation; and iv) the measure of intra-industry misallocation, \( AEM_{is} \). Notice that, since the first component is related to technical efficiency and the second component to relative factor abundance, they represent the “Ricardian” and “Heckscher-Ohlin” sources of comparative advantage, respectively, whereas the two latter terms summarize both inter- and intra-industry resource misallocation. I use these four components (in logs) as explanatory variables in a regression of the RCA measure derived from the fixed effects, to test our hypothesis.

1.2.3 Relation between RCA and misallocation measures

Ideally, the suggested regression would require measures of the four variables in a large set of countries and industries, and thus comparable firm-level data for several countries. Given the infeasibility of this approach, I propose a two-stage strategy that exploits the time variation in the measures of RCA for Colombia relative to the United States (US) using panel-data. In the first stage, I estimate the panel data-version of equation (1.1), allowing the fixed effects in each cross section vary over time. That is, with data for the same set of countries in the period 1991-1998, I run the regression:

\[
\ln X_{ist} = \delta_{ist} + \delta_{is} + \delta_{jst} + \varepsilon_{ijst}
\]  

where the exporter-industry-year fixed effect \( \delta_{ist} \) identifies the triple difference of bilateral flows across exporters \( i \) and \( i' \), sectors \( s \) and \( s' \) and years \( t \) and \( t' \); that is, the variation of \( RCA_{is} \) between time \( t \) and \( t' \), denoted by \( dRCA_{ist} \). To compute \( dRCA_{ist} \), instead of global means, I take as the reference country \( i' \) the US, the reference year \( t' \) the first year in the panel (1991), and the reference industry \( s' \) the sector with the median number of zeros bilateral flows in the data (footwear).19 In the second stage, I regress the estimates of \( dRCA_{ist} \) for Colombian industries on the four theoretical determinants of comparative advantage, constructed using micro-level data. Each variable is transformed to be expressed as the double difference first with respect to the reference industry and second with respect to the reference year, and then is normalized by the corresponding difference in the producer price index in the US (obtained from the NBER-CES manufacturing database), using the same industry and

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18Particularly if we set \( w_l = \rho R / \sum s' \bar{Z}_{is} \), where \( R \) is total revenue (\( \sum R_s \)), the values satisfy the solution for relative factor prices in general equilibrium for an allocative efficient closed economy, given by \( w_l = \bar{Z}_s \sum \bar{a}_{is} \beta_s / \bar{Z}_s \sum \bar{a}_{is} \bar{a}_{is} \beta_s \), where \( \bar{Z}_s \) is the total endowment of factor \( l \) (see Chapter 3).

19Therefore, letting \( \hat{\delta}_{ist} \) be an estimate of \( \delta_{ist} \) in the regression (1.3), \( dRCA_{ist} \) of country \( i \) in sector \( s \) at time \( t \) is defined as:

\[
dRCA_{ist} = \left[ \frac{\exp(\hat{\delta}_{ist}) \exp(\hat{\delta}_{is})}{\exp(\hat{\delta}_{is}')} \cdot \frac{\exp(\hat{\delta}_{is})}{\exp(\hat{\delta}_{i's})} \right] / \left[ \frac{\exp(\hat{\delta}_{is})}{\exp(\hat{\delta}_{i's})} \cdot \frac{\exp(\hat{\delta}_{i's})}{\exp(\hat{\delta}_{i's}')} \right]
\]

where \( i' = \text{US} \) and \( s' = \text{Footwear (7)} \). As I show below, the results are not very sensitive to the choice of \( s' \).
1.3. A model of firm-level misallocation in an open economy

The introduction of the time-dimension poses an additional challenge for the fixed effects estimators. Particularly, we must appraise the incidental parameter problem (Neyman and Scott (1948)), which generates an asymptotic bias for the fixed effects estimators when the number of time periods is small. Fernández-Val and Weidner (2016) prove that under exogenous regressors, in a Poisson model this bias is zero, which make PPML preferable over EK-Tobit as estimating method in the first stage. Thus, Table 1.2 displays the results for the standardized coefficients of the regression in the second stage, using PPML to obtain the exporter-industry-year fixed effects in the first stage. The estimation of the second stage is by weighted OLS, using the reciprocal of the error variance in the first stage as weighting matrix. In the first column I present the results for the measure of intra-industry misallocation $AEM_{is}$, based on the direct measures of firms’ TFPQ using plant-level deflators for firms’ inputs and outputs, that allows me to isolate the influence of demand shocks. In the second column, I use instead for the measure of intra-industry misallocation the within-industry variance of firms’ TFPR, corrected by measurement error following Bils et al.’s (2017) methodology. In both specifications, the measures of intra and inter-industry misallocation, once we control for the “natural” sources of export capability, are significantly correlated with our RCA measure and display the expected signs: positive for the intra-industry misallocation measure $AEM_{is}$ (negative in the case of the within-industry variance of TFPR) and negative for the inter-industry misallocation measure $L_{j}^{L} (1 + \bar{\theta}_{lis})^{\alpha_{l}}$. Moreover, the magnitude of the standardized coefficients suggests that both types of misallocation have a similar impact for shaping Colombian RCA, and they are not less important relative to the “Ricardian” and “Heckscher-Ohlin” determinants. These correlations are robust to the choice of the reference industry and the aggregation of countries. For instance, in column 3 I replicate the first specification using the sector with the lowest number of zeros as reference industry (machinery exc. electrical) whereas in column 4 I aggregate the 48 countries into 20 regions. The results are qualitatively similar. Therefore, the empirical evidence suggests that resource misallocation can play a role shaping the schedule of comparative advantage in Colombia. The model in the next section offers theoretical grounding to this insight.

In this section, I introduce a model of international trade à la Melitz (2003) in which the allocation of factors within and across industries is inefficient. Next, I derive a theoretically consistent gravity

\[ dRCA_{ist} = F((\frac{P_{is}}{P_{is}^{0}} / \frac{P_{st}}{P_{st}^{0}}) / (\frac{P_{is}}{P_{is}^{0}} / \frac{P_{st}}{P_{st}^{0}})). \]

Notice that in this approach we compare the growth on the relative prices (with respect to the reference year) across countries, so any difference in the measurement of relative prices across countries is absorbed by the difference over time.

The use of weighted OLS seeks to alleviate the impossibility to bootstrap standard errors. Given the high-dimensionality of the set of fixed effects involved in the non-linear regression by PPML in the first stage, the estimation is infeasible in standard econometric software as STATA, so I take advantage of the sparsity pattern of the problem and use a specialized solver that deals efficiently with sparse problems (SNOPT). However, the estimation is still highly time consuming.

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\(^{20}\)This transformation intends to reflect the fact that the variation in RCA should be related to the change in the relative producer price indices compared to the same change in the country of reference: $dRCA_{ist} = F((\frac{P_{is}}{P_{is}^{0}} / \frac{P_{st}}{P_{st}^{0}}) / (\frac{P_{is}}{P_{is}^{0}} / \frac{P_{st}}{P_{st}^{0}}))$. Notice that in this approach we compare the growth on the relative prices (with respect to the reference year) across countries, so any difference in the measurement of relative prices across countries is absorbed by the difference over time.

\(^{21}\)The use of weighted OLS seeks to alleviate the impossibility to bootstrap standard errors. Given the high-dimensionality of the set of fixed effects involved in the non-linear regression by PPML in the first stage, the estimation is infeasible in standard econometric software as STATA, so I take advantage of the sparsity pattern of the problem and use a specialized solver that deals efficiently with sparse problems (SNOPT). However, the estimation is still highly time consuming.
1.3. A model of firm-level misallocation in an open economy

equation following the lead of Arkolakis et al. (2012) and Melitz and Redding (2014), assuming
certain restrictions on the ex-ante joint distribution of TFPQ and factor distortions. Finally, I study
the effects of both intra- and inter-industry factor misallocation on the reduced-form expression of the
exporter-industry fixed effect derived from the gravity equation, my measure of RCA, using model
simulations under a simple parametrization.

1.3.1 Model setup

Denote by $m$ a single variety, $i$ the exporting country, $j$ the importing country, $s$ an industry and $l$ a
homogenous production factor. Assume there are $N$ possibly asymmetric countries, $S$ industries and
$L$ homogenous primary factors. Hereafter capital letters denote aggregates, lower case letters firm-
specific variables and for simplicity, I omit again sector subscripts for firm-specific variables. Each
country $i$ consumes according a two-tier utility function, with an upper-level CD with expenditure
shares $\beta_{is}$ across sectors and a lower-level CES with elasticity of substitution $\sigma$ across varieties; let
$\rho = \frac{\sigma-1}{\sigma}$. Each firm produces a variety $m$ using $L$ homogenous primary factors (each one denoted by $z_{ilm}$) and a CD production technology with factor intensities $\alpha_{ls}$ (different factor intensities across in-
dustries, but equal for the same industry across countries). Firms are characterized by a Hicks-neutral
physical productivity (TFPQ) $a_{im}$ and a vector of $L$ factor-distortions: $\tilde{\theta}_{im} = \{\theta_{1im}, \theta_{2im}, \ldots, \theta_{Lim}\}$, which
are drawn from a joint ex-ante distribution $G_{is}(a, \tilde{\theta})$. There is a fixed cost of production $f_{is}$ in terms
of the composite input bundle, and each industry faces an exogenous probability of exit $\delta_{is}$.

There is a fixed cost $f_{ij}^{ix}$ to access market $j$ from country $i$ in sector $s$, defined in terms of the
composite input bundle, and a transportation iceberg-type cost $\tau_{ij} \geq 1$, with $\tau_{iis} = 1$. Let $w_{il}$ denote
the price of factor $l$ in country $i$ in absence of distortions, unobservable and common for all firms.
Firms in country $i$ face an idiosyncratic distortion $\theta_{ilm}$ (given by the $l$-th element of $\tilde{\theta}_{im}$) in the market
of primary factor $l$, such that the input price perceived by the firm is $(1 + \theta_{ilm}) w_{il}$. Define $f_{ij} = f_{ij}^{ix} + f_{is}$ if $j \neq i$; $f_{ij} = f_{ij}^{ix} + f_{is}$ otherwise (so domestic market fixed costs incorporates both “market access” and
fixed production costs, whereas the export cost includes only the market access cost). The minimum
“operational” cost to sell a variety $m$ of country $i$ in country $j$ is:

$$c_{ijm}(q_{ijm}) = \omega_{is} \Theta_{im} \left( \frac{\tau_{js} q_{ijm}}{a_{im}} + f_{ij} \right) \quad (1.4)$$

where $\Theta_{im} = \prod_{l} (1 + \theta_{ilm})^{\alpha_{ls}}$ is a factor-intensity weighted geometric average of firm wedges and $\omega_{is} = \prod_{l} (w_{il} / \alpha_{ls})^{\alpha_{ls}}$ is the prevalent factor price of the composite input bundle for the firms with zero draws
of $\tilde{\theta}_{im}$. Hereafter I refer to this cost as the total “operational” cost, which includes the variable cost of
production and the fixed costs of production and delivery. Notice that this is a standard cost function
in a multi-factor Melitz-type setting, the only difference here is that the composite input bundle’s price
perceived by the firm is a combination of both distortions and the underlying factor prices. Moreover,
this cost function could be derived from a primal problem considering the following technology to
produce and deliver one unit of variety $m$ of country $i$ in country $j$:

$$q_{ijm} = \frac{a_{im}}{\tau_{ij}} \left( \prod_l \alpha_{ls} \tau_{ij} f_{js} \right) = \frac{a_{im}}{\tau_{ij}} (z_{ijm} - f_{ij}) \tag{1.5}$$

Here $z_{ijm}$ represents the total amount of primary factor $l$ “embedded” in the production and delivery of variety $m$ from country $i$ in country $j$, and $z_{ijm}$ the corresponding composite input bundle. Notice that $z_{ijm}$ includes the demand of primary factor $l$ to pay both variable and fixed costs.

Profit maximization implies a firm charges a price $p_{ijm}$ in each destination $j$ equal to a fixed mark-up $(\rho^{-1})$ over its marginal cost: $p_{ijm} = \tau_{ij} \Theta_{im} \omega_{is} / \rho a_{im}$. Quantities, revenues and profits of variety $m$ from country $i$ sold in country $j$ are (respectively):

$$q_{ijm} = p_{ijm} - \sigma_{ijm} E_{js} P_{djs} \sigma^{-1} ; r_{ijm} = p_{ijm} - \sigma_{ijm} E_{js} P_{djs} \sigma^{-1} ; \pi_{ijm} = \sigma r_{ijm} - \omega_{is} \Theta_{im} f_{ij} \tag{1.6}$$

where $E_{js}$ is the total expenditure of country $j$ in varieties of industry $s$ and $P_{djs}$ the corresponding consumer price index, variables that are defined below. It is straightforward to show the following relation between revenues from destination $j$ and the corresponding total “operational” cost: $c_{ijm} = \rho r_{ijm} + \omega_{is} \Theta_{im} f_{ij}$. Revenue productivity (TFPR) of selling variety $m$ in destination $j$, denoted by $\psi_{ijm}$, is the ratio between revenue and the input used in production: $\psi_{ijm} = r_{ijm} / (z_{ijm} - f_{ij}) = p_{ijm} a_{im} / \tau_{ij} = \Theta_{im} \omega_{is} / \rho$. Notice that although this destination-specific TFPR is not directly observable, since the allocation of factors to production for a given destination is unobservable, profit maximization implies that firms equate this value across all destinations, as the natural consequence of the absence of destination-specific frictions at the firm level. Hence, total TFPR must coincide with this value. In the absence of frictions in factor markets, there is TFPR equalization across firms within an industry (factor intensities make TFPR vary across sectors) for all destinations. Thus, in an efficient allocation, a firm’s performance with respect to its competitors depends uniquely on relative TFPQ. In contrast, in the presence of factor misallocation, firms with higher TFPQ or lower TFPR (due to a low geometric average of firm wedges, $\Theta_{im}$), holding the rest constant, set lower prices and hence sell higher quantities, obtaining higher revenues and profits in all markets.

Denote by $\xi_{ijlm}$ the marginal revenue product (MRP) of factor $l$ “embedded” in the production of variety $m$ from country $i$ to country $j$. Once again this MRP is not directly observable, but it is a useful concept to illustrate the consequences of factor misallocation. After some manipulation, it is possible to obtain the following relation between $\xi_{ijlm}$ and the total “operational” cost: $\xi_{ijlm} = \alpha_{ls} c_{ijm} / \rho z_{ijlm}$. Notice that because of the presence of fixed costs, the MRP is no longer directly proportional to the average revenue product, a result emphasized in Bartelsman et al. (2013). From the FOC of the minimization cost problem of the firm, we know that $(1 + \theta_{ilm}) w_{il} z_{ijlm} = \alpha_{ls} c_{ijm}$, which derives into $\xi_{ijlm} = (1 + \theta_{ilm}) \omega_{ls} / \rho$. That is, an efficient allocation of factors in an open economy requires MRP equalization across firms over all industries for all destinations, TFPR equalization within industries
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for all destinations, but because of fixed costs, there is not average revenue products equalization.

Firms produce for a given destination only if they can make non-negative profits. Since profits in each market depend on both TFPQ and TFPR, this condition defines a cutoff frontier \( a_{ijs}^*(\Theta) \) for each destination \( j \), such that \( \bar{\pi}_{ijs} \left( a_{ijs}^*(\Theta), \Theta \right) = 0 \, \forall \, i,j,s \). For a given combination of factor wedges \( \Theta \) of firms in country \( i \) industry \( s \), i.e., a given value of TFPR, \( a_{ijs}^*(\Theta) \) indicates the minimum TFPQ required to earn non-negative profits in destination \( j \). Define \( a_{ijs}^* \) as the TFPR cutoff value for firms with TFPR equal to \( \frac{\omega_s}{\rho} \) in destination \( j \), i.e. firms with draws of distortions equal to zero: \( a_{ijs}^* = a_{ijs}^*(1) \).

It is straightforward to derive the specific functional form of the cutoff functions in terms of \( a_{ijs}^* \) and \( \Theta \):

\[
a_{ijs}^*(\Theta) = a_{ijs}^* \Theta^\frac{1}{1-a} \text{ with } a_{ijs}^* = a_{ijs}^*(1) = \frac{\tau_{ijs}}{\rho} \left( \frac{E_{js} P_{js}^{\sigma-1} f_{is}/E_{js} P_{js}^{\sigma-1} f_{js}}{\sigma f_{ijs}} \right)^{\frac{1}{\sigma-1}} \frac{\omega_s^\frac{1}{\sigma}}{\forall \, i,j,s}. \tag{1.7}
\]

The function \( a_{ijs}^*(\Theta) \) is increasing in \( \Theta \) (and thus in TFPR) reflecting the fact that larger wedges reflect higher marginal cost of the inputs, becoming more difficult to sell to the corresponding market. The existence of these cutoff functions, instead of unique threshold values for physical productivity, implies that the introduction of factor misallocation triggers selection effects that are absent in the efficient allocation. For example, some firms productive enough to operate in an undistorted counterfactual can no longer keep producing either because their distortions draws turn their profits negative or because even with a small “good” draw, the possible strengthening of competition due to the presence of highly positive distorted firms does not make it profitable for them to stay in the respective market. And the opposite could occur with some low productive firms, which will be able to survive in each market leading to misallocation of resources.\(^{23}\)

To analyze the selection effects of resource misallocation, notice first that all cutoff functions across destinations share the same functional forms. Particularly, cutoff values for exporting to destination \( j \) are \( \Lambda_{ijs} = \tau_{ijs} \left( E_{js} P_{js}^{\sigma-1} f_{is}/E_{js} P_{js}^{\sigma-1} f_{js} \right)^{\frac{1}{\sigma-1}} \) times larger than domestic cutoff values. Thus, a simple representation of the firms in an open economy can be done in the space \( a \times \Theta \), illustrated in Figure 1.2. In this space, each firm in sector \( s \), characterized by a pair of draws \( (a, \Theta) \), is represented by a single point. Profits are an increasing function of TFPQ and a decreasing function of TFPR, so firms with draws closer to the upper-left corner are more profitable. For simplicity, consider the destination \( j \) different to \( i \) with the lowest ratio \( \Lambda_{ijs} \) for country \( i \) in sector \( s \) in Panel A. Only firms with draws \( (a, \Theta) \) above \( a_{ijs}^*(\Theta) \) export to destination \( j \), those with draws below \( a_{ijs}^*(\Theta) \) and above \( a_{iis}^*(\Theta) \) produce only for the domestic market, and those with draws below \( a_{iis}^*(\Theta) \) do not produce. Panel B represents the selection mechanism that distortions trigger. Let \( \tilde{a}_M \) represent the domestic productivity cutoff value in an allocative efficient economy (Melitz economy), and \( \bar{\Lambda}_{ijs} \) the corresponding value.

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\(^{22}\)Notice also that TFPR of variety \( m \) sold in destination \( j \) can be expressed as a factor-intensity weighted geometric average of the MRP: \( \psi_{jim} = \prod \xi_{jim} / \alpha_{is} \).

\(^{23}\)These selection channels are also present in the closed economy models of Bartelsman et al. (2013) and Yang (2017).
of \( \Lambda_{ijs} \). In such economy, firms with productivity above \( \tilde{\Lambda}_{ijs} \) export to \( j \), those with productivity between \( \tilde{\Lambda}_{ijs} \) and \( a^*_M \) produce only for the domestic market, and those with productivity less than \( a^*_M \) do not produce. Thus, each cutoff function in the allocative inefficient economy creates two effects in the set of firms that sell to each market, which can be represented by two sets of areas: the regions under the density function that show firms that as consequence of distortions can no longer produce (light dotted area A) or export to \( j \) (light dotted area B) and the regions that display firms that because of distortions operate in the domestic market (dark dashed area A) or in the exporting market (dark dashed area B). The difference between dotted and dashed areas represents the net impact of distortions on the set of firms of country \( i \) and sector \( s \), operating in the domestic and country-\( j \) markets (differences in A and B respectively).

The timing of information and decisions is as follows. Each time, there is an exogenous probability of exit given by \( d_{iis} \). A total of \( H_{iis} \) potential entrants at country \( i \) industry \( s \) decide whether to produce and export to each destination conditional on their draws of physical productivity and distortions from \( G_{iis} \). All potential entrants pay a fee \( f^e_{iis} \) to draw from \( G_{iis} \), which is paid in terms of the composite input bundle. The number of potential entrants is pinned down by the condition in which the expected discounted value of an entry is equal to the cost of entry. As usual in this kind of setup, let us consider no discounting and only stationary equilibria. Hence, the free entry condition is:

\[
\sum_{j} \sum_m M_{ijs} M_{ijs} = \omega_{iis} f^e_{iis} H_{iis} \forall i, s
\]  

(1.8)

Where \( M_{ijs} \) denotes the mass of operating firms in sector \( s \) of country \( i \) that is selling to country \( j \). Aggregate stability requires that in each destination the mass of effective entrants is equal to the mass of exiting firms:

\[
d_{iis} M_{ijs} = \left[ 1 - G_{iis} \left( a^*_{ijs} \left( \Theta \right) \right) \right] H_{iis} \forall i, j, s
\]  

(1.9)

Given CES demand and firms prices, the consumer price index \( P^d_{iis} \) in country \( i \) sector \( s \) satisfies

\[
\left( P^d_{iis} \right)^{1-\sigma} = \sum_{k} P^d_{kis}^{1-\sigma},
\]

with:

\[
P^d_{ijs} = \left( \frac{1}{\rho} \omega_{iis} r_{ijs} \right)^{1-\sigma} \sum_m \left( \frac{a^m_{ijs}}{\sigma_m} \right)^{\sigma-1}
\]  

(1.10)

Total expenditure in country \( i \) and sector \( s \) is \( E_{iis} = P^d_{iis} Q^d_{iis} \). By the upper-level utility function, the overall consumer price index (equal to unit expenditure) is \( P^d_i = \prod_s \left( P^d_{iis} / \beta_s \right)^{\beta_s} \) and satisfies \( E_{iis} = \beta_s E_i \), with \( E_i = \sum_s E_{iis} \) total country-\( i \) expenditure.

Now consider the aggregate variables. Let \( X_{ijs} = \sum_m r_{ijs} \) be the value of total exports from country \( i \) to destination \( j \) in industry \( s \). Analogously as at the firm-level, the total “operational” cost of exporting to country \( j \) incurred by all firms of country \( i \) in industry \( s \) can be written as

\[
24 \text{In general, } a^*_{iis} \text{ and } \Lambda_{ijs} \text{ are not related to } \tilde{a}^*_M \text{ and } \tilde{\Lambda}_{ijs} \text{ respectively. In Figure 1.2 it is arbitrarily assumed } a^*_{ijs} > \tilde{a}^*_M.
\]
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\[ C_{ij} = \rho X_{ij} + \delta_{ij}, \]
where \( \delta_{ij} = \sum_m \omega_m \Theta_{im} f_{ij} \) is the value of total expenditures in fixed costs. Similarly, denote by \( R_{is}, \delta_{is}, C_{is} \) the same aggregations but at the industry level, with \( R_i = \sum_s R_{is} \) representing total country \( i \)'s gross output. Denote the HWA of primary factor-\( l \) wedges \((1 + \theta_l)\) within industry \( s \) as \((1 + \hat{\theta}_{is})\), with weights given by the firm’s participation in \( C_{is} \). It is possible to show that \((1 + \hat{\theta}_{is}) = (\rho R_{is} + \delta_{is}) \alpha_{is} / \omega_{il} Z_{ils}^0 \) where \( Z_{ils}^0 \) is the aggregate demand of factor \( l \) for “operational” uses in country \( i \) in sector \( s \): \( Z_{ils}^0 = \sum_i \sum_m z_{ilm} \). Thus, this average wedge is the industry-level analogue of firm-level wedges and allows me to measure the degree of inter-industry misallocation, as in the closed-economy framework of the previous section. The total demand of primary factor \( l \) for “operational” uses in country \( i \) industry \( s \) can be expressed as:

\[ Z_{ils}^0 = \frac{\alpha_{is} C_{is}}{\omega_{il} (1 + \hat{\theta}_{is})} \]  \hfill (1.11)

Primary factors are used for “operational” (fixed and variable costs) and investment (entry) costs. The sectoral demand of the composite input bundle for entry costs is simply \( f_{is}^e H_{is} \). Therefore, the amount of primary factor \( l \) allocated to entry costs in country \( i \) sector \( s \) is \( Z_{ils}^e = \alpha_{is} \omega_{il} f_{is}^e H_{is} / \omega_{il} \), and the total allocation of the same factor, \( Z_{ils} \), is given by:

\[ Z_{ils} = Z_{ils}^0 + Z_{ils}^e = \frac{\alpha_{is} C_{is}}{\omega_{il} (1 + \hat{\theta}_{is})} + \frac{\alpha_{is} \omega_{il} f_{is}^e H_{is}}{\omega_{il}} \]  \hfill (1.12)

Notice that the inter-industry wedge only appears in the input allocated for operational uses. This is a consequence of the timing of the model, in which firms allocate first real resources (the entry fixed cost) to draw from the joint distribution. Only after this moment is the draw of the vector of distortions known to the firm. Factor-\( l \) market clearing condition in country \( i \) is then:

\[ \bar{Z}_{il} = \sum_s Z_{ils} \]  \hfill (1.13)

where \( \bar{Z}_{il} \) is the total endowment of primary factor \( l \) in country \( i \), and \( Z_{ils} \) is given by (1.12). Finally, the balanced trade condition requires equalization of the total revenues to total expenditures plus aggregate deficits:

\[ R_i = E_i + D_i \]  \hfill (1.14)

where \( D_i \) is the country’s trade balance (a positive value means surplus), an exogenous value in the model.

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25 By construction, total revenues are the sum of factor payments and profits: \( R_i = \sum_s \frac{(1 + \hat{\theta}_{is})}{\omega_{il}} Z_{ils}^0 + \sum_s \omega_{is} f_{is}^e H_{is} \). This can be shown decomposing sectoral revenues as:

\[ R_i = \rho R_{is} + \frac{1}{\sigma} R_{is} = \frac{1}{\gamma} (1 + \hat{\theta}_{is}) \omega_{il} Z_{ils}^0 - \delta_{is} + \frac{\sum_m (\pi_{ijs} + \omega_{il} \Omega_{im} f_{ij})}{\sum_{m} \omega_{il} \Omega_{im} f_{ij}}. \]

where the second equality is derived from (1.11) and the aggregation of firms’ revenues.
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Global trade balance requires: $\sum_i D_i = 0$. A summary of the whole system of equations and unknowns is given in Table 1.3. This table also offers the dimensionality of the problem.

1.3.2 Comparative advantage

Bilateral exports at the industry level can be expressed in terms of sectoral expenditures in the importer country ($E_{js}$) and trade shares of the importer country ($\pi_{ijs}$). The latter term can be re-written in terms of the bilateral price indices as:

$$X_{ijs} = \pi_{ijs} E_{js} = \left( \frac{P_{ijs}^{1-\sigma}}{\sum_k P_{kjs}^{1-\sigma}} \right) E_{js} \quad (1.15)$$

The trade share of country $i$ in country-$j$ expenditures in goods of industry $s$ only depends on the value of its bilateral price index $P_{ijs}$, relative to the same value for all competitors of country $i$ in such market. As I commented earlier, this is so because the price index $P_{ijs}$ is a measure of the unit price incurred by consumers of the destination country, and hence it is an indicator of country-$i$’s competitiveness.

To derive the reduced-form of the exporter industry fixed effect, consider the double difference of bilateral flows across exporters $i$ and $i'$ and sectors $s$ and $s'$ for a given importer $j$, i.e., $X_{ijs} X_{i'js'} X_{ijs'} X_{i'js}$. It is straightforward to see that this double difference is given by the difference in the relative price index, $(P_{ijs} P_{i'js'} P_{i'js} P_{ijs})^{1-\sigma}$. From (1.10) it is possible to disentangle these bilateral prices indices as follows:

$$P_{ijs} = \tau_{ijs} \rho_{ijs}^{1-\sigma} \psi_{ijs} A_{ijs} \quad (1.16)$$

where $A_{ijs}$ and $\psi_{ijs}$ are the industry-destination analogues of sectoral TFP and sectoral revenue productivity respectively, so $A_{ijs}$ represents the overall efficiency of exporting firms to destination $j$ and $\psi_{ijs}$ depicts the average cost of the factors faced by the same set of exporters. Therefore, equation (1.16) disentangles the four determinants of exporters’ competitiveness: i) their overall efficiency, which is a weighted average of exporters physical productivity and factor market frictions; ii) the average cost of factors for exporters; iii) the mass of exported varieties; and iv) bilateral trade costs. Of these components, factor misallocation has a direct impact on the average TFP and an indirect impact (through general equilibrium channels) on the formation of factor prices and the determination of the number of exported varieties. Notice also that the unit price is a combination of both extensive and intensive margins of trade. Thus, the model is very rich about the determinants of competitiveness. It is able to combine the sources of relative export capability in Ricardian and Heckscher-Ohlin models (where comparative advantage is due to differences in efficiency across industries in the first case and the interaction between the sizes of factor endowments and factor intensities across industries that pins

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26 This is: $A_{ijs} = \Theta_{ijs}(\frac{1}{\sum_m \alpha_m} \frac{\rho}{\Theta})^{\sigma-1} \frac{1}{\tau_{ijs}}$ and $\psi_{ijs} = \frac{\alpha_i \Theta_{ijs}}{\rho}$. Here $\Theta_{ijs} = \frac{1}{\sum_{j} (1+\hat{\theta}_{ijs})^{\alpha_i}}$. Here $(1+\hat{\theta}_{ijs})$ denote the HWA of factor-$l$ wedges of firms exporting to destination $j$ in industry $s$, with weights given by firm’s participation in the total cost of factors $C_{ijs}$. 20
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down relative factor prices, in the second case) with the motives for intra-industry trade in monopolistic competition models with Dixit-Stiglitz preferences (where the gains-from-variety effect induce reductions in unit costs) in an environment of micro-level resource misallocation, which in turn can also create “artificial” comparative advantage. In the next subsection, I perform numerical simulations to disentangle the effects of both intra- and inter-industry misallocation on each component of the relative unit prices.

At this point I need to impose a functional form for the joint distribution $G_{is}$ to derive the reduced-form equation of the exporter-industry fixed effect from the double difference in unit price. Let $G_{a_{is}}(a)$ be the univariate margin of $G_{is}$ with respect to $a$, and $G_{θ}^{θ}(θ)$ the multivariate margin of $G_{is}$ with respect to $θ$. Consider the following assumptions:

A. 1. (Pareto distribution) $\forall a_i > \bar{a}, G_{a_{is}}(a) = 1 - (\frac{a_{is}}{\bar{a}_{is}})^κ, \kappa > \sigma - 1$;

A. 2. (Ex-ante independence) $G_{is} = G_{is}(a, θ) = G_{a_{is}}(a)G_{θ}(θ)$

First, regarding Assumption A.1., the Pareto distribution is the common benchmark in the trade literature to model heterogeneity on physical productivity in the Melitz model. Not only does it have a good empirical performance approximating the observed distribution of firm size, but it also makes the model analytically tractable, allowing me to derive a particular expression for the gravity equation. And second, although Assumption A.2. seems problematic given the observed correlation between TFPQ and TFPR in the data, it is worth emphasizing that the assumed independence is only between the latent (ex-ante) marginal distribution of TFPQ and that of the vector of factor distortions. The observed (ex-post) distribution can exhibit any kind of correlation. In fact, given the functional forms of the cutoff functions, endogenous selection in the model implies the positive ex-post correlations between TFPQ and TFPR observed in the data. Furthermore, there is no restriction for the joint distribution of individual factor distortions $G_{θ_{is}}$, so covariances across factors wedges are completely allowed. I keep Assumptions A.1. and A.2. hereafter unless otherwise indicated.

Under Assumptions A.1. and A.2., the model exhibits an interesting set of features and offers a great simplification, which is done in detail in Appendix A.4.1 and summarized by the system of equations (1.21)-(1.24) below. First, it is possible to show that the property of a constant aggregate profits/revenue ratio of the Pareto-Melitz model still holds under factor misallocation: $R_{is} = \frac{κ}{\bar{θ}} Π_{is} = \frac{κ}{\bar{θ}} \alpha_{is} f_{is} H_{is}$ (see equation (A.5) in Appendix A.4.1). Thus, market clearing conditions can be re-stated as:

$$w_{il}Z_{ils} = \alpha_{is} \left[ (1 + \tilde{θ}_{ils})^{-1} \left(1 - \frac{ρ}{κ}\right) + \frac{ρ}{κ} \right] R_{is}$$

(1.17)

notice that the HW A wedge $(1 + θ_{ils})$ affects only the fraction of the total revenue that is allocated to “operational” costs: $1 - \frac{ρ}{κ}$. Denote the term in curly brackets by $v_{ils}$. Here, $v_{ils}$ measures the effective extent of inter-industry misallocation for primary factor $l$, considering all its possible uses

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27 This is, $G_{a_{is}}(a) = \lim a_{is}(a, \tilde{θ})$ and $G_{θ}^{θ}(θ) = \lim a_{is}(a, \tilde{θ})$

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Let \( v_{is} \) denote the factor-intensity weighted geometric average of these measures: 
\[
v_{is} = \prod_i v_{is}^{\alpha_{ls}}.
\]
Further, aggregate the sectoral demands of primary factors on an industry-level composite input bundle 
\[
Z_{is} = \prod_l Z_{is}^{\alpha_{ls}}.
\]
Thus, we can state \( v_{is} R_{is} = \omega_{is} Z_{is} \) and hence \( H_{is} = \frac{\omega_{is} Z_{is}}{\sum_{is} v_{is}} \), a solution for the mass of entrants similar to that obtained in the multi-sector Pareto-Melitz case (in which the mass of entrants is related to the total allocation of inputs in the sector). The only difference here is the presence of the inter-industry allocative inefficiency measure \( v_{is} \), which affects the total allocation of factors across sectors.

Second, it is possible to derive a relationship between the ex-post HW A wedge and the ex-ante joint distribution of distortions. Appendix A.4.2 shows that the following relation holds:

\[
(1 + \bar{\theta}_{is}) = \frac{\Gamma_{is}}{\Gamma_{is}} \tag{1.18}
\]

where \( \Gamma_{is} = \int_{\theta_1}^{\theta_1} \cdots \int_{\theta_L}^{\theta_L} \Theta^{1-\bar{\theta}} dG_{is}(\bar{\theta}) \) and \( \Gamma_{is} = \int_{\theta_1}^{\theta_1} \cdots \int_{\theta_L}^{\theta_L} \Theta^{1-\bar{\theta}} dG_{is}(\bar{\theta}) \), terms that only depend on the ex-ante joint distribution of firm-level distortions \( G_{is}^\theta \). Equation (1.18) makes evident the interaction between both types of factor misallocation under our assumptions, and depending on the parametric assumptions on the joint distribution \( G_{is}^\theta \), it allows me to recover some structural parameters from the values of observed HWA wedges.

Third, regarding the gravity equation, I show in Appendix A.4.3 that relative bilateral exports can be expressed as:

\[
\ln \left( \frac{X_{ijs}X_{ijs}'}{X_{ijs}'X_{ijs}} \right) = \ln \left[ \frac{\rho_{is} \rho_{i's}}{\rho_{i's} \rho_{is}} \frac{\Gamma_{is} \Gamma_{i's}}{\Gamma_{i's} \Gamma_{is}} \frac{R_{ijs} R_{i's}}{R_{i's} R_{ijs}} \frac{\omega_{is} \omega_{i's}}{\omega_{i's} \omega_{is}} \right] + B_{ijs} \tag{1.19}
\]

where \( B_{ijs} \) and \( \rho_{is} \) are constants that do not vary when we remove misallocation. The first term of the RHS of equation (1.19) is what \( \delta_{i's} \) identifies in the regression with fixed effects in (1.1). I show in Appendix A.4.3 how it can be decomposed in elements that capture the influence of each source of export capability in the model. Moreover, notice that changes in the extent of allocative inefficiency have a direct effect on the double difference of the term \( \Gamma_{is} \), and an indirect effect (through general equilibrium channels) on the product of the double differences of the terms \( R_{ijs} \) and \( \omega_{is}^{\frac{\bar{\theta}}{\bar{\theta}}} \). Thus, to figure out the total impact of factor misallocation on RCA, it is necessary to solve the full model in general equilibrium, which is done in section 1.4.

1.3.3 Simulations

To illustrate the effects of both intra- and inter-industry misallocation on comparative advantage, I use numerical simulations under a simple parametrization of the model. Consider a world with two countries, two factors and two sectors, with symmetric factor intensities across sectors. Sector 1 is factor 1-intensive. Country 1 faces factor misallocation in sector 1 (I will simulate distortions
on each factor, so the results are totally symmetric for factor misallocation in sector 2). Assume trade costs do not vary across sectors. Two objectives are pursued: first, to show how both types of factor misallocation of country 1 affect its comparative advantage, disentangling the total impact on its determinants; and second, to illustrate how sensitive these effects are to factor intensities and trade costs.

Both sectors in the two countries have the same Pareto TFPQ distribution. Country 1 is relatively abundant in factor 1 with respect to country 2, so in the allocative efficient scenario it has a comparative advantage in sector 1.\(^{29}\) I am interested in the RCA of country 1 in sector 1 relative to country 2 in sector 2, which I compute using equation (1.19). Assume also a log-normal distribution for distortions, with location and shape parameters \(\mu_l\) and \(\sigma_{l}^2\) for factor \(l\) respectively, and to simplify things, zero covariances. I show in Appendix A.4.4 that using equation (1.18) under log-normality it is possible to obtain the following relation between the ex-post HW A wedge and those parameters:

\[
\ln (1 + \bar{\theta}_{ls}) = \mu_{l/s} + \left(1 - \frac{\kappa}{\rho}\right) \alpha_{ls} - \frac{1}{2} \sigma_{l/s}^2 \tag{1.20}
\]

Equation (1.20) sheds light on the feedbacks between the two types of factor misallocation under endogenous selection of firms. For example, consider the case in which the location parameter is zero. Ex-ante, the average (log) distortion for the firms within the industry is zero. However, for a given value of the dispersion on these frictions (which generates intra-industry misallocation) we obtain \((1 + \bar{\theta}_{l/s}) < 1\); that is, ex-post inter-industry misallocation. This result is due to endogenous selection, since firms with both low TFPQ and high distortions exit for sure, pushing the value of the ex-post average of the prevalent distortions below zero, generating inter-industry misallocation.

**Only intra-industry misallocation**

To represent the impact of only intra-industry misallocation on comparative advantage, I first consider the impact of an increase in the variance of wedges of each factor separately, simultaneously adjusting the location parameter to ensure there is no inter-industry misallocation. Figure 1.3 displays the results. The first four graphs correspond to the total impact on the comparative advantage of sector 1 (first graph) and the decomposition of the sources of export capability explained above (average efficiency, returns of factors, and number of the mass of exported varieties; second to fourth graphs), following equation (A.9) in Appendix A.4.3. Each of these graphs plots the difference between the value of the endogenous variable under the parameters assumed for the distribution of distortions, which are displayed in the last graph, and the corresponding values in the allocative efficient equilibrium, so they capture the net effect of the considered allocative inefficiency. The fifth graph illustrates the implicit HWA of the prevalent distortions, following equation (1.20), to verify the degree of inter-industry

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\(^{29}\)Results do not change qualitatively in the case of the opposite relative factor endowments, or if the comparative advantage is countered or enhanced by Ricardian comparative advantage (through differences in the lower bound of the Pareto distribution). In those cases, there is a change in the initial RCA, but the effect of factor misallocation is qualitatively similar.
misallocation. Blue and red lines correspond to misallocation only in factors 1 and 2, respectively. I consider two trade regimes: free trade, represented by dashed lines, and costly trade, represented by continuous lines. The values for the whole set of parameters used in each simulation are displayed in Table 1.4.

Introducing only intra-industry misallocation of any factor used in sector 1 reduces its comparative advantage. The effect increases the larger the variance of the (log) wedges and, for the same value of the variance, if the misallocation affects the factor used intensively by industry. The total effect is also marginally larger under free trade for the range of variances considered in the graph. It is worth saying that for larger variances, there is a threshold in which with free trade the system falls in a regime of complete specialization, so the production of sector 1 shuts down. These results are consistent with the intuition that the larger the possibility to substitute goods across countries, the larger the impact of misallocation on industry revenue shares, boosting more reallocation of factors across sectors. Regarding the determinants of relative export capability, intra-industry misallocation creates well-known losses of TFP, as in a closed economy. However, to keep trade balanced, these losses are followed by an adjustment in relative factor prices, absent under autarky. Given endogenous selection, there is relative net exit of exporters in the distorted sector 1, which is a consequence of the reallocation of factors to the undistorted sector 2. The increase in the relative demand of the factor used intensively in sector 2 also reduces the relative price of the factor used intensively in sector 1. The combined effect on factor prices largely counters the effect of the loss in overall efficiency, but the sum of the two forces is still negative. Thus, the total impact on export capability is largely due to the adjustment in the extensive margin of trade, whereas the contribution of the intensive margin is smaller, but not zero.

**Only inter-industry misallocation**

Now consider the impact of inter-industry misallocation. For this, I shift the location parameter allowing it to take positive and negative values, keeping the shape parameter equal to zero. Then, there is no dispersion in wedges (and thus no intra-industry misallocation), but the ex-post HWA wedge varies with the location parameter, creating inter-industry misallocation. Figure (1.4) displays the results with the same graphs and conventions as in the previous exercise. The net impact on comparative advantage is inversely related to the sign on the location parameter. To understand this result, it is useful to think about positive values of the location parameter as an industry-level tax in the cost of the factor, which imply a HWA wedge greater than 1 (or a subsidy for negative values). For instance, consider the effects of introducing an industry-level factor tax. It becomes relatively more expensive to buy the corresponding input for all firms within the taxed industry, raising the average return of the composite input bundle. Some firms whose productivity draws prevent them from paying the new inputs’ cost

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30 For free trade I will consider a scenario without iceberg transportation costs but with fixed costs of exporting, since I am interested in keeping endogenous selection on exporting markets.

31 The prevalence of the extensive margin is probably linked to the Pareto assumption. On the consequences on Pareto’s distribution over the two margins of trade, see Fernandes et al. (2015).
must exit. Here, there is no TFP loss due to within-industry misallocation, because all firms in the industry face the same factor prices, so average TFP depends only on the physical productivities of the incumbents. Instead, there is selection of the more productive firms, so average TFP rises. Both impacts are larger if the taxed factor is the one used intensively in the sector (since it has more weight in the composite bundle) and under free trade (since reallocation of factors is larger). The increase on average TFP entirely compensates the loss in export capability due to the increase in the relative return of the factors, up to the point that net effect on comparative advantage through the intensive margin is positive, but small. Adding the negative effect on the extensive margin due to the exit of firms, which is not very affected by the trade regime or by the intensity in the use of the factors, the overall impact on export capability is negative.

In conclusion, each type of factor misallocation impacts industries’ comparative advantage through different general equilibrium channels. The extent of each impact depends on the interaction between factor intensities and the variances of distortions, in the case of intra-industry misallocation, and primarily on whether the HWA wedges are less or greater than one, in the case of inter-industry misallocation. The effect of both types of factor misallocation on the industries’ TFP is partially offset by changes in relative factor prices, so the intensive margin contributes less to the adjustment of relative unit prices relative to the extensive margin (the change in the mass of produced varieties due to the reallocation of factors across industries). Therefore, ignoring the general equilibrium effects caused by resource misallocation could lead to misguided conclusions. The next section presents a methodology to solve the model in general equilibrium to produce a counterfactual series of bilateral exports after removing allocative inefficiency in a country, and hence to evaluate its frictionless RCA.

