Talent Misallocation across Countries: Evidence from Educational Achievement Tests

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November 14, 2023

Abstract

Despite growing evidence on occupational and educational barriers in developing countries, there are few estimates of their effect on the aggregate productivity. This paper measures the magnitude of these barriers and their impact on aggregate productivity using the data on expected occupational choice of students. First, I document striking differences in the impact of students' academic skills on occupational choice across countries. In most developing countries academic skills of students have relatively little effect on skill intensity or earning potential of expected occupations. The observed lower sorting on skills suggests a higher incidence of occupational barriers in developing countries. Next, I evaluate the productivity costs of these sorting patterns by attributing them to latent occupational barriers and calibrate a model of occupational choice based on the Roy (1951) framework. I calibrate the model by combining the data skills and expected occupations from the PISA database with the data from nationally-representative samples of working adults. I find that occupational barriers are particularly high in developing countries in my sample and that their elimination can increase the aggregate output by up to twenty five percent.

JEL Classification: J24, J71, O11, O47, E24

Keywords: talent misallocation, discrimination, human capital, aggregate productivity, skill premium

* Department of Economics, University of Arkansas (e-mail: augarov@uark.edu). I am grateful to my adviser Arya Gaduh, as well as Robert Costrell, Gary Ferrier, Dongya Koh and participants of 2019 SED Meeting, 2018 AEA Meeting and 2017 Midwest Economics Association Meeting for comments and suggestions. All errors are my own. * Declarations of interest: none.

1 Introduction

Workers are not always optimally assigned to jobs, because other factors besides skills and preferences affect job assignment. For example, La Porta et al (1999) find that private firms are very often led by the relatives of owners, who use poor management practices (Bloom and van Reenen, 2007). Job referrals can also lower the quality of workers due to favoritism (Beamer and Magruder, 2012; Fafchamps and Moradu, 2015). Ethnic and caste discrimination can also lead to the mismatch between worker's skills, preferences and jobs (Banerjee and Knight, 1985; Hnatkovska et al, 2012). As evident from these examples, the talent misallocation can result both from the barriers faced by minorities as well as from more idiosyncratic and more latent barriers, resulting from favoritism and nepotism.

How large are these occupational barriers and how much do they affect the aggregate productivity? This paper measures the productivity losses resulting from both group-based and more latent occupational barriers, such as the differences in social connections or credit constraints in education. The losses resulting from these latent occupational barriers are harder to measure because we cannot attribute them to a particular group identifiable in statistics. Nevertheless, it is important to understand their magnitude in order to choose development policy priorities.

I find that the occupational barriers translate into sizable effects for the aggregate productivity. For example, Brazil can gain around 20-25% in aggregate output by reducing the barriers to the US level. This estimate results from a calibration of Roy model of occupational choice to the combination of Census data and data on cognitive skills and occupational choice of current high school students. The number includes both short-term gains of higher ability sorting across occupations and the potential effects of better sorting on physical and human capital accumulation.

The main piece of motivating evidence for this study comes from the Program of International Student Assessment (PISA). I find large cross-country differences in the relationship between academic skills in PISA and expected occupational choice. This difference in sorting is large enough that one has to apply around 90% random resorting of students between reported future occupations to move from the highest sorting level (Czech Republic) to the lowest sorting level in my sample (Costa Rica). The sorting patterns are consistent whether I consider a single-dimensional ability or a vector of academic and non-cognitive skills. In developing countries in my sample, academic skills tend to have a lower impact on occupational choice. Because we know about the large role of cognitive and academic skills in determining labor market outcomes in developed countries (Gould, 2002; Borghans et al, 2016), the difference in sorting patterns based on skills is highly suggestive of the presence of occupational barriers or differences in technology.

The first part of the paper describes two novel country-level measures of occupational sorting based on academic skills. These variables reflect the statistical dependency between students' skills and their expected occupations in PISA 2015 dataset. I show that the occupational sorting measures for students have a strong correlation with the occupational sorting measures for working adults.

In the second part of my paper, I construct and estimate the model of occupational choice to measure the productivity implications of observed differences in sorting patterns. The model is based on the Roy (1951) framework with Frechet-distributed skills (talents) in professional and non-professional occupations. The model includes occupational barriers in the form of a random event preventing a worker from taking a professional occupation.