1.4 Empirical implementation

In this section, I perform the counterfactual exercise of removing both (and separately) the observed intra and inter-industry misallocation in Colombia. I first show how to obtain the counterfactual equilibrium solving the model in relative changes. Next, I comment on the data employed, the method to measure the dispersion in the MRP of the factors under overhead costs, and the baseline results. Finally, I conduct some robustness checks and compare the baseline results with those obtained for the one-sector economy and the closed economy.
1.4. Empirical implementation

1.4.1 Counterfactual exercise

I show in Appendix A.4.1 that under assumptions A.1. and A.2. the entire system can be solved in terms of the following system of equations:

\begin{align*}
    w_{il}Z_{ils} & = \alpha_{ls}v_{ils}R_{is} \\
    \bar{Z}_{il} & = \sum_{s}^S Z_{ils} \\
    R_{is} & = \sum_{j}^N \pi_{ijs} \beta_{js} \left( \sum_{s}^S R_{js} - D_j \right) \\
    \pi_{ijs} & = \frac{\left( \prod_{l}^L \frac{w_{il}^{\frac{\sigma - 1}{\sigma}}}{\rho_{il}} \right) \Gamma_{is} \phi_{ijs} R_{is}}{\sum_{k}^N \left( \prod_{l}^L \frac{w_{kl}^{\frac{\sigma - 1}{\sigma}}}{\rho_{kl}} \right) \Gamma_{ks} \phi_{kjs} R_{ks}}
\end{align*}

where \( \phi_{ijs} = \frac{\beta_{js}}{\sum_{s}^S \pi_{ijs}^{\frac{\sigma - 1}{\sigma}} R_{is}} \) and \( \pi_{ijs} \) is the share of country \( i \) in total expenditures of country \( j \) in sector \( s \). Denote the share of factor \( l \) allocated to sector \( s \) in country \( i \) as \( \tilde{Z}_{ils} \), that is: \( \tilde{Z}_{ils} \equiv \frac{Z_{ils}}{\bar{Z}_{il}} \). Equations (1.21) and (1.22) can be re-stated as: \( w_{il} \tilde{Z}_{ils} \tilde{Z}_{il} = \alpha_{ls}v_{ils}R_{is} \), with the condition \( \sum_{s}^S \tilde{Z}_{ils} = 1 \forall i, l \).

Now I use the methodology of Dekle et al. (2008), adopted in other papers,\(^{32}\) to obtain the counterfactual equilibrium in relative changes. This approach, known as exact hat algebra, allows me to solve the model without assuming or estimating parameters that are hard to identify in the data, particularly all those which are embedded in the term \( \phi_{ijs} \) (trade variable and fixed costs, entry costs, lower bounds for TFPQ, probabilities of exit), and the current measures of intra-industry and inter-industry misallocation for all industries and countries. All these values are included in the initial trade shares, and because they do not change in the counterfactual equilibrium, they do not appear in the system in relative changes.

For any variable \( x \) in the initial equilibrium denote \( x' \) its counterfactual value and \( \hat{x} \equiv \frac{x'}{x} \) the proportional change. Then, the system in the final equilibrium can be rewritten as:

\begin{align*}
    \hat{w}_{il} & = \sum_{s}^S \tilde{Z}_{ils} \hat{R}_{is} \hat{v}_{ils} \\
    \hat{R}_{is} \hat{R}_{is} & = \sum_{j}^N \pi_{ijs}' \beta_{js} \left( \sum_{s}^S \hat{R}_{js} - \hat{D}_j \right) \\
    \pi_{ijs}' & = \frac{\pi_{ijs} \left( \prod_{l}^L \frac{\hat{w}_{il}^{\frac{\sigma - 1}{\sigma}}}{\rho_{il}} \right) \hat{\Gamma}_{is} \hat{R}_{is}}{\sum_{k}^N \pi_{kjs} \left( \prod_{l}^L \frac{\hat{w}_{kl}^{\frac{\sigma - 1}{\sigma}}}{\rho_{kl}} \right) \hat{\Gamma}_{ks} \hat{R}_{ks}}
\end{align*}

\(^{32}\)See for example Costinot and Rodríguez-Clare (2014), Caliendo and Parro (2015), Święcki (2017), among others.
The objective with this system is to analyze the impact of exogenous changes in both intra and inter-industry misallocation (through the terms $\hat{v}_{ils}$ and $\hat{\Gamma}_{is}$) of a country on the equilibrium outcomes $\hat{R}_{is}$ and $\hat{w}_{il}$. For this, the system can be solved for $\hat{R}_{is}$ and $\hat{w}_{il}$ (after imposing the usual normalization $\sum_i R_{is} \hat{R}_{is} = 1$) given values of the observable variables $\pi_{ij}$, $\hat{Z}_{ils}$ and $R_{is}$, technological and preference parameters $\alpha_{is}$ and $\beta_{is}$ respectively, and assumptions on parameters $\kappa$ and $\sigma$ and the variation of aggregate trade deficits $\hat{D}_j$. Since my interest is to remove factor misallocation only in a country, I set $\hat{v}_{ils} = \hat{\Gamma}_{is} = 1$ for all countries different from Colombia, so I only need values of $\hat{v}_{ils}$ of $\hat{\Gamma}_{is}$ for Colombia to derive the corresponding proportional changes.

Once $\hat{R}_{is}$ and $\hat{w}_{il}$ are obtained, it is straightforward to compute the relative changes in aggregate expenditure and trade shares, $\hat{E}_i$ and $\hat{\pi}_{ijs}$. With these variables it is possible to quantify the cost of each type of misallocation in terms of welfare, measured as total real expenditure. In Appendix A.4.5 I show that the relative change in aggregate real expenditure can be derived from:

$$\frac{\hat{E}_i}{\hat{P}_i} = \prod_s \left[ E_i \frac{1}{\hat{R}_{is} \hat{\Gamma}_{is}} \left( \frac{\hat{\pi}_{ils}}{\hat{\pi}_{is}} \right)^{\frac{1}{\kappa}} \prod_l \frac{a_{ils}^{\alpha_{ils}}}{\hat{w}_{il}^{\beta_{ils}}} \right]^{-\beta_s} \tag{1.28}$$

Notice that in the case of the undistorted economy with one factor of production, equation (1.28) collapses to the well-known Arkolakis et al.’s (2012) formula ($\prod_s \left[ \hat{\pi}_{is} \hat{Z}_{is} \right]^{-\frac{\kappa}{\kappa}}$) to evaluate the increase in welfare in response to any exogenous shock.

### 1.4.2 Data and model solution

I collect information on bilateral trade shares, gross output and sectoral factor shares for the same set of countries and manufacturing sectors used in section 1.2. I use a gross output specification for the production function with capital, materials, skilled and unskilled labor as inputs. I set factor intensities for all countries equal to the US cost shares, under the assumption that US cost shares reflect actual differences in technology across sectors instead of inter-industry misallocation. The primary source of information is the OECD’s Trade in Value Added (TiVA) database (2015’s release) for the year 1995, but I also use auxiliary information from several other sources; for a detailed description see Appendix A.1. For the calibrated parameters, I use in the baseline results $\kappa = 4.56$ and $\sigma = 3.5$, values consistent with those used in the literature.$^{33}$ Section 1.4.4 verifies how sensitive are the results to changes in those values. Given the static nature of the framework, the model is silent about the adjustment of aggregate trade deficits. Thus, for the counterfactual exercises, I assume that for all countries different from the RoW, trade deficits as a proportion of gross output remain constant in the counterfactual. The trade deficit of the RoW adjusts to ensure global trade balance.

To obtain the proportional changes in the measures of factor misallocation $\hat{v}_{ils}$ and $\hat{\Gamma}_{is}$ for Colombia, I assume that the joint distribution of factor distortions is log-normal. In Appendix A.4.4 I show

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$^{33}$These values are averages of the ones used by Melitz and Redding (2015) ($\kappa = 4.25$ and $\sigma = 4$) and the ones estimated by Eaton et al. (2011) ($\kappa = 4.87$ and $\sigma = 2.98$). Section 1.4.4 evaluates the sensitivity of the baseline results to changes in these values.
1.4. Empirical implementation

how equation (1.18) can be used to obtain an identity that relates the ex-post HWA wedges to the vector of location parameters and the variance-covariance matrix of the ex-ante joint distribution of the distortions $V_{is}$ (see equation (A.10)). Therefore, I only need measures of the HWA of wedges, which can be inferred from sectoral data using (1.17), and estimates of $V_{is}$ to obtain the latent location parameters and, consequently, both $v_{iis}$ and $\Gamma_{is}$. The counterfactual exercises involve removing: i) both types of misallocation; ii) only intra- and iii) only inter-industry misallocation for the homogenous production factors: capital, skilled and unskilled labor.34

To estimate $V_{is}$, I use Bils et al.’s (2017) method to compute the dispersion in the factors’ MRP in the presence of additive measurement error in revenue and inputs. Since overhead factors are analogous to an unobservable additive term in measured inputs, this approach deals also with the problem of inferring the variance of factors’ MRP directly from the observed dispersion of the average revenue products in the presence of fixed costs. The main idea of Bils et al.’s (2017) approach is to estimate a “compression factor” $\hat{\lambda}$ to correct the observed dispersion on TFPR, $\hat{\sigma}^2_{TFPR}$, as a measure of the dispersion in the “true” TFPR, $\sigma^2_{TFPR} (\hat{\lambda} = \sigma^2_{TFPR}/\hat{\sigma}^2_{TFPR})$, using panel data. The methodology exploits the fact that in the absence of measurement error the elasticity of revenues with respect to inputs should not vary for plants with different average products. Hence, panel data can be used to back out the “true” marginal product dispersion by estimating how such elasticity changes for plants with different average products. I estimate $\hat{\lambda}$ by GMM sector by sector, using the panel data from 1991 to 1998. In Appendix A.2, I present details about the methodology and the results of the replication.35 I correct the observed variance-covariance matrix of the average revenue products of factors by $\hat{\lambda}_s$ to obtain $\hat{V}_{is}$. Table 1.5 displays for each industry the employed values for the HWA wedges, the corresponding observed variances and covariances of factors’ average revenue products and the obtained “compressions factors” $\hat{\lambda}_s$, along with factor intensities.

The model is constituted by $N \times (S + L) = 1344$ equations. The multiplicity of non-linearities in the model implies that common optimization routines find multiple local solutions. To obtain the global solution, I employ both an algorithm to choose a set of ideal initial conditions and a state-of-the-art solver for large-scale nonlinear systems. Appendix A.3 offers details about these two aspects.

1.4.3 Baseline results

First, I describe the results of “extreme” reforms that remove the total extent of intra- and inter-industry misallocation in Colombia. The results of gradual reforms are presented in the next section. I compute the RCA measures for each counterfactual equilibrium using PPML. Similar to Figure 1.1, instead of choosing a pair importer-sector, I normalize by global means. The resulting RCA measures are displayed in Figure 1.5. All panels plot the actual RCA measures in the horizontal axis

34 Given the infeasibility of decomposing intermediate consumption into homogeneous inputs, I assume that all observed dispersion in the MRP of materials is due to actual heterogeneity in the input, instead of factor misallocation. Thus, the counterfactual equilibrium preserves both the observed within-industry dispersion and the inter-industry differences in the MRP of intermediate consumption.

35 The point estimates for $\hat{\lambda}_s$ vary in the range $[0.75, 0.87]$, indicating that around 20% of the observable dispersion in TFPR is attributable to measurement error.
and the counterfactuals in the vertical one. Panels A and B show the case of removing both types of misallocation. In Panel A the markers’ sizes represent the actual industries’ export shares and in Panel B the counterfactual ones.

Once both types of misallocation are removed, the ratio of exports to manufacturing GDP rises from 0.15 to 0.33 and welfare grows 75%. Although the impact of factor misallocation looks at first glance surprisingly large, these results are in line with the findings in much of the literature that assess the gains of similar reforms.\(^{36}\) Table 1.6 displays a decomposition of the aggregate results. The boost in exports is due to the increase in the dispersion of the Colombian schedule of comparative advantage. This is evident in Figure 1.6, which compares the location of the Colombian industries in the RCA world distribution for the initial and counterfactual equilibria, where each vertical line represents a single Colombian industry. This figure also evidences the fact that the counterfactual ranking is not related to the actual one. Industrial chemicals, other chemicals, glass and tobacco are the industries with the largest increases with respect to their initial RCA, whereas petroleum, machinery and equipment, transport equipment and computer, electronic and optical products, display the largest drops. The latter industries disappear when both types of misallocation are removed, indicating the presence of a non-interior solution in the counterfactual equilibrium,\(^{37}\) which explains in part the longer left tail in the counterfactual world distribution.\(^{38}\) The larger dispersion on the frictionless comparative advantage leads to higher degrees of industrial specialization in the frictionless equilibrium, which is evident comparing the export shares from panel A to panel B. For instance, the whole chemical sector (both industrial chemicals and other chemicals), an industry that ends up in the first percentile of the counterfactual RCA world distribution, concentrates 64% of the counterfactual Colombian exports, from 23% in the actual data.

The total impact on comparative advantage is a non-linear combination of the effects of removing both HWA wedges and the intra-industry dispersion on the returns of the factors. Panel C and Panel D of Figure 1.5 depict the RCA measures after removing only intra- and inter-industry misallocation respectively, with markers’ sizes representing the counterfactual export shares. In each exercise, I compute the counterfactual values \(v'_{ils}\) and \(\Gamma'_{is}\) such that the other type of misallocation remains un-

\(^{36}\)For example, HK find that without affecting firms’ selection, an intra-industry reform “would boost aggregate manufacturing TFP by 86%–115% in China, 100%–128% in India, and 30%–43% in the United States” (Hsieh and Klenow, 2009, pg. 1420). For Indonesia, Yang (2017) computes TFP gains of 207% from removing manufacturing intra-industry misallocation taking into account firms’ selection (97% in the case of a comparable reform to HK). All these large magnitudes are in part due to the extreme nature of the counterfactual, which implies a perfect allocation of factors across all firms, perhaps an unrealistic reform. This is the reason why some papers prefer experiments with gradual reforms (for our case see the next section), or with the reduction of misallocation to the levels observed in a reference country (i.e. the United States, as in HK).

\(^{37}\)The feasibility of non-interior solutions in multi-sector Pareto-Melitz type of models is recently evaluated by Kucheryavyy et al. (2017). These authors show that under the standard formulation of the model in which the elasticities of substitution do not vary between domestic and foreign varieties, as it is the case in this chapter, it is guaranteed that the general equilibrium is unique, but not necessarily an interior solution. Besides multiple factors and resource misallocation, the other difference that makes the model here different is the fact that fixed costs of exporting are paid in terms of factors of the source country.

\(^{38}\)The counterfactual equilibrium also involves large contractions (between 40% and 70%) in some industries of some of the main Colombian trade partners: 4 in Ecuador, 2 in Brazil, 1 in Venezuela and 1 in Hong Kong.
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changed. Notice that in both cases the dispersion of comparative advantage is lower than in Panels A and B, but larger with respect to the original one. Table 1.6 shows that in spite of both types of factor misallocation contributing to the total growth in exports, intra-industry misallocation seems quantitatively more important. Removing only intra-industry misallocation leads to an increase in 13 p.p. of the exports to GDP ratio and a rise in 56% in welfare, whereas removing only inter-industry misallocation causes smaller increases (7 pp. and 8% in each variable, respectively).

The directions and the magnitudes of the changes in the RCA due to each type of factor misallocation can be explained by the extent of its respective causes. The simulations performed in section 1.3.3 suggested that the magnitude of the effect of intra-industry misallocation depends on the interaction between factor intensities and the relative variances of distortions, whereas the impact of inter-industry misallocation depends on whether the HWA wedges are less or greater than 1. Figure 1.7 confirms this reasoning. Panel A plots the variation in the RCA when removing intra-industry misallocation against the intra-industry dispersion of the TFPR, equal to $\hat{\alpha}_s^{'i_s} \hat{\alpha}_s$ for sector $s$, where $\hat{\alpha}_s$ is a $L$-vector of factor intensities $\alpha_{ls}$. The positive correlation suggests that sectors in which firms’ TFPR is relatively more disperse, have larger gains in comparative advantage. Analogously, Panel B plots the variation in the RCA when removing inter-industry misallocation against the revenue productivity at the industry level. The positive correlation implies that industries with HWA wedges greater than one gain export capability when inter-industry misallocation is removed, otherwise they lose.

A further exploration of the latter results sheds light on the directions and extents of the general equilibrium effects that are present in the model. Similar to section 1.3.3, I use the decomposition (A.9) in Appendix A.4.3 to disentangle the effect of each type of misallocation on comparative advantage into the three sources of export capability in the model: average TFP, the cost of inputs and the number of varieties produced in each sector. Panel A of Figure 1.8 displays the effect of removing all misallocation (in the top graph), only intra (in the middle graph) and only inter-industry misallocation (in the bottom graph), in each sector’s RCA. Towards a better understanding of the results for the RCA, Panel B shows the same decomposition when the changes in the three sources of export capability are not compared across industries, but instead are relative only to the same industry in the reference country. Constructed in this way, the decomposition captures a measure that Hanson et al. (2015) denote the “absolute advantage” index.39 The numbers displayed correspond to the log-differences between the counterfactual values and the initial values of both measures of export capability, and the lengths of the bars represent the strength of each element in the decomposition, so they add up exactly to the number shown.

39Since I choose to normalize by world means, from (1.19) the log-differences in the measures of export capability are exactly identified by:

\[ \log \text{RCA}_{is} = \frac{\hat{\Gamma}_{is} \hat{\omega}_{is} - \bar{\delta}}{\prod_s (\hat{\Gamma}_{is} \hat{\omega}_{is} - \bar{\delta})^{1/N}} \]

\[ \log \text{AA}_{is} = \frac{\hat{\Gamma}_{is} \hat{\omega}_{is} - \bar{\delta}}{\prod_s \prod_i (\hat{\Gamma}_{is} \hat{\omega}_{is} - \bar{\delta})^{1/N}} \]

where AA denotes the “absolute advantage” index.

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First, regarding intra-industry misallocation, the gains on average TFP boost “absolute advantage” of all sectors, on average by 0.91 log points. However, these gains are countered by increases in relative factor prices, on average by 0.74 log points (a rise in relative factor prices is shown as a negative contribution). Thus, in spite of the intensive margin plays a role in the total adjustment of the “absolute advantage” measure, this latter is in a large part driven by the extent to which the number of varieties adjusts, i.e., the extensive margin. When we compute the same decomposition for RCA, its variation is almost entirely explained by the number of varieties. This is a result of the low dispersion in the adjustment of the intensive margin of the “absolute advantage” across sectors, contrary to what happens with the number of varieties. Second, regarding inter-industry misallocation, industries facing on average low returns of the factors ($\bar{\Theta}_i < 1$, see Table 1.5) increase their inputs’ cost, which improves average TFP through the selection of the more productive firms, compensating the adverse effect of factor prices in both RCA and “absolute advantage” measures, and vice versa. In this case, the magnitudes of the adjustments of average TFP and factor prices in the index of “absolute advantage” are lower than those obtained removing MRP dispersions within industries (for example, the median positive change due to average TFP is 0.25 log points). Nevertheless, despite their smaller magnitudes, those changes have a larger dispersion across sectors, enhancing the contribution of the intensive margin in the effect of inter-industry misallocation on the RCA measure.

1.4.4 Robustness checks and additional results

In this section, I first evaluate the robustness of the previous results to changes in the parameters $\kappa$ and $\sigma$. Next, I present the results of gradually removing misallocation. Finally, I compare the baseline results with those obtained in the cases of taking the whole manufacturing sector as a single industry and in the closed economy.

Changes in $\kappa$ and $\sigma$

Changes in $\kappa$ or in $\sigma$ do not importantly alter the ranking of RCA in the counterfactual equilibria and, if any, have a small effect on its dispersion. Figure 1.9 displays for the case of removing both types of misallocation the ranking of Colombian RCA measures under different values of $\kappa$ and $\sigma$. Changes in the ranking are negligible, and only small variations in the dispersion are noticeable (see column 5 in Table 1.6). However, for a given MRP distribution and RCA schedule, the extent of factor reallocations across sectors is increasing in $\kappa$ and decreasing in $\sigma$. This is due to the fact that in each industry a fraction $\nu_\kappa$ of the sectoral demand of factors is not affected by firm-level misallocation, the fraction that is allocated to entry. As a result, Table 1.6 shows that the rise in total exports and in the ratio exports to GDP is lower for $\kappa = 4$ or $\sigma = 4$ and larger for $\kappa = 5$ or $\sigma = 3$. 

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1.4. Empirical implementation

Gradual reforms

Figure 1.10 displays the effects of reforms that gradually remove both and separately the two types of misallocation on the welfare gains (Panel A) and exports growth (Panel B). The lines’ values in the extreme right - removing 100% misallocation - coincide with the numbers in Table 1.6. Even the smallest reform, which reduces 10% the extent of both types of misallocation, has a sizable impact on both welfare and exports (6.7% and 11% respectively). Moreover, it is noticeable that for any reduction in misallocation, the intra-industry type is quantitatively more important, although its contribution varies with the intensity of the reform.

One-sector vs. multiple sectors

To quantify the importance of industrial specialization in the exports of the frictionless economy, I perform the exercise of removing misallocation, taking the whole manufacturing sector as a single industry. By construction, there is now only intra-industry misallocation, and all industries face the same factor intensities. Thus, I recompute the corresponding US cost shares and the within-industry variances of firm’s wedges, values displayed in the last row of Table 1.5. The increase in welfare is similar to the baseline case (70%), but the increase in nominal exports is only 43%, leading to a decrease in the ratio of exports to GDP of 5 p.p. (see the last row in Table 1.6).

Closed vs. open economy

Since in the closed economy revenue shares are constant and equal to the expenditure shares in the demand system, there is no change in the industrial composition under the Cobb Douglas demand. However, it is possible to quantify the cost of the same measures of misallocation in terms of welfare. For this, notice that in the closed economy we have $\pi_{iis} = \hat{\pi}_{iis} = 1$ and $\hat{R}_{iis} = \hat{E}_{iis} = \hat{E}_i$, so we can express (1.28) as:

$$\left[ \frac{\hat{E}_i}{\hat{P}_d} \right]_{\text{closed}} = \prod_s \left[ \hat{\Gamma}_{is}^{-\frac{1}{\rho}} \prod_l \left( \sum_s \hat{Z}_{ils} \hat{v}_{ils} \right)^{\alpha_{ls}} \right]^{-\beta_s}$$

Thus, the welfare cost of misallocation in a closed economy with endogenous selection of firms can be derived only with measures of misallocation and factor shares in autarky. The last column in Table 1.6 shows the increase in welfare in the case in which Colombia was a closed economy, under the assumption that the measures of misallocation and factor shares were the same. Apart from the case of removing only inter-industry misallocation, the gains on welfare due to removing allocative efficiency are larger under a closed economy, suggesting that in the particular case of Colombia, international trade dampens the welfare cost of resource misallocation.

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40 The exports to GDP ratio only begins to increase after removing 20% misallocation, a threshold where the ranking of industries’s RCA starts to show alterations.

41 For the inter-industry case, the results are in line with Święcki (2017), who shows that simultaneously removing intersectoral wedges in labor in 61 countries and 16 industries leads to larger welfare gains in open economies relative to
1.5 Conclusions

Resource misallocation at the firm level can alter the relative unit cost of producing a good across sectors, distorting the “natural” comparative advantage of a country. This chapter offers a framework to compute for a country the export capabilities of its industries under frictionless factor markets, considering the general equilibrium effects of factors reallocations both within and across sectors. I perform the exercise with a sample of 48 countries, three production factors, and 25 tradable sectors for the observed misallocation in Colombia, a country whose firm-level data provide us with reliable measures of physical productivity.

I find that the reallocation of factors allows Colombia to specialize in industries with “natural” comparative advantage, especially the whole chemical sector (both industrial chemicals and other chemicals). Reallocation factors generates a rise in the ratio of exports to manufacturing GDP by 18 p.p. and an increase in welfare of 75%, for the case of an extreme reform in which factor misallocation is entirely removed. The specialization channel due to comparative advantage, that substantially transforms the industrial composition when removing firm-level factor misallocation, is an omitted mechanism in the workhorse models of firm-level resource misallocation in closed economies.

The impact of allocative efficiency on comparative advantage depends importantly of the adjustment in the extensive margin. In the case of factor misallocation within industries, I find that removing distortions increases comparative advantage for those sectors in which the returns of the factors used intensively are relatively more dispersed. The gains in terms of unit costs are mainly the result of an increase in the relative number of varieties produced because at the intensive margin the increases on average TFP are largely countered by the responses on relative factor prices, and there is not enough variation across industries of the residual effect. And for inter-industry misallocation, industries in which firms on average face factors’ returns larger than the allocative efficient values, increase their comparative advantage when misallocation is removed. In this case, the gains in export capability derive from the reduction of average factor costs, which compensates the adverse selection of firms within the sector, plus an increase in the number of varieties produced. The overall effect of factor misallocation on comparative advantage is a combination of these two forces.

These results suggest that the design of mechanisms that smooths the dispersion of factor returns across firms is a desirable policy. It can boost total productivity and welfare allowing for a more efficient pattern of specialization across industries, in which comparative advantage responds more to differences in efficiency across sectors and relative factor endowments, the “natural” sources of export capability. The growing literature exploring the causes of the dispersion on the factors’ returns is a fertile field of research to start exploring optimal policy instruments in an open economy.

closed ones (for Colombia, the gains are 18% in the open economy case and 11% under autarky). The intuition for his result is that in the closed economy distorted sectors cannot expand beyond the domestic demand for the sector’s output. However, adding firms’ endogenous selection can make the effect of trade on the cost of misallocation dependent on the joint distribution of TFPQ and wedges. In particular, trade will have a larger impact on welfare in an economy where the exiting plants due to trade contribute relatively more to the total intra-industry misallocation (i.e., where their TFPR dispersion is higher). In that sense, trade could mitigate or exacerbate the cost of misallocation, particularly of the intra-industry type.
1.6 Tables and figures

1.6.1 Tables

Table 1.1: Alternative explanations for dispersion in revenue productivity

<table>
<thead>
<tr>
<th>Source</th>
<th>Variable</th>
<th>Contribution*</th>
<th>Countries</th>
<th>Paper</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjustment costs</td>
<td>σ^2_{MRPK}</td>
<td>1%</td>
<td>China, Colombia, Mexico</td>
<td>David and Venkateswaran (2017)</td>
</tr>
<tr>
<td>Uncertainty about TFP</td>
<td></td>
<td>7%</td>
<td>Mexico</td>
<td></td>
</tr>
<tr>
<td>Variable markups</td>
<td></td>
<td>5%</td>
<td>China</td>
<td></td>
</tr>
<tr>
<td>Heterogeneity in technology</td>
<td>σ^2_{MRPL}</td>
<td>17%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Heterogeneity in workers ability</td>
<td></td>
<td>9%</td>
<td>Denmark</td>
<td>Bagger et al. (2014)</td>
</tr>
<tr>
<td>Additive measurement error in</td>
<td>σ^2_{TFPR}</td>
<td>45%</td>
<td>India</td>
<td>Bils et al. (2017)</td>
</tr>
<tr>
<td>revenues and inputs</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: σ^2_{TFPR} corresponds to the variance of the revenue productivity (TFPR), which is a function of the variances (and covariances) of the marginal revenue products (MRP), σ^2_{MRP}, for factor z. The table displays the contribution of causes different to misallocation to the corresponding variances of the MRP (for capital (K) and labor (L)) or directly to the TFPR. *Average contribution if the number of countries is greater than one.

Table 1.2: RCA explained by misallocation measures and determinants of export capability

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>dRCA\text{ist}</td>
<td>dRCA\text{ist}</td>
<td>dRCA\text{ist}</td>
<td>dRCA\text{ist}</td>
</tr>
<tr>
<td>Intra-ind. allocative efficiency</td>
<td>0.358***</td>
<td>0.575***</td>
<td>0.339***</td>
</tr>
<tr>
<td>(0.082)</td>
<td>(0.088)</td>
<td>(0.084)</td>
<td></td>
</tr>
<tr>
<td>Intra-ind. variance of TFPR</td>
<td>-0.145**</td>
<td>-0.241***</td>
<td>-0.202**</td>
</tr>
<tr>
<td>(0.060)</td>
<td>(0.088)</td>
<td>(0.063)</td>
<td>(0.085)</td>
</tr>
<tr>
<td>Inter-industry wedges</td>
<td>-0.351***</td>
<td>-0.241***</td>
<td>-0.202**</td>
</tr>
<tr>
<td>(0.081)</td>
<td>(0.088)</td>
<td>(0.103)</td>
<td>(0.088)</td>
</tr>
<tr>
<td>Efficient TFP</td>
<td>0.244**</td>
<td>0.234**</td>
<td>0.218**</td>
</tr>
<tr>
<td>(0.090)</td>
<td>(0.098)</td>
<td>(0.103)</td>
<td>(0.088)</td>
</tr>
<tr>
<td>Factor prices</td>
<td>-0.318***</td>
<td>-0.197**</td>
<td>-0.263***</td>
</tr>
<tr>
<td>(0.066)</td>
<td>(0.076)</td>
<td>(0.077)</td>
<td>(0.067)</td>
</tr>
<tr>
<td>Observations</td>
<td>208</td>
<td>208</td>
<td>208</td>
</tr>
<tr>
<td>R-square</td>
<td>0.327</td>
<td>0.266</td>
<td>0.551</td>
</tr>
</tbody>
</table>

Notes: * p<0.10, ** p<0.05 and *** p<0.01. The results correspond to the second-stage of the econometric strategy, where in the first stage the exporter-industry FE are estimated by PPML. The dependent variable is dRCA\text{ist}, the change in the RCA measure with respect to the first period. All independent variables are transformed to be changes with respect to the first period relative to the reference industry, normalized by the corresponding changes in the US PPI. (1) and (2) are the baseline results. (3) changes reference industry (to min. number of zeros), (4) changes set of countries (to 19). Standardized coefficients and heteroskedastic robust errors.
### 1.6. Tables and figures

#### Table 1.3: Equilibrium conditions and endogenous variables

<table>
<thead>
<tr>
<th>Equilibrium condition</th>
<th>Equation</th>
<th>Dimension</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor clearing</td>
<td>(1.13)</td>
<td>$N \times L$</td>
</tr>
<tr>
<td>Industry factor demand</td>
<td>(1.12)</td>
<td>$N \times L \times S$</td>
</tr>
<tr>
<td>Zero profit</td>
<td>(1.7)</td>
<td>$N \times N \times S$</td>
</tr>
<tr>
<td>Aggregate stability</td>
<td>(1.9)</td>
<td>$N \times N \times S$</td>
</tr>
<tr>
<td>Free profit</td>
<td>(1.8)</td>
<td>$N \times S$</td>
</tr>
<tr>
<td>Industry price</td>
<td>(1.10)</td>
<td>$N \times S$</td>
</tr>
<tr>
<td>Industry demand</td>
<td></td>
<td>$Q_{d\bar{ls}} = (\sum_k \sum_m d_{kim})^{\frac{1}{\rho}} N \times S$</td>
</tr>
<tr>
<td>Aggregate price</td>
<td>$P_{d\bar{i}} = \prod_s (\frac{p_{di}}{P_{di}})^{\beta_s} N$</td>
<td></td>
</tr>
<tr>
<td>Trade balance</td>
<td>(1.14)</td>
<td>$N$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Endogenous variable</th>
<th>Notation</th>
<th>Dimension</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary factor price</td>
<td>$w_{il}$</td>
<td>$N \times L$</td>
</tr>
<tr>
<td>Industry-level primary factor</td>
<td>$Z_{ils}$</td>
<td>$N \times L \times S$</td>
</tr>
<tr>
<td>Cutoffs for undistorted firms by dest.</td>
<td>$a_{is}^\gamma$</td>
<td>$N \times N \times S$</td>
</tr>
<tr>
<td>Mass of firms by destination</td>
<td>$M_{ij}^\gamma$</td>
<td>$N \times N \times S$</td>
</tr>
<tr>
<td>Mass of entrants</td>
<td>$H_{is}$</td>
<td>$N \times S$</td>
</tr>
<tr>
<td>Industry-level consumer price &amp; demand</td>
<td>$p_{d\bar{is}}, Q_{d\bar{is}}$</td>
<td>$2 \times N \times S$</td>
</tr>
<tr>
<td>Aggregate consumer price &amp; demand</td>
<td>$p_{d\bar{i}}, Q_{d\bar{i}}$</td>
<td>$2 \times N$</td>
</tr>
</tbody>
</table>

#### Table 1.4: Parameters used in simulations

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_{ls}$</td>
<td>Factor intensities</td>
<td>0.7 0.3</td>
</tr>
<tr>
<td>$\beta_{is}$</td>
<td>Expenditure shares</td>
<td>0.3 0.7</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Varieties’ elasticity of substitution</td>
<td>3.8</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>Pareto’s shape parameter</td>
<td>4.58</td>
</tr>
<tr>
<td>$\tilde{Z}_{il}$</td>
<td>Factor endowments</td>
<td>$[100 \ 90]$</td>
</tr>
<tr>
<td>$\tilde{a}_{is}$</td>
<td>Pareto’s location parameter</td>
<td>$[90 \ 100]$</td>
</tr>
<tr>
<td>$\delta_{ls}$</td>
<td>Exogenous probability of exit</td>
<td>$0.025 \forall i,s$</td>
</tr>
<tr>
<td>$f_{is}^e$</td>
<td>Fixed entry cost</td>
<td>$2 \forall i,s$</td>
</tr>
<tr>
<td>$f_{is}^e$</td>
<td>Fixed trade cost</td>
<td>$2 \forall i,j,s$</td>
</tr>
<tr>
<td>$\tau_{ij}$</td>
<td>Iceberg trade cost</td>
<td>Free trade: $1 \forall i,j,s$</td>
</tr>
<tr>
<td>$\sigma_{1l}$</td>
<td>Log-normal shape par. in sector 1</td>
<td>For figure 1.3: $[0, 0.5] \forall l$</td>
</tr>
<tr>
<td>$\mu_{1l}$</td>
<td>Log-normal location par. sector 1</td>
<td>For figure 1.4: $[0, \frac{1}{2} - (1 - \frac{\delta}{\alpha_{1l}}) \sigma_{1l}^2] \forall l$</td>
</tr>
</tbody>
</table>
Table 1.5: Factor intensities and misallocation measures used in counterfactuals

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Food</td>
<td>1435</td>
<td>0.31 0.06 0.09</td>
<td>1.90 1.01 1.14 1.15</td>
<td>1.07 1.09 1.20</td>
<td>0.19 0.19 0.86</td>
<td>0.81a 0.13</td>
</tr>
<tr>
<td>Beverage</td>
<td>142</td>
<td>0.36 0.06 0.06</td>
<td>1.05 0.98 1.14 1.33</td>
<td>0.90 0.76 0.75</td>
<td>0.00 -0.07 0.49</td>
<td>0.79 1.74</td>
</tr>
<tr>
<td>Tobacco</td>
<td>9</td>
<td>0.73 0.02 0.04</td>
<td>1.67 1.64 0.39 1.28</td>
<td>0.53 1.24 1.62</td>
<td>0.28 -0.34 0.94</td>
<td>0.76a 0.02</td>
</tr>
<tr>
<td>Textiles</td>
<td>465</td>
<td>0.22 0.08 0.18</td>
<td>0.81 1.08 0.88 1.02</td>
<td>1.33 0.71 0.69</td>
<td>-0.06 0.08 0.43</td>
<td>0.82 0.76</td>
</tr>
<tr>
<td>Apparel</td>
<td>944</td>
<td>0.23 0.10 0.17</td>
<td>1.25 0.40 0.26 0.72</td>
<td>1.27 0.65 0.61</td>
<td>0.11 0.16 0.29</td>
<td>0.87a 0.04</td>
</tr>
<tr>
<td>Leather</td>
<td>118</td>
<td>0.32 0.12 0.16</td>
<td>1.38 1.00 0.47 0.73</td>
<td>0.89 0.73 0.46</td>
<td>-0.01 -0.06 0.46</td>
<td>0.84a 0.09</td>
</tr>
<tr>
<td>Footwear</td>
<td>254</td>
<td>0.21 0.12 0.20</td>
<td>1.51 1.00 0.59 0.97</td>
<td>1.09 0.66 0.46</td>
<td>0.08 0.12 0.34</td>
<td>0.80 0.73</td>
</tr>
<tr>
<td>Wood</td>
<td>196</td>
<td>0.13 0.07 0.18</td>
<td>0.25 0.37 0.48 0.51</td>
<td>1.43 0.45 0.37</td>
<td>0.27 0.15 0.29</td>
<td>0.86a 0.12</td>
</tr>
<tr>
<td>Furniture</td>
<td>270</td>
<td>0.18 0.11 0.25</td>
<td>0.70 0.27 0.32 0.50</td>
<td>1.45 0.40 0.40</td>
<td>0.12 0.01 0.20</td>
<td>0.85 0.58</td>
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<tr>
<td>Paper</td>
<td>170</td>
<td>0.21 0.09 0.18</td>
<td>0.64 2.40 2.62 1.17</td>
<td>0.94 0.80 1.10</td>
<td>0.05 -0.03 0.68</td>
<td>0.79c 0.44</td>
</tr>
<tr>
<td>Printing</td>
<td>434</td>
<td>0.23 0.15 0.26</td>
<td>1.02 0.83 1.62 1.02</td>
<td>0.74 0.50 0.50</td>
<td>-0.05 -0.09 0.20</td>
<td>0.85a 0.03</td>
</tr>
<tr>
<td>Chemicals</td>
<td>177</td>
<td>0.37 0.07 0.08</td>
<td>1.23 1.96 1.77 1.08</td>
<td>1.43 0.78 0.76</td>
<td>0.11 -0.06 0.54</td>
<td>0.83a 0.06</td>
</tr>
<tr>
<td>Other chemicals</td>
<td>356</td>
<td>0.36 0.12 0.09</td>
<td>2.50 1.13 1.49 1.53</td>
<td>1.02 0.71 0.85</td>
<td>-0.07 -0.11 0.50</td>
<td>0.81 0.98</td>
</tr>
<tr>
<td>Petroleum</td>
<td>46</td>
<td>0.15 0.02 0.02</td>
<td>0.65 0.98 0.86 1.28</td>
<td>2.02 1.14 1.47</td>
<td>0.82 0.97 1.20</td>
<td>0.76a 0.01</td>
</tr>
<tr>
<td>Rubber</td>
<td>9</td>
<td>0.20 0.12 0.22</td>
<td>0.63 2.01 1.64 1.05</td>
<td>0.68 0.61 0.48</td>
<td>0.20 0.20 0.33</td>
<td>0.83 1.24</td>
</tr>
<tr>
<td>Plastic</td>
<td>428</td>
<td>0.10 0.08 0.28</td>
<td>0.38 0.95 1.74 1.04</td>
<td>0.83 0.61 0.59</td>
<td>-0.01 -0.04 0.39</td>
<td>0.83a 0.02</td>
</tr>
<tr>
<td>Pottery</td>
<td>13</td>
<td>0.27 0.13 0.30</td>
<td>1.16 1.19 1.38 1.11</td>
<td>0.18 0.46 0.73</td>
<td>-0.06 -0.08 0.56</td>
<td>0.80a 0.01</td>
</tr>
<tr>
<td>Glass</td>
<td>82</td>
<td>0.26 0.29 0.12</td>
<td>0.91 4.59 0.70 1.38</td>
<td>0.97 0.53 0.49</td>
<td>-0.15 0.02 0.33</td>
<td>0.80 2.72</td>
</tr>
<tr>
<td>Other non-metallic</td>
<td>365</td>
<td>0.21 0.07 0.14</td>
<td>0.46 1.36 1.11 1.05</td>
<td>1.28 0.72 0.91</td>
<td>0.02 -0.01 0.64</td>
<td>0.80 2.59</td>
</tr>
<tr>
<td>Iron and steel</td>
<td>86</td>
<td>0.18 0.10 0.21</td>
<td>0.50 2.74 3.01 1.28</td>
<td>0.91 1.08 1.35</td>
<td>-0.15 -0.12 1.07</td>
<td>0.78a 0.01</td>
</tr>
<tr>
<td>Non-ferrous metal</td>
<td>42</td>
<td>0.18 0.10 0.27</td>
<td>0.38 0.56 0.94 0.39</td>
<td>0.44 0.78 1.22</td>
<td>-0.14 -0.40 0.89</td>
<td>0.82a 0.03</td>
</tr>
<tr>
<td>Metal products</td>
<td>664</td>
<td>0.21 0.12 0.17</td>
<td>1.09 1.20 0.72 0.99</td>
<td>1.27 0.58 0.55</td>
<td>0.09 0.08 0.39</td>
<td>0.84b 0.35</td>
</tr>
<tr>
<td>Mach. &amp; equipment</td>
<td>374</td>
<td>0.25 0.11 0.09</td>
<td>1.50 0.83 0.36 1.04</td>
<td>0.94 0.43 0.46</td>
<td>0.02 0.12 0.28</td>
<td>0.83a 0.02</td>
</tr>
<tr>
<td>Electric./ Profess.</td>
<td>276</td>
<td>0.19 0.02 0.08</td>
<td>1.00 1.27 0.74 1.01</td>
<td>0.94 0.59 0.62</td>
<td>0.05 0.06 0.43</td>
<td>0.78 0.58</td>
</tr>
<tr>
<td>Transport</td>
<td>274</td>
<td>0.24 0.15 0.13</td>
<td>2.23 0.45 0.91 1.20</td>
<td>0.93 0.48 0.73</td>
<td>0.19 0.23 0.38</td>
<td>0.84a 0.02</td>
</tr>
<tr>
<td>One-sector</td>
<td>7713</td>
<td>0.24 0.09 0.13</td>
<td>1.00 1.00 1.00 1.00</td>
<td>1.13 1.05 0.86</td>
<td>0.08 0.08 0.63</td>
<td>0.85a 0.33</td>
</tr>
</tbody>
</table>

Notes: *Point estimates for $\lambda_s$ using Bils et al. (2017) (see Appendix A.2). Levels of significance: c $p < 0.1$, b $p < 0.05$, a $p < 0.01$.

***"Corrected" values correspond to the product of the observed dispersion (after removing outliers and trimming 1% tails) and the corresponding value for $\lambda_s$.

For non-significant values of $\lambda_s$, the value of the last row is used, a specification that controls for industry×years fixed effects.
### 1.6. Tables and figures

#### Table 1.6: Counterfactuals

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>Baseline results</th>
<th>Robustness: Both types</th>
<th>Robustness: One-sector</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Decreasing $\sigma$ (to 3)</td>
<td>Increasing $\sigma$ (to 4)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.59 2.35 5.22 0.19 2.68 1.90 1.99</td>
<td>1.50 2.14 4.51 0.17 2.69 1.67 1.76</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.61 2.38 5.36 0.19 2.61 1.84 1.92</td>
<td>Only intra-industry 1.58 2.32 1.43 -0.05 - 1.70 1.87</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Only inter-industry 1.04 1.09 1.57 0.07 1.69 1.08 1.07</td>
</tr>
</tbody>
</table>

Note: Each cell shows the proportional change in each variable between the counterfactual equilibrium and the actual data. For variables marked by *, the simple difference in the measure is displayed.