I calibrate the model's parameters by using the combination of representative samples of working adults and PISA data on academic abilities and expected occupations of high school students for 22 countries. In the first stage, I calibrate the talent distribution parameters to the longitudinal US data while assuming no occupational barriers. Next, I use the simulated method of moments to estimate country-specific productivities and the incidence of occupational barriers for all the countries in my sample. The model provides an almost perfect fit for the average cognitive skill, wage and employment in each occupational category for most countries, despite using just four country-specific parameters for six empirical moments. I find that the incidence of occupational barriers in most developed countries except for Japan and the Republic of Korea is close to zero. For developing countries, the calibration implies that up to 70% of individuals are constrained in their occupational choice.

I use the calibrated model to study the productivity gains from reducing the incidence of occupational barriers to zero. The productivity gains depend both on the incidence of occupational barriers and on the productivity of professional and non-professional occupations. According to my calculation, removing occupational barriers results in approximately 23% gain in productivity in Brazil and in about 16% gain in Mexico. The gains for most developed countries do not exceed 7%. The magnitude of productivity effects varies little with the value of elasticity of substitution between professional and non-professional occupations. The results also do not significantly change if instead of occupational barriers I use a random wage distortions model similar to Hsieh et al (2018). As my first-stage calibration to the US data assumes no frictions, these results can be also interpreted as the lower bound estimates of productivity gains from reducing the occupational barriers to the level of the US.

My paper contributes to the literature on aggregate effects of talent misallocation. Previous research mostly concentrates on occupational barriers faced by minorities. For example, Hsieh et al (2018) find that removing occupational barriers for women and racial minorities explains approximately a quarter of the economic growth in the US in 1960-2010. Lee (2016) uses cross-country data and finds that occupational barriers faced by women in non-agricultural jobs reduce output by approximately six percent for an average country. Mies, Monge-Naranjo and Tapita (2018) measure the barriers faced by different gender and age groups and also find large productivity losses. In contrast to previous research, this study potentially captures both the barriers faced by the minorities as well as more latent barriers, such as credit constraints and family connections on the labor market.

The model in this paper also differs from most other models of talent misallocation based on the Roy model framework as it allows for correlation between the talents in different areas. The correlation between talents is usually assumed to equal zero (Lee, 2016; Hsieh et al, 2018; Mies, Monge-Naranjo and Tapia, 2018), because the identification of the correlation parameter is problematic in the presence of only wage and occupational choice data. In this paper, I assume that the individual's performance on PISA academic proficiency test represents one of the talents. This assumption allows me to use the distribution of test scores in each occupational group to identify the correlation between talents. I find that the correlation between talents is positive and that its value strongly affects my results.

The second contribution of the paper is the measurement of the role of academic skill in occupational sorting for a large set of developed and developing countries. Until 2012 most studies of skill effects on wages and occupational choice rely on small samples from developed countries (Neal and Johnson, 1996). In last five years, studies based on new international datasets demonstrate a large variation in returns to skill in developing countries for adult respondents (Hanushek et al, 2017). This paper, to my knowledge, is the first to study the impact of skill as perceived by students making educational decisions, which potentially differs from the actual returns.

My paper also relates to the credit constraints literature by providing upper bounds on effects of credit constraints in education. The occupational barriers in this paper potentially capture the effect of credit constraints in higher education. There is no widely accepted view on the incidence and effects of credit constraints in the USA with most studies finding no effect (Kean and Wolpin, 2001) or moderate effects (Brown, Scholz and Seshadri, 2012). The evidence for developing countries is even scarcer but tends to find more significant barriers (Attanasio and Kaufmann, 2009). Consistent with most of the previous literature, I find that the incidence of all kinds of occupational barriers, including the barriers resulting from credit constraints, is low in developed countries. On other hand, my findings are consistent with a large role of credit constraints in a few countries in my sample.

This paper is not the first to measure human capital by using PISA test scores. For example, Cubas, Ravikumar and Ventura (2016) use PISA test scores to argue that the large portion of observed variation in TFP across countries comes from the variation in quality of skilled labor. My paper additionally accounts for occupational barriers which also contribute to cross-country variation in both skill premium and in total factor productivity.

While my paper concentrates on barriers preventing individuals from taking certain occupations, labor misallocation literature also studies the efficiency of labor allocation across sectors. In particular, several papers find that the marginal product of labor is often lower in agriculture as compared to other sectors which could indicate misallocation of labor across sectors (Chanda and Dalgaard, 2008; Cordoba and Ripoll, 2009; Gollin, Lagakos and Waugh, 2012). Large variation in marginal product of labor, however, does not seem to lead to drastic productivity losses. For example, Vollrath (2014) finds that equalizing marginal product of labor across sector typically adds less than five percent to output and no more than ten percent in few rare cases.

The rest of the paper is organized as follows. In Section 2, I describe the construction of occupational sorting measures. It starts with explaining the logic of occupational sorting measures in the subsection 2.1. The second subsection explains the procedures and the data used to construct the variables. In subsection 2.2, I analyze the alternative explanations for the variation in measures which do not involve the actual occupational sorting. I also demonstrate the correlation between the sorting measures based on PISA scores with similar measures constructed on the adults' sample. The concluding subsection analyzes the correlation of my measures with other measures of inequality and social mobility as well as with different variables which previous literature expects to correlate with the occupational sorting. Section 4 sets up the theoretical model and describes the calibration approach. Section 5 describes the effects of occupational barriers on productivity differences, wage inequality and the robustness of my results to different modeling choices and calibration approaches.

2 The Importance of Skills

2.1 Intuition

In this section, I construct two country-level measures of occupational sorting based on academic skill. The objective is two-fold. First, I want to construct occupational sorting measures that can reveal any cross-country differences in efficiencies of labor sorting across countries. Second, it can be used to limit the choice of sorting and matching models in the future to make models more consistent with new empirical evidence.

Both measures describe sorting across occupations based on skills. Most single-index matching models of job assignments (Sattinger, 1979; Costrell and Loury, 2004) predict either positive assortative matching or negative assortative matching with skill perfectly predicting job assignment in both cases. Noisier or weaker sorting in this setup indicates the mismatch between skills and jobs. For example, the productivity of a surgeon is more sensitive to his cognitive skills than the productivity of a janitor. If in some country A, low-skilled individuals become surgeons, while high-skilled individuals become janitors, the output of country A reduces relative to its potential output. My measures of occupational sorting will be low in country A as skills there have only a small impact on the occupational choice.

For each country in the PISA dataset, I measure the dependency between academic skills and expected future occupations of high school students. These measures are similar to the returns to skill of Hanushek (2017) with two significant caveats. First, they correlate skills with occupational choices instead of labor incomes. Second, my measures rely on expected and not actual labor outcomes. By using high school students my approach eliminates the confounding reverse effect of occupation on cognitive skill arising when workers in skilled occupations use and develop their skills more than workers in unskilled occupations. Instead, I measure skills before on-the-job learning occurs and also get the benefit of measuring them at roghly the same age. The approach taken in this paper is similar to the recent paper of Guvenen et al (2015) which juxtapose aptitude tests of US high school students with their occupational choices later in life. While my paper have to rely on expected occupational choices, it extends this approach to the cross-country level.

2.2 Data

My main data comes from the Program for International Student Assessment (PISA) 2015 micro dataset. The Program conducts the survey of skills, background, and attitudes of 15-year old high school students. The 2015 dataset covers 72 countries, including at least 40 developing countries. On average, each country's sample contains a nationally representative sample of 7500 students with a maximum of 32330 students for Spain and a minimum of 1398 for Puerto-Rico. The sample is stratified by school with an average of 140 students coming from each school.

My measures of occupational sorting utilize the students' self-reported expected occupation and data on their cognitive and non-cognitive skills. The future occupation variable comes from the responses to the PISA question "What kind of job do you expect to have when you are about 30 years old?" Almost 80% of students have indicated some future occupation with the remaining 20% either giving a vague description, stating no future employment (housewife, student, unemployed), or answering that they do not know the answer.

PISA also provides the measurement of abilities both through the PISA subject scores (mathematics, reading and science) and through the psychological self-assessment. For each subject score PISA reports 10 plausible values. Each plausible value constitutes one random draw from the conditional distribution of score based on student's responses. I calculate my sorting measures for each plausible value separately and then calculate the average.

The dataset also contains three metrics constructed from different self-assessment questions, which I use to proxy for non-cognitive skills. "Collaboration and Teamwork disposition" metric shows the degree to which students enjoy cooperation. "Student Attitudes, Preferences and Self-related beliefs: Achieving motivation (WLE)" metrics describes the student's drive for achievement. Finally the third measure "Subjective well-being: Sense of Belonging to School (WLE)" can proxy both for interpersonal skills and for the school learning atmosphere.