#### 1.6.2 A.1 Figures

Figure 1.1: Revealed comparative advantage (RCA) measures for Colombia

Notes: Markers’ sizes represent export shares, and the line the best linear fitting.
Figure 1.2: Cutoff functions and selection effects of distortions

Panel A: Cutoff functions for country $i$ sector $s^*$

- Exporters to destination $j$:

  \[ a_{ij}^*(\Theta) = a_{ij}^* \frac{1}{\tilde{\sigma}} \]

- Producers only for domestic market $i$:

  \[ a_{ii}^*(\Theta) = a_{ii}^* \frac{1}{\tilde{\sigma}} \]

- Exiting firms:

  \[ a_{ij}^* = \Lambda_{ij} a_{ii}^* \]

Panel B: Selection effects of distortions

- Entry due to distortions: for firms producing to domestic market (A) and exporters (B)

- Exit due to distortions: for firms producing to domestic market (A) and exporters (B)

\[ \tilde{\Theta}_M = a_{ii}^{*-1} (\tilde{\alpha}_M) \]

*For the domestic market and the destination $j$ with lowest $\Lambda_{ij}$
1.6. Tables and figures

Figure 1.3: Effects of factor misallocation within industries on RCA and its determinants

![Graphs showing effects of factor misallocation within industries on RCA and its determinants.]

Figure 1.4: Effects of factor misallocation across industries on RCA and its determinants

![Graphs showing effects of factor misallocation across industries on RCA and its determinants.]

Values of parameters:
- $\mu_{11}$
- $\sigma_{11}$
- $\sigma_{21}$

Legend:
- Red: Wedges on fac. 1, costly trade
- Blue: Wedges on fac. 2, costly trade
- Green: Wedges on fac. 1, free trade
- Purple: Wedges on fac. 2, free trade
1.6. Tables and figures

Figure 1.5: Allocative efficient RCA and observed RCA for Colombia

Panel A: Intra- and inter-industry allocative efficient RCA and observed RCA (observed export shares)

Panel B: Intra- and inter-industry allocative efficient RCA and observed RCA (counterfactual export shares)

Panel C: Only intra-industry allocative efficient RCA and observed RCA (counterfactual export shares)

Panel D: Only inter-industry allocative efficient RCA and observed RCA (counterfactual export shares)

Notes: Each panel compares the RCA measures in the corresponding counterfactuals to the observed RCA measures. Markers’ sizes represent the indicated export shares.
1.6. Tables and figures

Figure 1.6: Colombian industries in the world distribution of RCA

Panel A: Distribution under observed data

Panel B: Distribution under Colombia’s efficient allocation

Note: Each vertical line represents the location of a Colombian industry in the RCA world distribution.

Figure 1.7: Changes in Colombian RCA and their causes

Panel A: Change in RCA by removing intra-industry misallocation and within-industry variance of TFPR

Panel A: Change in RCA by removing inter-industry misallocation and sectoral TFPR for Colombia

Notes: Intra-industry variance of log TFPR in Panel A is constructed as the weighted average of the within-industry dispersion of the factors’ MRP that face misallocation: capital, skilled and unskilled labor. Similarly, sectoral TFPR in Panel B is computed using only capital, skilled and unskilled labor as inputs.
1.6. Tables and figures

Figure 1.8: Changes in determinants of Colombian RCA

Panel A: Changes in comparative advantage determinants  Panel B: Changes in absolute advantage determinants

1. Removing intra- and inter-industry misallocation

2. Removing only intra-industry misallocation

3. Removing only inter-industry misallocation

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1.6. Tables and figures

Figure 1.9: Rankings of RCA for different values of $\kappa$ and $\sigma$

Panel A: Changes in $\sigma$

Panel B: Changes in $\kappa$

Figure 1.10: Welfare gains and export growth from gradual reforms

Panel A: Welfare gains

Panel B: Export growth
Chapter 2

Barriers to Mobility or Sorting? Sources and Aggregate Implications of Income Gaps across Sectors and Locations in Indonesia

2.1 Introduction

Large and persistent gaps in average incomes of agricultural and non-agricultural workers in developing countries have been well documented. What exactly accounts for these gaps is still debated, however. A common view is that the gaps exist because workers cannot arbitrage them away due to broadly understood barriers to mobility across sectors and locations. Such barriers would suggest that labor is inefficiently allocated. An opposing view, recently gaining influence, is that the gaps simply reflect an efficient sorting of heterogeneous workers based on their observable and unobservable characteristics. The goal of this chapter is to evaluate the contribution of mobility barriers and sorting to the observed income gaps in Indonesia and to assess whether these gaps are a source of aggregate inefficiency.

The relative plight of agricultural workers compared to non-agricultural workers in developing countries is at first sight staggering. For example, wage workers outside of agriculture earn 80% more than workers in agriculture in a median of 13 countries studied by Herrendorf and Schoellman (2018). Similarly large gaps emerge when workers are split according to their place of residence rather than the sector of their occupation. For example, urban households in Vietnam in 1998 had real per capita consumption twice as high as rural households (Nguyen et al. (2007)). Such gaps could in principle merely reflect differences in the composition of workforce. For example, to the extent that urban workers are typically better educated than rural workers, the differences in their average wages could simply be picking up the return to additional human capital of urban workers. But studies for various developing countries find evidence that substantial rural-urban gaps remain after factoring out the effect due to differences in schooling achievement and other observable individual characteristics (see, e.g., Hnatkovska and Lahiri (2016) for India and Qu and Zhao (2008) for China). These residual gaps have been documented for wages, broader measures of income, expenditure, and consumption. Similar gaps have also been identified in a parallel literature using value added data.
2.1. Introduction

to compare productivity of workers across sectors. Gollin et al. (2014) show using a wide sample of countries that workers in non-agriculture are twice as productive as workers in agriculture, after taking into consideration the differences in hours worked, schooling and quality of schooling between rural and urban areas. Given the ubiquity of large residual gaps estimated using different countries, measures, and methodologies, they appear to be a real phenomenon rather than merely a measurement artifact.

It is therefore a puzzle why such gaps persist. Why do workers not switch to sectors and locations offering higher income to workers with their observable characteristics, eroding the premia? There are two main hypotheses in the literature. The first one is that the gaps are a manifestation of barriers to mobility. To the extent that these barriers are at least partially induced by policies, this view implies that labor is misallocated. Given the magnitude of the gaps, there are potentially large aggregate efficiency gains from mitigating the mobility frictions. In this spirit, Restuccia et al. (2008) calculate that distortions to the allocation of labor between agriculture and non-agriculture play an important role in explaining cross-country income differences.

An alternative explanation for the residual income gaps is that it is a result of sorting of workers across sectors or locations based on characteristics known to them but not observed by researchers. For example, a positive urban premium can be observed if workers choosing urban locations have on average more unobservable skills than rural workers conditional on their education attainment. This mechanism is the explanation of the urban premium recently proposed by Young (2013), who builds on an adaptation of the Roy (1951) model by Lagakos and Waugh (2013). Importantly, in this view residual gaps across sectors or locations can exist despite the allocation of labor being efficient.

Given the different implications of the two canonical explanations of income gaps for allocative efficiency, it is important to know which view is a better description of reality. A major shortcoming of the existing literature accounting for income gaps is that it relies on cross-sectional data. But as is well-known following Heckman and Honoré (1990), the estimation of selection models using only cross-sectional data faces identification challenges. Existing studies therefore need to rely on functional form assumptions (Bryan and Morten (2018)) or on indirect ways of detecting sorting (Young (2013)). In this chapter, we argue that augmenting a standard model of sorting by including barriers to sectoral mobility requires longitudinal data to identify the parameters of interest, even when imposing functional forms assumptions. We exploit the panel dimension of a dataset collected in Indonesia, to provide more direct evidence of the extent barriers to sectoral mobility in a context of self-selection.

The Indonesia Family Life Survey (IFLS, Strauss et al. (2016)) we use is uniquely well fitted for our goals. First, it is a longitudinal survey spanning a relatively long period of time, with five waves of the survey conducted between 1993 and 2014. Second, a feature of the survey design and implementation is that it exerts particular effort to track households and individuals even if they migrate, a critical feature for a country undergoing a process of urbanization. Third, IFLS records a rich set of

\[\text{Herrendorf and Schoellman (2015)}\] caution that such gaps might overestimate true productivity differences due to potential measurement problems in agricultural value added.
socio-economic information on surveyed individuals. Fourth, with about 20000 surveyed individuals it is a large survey representative of more than 80% of the Indonesian population. Fifth, with roughly 40%/60% split between agricultural and non-agricultural workforce Indonesia is a relevant setting to investigate the gaps across boundaries traditionally used for developing countries. Finally, being the forth most populous country in the world Indonesia is an important country to study in its own right.

We begin our analysis in the next section by documenting some robust features of the Indonesian data. Just like in other developing countries, the ILFS data shows the existence of a large income gap across sectors in Indonesia. Controlling for observable worker characteristics, workers outside of agriculture earn 67% more than workers in agriculture. This is the non-agriculture premium we want to understand better.

Importantly, this premium already conditions on the rural vs. urban location. Much of the literature tends to associate rural employment with agriculture and urban employment with non-agriculture. This implicit isomorphism might lead to an intuition that non-agricultural premium is to be expected even in the absence of sorting or frictions because it compensates workers for the real cost of rural-to-urban migration. We find that logic to be misguided. In Indonesia 45% of rural workforce has primary employment outside of agriculture and 11% of urban workforce is employed primarily in agriculture, so we can meaningfully separate the non-agricultural and urban premia. In this chapter we emphasize the sectoral dimension more because most of the rural-urban residual income gap can be accounted for by differences in sectoral composition of rural and urban areas combined with the large non-agriculture premium. The direct urban premium estimated at 26% in the cross-section of workers, while not trivial, is substantially smaller than the 67% non-agriculture premium.

Moving beyond these cross-sectional premia, we exploit the panel structure of our data by relying on within-worker variation in income across sectors and locations. This approach follows Katz and Summers (1989) and the subsequent long tradition of estimating inter-industry wage differentials in developed countries. In Indonesia, it reduces the residual gaps roughly by half, to 29% for non-agriculture and 9% for urban locations. Digging even deeper, we compare the income growth of workers moving out of agriculture relative to those staying in agriculture, and of workers moving out of non-agriculture relative to those who stay employed in non-agriculture. Because we also have detailed migration data, we can do this calculation even conditional on staying in the same very narrowly defined geographical areas (village level). Perhaps our most surprising finding is that the non-agriculture premium exists even within such local markets and that it is approximately symmetric for switches in both directions. Workers who move out of agriculture see an income gain of 19% while those who move into agriculture see a loss of 19%, even if they stay in the same village. The reported premia are robust to a host of concerns about sample selection, estimation method, and measurement issues.

The fact that half of the non-agriculture premium disappears after controlling for time-invariant unobserved heterogeneity informally suggests that sorting does indeed occur and is important. The question is if the 19% average excess income gain received by a worker who switches from agriculture to non-agriculture can be reconciled with an efficient sorting based on comparative advantage alone.
In principle, it can. This is because the industry premia, even estimated using within-worker variation, have by themselves little empirical content. We show this by extending a standard model of self-selection based on both permanent and transitory components of comparative advantage to include different types of barriers to sectoral mobility. In particular, we consider utility costs of switching sectors (Dixit and Rob (1994); Cameron et al. (2007); Artuç et al. (2010); Dix-Carneiro (2014)) and frictions preventing individuals from working in their preferred sectors (akin to search costs as in Taber and Vejlin (2016)). We demonstrate that the same cross-sectional and within-worker non-agriculture premia can be rationalized by different combinations of comparative advantage shock processes and barriers to mobility. In particular, by picking the right covariance matrix for the transitory component of comparative advantage we can generate large within-worker premia in the absence of any barriers. Similarly, we can have large barriers to mobility despite observing zero non-agricultural premia. The premia alone cannot tell us if there is any worker misallocation or not.

The comparative advantage process and barriers to mobility can be separately identified once we impose some parametric structure and exploit a richer set of moments of the joint sector-income distribution over time. We use indirect inference (Gourieroux et al., 1993) for the structural estimation of our model, where the selected auxiliary models are the main reduced-form regressions that characterize the data features we are interested in and that allow us to identify the full set of structural parameters, including the mobility barriers.

Our findings suggest that both types of barriers - utility switching costs and inability to select the preferred sector - significantly improve the overall fit of the model compared to the frictionless specification. They are both able to qualitatively match simultaneously the sectoral premia and the patterns of the moments of the joint distribution of income. For the switching costs specification, we estimate opposite signs for the switching costs away from and towards agriculture. This pattern is observationally similar to receiving a positive compensating differential for working in agriculture. If we assume that the choice of a sector is always voluntary (but switching is costly), then the model uses utility compensation for moving to agriculture to rationalize why so many workers make the move despite taking an income cut.

A considerably better fit to the data, however, is offered by the model which recognizes that not all sectoral transitions are voluntary. In fact, our central estimate implies that half of the transitions between non-agriculture and agriculture we see happen for random reasons (these can be interpreted as life events forcing an individual to switch the sector of employment) rather than in response to shocks to the comparative advantage. Once a worker lands in her sub-optimal sector, moving to the preferred sector is difficult as it requires a lucky draw. Given its superior empirical performance, our preferred model relies on this type of mobility friction.

The barriers to mobility are quantitatively important. To make this point, we conduct a counterfactual in which the frictions are removed entirely from our baseline model. This thought experiment is standard in the misallocation literature, though of course extreme because we do not know how the frictions could be completely eliminated in practice. With that caveat in mind, removing all barriers to intersectoral mobility would result in large reallocation of workers. Overall, 30% of workforce would
work in a different sector than in the baseline equilibrium. Since the initially misallocated workers reap large income gains from the reallocation (their income doubles on average), the adjustment has a sizable effect on aggregate output, raising it by 17%. Agricultural employment contracts by nearly 6 p.p., but output and productivity increase by double digits in both sectors.

Among the large literature on the income gap between agriculture and non-agriculture, the most closely related work consists of a handful of papers that also exploit individual-level panel information for developing countries. Beegle et al. (2011) offer early evidence of large within-individual gains in Kenia, but their focus is on consumption gains from migration rather than the more puzzling income gains from sector switching conditional on not migrating. Perhaps the closest, in concurrent work Hicks et al. (2017) also use the IFLS and find smaller within-individual non-agricultural premium. As we explain in section 2.11, our substantive differences stem from different data selection and focusing on different measures of interest. More importantly, we argue that the non-agricultural premium by itself is not necessarily an informative statistic, and we estimate a structural model that allows us to quantitatively evaluate the importance of barriers to sectoral mobility.

While our results are non-experimental and the magnitudes we report depend on the structural assumptions we make, we believe our key finding of barriers to mobility is also broadly consistent with the limited existing experimental evidence. In a randomized small-scale setting, Bryan et al. (2014) find substantial gains from inducing workers in Bangladesh to work outside their village, though again the focus is on consumption gains from migration making direct comparison difficult. More closely, Sarvimaki et al. (2018) using a natural experiment in Finland find large income gains for workers who abandoned farming as a result of forced migration.

2.2 Data

In this section we describe the data, only highlighting the features of the dataset most relevant for our analysis. Comprehensive details about the design and implementation of the IFLS are reported in Strauss et al. (2016).

Our primary source of data is the Indonesia Family Life Survey. The first IFLS was conducted in 1993, with subsequent waves in 1997, 2000, 2007, and 2014. From the outset the IFLS was designed as a long-term panel survey, which allows us to compare life trajectories of individuals making different occupational and locational choices. Furthermore, the IFLS puts considerable effort into tracking individuals over time. This feature is rare among longitudinal household surveys in developing countries, which typically lose respondents who move out of an original survey area. As a measure of tracking success, Thomas et al. (2012) report that the 2007 IFLS managed to interview 87% of individuals who were eligible to be tracked. Tracking movers is crucial for drawing conclusions from a comparison of migrants and stayers when the decision to migrate is not random.

The IFLS is a large-scale survey, conducted in 13 of the 27 Indonesian provinces. Because the ones excluded are mostly outlying provinces, the sample is representative of 83% of Indonesian population. The first wave interviewed 22019 individuals and the number of respondents grew to 58337 in the
2.3. Income gaps across sectors and locations

fifth wave. In our analysis we restrict attention to adults (15 years or older) who are employed and therefore answer the detailed work module of the survey. The definition of employed is expansive and comprises all persons who answered affirmatively to any of the following categories: i) their primary activity during the past week was working, trying to work or helping to earn income; ii) had worked for pay at least 1 hour during the past week; iii) had a job or business, but were temporarily not working during the past week; iv) had worked at a family-owned (farm or non-farm) business during the past week.

For those individuals, the dataset we construct records their annual income, the sector where they worked according to the job that consumed the most time, years of schooling, work experience by sector and standard demographic characteristics such as age and gender. In addition, we use information on the household location in each survey wave and the movements recorded in the migration module of the survey to construct individual location histories at various levels of administrative detail.

Our main outcome variable of interest is annual income. The annual income can be derived from wages, from net profits of a business (such as a farm), or from other sources such as government transfers. We believe that total income is the appropriate measure in a setting where work on a family farm is pervasive and where half of the workforce does not report any wage work.

Following a standard distinction for developing countries, we split locations according to whether they are rural or urban. The rural-urban status of each survey location is determined by the Indonesian Central Bureau of Statistics (BPS) based on multiple criteria. Along a sectoral dimension, we classify workers as employed either in agriculture or in non-agriculture comprising all other sectors.

Table 2.1 reports descriptive statistics for the constructed dataset. Overall we have 85869 observations for 38112 individuals. In our analysis below we focus on the 22829 individuals whom we observe in at least two waves of the survey, for a total of 70586 observations.

2.3. Income gaps across sectors and locations

2.3.1 Baseline results

In this section we present the key patterns of income gaps across sectors and locations in Indonesia. The gaps are estimated using Mincerian regressions with the following general form

\[ \ln y_{islt} = X_i \beta + D_N + D_U + D_i + \epsilon_{islt}, \]  

(2.1)

where \( y_{islt} \) denotes income of an individual \( i \) working in sector \( s \) (agriculture or non-agriculture), living in location type \( l \) (rural or urban) in year \( t \). \( X_i \) collects standard individual covariates such as sex, years of education, experience and experience squared, as well as year and province dummies. \( D_N \)

43This two-sector partition is common in macro-development literature and is sufficient to illustrate the puzzle of low agricultural incomes. We have also divided non-agriculture further into manufacturing and services. The income gaps between manufacturing and services are small relative to the gaps between those two sectors and agriculture.

44Depending on the specification the effective sample size can be smaller as we do not observe all variables for all individuals.
and $D_U$ capture the non-agriculture and urban premia of interest, while $D_i$ captures the time-invariant component individual heterogeneity.

The baseline specification is a reduced form relationship between income and certain observable and unobservable worker characteristics. If workers switch between sectors randomly, then the $D_N$ premium has a simple interpretation of an average gain that a worker can get by moving from agriculture to non-agriculture. If, on the other hand, workers sort across sectors (and locations) based on their unobserved comparative advantage as in Roy (1951) then the premia estimated using equation (2.1) need not have a simple interpretation and a structural model is needed for an exhaustive analysis.

While our argument in this chapter is that sorting is indeed important and we therefore estimate a structural model later, we begin by discussing the reduced form OLS estimates as they have a long tradition and they will be used as auxiliary models in our structural estimation.

As a starting point we estimate equation (2.1) without any controls except for the sector dummies. This specification simply compares average incomes across sectors and, as can be seen in the first column of Table 2.2, these incomes vary greatly. Compared to agriculture, incomes in non-agriculture are on average 84 log points [lp] (or 131%) higher. The second column compares urban and rural incomes. The urban premium stands at a similarly dramatic 65 lp (or 91%). A natural question is whether the urban and sectoral premia capture the same variation in the data.

Many studies take a dichotomous view of economic activity in developing countries. A classical divide in development literature goes along the rural vs. urban dimension. Macroeconomists tend to work with sectoral data and hence use the agriculture vs. non-agriculture split. But both literatures often implicitly consider both partitions as interchangeable, for example by associating structural transformation (decline of agricultural employment share) with urbanization (increase in urban share). The joint distribution of workers across sectors and locations shown in Table 2.1 suggests that such interchangeability is too crude in Indonesia. In 2000 (around the middle of our sample period) the share of rural workers at 59% was quite a bit higher than the 37% share of agricultural workers. Among rural workers 45% had primary employment outside of agriculture, while 11% of urban workforce was employed in agriculture.

So can the raw urban premium be explained by different composition of sectors in rural and urban locations or are urban workers paid more in the same sectors? Column 3 of Table 2.2 estimates the urban and sectoral premia jointly. Controlling for sectors reduces the urban premium almost by half, yet it is still high at 41 lp. Controlling for type of location has a smaller impact on sectoral premia, still at 69 lp. These numbers are the first indication that sector of employment might have a stronger effect on income than place of residence directly.

This point is further strengthened by controlling for individual worker characteristics in the Mincer regression. Column 4 shows the urban premium of 21 lp and non-agriculture premium of 57 lp.

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45 In all specifications we control for year and province fixed effects. Observations are weighted by their longitudinal survey weights and standard errors are clustered at the level of primary sampling units of the survey.
46 Because the coefficients of interest are often large in magnitude we report them directly in log points and only occasionally translate them to exact percentage differences.
47 Reported coefficients are statistically significant at 5% level or lower unless mentioned otherwise.
Controlling for observables reduces the urban premium by half once again, while the sectoral premium again changes much less. These residual (controlling for observables) income gaps are also about as much as what can be calculated with cross-sectional data. They therefore correspond most directly to the gaps calculated in other studies.

Using the panel structure of our data we are in a position to begin addressing the issue of sorting on unobservables. The specification in column 5 adds worker fixed effects to the set of controls. Using only within-worker variation to identify the gaps reduces the urban premium by more than half to 8 lp. While not trivial, a 9% additional income gain associated with moving from rural to urban location while keeping the same sector of employment is not shocking either. In contrast, the non-agriculture premium is still surprisingly large. The same worker switching from agriculture to non-agriculture without changing the rural-urban status sees on average an additional income gain of 33 lp (or 39%). Column 6 paints a similar picture using slightly more flexible specification with a full set of interactions between sector and urban dummies. Staying in a rural area and switching away from agriculture gives an income boost of 33 lp. Sectoral gaps of this magnitude are hard to explain without thinking about some barriers preventing workers from moving out of agriculture despite better opportunities in other sectors.

Because the premia estimated on switchers are most novel and surprising, we now explore the mobility pattern in our data more carefully. The first panel of Table 2.3 presents the count of wave-to-wave transitions between sectors and the third panel shows the associated transition matrix. About 20% of workers in agriculture transition to non-agriculture between survey waves, and 12% on workers in non-agriculture switch to agriculture. Overall, 24% of workers change the sector at least once while in our sample. The fact that there are almost as many cases of workers moving into agriculture as cases of workers moving out of agriculture is puzzling in light of the large negative premium associated with working in agriculture. The second and fourth panels of Table 2.3 records analogous transitions along the rural-urban dimension. There is less mobility between rural and urban areas, with a change in location status in 9% of cases. About 17% of workers move between rural and urban locations at least once while in our sample. As expected in a developing country, there are more than twice as many transitions from rural to urban than in the opposite direction, resulting in net migration to urban areas.

The sectoral and urban premia reported so far show an average effect of moving in and out of the sector or location. We now reevaluate the income gaps while taking the direction of transitions into account. The estimating equation now takes the form

\[ \Delta \ln y_{istt} = \Delta X_{it} \beta + \Delta D_{ss'} + \Delta D_{ll'} + \Delta \epsilon_{istt}, \]  

(2.2)

where \( \Delta D_{ss'} \) and \( \Delta D_{ll'} \) capture the direction of sectoral and locational transition. Results are reported in the first column of Table 2.4. Along the locational dimension, workers who move from rural to urban

48These are not year-to-year transitions but transitions between two consecutive observations for each worker. The time between the waves of the survey varies from two to seven years.
2.3. Income gaps across sectors and locations

areas see an income increase of 9 lp relative to those who stay in rural areas. Workers who move into rural areas have an income shortfall of 16 lp relative to those who stay in urban areas. Results for the non-agriculture premium are once again even stronger. Relative to workers who remain in agriculture, workers switching out of agriculture see an additional income growth of 22 lp. Workers who switch from non-agriculture to agriculture see an income loss of 33 lp relative to workers remaining in non-agriculture.

So far we have established existence of a significant income premium for working in non-agriculture controlling for movements between rural and urban locations. But it is still conceivable that movements within rural and urban locations, if correlated with sector switching and having an independent effect on income, might bias the estimates of the sectoral premium. Now we isolate geographic mobility completely using the detailed migration information provided by our dataset. We interact the direction of sectoral transition variable $\Delta D_{ss}'$ with an indicator for whether a worker migrated across village boundary (or correspondingly fine location for cities). The second column of Table 2.4 displays the results, with workers staying in agriculture and staying within a village as a reference category. Workers who migrate and move out of agriculture have the largest income gains; workers who migrate and move into agriculture suffer largest relative income losses. But perhaps the most striking results are for workers who do not migrate: those who switch out of agriculture gain additional 20 lp in income relative to those who remain in agriculture. Those switching into agriculture see an income loss of 26 lp relative to non-movers who remain employed in non-agriculture.

That such large non-agricultural premium can be identified from within-worker sector switches within very narrow geographical areas is truly surprising. Moreover, it is not easily reconciled with the workhorse models of labor markets in developing countries. If workers are sorting across sectors according to comparative advantage that is fixed over time and switching is costless then we should not expect to see a large premium for switchers, and we should expect flows to be in one direction only. If switching is costly and occurs only if the income gain justifies incurring the mobility cost then we should see a positive premium regardless of the direction of the voluntary switch. In contrast, we see workers switching to agriculture taking systematic cuts to their income that is of similar magnitude as gain for workers switching in the opposite direction. Thus it seems that there is a pure premium associated with working in non-agriculture. There are several possible rationalizations for this finding. First, it might suggest existence of some additional friction that allows this premium to exist in equilibrium. We explore both asymmetric switching costs and compensating differentials as a possible rationalization of the observed choices. In the case of compensating differentials, workers simply attach higher non-monetary value to working on a farm than for other jobs. Our concern is that given the harsh realities of farm work in developing countries this explanation is not quite compelling. For that reason, we also consider an alternative friction that results in workers switching sectors involuntarily. Finally, as we argue later, the premium can arise even in the frictionless setting when switching happens because of idiosyncratic shocks to comparative advantage over time.
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2.3.2 Robustness

In this subsection we illustrate that the existence of a non-agriculture premium is robust to a number of concerns about measurement, interpretation and estimation. Our baseline point of reference is the 57 lp cross-sectional premium and 33 lp within-worker premium reported earlier in column 4 and 5 of Table 2.2.

Job type

The first exercise incorporates information on a type of job workers engage in as this helps to illuminate the nature of labor markets in Indonesia. Workers in IFLS can be consistently classified into 4 categories: self-employed, private workers, government workers and unpaid family workers. As Table 2.5 reports, self-employment is the most common work status, accounting for almost half of employment. Private sector workers earning wages and salaries - a category that would usually be the focus in studies based on developed countries - constitutes less that a third of the workforce. Almost 15% of workers who typically help in household work or in a family business or farm are classified as unpaid family workers. These workers nevertheless can report income and are included in the analysis, but our results are robust to dropping this category altogether. The second panel of Table 2.5 also reports the 10 most common occupations. The point of this table is to show what non-agriculture typically means in Indonesia. It is more about being a self-employed street vendor rather than having a formal factory job in manufacturing.

Controlling for the job type has a small impact on the non-agriculture premium, e.g., reducing it from 33 lp to 29 lp in the worker fixed effects regression. More interestingly, Table 2.6 reports the results of interacting job type with a direction of switch. For the two main categories, self-employed and private workers, there is about 25 lp premium for switching to non-agriculture relative to staying in agriculture. Workers switching away from non-agriculture suffer a loss of similar magnitude relative to workers remaining in non-agriculture. The similarity of results for self-employed and wage workers can come as a surprise. The non-agriculture premium for wage workers could be in principle rationalized along similar lines as intersectoral or even inter-firm wage differentials documented for developing countries. There might be good non-agricultural jobs that pay more than bad agricultural jobs because employers in non-agriculture for some reason share rents with their employees. But such rent-sharing explanation would be silent as to why we see a similar premium for self-employed workers switching sectors since they are the residual claimants of their effort. The sectoral premium for the self-employed is thus perhaps our most surprising finding.

Going back to earlier discussion, the non-agriculture premium could reflect compensating differentials, if, e.g., workers value flexible schedule associated with farm work. But the fact that the premium exists for self-employed in both sectors makes compensating differentials less compelling as an explanation. Furthermore, going one step further we can show that the premium of the same magnitude exists even for self-employed workers switching sectors while staying in the same narrow location. We do not find it plausible that workers willingly give up 25% of their income because they
prefer to run a farm than a non-farm business in the same village.

**Wages and consumption**

While our preferred outcome variable is annual income, there can be concerns about the quality of that self-reported measure. The problem could be particularly stark for self-employed who often have to allocate family business income to individuals. As a robustness check we now restrict attention to annual wage income that is less likely to suffer from measurement problems. Doing so comes at the expense of restricting the sample by more than half to individuals who work for wages in the private or government sector. Table 2.7 illustrates that the same pattern of premia can be observed using data for wages as for total income, though the magnitudes are a little smaller. Controlling for worker fixed effects, the non-agriculture premium is 23 lp, while the urban premium 11 lp. Despite the sample size being significantly reduced the premia are still precisely estimated.

Since the IFLS records consumption expenditure, it offers an additional way of verifying that working in non-agriculture allows a higher standard of living. One drawback of consumption data in the present context is that it is recorded at a household level, whereas the focus of the chapter is on individual decisions. This requires some adjustments to make the results comparable. The first column of Table 2.8 reports results of a household-level cross-sectional regression of log per capita expenditure (Log PCE) on a continuous variable measuring the share of household income derived from non-agriculture and an urban dummy. Column 4 reports a corresponding calculation for per capita household income. Households that derive higher share of income from non-agriculture have a higher per capita consumption, though the elasticity is not as large as for income. The rest of Table 2.8 reverts to individual level regressions, but with dependent variables still at the household level. Column 3 results indicate that if a member of a household moves from agriculture to non-agriculture than the average consumption in the household increases by over 7 lp. This might appear as a modest number compared to the baseline income premium so two comments are in order. First, since a survey worker typically accounts for less than 60% of income in his household, the coefficient should be scaled by the inverse of that share to be interpretable as an increase in consumption associated with all household workers switching to non-agriculture. This transformation would increase the non-agriculture consumption premium to about 13 lp. To illustrate that this transformation is reasonable column 6 performs it on per capita income variable. The transformed coefficient of 35 lp is very close to the baseline non-agricultural premium. Second, in similar specifications the consumption premium is still only 1/3-1/2 as large as income premium. In light of permanent income logic perhaps it should not be surprising that an income shock associated with switching sectors has only partial pass-through to consumption.

**Heterogeneity in Mincerian returns**

The baseline regressions control for standard Mincerian determinants of income such as education and experience. The coefficients on these determinants do not vary between sectors and rural/urban
locations, however. A recent paper by Herrendorf and Schoellman (2018) argues that this might lead to an overstatement of the residual income gaps, if, e.g., non-agriculture offers higher returns to education and experience. To address this concern, we now allow the Mincerian returns to vary by sector and location. Table 2.9 reports the associated premia, calculated as the average marginal effects of switching for the population. While some underlying returns do indeed differ by sector, this has no significant effect on the estimated premia of interest.

Additional jobs and home production

Workers are assigned to a sector according to whether their main job is in agriculture or non-agriculture. Correspondingly, the annual income is constructed using the income from the main job. Some workers, however, have more than one job. If having a secondary job is more common for agricultural and rural workers then we might overestimate the non-agriculture and urban premia. Columns 3 and 4 of Table 2.10 show the premia estimated when instead we take into account income from worker’s both primary and secondary jobs. This adjustment reduces the premia by about a fifth.

Another concern is that by focusing on income we are not taking into account home production which is not trivial in developing countries. If agricultural households do not include food produced and consumed in-house in their income then this could lead to an overstatement of the non-agriculture premium. The IFLS data allows us to assess how important this consideration is because it asks households to report the value of goods and services produced for own consumption. The average share of self-produced consumption is about 10%, but is predictably higher in rural areas (13%) than in urban areas (7%). As a robustness check we therefore scale up individual incomes (from both main and secondary job) by the inverse of the share of self-produced consumption in a household the individual belongs too. This effectively increases incomes of workers in rural and predominantly agricultural households. As columns 5 and 6 report, this has little effect on the estimated premia. Columns 7 and 8 consider an adjustment even more favorable for agriculture - scaling incomes by the inverse of the share of home-produced food in total food consumption. This again does not affect the estimated non-agriculture premium much, though the urban premium becomes insignificant.

Hours worked

All the results so far show that workers in agriculture have lower annual income than workers in non-agriculture. One natural question is to what degree this income difference is driven by systematic differences in labor supply across sectors. To investigate this issue, Table 2.11 adds hours worked per year to the set of individual controls. Controlling for hours worked reduces the non-agriculture premium by about a fifth. In particular, comparison of columns 2 and 4 shows that the premium identified from switchers falls from the baseline level of 33 lp to 27 lp. This reflects the fact that

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49Results are similar if we calculate the average marginal effects for switchers instead.

50Using a continuous measure of the share of income a worker derives from non-agriculture instead of a dummy for the primary job leads to similar results, with a cross-sectional premium of 47 lp and 26 lp in the specification with worker fixed effects.
workers in non-agricultural work more hours, as illustrated in Table B.2 in the Appendix. Column 2 of that table shows that the same workers supply on average 15% more hours when they switch to non-agriculture.

Whether one actually should condition on hours worked in calculating the sectoral premia can be debated. The answer depends on the interpretation one wants to give to the premia and on the reason hours differ across sectors. In this chapter, the non-agricultural premium is meant to capture an increase in the annual income that can be expected by a worker switching away from agriculture. To the extent that the switch is associated with higher labor supply, this increase in hours should be included as part of the benefit of switching. Our baseline measure therefore does not control for hours. In our view, thus calculated premium is a more interesting object than a premium netting out the effect of hours. The reason is that a sector of employment and supply of hours are best seen as a package. Our conjecture is that lower hours worked in agriculture observed for the same individuals are an indication that these individuals are frequently underutilized in agriculture, perhaps because of intrinsic seasonality of farm work.\footnote{Table B.1 and column 3-4 of Table B.2 show that the results are robust to including the secondary job. This alleviates a concern that lower hours in the main job for agricultural workers are offset by having a second job.} If workers are forced to be idle for stretches of time in agriculture, then their low average utilization should be considered as a part of the productivity gap between agriculture and non-agriculture.

Another interesting feature seen in columns 3 and 4 in Table 2.11 is that the elasticity of annual income with respect to annual hours worked is only about one half. This means that income per hour is declining in hours worked, consistent with diminishing returns to labor. Combining this observation with higher hours in non-agriculture explains why the non-agricultural premium in terms of income per hour (columns 5 and 6) is smaller than the premium controlling for hours (columns 3 and 4).\footnote{If we control for hours worked in the income per hour specifications in columns 5 and 6 then the premia would be identical to those in columns 3 and 4.} However, even when identified off switching workers income per hour is still significantly (19 lp) higher in non-agriculture. We report these numbers mainly because some of the literature interprets measures of income per hour as “wages” and uses them to calculate sectoral wage premia. In particular, in a concurrent paper also using the IFLS data Hicks et al. (2017) argue that non-agricultural premium in Indonesia largely disappears when they use their preferred regression of income per hour with worker fixed effects. There are two main reasons why our substantive findings are different. First, in our implementation we only rely on information on income and hours reported contemporaneously by the survey respondents. In contrast, Hicks et al. (2017) also rely on recall information for several years prior to the survey. As discussed in more detail in Appendix B.2, the recall information is likely subject to non-classical measurement error which can bias the estimated non-agricultural premium downwards. Second, even though our results are robust to controlling for hours and looking at hourly income, as argued earlier our conceptually preferred specification does not take hours into account. Comparing income per hour could indeed be preferable in a setting in which workers are offered constant hourly wages and freely choose the sector to which to allocate their marginal hour of work. But
2.3. Income gaps across sectors and locations

if hours are largely dictated by the nature of work in a sector then sector is the relevant “marginal” choice. Since we find the second case to be more plausible in the context of Indonesian labor markets we do not adjust our preferred non-agricultural premia for differences in hours.

Long-run income growth

One of our most surprising findings is that workers who switch from non-agriculture to agriculture suffer an income loss of around 30%. To be more precise, an interpretation of coefficients in the first column of Table 2.4 is that a worker who switches away from non-agriculture between two survey waves has an income growth over that period 33 lp lower relative to what he would be expected to get if he remained in non-agriculture. Taking a large income cut could nevertheless be a rational decision for a worker maximizing his lifetime discounted income if he expects that the current loss of income will be compensated by higher future income growth in agriculture. This argument potentially has some merit because over our sample period average income growth was indeed higher in agriculture. To illustrate these differential trends, Table B.3 in the appendix shows the evolution of the non-agricultural premium over time. While it is strong and statistically significant throughout, it does decline over our sample period, especially in the cross-section, consistent with agricultural incomes partially converging to those in non-agriculture.

However, if switching workers could accurately predict the future income path then we would expect that over a long period of time those who took a cut switching to agriculture are not worse off than workers who remained in non-agriculture. As a first test of this hypothesis we look at income growth over the entire 21-year period spanned by IFLS 1-5. Column 1 of Table 2.12 shows that workers who started in non-agriculture in 1993 but switched to agriculture by 2014 had income growth over that period lower by 37 lp compared to those who began and finished in non-agriculture. This result suggests that switchers to agriculture do not make up their initial loss even after a prolonged time.

By using a single long time difference, the previous exercise identifies an average effect of switching among workers with diverse interim sectoral employment histories. Our second exercise exploits this interim information. For this purpose, we consider employment histories spanned by three observations at equal 7-year intervals (i.e. those individuals with data for 1993, 2000, 2007 or 2000, 2007, 2014). We are interested in comparing the change in income over the 14-year span for workers who made different sectoral decisions during that period. Figure 2.1 shows the mean log wages for a few key histories. In particular, compare income of NAA-history workers (i.e. those who switched from non-agriculture to agriculture during the first 7-year period and stayed in agriculture during the second 7-year period)_to income of NNN-history workers (who remained in non-agriculture throughout). Before the switch, NAA-workers had on average lower incomes, consistent with idea that those who switch are negatively selected from non-agricultural workers. More importantly, after the switch their incomes decline relative to NNN-workers. This is another reflection of the loss from switching emphasized in this chapter. But the gap between NAA- and NNN-workers does not significantly
narrow over the subsequent 7-year period. So crucially, over the entire 14-year period incomes of non-agricultural workers who permanently switched in the first half of the period fall back relative to those who stayed in non-agriculture.

Column 2 of Table 2.12 casts this analysis into a regression framework with the usual controls. We find that workers who switched from non-agriculture to agriculture during the first 7-year period and were still in agriculture at the end of the second 7-year period had a cumulative growth over 14 years lower by 19 lp (significant at 0.05 level) than if they had remained in non-agriculture over this period. Similarly, workers who switched into non-agriculture in the first period and remained there had long-run income higher by 15 lp than if they had remained in agriculture, though that effect is less precisely estimated (significant at 0.10 level). Overall we take these results as evidence that workers who chose agriculture have lower incomes even in the long run.

2.4 Model of sorting across sectors with barriers to sectoral mobility

In this section we introduce a simple discrete-time model of the labor supply in which heterogeneous workers self-select into sectors in each period based on the value of their human capital. Workers switch across sectors due to exogenous variation in the prices of human capital over time and due to the presence of an idiosyncratic time-varying component in their sector-specific human capital that resembles transitory productivity shocks. As we argue in the next section, the latter component is able to generate by itself a within-individual sectoral premium, depending on the magnitude of its relative dispersion across sectors. However, our structural estimation suggests that in order to simultaneously fit the magnitudes of the premia, the allocation and transition of workers across sectors over time and the moments of the joint income distribution, some frictions to sectoral mobility are needed in the model.

For that reason, we evaluate different types of barriers to sectoral mobility that misallocate workers across sectors. We first consider switching costs across sectors (Dixit and Rob (1994); Cameron et al. (2007); Artuç et al. (2010); Dix-Carneiro (2014)) and, relatedly, compensating differentials (Rosen (1986); Taber and Vejlin (2016)). Switching costs act as utility burdens that constrain voluntary switches, inducing misallocation across sectors. Since we estimate opposite signs for the switching costs away from and towards agriculture, the model with switching costs performs similarly to a specification in which workers receive a positive compensating differential for working in agriculture. Next, we consider a specification with imperfect self-selection, where we allow for frictions that prevent individuals from working in their preferred sector. These frictions could be rationalized by on-the-job searching frictions (Gautier et al. (2010); Gautier and Teulings (2015)), for example. In contrast to the case of utility costs, where mobility barriers bind only for workers with relatively small differences in comparative advantage, in the alternative specification even workers with a strong

\[\text{In principle we could construct even longer histories which would allow us to control for pre- and post-trends of various groups. Unfortunately, between the number of possible histories increasing and the number of individuals with required data decreasing with history lengths, these longer histories would have limited statistical power.}\]
comparative advantage in one sector can be affected by the frictions. Because frictions affect the inframarginal workers, the induced allocative inefficiency in this case generates a larger impact on the aggregate income.

2.4.1 Frictionless economy

Suppose agents choose their sector at each time $t$ to maximize contemporaneous utility\(^{54}\). Let $\Omega_{it}$ be a vector of state variables for an individual $i$ at time $t$. The income an individual receives in sector $s$ is a product of the exogenous price of human capital in sector $s$ at time $t$, $R^s_t$, and the amount of human capital the worker can supply to that sector:

$$y^s_i (\Omega_{it}) = R^s_t h^s (\Omega_{it}).$$

The supply of human capital depends on both observable and unobservable components. The former are gathered in a vector of covariates $X_{it}$, which in our estimation includes gender, the urban-rural location, years of schooling, years of working experience and the square of working experience. Notice that since we emphasize in this chapter the sectoral dimension of the residual wage premia, we abstract from the choice of location, and treat the urban-rural choice just as another covariate. Since the sectoral premia are robust to heterogeneous Mincerian returns across sectors, we assume for simplicity homogenous returns on covariates, and hence we focus our attention on self-selection based on the unobservable components. Regarding the set of unobservables, it includes a time invariant component $\theta^i_s$, representing the permanent comparative advantage of worker $i$ in sector $s$, and an idiosyncratic time-varying term $\varepsilon^i_{st}$, resembling a transitory productivity shock that affects the comparative advantage of the same worker $i$ in sector $s$ at time $t$:

$$h^s (\Omega_{it}) = \exp (X^t_{it}' \beta + \theta^i_s + \varepsilon^i_{st}).$$

As in standard selection models, the functional form assumptions on the distribution of the components of comparative advantage are key for identification. We assume that the permanent component $\theta^i_s$ is i.i.d. across individuals, drawn from a normal distribution $N(\mu_\theta, \Sigma_\theta)$. Productivity shocks are also normal i.i.d. across individuals and time, $\varepsilon^i_{st} \sim N(\mu_\varepsilon, \Sigma_\varepsilon)$ and for identification purposes, orthogonal across sectors. We impose the normalization $\mu_\theta = \mu_\varepsilon = 0$ in order to identify the evolution of prices of human capital over time.