2.3 Measuring Occupational Sorting

In this section I construct two measures of dependency between skills and the occupational choice to capture the occupational sorting based on skills. The first measure is a single-dimensional Spearman rank correlation between skill and occupational prestige score. My second measure is the multi-dimensional chi-square (Cramer V) for the dependency between the achievement scores, motivation, gender and occupations. To my knowledge, these measures are novel in the literature with the closest analogue being skill mismatch measures (Sicherman, 1991; Slonimczyk, 2011; Guvenen et al, 2015). In contrast to the skill mismatch measures, my measures describe not the dependency between current skills and current occupations, but the dependency between skills close to high school graduation and the intended occupational choice. It solves the problem of skill endogeneity in which the occupation chosen affects measured skills. My second measure also allows to study the sorting based on multiple characteristics of students and does not require any assumptions on the intensity of skill use in different occupations (in contrast to Guvenen et al, 2015).

Spearman rank correlation. The first approach relies on the assumption that both skill and occupational assignment can be described by single-dimensional indexes. The first principal component of student's reading and mathematics score describes the aggregate academic skill. I use the ISEI occupational prestige score to proxy for the skill intensity of different occupations. The occupational prestige score assigns a number to each occupation according to the combination of average years of education of workers in this occupation and the average wage. The first measure is the Pearson correlation between the percentile of a student by skill in the national sample distribution and the percentile of student by the prestige of expected occupation in the national sample.

Most studies of returns to skill also assume that both skills and labor outcome are single-dimensional. In these studies numeracy skills or aptitude tests often describe the skill (Neal and Johnson, 1996; Hanushek et al, 2013), while the wage rate is the outcome variable. The cross-country comparisons also require an assumption that countries have a similar ranking of occupations by sensitivity of productivity to skill (same occupations ladder). Using country-specific ranking of occupations based on average incomes in each occupation does not significantly affect my results as I show in Appendix 1.

Cramer V. If skills are actually multi-dimensional, then using the single-dimensional indexes might indicate a strong skill mismatch in cases when sorting is perfectly optimal (Lindenlaub, 2016). The second occupational sorting measure instead uses several dimensions to describe skill and do not assume a particular ordering of occupations. It measures the dependency between the students' characteristics and their expected occupations. I use the vector of reading and mathematics scores to describe cognitive skills, and motivation to describe non-cognitive skills. Then for each of the three skill measures I separate a national sample into four quartiles.

The skill category of a student is a combination of her reading, mathematics and motivation quintiles as well as gender, giving in total 128 categories. I also separate all the reported expected occupations into 10 aggregate occupations based on the digit of occupational code in ISCO-08 classification. The value of the multidimensional index is equal to the χ^2 statistics of dependency between skill and occupation categories scaled to 0-1 range according to the sample size (Cramer V statistic):

$$V = \sqrt{\frac{\chi^2}{N \min(k-1, r-1)}}$$

In this equation N corresponds to the sample size, $k = 128$ is the number of rows (skill categories) in the correspondence table and $r = 10$ is the number of columns or occupations.

In contrast to the single-dimensional measure, the multidimensional index does not rely on the assumption that there is a common ladder of occupations across countries based on their skill intensity. If, for example, a job of a computer programmer in Poland is more skill-intensive than a job of a doctor, the multidimensional measure will still be high as long as high-skilled students want to become programmers rather than doctors. On other hand, this measure hardly relates to actual returns to skill. Even if the best workers sort into the least demanding jobs, the multidimensional index can still be very high. Both measures vary from 0 to 1 with 1 indicating the perfect dependency between skills and occupational choice. For both variables a higher level of dependency indicates a lower level of skill misallocation.

Occupational sorting measures strongly vary between countries in my sample. Czech Republic has the highest values of both single-dimensional and multidimensional measures, indicating the highest impact of skills on occupational choice or the lowest skill misallocation. The correlation between the rank of ability and the occupational prestige rank is equal to 0.58, while the multi-dimensional index (Cramer V) is equal to 0.24. Costa Rica lies on the other side of the spectrum with the single-dimensional measure equal to 0.05 and the multi-dimensional measure equal to 0.096. Surprisingly USA lies in the middle of distribution for both the single-dimensional measure and for the multi-dimensional one.

Two measures of occupational sorting are also highly correlated. The Pearson correlation between the two variables equals to 0.87 (Table 1). This high correlation implies that the variation in the first single-dimensional measure of occupational sorting does not result from the variation in prestige of particular occupations or in the role of non-cognitive skills, as the calculation of multi-dimensional measure does not utilize these assumptions.

3 Model

So far, I find that there is a large variation in the role of cognitive skills in occupational choice between countries. How large will the productivity gains be if a country with the worst sorting based on skills improve its occupational sorting to the best possible level? In this section I construct and calibrate the model to, first, explain the difference in sorting patterns by using both variation in technology and matching frictions and, second, to measure the productivity losses resulting from the frictions.

My model is based on the Roy (1951) model with Frechet-distributed skills which is also used in Lagakos and Waugh (2012) and Hsieh et al (2018). This is a static model with a continuum of workers and firms taking one of J economic occupations. Each worker has a vector of occupation-specific talents drawn from the multidimensional Frechet distribution. Into this framework, I introduce the labor market frictions in the form of occupational barriers preventing a subset of workers from taking a skilled occupation. By matching the size of these frictions to the data and calculating the output in the model, I estimate the potential productivity gains from removing the sorting frictions.

Workers. Each worker is endowed with a vector of talents $\epsilon \in R^J$ drawn from the multidimensional Frechet distribution. Following Lagakos and Waugh (2012), I assume that the talents are correlated between occupations resulting in the following cumulative distribution function of talents:

$$F(\epsilon_1, \epsilon_2, ..\epsilon_J) = \exp\left(- \left[\sum_{j=1}^{J} \epsilon_j^{\frac{-\theta_j}{1-\rho}} \right]^{1-\rho} \right), j \in \{A, S, NS\} \tag{1}$$

In this expression, $\rho \in [0, 1]$ represents the correlation between the talents. If $\rho = 0$, the talents are completely independent and if $\rho = 1$ we get into the world of single-dimensional skill as in Sattinger (1979), Costrell and Loury (2004) or Groes, Kircher and Manovski (2014). By allowing ρ to vary, I take a more realistic middle ground, allowing both the extreme cases and some imperfect correlation[1].

To make the model's calibration more tractable and robust I assume that the talents include talents for non-skilled occupations ($j = NS$), talents for skilled occupations ($j = S$) and the academic talent ($j = A$). The academic talent does not directly affect worker's productivity, but determines the performance on academic achievement tests. In empirical studies, academic achievement tests have significant and robust correlation with lifetime labor outcomes (Borghans et al, 2016). By including the academic talent into the list of talents, I tie the unobserved talents in occupation to the measured PISA outcome and impose additional discipline on measurement of talents correlation ρ.

Parameters θ describe the shapes of talent distribution in each occupation. The variation in

[1]This particular CDF results from the Clayton's copula transformation of independent Frechet-distributed random variables.

θ also distinguishes this model from the model of Hsieh et al (2018), which assumes constant θ across all occupations. Higher θ means that the distribution of talents in occupation j is more compressed and has thinner tails. For example, one can expect that an individual talent in most non-skilled occupations (dish washing, truck driving) does not vary as much as a talent in skilled occupations such as programming or composing music. In the model this scenario translates to lower θ for skilled occupations.

Worker's occupation-specific productivity h_{ij} depends on education s_i, learning effort e_i and the talent ϵ_{ij}:

$$h_{ij} = \epsilon_{ij} e_{ij}^{\eta} s_i^{\beta_j} \tag{2}$$

Here $0 < s_i < 1$ represents worker's education measured as the proportion of life spent in school and $\beta_j > 0$ is the return to education in occupation j. In the absence of occupational barriers, workers choose their occupation j and education s to maximize utility, which is equal to after-tax wages $T(w_{ij}) = T(w(\epsilon_{ij}, s_i))$ accumulated during the working period of life $1 - s_{ij}$ minus the disutility of pursuing a particular occupation C_j and effort e_{ij}:

$$U = \max_{j \in \{NS,S\}, s_i, e_{ij}} [T(w_{ij})(1 - s_{ij}) - C_j - e_{ij}] \tag{3}$$

The function of after-tax income $T(\cdot)$ is a continuously differentiable strictly increasing function. I use the following functional form which is a slightly simplified version of the tax function used in Guvenen, Kuruscu and Ozkan (2014):

$$T(w) = \lambda_0 + \lambda_1 w^{\lambda_2} \tag{4}$$

The disutility C_j of pursuing an occupation j incorporates both amenities associated with an occupation and the monetary costs of attaining it (such as tuition). It can take negative values if amenities of professional occupations outweigh tuition costs and disutility of additional education. I normalize the disutility to zero for non-professional occupations and do not impose any constraints on the disutility of professional occupations.