Let us now describe the worker’s problem. The worker is choosing at the beginning of period $t$ where to work. At the time of the decision she knows the value of the comparative advantage components and the human capital prices. Her problem is:

$$V (\Omega_{it}) = \max_s \{ V^s (\Omega_{it}) \},$$

\(^{54}\)We abstract from a model with inter-temporal optimization because our empirical findings do not support the hypothesis of maximization of lifetime discounted income (see section 2.3.2).
where the value of the human capital in sector $s$ in the frictionless case is simply the log of the income,

$$V^s(\Omega_{it}) = V_{st}^s(\Omega_{it}) = \ln y^s_t(\Omega_{it}).$$

Finally, we assume the researcher observes individual income $\hat{y}^s_{it}$ subject to a pure idiosyncratic measurement error $v_{it}$:

$$\ln \hat{y}^s_{it} = \ln y^s_t(\Omega_{it}) + v_{it}.$$  

We assume measurement errors have mean zero and are normal i.i.d. across individuals and time, $v_{it} \sim N(0, \sigma^2_v)$. Notice that an alternative interpretation of these errors is as ex-post productivity shocks that affect observable worker’s income, but not her sectoral choice. Since in this case ex-post shocks do not affect workers’ self-selection into sectors, the model delivers the same predictions under both specifications.

Our model abstracts from the possibility that workers drop out from the labor market, to focus attention on the role of sorting and the barriers to sectoral mobility introduced in the next section in explaining non-agriculture premia among active workers. For this reason, in the structural estimation we use the balanced panel of workers with income recorded in the five available waves of IFLS. Denote by $\Theta$ the set of all structural parameters. The elements of $\Theta$ are listed and described in the first column of Table 2.13.

### 2.4.2 Economies with barriers to sectoral mobility

The first type of barrier to sectoral mobility that we consider is a utility cost of switching across sectors. This cost could reflect tangible expenditures such as training or transportation costs, or intangibles such as social adjustment costs. Denote by $\phi_{ss'}$ the utility cost for switching from sector $s$ (which was chosen in $t-1$) to sector $s'$, common to all individuals. The value of the human capital supplied to sector $s$ is then:

$$V_{sc}^s(\Omega_{it}) = \ln y^s_t(\Omega_{it}) - \ln C_{s-1}^{s'}(\Omega_{it}),$$

where

$$C_{s-1}^{s'}(\Omega_{it}) = \begin{cases} \phi_{ss'} & \text{if } s \neq s' \\ 1 & \text{if } s = s' \end{cases}.$$  

The problem of the worker is the same as in (2.3), the only difference here is the definition of the value of the human capital, $V^s(\Omega_{it}) = V_{sc}^s(\Omega_{it})$. We only constrain the magnitude of $\phi_{ss'}$ to be positive, so in principle switching costs could also measure a utility compensation for $\phi_{ss'} < 1$.

As we show in the next section, we estimate opposite signs for $\ln \phi^{AN}$ and $\ln \phi^{NA}$ (where $A$ and $N$ denote agriculture and non-agriculture, respectively), a pattern that is observationally similar to receiving a positive compensating differential for working in agriculture. In the case of a compensating differential, the value of the human capital can be defined as:

$$V_{cd}^s(\Omega_{it}) = \ln y^s_t(\Omega_{it}) + \ln C^s,$$
where

\[ C^s = \begin{cases} 
  cd & \text{if } s = A \\
  1 & \text{if } s = N 
\end{cases} \]

and thus the differential \( cd \) measures the additional utility that a worker obtains by working in agriculture (relative to working in non-agriculture). This differential can be related to any attribute of the agricultural work that is valued by individuals: less exposure to pollution, crime, or crowding, more flexible work schedules, etc. Note that both switching costs and compensating differentials act as if proportionally scaling down or up income, so they can be interpreted in terms of annual earnings. Further, notice that the specification with switching costs adds two parameters (\( \phi^A, \phi^N \)) to \( \Theta \), whereas the model with a compensating differential only adds one (\( cd \)).

Finally, we also consider a different kind of barrier to the allocation of workers across sectors. We want to capture an idea that workers do not always get to work in a sector that they would like, even if they have a strong comparative advantage in that sector. These frictions can be interpreted as life events forcing an individual to switch the sector of employment, and are meant to capture in a simple way the underlying search frictions. Specifically, we assume that at the beginning of each period an individual gets a random draw such that she will be able to choose the sector she desires with probability \( 1 - p(\Omega_{it}) \) and she will be forced to work in the other sector with probability \( p(\Omega_{it}) \). The probability \( p \) of being forced to accept a job in a sector other than desired can depend on the worker’s state. In particular, we want to allow for the possibility that it might be more difficult to switch a sector than keep working in the same sector, by letting the probability differ between those who desire to switch and those who desire to stay:

\[ p^{s_{it-1}s_{it}}(\Omega_{it}) = p^{s's'} = \begin{cases} 
  p^T & \text{if } s \neq s' \\
  p^S & \text{if } s = s' 
\end{cases} \]

Similarly as with the switching costs, this specification adds two parameters (\( p^T, p^S \)) to \( \Theta \).

### 2.5 Structural estimation

In this section, we describe the estimation procedure and the identification of the parameters of the structural model. The estimation method is Indirect Inference (Gourieroux et al. (1993)). We rely on the functional form assumptions to deliver a proof for identification in a simplified version of the model.

#### 2.5.1 Estimation procedure

The first step in the estimation procedure is to choose a set of auxiliary regression models that summarize the main features of the data we want to capture: the sectoral premia, the moments of the joint distribution of income and the workers’ sectoral decisions over time. Those auxiliary models are
2.5. Structural estimation

used to compute the Indirect Inference loss function to be minimized, and hence they must be simple to estimate multiple times. As we explain below, for identification this method does not require that those auxiliary regressions are well specified (i.e. models which are exact reduced forms of the structural model, in which case Indirect Inference is equal to MLE). However, we do need that the selected models provide us enough information about the moments in the data that allow us to identify the set of structural parameters \( \Theta \).

First of all, given the assumption of homogeneity in the Mincerian returns, the role of observables in self-selecting workers across sectors is innocuous. Hence, we can map the parameters in \( \beta \) to the estimated coefficients on observables in a log-income linear regression on observables controlling for the interaction between sectoral choice and year, in order to estimate the structural model using only residual income. An identical estimation could be performed including \( \beta \) and using log-income to compute all auxiliary regressions, controlling for observables. This is why we can safely drop the effects of observables from our identification proof in Appendix B.4.

We select the following seven auxiliary models: i) a log-residual income linear regression on the sector choice, controlling for time fixed effects; ii) a log-residual income linear regression on the sector choice, controlling for time and individual fixed effects; iii) a log-residual income linear regression on the direction of sector switching between waves, controlling for time fixed effects; iv) a log-residual income linear regression in first differences on the direction of sector switching between waves, controlling for the first differences in years of the waves; v) a log-residual income linear regression on the interaction between sectoral choice and year; vi) a sectoral choice linear probability model on time dummy variables; and vii) a sectoral choice linear probability model on the previous sectoral choice. The role of each of these models in identifying the structural parameters is explained in the next subsection.

For efficiency reasons, we only use the coefficients of interest of the selected auxiliary regressions in the Indirect Inference loss function. Hence, we use the following 29 coefficients of the seven auxiliary models: 1-2) the non-agriculture premia in models i) and ii); 3-6) the sector-specific premia for switching workers from models iii) and iv); 7-23) the full set of estimated coefficients from models v) to vii); 24-25) sector-specific residual variance in model v); and 26-29) sector-specific residual variance for non-switching and switching workers in model iv). Table 2.14 summarizes the auxiliary models as well as the selected coefficients.

Arrange the values of the selected coefficients estimated in the actual data in the vector \( \hat{\delta} \). The elements of vector \( \hat{\delta} \) are displayed in the third column of Table 2.15 and remain fixed during the estimation procedure. The Indirect Inference loss function is computed as the weighted sum of the squared differences between the values in \( \hat{\delta} \) and the values for the same set of coefficients obtained from simulations of the structural model. For weights, we use factors that represent the importance of the estimated coefficient in the identification of the structural parameters of the model, assigned after extensive experimentation. Appendix B.3 describes their magnitudes and presents technical aspects of the estimation procedure in more detail.

Finally, in the models with switching costs or involuntary choices there is an issue of endogeneity
of observing workers’ initial sector allocation in the panel. We address it by introducing a pre-sample period zero with sectoral choice free of switching costs in the first case, and with a probability of being forced to work in the undesired sector independent of the worker’s state\footnote{We make this probability equal to $p^S$.}, in the second case. We use pre-sample information on covariates when available to construct the distribution of the initial conditions. This way, although the auxiliary regressions are computed only for the five years in the sample, the data generating process of the model produces draws also for period zero.

### 2.5.2 Identification

In this section we discuss how from the selected coefficients of the auxiliary regressions we obtain the set of moments that allows us to identify the parameters in $\Theta$. Those moments are enumerated in Appendix B.4, where we demonstrate how $\Theta$ is identified in a simplified version of the model with two periods. In the proof, we take advantage of the functional form assumptions to extend the standard cross-sectional moments by including moments of the income distribution of the switching workers across waves, available only thanks to the panel dimension of the data, with the aim to set up a system of equations to solve for all parameters in $\Theta$. We fully expect our reasoning to generalize to the same setting with a larger number of years. To verify this hypothesis, we generate multiple samples from the model with simulated covariates over the number of years as observed in the data, using different sets of parameters values. We find that the chosen auxiliary regressions allow the estimation procedure to obtain the values of parameters used to generate each sample.

Let us first comment on the main insights from the demonstration in Appendix B.4. In the frictionless economy sectoral decisions do not depend on workers’ histories, so the model behaves in each period $t$ as the standard log-normal Roy model with comparative advantage $u^i = \theta^i + \epsilon^i$. In this case, we can use standard arguments of (Heckman and Honoré (1990)) to identify from repeated cross-sectional moments the prices of human capital (which, given our normalizations, act as the means of the distribution comparative advantage) and the variance matrix of $u^i$ in each period augmented by the variance of measurement error. Only with panel data we can separately identify the variances of the permanent and transitory components of comparative advantage and the variance of measurement error, inferred from the moments of the growth in income of switchers. The intuition is that the amount of additional information that switchers provide about the joint distribution of income in response to changes in relative human capital prices is similar to the information obtained from exclusion restrictions and support conditions in the process of non-parametric identification of cross-sectional non-normal Roy models.\footnote{See French and Taber (2011) for a detailed discussion about parametric identification of selection models through distributional assumptions and nonparametric identification using exclusion restrictions and support conditions.}

We are able to find the analytical expressions for the moments of the income distribution of the employment transition groups across waves exploiting the property that draws of $u^i$ in different periods of time are joint normally distributed, since each one is the sum of two normally distributed random variables. In this way, we can express the transition probabilities across waves and the observed mo-
ments of the growth in income for switchers using upper truncated multivariate normal distributions, where the prices of human capital in the two periods affect the truncation values. We verify that by adding this information from the switchers to the standard cross-sectional moments we can set up a system of equations with a unique solution for all parameters in $\Theta$.

For the case of switching costs and frictions, sectoral choices depend on workers’ histories and with only repeated cross-sectional data we can no longer identify either the prices of human capital or the variance matrix of $u_{it}$ augmented by the variance of measurement error. That is, we obtain the non-identification result that even with the log-normality assumptions, the standard Roy model is not identified in the presence of barriers to sectoral mobility. We can generate two combinations of $\Theta$, with different values for at least one parameter other than the corresponding barriers, that produce exactly the same set of cross-sectional moments. This is due to the fact that the cross-sectional moments depend on the distribution of the previous sectoral choices. Therefore, in order to identify the full set of parameters in $\Theta$ we need panel data even under log-normality assumptions.

In a similar way as with the moments of the employment transition groups in the frictionless economy, for the models with barriers to sectoral mobility we can derive the closed-form solutions of the cross-sectional moments, the transition probabilities and the moments of the growth in income for switchers, expressed all of them in terms of moments of upper truncated multivariate normal distributions, but with a dimensionality that grows with the number of time periods in the panel. Switching costs affect the truncation values of the distributions, similar to the human capital prices, whereas the probabilities of forced switches shift the entire distribution. We verify again that adding the moments of the growth in income for switchers and the transition probabilities to the standard cross-sectional moments we obtain a system of equations with an unique solution for all parameters in $\Theta$, including switching costs.

Now we discuss in detail how the selected coefficients of the auxiliary regressions in our Indirect Inference loss function capture the set of required moments for identification. First, linear probability models vi) and vii) describe the distribution of sectoral choice in each cross-section and the average transition probabilities between waves, respectively. Combined, these models characterize the evolution of the joint distribution of sectoral choice over time, and hence they deliver the probabilities of sectoral transition across all waves. Second, for the moments of income growth, we use for the first moments both the within-individual premium from model ii) and the premia for switching workers relative to stayers in the model in first differences iv). The difference between the two is that the latter model takes into account the direction of transition, so it can actually inform the estimation procedure with the observed gains of switchers to non-agriculture and the losses of workers switching to agriculture separately, unlike the fixed-effects premium. For the second moments we use the residual variances for workers switching to each sector from model iv).

For the cross sectional moments, model v) informs us about the conditional expected incomes in each combination sector-year, since it includes a full set of interactions for sector and year. Those coefficients, taking together with the cross-sectional premium in model i), characterize the first cross-sectional moments. We collect the residual variances for the pool of workers in each sector from
2.6. Results

In this section we present the structural estimation results and use them to quantify the importance of barriers to mobility and of self-selection. We begin with a frictionless model and show that it fails to explain some salient features of the data. Models featuring frictions provide a much better fit to the data and imply a large extent of misallocation in Indonesia. Finally, we discuss the empirical content of the reduced form non-agriculture premia when viewed through the lens of the model.

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57 The grids (one per each structural parameter) of 29 plots (one per each selected coefficient of the auxiliary regressions) are available upon request.
2.6. Results

2.6.1 Estimation results

Column (1) of Table 2.13 shows the values of the Indirect Inference point estimates for the 16 structural parameters in the frictionless economy. Given those estimated parameters the model generates the values for the 29 coefficients of the auxiliary regressions displayed in column (4) of Table 2.15. The last row of this table shows the value of the loss function, indicating the overall fit of the model (with smaller values indicating a better fit).

Perhaps surprisingly, the model without any frictions is not only able to replicate the cross-sectional non-agriculture premium, but also to generate a sizable within-individual premium. In the estimated frictionless economy, workers who switch from non-agriculture to agriculture see their incomes decline by 24 lp on average. This striking result can be explained by a selection effect generated by the transitory productivity shocks. As a result of this mechanism the fixed effect premium is shaped largely by the variance of transitory shocks across sectors. We formally state this result for a simplified version of the model in the following proposition.

**Proposition 1.** Consider the frictionless model with two periods and human capital prices equal across sectors and over time. Then the average growth of log income of workers switching from agriculture to non-agriculture is positive if and only if \( \sigma_{\varepsilon N}^2 > \sigma_{\varepsilon A}^2 \). Furthermore, the average growth of log income of workers switching from non-agriculture to agriculture has the same magnitude but is of the opposite sign.

*Proof.* See Appendix B.5.

Since with two periods the fixed effects premium is simply equal to to the average growth of log income of switchers (taken with appropriate signs), we immediately have the following implication.

**Corollary 2.** Under the same conditions as in Proposition 1, the non-agriculture premium identified from a regression with worker fixed effects is positive if and only if \( \sigma_{\varepsilon N}^2 > \sigma_{\varepsilon A}^2 \).

To understand these results, observe that after workers sort themselves into sectors in the first period, the only reason a worker would switch to a different sector next period is a change in the balance of productivity shocks, \( \varepsilon_{it}^N - \varepsilon_{it}^A \). With equal variances of shocks across sectors, the average growth in income is the same for switchers in both directions, so the within-individual premium is null. But in the case of asymmetric variances, the shocks with a larger dispersion have a higher chance to take extreme values, resulting in larger average increase in income of workers shifting to the sector with the larger variance. Thus, the sign of the non-agriculture premium after controlling for worker fixed effects depends only on the relative size of the variance of the productivity shocks: it is positive when the variance is larger in non-agriculture, and negative otherwise. This reasoning carries over quantitatively to the estimated general model with multiple periods and evolving human capital prices.

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58 We are currently computing standard errors from 200 bootstraps.
2.6. Results

The main message from this discussion is that finding a large non-agricultural income premium after controlling for worker fixed effects, as we find for Indonesia, by itself does not indicate that workers face any frictions in choosing their sector of employment. In principle, the premium can be explained simply by larger dispersion of productivity shocks faced by non-agricultural workers. But the pattern of variances have observable implications for moments other than sectoral premia. In particular, the frictionless model struggles to simultaneously account for non-agricultural premia and the pattern of the residual variances of workers’ earnings in the data (the variance is larger in the agriculture sector). To generate the cross-sectional and fixed effects non-agriculture premia, the frictionless model forces the relative magnitudes of the variances for both the permanent and transitory components of comparative advantage to be opposite to the pattern observed in the residual variances. This enables it to display a relatively good fit for the premia (0.56 lp and 0.23 lp in the model versus 0.57 lp and 0.40 lp in the data for the cross-sectional and the fixed-effects premia, respectively), but at the expense of generating residual variances that are completely reversed relative to the data (compare coefficients $\delta_{24}$, $\delta_{25}$ and $\delta_{26}$, $\delta_{27}$ in columns (2) and (4) of Table 2.15). To explain jointly the premia and the patterns of the residual variances, we need to introduce some frictions to the sectoral allocation in the model.

The first type of friction is represented by utility costs of switching sectors. When we restrict the switching costs to be positive, which is a standard and perhaps natural case, we find that they have effectively no impact on the estimates. The reason is that the estimated costs are small in magnitude, and in particular, the zero bound for the cost of switching from non-agriculture to agriculture is binding. This result might seem surprising, given that the literature estimating utility costs of switching sectors typically finds them to be large, often equivalent to multiples of a worker’s annual income (e.g. Artuc et al. (2015)). But the magnitudes might not be easily comparable across studies, as they depend on what other mechanisms of sector determination are built into the respective models. In our case, when we allow for self-selection according to comparative advantage then positive switching costs do not have much additional explanatory power. In particular, if switching to agriculture was costly then it would be even more puzzling why so many workers make the move.

The situation is different if we remove the restriction on the sign of the switching costs. Column (2) of Table 2.13 shows the estimates for the model with unrestricted switching costs, and column (5) of Table 2.15 the corresponding coefficients of the auxiliary models. The switching costs are of opposite signs, approximately symmetric in magnitude, and of a large magnitude. A worker switching from agriculture to non-agriculture faces a cost of 71 lp of annual income equivalent (i.e. roughly equivalent to her annual income). That is, a worker who actually moves from agriculture to non-agriculture, must have a value of her human capital in non-agriculture at least twice as large as in agriculture. For smaller differences, the worker remains in agriculture. A worker switching towards agriculture receives a utility compensation equivalent to almost doubling her new agricultural income. That is, a worker who actually switches from non-agriculture to agriculture, could have a value of her human capital in agriculture as much as 47% smaller than in non-agriculture.

Because of this implied compensation, the model now has an easier time justifying why workers
2.6. Results

switch to agriculture. It can rationalize the income cuts of workers switching to agriculture in terms of negative switching cost so it does not need to rely on the counterfactual pattern of residual income variances. It can therefore generate both a within-individual premium that is close to the one observed in the data (0.35 lp in the model versus 0.40 lp in the data) and deliver the correct qualitative patterns for the residual variances (larger variances in agriculture, see coefficients $\delta_{24}$ to $\delta_{27}$ of Table 2.15). In summary, the overall fit of the model with switching costs is substantially better (last row of Table 2.15).

Since the estimated switching costs are nearly symmetric (i.e. $\phi_{AN}/\phi_{NA}$ is close to 1), the model with switching is similar to a specification with a single positive compensating differential for working in agriculture.\(^{59}\) Columns (3) in Table 2.13 and (6) in Table 2.15 show, respectively, the estimated parameters and the obtained auxiliary coefficients for the latter model. In this case, individuals are willing to be paid less to work in agriculture simply because it is a sector they enjoy more. This estimated preference is strong, as it is equivalent to increasing a worker’s agricultural income by 61 lp (or 89%). Comparing columns (5) and (6) in Table 2.15 shows that the compensating differential model fits the data nearly as well as the more flexible model with switching costs.

These estimates demonstrate that in order to be consistent with the salient features of worker-level panel data on sectoral employment and income, a model built on revealed preferences (i.e. voluntary choices) needs to make switching to agriculture attractive in some non-pecuniary terms. While estimating compensating differentials has a long history, we recognize that in our context they are not a particularly satisfying explanation. Ultimately, such utility-based compensation is a residual force that allows the model to rationalize choices otherwise difficult to explain. We therefore explore an alternative conceptual approach to think about barriers to sectoral mobility. Instead of treating all observed sectoral transitions as a result of voluntary choices, the alternative is to recognize that sometimes workers switch sectors for reasons independent of their productivity.

First we consider a specification with a single probability $p$ of a worker being forced to a different sector than she would desire. This probability is estimated to be 0.05 (see column (4) in Table 2.13), which might not seem large, but in fact implies that most of the observed switches are of this random nature. This parsimonious explanation fits the data noticeably better (see column (7) in Table 2.15) than the models with utility switching costs.

Next, we increase the model’s flexibility by allowing the probability of the involuntary sector allocation to depend on whether the workers wants to switch or to remain in the same sector as in the previous period. This specification captures the notion that switching a sector might be more difficult than staying put. This is indeed the case: as reported in column (5) in Table 2.13, the probability that a worker who wants to remain in a sector has to switch anyway is $p^S = 0.09$, whereas a worker wanting to switch most likely will not get the chance to do so ($p^T = 0.77$). These numbers imply that 57% of the observed transitions from non-agriculture to agriculture are driven by chance rather than in response to productivity shocks. The effect is not symmetric, in that only 25% of switches to

\(^{59}\)The model with a compensating differential $cd$ is observationally equivalent to a model with switching costs $\phi_{AN} = cd$, $\phi_{NA} = 1/cd$. 

68
non-agriculture are forced by randomness.

The explanation offered by this model for the prevalence of income-reducing transitions to agriculture is thus that these transitions are largely random events. Furthermore, once a worker finds herself in a non-desired sector she can be “trapped” there for a while, because it is difficult to transition to the other sector. The model with these features provides a considerably better fit to the data than all the alternatives presented above, as can be seen from column (8) in Table 2.15. In particular, it can match closely not only the qualitative pattern of non-agriculture premia and residual variances but also their magnitudes. It is also the only specification that can replicate the asymmetry in the magnitude of income growth of switchers to agriculture and switchers to non-agriculture (coefficients $\delta_5$ and $\delta_6$) that is observed in the estimation sample. Since this model offers superior empirical performance and what we believe is a compelling underlying mechanism, it is our preferred specification and the basis for further analysis.

2.6.2 Counterfactual exercises

We now proceed to quantify the importance of mobility barriers across sectors by computing the counterfactual equilibrium in which the barriers are removed. While this counterfactual is intended to illustrate the response of labor supply to the removal of such frictions, it is worth pointing out that the exercise lacks a general equilibrium adjustments of factor prices. Such adjustments can dampen the reallocation of workers, so our results should be regarded as an upper limit of the full impact.

We simulate counterfactual data setting $p^S = p^T = 0$ while keeping the remaining elements of $\hat{\Theta}$ and the values of covariates as in our baseline model. We first discuss the implications of eliminating the frictions for aggregate income and then present sectoral outcomes. Denoting by $N$ the total number of individuals in the panel, we compute the number of individuals reallocated after the barriers are removed, equal to $M$, and the fraction of the population that is reallocated, $m = \frac{M}{N}$. To decompose the impact of workers’ misallocation on total income $Y$ into its different margins, denote by $Y_m$ the sum of earnings of the misallocated individuals. Further, denote by $\psi_m$ the ratio of the average income of the misallocated individuals to the average income in the population, $\psi_m \equiv \frac{N \bar{Y}_m}{N \bar{Y}}$. Thus, the percentage growth rate of total income after removing mobility frictions can be expressed as the product of three terms:

$$\Delta \% Y = m \psi_m \Delta \% Y_m.$$  

(2.4)

The first term represents the fraction of the population that is reallocated, the second term how impor-
2.6. Results

tant on average is the income of those individuals relative to the whole population in the data, and the third term the growth rate in the total income of all misallocated individuals.

Table 2.16 presents the results of the calculation. The main finding is that removing workers’ mobility barriers across sectors leads to a significant reallocation of workers towards non-agriculture (30% of the total labor force) and to a large increase in income of misallocated workers (which doubles on average). As a result, it produces a sizable impact in aggregate terms: an increase of around 17% in total income (pooled across all years). It is worth noting that the effect would have been even larger if the misallocated workers were average earners. However, in our estimated model, the representative misallocated worker earns 54% of what the average worker earns in the whole panel (largely because the misallocated workers cannot realize their full earning potential when they are in the wrong sector). This fact moderates the effect of the reallocation of those workers on the adjustment in the aggregate income. It is also worth noting that in our baseline specification income is the only determinant of utility, so increases in income result in identical increases in welfare.\textsuperscript{63}

Table 2.17 breaks down the results further by sector. Removing barriers to mobility would result in an agricultural employment shrinking by 5.8 p.p. as a share of total workforce. While this net change is not small, it is significantly smaller than the 30 p.p. gross flows of workers between sectors. Gross flows exceed net flows because there are workers wrongly allocated in both sectors. Furthermore, because the misallocated workers have on average lower productivity than the average worker in their sector, removing the misallocation increases (labor) productivity in both sectors, by 7.9% in non-agriculture and a whooping 39.1% in agriculture.\textsuperscript{64} Consequently, output increases in both sectors. In particular, it increases by 15.7% in agriculture despite the sector contracting in terms of employment.

In summary, our results indicate that labor is misallocated to a significant degree in Indonesia because of barriers to mobility across sectors. Eliminating such barriers would potentially lead to large aggregate productivity gains. Our work does not offer a practical guide to how the barriers can be eliminated in practice, but it highlights that policies easing frictions workers face in making sectoral choices could have a large positive impact on the economy.

2.6.3 Industry premia revisited

With the structural model at our disposal, we now use it to shed more light on the empirical content of the reduced-form sectoral premia of the kind we estimated in section 2.3.

There is a strand in the literature (e.g., Hicks et al. (2017), Herrendorf and Schoellman (2018)) arguing that if substantial cross-sectional non-agriculture premium largely disappears after controlling for worker fixed effects, then the data can be explained by an efficient sorting of workers. In section 2.6.1 we explained that frictionless sorting does not imply that there should be zero premium identified from within-worker variation. The flipside of this argument is that once we allow for barriers to

\textsuperscript{63}In contrast, in a model with barriers to mobility modeled as utility costs of switching, income and welfare would diverge, with the average growth in utility smaller than in income, but positive.

\textsuperscript{64}The estimated processes of permanent and transitory components of comparative advantage draws imply that both sectors are “standard” in the Roy model terminology of Heckman and Honoré (1990).
2.7. Conclusions

sectoral mobility, the absence of the within-worker premium does not imply that the allocation is efficient. There can be many combinations of processes for permanent and transitory components of comparative advantage draws and barriers to mobility that result in the same cross-sectional and (possibly zero) within-worker premia. To separately identify the role of frictions and of sorting we have to look beyond industry premia at a rich set of moments observable in a panel of workers.

To illustrate this discussion, column (2) in Table 2.18 reports the cross-sectional and within-worker non-agriculture premia obtained from data simulated in a counterfactual removing frictions in our baseline model (discussed in the previous subsection). Even though the allocation is perfectly efficient in this case, the non-agriculture premium from a regression with worker fixed effects is not zero, but in fact strongly negative at -35 lp. The negative premium is a natural consequence of larger variance of productivity shocks faced by workers in agriculture.

The level of the fixed-effect premium by itself therefore does not have clear implications for the strength of barriers to mobility if sorting is also present. But the difference between the fixed effect and cross-sectional premia does indeed indicate the presence of sorting. To illustrate this point, we consider an alternative counterfactual scenario in which self-selection is eliminated. Specifically, we set $\sigma_{\theta A}^2$, $\sigma_{\theta N}^2$, $\sigma_{\varepsilon A}^2$, $\sigma_{\varepsilon N}^2$ all to zero. In this case all workers are identical and would prefer non-agriculture as it offers higher prices for human capital. There is no sorting, and both sectors employ workers because of the frictions restricting workers from selecting their preferred sector. As column (3) in Table 2.18 confirms, when transitions between sectors are purely random the fixed effect premium takes the same value as the cross-sectional premium.

To summarize, comparing the cross-sectional and within-worker sector premia can be a useful diagnostic for detecting self-selection. But detecting barriers to sectoral mobility in observational data requires imposing sufficient structure and using data beyond the sectoral premia.

2.7 Conclusions

We present extensive reduced-form evidence of a substantial premium for working outside of agriculture in Indonesia. The same individual switching to work in non-agriculture gains about 25-30% income, while an individual switching in the opposite direction faces an income loss of a similar magnitude. We argue that in order to generate simultaneously those premia and the main moments of the joint distribution of income, we need to extend the models that attribute income gaps across sectors only to sorting of workers by including barriers to sectoral mobility that misallocate workers across sectors.

Our preferred way of thinking about barriers to mobility is that they restrict the ability of workers to work in their desired sectors. Such frictions misallocate a large fraction of workers across sectors (30% in our baseline specification), and imply large income gains (of around 100%) for the misallocated workers when they reallocate. As a result, output in Indonesia could increase by as much as 17% if barriers to mobility across sectors were removed.
2.7. Conclusions

In this chapter we are agnostic about the root causes of the barriers to sectoral mobility. Investigating what constitutes such barriers, why they persist, and what policies can be used as a remedy would be fruitful avenue for future research.
### 2.8 Tables and figures

#### 2.8.1 Tables

Table 2.1: Descriptive statistics

<table>
<thead>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of male</td>
<td>0.60</td>
<td>0.62</td>
<td>0.59</td>
<td>0.58</td>
<td>0.57</td>
</tr>
<tr>
<td>Mean age</td>
<td>41.4</td>
<td>38.1</td>
<td>39.0</td>
<td>40.7</td>
<td>41.2</td>
</tr>
<tr>
<td>Mean years of schooling</td>
<td>5.4</td>
<td>6.1</td>
<td>7.1</td>
<td>7.8</td>
<td>8.7</td>
</tr>
</tbody>
</table>

Joint distribution over sectors and locations

<table>
<thead>
<tr>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Agriculture</td>
<td>0.45</td>
<td>0.35</td>
<td>0.36</td>
<td>0.36</td>
<td>0.29</td>
</tr>
<tr>
<td>Rural Agriculture</td>
<td>0.42</td>
<td>0.31</td>
<td>0.32</td>
<td>0.31</td>
<td>0.24</td>
</tr>
<tr>
<td>Urban Agriculture</td>
<td>0.03</td>
<td>0.03</td>
<td>0.04</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>Total Non-Agriculture</td>
<td>0.55</td>
<td>0.65</td>
<td>0.64</td>
<td>0.64</td>
<td>0.71</td>
</tr>
<tr>
<td>Rural Non-Agriculture</td>
<td>0.27</td>
<td>0.30</td>
<td>0.27</td>
<td>0.25</td>
<td>0.27</td>
</tr>
<tr>
<td>Urban Non-Agriculture</td>
<td>0.28</td>
<td>0.35</td>
<td>0.37</td>
<td>0.39</td>
<td>0.44</td>
</tr>
<tr>
<td>Total Rural</td>
<td>0.69</td>
<td>0.62</td>
<td>0.59</td>
<td>0.56</td>
<td>0.50</td>
</tr>
<tr>
<td>Total Urban</td>
<td>0.31</td>
<td>0.38</td>
<td>0.41</td>
<td>0.44</td>
<td>0.50</td>
</tr>
</tbody>
</table>

|                          |             |             |             |             |             |
| No. observations         | 9714        | 12875       | 17931       | 20874       | 24475       |

Main sample: panel of workers with 2+ observations

|                          |             |             |             |             |             |
| No. observations         | 70586       |             |             |             |             |
| No. individuals          | 22829       |             |             |             |             |
### 2.8. Tables and figures

**Table 2.2: Sectoral and urban income premia**

<table>
<thead>
<tr>
<th></th>
<th>(1) Log Income</th>
<th>(2) Log Income</th>
<th>(3) Log Income</th>
<th>(4) Log Income</th>
<th>(5) Log Income</th>
<th>(6) Log Income</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-Agriculture</td>
<td>0.839***</td>
<td>0.686***</td>
<td>0.574***</td>
<td>0.332***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.040)</td>
<td>(0.036)</td>
<td>(0.033)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>0.647***</td>
<td>0.405***</td>
<td>0.207***</td>
<td>0.084**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.042)</td>
<td>(0.036)</td>
<td>(0.032)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agr.×Urban</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.062</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.055)</td>
<td></td>
</tr>
<tr>
<td>Non-Agr.×Urban</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.416***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.046)</td>
<td></td>
</tr>
<tr>
<td>Non-Agr.×Rural</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.326***</td>
<td></td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
<td>(0.039)</td>
<td></td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Province FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Indiv. cont.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Individual FE</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Observations</td>
<td>48299</td>
<td>48308</td>
<td>48299</td>
<td>44494</td>
<td>44497</td>
<td>44497</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.412</td>
<td>0.394</td>
<td>0.424</td>
<td>0.503</td>
<td>0.518</td>
<td>0.518</td>
</tr>
</tbody>
</table>

Notes: Individual controls: education, experience, experience sq., and sex. Observations weighted by longitudinal survey weights. Standard errors clustered by enumeration areas (primary sampling units of the survey) in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

**Table 2.3: Transitions across sectors and locations**

<table>
<thead>
<tr>
<th>Sector transitions</th>
<th>No. of cases</th>
<th>Share of total</th>
<th>Location transitions</th>
<th>No. of cases</th>
<th>Share of total</th>
</tr>
</thead>
<tbody>
<tr>
<td>AA</td>
<td>13214</td>
<td>27.68</td>
<td>RR</td>
<td>23299</td>
<td>48.79</td>
</tr>
<tr>
<td>AN</td>
<td>3886</td>
<td>8.14</td>
<td>RU</td>
<td>3171</td>
<td>6.64</td>
</tr>
<tr>
<td>NA</td>
<td>3546</td>
<td>7.43</td>
<td>UR</td>
<td>1166</td>
<td>2.44</td>
</tr>
<tr>
<td>NN</td>
<td>27098</td>
<td>56.76</td>
<td>UU</td>
<td>20121</td>
<td>42.13</td>
</tr>
<tr>
<td>Total</td>
<td>47744</td>
<td>100.00</td>
<td>Total</td>
<td>47757</td>
<td>100.00</td>
</tr>
<tr>
<td>Indiv. who switch at least once</td>
<td>23.89</td>
<td></td>
<td>Indiv. who switch at least once</td>
<td>16.91</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sector in T</th>
<th>Agricult.</th>
<th>Non-Agr.</th>
<th>Location in T+1</th>
<th>Rural</th>
<th>Urban</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricult.</td>
<td>0.78</td>
<td>0.22</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-Agr.</td>
<td>0.12</td>
<td>0.88</td>
<td>Location in T+1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rural</td>
<td></td>
<td></td>
<td>Rural</td>
<td>0.90</td>
<td>0.10</td>
</tr>
<tr>
<td>Urban</td>
<td></td>
<td></td>
<td>Urban</td>
<td>0.05</td>
<td>0.95</td>
</tr>
</tbody>
</table>

Notes: XY indicates a transition from sector (or location type) X to Y between two consecutive observations for an individual. A - Agriculture, N - Non-agriculture, R - Rural, U - Urban.
### 2.8. Tables and figures

#### Table 2.4: Premia for switchers and stayers

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<tr>
<th></th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Δ Log Income</td>
<td>Δ Log Income</td>
</tr>
<tr>
<td><strong>Sector transitions</strong></td>
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</tr>
<tr>
<td>AN</td>
<td>0.220***</td>
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<td>(0.050)</td>
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<tr>
<td>NA</td>
<td>-0.392***</td>
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<tr>
<td>(0.049)</td>
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<tr>
<td>NN</td>
<td>-0.066***</td>
<td></td>
</tr>
<tr>
<td>(0.023)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Location transitions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RU</td>
<td>0.091*</td>
<td></td>
</tr>
<tr>
<td>(0.047)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>UR</td>
<td>-0.199***</td>
<td></td>
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<tr>
<td>(0.058)</td>
<td></td>
<td></td>
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<tr>
<td>UU</td>
<td>-0.040*</td>
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<td>(0.023)</td>
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<tr>
<td><strong>Sector trans. × Migration</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AA × Migrate</td>
<td>-0.108</td>
<td></td>
</tr>
<tr>
<td>(0.092)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AN × Stay</td>
<td>0.196***</td>
<td></td>
</tr>
<tr>
<td>(0.053)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AN × Migrate</td>
<td>0.275**</td>
<td></td>
</tr>
<tr>
<td>(0.108)</td>
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<td></td>
</tr>
<tr>
<td>NA × Stay</td>
<td>-0.379***</td>
<td></td>
</tr>
<tr>
<td>(0.054)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NA × Migrate</td>
<td>-0.472****</td>
<td></td>
</tr>
<tr>
<td>(0.110)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NN × Stay</td>
<td>-0.117***</td>
<td></td>
</tr>
<tr>
<td>(0.021)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NN × Migrate</td>
<td>-0.008</td>
<td></td>
</tr>
<tr>
<td>(0.039)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Δ Year FE</strong></td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Δ Province FE</strong></td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Δ Indiv. cont.</strong></td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>27697</td>
<td>24858</td>
</tr>
<tr>
<td><strong>R²</strong></td>
<td>0.075</td>
<td>0.075</td>
</tr>
</tbody>
</table>

Notes: XY indicates a transition from sector (or location type) X to Y between two consecutive observations for an individual. A - Agriculture, N - Non-Agriculture, R - Rural, U - Urban. Migrate indicates movement outside of the village boundary. Omitted categories: staying in agriculture (AA) and staying in rural area (RR) in column 1; staying in agriculture within the same village (AA×Stay) in column 2. Individual controls: education, experience, experience sq., and sex. Observations weighted by longitudinal survey weights. Standard errors clustered by enumeration areas (primary sampling units of the survey) in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.
### 2.8. Tables and figures

#### Table 2.5: Job top occupations and types

<table>
<thead>
<tr>
<th>Top 10 Occupations</th>
<th>Empl. share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricultural and animal husbandry workers</td>
<td>0.352</td>
</tr>
<tr>
<td>Salesmen, shop assistants and related workers</td>
<td>0.136</td>
</tr>
<tr>
<td>Bricklayers, carpenters and other construction workers</td>
<td>0.038</td>
</tr>
<tr>
<td>Maids and related housekeeping service workers NEC</td>
<td>0.038</td>
</tr>
<tr>
<td>Working proprietors (catering and lodging services)</td>
<td>0.034</td>
</tr>
<tr>
<td>Transport equipment operators</td>
<td>0.032</td>
</tr>
<tr>
<td>Teachers</td>
<td>0.031</td>
</tr>
<tr>
<td>Food and beverage processors</td>
<td>0.027</td>
</tr>
<tr>
<td>Working proprietors (wholesale and retail trade)</td>
<td>0.026</td>
</tr>
<tr>
<td>Service workers NEC</td>
<td>0.025</td>
</tr>
<tr>
<td><strong>Cumulative</strong></td>
<td><strong>0.739</strong></td>
</tr>
</tbody>
</table>

Notes: Employment shares reported for IFLS 4 (2007).

#### Table 2.6: Premia for switchers and stayers by job type

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Self-employed</td>
<td>Private Worker</td>
<td>Government</td>
<td>Unpaid Family</td>
</tr>
<tr>
<td>AN-AA</td>
<td>0.259***</td>
<td>0.245***</td>
<td>0.111</td>
<td>0.335</td>
</tr>
<tr>
<td></td>
<td>18.31</td>
<td>11.98</td>
<td>0.43</td>
<td>1.21</td>
</tr>
<tr>
<td>NA-NN</td>
<td>-0.309***</td>
<td>-0.274***</td>
<td>-0.225</td>
<td>-0.871*</td>
</tr>
<tr>
<td></td>
<td>33.61</td>
<td>17.89</td>
<td>1.02</td>
<td>3.79</td>
</tr>
</tbody>
</table>

Notes: Table presents tests based on results of a first-difference regression (2.2) (c.f. column 1 in Table 2.4) with direction of sectoral switch interacted with job type. Reported are the difference in coefficients of interest and the value of an $F(1,296)$ test that the difference is zero. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

#### Table 2.7: Wage premia

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log Income</td>
<td>Log Income</td>
<td>Log Wage</td>
<td>Log Wage</td>
</tr>
<tr>
<td>Non-Agriculture</td>
<td>0.574***</td>
<td>0.332***</td>
<td>0.490***</td>
<td>0.231***</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.033)</td>
<td>(0.051)</td>
<td>(0.050)</td>
</tr>
<tr>
<td>Urban</td>
<td>0.207***</td>
<td>0.084**</td>
<td>0.193***</td>
<td>0.119***</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.032)</td>
<td>(0.042)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Province FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Indiv. cont.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Individual FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>44494</td>
<td>44497</td>
<td>23139</td>
<td>23140</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.503</td>
<td>0.518</td>
<td>0.556</td>
<td>0.601</td>
</tr>
</tbody>
</table>

Notes: Individual controls: education, experience, experience sq., and sex. Observations weighted by longitudinal survey weights. Standard errors clustered by enumeration areas (primary sampling units of the survey) in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.
### 2.8. Tables and figures

#### Table 2.8: Consumption premia

<table>
<thead>
<tr>
<th></th>
<th>(1) Log PCE</th>
<th>(2) Log PCE</th>
<th>(3) Log PCE</th>
<th>(4) Log PCI</th>
<th>(5) Log PCI</th>
<th>(6) Log PCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>NA sh. in HH income</td>
<td>0.305***</td>
<td>0.702***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.040)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-Agr.</td>
<td>0.214***</td>
<td>0.075***</td>
<td>0.492***</td>
<td>0.197***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.013)</td>
<td>(0.030)</td>
<td>(0.024)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>0.315***</td>
<td>0.161***</td>
<td>0.416***</td>
<td>0.225***</td>
<td>0.063*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.024)</td>
<td>(0.043)</td>
<td>(0.034)</td>
<td>(0.037)</td>
<td></td>
</tr>
<tr>
<td>Non-Agr./(Y_{th}/Y_h)</td>
<td></td>
<td>0.382</td>
<td>0.134</td>
<td>0.884</td>
<td>0.352</td>
<td></td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Province FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Indiv. cont.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Individual FE</td>
<td></td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>40168</td>
<td>53546</td>
<td>53550</td>
<td>38365</td>
<td>51690</td>
<td>51693</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.707</td>
<td>0.742</td>
<td>0.784</td>
<td>0.504</td>
<td>0.520</td>
<td>0.541</td>
</tr>
</tbody>
</table>

Notes: Specifications (1) and (4) estimated at a household level with observations weighted by longitudinal household survey weights. (1) also includes the number of household members (level and squared) as controls. NA sh. in HH Income is a continuous variable measuring the share of non-agriculture in household’s income. Specifications (2)-(3) and (5)-(6) estimated at an individual level. Individual controls: education, experience, experience sq., and sex. Observations weighted by longitudinal survey weights. Standard errors clustered by enumeration areas (primary sampling units of the survey) in parentheses. Significance levels: * \(p<0.10\), ** \(p<0.05\), *** \(p<0.01\).