If s_{ij}^* is the optimal education for worker i conditional on choosing occupation j and e_{ij}^* is the optimal effort, then the optimal choice of occupation j_i^* is:

$$j_i^* = \arg \max_{j \in \{NS,SC\}} [T(w_{ij})(1 - s_{ij}^*) - C_j - e_{ij}^*]$$

Firms. The economy includes two intermediate service sectors corresponding to non-professional and professional occupations and one final goods production sector. Each firm producing the intermediate service hires only one worker. The output of a firm in occupation j hiring a worker i equals to the worker's occupation-specific human capital h_{ij}:

$$y_{ij} = h_{ij}$$

The intermediate output of each occupation Y_j is equal to the sum of outputs of all workers employed in the occupation:

$$Y_j = \int_{j_i^*(\epsilon)=j} y_{ij} dF(\epsilon), j = NS, S \tag{5}$$

The final good is produced by a representative firm from intermediate products Y_j supplied by workers from both occupations and capital K:

$$Y = K^\alpha \left(A_S Y_S^{\frac{\sigma-1}{\sigma}} + A_{NS} Y_{NS}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma(1-\alpha)}{\sigma-1}} \tag{6}$$

To close the model, I assume that firms have an access to capital at fixed country-specific rate r_J. Most countries in my sample, except the US, are small enough in terms of investment to have little effect on the world interest rates. The assumption of access to the world market of capital allows me to abstract from household's saving decisions. The assumption of country-specific interest rate potentially account for country-specific investment risks and taxes.

Equilibrium. In equilibrium, the perfect competition on the market of intermediate goods guarantees that the prices of intermediate services p_j of each occupation are equal to their marginal contribution to the output of the final good:

$$p_j = \frac{\partial Y}{\partial Y_j} = \left(\frac{Y}{Y_j} \right)^{\frac{1}{\sigma}} A_j \tag{7}$$

The market of capital clears by equalizing the marginal product of capital with the required return on investment:

$$r_j = \alpha K^{\alpha-1} \left(A_S Y_S^{\frac{\sigma-1}{\sigma}} + A_{NS} Y_{NS}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma(1-\alpha)}{\sigma-1}} \tag{8}$$

Perfect competition on the market of intermediate goods guarantees that each worker is paid a full product of his labor as long as there are no additional frictions assumed. If p_i is the price of intermediate service in terms of the final good, the worker i's wage in occupation j is:

$$w_{ij} = p_j y_{ij} = \epsilon_{ij} e_i^\eta s_i^{\beta_j} \tag{9}$$

By substituting the equation (4) into the utility function (3) and finding the first-order condition one can obtain expressions for the optimal choice of education and effort. The optimal choice of education is the same for all the workers taking the same occupation, meaning that talents affect education only through the occupational choice:

$$s_{ij}^* = \frac{\beta_j}{1 + \beta_j} \tag{10}$$

Given the after-tax income function, the optimal choice of effort is:

$$e^* = (\eta\lambda_1\lambda_2 p_j \epsilon_{ij} s_i^{\beta_j})^{\frac{1}{(1-\lambda_2\eta)}} \tag{11}$$

Occupational Barriers. To explain the difference in sorting patterns between countries, I assume that some workers are restricted from taking skilled occupations. The restriction can happen for at least two reasons. First, some individuals can be constrained from accessing higher education due to credit constraints (Flug et al, 1998; Cordoba and Ripoll, 2011), effectively preventing them from getting many skilled jobs. Next, workers can believe that they lack the connections necessary to obtain a skilled occupation even after investing in education. For example, Zimmerman (2017) finds that graduating from elite educational institutions in Chile increases the student's chance of reaching the elite status afterwards only if combined with elite private schooling. It suggests that a prior elite status of family might be a prerequisite for taking some jobs.

The model incorporates barriers by assuming that with a probability q a worker cannot choose a skilled occupation. The occupational barrier is independent from the worker's skill $q = E(q|\epsilon)$ and is not observed in the data. Workers know if the barrier is present before making investments in education. If a worker faces a barrier, he or she always takes the unskilled occupation.

More formally, let ζ_i be the binomial random variable taking the value 1 with probability q. I assume that ζ_i is independent from ability. The occupational choice in the model with barriers is given by the following expression:

$$j^*(\epsilon_i, \zeta_i) = \{ \arg \max_{j \in \{NS,S\}} [T(w_{ij})(1 - s^*_{ij}) - C_j - e^*_{ij}], \zeta_i = 0 NS, \zeta_i = 1; (Prob(\zeta_i = 1) = q) \tag{12}$$

The incidence of occupational barriers directly affects both the occupational sorting on ability and the productivity of the economy. As long as some workers with high talent in skilled occupations face a binding barrier on entering skilled occupations, the supply of talent in skilled occupation goes down. It results in an increase in equilibrium skill prices, which attracts less talented unconstrained workers and reduces the average ability in the skilled group.

The effect of occupational barriers on the average talent in the unskilled occupation is ambiguous and depends on the correlation parameter ρ between the talents. If the correlation is high, the barrier tends to increase the talent pool in the unskilled group as talented skilled workers tend to be also talented unskilled workers. If the correlation is low, occupational barriers lower the average talent in both occupations.

4 Inference

4.1 Estimation Approach

The model as given by equations (1)-(7) and (10) contains 12 parameters, including the returns to education β_j. In order to measure the potential productivity losses from occupational barriers I have to pin down the values of all of the model's parameters. I achieve this goal through a combination of direct matching, normalization and joint calibration.

There are several parameters which can be matched directly or taken from the literature. The equation 10 connects the proportion of life spent in formal schooling with the returns to education. This allows me to directly match country and occupation-specific returns to education β_j to the average proportion of life spent in school s_j for each country in my sample. Country-specific returns help to explain a large variation in years of education across countries for workers taking non-professional jobs. I also calibrate the model with identical returns to education to find that, first, the model fit becomes significantly worse and, second, the productivity effects of occupational barriers demonstrate only a weak response to this change.

I classify occupations into skilled and non-skilled according to the occupational prestige index (ISEI). All the occupations with ISEI equal or higher than 50 are considered to be skilled or professional occupations in my sample while all the occupations with ISEI less than 50 are non-skilled. The group of skilled occupations roughly corresponds to a group of professional occupations with a large proportion of medical workers, engineers, lawyers and other professions requiring advanced degrees. As all individuals in my sample have at least some high school education, the proportion of workers choosing skilled occupations varies between 22% to 48% and allows for relatively precise estimation. Non-skilled occupations in my classification still often require specific skills (manufacturing supervisor, nurse), but usually not a graduate degree.

I rely on existing literature to quantify the elasticity of substitution between professional and non-professional occupations σ, because my data lacks the time variation in human capital to estimate it directly. Katz and Murphy (1992) limit the range of σ to the interval of $[1, 2]$. Following Jones (2014) I choose $\sigma = 1.3$ as my preferred parameter value, but report productivity effects estimates for the range of σ values.

To estimate the country-specific parameters of after-tax income function 4, I use the OECD dataset on total labor income tax for different levels of income[2]. The dataset describes tax as a proportion of total labor income for different income brackets. For each country the data provides seven data points to estimate three parameters $\lambda_0, \lambda_1, \lambda_2$. The chosen functional form (4) provides a very good fit to the data with $R^2 = 0.98$ and results in sensible top labor tax rates.

In the estimation of talent distribution parameters, the paper assumes that inherent talents are equal across countries. The talent distribution parameters $\theta_S, \theta_{NS}, \theta_C$ and ρ are not country-specific. Hence I can estimate these parameters by using the moments from one country in

[2]OECD tax database, Table I.5

which frictions can be neglected and then estimate the frictions for other countries holding the distribution of talents constant. I also allow for cross-country variation in technology, which is needed to explain the large cross-country variation in wages observed in the data.

My calibration approach for the rest of the parameters includes two steps. On the first step, I estimate the distribution of talents and technology parameters in a country with little labor market frictions. For this country, I assume that the incidence of occupational barriers is zero ($q = 0$). On the second step, I estimate the technology parameters A_S, A_{NS}, and the incidence of occupational barriers for the sample of 22 countries from which I have enough data to calculate all the empirical moments.