#### Table 2.9: Premia with heterogeneity in Mincerian returns

<table>
<thead>
<tr>
<th></th>
<th>(1) Log Income</th>
<th>(2) Log Income</th>
<th>(3) Log Income</th>
<th>(4) Log Income</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-Agriculture</td>
<td>0.574***</td>
<td>0.332***</td>
<td>0.625***</td>
<td>0.314***</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.033)</td>
<td>(0.039)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Urban</td>
<td>0.207***</td>
<td>0.084**</td>
<td>0.200***</td>
<td>0.074**</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.032)</td>
<td>(0.034)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Province FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Indiv. controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Individual FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Het. in Mincer</td>
<td></td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>44494</td>
<td>44497</td>
<td>44494</td>
<td>44497</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.503</td>
<td>0.518</td>
<td>0.506</td>
<td>0.520</td>
</tr>
</tbody>
</table>

Notes: Columns (3) and (4) allow for differences in Mincerian returns across sectors and locations. Average marginal effect for the population reported. Average effects for switchers are similar. Individual Mincerian controls: education, experience, experience sq., and sex. Observations weighted by longitudinal survey weights. Standard errors clustered by enumeration areas (primary sampling units of the survey) in parentheses. Significance levels: * \(p<0.10\), ** \(p<0.05\), *** \(p<0.01\).
### Table 2.10: Premia with additional jobs and home production

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-Agr.</td>
<td>0.574*** (0.036)</td>
<td>0.332*** (0.033)</td>
<td>0.501*** (0.034)</td>
<td>0.264*** (0.032)</td>
<td>0.462*** (0.033)</td>
<td>0.251*** (0.032)</td>
<td>0.447*** (0.032)</td>
<td>0.245*** (0.032)</td>
</tr>
<tr>
<td>Urban</td>
<td>0.207*** (0.036)</td>
<td>0.084** (0.032)</td>
<td>0.171*** (0.034)</td>
<td>0.063* (0.034)</td>
<td>0.141*** (0.033)</td>
<td>0.057* (0.034)</td>
<td>0.124*** (0.033)</td>
<td>0.051</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Province FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Indiv. cont.</td>
<td>Yes</td>
<td>Yes</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Individual FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>44494</td>
<td>44494</td>
<td>44489</td>
<td>44492</td>
<td>44489</td>
<td>44492</td>
<td>44489</td>
<td>44492</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.503</td>
<td>0.518</td>
<td>0.514</td>
<td>0.538</td>
<td>0.513</td>
<td>0.540</td>
<td>0.515</td>
<td>0.545</td>
</tr>
</tbody>
</table>

Notes: *Base* is the baseline specification involving primary job only. *Add. Job* also includes secondary job. *HH TC* scales income by the inverse of the share of self-produced consumption in household’s overall consumption. *HH FC* scales income by the inverse of the share of self-produced food in household’s food consumption. Individual controls: education, experience, experience sq., and sex. Observations weighted by longitudinal survey weights. Standard errors clustered by enumeration areas (primary sampling units of the survey) in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.
### 2.8. Tables and figures

#### Table 2.11: Premia with hours worked

<table>
<thead>
<tr>
<th></th>
<th>(1) Log Income</th>
<th>(2) Log Income</th>
<th>(3) Log Income</th>
<th>(4) Log Income</th>
<th>(5) Log Inc./Hour</th>
<th>(6) Log Inc./Hour</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-Agriculture</td>
<td><strong>0.574</strong>*</td>
<td><strong>0.332</strong>*</td>
<td><strong>0.441</strong>*</td>
<td><strong>0.271</strong>*</td>
<td><strong>0.297</strong>*</td>
<td><strong>0.185</strong>*</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.033)</td>
<td>(0.034)</td>
<td>(0.032)</td>
<td>(0.036)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Urban</td>
<td><strong>0.207</strong>*</td>
<td><strong>0.084</strong></td>
<td><strong>0.160</strong>*</td>
<td><strong>0.084</strong>*</td>
<td><strong>0.109</strong>*</td>
<td><strong>0.076</strong>*</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.032)</td>
<td>(0.031)</td>
<td>(0.026)</td>
<td>(0.029)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Log Hours/Year</td>
<td><strong>0.496</strong>*</td>
<td><strong>0.432</strong>*</td>
<td><strong>0.496</strong>*</td>
<td><strong>0.432</strong>*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.011)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Province FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Indiv. cont.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Individual FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>44494</td>
<td>44497</td>
<td>43841</td>
<td>43843</td>
<td>43841</td>
<td>43843</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.503</td>
<td>0.518</td>
<td>0.592</td>
<td>0.595</td>
<td>0.478</td>
<td>0.493</td>
</tr>
</tbody>
</table>

Notes: Individual controls: education, experience, experience sq., and sex. Observations weighted by longitudinal survey weights. Standard errors clustered by enumeration areas (primary sampling units of the survey) in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

#### Table 2.12: Long run premia

<table>
<thead>
<tr>
<th></th>
<th>1993-2014</th>
<th>93-07/00-14</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Δ Log Income</td>
<td>(2) Δ Log Income</td>
</tr>
<tr>
<td>AA-AN</td>
<td>0.172</td>
<td>1.38</td>
</tr>
<tr>
<td>NA-NN</td>
<td>-0.369***</td>
<td>9.10</td>
</tr>
<tr>
<td>ANN-AAA</td>
<td>0.147*</td>
<td>2.79</td>
</tr>
<tr>
<td>NAA-NNN</td>
<td>-0.186**</td>
<td>4.62</td>
</tr>
<tr>
<td>Observations</td>
<td>2567</td>
<td>7857</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.105</td>
<td>0.098</td>
</tr>
</tbody>
</table>

Notes: Column 1 presents tests based on results of a first-difference regression (2.2), where the difference is over the period 1993-2014. Reported are the difference in coefficients of interest and the value of an $F(1,288)$ test that the difference is zero. Column 2 presents tests based on a first-difference specification over 14 years (1993-2007 or 2000-2014) controlling for direction of switch during the first and second 7-year period. Reported are the difference in coefficients of interest and the value of an $F(1,292)$ test that the difference is zero. Other controls and weights are as in column 1 in Table 2.4. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.
2.8. **Tables and figures**

Table 2.13: Parameter estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Frictionless</th>
<th>Unrestricted switching costs</th>
<th>Compensating differential</th>
<th>Single probability of involuntary choices</th>
<th>Heterogeneous probabilities of involuntary choices</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance of permanent comparative advantage in sector s ($\sigma_{\theta s}^2$) and covariance ($\sigma_{\theta AN}$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_{\theta s}^2$</td>
<td>0.27</td>
<td>0.56</td>
<td>0.52</td>
<td>0.32</td>
<td>0.39</td>
</tr>
<tr>
<td>$\sigma_{\theta AN}$</td>
<td>0.50</td>
<td>0.22</td>
<td>0.31</td>
<td>0.53</td>
<td>0.45</td>
</tr>
<tr>
<td>$\sigma_{\theta AN}$</td>
<td>0.55</td>
<td>0.45</td>
<td>0.46</td>
<td>0.68</td>
<td>0.63</td>
</tr>
<tr>
<td>Variance of transitory productivity shocks in sector s ($\sigma_{\varepsilon s}^2$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
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<td>0.12</td>
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<tr>
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<tr>
<td>Variance of measurement error ($\sigma_{\nu}^2$)</td>
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<tr>
<td>$\sigma_{\nu}^2$</td>
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<td>0.71</td>
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<td>0.51</td>
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<tr>
<td>Price of human capital in sector s at time $t$ ($R_t^s$)</td>
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<tr>
<td>$R_{1A}^s$</td>
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<td>0.41</td>
<td>0.44</td>
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<td>0.73</td>
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<tr>
<td>$R_{1N}^s$</td>
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<td>0.61</td>
<td>0.64</td>
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<tr>
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<td>0.52</td>
<td>0.59</td>
<td>1.07</td>
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<tr>
<td>$R_{2N}^s$</td>
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<td>0.73</td>
<td>0.81</td>
<td>1.30</td>
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<tr>
<td>$R_{3A}^s$</td>
<td>1.61</td>
<td>0.94</td>
<td>1.00</td>
<td>1.60</td>
<td>1.83</td>
</tr>
<tr>
<td>$R_{3N}^s$</td>
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<td>1.32</td>
<td>1.37</td>
<td>1.23</td>
<td>1.47</td>
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<tr>
<td>$R_{4A}^s$</td>
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<td>2.11</td>
<td>1.88</td>
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<td>1.74</td>
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<td>1.68</td>
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<tr>
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<td>2.03</td>
<td>2.22</td>
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<tr>
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<td>2.58</td>
<td>2.62</td>
<td>2.52</td>
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<td>Switching cost of moving from sector s to sector $s'$ ($\phi_{ss'}$)</td>
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<tr>
<td>$\ln \phi_{AN}$</td>
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<tr>
<td>$\ln \phi_{NA}$</td>
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<td>-0.63</td>
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<tr>
<td>$\ln cd$</td>
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<td>0.61</td>
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<td>–</td>
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<td>Probabilities of involuntary choices</td>
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<tr>
<td>$p$</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>0.05</td>
<td>–</td>
</tr>
<tr>
<td>$pS$</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>0.09</td>
<td>–</td>
</tr>
<tr>
<td>$pT$</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>0.77</td>
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</tr>
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</table>

Notes: We are currently computing standard errors from 200 bootstraps.
2.8. Tables and figures

Table 2.14: Auxiliary models and selected coefficients

<table>
<thead>
<tr>
<th>Auxiliary model</th>
<th>Selected coefficients</th>
<th>Coefficient description</th>
</tr>
</thead>
<tbody>
<tr>
<td>i) Log-residual income linear regression on the sector choice:</td>
<td>( \delta_1 )</td>
<td>Non-agriculture premium (cross-sectional)</td>
</tr>
<tr>
<td>( \ln \tilde{y}<em>{its} = c + 1 { d</em>{it} = N } \delta_1 + D_t + \varepsilon_{ist} )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ii) Log-residual income linear regression on the sector choice:</td>
<td>( \delta_2 )</td>
<td>Non-agriculture premium (within-individual)</td>
</tr>
<tr>
<td>( \ln \tilde{y}<em>{its} = c + 1 { d</em>{it} = N } \delta_2 + D_t + D_{it} + \varepsilon_{ist} )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>iii) Log-residual income linear regression on the direction of sector switching:</td>
<td>( \delta_3 = \gamma_{NA} )</td>
<td>Premia for switchers to each sector relative to their peers post-switch</td>
</tr>
<tr>
<td>( \ln \tilde{y}<em>{its} = c + 1 { d</em>{it-1} = s, d_{it} = s' } \gamma_{s's'} + D_t + \varepsilon_{ist} )</td>
<td>( \delta_4 = \gamma_{AN} - \gamma_{NN} )</td>
<td></td>
</tr>
<tr>
<td>iv) Log-residual income linear regression in first differences on the direction of sector switching:</td>
<td>( \delta_5 = \delta_{NA} \delta_6 = \delta_{NA} - \delta_{NN} )</td>
<td>Premia for switchers to each sector relative to non-switching workers</td>
</tr>
<tr>
<td>( \Delta \ln \tilde{y}<em>{its} = 1 { d</em>{it-1} = s, d_{it} = s' } \gamma_{s's'} + \Delta D_t + \varepsilon_{ist} )</td>
<td>( \delta_7 = \delta_{s's'} )</td>
<td>Constant Interactions sector and year</td>
</tr>
<tr>
<td>v) Log-residual income linear regression on the interaction between sector choice and year:</td>
<td>( \delta_8 = \gamma_{s's'} \ldots \delta_{16} = \gamma_{N \times 5} )</td>
<td></td>
</tr>
<tr>
<td>( \ln \tilde{y}<em>{its} = \delta_7 + 1 { d</em>{it} = N } \times 1 { d_{it} = t } \gamma_{s's'} + \varepsilon_{ist} )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>vi) LPM of sector choice on time dummy variables:</td>
<td>( \delta_{17} )</td>
<td>Constant Year dummies</td>
</tr>
<tr>
<td>( 1 { d_{it} = N } = \delta_{22} + 1 { d_{it} = t } \gamma + \varepsilon_{ist} )</td>
<td>( \delta_{18} = \gamma \ldots \delta_{21} = \gamma )</td>
<td></td>
</tr>
<tr>
<td>vii) LPM of sector choice on previous sector choice:</td>
<td>( \delta_{22}, \delta_{23} )</td>
<td>Constant and lagged sector choice</td>
</tr>
<tr>
<td>( 1 { d_{it} = N } = \delta_{27} + 1 { d_{it-1} = N } \delta_{28} + \varepsilon_{ist} )</td>
<td>( \delta_{24}, \delta_{25} )</td>
<td>For workers in each sector from model v)</td>
</tr>
<tr>
<td>( \delta_{26}, \delta_{27} )</td>
<td>For non-switching workers in each sector from model iv)</td>
<td></td>
</tr>
<tr>
<td>viii) Residual variances:</td>
<td>( \delta_{28}, \delta_{29} )</td>
<td>For switching workers to each sector from model vi)</td>
</tr>
</tbody>
</table>

Notes: LPM stands for linear probability model. \( \tilde{y}_{its} \) is the residual income of individual \( i \) in time \( t \) working in sector \( s \), that satisfies \( \ln \tilde{y}_{its} = \ln \gamma_{its} - X_{it}'\hat{\beta} \), where \( \gamma_{its} \) is the observed income, \( X_{it}' \) is the set of observables that includes gender, urban-rural location, years of schooling, years of working experience and square of years of working experience, and \( \hat{\beta} \) is the vector of estimated coefficients on observables in the log-income linear regression on the interaction between sector choice and year conditional on observables: \( \ln \gamma_{its} = \delta + X_{it}'\hat{\beta} + 1 \{ d_{it} = N \} \times 1 \{ d_{it} = t \} \gamma_{s's'} + \varepsilon_{ist} \). \( D_t \) corresponds to year fixed-effects and \( D_{it} \) to individual fixed-effects. \( \Delta x \) is the first difference of variable \( x \). \( 1 \{ d_{it} = N \} \) is a dummy indicating whether individual \( i \) works in non-agriculture in period \( t \), \( 1 \{ d_{it-1} = s, d_{it} = s' \} \) is a set of dummies indicating whether individual \( i \) in period \( t - 1 \) worked in sector \( s \) and in period \( t \) worked in sector \( s' \), and \( 1 \{ d_{it} = t \} \) is a set of dummies indicating whether the observation of worker \( i \) corresponds to period \( t \). The omitted category in models iii) and iv) is AA, in model v) is \( A \times 1 \) and in model vi) is \( t = 1 \).
Table 2.15: Coefficients of auxiliary regression models

<table>
<thead>
<tr>
<th>Coefficients $\delta$ (weight $\Omega_i$)</th>
<th>Data ($\hat{\delta}$)</th>
<th>Standard error in the data</th>
<th>Frictionless switching costs</th>
<th>Unrestricted switching costs</th>
<th>Compensating differential probability of involuntary choices</th>
<th>Single probability of involuntary choices</th>
<th>Heterogenous probabilities of involuntary choices</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
</tr>
<tr>
<td>Non-agriculture premia: cross-sectional ($\delta_1$) and within-individual ($\delta_2$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta_1$ (1)</td>
<td>0.57 (0.03)</td>
<td>0.56</td>
<td>0.62</td>
<td>0.62</td>
<td>0.60</td>
<td>0.60</td>
<td>0.51</td>
</tr>
<tr>
<td>$\delta_2$ (1)</td>
<td>0.40 (0.05)</td>
<td>0.24</td>
<td>0.35</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.40</td>
</tr>
<tr>
<td>Premia for switchers to agriculture ($\delta_3$, $\delta_6$) and to non-agriculture. ($\delta_4$, $\delta_5$). The first element in $(a, b)$ is relative to peers post-switch; the second to non-switching workers</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta_3$ (5)</td>
<td>-0.05 (0.06)</td>
<td>-0.07</td>
<td>-0.08</td>
<td>-0.08</td>
<td>-0.11</td>
<td>-0.11</td>
<td>-0.06</td>
</tr>
<tr>
<td>$\delta_4$ (5)</td>
<td>-0.31 (0.05)</td>
<td>-0.42</td>
<td>-0.39</td>
<td>-0.39</td>
<td>-0.41</td>
<td>-0.41</td>
<td>-0.28</td>
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<tr>
<td>$\delta_5$ (5)</td>
<td>0.15 (0.07)</td>
<td>0.23</td>
<td>0.31</td>
<td>0.29</td>
<td>0.31</td>
<td>0.31</td>
<td>0.26</td>
</tr>
<tr>
<td>$\delta_6$ (5)</td>
<td>-0.42 (0.06)</td>
<td>-0.24</td>
<td>-0.35</td>
<td>-0.34</td>
<td>-0.35</td>
<td>-0.35</td>
<td>-0.40</td>
</tr>
<tr>
<td>Constant ($\delta_7$) and coefficients on interaction sector and year ($\delta_8 : A \times 2$, $\delta_9 : A \times 3$, ..., $\delta_{16} : N \times 5$)</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>$\delta_7$ (5)</td>
<td>-0.17 (0.10)</td>
<td>-0.17</td>
<td>-0.19</td>
<td>-0.19</td>
<td>-0.19</td>
<td>-0.19</td>
<td>-0.17</td>
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<tr>
<td>$\delta_8$ (1)</td>
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<td>0.41</td>
<td>0.42</td>
<td>0.46</td>
<td>0.46</td>
<td>0.39</td>
</tr>
<tr>
<td>$\delta_9$ (1)</td>
<td>0.34 (0.07)</td>
<td>0.34</td>
<td>0.29</td>
<td>0.30</td>
<td>0.35</td>
<td>0.35</td>
<td>0.38</td>
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<tr>
<td>$\delta_{10}$ (1)</td>
<td>0.63 (0.07)</td>
<td>0.62</td>
<td>0.50</td>
<td>0.56</td>
<td>0.54</td>
<td>0.54</td>
<td>0.65</td>
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<tr>
<td>$\delta_{11}$ (1)</td>
<td>0.85 (0.08)</td>
<td>0.77</td>
<td>0.75</td>
<td>0.77</td>
<td>0.77</td>
<td>0.77</td>
<td>0.90</td>
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<tr>
<td>$\delta_{12}$ (5)</td>
<td>0.76 (0.06)</td>
<td>0.58</td>
<td>0.64</td>
<td>0.66</td>
<td>0.63</td>
<td>0.63</td>
<td>0.69</td>
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<tr>
<td>$\delta_{13}$ (1)</td>
<td>1.10 (0.06)</td>
<td>1.05</td>
<td>1.04</td>
<td>1.07</td>
<td>1.05</td>
<td>1.05</td>
<td>1.12</td>
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<tr>
<td>$\delta_{14}$ (1)</td>
<td>0.89 (0.06)</td>
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<td>0.94</td>
<td>0.94</td>
<td>0.81</td>
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<tr>
<td>$\delta_{15}$ (1)</td>
<td>1.05 (0.06)</td>
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<td>1.09</td>
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<td>1.12</td>
<td>1.12</td>
<td>1.04</td>
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<td>$\delta_{16}$ (1)</td>
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<td>1.39</td>
<td>1.39</td>
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<tr>
<td>Constant ($\delta_{17}$) and coefficients on year dummies ($\delta_{18} : t = 2$, $\delta_{19} : t = 3$)</td>
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<td>0.70 (0.01)</td>
<td>0.73</td>
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<td>0.72</td>
<td>0.73</td>
<td>0.73</td>
<td>0.70</td>
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<td>-0.01</td>
<td>-0.01</td>
<td>-0.02</td>
</tr>
<tr>
<td>$\delta_{19}$ (10)</td>
<td>-0.02 (0.02)</td>
<td>-0.04</td>
<td>0.01</td>
<td>-0.02</td>
<td>-0.02</td>
<td>-0.02</td>
<td>-0.05</td>
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<tr>
<td>$\delta_{20}$ (10)</td>
<td>-0.03 (0.02)</td>
<td>-0.04</td>
<td>-0.06</td>
<td>-0.05</td>
<td>-0.03</td>
<td>-0.03</td>
<td>-0.07</td>
</tr>
<tr>
<td>$\delta_{21}$ (10)</td>
<td>-0.04 (0.02)</td>
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<td>0.00</td>
<td>0.00</td>
<td>-0.09</td>
</tr>
<tr>
<td>Constant ($\delta_{22}$) and lagged sector choice ($\delta_{23}$)</td>
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</tr>
<tr>
<td>$\delta_{22}$ (10)</td>
<td>0.21 (0.01)</td>
<td>0.22</td>
<td>0.22</td>
<td>0.24</td>
<td>0.23</td>
<td>0.23</td>
<td>0.17</td>
</tr>
<tr>
<td>$\delta_{23}$ (10)</td>
<td>0.68 (0.01)</td>
<td>0.69</td>
<td>0.65</td>
<td>0.64</td>
<td>0.68</td>
<td>0.68</td>
<td>0.71</td>
</tr>
<tr>
<td>Residual variance of workers in agriculture ($\delta_{24}$) and non-agriculture ($\delta_{25}$)</td>
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<td></td>
</tr>
<tr>
<td>$\delta_{24}$ (3)</td>
<td>1.24 (0.04)</td>
<td>0.98</td>
<td>1.14</td>
<td>1.13</td>
<td>0.96</td>
<td>1.13</td>
<td>1.13</td>
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<tr>
<td>$\delta_{25}$ (3)</td>
<td>0.95 (0.03)</td>
<td>1.16</td>
<td>1.08</td>
<td>1.10</td>
<td>1.17</td>
<td>1.17</td>
<td>1.06</td>
</tr>
<tr>
<td>Residual variance of non-switching/switching workers in/to agriculture ($\delta_{26}$, $\delta_{29}$) and in/to non-agriculture ($\delta_{27}$, $\delta_{28}$)</td>
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<tr>
<td>$\delta_{26}$ (3)</td>
<td>1.43 (0.06)</td>
<td>1.44</td>
<td>1.63</td>
<td>1.59</td>
<td>1.30</td>
<td>1.30</td>
<td>1.48</td>
</tr>
<tr>
<td>$\delta_{27}$ (3)</td>
<td>1.08 (0.04)</td>
<td>1.57</td>
<td>1.41</td>
<td>1.43</td>
<td>1.31</td>
<td>1.31</td>
<td>1.01</td>
</tr>
<tr>
<td>$\delta_{28}$ (3)</td>
<td>1.73 (0.14)</td>
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<td>1.51</td>
<td>1.52</td>
<td>1.74</td>
<td>1.74</td>
<td>1.79</td>
</tr>
<tr>
<td>$\delta_{29}$ (3)</td>
<td>1.86 (0.14)</td>
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<td>1.56</td>
<td>1.54</td>
<td>1.77</td>
<td>1.77</td>
<td>1.82</td>
</tr>
<tr>
<td>Overall fit</td>
<td>1.914</td>
<td>1.306</td>
<td>1.312</td>
<td>1.005</td>
<td>0.315</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: A description of the auxiliary regressions is done in Table 2.14. $\Omega_i$ refers to the $i$–th element of the diagonal of the matrix $\Omega$. 

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### 2.8. Tables and figures

#### Table 2.16: Counterfactual: Aggregate income

<table>
<thead>
<tr>
<th>Variable</th>
<th>Notation</th>
<th>Counterfactual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Growth rate (%) in total income: (1) * (2) * (3)</td>
<td>$\Delta Y_i$</td>
<td>16.9</td>
</tr>
<tr>
<td>(1) Fraction of the population reallocated</td>
<td>$m$</td>
<td>0.30</td>
</tr>
<tr>
<td>(2) Ratio of average income of reallocated workers to average income</td>
<td>$\psi_m$</td>
<td>0.54</td>
</tr>
<tr>
<td>(3) Growth rate (%) in total income of reallocated workers</td>
<td>$\Delta Y_{m}$</td>
<td>105.6</td>
</tr>
</tbody>
</table>

Notes: Results correspond to the counterfactual exercise of eliminating involuntary switches.

#### Table 2.17: Counterfactual: Sectoral allocation and productivity

<table>
<thead>
<tr>
<th>Variable</th>
<th>Agriculture</th>
<th>Non-Agriculture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline employment share</td>
<td>0.34</td>
<td>0.66</td>
</tr>
<tr>
<td>Counterfactual employment share</td>
<td>0.29</td>
<td>0.71</td>
</tr>
<tr>
<td>Counterfactual employment growth (%)</td>
<td>-16.8</td>
<td>8.8</td>
</tr>
<tr>
<td>Counterfactual output growth (%)</td>
<td>15.7</td>
<td>17.3</td>
</tr>
<tr>
<td>Counterfactual productivity growth (%)</td>
<td>39.1</td>
<td>7.9</td>
</tr>
</tbody>
</table>

Notes: Results correspond to the counterfactual exercise of eliminating involuntary switches.

#### Table 2.18: Sectoral premia in counterfactuals

<table>
<thead>
<tr>
<th>Coef.</th>
<th>(1) Baseline model</th>
<th>(2) No frictions</th>
<th>(3) No sorting</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta_1$</td>
<td>0.51</td>
<td>0.20</td>
<td>0.50</td>
</tr>
<tr>
<td>$\delta_2$</td>
<td>0.40</td>
<td>-0.35</td>
<td>0.50</td>
</tr>
</tbody>
</table>

Notes: Baseline model is from column (8) of Table 2.15. No frictions imposes $p^f = p^s = 0$. No sorting imposes $\sigma^2_{\theta_A}, \sigma^2_{\theta_N}, \sigma^2_{\epsilon_A}, \sigma^2_{\epsilon_N}$ all equal to zero.
2.8.2 Figures

Figure 2.1: Mean log income by employment history

Notes: Figure plots mean log income (after controlling for year and province fixed effects) by employment history spanned by three observations at 7-year intervals. XYZ indicates that worker was in sector X during the first observation (in 1993 or 2000), in sector Y during the second observation 7 years later (in 2000 or 2007), and in sector Z during the third observation 14 years later (in 2007 or 2014). A - Agriculture, N - Non-Agriculture. For clarity only histories of switchers who stick to their new sector and of always stayers are reported.
Chapter 3

Demand Shocks and Inter-industry Distortions under Firm-level Factor Misallocation

3.1 Introduction

In recent years, a growing body of research has strived to understand how factor misallocation across heterogeneous firms can account for differences in aggregate TFP across countries. The main insight from this literature is that, given a fixed endowment of production factors in the economy and a certain distribution of physical productivity across firms, the inefficient allocation of inputs across production units within industries generates sizable losses in aggregate TFP. Under standard assumptions on the demand and production structure, and regardless the underlying cause of the inefficient use of resources – regulations, financial constraints, information asymmetries, crony capitalism, etc. – the amount of misallocation can be measured by the extent to which the marginal returns to factors varies within countries. Some evidence suggests a broader dispersion of those returns in developing economies (Banerjee and Duflo (2005), Hsieh and Klenow (2009), Bartelsman et al. (2013)), implying larger productivity losses for those countries. In this way, factor misallocation has become one of the explanations of the observed TFP gaps across countries.

In this chapter I extend the standard model of firm-level factor misallocation in a closed economy (Hsieh and Klenow (2009), HK hereafter) in two dimensions. First, I incorporate idiosyncratic demand shocks. Introducing firm-specific demand shifts do not affect the main predictions of the model. Particularly, demand shocks do not alter the main result of revenue productivity equalization across firms in the frictionless allocation. Hence, the TFP gains from removing misallocation remain unchanged. This is the main reason of why measuring physical productivity as in HK, that could reflect variations not only in efficiency but also in demand shocks, does not bias the estimated TFP gains. However, this extension is useful to test the ability of the usual metrics of factor misallocation in explaining plants’ survival, since demand shocks are a key determinant of profitability. This test has been recently used to argue that misallocation measures, based on dispersion revenue productivity, suffer from an apparent lack of empirical content (Haltiwanger et al. (2018)). One of the findings to support this claim consists in observing that efficiency, demand shocks and revenue productivity (a

For an extensive review, see Restuccia and Rogerson (2013) or Hopenhayn (2014a).
measure of factor distortions in the misallocation model) are all unconditionally positively associated with survival, but once we control for efficiency and demand shocks, the coefficient on revenue productivity flips sign. Using Colombian data, with which I can recover measures of demand shocks due to the availability of firm-level price indices, I obtain similar empirical findings. However, I argue that explaining plants’ survival only with unconditional determinants of profitability produces biased estimates, and that including endogenous selection in the model as it has been done by Bartelsman et al. (2013), Yang (2017), Adamopoulos et al. (2017) or in the first chapter of this thesis, can rationalize the signs of the bias and the data findings, addressing Haltiwanger et al.’s (2018) objections.

Second, I account for the possibility that production factors are misallocated both within and across industries. I provide closed-form solutions to evaluate the gains on aggregate TFP from removing each type of misallocation, leading to a more straightforward computation relative to the methods proposed in the literature (Oberfield (2013), Brandt et al. (2013)). Naturally, the magnitude of the gains from removing each type depends on the considered industry aggregation. Using data from China and Colombia, I show how under the most used industry classifications (3 and 4 digits ISIC) the contribution of the inter-industry type can be as high as 35% of the total gains from removing factor distortions. Given the relevance of inter-industry misallocation, it is worth to know whether the TFP loss induced by its presence is larger in less developed economies, as it is the case with within-industry misallocation. I use cross-country data to show that this is the case, suggesting that the TFP gaps attributed to factor misallocation can be larger than the ones computed using only intra-industry reforms.

### 3.2 Demand shocks and plant survival

In this section, I extend HK’s model of firm-level factor misallocation in a closed economy to account for idiosyncratic demand shifters. I first show that the TFP gains of removing misallocation are not affected by the introduction of demand shocks in the model. Next, I discuss the ability of the standard metrics of misallocation in explaining plants’ survival when demand shocks are taken into account. In particular, I argue that the apparent contradiction in the signs of the unconditional estimates of the determinants of profitability in the misallocation model, instead of suggesting a lack of empirical content of the misallocation measures, can be the natural result of a process of selection of firms in the economy.

#### 3.2.1 Demand shocks and TFP gains from removing misallocation

HK assume a standard monopolistic competition model where each variety \( m \) in a manufacturing industry \( s \) is produced using a set of \( L \) homogenous factors \( z_{lm} \) (\( l \) denotes the factor of production; I omit industry subscripts for firm-specific variables). Industry demand \( Q_s \) is a CES aggregate of \( M_s \)

\[^{66}\text{HK assume two production factors (capital and labor), but the model can be easily extended to account for more factors, as I do in this section.}\]
3.2. Demand shocks and plant survival

varieties with elasticity of substitution $\sigma$ (I denote sectoral aggregates with capital letters, let $\rho = \frac{\sigma - 1}{\sigma}$ denote the inverse of the mark-up). Firms use a Cobb-Douglas (CD) technology with constant returns to scale and factor intensities $\alpha_l$, common for all firms within the industry. Firms differ in terms of efficiency, i.e. on Hicks-neutral physical productivity, or TFPQ, defined as the ratio between output $q_m$ and the input use, given by the composite bundle $\bar{z}_l^{\alpha_l}$. Define revenue productivity, or TFPR, as the ratio between revenue, $r_m = p_m q_m$, and the same input bundle. Since profit maximization entails firms’ prices $p_m$ are a constant mark-up over their marginal cost, the cost function automatically implies that if all firms are price-takers there is TFPR equalization within industries.\footnote{In this case the marginal cost is simply $MC_m = \frac{1}{TPFPQ_m} \bar{z}_l^{\alpha_l} \frac{1}{\bar{w}_l^{\alpha_l}}$, where $w_l$ is the price of factor $l$. Profit maximization implies that firm’s output price is a constant markup over its marginal cost, $p_m = \frac{1}{\rho} MC_m$. Hence, given that marginal and unit costs are equal under constant returns to scale, revenues are $1/\rho > 1$ times the total cost. Revenue productivity for the firm is $TFPR_m = \frac{r_m q_m}{\bar{z}_l^{\alpha_l}} = p_m TFPQ_m = \frac{1}{\rho} \frac{1}{\bar{w}_l^{\alpha_l}}$, i.e. the return of the composite bundle $\bar{z}_l^{\alpha_l}$, which does not depend on $m$. Thus, TFPR should be equal for all firms within an industry, and the only differences across industries are due to factor intensities.} That is, a standard monopolistic framework with heterogeneous firms and frictionless factor markets allows firms to vary and the input use, given by the composite bundle $\bar{z}_l^{\alpha_l}$, that if all firms are price-takers there is TFPR equalization within industries.\footnote{See Table 1.1 in the first chapter for a review of the literature regarding the contribution of other possible sources of variation in the TFPR that do not imply factors are misallocated.}

That assumption of no self-selection of firms, $\tilde{\text{TPF}}$, or TFP is simply the power mean of physical productivities: $\tilde{\phi}_m$ where $\bar{z}_l^{\alpha_l}$ summarizes the main features of HK’s model. Notice that HK assume a CES demand for varieties with elasticity of substitution $\sigma$, such that the demand equation is:

$A_s^{\sigma - 1} = \frac{1}{M_s} \sum_m \frac{a_m \psi_s}{\psi_m} \frac{1}{\sigma - 1}$ (3.1)

where $\psi_s$ is the sectoral revenue productivity. If a reform equalizes TFPR across firms, the sectoral (efficient) TFP is simply the power mean of physical productivities: $\tilde{A}_s^{\sigma - 1} = \tilde{M}_s^{-1} \sum_m a_m^{\sigma - 1}$. With the assumption of no self-selection of firms, $\tilde{M}_s = M_s$ and the percentage gains on sectoral TFP due to TFPR equalization are:

$\text{Gains}_{s intra} = 100(\frac{\tilde{A}_s}{A_s} - 1) = 100(\frac{1}{\tilde{M}_s} \sum_m \frac{a_m \psi_s}{A_s \psi_m} \frac{1}{\sigma - 1} - 1)$ (3.2)

Equation (3.2) is the cornerstone of HK’s counterfactual exercise, and the description until here provided summarizes the main features of HK’s model. Notice that HK assume a CES demand for variety $m$ that allows us to obtain a demand equation of the form $q_m = p_m^{-\sigma} \phi_s Q_s$, that is, an isoelastic demand function, which is linear in logs. Now, let me introduce a firm-specific demand shifter $\gamma_m$ for variety $m$, such that the demand equation is:

$q_m = \gamma_m p_m^{-\sigma} \phi_s Q_s$ (3.3)
3.2. Demand shocks and plant survival

The demand shifter $\gamma_m$ could represent not only differences in idiosyncratic demand, but also differences in quality. The sectoral demand function that rationalizes the demand shifter is $Q^\rho_S = \sum_{m} \gamma_m^\rho q_m^\rho$ and the corresponding price index is $P^1_{S} - \sigma S = \sum_{m} \gamma_m p_m^{-\sigma}$. Thus, sectoral TFP $A_{s,d}$ can be obtained in this case through:

$$A_{s,d}^{\sigma-1} = \frac{1}{M_s} \sum_{m} \gamma_m \left( \frac{a_m \psi_s}{\psi_m} \right)^{\sigma-1}$$

(3.4)

while the sectoral efficient TFP $\tilde{A}_{s,d}$ is now $\tilde{A}_{s,d}^{\sigma-1} = \frac{1}{\tilde{M}_s} \sum_{m} \gamma_m a_m^{\sigma-1}$.

The choice between equations (3.1) and (3.4) to compute the sectoral TFP (and their corresponding efficient TFP and the gains from removing misallocation) depends on the availability of measures of $\gamma_m$. These shocks can in turn be recovered as residuals from (3.3) with information of prices or quantities at the firm-level. One possibility is to employ econometric techniques to back out prices or quantities, an option that necessarily requires additional (and strong) assumptions. Other possibility is to take advantage of datasets with direct measures of firms’ prices or quantities; an approach followed by Haltiwanger et al. (2018) with U.S data and in this chapter thanks to the availability of firm-level prices in the Colombian data.69

The availability of information of prices or quantities at the firm-level allows us to recover not only a demand shifter but also a direct measure of TFPQ that captures only technical efficiency. In this way, we do not need to rely in the usual method to compute TFPQ in the misallocation literature, which assumes firms’ prices satisfy the CES demand equation, and thus TFPQ reflect variations not only in efficiency but also in the quality of the products or in demand shocks. Particularly, to obtain TFPQ, HK use:

$$a_m^{HK} = \kappa_s \left( \frac{p_m q_m}{\psi_m} \right)^{\sigma-1}$$

(3.5)

where $\kappa_s$ collects sectoral values and thus can be omitted in the case of computing the TFP gains from removing intra-industry misallocation. Notice that $a_m^{HK}$ is proportional to $\gamma_m^{-\sigma-1} a_m$, and thus the TFP gains computed using $a_m^{HK}$ in equation (3.1) (which require TFPQ to the power of $\sigma - 1$, that is, $\gamma_m a_m^{\sigma-1}$) are the same than those obtained using individual measures for $\gamma_m$ and $a_m$ in equation (3.4) (which require $\gamma_m a_m^{\sigma-1}$).

This equivalence result is consequence of the fact that in the CES case demand shocks do not alter the main implication of the misallocation model, the revenue productivity equalization across firms in the frictionless allocation, since prices for variety $m$ are not affected by $\gamma_m$. Demand shocks impact firms’ profits, but not the allocation of factors, since this allocation depends exclusively on the firm’s cost minimization problem. Hence, the dispersion in TFPR is still a valid measure of firm-level factor misallocation under idiosyncratic demand shocks.

69I use the firm-level prices constructed by Eslava et al. (2004) for the period 1984-1998. See the data appendix in chapter 1 for details about the dataset and the cleaning procedure to reduce the influence of measurement error and outliers.
3.2. Demand shocks and plant survival

3.2.2 Misallocation measures and survival of firms

A recent paper by Haltiwanger et al. (2018) raises concerns about the empirical content of the measures of misallocation based on the dispersion in TFPR. One of their arguments is based on the fact that once we have access to direct measures of efficiency and demand shifters as determinants of firm’s profitability, we can analyze the ability of misallocation measures in predicting plants’ survival. Particularly, they show with U.S. data that efficiency, demand shocks and TFPR are all unconditionally positively associated with survival, but once we control for efficiency and demand shocks, the coefficient on TFPR flips sign. They conclude: “measured distortions do include information about something that is a true distortion, but this component of the measure is empirically swamped by other sources of variation that are instead associated with (positive) fundamentals about producer profitability [efficiency and demand shocks]” (Haltiwanger et al. (2018, pg. 31)).

In more detail, notice first that selection of firms is on profits: more profitable firms are more likely to remain in the market whereas unprofitable firms tend to exit. In the above framework, profits from variety \( m \) are proportional to \( p_{m}^{1-\sigma} \gamma_{m} \). Then, profits are an increasing function of firm’s TFPQ (as an indicator of efficiency) and of the demand shifter \( \gamma_{m} \), and a decreasing function of its TFPR (as an indicator of frictions in all factor markets). A regression of the probability of survival on TFPQ, \( \gamma_{m} \) and TFPR controlling for relevant observables, should display positive signs in the two first cases, and a negative sign in the third case.

Table 3.1 presents the results for the linear probability models of firms’ survival. Columns (1)-(3) display the results of the regressions on each of the three determinants of profitability. I control for year and 4-digit industry fixed effects. The only determinant that shows the opposite sign is TFPR, a similar result than the obtained by Haltiwanger et al. (2018). However, for the regression including the three determinants in column (4), the coefficient on the TFPR flips sign, suggesting that TFPR, conditional on TFPQ and demand shocks, is inversely related to profits, as is suggested by the misallocation model, while the signs on the TFPQ and \( \gamma_{m} \) are still the expected. These findings are robust to the inclusion of firm observables (size, age and lagged capital, results displayed in column (7)) and geographic fixed effects (results in column (8)). That is, we obtain the same type of “anomaly” than the documented by Haltiwanger et al. (2018) with U.S. data, and that leads them to conclude than the distortionary component of the TFPR is empirically swamped by the other determinants of profitability.

My argument here, following a similar reasoning as in Yang (2017), is that the results in Table 3.1 are perfectly consistent with the misallocation framework if we augment the model to account for firms selection (which is very likely to occur in the data), as is done in closed economy settings by Bartelsman et al. (2013), Yang (2017) or Adamopoulos et al. (2017), or for an open economy in the first chapter of this thesis. Regressions in columns (1)-(3) suffer from omitted variable bias since the remaining determinants of profitability are excluded. In a model with selection of firms, TFPR is positively correlated with both demand shocks and TFPQ, since firms with bad draws of TFPQ or demand shocks and high TFPR are not active (for these firms profits are the lowest). Since the “true” signs of the omitted determinants in column (2) (TFPQ and \( \gamma_{m} \)) are both positive, the bias in the
3.3 Intra- and inter-industry misallocation

The coefficient of the TFPR is positive, and hence the estimated coefficient on the TFPR in (2) is greater than the “true” conditional value. In practice, this bias can reverse the “true” sign in an unconditional regression as in column (2).\(^{70}\) Similarly, regressions of columns (1) and (3) suffer from similar bias, but in those cases it is not possible to know the sign of the bias since the omitted determinants (TFPR and \(\gamma_m\) in column (1) and TFPQ and TFPR in column (3)) have opposite “true” signs. Nevertheless, to explore this bias and confirm the intuitions, I could use the approach of HK to measure TFPQ as in (3.5), that mixes up true efficiency and demand shocks in only one measure, \(a_{m}^{HK}\), to replicate the exercise. Column (4) shows the results for the unconditional estimate of \(a_{m}^{HK}\), whereas column (5) controls for TFPR. The conclusion for the bias on the TFPR is the same. However, since we now know that the “true” sign of the omitted variable in (4) (TFPR) is negative, we should obtain a negative bias in the coefficient of \(a_{m}^{HK}\) in (4), and thus an estimated value smaller than its “true” value in (5), exactly as it is shown in Table 3.1.

In an open economy setting as in Chapter 1, factor misallocation should also affect the selection of exporters. Since only firms with enough profits to pay the costs of international trade become exporters, the decision of being an exporter is also influenced by TFPQ, TFPR and demand shocks. Table 3.2 presents the results of the regressions of the probability of being an exporter on the same variables as in Table 3.1, using a shorter panel due to the availability of firm-level exports in the Colombian data.\(^{71}\) The signs on both TFPQ, TFPR and demand shocks remain the same in all specifications. The only exception is for TFPQ in column (1), that does not show a significant coefficient, confirming the bias of the unconditional estimations. Therefore, including firms selection in the model can rationalize the signs of the bias and the empirical findings, addressing the objections of Haltiwanger et al. (2018) about the empirical content of the TFPR as a measure of factor distortions.

3.3 Intra- and inter-industry misallocation

In this section I extend the model to account for misallocation both within and across industries. I first present the closed form formulas to compute the TFP gains from removing each type of factor misallocation under the standard two-tier (Cobb Douglas-CES) demand system. Next, I explore how robust are the results to the production function specification and to the elasticity of substitution across sectors. Finally I compare the gains of removing inter-industry misallocation with cross-country data, to show that TFP gaps attributed to factor misallocation might be larger than the obtained using only intra-industry reforms.

\(^{70}\) I have numerically tested this proposition assuming a functional form for the joint distribution of TFPQ and \(\gamma_m\) (jointly normal), selecting firms according a cutoff function as in Chapter 1, and running the regressions with the selected data. For a broad range of parameters of the joint distribution, the sign reversal is feasible.

\(^{71}\) Eslava et al.’s (2004) dataset does not include information on exports. So I match my original dataset with the panel employed by Bombardini et al. (2012b) for 1978-1991, which has been used extensively in the literature, to obtain exports. See details in Appendix B1.
3.3. Intra- and inter-industry misallocation

3.3.1 Accounting for inter-industry factor misallocation

Panel A of Figure 3.1 shows the distributions of TFPQ and TFPR for the Colombian manufacturing sector controlling for 4-digit International Standard Industrial Classification (ISIC) industries and year fixed effects. I use a gross-output specification for the production function with four inputs: capital, skilled labor, unskilled labor and materials. Although Figure 3.1 shows a larger variance in TFPQ, the dispersion of TFPR suggests allocative inefficiencies. This dispersion of is a result of the misallocation of all inputs. With a CD technology, TFPR can be expressed as the weighted geometric average of the marginal revenue products (MRP) of the factors, using factor intensities as weights. In frictionless factor markets, there should be MRP equalization for all firms in the economy. Constant returns to scale imply the MRP are directly proportional to the average revenue products of factors, which are observable measures. Panel B of Figure 3.1 displays the distributions of MRP for the homogenous inputs (capital, skilled labor and unskilled labor) used in the construction of TFPR above, exploiting the proportionality between the marginal and average returns. The observed dispersions suggest that although the factor with the most extensive misallocation is capital, all factors seem to contribute in some degree to variation in the TFPR. Moreover, the extent of misallocation varies across sectors. Figure 3.2 compares the same distributions for three different industries: food, chemicals and transport equipment. Not only does the dispersion vary across industries but also the expected values, suggesting the presence of inter-industry factor misallocation, which I aim to quantify in this section.

To characterize the observed dispersion in factors MRP we can use wedge analysis. In an efficient allocation, all firms should face the same price for inputs, say \( w_l \) for factor \( z_{lm} \). To replicate the dispersions in the factors MRP, I assume that firms face an idiosyncratic distortion \( \theta_{lm} \) in the market of factor \( z_{lm} \) such that the observed return of the factor is \( (1 + \theta_{lm}) \frac{w_l}{\rho} \). Thus, the wedge \( (1 + \theta_{lm}) \) for the firm producing variety \( m \) represents the difference between the observed MRP of factor \( l \), \( \frac{\alpha_l r_m}{z_{lm}} \), and its return in the efficient allocation, \( \frac{w_l}{\rho} \):

\[
(1 + \theta_{lm}) = \frac{\rho \alpha_l r_m}{w_l z_{lm}}
\]

Since the interest here is to recreate the dispersion in the factors MRP, being agnostic about the underlying cause that creates the misallocation, factor wedges are taken as primitives in the model. This strategy is denoted by Restuccia and Rogerson (2013) as the “indirect approach” to quantitatively assessing the implications of resource misallocation. Denote by \((1 + \bar{\theta}_{ls})\) the harmonic weighted average (HWA) of all factor-\(l\) wedges \((1 + \theta_{lm})\) in sector \(s\), with weights given by firms’ shares in total industry revenue \((R_s)\), this is:

\[
(1 + \bar{\theta}_{ls}) = \left( \sum_m \frac{1}{(1 + \theta_{lm}) \frac{p_m q_m}{P_s Q_s}} \right)^{-1} = \frac{\rho \alpha_l R_s}{w_l Z_{ls}}
\]

where \(Z_{ls}\) is the total demand of factor \(l\) and \(M_s\) is the number of firms in sector \(s\). The second equality

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72 As it is point out by Bartelsman et al. (2013), the proportionality is not valid when the production function includes overhead factors (fixed costs), since the production function is no longer homogenous.
3.3 Intra- and inter-industry misallocation

in equation (3.7) shows that this average wedge is the industry-analogue of a wedge at the firm-level for each production factor. Thus, this average wedge, which only needs information at the industry-level to be computed, can be used to quantify the amount of factor misallocation across industries. Revenue productivity at the industry level, computed as the ratio between sectoral revenue and total input use, can be expressed as the geometric average of \((1 + \bar{\theta}_{ls})^{w_l/\rho}\) over all factors, with weights given by each input intensity. In this way, sectoral revenue productivity is a measure of the returns of factors that on average firms are facing in the industry. In the inter-industry efficient allocation, sectoral revenue productivities should differ only by factor intensities.

To visualize the problem of both intra- and inter-industry factor misallocation, Panel A of Figure 3.3 represents all firms of two industries (food and vehicles) in the space (TFPQ, TFPR). When removing only intra-industry factor misallocation, which is the exercise proposed by HK, all firm-level wedges \((1 + \theta_{lm})\) collapse to their industry’s HWA \((1 + \bar{\theta}_{ls})\). Thus, the new values for firms’ TFPR coincide exactly with the corresponding industry’s revenue productivities, which are represented by the dashed lines in the graph. However, the revenue productivities at the industry level are not necessarily allocative efficient. Frictionless factor markets require that sectoral revenue productivities differ only by factor intensities, so all firms face the same prices for primary factors. Assuming values of \(w_l\) such that the HWA of sectoral \((1 + \bar{\theta}_{ls})\) is equal to one,\(^{73}\) the inter-industry allocative efficient sectoral revenue productivities are given by the weighted geometric average of \(\bar{w}_l\) over all factors, with weights given by the factor intensities. The values of the inter-industry efficient allocation are represented by the continuous lines in the graph. Panel B of Figure 3.3 shows both the intra-industry and the inter and inter-industry efficient allocation for all firms of the two studied industries.

To quantify the importance of each type of allocative inefficiency in the data, it is useful to compute the contribution of each one to the total TFP loss due to factor misallocation. Denote by \(\bar{\xi}_{lm}\) the MRP of the input \(l\). Let \(\bar{\xi}_{ls}\) denote the HWA of \(\xi_{lm}\), with weights given by the participations of firm’s revenues in total industry revenue. Note that \(\bar{\xi}_{ls} = (1 + \bar{\theta}_{ls})^{w_l/\rho}\). Assume that the production of the final good involves the output of \(S\) industries using a Cobb-Douglas (CD) technology with revenue shares \(\beta_s\). Using the cost minimization condition of the CD aggregator across sectors, total demand of factor-\(l\) in industry \(s\) can be expressed as:

\[
Z_{ls} = \frac{\alpha_{ls} \beta_s / \bar{\xi}_{ls}}{\sum_s \alpha_{ls} \beta_s / \bar{\xi}_{ls}} \bar{Z}_l
\]

(3.8)

where \(\bar{Z}_l = \Sigma_s Z_{ls}\) correspond to the fixed endowment of factor-\(l\) in the economy.

The gains from removing intra-industry misallocation in (3.2) are the same if the reform equalizes

\[^{73}\]I use \(w_l = \rho R/S \sum_s \bar{Z}_{ls}\) where \(R\) is total revenue, \(\Sigma_s R_s\). These values satisfy the solution for relative factor prices in general equilibrium for an allocative efficient closed economy, which is given by \(w_l = Z_j \Sigma_s \alpha_{ls} \beta_s / Z_j \Sigma_s \alpha_{ls} \beta_s\) where \(Z_j\) is the total endowment of factor \(l\) (see Appendix D). Further, these factor prices allow me to interpret all wedges as deviations with respect to one. Firms with wedges greater than one employ a smaller amount of the factor with respect to the efficient allocation; and vice versa.
3.3. Intra- and inter-industry misallocation

firms’ TFPR to \( \bar{\psi}_s \), so the factors’ MRP are equal to their HWA in the industry, or to the inter-industry efficient allocation, in which case the factors’ MRP are equated to \( \frac{w_l}{P} \). However, only in the first case it is ensured there are no factor reallocations across sectors (which is evident from equation 3.8), so the sectoral TFP gains in equation (3.2) are identical to the gains in industry output, \( 100(\frac{Q_s}{Q_s} - 1) \). In this specific case, total output gains in the economy can be computed simply by aggregating sectoral productivities up using the CD aggregator across industries:

\[
Gains^{\text{intra}} = 100\left( \prod_s \left( \frac{\bar{A}_s}{A_s} \right)^{\beta_s} - 1 \right) \quad (3.9)
\]

Clearly, total gains in (3.9) are only due to resource reallocation within industries: by assumption, there are no factor reallocations across sectors. In this case, there is MRP equalization within industries, but not necessarily across them. In the more general case in which I impose MRP equalization not only within but across industries (i.e. removing all wedges), sectoral TFP gains are the same as in (3.2), but output gains in each industry are no longer equal to the corresponding TFP gains, due to factor reallocation across sectors. From (3.8), the allocative efficient demand of factors at the industry level is given by \( \bar{Z}_{ls} = \alpha_{ls} \beta_s \bar{Z}_l / \sum_s \alpha_{ls} \beta_s \). Industry’s output in frictionless factor markets is given by \( \bar{Q}_s = \bar{A}_s \bar{M}^{\frac{1}{\sigma - 1}} \prod_l \bar{Z}_{ls} \alpha_{ls} \). Thus, the variation in sectoral output due to a reform that removes all wedges is a consequence of both a rise in the TFP and a variation in the use of factors in the whole sector, which depends exclusively on the sign of \( \bar{\theta}_{ls} \) (the extent of inter-industry misallocation). At the aggregate level, factor endowments between the distorted economy and the allocative efficient counterfactual are kept constant. So any change in aggregate output \( Q \) is attributable to variations in the aggregate TFP, and it is due to resource reallocation, both within and between industries. Gains in aggregate TFP can be caused by increases in sectoral TFP, term denoted \( Gains^{\text{intra}} \) above, or by reallocation of factors between industries, given by:

\[
Gains^{\text{inter}} = 100\left( \prod_s \prod_l \bar{Z}_{ls} \alpha_{ls} \beta_s - 1 \right) = 100\left( \frac{s}{S} \frac{\sum_s (\alpha_{ls} \beta_s / \bar{\xi}_{ls})}{\sum_s (\sum_s \alpha_{ls} \beta_s / \bar{\xi}_{ls})} \right) - 1 \quad (3.10)
\]

Where I use equation (3.8) and the expression for \( \bar{Z}_{ls} \) to obtain the explicit closed-form solution.

Thus, inter-industry gains only depend on the industry average MRP interacted with technological parameters, a plain consequence of the sectoral demand of factors in equation (3.8). These gains can be computed only with industry-level data, a fact that allows me to make cross-country comparisons to evaluate whether this component also explains the TFP gaps observed across countries, an exercise that is performed below. Finally, total gains in the economy, given by the variation on total output (or

74 This is, in the case that all sectors have the same revenue shares, the efficient allocation of factors across sectors implies that more intensive industries should have a larger proportion of the corresponding factor. Similarly, in the case that all sectors have the same factor intensities, the factors should be allocated in proportion only on sectoral revenue shares. The efficient factor allocation across industries is the combination of these two forces.
3.3. **Intra- and inter-industry misallocation**

aggregate TFP), are a combination of both sources of gains:

\[ Gains = 100(\frac{\bar{Y}}{Y} - 1) = 100\left[\frac{Gains_{\text{inter}}}{100} + 1\right]\left[\frac{Gains_{\text{intra}}}{100} + 1\right] - 1 \]  

(3.11)

The importance of each type of misallocation depends, of course, on the considered industry aggregation. For example, in the extreme case in which the whole manufacturing sector is represented as a single industry, the entire TFP loss due to allocative inefficiency proceeds from the intra-industry type, whereas in the opposite extreme, the whole loss proceeds from the inter-sectoral type. Using a 4-digit ISIC industry classification, a value added specification for the production function, and average US cost shares at the corresponding aggregation level from the NBER-CES Manufacturing Industry Database during the same period, the same set of specifications than the used in HK’s baseline, I find that the inter-sectoral component contributes on average up to 35% of the total reallocation gains of a comprehensive reform that removes all factor misallocation in Colombia, for the period 1982-1998. As a robustness check, I replicate the exercise with firm-level data from China, a country that offers external validation using the calculations provided by HK. In Figure 3.4 I report using continue lines the total gains (blue) and the intra-sectoral gains (red) from removing distortions for both countries, when the 4-digit ISIC industry aggregation is used. The difference between both lines is due to the gains from inter-sectoral reallocation. For China I find similar TFP gains as in HK in the case of removing only intra-industry misallocation, and an average contribution of 30% of the inter-sectoral component for the complete reform.

In general, gains from removing distortions are larger for China, although the time periods are not comparable. The graph shows that over time in both countries there are not significant improvements in allocative efficiency in the considered periods; indeed, there is a slight worsening at the end of each one. When I move to the 3-digit ISIC classification, the predictions from the decomposition seem to hold. The dashed lines in Figure 3.4 report once again the total gains (blue) and the intra-sectoral gains (red) from removing distortions, but now at the 3-digit ISIC classification. Both total gains fluctuate around a similar range. However, the intra-industry gains rise in a larger proportion than the total gains, so their average contribution is now 68% and 73% for Colombia and China, respectively. This confirms that as the level of disaggregation increases, the intra-industry gains are lower.

### 3.3.2 Robustness checks

The source of inter-industry gains is neither related to the use of US cost shares instead of domestic factor intensities in the sectoral production function nor to the use of a value-added specification. For example, Figure 3.5 displays for the Colombian case that using a gross-output specification (Panel

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75For the 4-digit classification in the Colombian case, due to small number of observations, 14 industries were reclassified to its closest 4-digit industry or to the 4-digit sector within the same 3-digit industry that merges the products not elsewhere classified.

76For China, I use the panel from the Annual Survey of Industrial Production collected by the Chinese government’s National Bureau of Statistics, for the period 1999-2007.
3.3. Intra- and inter-industry misallocation

A) or changing the production function coefficients for Colombian cost shares (Panel B) does not alter importantly the key insights. In the latter case, factor intensities are now equal to the observed share costs, but they are still different to the optimal share cost in monopolistic competition (where the total cost is \( \rho \) times the revenue), which is what matters in the efficient allocation. However, the use of Colombian cost shares reduces the relative importance of inter-sectoral reallocation: its average contribution shrinks to 23%.

Further, the total gains and the contribution of the inter-sectoral component increase using a higher elasticity of substitution across sectors. This is completely in line with the HK prediction that when sectors outputs are better substitutes, inputs are reallocated toward sectors with bigger productivity gains, so there are larger TFP gains. We can show this with a CES demand across sectors. In this case, there is not a closed-form solution for each component, but it is possible to implement a numerical procedure to obtain both gains. Appendix C.2 offers details about its implementation. Figure 3.6 shows that for different values of the elasticity of substitution across sectors (\( \phi \)), the components of the gains behave as predicted. The numerical procedure replicates the results of the close-form solutions for the CD aggregator for both components in the case \( \phi = 1 \), whereas total gains and the contribution of the inter-sectoral component increases when \( \phi = 2 \) (up to 50% from 43% in the latter case) and decreases when \( \phi = 0.5 \) (to 36% in the latter case). In those exercises the change in the intra-sectoral gains is negligible.

3.3.3 Inter-industry misallocation and development

Another important question about the relevance of inter-industry misallocation is whether its associated TFP loss is larger in less developed economies, as is the case with intra-industry misallocation, the core result of HK’s paper. If the inter-sectoral gains vary systematically across countries, omitting the inter-sectoral component implies an under-estimation of the TFP gap attributed to factor misallocation, if the latter is computed only with intra-industry reforms, as in HK. In the case of the CD aggregator across sectors, the closed form solution for the TFP gains of removing inter-industry misallocation only requires information at the industry level. Thus, I use information from the socio-economic accounts of the World Input Output Database - WIOD (Timmer et al. (2015)), which contains industry-level data for 40 countries and 35 industries mostly at the 2-digit ISIC level, covering the overall economy, to compute those gains.

Figure 3.7 presents how the gains from inter-sectoral reallocation vary with the GDP per capita by country.\(^{77}\) For this calculation, I use a gross output specification for the sectoral production function with 3 inputs (hours worked, capital and materials) and US cost shares. The linear correlation between both variables in this baseline is -0.75 (Figure 3.7 also shows the best linear fit). The negative correlation is robust to the use of value added specification or own country’s cost shares in the production

\(^{77}\)Each dot corresponds to the average value between 1995 and 2007 of the intersectoral gains calculated using (3.10) for each country and the average GDP per capita in constant 2005 US dollars obtained from the World Bank. The results are very similar if median values are used. Two small countries with many zeros in sectoral data were dropped from the WIOD sample (Luxembourg and Malta). Likewise, Taiwan was dropped to make comparable WIOD and World Bank data.
function; to restrict the set of sectors to only manufacturing industries and to measure labor with the wage bill and materials in nominal values to control for heterogeneity in labor and for differences in quality of intermediate inputs respectively, graphs shown in Figure C.1 in Appendix. Therefore, there is evidence that less developed economies tend to have greater inter-sectoral gains for removing distortions. This is consistent with the insights of multi-country studies as Tombe (2015) or Święcki (2017) which focus on inter-sectoral misallocation, that find larger intersectoral distortions in poor countries. Thus, omitting the inter-sectoral component of the total gains from removing distortions understates the common TFP gaps attributed to firm-level misallocation.

### 3.4 Conclusions

In this chapter the standard model of firm-level misallocation in a closed economy (Hsieh and Klenow (2009)) is augmented in two dimensions. First, idiosyncratic demand shocks are introduced to test the ability of the usual metrics of factor misallocation in explaining plants’ survival, a test that has been recently used to argue that misallocation measures are empirically swamped by other determinants of profitability, mainly demand shocks (Haltiwanger et al. (2018)). I obtain similar empirical findings using Colombian data with which I can recover demand shock measures due to firm-level price indices availability. However, I argue that explaining plants’ survival with unconditional determinants of profitability produces biased estimates, and that including firms selection in the model can rationalize the signs of the bias and the data findings, addressing Haltiwanger et al.’s (2018) objections.

Second, the model is extended to account for the possibility that production factors are misallocated both within and across industries. I document that in Colombia and China the contribution of inter-industry misallocation can be as high as 35% of the total gains from removing misallocation. Given the relevance of inter-industry misallocation in these two cases of study, I use cross-country data to show that including this type of misallocation can amplify the usual TFP gaps attributed to factor misallocation based exclusively on intra-industry reforms. Hence, from a macro perspective, the simultaneously study of both intra- and inter-industry misallocation, as it is done for example in the first chapter of this thesis, enriches the comprehension of the total impact of factor misallocation in an economy.
3.5 Tables and figures

### 3.5.1 Tables

#### Table 3.1: Probability of survival explained by determinants of profitability

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* p<0.10, ** p<0.05 and *** p<0.01. Dependent variable: probability of survival. All independent variables are in deviations over industry means. Firm controls include age, size and lagged capital. Standard errors cluster by plant. Source: EAM Colombia, 1982-1998

#### Table 3.2: Probability of being a exporter explained by determinants of profitability

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* p<0.10, ** p<0.05 and *** p<0.01. Dependent variable: probability of being an exporter. All independent variables are in deviations over industry means. Firm controls include age, size and lagged capital. Standard errors cluster by plant. Source: EAM Colombia, 1982-1991
3.5. Tables and figures

3.5.2 Figures

Figure 3.1: TFPQ, TFPR and MRP distribution in Colombia

Panel A: Observed TFPQ and TFPR and efficient TFPR*

Panel B: Observed MRP*

Figure 3.2: MRP distribution for selected industries
3.5. Tables and figures

Figure 3.3: Removing intra- and inter-industry factor misallocation

Panel A: TFPQ and TFPR in two sectors

Panel B: Intra and inter-industry efficient allocation

Figure 3.4: TFP gains from factor reallocation in a closed economy

Panel A: China

Panel B: Colombia

Note: In Panel A, $\times$ correspond to the values found by HK.
3.5. Tables and figures

Figure 3.5: Sensitivity to production function specification and factor intensities

Panel A: TFP gains using gross output specification
(Colombia, US cost shares)

Panel B: TFP gains by set of cost shares
(Colombia, 4-dig, gross output specification)

Figure 3.6: Sensitivity to elasticity of substitution across sectors

Note: $\phi$ corresponds to the elasticity of substitution across sectors.
3.5. Tables and figures

Figure 3.7: TFP gains from removing inter-industry misallocation and GDP per capita

Note: Each dot corresponds to the average gains from removing inter-industry misallocation and the corresponding average GDP per capita in the period 1991-2007. The source of the data is WIOD and the World Bank development indicators.


Bibliography


Bibliography


Appendix A

Appendix to Chapter 1

A.1 Description of the dataset

This chapter uses two types of data: A “macro” dataset with information at the country-sectoral level, and a “micro” dataset, with information at the firm level for Colombia.

The “macro” dataset collects sectoral information of gross output, bilateral trade flows, intermediate consumption and shares of employment and capital for a sample of 48 countries and 25 manufacturing industries (3-digit ISIC rev. 2 level), for the year 1995. Table A.1 and Table A.2 at the end of this section display the considered industries and countries respectively.

Data for sectoral gross output, bilateral trade flows and intermediate consumption come from OECD’s Trade in Value Added (TiVa) database (2015’s release). This dataset contains a range of indicators derived from the OECD’s Inter-Country Input-Output (ICIO) database. The latter is constructed by OECD from various national and international data sources, all drawn together and balanced under constraints based on official National Accounts (SNA93). Information on gross output and trade flows was collected for all available manufacturing sectors in TiVa (16), and an imputation scheme was implemented to obtain output and bilateral flows for the remaining sectors and for two countries not available in TiVa (Venezuela and Ecuador, which were included given their relevance as Colombia’s trade partners), based on production and trade shares computed from the CEPII database.

I derive imports from home from the difference between gross output and total exports. As it is known in the literature, this procedure could generate negative values for some country-industry pairs (for instance if the country-sector has high amount of reexports). To solve this issue, I follow Costinot and Rodríguez-Clare (2014) and Święcki (2017), adjusting those negative flows rescaling exports to all destinations until the ratio total exports to gross output is as in the sector with the highest ratio still less than one in that country. This adjustment was needed in the case of six country-industry observations.

Factors shares were constructed using information from several sources. For materials, I compute the shares using the series of intermediate consumption from TiVa. Data for the remaining industries and for Venezuela and Ecuador was imputed using shares from UNIDO’s INDSTAT2 database (2015’s release), which contains information at the 2-digit ISIC rev. 3 level only for manufacturing industries.

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78 The underlying sources used are notably: i) National supply and use tables; ii) National and harmonized Input-Output Tables, iii) Bilateral trade in goods by industry and end-use category; and iv) Bilateral trade in services. For more information, see www.oecd.org/trade/valueadded
A.1. Description of the dataset

The information was gathered adjusting each country’s available aggregation to the one used here. For labor, ICIO database contains information of employment (measured in number of persons engaged) for 42 of the 48 countries considered here. For the remaining sectors and countries, data was collected using UNIDO’s INDSTAT2 database. Skilled and unskilled labor shares were allocated using GTAP-5 database, which are drawn on labor force surveys and national censuses where they are available, or the statistical model proposed by Liu et al. (1998) otherwise.

For capital, shares were constructed as follows. First, the Social Economics Accounts of the World Input Output Database (WIOD, see Timmer et al. (2015)) contain calculations of the stocks of capital at the two-digit ISIC rev. 3 level or groups thereof for 36 countries of the 48 countries considered here (in the 2013’s release). For the remaining countries, I apply the steady-state approach on the calculation of the initial stock of capital in the perpetual inventory method\textsuperscript{79}, using information of gross fixed capital formation (GCFC) from INDSTAT2 database. For country $i$-industry $s$ the share of capital $\gamma_{iks}$ was imputed as:

$$\gamma_{iks} = \frac{GCFC_{is}}{\sum_s GCFC_{is}}$$

where $GCFC_{is}$ is the average GCFC over the five-year window centered on the reference year, $g_{is}$ is the growth rate of the GDP of the sector in the same period, and $\delta_{is}$ is an exogenous depreciation rate, which are computed using the NBER-CES Manufacturing Industry database for US\textsuperscript{80}. I compute capital shares using this methodology even for the countries with available information from WIOD, to assess the fit of the imputation procedure. I evaluate the imputation results in terms of cross correlations and mean absolute errors using three approximations: i) Setting $g_{is} = \delta_{is} = 0 \forall i, s$ (thus I use only information on GCFC); ii) Setting $g_{is} = 0 \forall i, s$ (hence I use information on GCFC and US depreciation rates); iii) Using the full set of information. I found the best adjustment under the second approach. Therefore, capital shares for the remaining countries were imputed using only series of GCFC and US depreciation rates.

For the “micro” dataset I use the panel of manufacturing plants created by Eslava et al. (2004) (hereafter EHKK) for the period 1984-1998 from the Colombian Annual Manufacturing Survey (AMS), collected by the Departamento Administrativo Nacional de Estadística (DANE), the Colombian national statistical agency\textsuperscript{81}. The AMS is a census of plants with 10 or more workers or annual sales above certain limit, which is adjusted over time\textsuperscript{82}. A unique feature of the AMS is that, in conjunction with the main variables of standard surveys (output and sales values, overall cost, energy consumption, payroll, number of workers and book values of equipment and structures), the DANE collects

\textsuperscript{79}For reference, see for example Berlemann and Wesselhöft, 2014
\textsuperscript{80}I use five-year windows to prevent that short-run volatility in the GCFC bias the imputation results. Notice that since I only need sectoral factor shares, a temporal shock that affects homogeneously the whole economy does not affect the imputation results.
\textsuperscript{81}The dataset was made available to research by the DANE.
\textsuperscript{82}For 1998, the last year of the panel, was around US$35000. This criterium was introduced in the AMS in 1992 to increase coverage.
A.1. Description of the dataset

information at the product level (with a disaggregation comparable to the 6-digit HS) on the value and physical quantities of outputs and inputs (valued at factory-gate prices). This allows EHKK to obtain prices as unit values for each output and input produced and used by every plant, and hence to construct specific firm prices of total output and materials using Tornqvist indices (see EHHK Appendix for details).

I perform the detailed cleaning procedure of Kugler and Verhoogen (2012) to reduce the influence of measurement error and outliers (see their data Appendix). Next, I follow HK and remove 1% tails of the distributions of $\log(\psi_m/\bar{\psi}_s)$ and $\log(M_s^{\frac{1}{M_s}} a_m/\bar{A}_s)$ to drop remaining influential observations. Following the misallocation literature, to obtain TFP measures I use as a factor intensities average U.S. cost shares at the corresponding aggregation levels from the NBER-CES Manufacturing Industry Database during the same period of time. Since for the selected years the AMS uses ISIC rev-2 adapted for Colombia, I match the NAICS97 US code with the ISIC rev-3, and afterwards with the Colombian one. The purpose of using US cost shares is to employ factor intensities that reflect true technological differences across industries instead of frictions in factor markets, since domestic cost shares can be affected by the extent of inter-industry factor misallocation.

The final panel contains around 4700 plants on average in a typical year. On average, around 390 firms enter each year while 450 exit, which corresponds to an entry/exit rate of 8 and 9 percent respectively. For the computation of the misallocation measures in the counterfactual exercise, I use information only for the reference year (1995). Despite its coverage, EHHK’s dataset does not include exports. Thus, I use the panel employed by Bombardini et al. (2012b) for 1978-1991, which has been used extensively in the literature, to obtain exports. I merge both panels using variables in quantities (year, 4-digit ISIC, production and non-production workers and energy consumption). For the overlapping period, plants representing between 2% and 3% of the original nominal production were unmatched, and therefore dropped from the sample. I also keep only plants with positive and non-missing values for production and inputs. Up to 1991, on average around 13 of each 100 firms were exporters, while the total value exported represents in average 8% of industry’s gross revenue, with a large variation across sectors.

With the goal to ensure consistency between the macro and the micro dataset, two procedures were executed. First, since the calculation of factor shares in the macro dataset is independent on the series of gross output and bilateral trade flows, factor shares for Colombia were taken directly from the AMS. It is worth to say that the factor shares computed by both sources are very similar, minor differences occur due to the exclusion of outliers in the micro dataset. Second, revenues of all firms within each industry were re-scaled to ensure that the revenue share included in the TiVA database coincide with the corresponding shares on the AMS. Once again, revenue shares from the two sources are very alike, and the small discrepancies also occur for the exclusion of outliers.

83 For the definitions of $\bar{\psi}_s$, $M_s$ and $\bar{A}_s$ see Appendix D.

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### A.1. Description of the dataset

#### Table A.1: Sectors in the sample

<table>
<thead>
<tr>
<th>No.</th>
<th>Sector</th>
<th>Sector Description</th>
<th>ISIC Rev. 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Food</td>
<td>Food manufacturing</td>
<td>311-312</td>
</tr>
<tr>
<td>2</td>
<td>Beverage</td>
<td>Beverage industries</td>
<td>313</td>
</tr>
<tr>
<td>3</td>
<td>Tobacco</td>
<td>Tobacco manufactures</td>
<td>314</td>
</tr>
<tr>
<td>4</td>
<td>Textiles</td>
<td>Manufacture of textiles</td>
<td>321</td>
</tr>
<tr>
<td>5</td>
<td>Apparel</td>
<td>Wearing apparel, except footwear</td>
<td>322</td>
</tr>
<tr>
<td>6</td>
<td>Leather</td>
<td>Leather and products of leather and footwear</td>
<td>323</td>
</tr>
<tr>
<td>7</td>
<td>Footwear</td>
<td>Footwear, except vulcanized or moulded rubber or plastic footwear</td>
<td>324</td>
</tr>
<tr>
<td>8</td>
<td>Wood</td>
<td>Wood and products of wood and cork, except furniture</td>
<td>331</td>
</tr>
<tr>
<td>9</td>
<td>Furniture</td>
<td>Furniture and fixtures, except primarily of metal</td>
<td>332</td>
</tr>
<tr>
<td>10</td>
<td>Paper</td>
<td>Paper and paper products</td>
<td>341</td>
</tr>
<tr>
<td>11</td>
<td>Printing</td>
<td>Printing, publishing and allied industries</td>
<td>342</td>
</tr>
<tr>
<td>12</td>
<td>Chemicals</td>
<td>Industrial chemicals</td>
<td>351</td>
</tr>
<tr>
<td>13</td>
<td>Other chemicals</td>
<td>Other chemicals (paints, medicines, soaps, cosmetics)</td>
<td>352</td>
</tr>
<tr>
<td>14</td>
<td>Petroleum</td>
<td>Petroleum refineries, products of petroleum and coal</td>
<td>353-354</td>
</tr>
<tr>
<td>15</td>
<td>Rubber</td>
<td>Rubber products</td>
<td>355</td>
</tr>
<tr>
<td>16</td>
<td>Plastic</td>
<td>Plastic products</td>
<td>356</td>
</tr>
<tr>
<td>17</td>
<td>Pottery</td>
<td>Pottery, china and earthenware</td>
<td>361</td>
</tr>
<tr>
<td>18</td>
<td>Glass</td>
<td>Glass and glass products</td>
<td>362</td>
</tr>
<tr>
<td>19</td>
<td>Other non-metallic</td>
<td>Other non-metallic mineral products (clay, cement)</td>
<td>369</td>
</tr>
<tr>
<td>20</td>
<td>Iron and steel</td>
<td>Iron and steel basic industries</td>
<td>371</td>
</tr>
<tr>
<td>21</td>
<td>Non-ferrous metal</td>
<td>Non-ferrous metal basic industries</td>
<td>372</td>
</tr>
<tr>
<td>22</td>
<td>Metal products</td>
<td>Fabricated metal products, except machinery and equipment</td>
<td>381</td>
</tr>
<tr>
<td>23</td>
<td>Mach. &amp; equipment</td>
<td>Machinery and equipment except electrical</td>
<td>382</td>
</tr>
<tr>
<td>24</td>
<td>Electric. / Profess.</td>
<td>Electrical machinery apparatus, appliances and supplies &amp; professional and scientific, measuring and controlling equipment</td>
<td>383-385</td>
</tr>
<tr>
<td>25</td>
<td>Transport</td>
<td>Transport equipment</td>
<td>384</td>
</tr>
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</table>

#### Table A.2: Countries in the sample

<table>
<thead>
<tr>
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<th></th>
<th></th>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>AUS</td>
<td>Korea</td>
<td>KOR</td>
<td>Argentina</td>
<td>ARG</td>
</tr>
<tr>
<td>Austria</td>
<td>AUT</td>
<td>Mexico</td>
<td>MEX</td>
<td>Brazil</td>
<td>BRA</td>
</tr>
<tr>
<td>Belgium</td>
<td>BEL</td>
<td>Netherlands</td>
<td>NLD</td>
<td>China</td>
<td>CHN</td>
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<tr>
<td>Canada</td>
<td>CAN</td>
<td>New Zealand</td>
<td>NZL</td>
<td>Colombia</td>
<td>COL</td>
</tr>
<tr>
<td>Chile</td>
<td>CHL</td>
<td>Norway</td>
<td>NOR</td>
<td>Ecuador</td>
<td>ECU</td>
</tr>
<tr>
<td>Denmark</td>
<td>DNK</td>
<td>Poland</td>
<td>POL</td>
<td>Hong Kong</td>
<td>HKG</td>
</tr>
<tr>
<td>Finland</td>
<td>FIN</td>
<td>Portugal</td>
<td>PRT</td>
<td>India</td>
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</tr>
<tr>
<td>France</td>
<td>FRA</td>
<td>Czech Republic</td>
<td>CZE</td>
<td>Indonesia</td>
<td>IDN</td>
</tr>
<tr>
<td>Germany</td>
<td>DEU</td>
<td>Spain</td>
<td>ESP</td>
<td>Malaysia</td>
<td>MYS</td>
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<tr>
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<td>GRC</td>
<td>Sweden</td>
<td>SWE</td>
<td>Philippines</td>
<td>PHL</td>
</tr>
<tr>
<td>Hungary</td>
<td>HUN</td>
<td>Switzerland</td>
<td>CHE</td>
<td>Rest of the World</td>
<td>ROW</td>
</tr>
<tr>
<td>Ireland</td>
<td>IRL</td>
<td>Turkey</td>
<td>TUR</td>
<td>Romania</td>
<td>ROU</td>
</tr>
<tr>
<td>Israel</td>
<td>ISR</td>
<td>United Kingdom</td>
<td>GBR</td>
<td>Russia</td>
<td>RUS</td>
</tr>
<tr>
<td>Italy</td>
<td>ITA</td>
<td>United States</td>
<td>USA</td>
<td>Saudi Arabia</td>
<td>SAU</td>
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<tr>
<td>Japan</td>
<td>JPN</td>
<td>Russia</td>
<td>SGP</td>
<td>Singapore</td>
<td>SGP</td>
</tr>
<tr>
<td></td>
<td></td>
<td>South Africa</td>
<td>ZAF</td>
<td>Thailand</td>
<td>THA</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Thailand</td>
<td></td>
<td>Taiwan</td>
<td>TWN</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Venezuela</td>
<td></td>
<td></td>
<td>VEN</td>
</tr>
</tbody>
</table>
A.2 Bils, Klenow and Ruane’s (2017) method and results for Colombia

Here I succinctly introduce Bils et al.’s (2017) method to estimate the dispersion in the factors’ MRP in the presence of additive measurement error in revenue and inputs, which in the latter case can be also interpreted as overhead factors. Define measured revenues and inputs for firm producing variety \( m \) as the sum of the “real” values plus an idiosyncratic measurement error: 
\[
\hat{R}_m = R_m + f_m \quad \text{and} \quad \hat{I}_m = I_m + g_m.
\]
Denote \( \Delta \) the log-difference and \( \triangle \) the absolute difference. Bils et al. (2017) find, under some reasonable assumptions, that the elasticity of \( \Delta \hat{R} \) with respect to \( \Delta \hat{I} \), 
\[
\hat{\beta} = \frac{\sigma_{\Delta \hat{R} \Delta \hat{I}}}{\sigma_{\Delta \hat{I}}^2},
\]
satisfies:
\[
E \left\{ \hat{\beta} \mid \ln(T F P R_m) \right\} = [\Psi + \Lambda(\ln(T F P R_m))^2] \left[ 1 - (1 - \lambda) \ln(T F P R_m) \right]
\]
with \( \lambda = \frac{\sigma_{\Delta \hat{R}}}{\sigma_{\Delta T F P R}} \), the ratio between the dispersion of the factor’s MRP and the dispersion of the observed TFPR, our measure of interest; \( \Psi = 1 + \Omega_\Theta - \Omega_f \), where \( \Omega_\Theta = \frac{\sigma_{\Delta \hat{R} \Delta \hat{I}}}{\sigma_{\Delta \hat{I}}^2} \), \( \Omega_f = \frac{\sigma_{\Delta \hat{I} \Delta \hat{I}}}{\sigma_{\Delta \hat{I}}^2} \), \( \triangle f' = \frac{\triangle f}{\Delta m} \); and \( \Lambda \) a constant that depends on the stochastic process of \( \Theta \), which is assumed is stationary. In the absence of measurement error (\( \lambda = 1 \)) the elasticity of revenues with respect to inputs should be the same (\( \Psi \)) for plants with different average products. The quadratic term \( \Lambda(\ln(T F P R_m))^2 \) is included to reflect the possibility of mean reversions in the stochastic process of \( \Theta \), given the stationary assumption. Therefore, \( \lambda \) can be estimated by GMM through the non-linear regression:
\[
\Delta \hat{R}_m = \phi \ln(T F P R_m) + \Psi \Delta \hat{I}_m - \Psi (1 - \lambda) \ln(T F P R_m) \Delta \hat{I}_m \tag{A.1}
\]
\[
+ \Gamma (\ln(T F P R_m))^2 + \Lambda (1 - \lambda) (\ln(T F P R_m))^2 \Delta \hat{I}_m \]
\[
+ \Upsilon (\ln(T F P R_m))^3 + \Lambda (1 - \lambda) (\ln(T F P R_m))^3 \Delta \hat{I}_m + \epsilon_m
\]

With Colombian data, I follow closely Bils et al. (2017) for the construction of the variables. I estimate equation (A.1) by GMM sector by sector, controlling for year fixed effects, in the panel from 1991 to 1998. Standard errors are clustered at the firm-level. The last two columns in Table 1.5 show the point estimates for \( \hat{\lambda}_s \) and its standard errors. For sectors in which the method does not deliver significative values, probably due to the influence of remaining outliers, I use the results from estimating (A.1) in the whole manufacturing sector controlling for a full set of sector-year fixed effects (as in Bils et al. (2017)), values that are displayed in the last row.

I use the estimated values of \( \hat{\lambda}_s \) to compress the observed dispersions in the average revenue products of the factors to obtain variances and covariances of the MRP, and hence to derive \( \hat{V}_{is} \).

A.3 Solution of the model

To obtain the global solution of the system of equations, I employ both an algorithm to choose ideal initial conditions and a state-of-the-art solver for large-scale nonlinear systems. The proposed algorithm consists of the following three steps:

1. Choose ideal initial conditions.
2. Solve the system of equations using a state-of-the-art solver.
3. Evaluate the solution for convergence and adjust as necessary.

With these steps, I achieve a robust and accurate solution for the model.
1. **Step 1:** I start solving the model for a two-country world composed by Colombia and an aggregate adding the rest of countries up (the number of equations is \(N \times (S + L) = 56\)). The purpose of this step is to find ideal initial conditions for Colombia and the rest of the world in step 2. To solve this two-country model I perform first a global search using particles swarm optimization a sufficient large number of times (500), to remove the influence of randomness in the initial position of the particles. Next, I use a local solver initialized in each of the 50 best solutions of the global search. For the local solver, I use auto-differentiation to obtain information about the gradient and the hessian of the objective function, and Knitro, a solver that implements both novel interior-point and active-set methods for solving large-scale nonlinear optimization problems. The final solution is the best point of those 50 local solutions. It is worth to say that the obtained solution behaves according to the predictions of a small-open economy model, where the small country cannot influence foreign factor prices.

2. **Step 2:** Next, I solve the model \(N - 1\) times, in each case for a small-scale version of the world with the following three countries: Colombia, each country in the dataset and an aggregate adding the remaining countries up (the model is solved for \(N \times (S + L) = 84\) equations). The objective of this step is to find ideal initial points for every country to solve the full model in step 3. In each of the \(N - 1\) times I initialize the local solver using for Colombia the solution found in step 1, and for the remaining two countries the solution for the rest of the world in step 1. I use the same local-solver and auto-differentiation as in step 1.

3. **Step 3:** Finally, I collect the solution for each country in step 2 to initialize the local solver for the model with the full set of countries; while for Colombia I initialize with a median of its \(N - 1\) solutions found in step 2 (such solutions have low dispersion). I use the same local-solver and auto-differentiation as in steps 1 and 2. The number of equations in this case is \(N \times (S + L) = 1344\).

### A.4 Mathematical derivations

#### A.4.1 Model solution under assumptions A.1 and A.2

Under assumptions A.1 and A.2, it is possible to express:

\[
\sum_m \left( \frac{a_{im}}{\Theta_{im}} \right)^{\sigma - 1} = \frac{H_n}{\Delta a} \int_{\theta_1} \ldots \int_{\theta_L} \int_{a_{ij}}^\infty \left( \frac{a_{im}}{\Theta_{im}} \right)^{\sigma - 1} dG_{is} = \frac{H_n \chi a}{\Delta a} \int_{\theta_1} \ldots \int_{\theta_L} \int_{a_{ij}}^\infty a_{im}^{\sigma - 2} \Theta_{im}^{-\sigma} dG_{is}
\]

Using the formula of the cutoff function in (1.7), the last expression can be simplified as:

\[
\sum_m \left( \frac{a_{im}}{\Theta_{im}} \right)^{\sigma - 1} = \frac{H_n}{\Delta a} \frac{\kappa}{1 + \kappa - \sigma} \left( \frac{\Delta a}{a_{ij}} \right)^\kappa a_{ij}^{\sigma - 1} \Gamma_{is}
\]

(A.2)

---

8I use auto-differentiation and the Knitro solver through the Tomlab optimization environment in Matlab.
A.4. Mathematical derivations

with \( \Gamma_{is} \) defined as in the text. Applying the formulas for firm-level profits and revenues, the free entry condition can be restated as:

\[
\sum_{j}^{NM_{is}} \left( \frac{\tau_{js} \Theta_{im}}{\rho a_{im}} \right)^{1-\sigma} \omega_{is}^{-\sigma} E_{js} \sigma^{-1} f_{js}/f_{js} - \sum_{j}^{NM_{is}} \Theta_{im} f_{js} = f_{is}^{e} H_{is}
\]

Notice that \( M_{im} \sum_{m} \Theta_{im} = H_{is} (\bar{a}_{ij}^e)^{\kappa} \Gamma_{is} \). Combining with equation (A.2), it is possible to obtain:

\[
\sum_{j}^{N} \left( \frac{\tau_{js}}{\rho} \right)^{1-\sigma} \omega_{is}^{-\sigma} E_{js} \sigma^{-1} f_{js}/f_{js} - \sum_{j}^{N} f_{js} (\bar{a}_{ij}^e)^{\kappa} \Gamma_{is} = f_{is}^{e}
\]

Using the definition of the productivity cutoff value for the undistorted firms in (1.7) to substitute in \( a_{ij}^{e^{\sigma^{-1}}} \), the expression can be simplified to:

\[
\sum_{j}^{N} (\bar{a}_{ij}^e)^{\kappa} f_{js} = \frac{d_{is} \sigma f_{is}^{e} (1 + \kappa - \sigma)}{\Gamma_{is} (\sigma - 1)} \tag{A.3}
\]

On the other hand, applying again (A.2) and the definition of the productivity cutoff value, bilateral exports \( X_{ij} = \sum_{m} r_{ijm} \) are given by:

\[
X_{ij} = \sum_{m}^{M_{js}} \left( \frac{\tau_{ij} \Theta_{im} \omega_{is}}{\rho a_{im}} \right)^{1-\sigma} E_{ij} \sigma^{-1} f_{ij} - \sum_{j}^{N} f_{js} (\bar{a}_{ij}^e)^{\kappa} \Gamma_{is} = f_{is}^{e}
\]

Hence, from (A.3), sectoral revenues \( R_{is} = \sum_{j}^{N} X_{ij} \) are given by:

\[
R_{is} = \frac{\kappa}{\rho} \omega_{is} f_{is}^{e} H_{is} \tag{A.5}
\]

Free entry requires that the aggregate sectoral profits, \( \Pi_{is} \), are equal to the expenditures in entry, \( \omega_{is} f_{is}^{e} H_{is} \). This means the Pareto property of a constant profits/revenue ratio is not affected by distortions: \( R_{is} = \frac{\rho}{\omega} \Pi_{is} \). From equations (1.11) and (1.12), the sectoral demand of primary factor \( l \) for both operational (fixed and variable costs) and entry uses is given by:

\[
Z_{ils} = Z_{ils}^{o} + Z_{ils}^{e} = \frac{\rho \alpha_{ils} R_{is}}{w_{il}(1 + \theta_{ils})} + \frac{\alpha_{ils} \tilde{v}_{is}}{w_{il}(1 + \theta_{ils})} + \frac{\alpha_{ils} \omega_{ils} f_{ils}^{e} H_{is}}{w_{il}} \tag{A.5}
\]

Substituting the expression for \( \sum_{m}^{M_{is}} \Theta_{im} \) from above in the definition of \( \tilde{v}_{is} \) and using again equation (A.5), it is straightforward to obtain equation (1.17), the total demand of primary factor \( l \) in terms of sector revenue, underlying factor prices and the HWA wedges. With the definition of \( v_{ils} \) as in the text, equation (1.21) is evident.
A.4. Mathematical derivations

Finally, combining (A.4) with the gravity equation, I obtain:

\[
X_{ijs} = \frac{X_{ijs} E_{js}}{\sum_k X_{kjs}} = \frac{\frac{\omega_k H_{is}}{d_{is}} (\frac{\bar{a}_{is}}{a_{ijs}})^r \Gamma_{is} f_{ijs}}{\sum_k \frac{\omega_k H_{ks}}{d_{ks}} (\frac{\bar{a}_{ks}}{a_{kjs}})^r \Gamma_{ks} f_{kjs}} E_{js}
\]

By definition of the cutoff function in (1.7), it is possible to show the following relation between the cutoffs for the undistorted firms of country \( i \) and country \( i' \) for the same destination \( j \):

\[
\frac{a^*_{ijs}}{a^*_{i'js}} = \left( \frac{\tau_{ijs}}{\tau_{i'js}} \right) \left( \frac{\omega_{is}}{\omega_{i's}} \right)^{1-r} \left( \frac{f_{ijs}}{f_{i'js}} \right)^{r-\sigma-1} \tag{A.6}
\]

Using the formula in (A.6) into the denominator of bilateral exports, I obtain:

\[
X_{ijs} = \frac{\frac{1}{d_{is}} \omega_{is}^{1-r} H_{is} \bar{a}_{is}^r \left( \frac{1}{\bar{a}_{is}} \right)^r \left( \frac{f_{ijs}}{f_{i'js}} \right)^{r-\sigma-1} \Gamma_{is}}{\sum_k \frac{1}{d_{ks}} \omega_{ks}^{1-r} H_{ks} \bar{a}_{ks}^r \left( \frac{1}{\bar{a}_{ks}} \right)^r \left( \frac{f_{kjs}}{f_{k'js}} \right)^{r-\sigma-1} \Gamma_{ks}} E_{js}
\]

Using (A.5) to substitute for the mass of entrants in terms of sectoral revenue, it simplifies to:

\[
X_{ijs} = \frac{\omega_{is}^r R_{is} \phi_{ijs} \Gamma_{is}}{\sum_k \omega_{ks}^r R_{ks} \phi_{kjs} \Gamma_{ks}} E_{js} \tag{A.7}
\]

where \( \phi_{ijs} \) is as in the text. Hence, trade shares are given by (1.24). The model is closed combining (A.7) with the definitions of sectoral and aggregate revenues \((R_{is} = \sum_j X_{ijs} \text{ and } R_i = \sum_s R_{is})\), the Cobb-Douglas solution for sectoral expenditures, \(E_{js} = \beta_{js} E_j\) and the trade balance condition: \(E_j = \sum_s R_{js} - D_j\), which results on equation (1.23).

The system can be solved for the values of \( R_{is} \) for a given set of values of factor intensities \( a_{is} \), factor endowments \( Z_{il} \), expenditure shares \( \beta_{js} \), aggregate trade deficits \( D_j \), deep parameters \( \phi_{ijs}, \kappa \) and \( \rho \), and misallocation measures \( \Gamma_{is} \) and \( \nu_{ijs} \). Once the solution of \( R_{is} \) is computed, the values of all remaining variables can be found following the next sequence: i) factor prices and sectoral factor allocations from (1.21) and (1.22); ii) expenditures from the trade balance condition; iii) bilateral exports from (A.7); iv) mass of entrants from (A.5); v) bilateral cutoffs values for the undistorted firms from (A.4); vi) mass of operating firms from (1.9).

A.4.2 Demonstration of equation (1.18)

Here I deduce the formula for the ex-post HWA wedge in equation (1.18).
A.4. Mathematical derivations

Proof. Starting by the definition of the HWA wedge:

\[(1 + \tilde{\theta}_{ils}) \equiv \left( \sum_{j} \sum_{m} \frac{1}{1 + \theta_{im}} \frac{c_{jm}}{c_{is}} \right)^{-1} = \left( \sum_{j} \sum_{m} \frac{1}{1 + \theta_{im}} \frac{\rho_{jm} \Theta_{im} f_{il}}{\rho R_{is} + \tilde{\delta}_{is}} \right)^{-1}\]

Substituting firm level exports from \(i\) to \(j\) and after few algebraic manipulations we can write:

\[
\frac{(1 + \tilde{\theta}_{ils})}{\rho R_{is} + \tilde{\delta}_{is}} = \left( \sum_{j} \sum_{m} \rho \frac{\gamma_{jm} \Theta_{im} \rho_{jm}}{\rho a_{im}} \right)^{-1} - \sigma E_{js} P_{js}^{-1} \frac{1}{(1 + \theta_{im})} (1 - \sigma) - \omega_{is} \sum_{j} f_{js} \frac{M_{js}}{m} \frac{\Theta_{im}}{(1 + \theta_{im})}^{-1}
\]

Similar to how it is done in the precedent section, it is possible to show that:

\[
\frac{(1 + \tilde{\theta}_{ils})}{\rho R_{is} + \tilde{\delta}_{is}} = \left( \frac{\rho}{\rho} \right)^{1 - \sigma} \sum_{j} N \gamma_{jm} \Theta_{im} \rho_{jm} \left( \frac{\Theta_{im}}{(1 + \theta_{im})} \right)^{1 - \sigma} - \omega_{is} \sum_{j} f_{js} \frac{M_{js}}{m} \frac{\Theta_{im}}{(1 + \theta_{im})}^{-1}
\]

Substituting the definition of the productivity cutoff value for the undistorted firms in (1.7) in \(a_{ils}^{\sigma - 1}\), I obtain:

\[
\frac{(1 + \tilde{\theta}_{ils})}{\rho R_{is} + \tilde{\delta}_{is}} = \left( \frac{\rho}{\rho} \right)^{1 - \sigma} \sum_{j} f_{js} \left( \frac{a_{ils}^{\sigma - 1}}{\Theta_{im}} \right)^{1 - \sigma} - \omega_{is} \sum_{j} f_{js} \frac{M_{js}}{m} \frac{\Theta_{im}}{(1 + \theta_{im})}^{-1}
\]

Using the free entry condition in (A.3):

\[
\frac{(1 + \tilde{\theta}_{ils})}{\rho R_{is} + \tilde{\delta}_{is}} = \left( \frac{\rho}{\rho} \right)^{1 - \sigma} \sum_{j} f_{js} \left( \frac{a_{ils}^{\sigma - 1}}{\Theta_{im}} \right)^{1 - \sigma} - \omega_{is} \sum_{j} f_{js} \frac{M_{js}}{m} \frac{\Theta_{im}}{(1 + \theta_{im})}^{-1}
\]

Substituting the expression for \(\sum_{m} \Theta_{im}\) given in Appendix C.1. in the definition of \(\tilde{\delta}_{is}\) and using again equation (A.5) it is possible to show \(\rho R_{is} + \tilde{\delta}_{is} = \omega_{is} M_{ij}^{e} f_{i}^{\sigma + 1 - \sigma} (\sigma - 1)^{-1}\) and hence:

\[
(1 + \tilde{\theta}_{ils}) = \frac{\Gamma_{is}}{\Gamma_{ils}}
\]

It is possible to repeat the proof to derive an expression for the HWA wedge of the firms able to sell in each market \(j\). Doing so, it follows \((1 + \tilde{\theta}_{jils}) = (1 + \tilde{\theta}_{ils})\), this is, the HWA wedge does not vary across destinations. Even though this result looks at first glance counterintuitive, since this average it is not computed for the same set of firms (for example, \((1 + \tilde{\theta}_{jils})\) includes the firms that only sell in the domestic market, who must have, conditional on TFPQ, higher wedges than the firms exporting to
A.4. Mathematical derivations

Using the expression for \( M \) brackets, without simplifying across terms. Using the definitions of \( \bar{\psi}_{ij} \), for this reason, in the next lines I develop the RHS of (A.8) keeping each term separated in square brackets, the industry-exporter fixed effect on single components that come from each of the mentioned sources.

My interest is twofold. First, I will provide a proof of equation (1.19), and second I will decompose (A.8) can be written as:

\[
\left( \frac{P_{ij} P_{j'}}{P_{ij'} P_{j}} \right)^{1-\sigma} = \left( \frac{\tau_{ij} \tau_{j'}}{\tau_{ij'} \tau_{j}} \right)^{1-\sigma} \left( \frac{M_{ijs} M_{js'}}{M_{ij's} M_{js}} \right) \left( \frac{\psi_{ij} \psi_{j'}}{\psi_{ij'} \psi_{j}} \right)^{1-\sigma} A_{ijs} A_{j'} A_{j's} \]  

(A.8)

My interest is twofold. First, I will provide a proof of equation (1.19), and second I will decompose the industry-exporter fixed effect on single components that come from each of the mentioned sources. For this reason, in the next lines I develop the RHS of (A.8) keeping each term separated in square brackets, without simplifying across terms. Using the definitions of \( \bar{\psi}_{ij} \) and \( \bar{\psi}_{js} \) in the text, equation (A.8) can be written as:

\[
\left( \frac{P_{ij} P_{j'}}{P_{ij'} P_{j}} \right)^{1-\sigma} = \left( \frac{\omega_{i} \omega_{j} \bar{\psi}_{ij} \bar{\psi}_{j'}}{\omega_{ij} \omega_{j} \bar{\psi}_{ij'} \bar{\psi}_{j}} \right)^{1-\sigma} A_{ijs} A_{j'} A_{j's} \]  

Using the expression for \( \sum_{m} \left( \frac{a_{im}}{\Theta_{im}} \right) \sigma^{-1} \) in equation (A.2) and the fact \( \bar{\psi}_{ijs} = \bar{\psi}_{is} \) derived in Appendix C.2, this reduces to:

\[
\left( \frac{P_{ij} P_{j'}}{P_{ij'} P_{j}} \right)^{1-\sigma} = \left( \frac{\omega_{i} \omega_{j} \bar{\psi}_{ij} \bar{\psi}_{j'}}{\omega_{ij} \omega_{j} \bar{\psi}_{ij'} \bar{\psi}_{j}} \right)^{1-\sigma} A_{ijs} A_{j'} A_{j's} \]  

Under assumptions A.1 and A.2, the aggregate stability condition (1.9) can be solved to obtain \( M_{ijs} = \frac{H_{i} Y_{i}}{\Theta_{i}} \left( \frac{a_{ij}}{a_{ij'}} \right)^{\kappa} \) with \( Y_{is} = \int_{\Theta_{i}} \cdots \int_{\Theta_{i}} \bar{\psi}_{ijs} \frac{\partial G}{\partial \bar{\psi}_{ijs}}(\bar{\Theta}) \), an expected value that depends only on the joint distribution of distortions. Substituting this expression in the first and third terms, and using

\[
M_{ijs} = \frac{H_{i} Y_{i}}{\Theta_{i}} \left( \frac{a_{ij}}{a_{ij'}} \right)^{\kappa} \]  

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equation (A.6), I obtain for the RHS:

\[
(\tau_{ij}s, \omega_{is}) \cdot \ln(\bar{\theta}_{is} \Gamma_{js}^{1-\sigma} - \kappa - \frac{\bar{\theta}_{js}^{1-\sigma}}{f_{ij}s})
\]

Using \( H_{is} = \frac{R_{ijs}}{\omega_{is}f_{is}} \) and applying logs to separate the components that only depend on exporter-industry terms and simplifying, I finally obtain for the RHS of (A.8):

\[
= \log \left( \frac{\rho_{is}R_{ijs} Y_{is} Y_{js}}{\rho_{i's} R_{i's} Y_{i's} Y_{j's}} \left( \frac{\omega_{is}}{\omega_{i's}} \frac{\omega_{js}}{\omega_{j's}} \right)^{-\frac{\sigma}{2}} \right) - \frac{\sigma}{2} - 1 + \log \left( \frac{\omega_{is} \omega_{i's} \bar{\theta}_{is} \bar{\theta}_{i's}}{\omega_{js} \omega_{j's}} \right)^{1-\sigma}
\]

\[
+ \log \left( \frac{\bar{\theta}_{is} \bar{\theta}_{i's}}{\bar{\theta}_{js} \bar{\theta}_{j's}} \right)^{1-\sigma} \left( \frac{\omega_{is}}{\omega_{i's}} \frac{\omega_{js}}{\omega_{j's}} \right) \left( \Gamma_{is} \Gamma_{j's} Y_{is} Y_{js} \right)
\]

where \( B_{ij} = \ln \left[ \left( \bar{\theta}_{ij} \right)^{1-\sigma} - \frac{\bar{\theta}_{ij}^{1-\sigma}}{f_{ij}} \right] \) and \( \rho_{is} = \frac{\partial \bar{\theta}_{is}}{\partial \omega_{is}} \). Canceling out the double differences of \( \bar{\theta}_{is} \) and \( \Gamma_{is} \) across terms and simplifying the double differences of \( \omega_{is} \) it is straightforward to derive the gravity equation in (1.19). Furthermore, equation (A.9) offers a decomposition of the exporter-industry fixed effect on the three sources of interest: number of exporters (first term in log), average factor returns (second term in log) and TFP (third term in log).

This decomposition is used in section 1.3.3 as follows. Denote \( \bar{x} \) the value in the allocative efficient equilibrium of \( x \), and \( \bar{x} = \frac{\bar{x}}{x} \) the proportional change when we introduce distortions. Thus figure 1.3 plots in each chart the following terms:

\[
\log \left( \frac{\bar{X}_{ij} \bar{X}_{js}}{X_{ij} X_{js}} \right) = \log \left( \frac{\bar{R}_{ijs} R_{ijs} \Gamma_{js}^{1-\sigma} Y_{is} Y_{js}}{\bar{R}_{ij's} R_{ij's} \Gamma_{j's}^{1-\sigma} Y_{i's} Y_{j's}} \left( \frac{\omega_{is}}{\omega_{i's}} \frac{\omega_{js}}{\omega_{j's}} \right)^{-\frac{\sigma}{2}} \right) - \frac{\sigma}{2} - 1 + \log \left( \frac{\omega_{is} \omega_{i's} \bar{\theta}_{is} \bar{\theta}_{i's}}{\omega_{js} \omega_{j's}} \right)^{1-\sigma}
\]

\[
+ \log \left( \frac{\bar{\theta}_{is} \bar{\theta}_{i's}}{\bar{\theta}_{js} \bar{\theta}_{j's}} \right)^{1-\sigma} \left( \frac{\omega_{is}}{\omega_{i's}} \frac{\omega_{js}}{\omega_{j's}} \right) \left( \Gamma_{is} \Gamma_{j's} Y_{is} Y_{js} \right)
\]

with \( i = 1, i' = 2, j = 2, s = 1, s' = 2 \).

A.4.4 Solution for \( \Gamma_{is} \) under log-normal

By definition of \( \Gamma_{is} \) in the text:

\[
\Gamma_{is} = \int_{\bar{\theta}_{is}} \int_{\bar{\theta}_{i's}} \Theta_{is}^{1-\sigma} dG_{is}^{0} = E \left[ (1 + \Theta_{is})^{1-\sigma} \right]
\]

Assume \( \tilde{\theta}_{is} = \{ \theta_{1is}, \theta_{2is}, \ldots, \theta_{Lis} \} \) has a multivariate log-normal distribution, such the transformed vector \( \tilde{\theta}_{is}^{*} = \{ \ln(\theta_{1is}), \ln(\theta_{2is}), \ldots, \ln(\theta_{Lis}) \} \) has a multivariate normal distribution with expected value \( \mu_{is} \) (1 x L vector) and variance \( V_{is} \) (L x L matrix). Let \( \bar{\alpha}_{s} \) a (column) vector with elements: \( \bar{\alpha}_{s} = \{ (1 - \frac{\sigma}{2})\alpha_{is}, (1 - \frac{\sigma}{2})\alpha_{2is}, \ldots, (1 - \frac{\sigma}{2})\alpha_{Lis} \}^{T} \). Then the product \( \hat{\theta}^{T} (1 + \Theta_{is})^{1-\sigma} \) is log-normal distributed with location parameter \( (\bar{\alpha}_{s})^{T} \mu_{is} \) and shape parameter \( (\bar{\alpha}_{s})^{T} V_{is} \bar{\alpha}_{s} \). Under log-normality, the required
expected value is then:

\[ \Gamma_{il} = \exp \left( (\bar{\alpha}_s)' \mu_{is} + \frac{1}{2} (\bar{\alpha}_s)' V_{il} \bar{\alpha}_s \right) \]

On the other hand, the definition of \( \Gamma_{il} \) in the text:

\[ \Gamma_{il} = \int_{a_0}^{a_1} \cdots \int_{a_{n-1}}^{a_n} \prod_{l}^{1-\frac{k}{\rho}} dG_{il}^{\rho} = E[(1 + \theta_1)^{(1 - \frac{k}{\rho})\alpha_0} \cdot \prod_{l}^{i} (1 + \theta_l)^{(1 - \frac{k}{\rho})\alpha_l}] \]

By the same token, let \( \bar{\alpha}_is \) a (column) vector with elements: \( \bar{\alpha}_is = \{(1 - \frac{k}{\rho})\alpha_{is}, ..., (1 - \frac{k}{\rho})\alpha_{ils} \}' \). This is, \( \bar{\alpha}_is \) has the same elements of \( \bar{\alpha}_s \) with exception to the element in position \( l \), which is \( (1 - \frac{k}{\rho})\alpha_{ils} - 1 \). Thus the product \( (1 + \theta_{ils})^{(1 - \frac{k}{\rho})\alpha_0} \cdot \prod_{l}^{i} (1 + \theta_l)^{(1 - \frac{k}{\rho})\alpha_l} \) is log-normal distributed with location parameter \( (\bar{\alpha}_is)' \bar{\mu}_is \) and shape parameter \( (\bar{\alpha}_is)' V_{ils} \bar{\alpha}_is \). Accordingly, its expected value is:

\[ \Gamma_{ils} = \exp \left( (\bar{\alpha}_is)' \bar{\mu}_is + \frac{1}{2} (\bar{\alpha}_is)' V_{ils} \bar{\alpha}_is \right) \]

Now, using the formula for \( (1 + \bar{\theta}_{ils}) \) in (1.18) we obtain:

\[ \ln(1 + \bar{\theta}_{ils}) = (\bar{\alpha}_s)' \bar{\mu}_is + \frac{1}{2} (\bar{\alpha}_s)' V_{ils} \bar{\alpha}_s - (\bar{\alpha}_s)' \bar{\mu}_is - \frac{1}{2} (\bar{\alpha}_s)' V_{ils} \bar{\alpha}_is \]

\[ = \mu_{ils} + \frac{1}{2} ( (\bar{\alpha}_s)' V_{ils} \bar{\alpha}_s - (\bar{\alpha}_s)' V_{ils} \bar{\alpha}_is ) \quad (A.10) \]

**A.4.5 Welfare**

Combining the formula of the consumer price index in sector \( s \) and equation (A.2) we obtain:

\[ \left( p_{ls}^{d} \right)^{1 - \sigma} = \sum_{k}^{N} \frac{1 - \sigma}{p} - \sum_{m}^{N} \omega_{ks} \frac{M_{ls}}{\hat{\theta}_{km}} (\sigma_{km})^{\sigma - 1} = \sum_{k}^{N} \frac{\omega_{ks} H_{ls}}{d_{ks}} \frac{1 + \kappa - \sigma}{\kappa} (\bar{\alpha}_{ks}^{*})^{\kappa} \sigma^{-1} \Gamma_{ks} \]

Inserting the definition of the productivity cutoff value for the undistorted firms in (1.7) in the term \( \alpha_{kis}^{*} \sigma^{-1 - \kappa} \), the price index can be written as:

\[ \left( p_{ls}^{d} \right)^{-\kappa} = E_{ls}^{1 - \sigma} - \sum_{k}^{N} \omega_{ks} \frac{H_{ls}}{d_{ks}} \frac{1 - \frac{k}{\rho}}{1 + \kappa - \sigma} (\bar{\alpha}_{ks}^{*})^{\kappa} (\sigma_{f_{ks}}) \frac{1}{1 - \frac{\kappa}{\rho}} \Gamma_{ks} \]

Using the country \( i \)'s share of expenditure on itself within sector \( s \) from equation (A.7), we obtain:

\[ \left( p_{ls}^{d} \right)^{-\kappa} = \zeta_{ls}^{e} E_{ls}^{1 - \sigma - 1} \omega_{ls}^{\frac{\kappa}{\rho}} R_{ls}^{\frac{1}{\kappa}} \Gamma_{ls}^{\frac{1}{\kappa}} \]

where \( \zeta_{ls} = \left( \frac{p_{ls}^{d}}{\hat{p}_{ls}} \right)^{\kappa} \frac{1}{d_{ls}} \frac{1}{1 + \kappa - \sigma} (\frac{\kappa}{\rho})^{1 + \kappa - \sigma} \) a term that does not vary in the counterfactual exercise. Hence, the proportional change of the price index from the initial equilibrium to the counterfactual one can be written as:

\[ \hat{p}_{ls}^{d} = \hat{E}_{ls}^{1 - \sigma + \frac{\kappa}{2}} \hat{\omega}_{ls}^{\frac{\kappa}{2}} \hat{R}_{ls}^{\frac{1}{2}} \hat{\Gamma}_{ls}^{\frac{1}{2}} (\hat{\zeta}_{ls}^{e}) \]
A.4. Mathematical derivations

Using the fact that \( \hat{P}_i^d = \prod_{s}(\hat{P}_{is}^d)^{\beta} \), \( \hat{E}_{is} = \hat{E}_i \) and equation (1.25) to substitute \( \hat{\omega}_{is} \), the derivation of equation (1.28) is straightforward. Moreover, notice that in the case of the undistorted economy with one factor production, \( \hat{R}_{is} = \hat{\omega}_{is} \hat{Z}_{is} \) and \( \hat{\omega}_{is} = \hat{w}_{is} = \hat{E}_i \) so the increase in the sectoral price index is \( \hat{P}_{is}^d = \hat{w}_{is}(\hat{\pi}_{is}^{\text{in}} \hat{Z}_{is})^{1/k} \), which leads to the Arkolakis et al. (2012)'s formula to compute the increase in welfare in response to any exogenous shock.
## Appendix B

### Appendix to Chapter 2

#### B.1 Additional tables

**Table B.1: Premia with hours worked: Additional jobs**

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log Income</td>
<td>Log Income</td>
<td>Log Income</td>
<td>Log Income</td>
<td>Log Inc./Hour</td>
<td>Log Inc./Hour</td>
</tr>
<tr>
<td>Non-Agriculture</td>
<td>0.501***</td>
<td>0.264***</td>
<td>0.390***</td>
<td>0.216***</td>
<td>0.275***</td>
<td>0.150***</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.032)</td>
<td>(0.032)</td>
<td>(0.031)</td>
<td>(0.034)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Urban</td>
<td>0.171***</td>
<td>0.063*</td>
<td>0.143***</td>
<td>0.063**</td>
<td>0.112***</td>
<td>0.057**</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.034)</td>
<td>(0.030)</td>
<td>(0.026)</td>
<td>(0.028)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Log Hours/Year</td>
<td></td>
<td></td>
<td>0.509***</td>
<td>0.445***</td>
<td>(0.011)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Year &amp; province FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Indiv. cont.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Individual FE</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>44489</td>
<td>44492</td>
<td>43819</td>
<td>43821</td>
<td>43819</td>
<td>43821</td>
</tr>
<tr>
<td>R²</td>
<td>0.514</td>
<td>0.538</td>
<td>0.603</td>
<td>0.615</td>
<td>0.495</td>
<td>0.514</td>
</tr>
</tbody>
</table>

Notes: Income and hours from both the main job and the secondary job. Individual controls: education, experience, experience sq., and sex. Observations weighted by longitudinal survey weights. Standard errors clustered by enumeration areas (primary sampling units of the survey) in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

**Table B.2: Hours worked**

<table>
<thead>
<tr>
<th></th>
<th>Base (1)</th>
<th>Base (2)</th>
<th>Add. Job (3)</th>
<th>Add. Job (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log Hours</td>
<td>Log Hours</td>
<td>Log Hours</td>
<td>Log Hours</td>
</tr>
<tr>
<td>Non-Agriculture</td>
<td>0.286***</td>
<td>0.152***</td>
<td>0.234***</td>
<td>0.119***</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.029)</td>
<td>(0.022)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Urban</td>
<td>0.101***</td>
<td>0.014</td>
<td>0.062***</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.031)</td>
<td>(0.018)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Year &amp; province FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Indiv. cont.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Individual FE</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>43841</td>
<td>43843</td>
<td>43819</td>
<td>43821</td>
</tr>
<tr>
<td>R²</td>
<td>0.053</td>
<td>0.023</td>
<td>0.052</td>
<td>0.026</td>
</tr>
</tbody>
</table>

Notes: Base is the baseline specification involving primary job only. Add. Job also includes secondary job. Individual controls: education, experience, experience sq., and sex. Observations weighted by longitudinal survey weights. Standard errors clustered by enumeration areas (primary sampling units of the survey) in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.
### B.2 Recall bias

Each wave of the IFLS asks respondents about the income they earned over the past year. Throughout the chapter we use this contemporaneously recorded income as our main dependent variable. In addition, the survey asks respondents to retrospectively recall employment information for several years prior to the survey. While this recall information can in principle be used to supplement the contemporaneous data and increase the sample size, retrospective survey data is known to raise serious quality

---

#### Table B.3: Premia over Time

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Income Non-Agriculture</td>
<td>0.574***</td>
<td>0.792***</td>
<td>0.721***</td>
<td>0.547***</td>
<td>0.461***</td>
</tr>
<tr>
<td>Log Income Urban</td>
<td>0.207***</td>
<td>0.388***</td>
<td>0.271***</td>
<td>0.227***</td>
<td>0.204***</td>
</tr>
</tbody>
</table>

| Year FE | Yes |
|Province FE | Yes | Yes | Yes | Yes | Yes |
|Indiv. cont. | Yes | Yes | Yes | Yes | Yes |

| Observations | 44494 | 5296 | 8548 | 10293 | 10619 | 9738 |
| $R^2$      | 0.503 | 0.382 | 0.333 | 0.244 | 0.267 | 0.249 |

<table>
<thead>
<tr>
<th>(b) Premia with Worker Fixed Effect</th>
<th>1993-97</th>
<th>1997-00</th>
<th>2000-07</th>
<th>2007-14</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Income Non-Agriculture</td>
<td>0.332***</td>
<td>0.339***</td>
<td>0.292***</td>
<td>0.303***</td>
</tr>
<tr>
<td>Log Income Urban</td>
<td>0.084**</td>
<td>0.210***</td>
<td>0.097</td>
<td>0.156***</td>
</tr>
</tbody>
</table>

| Year FE | Yes | Yes | Yes | Yes | Yes |
|Province FE | Yes | Yes | Yes | Yes | Yes |
|Indiv. cont. | Yes | Yes | Yes | Yes | Yes |

| Observations | 44497 | 13844 | 18841 | 20912 | 20360 |
| $R^2$      | 0.518 | 0.242 | 0.205 | 0.396 | 0.282 |

Notes: *Pooled* is the baseline sample with observations from IFLS 1-5. Panel A: cross-sectional regressions run separately for each survey wave. Panel B: panel regressions run separately for each two consecutive survey waves. Individual controls: education, experience, experience sq., and sex. Observations weighted by longitudinal survey weights. Standard errors clustered by enumeration areas (primary sampling units of the survey) in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.
B.2. Recall bias

Concerns (cf. Bound et al. (2001)). For this reason we do not use retrospective income information in our analysis. In this appendix we explain this choice in more detail and argue that it can largely explain why our results differ from those concurrently obtained by Hicks et al. (2017).

The first three columns of the first panel of Table B.4 show the non-agricultural premia estimated on the contemporaneous data recorded by the IFLS. These numbers are similar to those reported in Table 2.11 (columns 3, 4, and 6) in the main text, but not identical because the specifications and sample are modified to ease comparison with Hicks et al. (2017). In particular, we discard the information from the most recent wave of IFLS as it has not been incorporated by these authors. Columns 4-6 show the corresponding premia estimated on data from retrospective recall. Compared to the contemporaneous estimates, the cross-sectional premium (controlling for hours) drops from 71 lp to 53 lp, premium with worker fixed effects (controlling for hours) drops from 25 lp to 11 lp, and the 19 lp premium in terms of income per hour (with worker FE) disappears entirely.

These patterns are not surprising in light of research on biases arising in recall surveys. One such well documented bias is that past income reported by workers is biased towards their usual income.\footnote{Another bias with similar implications in this context is an anchoring bias, where respondents use an answer to a previously answered question as a mental anchor for subsequent answers. Godlonton et al. (2016) find strong evidence of this behavior in a survey of Central American farmers: retrospectively recalled income correlates more highly with current income (about which the respondents are asked first) than with income over the recall period that had been reported contemporaneously in the past. This type of cognitive bias is likely to be present in IFLS too, since IFLS also first asks about contemporaneous income and then asks respondents to retrospectively recall past income.} For example, Gibson and Kim (2010) show the extent of this bias for US wage workers by comparing their self-reported retrospective earnings with administrative records. They also demonstrate that underreporting transitory income changes generates non-classical measurement error that biases the regression coefficients towards zero if the mismeasured variable is the dependent variable. This result is consistent with the reduced non-agricultural premia we find using recall data if workers cannot accurately recall how much higher their income was in years in which they worked in non-agriculture. Furthermore, the problem is likely to be exacerbated when the identifying variation comes from changes in income of individual workers over time. This would explain why the fall in the premium is proportionately much larger in the specification with worker fixed effects. Finally, the problems with measurement error are likely to be compounded when the dependent variable is constructed by dividing reported income by reported hours. That retrospectively recalled hours are unreliable is suggested by comparing coefficients on hours in columns 5 and 2. The elasticity of income with respect to hours implied by column 5 is less than 0.15, only 1/3 of the 0.44 elasticity implied by the corresponding column 2 for contemporaneous data. The implausibly low elasticity for recalled hours indicates that their relationship to income should be treated with great caution in recall data. In a rare validation study observing both hours worked and earnings, Duncan and Hill (1985) find that “interview reports of average hourly earnings, obtained by dividing the interview reports of annual earnings by reports of annual work hours, appeared to be exceedingly unreliable” and caution against their use. The particularly low signal-to-noise ratio in income per hour derived from retrospective data can explain why the results become insignificant in column 6.
B.3. Estimation procedure

The take-away message from this discussion is that using data from retrospective recall in our application would introduce biases in our key results. These recall biases can be strong in IFLS since the respondents are asked retrospective questions about multiple years prior to the survey (up to a maximum of 10 years), and the quality of recall information deteriorates with time elapsed from the pertaining event (see, e.g. de Nicola and Giné (2014) in a developing country context). There are no obvious offsetting benefits to including the retrospective data. Statistical power, in particular, is not an issue, since the baseline sample of contemporaneous responses is large enough to allow us to estimate the key non-agricultural premium precisely.

We conclude this appendix by showing that the inclusion of retrospective data is likely the main reason why the substantive results on the strength of the non-agricultural premium reported by Hicks et al. (2017) are different than ours. In contrast to our results, they argue that the non-agricultural premium in Indonesia mostly disappears once individual fixed effects are allowed for. To aid comparison, columns 1-3 in the second panel of Table B.4 repeat the same exercise as columns 1-3 and 4-6 in panel A, but now on a sample pooling the contemporaneous and retrospective responses. The estimates lie roughly half way between the two corresponding numbers reported in the first panel. This means that the pooled-sample estimates are significantly attenuated relative to those based on better-measured contemporaneous data that we favor. For comparison, columns 4-6 copy the corresponding estimates from Hicks et al. (2017) (columns 2, 6, and 7 of their Table 5A), who use pooled contemporaneous and retrospective data. While we cannot replicate their results exactly without detailed knowledge of their data processing protocol, the estimates in columns 1-3 come close. Based on this exercise, we expect that their results would much have been much more in line with ours had they not used the retrospective data.86

B.3 Estimation procedure

This Appendix presents some technical aspects about the estimation procedure. The vector of structural parameters in the frictionless economy, denoted by \( \Theta \), is constituted by the following set of 21 elements: \( \{ R_s^t, \beta, \sigma_{\theta s}^2, \sigma_{\alpha s}^2, \sigma_{\epsilon s}^2 \} \) for \( t = 1,..5 \) and \( s = A,N \) (denoting agriculture and non-agriculture, respectively). In this set, \( \sigma_{\theta s}^2 \) and \( \sigma_{\epsilon s}^2 \) denote the variances in \( \Sigma_\theta \) and \( \Sigma_\epsilon \) respectively, \( \sigma_{\alpha s} \) the covariance in \( \Sigma_\theta \), and \( \beta \) is comprised of the Mincerian returns on the five mentioned covariates, denoted \( \beta_{sex}, \beta_{loc}, \beta_{edu}, \beta_{exp} \) and \( \beta_{exp2} \), respectively. For the model with switching costs, \( \Theta \) is augmented by \( \{ \phi AN, \phi NA \} \), whereas for the model with compensating differentials \( \Theta \) is augmented by \( cd \). The Indirect Inference loss function, denoted by \( Q(\Theta) \), is computed as the weighted sum of the squared differences between the values in \( \hat{\delta} \) and the values for those obtained from simulations of the structural model, that is:

\[
Q(\Theta) = \left( \hat{\delta} - \hat{\delta}^*(\Theta) \right)' \Omega \left( \hat{\delta} - \hat{\delta}^*(\Theta) \right)
\]

86Furthermore, their headline result depends on using income per hour as their preferred measure. We do not use hours data in our preferred specifications, both because of measurement issues for hours described in this appendix and conceptual issues discussed in section 2.3.2.
### B.3. Estimation procedure

Table B.4: Retrospective Recall

(a) Contemporaneous vs. Recall Data

<table>
<thead>
<tr>
<th></th>
<th>Contemporaneous</th>
<th>Retrospective</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>Log Inc.</td>
<td>Log Inc.</td>
</tr>
<tr>
<td>Non-Agriculture</td>
<td>0.707***</td>
<td>0.245***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Log Hours</td>
<td>0.604***</td>
<td>0.462***</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>Log Hours Squared</td>
<td>0.000</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Age squared</td>
<td>-0.000***</td>
<td>-0.000***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Individual FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>48626</td>
<td>48626</td>
</tr>
<tr>
<td>R-sq</td>
<td>0.423</td>
<td>0.540</td>
</tr>
</tbody>
</table>

(b) Pooled Data vs. Hicks et al. (2017)

<table>
<thead>
<tr>
<th></th>
<th>Pooled Data</th>
<th>Hicks et al. (2017)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>Log Inc.</td>
<td>Log Inc.</td>
</tr>
<tr>
<td>Non-Agriculture</td>
<td>0.588***</td>
<td>0.173***</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Log Hours</td>
<td>0.385***</td>
<td>0.206***</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>Log Hours Squared</td>
<td>0.006</td>
<td>0.009**</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Age squared</td>
<td>-0.000***</td>
<td>-0.000***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Individual FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>107933</td>
<td>107933</td>
</tr>
<tr>
<td>R-sq</td>
<td>0.303</td>
<td>0.353</td>
</tr>
</tbody>
</table>

Notes: *Contemporaneous* measures based on values reported for last year. *Retrospective* measures obtained from recall part of the survey. *Pooled Data* combines contemporaneous and retrospective observations. Sample restricted to IFLS 1-4. Sample includes all individuals with at least one observation of income and hours worked. *Income* is average monthly labor income from primary and secondary job. Contemporaneous income obtained by dividing annual income by 12. *Hours* are average monthly hours from primary and secondary job obtained as (weeks worked per year)*(normal hours per week)/12. Observations are not weighted. Standard errors clustered at the individual level in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. Columns 4-7 in Panel B are columns 2, 6, 7, respectively, from Table 5A in Hicks et al. (2017).
where \( \hat{\delta}'(\Theta) \) corresponds to the same vector of selected coefficients of the auxiliary models estimated with data simulated from the structural model with parameters \( \Theta \), and \( \Omega \) is a diagonal weighting matrix. For weights, we use factors that represent the importance of the estimated coefficient in the identification of the structural parameters of the model. The values of those factors, displayed in the second column of Table 2.15, were assigned after extensive experimentation with simulations of the model. We proceed next to comment on their magnitudes, particularly for those weights that differ from one.

As we argue in the main text, the within-individual variation is key for identification. Our priority in the estimation procedure is to make the structural model able to deliver the observed premia for switchers in the data. Procuring the right amount of switchers in each year is crucial because of their size depends the precision of the obtained premia. For this reason, the coefficients of the linear probability models have the largest weights in the loss function, by a factor of 10. Moreover, we also impose larger weights (by a factor of 5) to the two sets of switchers’ sectoral premia in which we are interested in. First, to the premia in the model in differences iv), since this regression actually forces the structural model to deliver both the gains of switchers to non-agriculture and the cuts in income of workers switching to agriculture, allowing the estimation procedure to identify any possible asymmetry in the switching costs across sectors. Second, to the premia in model iv), which compares the average performance of a switching worker to each sector with their peer group after the switch, informing about the nature of sorting. In addition, we know that the estimated coefficients of the interactions in model iv) help to identify the growth in relative human capital prices. Thus, the information about the full path of these prices can be recovered once the regression pin down the conditional expected income in each sector in the first year. For this reason, we force a greater accuracy in the coefficients of the constant and the interaction term of non-agriculture and the first year through larger weights, by a factor of 5. Finally, given the importance of the residual variances to identify the joint distribution of comparative advantage, they also have larger weights in the loss function, in this case by a factor of 3.

We minimize \( Q(\Theta) \) using in each evaluation \( H \) different simulated samples each with size equal to the number of observations in the balanced panel \( (N \times T = 8760) \). For observables, we take in each simulated sample the same values we observe in the data. To choose \( H \), we numerically explore how \( Q(\Theta) \) varies in a fixed number of simulations only due to changes in the seed of the random numbers, as a function of the number of individuals. We found that the range of variation of \( Q(\Theta) \) starts to stabilize after we include 80000 individuals. Thus, we choose \( H = 40 \approx 80000/1752 \).

Optimizing \( Q(\Theta) \) is challenging since the discrete choices in the selection model create a non-smooth function, that behaves as a step function in some regions of the parameters’ space. To deal with this problem, we use an algorithm with repeated iterations of an evolutionary method, particularly particles-swarm optimization, to find the solution. We start with 16 implementations of

---

87 We use the approach to compute the solution on the sample generated by \( H \times N \times T \) observations, a method that is equivalent to compute the average of \( H \) times the solution of each sample of \( N \times T \) observations, although computationally it is more efficient.

88 Other possibilities recently developed in the literature include the use of a logistic-kernel of simulated latent utilities instead of endogenous variables (Bruins et al., 2018) or Monte Carlo importance sampling (Sauer and Taber, 2017). How-
particles-swarm optimization in a wide range of the feasible parameter space. In each of these 16 implementations we work with 96 particles, that initially are randomly and uniformly distributed. In a second stage, we perform 8 implementations of particles-swarm optimization in a range of the parameter space bounded by the smallest and largest solution for each parameter in the first stage, plus a parameter-dependent margin error. In this stage we use the same number and distribution for the initial particles. Finally we perform an additional optimization in which we initialize 8 of the 96 particles in the solutions found in the second stage. The estimate \( \hat{\Theta} \) is the solution that minimizes \( Q(\Theta) \) in the 25 implementations described of particles-swarm optimization. Using several numerical simulations we test that our algorithm ensures two-decimal accuracy in the solutions, as opposed to alternative optimization techniques.

### B.4 Identification

In this Appendix we demonstrate how parameters in \( \Theta \) are identified for the same model as in our baseline specification, but with only two periods and abstracting from the effect of observables in income. For illustrative purposes, we first show how identification is achieved in the frictionless economy, and next we proceed to the model with switching costs. We refer to the Agriculture sector as \( A \) and to the Non-Agriculture sector as \( N \). We denote \( r_t = r^A_N - r^A_t \), \( u^A_t = \theta^A_t + \varepsilon^A_t \) for \( s = A, N \) and \( \sigma^2_{ks} = \sigma^2_{kA} - \sigma^2_{kAN} \) for \( k = u, \theta \) and \( s = A, N \). Notice that \( \sigma^2_{us} = \sigma^2_{\theta s} + \sigma^2_{\varepsilon s} \) for \( s = A, N, AN \). Further, we denote the st. dev. of \( u_{it} \equiv (u^A_{it} - u^N_{it}) \) as \( \sigma^*_u = \sqrt{\hat{\sigma}^2_{uA} + \hat{\sigma}^2_{uN}} \) and the st. dev. of \( \theta_i \equiv (\theta^A_i - \theta^N_i) \) as \( \sigma^*_\theta = \sqrt{\hat{\sigma}^2_{\theta A} + \hat{\sigma}^2_{\theta N}} \).

#### Model for the frictionless economy

Without switching costs, sectoral decisions do not depend on workers’ histories, so the model behaves in each period \( t \) as the standard Roy model with comparative advantage \( u^A_t \), where, excluding the variance of measurement error, we can identify the variance matrix \( \Sigma_u \) and the prices of human capital \( r^s_t \) from cross-sectional data. This is consequence of the normality assumptions on the distribution of both \( (\theta^A_t, \theta^N_t) \) and \( (\varepsilon^A_t, \varepsilon^N_t) \), which imply that in each period \( (u^A_{it}, u^N_{it}) \) is joint normally distributed with variance \( \Sigma_u \), and hence standard arguments of Heckman and Honoré (1990) for identification in the normal case can be applied. However, only with panel data we can decompose \( \Sigma_u \) into \( \Sigma_{\theta} \) and \( \Sigma_{\varepsilon} \), the variances of the permanent and transitory components respectively, and identify \( \sigma^2_\gamma \), the variance of measurement error, using the information obtained from the switching workers in the panel.

Letting \( \lambda(\cdot) = \frac{\phi(\cdot)}{\Phi(\cdot)} \) with \( \phi \) and \( \Phi \) the PDF and CDF of a standard normal, and using properties of normal random variables following Heckman and Honoré (1990), we can obtain the following

---

ever, the possibility to use those techniques is model-dependent. As we argue next, our algorithm does not face problems to find an accurate solution.
derivations for the first three observed moments of the income distribution in each period $t$:

$$P(t = N) = \Phi \left( \frac{r_t}{\sigma_u^2} \right) \quad \text{(B.1)}$$

$$E \left( y_a^N | t = N \right) = r_t^N + \frac{\sigma_{aN}^2}{\sigma_u^2} \lambda \left( \frac{r_t}{\sigma_u^2} \right) \quad \text{(B.2)}$$

$$E \left( y_a^A | t = A \right) = r_t^A + \frac{\sigma_{aA}^2}{\sigma_u^2} \lambda \left( \frac{-r_t}{\sigma_u^2} \right) \quad \text{(B.3)}$$

$$\text{Var} \left( y_a^N | t = N \right) = \sigma_{aN}^2 + \left( \frac{\sigma_{aN}^2}{\sigma_u^2} \right) \lambda \left( \frac{r_t}{\sigma_u^2} \right) \lambda \left( \frac{-r_t}{\sigma_u^2} \right) \quad \text{(B.4)}$$

$$\text{Var} \left( y_a^A | t = A \right) = \sigma_{aA}^2 + \left( \frac{\sigma_{aA}^2}{\sigma_u^2} \right) \lambda \left( \frac{-r_t}{\sigma_u^2} \right) \lambda \left( \frac{-r_t}{\sigma_u^2} \right) \quad \text{(B.5)}$$

$$E \left( \left[ y_a^N - E \left( y_a^N | t = N \right) \right]^3 | t = N \right) = \left( \frac{\sigma_{aN}^2}{\sigma_u^2} \right) \left[ 3 \left( \frac{r_t}{\sigma_u^2} \right) 2 \lambda \left( \frac{r_t}{\sigma_u^2} \right) + 3 \lambda \left( \frac{r_t}{\sigma_u^2} \right) \left( \frac{r_t}{\sigma_u^2} \right) \right] - 1 \quad \text{(B.6)}$$

$$E \left( \left[ y_a^A - E \left( y_a^N | t = A \right) \right]^3 | t = A \right) = \left( \frac{\sigma_{aA}^2}{\sigma_u^2} \right) \left[ 3 \left( \frac{-r_t}{\sigma_u^2} \right) 2 \lambda \left( \frac{-r_t}{\sigma_u^2} \right) - 3 \lambda \left( \frac{-r_t}{\sigma_u^2} \right) \left( \frac{r_t}{\sigma_u^2} \right) \right] - 1 \quad \text{(B.7)}$$

With information of $T = 2$ repeated cross sections to compute the LHS of this system of 14 equations, we can identify $r_t^N$, $r_t^A$ and the combination $\sigma_u^2 N_2 + \Sigma_u$ (8 parameters). Let us now show the additional information we can obtain from panel data. We exploit the property that $(u_{it}, u_{it'})$ for $t' \neq t$ and $(u_{it}, u_{it})$ for $s = A, N$ are jointly normally distributed, since each element is the sum of two normally distributed random variables. Denoting the CDF of a bivariate normal distribution with mean $\theta'$ and variance $\Sigma$ evaluated at the vector $A$ as $\Phi(A, \Sigma)$, the probability of transition from $N$ to $N$ is given by:

$$P(2 = N, 1 = N) = P \{ \{ r_2^N + u_{12}^N < r_2^N + u_{11}^N \}, \{ r_1^N + u_{11}^N < r_1^N + u_{11}^N \} \}$$

$$= P \{ \{ u_{12} < r_2 \}, \{ u_{11} < r_1 \} \}$$

$$= \Phi (\vec{r}_{NN}, \Sigma_T) \quad \text{(B.8)}$$

with $\vec{r}_{NN} = [r_2, r_1]'$ and $\Sigma_T = \begin{bmatrix} \sigma_u^2 & \sigma_\theta^2 \\ \sigma_\theta^2 & \sigma_u^2 \end{bmatrix}$. The probability of transition from $N$ to $A$ is given by:

$$P(2 = A, 1 = N) = P \{ \{ -u_{12} < -r_2 \}, \{ u_{11} < r_1 \} \}$$

$$= \Phi (\vec{r}_{NA}, \Sigma_W) \quad \text{(B.9)}$$

with $\vec{r}_{NA} = [-r_2, r_1]'$ and $\Sigma_W = \begin{bmatrix} \sigma_u^2 & -\sigma_\theta^2 \\ -\sigma_\theta^2 & \sigma_u^2 \end{bmatrix}$. Similarly:

$$P(2 = N, 1 = A) = \Phi (\vec{r}_{AN}, \Sigma_W) \quad \text{(B.10)}$$

$$P(2 = N, 2 = A) = \Phi (\vec{r}_{AA}, \Sigma_T) \quad \text{(B.11)}$$
with \( \mathbf{r}_{AN} = [r_2, -r_1]^\prime \) and \( \mathbf{r}_{AA} = [-r_2, -r_1]^\prime \).

Now consider the values of the expected income in the second period for each transition group of workers. In the frictionless economy we do not need directly those expected values, but we illustrate here how to compute them to introduce some notation that we use hereafter. The income of stayers in

\( N \) in period 2 is given by:

\[
E \left( Y_{i2}^N \mid 2 = N, 1 = N \right) = r_2^N + E \left( u_{i2}^N \mid 2 = N, 1 = N \right)
\]

\[
= r_2^N + E \left( u_{i2}^N \mid \{u_{i2} < r_2\}, \{u_{i1} < r_1\} \right)
\]

Notice that the expected value in the second term of the RHS can be expressed as:

\[
E \left( X_{i1}^k X_{i2}^k X_{i3}^k \mid -\infty < X_i < b_i, k = 1, 2, 3 \right) \tag{B.12}
\]

with \( X_1 = u_{i2}^N, X_2 = u_{i2}, X_3 = u_{i1}, k_1 = 1, k_2 = k_3 = 0, b_1 = \infty, b_2 = r_2 \) and \( b_3 = r_1 \). This expected value is the moment of the upper truncated multivariate normal distribution with mean \( \mathbf{0} \) and variance:

\[
\Sigma_{NN} = \begin{bmatrix}
\sigma_{iN}^2 & -\sigma_{iN}^2 & -\sigma_{iN}^2 \\
-\sigma_{iN}^2 & \sigma_{iN}^2 & \sigma_{iN}^2 \\
-\sigma_{iN}^2 & \sigma_{iN}^2 & \sigma_{iN}^2
\end{bmatrix}
= \begin{bmatrix}
\Lambda_{NN} \\
\Lambda_{NN} \\
\Lambda_{NN}
\end{bmatrix}
\]

where the vector \( \Lambda_{NN} \) is defined as \( \Lambda_{NN} = [-\sigma_{iN}^2, -\sigma_{iN}^2] \). In general terms, we can denote the expected value in (B.12) for the particular case \( k_2 = k_3 = 0 \) and \( b_1 = \infty \) as the function \( M_3(\cdot) \) of the variance matrix \( \Sigma \), the elements \( b_2 \) and \( b_3 \) stacked up in a vector \( B \) and the coefficient \( k = k_1 \), that is:

\[
M_3(B, \Sigma, k) \equiv E \left( X_{i1}^k \mid -\infty < X_1 < \infty, -\infty < X_2 < B_1, -\infty < X_3 < B_2 \right)
\]

with \( \{X_1, X_2, X_3\} \sim N(\mathbf{0}, \Sigma) \). Then we can rewrite:

\[
E \left( Y_{i2}^N \mid 2 = N, 1 = N \right) = r_2^N + M_3(\mathbf{r}_{NN}, \Sigma_{NN}, 1)
\]

To evaluate \( M_3(\cdot) \) we can use for example the recurrence relations developed by Kan and Robotti (2017) to compute numerically the moment generating function of the truncated multivariate normal distribution (first obtained by Tallis (1961))\(^{89}\). Following similar arguments, we can show that the income of each transition group in period 2 is given by:

\[
E \left( Y_{i2}^N \mid 2 = N, 1 = N \right) = r_2^A + M_3(\mathbf{r}_{NA}, \Sigma_{NA}, 1)
\]

\[
E \left( Y_{i2}^N \mid 2 = N, 1 = A \right) = r_2^N + M_3(\mathbf{r}_{AN}, \Sigma_{AN}, 1)
\]

\[
E \left( Y_{i2}^A \mid 2 = A, 1 = A \right) = r_2^A + M_3(\mathbf{r}_{AA}, \Sigma_{AA}, 1)
\]

\(^{89}\) Particularly, we can use the function multivatmom developed by Kan and Robotti (2017) in the Matlab package ftnorm. The instruction to compute \( M_3(B, \Sigma, k) \) is simply multivatmom([k 0 0], [inf B_1 B_2], [0 0 0], \Sigma).
B.4. Identification

with \( \Sigma_{NA} = \begin{bmatrix} \sigma_{NA}^2 & \Lambda_{NA} \\ \Lambda_{NA}^T & \Sigma_W \end{bmatrix} \), \( \Sigma_{AN} = \begin{bmatrix} \sigma_{AN}^2 & \Lambda_{AN} \\ \Lambda_{AN}^T & \Sigma_W \end{bmatrix} \) and \( \Sigma_{AA} = \begin{bmatrix} \sigma_{AA}^2 & \Lambda_{AA} \\ \Lambda_{AA}^T & \Sigma_T \end{bmatrix} \) where \( \Lambda_{NA} = [\sigma_{\theta A}^2, \sigma_{\theta A}^2] \), \( \Lambda_{AN} = [\sigma_{\theta A}^2, \sigma_{\theta A}^2] \) and \( \Lambda_{AA} = [-\sigma_{\theta A}^2, -\sigma_{\theta A}^2] \). Notice that the second and third moments of each transition group can be computed as functions of \( M_3(\cdot, \cdot, 2) \) and \( M_3(\cdot, \cdot, 3) \) respectively. We do not need those expressions here, so we deduce those moments only for the model with switching costs.

Now let us compute the moments of the growth in income for switchers. For switching workers from \( A \) to \( N \), the first moment is:

\[
E \left( y_{12}^N - y_{11}^A | 2 = N, 1 = A \right) = r_2^N - r_1^N + E \left( u_{12}^N - u_{11}^A | 2 = N, 1 = A \right) \\
= r_2^N - r_1^N + E \left( u_{12}^N - u_{11}^A | \{u_{12} < r_2\}, \{-u_{11} < -r_1\} \right) \\
= r_2^N - r_1^N + \Sigma_3(\delta_{AN}, \delta_{NA}, 1) \tag{B.13}
\]

with \( \delta_{AN} = \begin{bmatrix} \sigma_{\theta A}^2 + \sigma_{\theta A}^2 - 2\sigma_{\theta AN} \\ \Lambda_{AN} \end{bmatrix} \) and \( \delta_{NA} = [-\sigma_{\theta A}^2, -\sigma_{\theta A}^2, \sigma_{\theta A}^2 + \sigma_{\theta A}^2] \). Similarly, the expected value of the growth in income for switchers from \( N \) to \( A \) is:

\[
E \left( y_{12}^N - y_{11}^A | 2 = A, 1 = N \right) = r_2^N - r_1^N + \Sigma_3(\delta_{NA}, \delta_{AN}, 1) \tag{B.14}
\]

where \( \delta_{NA} = \begin{bmatrix} \sigma_{\theta A}^2 + \sigma_{\theta A}^2 - 2\sigma_{\theta AN} \\ \Lambda_{NA} \end{bmatrix} \) and \( \delta_{AN} = [-\sigma_{\theta A}^2, -\sigma_{\theta A}^2, \sigma_{\theta A}^2 + \sigma_{\theta A}^2] \). The variances of the growth in income for switchers are defined as:

\[
Var \left( y_{12}^N - y_{11}^A | 2 = N, 1 = A \right) = E \left( (u_{12}^N - u_{11}^A)^2 | \{u_{12} < r_2\}, \{-u_{11} < -r_1\} \right) - E \left( u_{12}^N - u_{11}^A | 2 = N, 1 = A \right)^2 + 2\sigma_\nu^2 \\
= \Sigma_3(\delta_{AN}, \delta_{NA}, 2) + (\Sigma_3(\delta_{AN}, \delta_{NA}, 1))^2 + 2\sigma_\nu^2 \tag{B.15}
\]

And similarly:

\[
Var \left( y_{12}^N - y_{11}^A | 2 = A, 1 = N \right) = \Sigma_3(\delta_{NA}, \delta_{AN}, 2) + (\Sigma_3(\delta_{NA}, \delta_{AN}, 1))^2 + 2\sigma_\nu^2 \tag{B.16}
\]

The system of 22 equations (B.1)-(B.11) and (B.13)-(B.16) has a unique solution for the 10 elements of \( \Theta \). We verified this after extensive experimentation using global solvers over a broad range of feasible values for \( \Theta \). This shows that the cross-sectional moments, the transition probabilities across waves for each group of workers and the two first moments of the income growth for switchers are enough moments to identify the full set of parameters.

Model with switching costs across sectors

In the model with switching costs, we will require exactly the same set of 22 moments computed above to identify the 12 elements of \( \Theta \). The difficulty to obtain expressions for those moments relies
on the fact that sectoral decisions depend now on workers’ histories, and hence all moments, including the cross-sectional ones, depend on the income distributions of the previous periods. We deduce here the general rules to deduce expressions for those moments. Denote the CDF of a multivariate normal distribution with mean $\mathbf{0}'$ and variance $\Sigma$ evaluated at the vector $A$ as $\Phi(A, \Sigma)$. To compute the cross sectional moments in period 1, we need first the distribution of sectoral choices, that depend on the frictionless decisions in period zero. The probability of choosing non-agriculture in period 1 is:

$$ P(1 = N) = P(1 = N, 0 = A) + P(1 = N, 0 = N) $$

$$ = P\left( \{ r_1^A + u_{i1}^A < r_1^N + u_{i1}^N \ln \phi^{AN} \} \right. + P\left( \{ r_1^A + u_{i1}^A - \ln \phi^{NA} < r_1^N + u_{i1}^N \} \right)$$

$$ = P\left( \{ u_{i1} < r_1 - \ln \phi^{AN} \} \right) + P\left( \{ u_{i1} < r_1 + \ln \phi^{NA} \} \right) $$

$$ = \Phi(\tilde{r}_{AN}, \Sigma_W) + \Phi(\tilde{r}_{NN}, \Sigma_T) $$

where now: $\tilde{r}_{AN} = [r_1 - \ln \phi^{AN}, -r_0]'$, $\tilde{r}_{NN} = [r_1 + \ln \phi^{NA}, r_0]'$ and $\Sigma_W$ and $\Sigma_T$ as in the model without switching costs. The values of the expected income in $N$ the first period are:

$$ E(\gamma_{i1}^N | 1 = N) $$

$$ = r_1^N + E(u_{i1}^N | 1 = N) $$

$$ = r_1^N + \frac{E(u_{i1}^N | 1 = N, 0 = A) P(1 = N, 0 = A) E(u_{i1}^N | 1 = N, 0 = N) P(1 = N, 0 = N)}{P(1 = N)} $$

$$ = r_1^N + \frac{M_3(\tilde{r}_{AN}, \Sigma_{AN}, 1) \Phi(\tilde{r}_{AN}, \Sigma_W) + M_3(\tilde{r}_{NN}, \Sigma_{NN}, 1) \Phi(\tilde{r}_{NN}, \Sigma_T)}{\Phi(\tilde{r}_{AN}, \Sigma_W) + \Phi(\tilde{r}_{NN}, \Sigma_T)} $$

with $M_3(\cdot)$, $\Sigma_{AN}$, $\Sigma_{NN}$ as in the model without switching costs. Similarly:

$$ E(\gamma_{i1}^A | 1 = A) = r_1^A + \frac{M_3(\tilde{r}_{AA}, \Sigma_{AA}, 1) \Phi(\tilde{r}_{AA}, \Sigma_T) + M_3(\tilde{r}_{NA}, \Sigma_{NA}, 1) \Phi(\tilde{r}_{NN}, \Sigma_T)}{\Phi(\tilde{r}_{AA}, \Sigma_T) + \Phi(\tilde{r}_{NA}, \Sigma_W)} $$

where $\tilde{r}_{AA} = [-r_1 + \ln \phi^{AN}, -r_0]'$, $\tilde{r}_{NA} = [-r_1 - \ln \phi^{NA}, r_0]'$ and $\Sigma_{AA}$, $\Sigma_{NA}$ as in the model without switching costs.

The variances can be computed simply by:

$$ Var(\gamma_{i1}^N | 1 = N) $$

$$ = \frac{M_3(\tilde{r}_{AN}, \Sigma_{AN}, 2) \Phi(\tilde{r}_{AN}, \Sigma_W) + M_3(\tilde{r}_{NN}, \Sigma_{NN}, 2) \Phi(\tilde{r}_{NN}, \Sigma_T)}{\Phi(\tilde{r}_{AN}, \Sigma_W) + \Phi(\tilde{r}_{NN}, \Sigma_T)} - E(u_{i1}^N | 1 = N)^2 + \sigma_\mu^2 $$

$$ Var(\gamma_{i1}^A | 1 = A) $$

$$ = \frac{M_3(\tilde{r}_{AA}, \Sigma_{AA}, 2) \Phi(\tilde{r}_{AA}, \Sigma_T) + M_3(\tilde{r}_{NA}, \Sigma_{NA}, 2) \Phi(\tilde{r}_{NN}, \Sigma_T)}{\Phi(\tilde{r}_{AA}, \Sigma_T) + \Phi(\tilde{r}_{NA}, \Sigma_W)} - E(u_{i1}^A | 1 = A)^2 + \sigma_\mu^2 $$

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B.4. Identification

The third central moments are computed as:

\[
E \left( \left[ y_{N}^{N} - E \left( y_{N}^{N} \mid 1 = N \right) \right]^3 \mid 1 = N \right) \\
= \frac{M_3(\overrightarrow{r}_{AN}, \Sigma_{AN}, 3) \Phi(\overrightarrow{r}_{AN}, \Sigma_W) + M_3(\overrightarrow{r}_{NN}, \Sigma_{NN}, 3) \Phi(\overrightarrow{r}_{NN}, \Sigma_T)}{\Phi(\overrightarrow{r}_{AN}, \Sigma_W) + \Phi(\overrightarrow{r}_{NN}, \Sigma_T)} \\
- 3E \left( u_{N}^{N} \mid 1 = N \right) \left[ \text{Var} \left( y_{N}^{N} \mid 1 = N \right) - \sigma_u^2 \right] - \left[ E \left( u_{N}^{N} \mid 1 = N \right) \right]^3 \\
E \left( \left[ y_{N}^{N} - E \left( y_{N}^{N} \mid 1 = N \right) \right]^3 \mid 1 = N \right)
\]

Now let examine the cross sectional moments for period 2. To compute the probability of being in a sector, we need to know the probability of occurrence of all possible paths that an individual can exhibit before choosing a given sector\(^90\). This is, \(P(2 = N) = P(2 = N, 1 = N) + P(2 = N, 1 = A)\) where in turn the probability of transition from \(N\) to \(N\) is given by:

\[
P(2 = N, 1 = N) = P(2 = N, 1 = N, 0 = A) + P(2 = N, 1 = N, 0 = N) \\
= P(\{u_{t2} < r_2 + \ln \phi^{NA}\}, \{u_{t1} < r_1 - \ln \phi^{AN}\}, \{-u_{t0} < -r_0\}) \\
+ P(\{u_{t2} < r_2 + \ln \phi^{NA}\}, \{u_{t1} < r_1 + \ln \phi^{NA}\}, \{u_{t0} < r_0\}) \\
= \Phi(\overrightarrow{r}_{ANN}, \Sigma_{WT}) + \Phi(\overrightarrow{r}_{NNN}, \Sigma_{TT})
\]

with: \(\overrightarrow{r}_{ANN} = [r_2 + \ln \phi^{NA}, \overrightarrow{r}_{AN}]', \overrightarrow{r}_{NNN} = [r_2 + \ln \phi^{NA}, \overrightarrow{r}_{NN}]'\) and:

\[
\Sigma_{WT} = \begin{bmatrix}
\sigma_u^2 & \sigma_\theta^2 & -\sigma_\theta^2 \\
\sigma_\theta^2 & \sigma_u^2 & -\sigma_\theta^2 \\
-\sigma_\theta^2 & -\sigma_\theta^2 & \sigma_u^2
\end{bmatrix}, \Sigma_{TT} = \begin{bmatrix}
\sigma_u^2 & \sigma_\theta^2 & \sigma_\theta^2 \\
\sigma_\theta^2 & \sigma_u^2 & \sigma_\theta^2 \\
\sigma_\theta^2 & \sigma_\theta^2 & \sigma_u^2
\end{bmatrix}
\]

Following similar arguments, we can show that the remaining probabilities of transition can be expressed as:

\[
P(2 = A, 1 = N) = \Phi(\overrightarrow{r}_{ANA}, \Sigma_{WW}) + \Phi(\overrightarrow{r}_{NNA}, \Sigma_{TW}) \\
P(2 = A, 1 = A) = \Phi(\overrightarrow{r}_{AAA}, \Sigma_{TT}) + \Phi(\overrightarrow{r}_{NAA}, \Sigma_{WT}) \\
P(2 = N, 1 = A) = \Phi(\overrightarrow{r}_{AAN}, \Sigma_{TW}) + \Phi(\overrightarrow{r}_{NAN}, \Sigma_{WW})
\]

with: \(\overrightarrow{r}_{ANA} = [-r_2 - \ln \phi^{NA}, \overrightarrow{r}_{AN}]', \overrightarrow{r}_{NNA} = [-r_2 - \ln \phi^{NA}, \overrightarrow{r}_{NN}]'\).

\(^{90}\)Unfortunately, we cannot use Bayes’ rule to derive the expressions of the joint probability from the marginals, since for the latter ones there is no closed form solution.
\[ \overrightarrow{\theta}_{AAA} = [-r_2 + \ln \phi^{AN}, \overrightarrow{\theta}_{AA}]', \overrightarrow{\theta}_{NAA} = [-r_2 + \ln \phi^{AN}, \overrightarrow{\theta}_{NA}]', \overrightarrow{\theta}_{NAN} = [r_2 - \ln \phi^{AN}, \overrightarrow{\theta}_{AN}]' \] and:

\[
\Sigma_{WW} = \begin{bmatrix}
\sigma^2_u & -\sigma^2_\theta & \sigma^2_\theta \\
-\sigma^2_\theta & \sigma^2_u & -\sigma^2_\theta \\
\sigma^2_\theta & -\sigma^2_\theta & \sigma^2_u
\end{bmatrix}, \Sigma_{TW} = \begin{bmatrix}
\sigma^2_u & -\sigma^2_\theta & -\sigma^2_\theta \\
-\sigma^2_\theta & \sigma^2_u & \sigma^2_\theta \\
-\sigma^2_\theta & \sigma^2_\theta & \sigma^2_u
\end{bmatrix}
\]

Now consider the values of the expected income in the second period. Again, we need to know the expected income for each transition group. The income of stayers in \( N \) in period 2 is given by:

\[
E \left( y^N_2 \mid 2 = N, 1 = N \right) = r^N_2 + E \left( u^N_2 \mid 2 = N, 1 = N \right)
\]

Similarly, consider the moment \( E \left( x^k_i k_1 x^k_2 x^k_3 x^k_4 \mid -\infty < X_i < b_i, i = 1, 2, 3, 4 \right) \) of the upper truncated multivariate normal distribution \( N(0, \Sigma) \) with \( k_2 = k_3 = k_4 = 0 \) and \( b_1 = \infty \) as a function \( M_4(B, \Sigma, k) \) of the variance \( \Sigma \), the elements \( b_2, b_3 \) and \( b_4 \) stacked up in a vector \( B \) and the coefficient \( k = k_1 \) that is:

\[
M_4(B, \Sigma, k) \equiv E \left( X^k_1 \mid -\infty < X_1 < -\infty, X_2 < B_1, -\infty < X_3 < B_2, -\infty < X_4 < B_3 \right)
\]

So we can express:

\[
E \left( y^A_2 \mid 2 = A, 1 = N \right) = r^A_2 + \frac{M_4(\overrightarrow{\theta}_{AN}, \Sigma_{AN}, 1) \Phi(\overrightarrow{\theta}_{AN}, \Sigma_{WT}) + M_4(\overrightarrow{\theta}_{NN}, \Sigma_{NN}, 1) \Phi(\overrightarrow{\theta}_{NN}, \Sigma_{TT})}{\Phi(\overrightarrow{\theta}_{AN}, \Sigma_{WT}) + \Phi(\overrightarrow{\theta}_{NN}, \Sigma_{TT})}
\]

with: \( \Sigma_{NNN} = \begin{bmatrix}
\sigma^2_u & \Lambda_{NN} \\
\Lambda_{NN}' & \Sigma_{TT}
\end{bmatrix} \) and \( \Sigma_{ANN} = \begin{bmatrix}
\sigma^2_u & \Lambda_{AN} \\
\Lambda_{AN}' & \Sigma_{WT}
\end{bmatrix} \), where \( \Lambda_{NNN} = [-\sigma^2_u, -\sigma^2_\theta, -\sigma^2_\theta] \) and \( \Lambda_{ANN} = [-\sigma^2_u, -\sigma^2_\theta, -\sigma^2_\theta] \). Similarly, the expected incomes in period 2 for the remaining groups are:

\[
E \left( y^A_2 \mid 2 = A, 1 = A \right) = r^A_2 + \frac{M_4(\overrightarrow{\theta}_{AA}, \Sigma_{AA}, 1) \Phi(\overrightarrow{\theta}_{AA}, \Sigma_{WT}) + M_4(\overrightarrow{\theta}_{NA}, \Sigma_{NA}, 1) \Phi(\overrightarrow{\theta}_{NA}, \Sigma_{TT})}{\Phi(\overrightarrow{\theta}_{AA}, \Sigma_{WT}) + \Phi(\overrightarrow{\theta}_{NA}, \Sigma_{TT})}
\]
\[ E \left( y_{12}^N \right) = N, 1 = A \]
\[ = r_2^N + \frac{\mathbf{M}_4(\mathbf{\tilde{r}}_{AAN}, \Sigma_{AAN}, 1) \Phi(\mathbf{\tilde{r}}_{AAN}, \Sigma_{TW}) + \mathbf{M}_4(\mathbf{\tilde{r}}_{NAN}, \Sigma_{NAN}, 1) \Phi(\mathbf{\tilde{r}}_{NAN}, \Sigma_{WW})}{\Phi(\mathbf{\tilde{r}}_{AAN}, \Sigma_{TW}) + \Phi(\mathbf{\tilde{r}}_{NAN}, \Sigma_{WW})} \]

with:

\[ \Sigma_{ANA} = \begin{bmatrix} \sigma_{uA}^2 & \Lambda_{ANA} \\ \Lambda_{ANA}' & \Sigma_{WW} \end{bmatrix}, \quad \Sigma_{NNA} = \begin{bmatrix} \sigma_{uA}^2 & \Lambda_{NNA} \\ \Lambda_{NNA}' & \Sigma_{TW} \end{bmatrix}, \quad \Sigma_{AAA} = \begin{bmatrix} \sigma_{uA}^2 & \Lambda_{AAA} \\ \Lambda_{AAA}' & \Sigma_{TT} \end{bmatrix} \]
\[ \Sigma_{NAA} = \begin{bmatrix} \sigma_{uA}^2 & \Lambda_{NAA} \\ \Lambda_{NAA}' & \Sigma_{WT} \end{bmatrix}, \quad \Sigma_{AAN} = \begin{bmatrix} \sigma_{uA}^2 & \Lambda_{AAN} \\ \Lambda_{AAN}' & \Sigma_{TW} \end{bmatrix}, \quad \Sigma_{NAN} = \begin{bmatrix} \sigma_{uA}^2 & \Lambda_{NAN} \\ \Lambda_{NAN}' & \Sigma_{WW} \end{bmatrix} \]

where \( \Lambda_{ANA} = [-\hat{\sigma}_{uA}^2, \hat{\sigma}_{BA}^2, -\hat{\sigma}_{BA}^2], \Lambda_{NNA} = [-\hat{\sigma}_{uA}^2, \hat{\sigma}_{BA}^2, \hat{\sigma}_{BA}^2], \Lambda_{AAA} = [-\hat{\sigma}_{uA}^2, -\hat{\sigma}_{BA}^2, -\hat{\sigma}_{BA}^2], \Lambda_{NAA} = [-\hat{\sigma}_{uA}^2, -\hat{\sigma}_{BA}^2, \hat{\sigma}_{BA}^2], \Lambda_{AAN} = [-\hat{\sigma}_{uA}^2, \hat{\sigma}_{BA}^2, \hat{\sigma}_{BA}^2], \Lambda_{NAN} = [-\hat{\sigma}_{uA}^2, \hat{\sigma}_{BA}^2, -\hat{\sigma}_{BA}^2]. \) Combining the last three equations with the probabilities of transition into each sector, it is straightforward to derive the first moments of the cross-sectional distribution of earnings in period 2. The second and third moments can be derived as in period 1, as functions of \( \mathbf{M}_4(\cdot, \cdot, 2) \) and \( \mathbf{M}_4(\cdot, \cdot, 3) \) respectively.

Finally consider the growth in income for switchers from \( A \) to \( N \), that is:

\[ E \left( y_{12}^N - y_{11}^A \right) | 2 = N, 1 = A \]
\[ = r_2^N - r_1^A + E \left( u_{12}^N - u_{11}^A | 2 = N, 1 = A \right) \]
\[ = r_2^N - r_1^A + \left[ E \left( u_{12}^N - u_{11}^A | 2 = N, 1 = A, 0 = A \right) P(2 = N, 1 = A, 0 = A) \right. \]
\[ + \left. E \left( u_{12}^N - u_{11}^A | 2 = N, 1 = A, 0 = N \right) P(2 = N, 1 = A, 0 = N) \right] / P(2 = N, 1 = A) \]

The unknown terms are those that involved expected values, that can be obtained from \( \mathbf{M}_4(\mathbf{\tilde{r}}_{AAN}, \bar{\Sigma}_{AAN}, 1) \) and \( \mathbf{M}_4(\mathbf{\tilde{r}}_{NAN}, \bar{\Sigma}_{NAN}, 1) \) respectively, with:

\[ \Sigma_{AAN} = \begin{bmatrix} \sigma_{uA}^2 + \sigma_{2N}^2 - 2\sigma_{BAN} & \bar{\Lambda}_{AAN} \\ \bar{\Lambda}_{AAN}' & \Sigma_{TW} \end{bmatrix}, \quad \Sigma_{NAN} = \begin{bmatrix} \sigma_{uA}^2 + \sigma_{2N}^2 - 2\sigma_{BAN} & \bar{\Lambda}_{NAN} \\ \bar{\Lambda}_{NAN}' & \Sigma_{WW} \end{bmatrix} \]

where:

\[ \bar{\Lambda}_{AAN} = [-\hat{\sigma}_{uA}^2 - \hat{\sigma}_{BA}^2, \hat{\sigma}_{BA}^2 + \hat{\sigma}_{BA}^2, \hat{\sigma}_{uA}^2 + \hat{\sigma}_{BA}^2], \quad \bar{\Lambda}_{NAN} = [-\hat{\sigma}_{uA}^2 - \hat{\sigma}_{BA}^2, \hat{\sigma}_{BA}^2 + \hat{\sigma}_{BA}^2, -\hat{\sigma}_{uA}^2 - \hat{\sigma}_{BA}^2] \]

The variance can be expressed in terms of \( \mathbf{M}_4(\mathbf{\tilde{r}}_{AAN}, \bar{\Sigma}_{AAN}, 2) \) and \( \mathbf{M}_4(\mathbf{\tilde{r}}_{AAN}, \bar{\Sigma}_{AAN}, 2) \), as in the frictionless case.

Similarly, for the growth in income for switchers from \( N \) to \( A \) we need expressions for:

\[ E \left( u_{12}^A - u_{11}^N | 2 = A, 1 = N, 0 = A \right) \]
\[ E \left( u_{12}^A - u_{11}^N | 2 = A, 1 = N, 0 = N \right) \]
that can be obtained from $\mathbf{M}_4(\overrightarrow{\rho}_{ANA}, \overline{\Sigma}_{ANA}, 1)$ and $\mathbf{M}_4(\overrightarrow{\rho}_{NNA}, \overline{\Sigma}_{NNA}, 1)$ respectively, with:

$$
\Sigma_{ANA} = \begin{bmatrix}
\sigma_{\theta u}^2 + \sigma_{\theta u}^2 - 2\sigma_{\theta u\theta u} & \Lambda_{ANA} \\
\Lambda_{ANA}' & \Sigma_{WW}
\end{bmatrix},
\Sigma_{NNA} = \begin{bmatrix}
\sigma_{\theta u}^2 + \sigma_{\theta u}^2 - 2\sigma_{\theta u\theta u} & \Lambda_{NNA} \\
\Lambda_{NNA}' & \Sigma_{TW}
\end{bmatrix}
$$

where:

$$
\Lambda_{ANA} = \begin{bmatrix}
-\tilde{\sigma}_{\theta u}^2 - \tilde{\sigma}_{\theta u}^2 + \tilde{\sigma}_{\theta u}^2 - \tilde{\sigma}_{\theta u}^2
\end{bmatrix};
\Lambda_{NNA} = \begin{bmatrix}
-\tilde{\sigma}_{\theta u}^2 - \tilde{\sigma}_{\theta u}^2 + \tilde{\sigma}_{\theta u}^2 + \tilde{\sigma}_{\theta u}^2
\end{bmatrix}
$$

The variance can be expressed in terms of $\mathbf{M}_4(\overrightarrow{\rho}_{ANA}, \overline{\Sigma}_{ANA}, 2)$ and $\mathbf{M}_4(\overrightarrow{\rho}_{NNA}, \overline{\Sigma}_{NNA}, 2)$. As in the frictionless case, we verified the system of 22 moments has a unique solution for the 12 elements of $\Theta$.

**B.5 Proofs**

**Proof of Proposition 1**

Under the assumptions of Proposition 1, the expression for expected log income growth of switchers to from agriculture to non-agriculture given in (B.13) simplifies to:

$$
E\left(y_{i2}^N - y_{i1}^N \mid 2 = N, 1 = A\right) = \mathbf{M}_3(\overrightarrow{\rho}, \overline{\Sigma}_{AN}, 1),
$$

and where $\overline{\Sigma}_{AN}$ can be simplified to

$$
\overline{\Sigma}_{AN} = \begin{bmatrix}
\sigma_{\theta u}^2 + \sigma_{\theta u}^2 + \sigma_{\theta u}^2 & -\left(\sigma_{\theta u}^2 + \sigma_{\theta u}^2\right) & \sigma_{\theta u}^2 + \sigma_{\theta u}^2 \\
-\left(\sigma_{\theta u}^2 + \sigma_{\theta u}^2\right) & \sigma_{\theta u}^2 + \sigma_{\theta u}^2 + \sigma_{\theta u}^2 & -\sigma_{\theta u}^2 \\
\sigma_{\theta u}^2 & -\sigma_{\theta u}^2 & \sigma_{\theta u}^2 + \sigma_{\theta u}^2 + \sigma_{\theta u}^2
\end{bmatrix}.
$$

Re-write $\overline{\Sigma}_{AN}$ in terms of the correlation matrix $\mathbf{C}_{AN}$:

$$
\mathbf{C}_{AN} = \begin{bmatrix}
1 & \frac{-\left(\sigma_{\theta u}^2 + \sigma_{\theta u}^2\right)}{\sigma_{\theta u}^2 + \sigma_{\theta u}^2 + \sigma_{\theta u}^2} & \frac{\sigma_{\theta u}^2 + \sigma_{\theta u}^2}{\sigma_{\theta u}^2 + \sigma_{\theta u}^2 + \sigma_{\theta u}^2} \\
\frac{-\left(\sigma_{\theta u}^2 + \sigma_{\theta u}^2\right)}{\sigma_{\theta u}^2 + \sigma_{\theta u}^2 + \sigma_{\theta u}^2} & 1 & \frac{-\sigma_{\theta u}^2}{\sigma_{\theta u}^2 + \sigma_{\theta u}^2 + \sigma_{\theta u}^2} \\
\frac{\sigma_{\theta u}^2}{\sigma_{\theta u}^2 + \sigma_{\theta u}^2 + \sigma_{\theta u}^2} & \frac{-\sigma_{\theta u}^2}{\sigma_{\theta u}^2 + \sigma_{\theta u}^2 + \sigma_{\theta u}^2} & 1
\end{bmatrix}
$$

and denote $\rho_{ij}^{AN}$ the $(i, j)$ element of $\mathbf{C}_{AN}$. Using our definition of $\mathbf{M}_3(\cdot)$ and explicit formulas for the moments of the upper-truncated multivariate normal distribution in the trivariate case (derived from recurrence relations) from Kan and Robotti (2017), $\mathbf{M}_3(\overrightarrow{\rho}, \overline{\Sigma}_{AN}, 1)$ can be re-written as:

$$
\mathbf{M}_3(\overrightarrow{\rho}, \overline{\Sigma}_{AN}, 1) = -\sqrt{\sigma_{\theta u}^2 + \sigma_{\theta u}^2 + \sigma_{\theta u}^2} \begin{bmatrix}
\rho_{12}^{AN} \Phi_2(\infty, 0; \rho_{13}^{AN}) \\
\rho_{13}^{AN} \Phi_2(\infty, 0; \rho_{12}^{AN}) \\
\rho_{12}^{AN} \Phi_3(\infty, 0; \rho_{13}^{AN}) + \rho_{13}^{AN} \Phi_3(\infty, 0; \rho_{12}^{AN})
\end{bmatrix}
$$
with \( \rho_{ij}^{AN} = \frac{\rho_{ij}^{AN} - \rho_{ik}^{AN} \rho_{jk}^{AN}}{\sqrt{\left(1 - \rho_{ik}^{AN}\right)^2 \left(1 - \rho_{jk}^{AN}\right)^2}} \). Noticing that in our case \( \Phi_2 \left([\infty, 0] ; \rho_{ij}^{AN}\right) = \frac{1}{2} \forall i, j, k \), we have

\[
M_3(\overrightarrow{0}, \mathcal{S}_{AN}, 1) = \frac{\phi(0) \left(\sigma_{EN}^2 - \sigma_{EA}^2\right)}{2\sqrt{\sigma_{\theta}^2 + \sigma_{EA}^2 + \sigma_{EN}^2 \Phi_3([\infty, 0, 0] ; C_{AN})}},
\]

which is positive if and only if \( \sigma_{EN}^2 > \sigma_{EA}^2 \). Following the same steps we find the expected log income growth of switchers to from non–agriculture to agriculture as:

\[
M_3(\overrightarrow{0}, \mathcal{S}_{NA}, 1) = -\frac{\phi(0) \left(\sigma_{EN}^2 - \sigma_{EA}^2\right)}{2\sqrt{\sigma_{\theta}^2 + \sigma_{EA}^2 + \sigma_{EN}^2 \Phi_3([\infty, 0, 0] ; C_{NA})}},
\]

Furthermore, it can be verified that \( \Phi_3 ([\infty, 0, 0] ; C_{NA}) = \Phi_3 ([\infty, 0, 0] ; C_{AN}) \), which implies that \( M_3(\overrightarrow{0}, \mathcal{S}_{AN}, 1) \) and \( M_3(\overrightarrow{0}, \mathcal{S}_{NA}, 1) \) have the opposite sign but the same magnitude. QED.
Appendix C

Appendix to Chapter 3

C.1 Additional figures

Figure C.1: Inter-sectoral gains and GDP per capita: Alternative specifications

Note: Averages 1994-2007. Data source: WIOD (Timmer et al., 2015), World Bank Development Indicators
C.2 CES aggregator across sectors

With a CES aggregator of the form \( Y^\phi = \sum_s \beta_s Y_s^\phi \), where \( \phi = \frac{\phi - 1}{\phi} \) and \( \phi \) is the elasticity of substitution across sectors, the sectoral factor demand is now:

\[
Z_{ls} = \frac{\alpha_{ls} \beta_s^\phi p_s^{1-\phi} / \bar{\xi}_{ls}}{\sum_s \alpha_{ls} \beta_s^\phi p_s^{1-\phi} / \bar{\xi}_{ls}} \tag{C.1}
\]

Thus, in the efficient inter-industry allocation, not only factor intensities and revenue shares play a role, but also the efficient sectoral price indexes as indicators of productivity. The direction and strength of their influence depends on the magnitude of \( \phi \). For \( \phi > 1 \) (\( \phi < 1 \)), if factor intensities and shares of sectoral revenue are constant across sectors, factors should be allocated to more (less) productive sectors. The interaction of these three sectoral forces (factor intensities, revenue shares and aggregate productivities) is what determines the efficient inter-sectoral allocation. Notice that to find \( \bar{Z}_{ls} \) it is necessary to solve for \( \bar{P}_s \), which implies to find firm’s output prices in the efficient allocation. These prices can be obtained by solving the non-linear system that includes all firm-level prices, through numerical algorithms. Once \( \bar{Z}_{ls} \) are obtained, it is simple to calculate both components, using the counterfactual aggregate output generated by \( \bar{A}_s \) and \( Z_{ls} \). The variation between current output and this counterfactual represent the intra-sectoral gains, whereas the difference between this counterfactual and the allocative efficient aggregate output represents the inter-sectoral gains:

\[
Gains_{\text{intra}} = 100\left(\frac{\sum_s \bar{A}_s \bar{Z}_{ls} \alpha_{ls}^\phi}{\sum_s \bar{A}_s \bar{Z}_{ls} \alpha_{ls}^\phi} \right)^{\frac{1}{\phi}} - 1; \quad Gains_{\text{inter}} = 100\left(\frac{\sum_s \bar{A}_s \bar{Z}_{ls} \alpha_{ls}^\phi}{\sum_s \bar{A}_s \bar{Z}_{ls} \alpha_{ls}^\phi} \right)^{\frac{1}{\phi}} - 1
\]

Total gains can be calculated in the same way as in (3.11).