I use the combined data from NYLS, PISA and from representative samples of adult workers to perform my two-stage calibration. The sample of adult workers is based on national census data (for Brazil and Mexico) and the PIAAC survey (for other countries). I use the national census data because the PIAAC data are unavailable or incomplete for these countries. To make adult PIAAC population comparable to PISA sample of high school students, I select in PIAAC only the individuals with at least 10 years of education.

4.2 SMM Estimation

I use the simulated method of moments (McFadden, 1989) to jointly estimate both the distribution of talents on the first stage and the country specific parameters on the second stage. The SMM objective function is the weighted sum of squared distances between empirical and model-generated moments:

$$\hat{\beta} = arg \min_{\beta}[(\hat{m}(X) - m(\beta)))'W(\hat{m}(X) - m(\beta))]$$

The optimal weighting matrix W equals to the inverse of empirical moments' covariance matrix (Gourieroux, Monfort and Renault, 1993). To approximate the optimal weighting matrix I use the two-stage estimation strategy. On the first stage of the SMM estimation I use the identity weighting matrix. The weighting matrix for the second stage is calculated as in the inverse covariance matrix of moments at the first-stage solution. The first-stage estimates are consistent as long as the model is correctly specified, meaning that the model-generated covariance matrix is a consistent estimate of the actual covariance matrix of the empirical moments. This approach avoids the need to bootstrap the data from the two different samples of adults and students.

First-Stage (Talent Distribution). Following the long tradition of macroeconomic modeling, I pick the US as the benchmark country to make a first-stage estimation of the talent distribution parameters. The US has liberal labor market legislation with few restrictions on hiring and firing and relatively low minimum wage. In 2018 the US had the second-highest value of index of labor freedom after Singapore[3]. Title VII of Civil Rights Act of 1964 specifically prohibits labor discrimination on the basis of sex, race, skin color, religion and national origin. Equal Pay Act of 1964 additionally require employers to provide equal pay to male and female employees performing the same task. Off course, the US is not completely free of occupational and especially educational barriers. Brown, Scholz and Seshadri (2012) and Caucutt and Lochner (2012) provide evidence that credit constraints significantly affect human capital accumulation in the US. As I do not account for these inefficiencies during the first stage of my calibration, my second-stage estimates of occupational barriers essentially measure the incidence of occupational barriers with respect to the baseline level of the US.

In order to fully utilize the dynamic aspect of my data, I extend the baseline model in two ways. First, I assume that workers draw idiosyncratic wage shocks ω_{ijt} in each period. Shocks are independent both across periods and between occupations. Second, I assume that switching occupations involves paying a one-period wage penalty which is equal to the proportion of wage ϕw_{ij} received in this period in a new occupation. The penalty prevents excessive occupational mobility.

The model also allows for the ability measurement error. The observed ability is $\epsilon_A^o = \epsilon_A + \sigma_\gamma \gamma, \gamma \sim N(0,1)$. In calibration the observed ability corresponds to the individual's percentile on the Armed Services Vocational Aptitude Battery test (ASVAB) transformed to a standard normal variable.

I use the relatively rich National Longitudinal Survey of Youth 1997 cohort (NLSY-97) dataset to construct most of my empirical moments[4]. NLSY97 is a longitudinal dataset of Americans born between 1980 and 1984. At 2015 the survey respondents were approximately 30 year old which is comparable to the age for which PISA students report their future occupations. The dataset also reports ASVAB test scores which I use to construct my measure of academic ability.

My first moment is the share of workers with skilled occupations in the adult sample. This moment increases with the skill price of skilled labor p_S and decreases with the shape parameter of the talent distribution θ_{NS} (Figure 1). Next, average log-wages in each occupational group identify skill prices p_S, p_{NS} as both wages increase with skill prices. I use skill prices and the equation 7 to calculate productivities A_S, A_{NS}.

I use OLS regression coefficients of log-wages on ability as two additional moments. Returns to ability monotonically increase with an increase in correlation ρ between talents and decrease with the measurement noise σ_γ. Average ability of skilled workers also helps to identify the measurement noise σ_γ as ability decreases with the measurement noise.

Long-run variation of wages helps to identify the dispersion of talent in skilled occupations θ_S. This moment is equal to the standard deviation of individual's average log-wage. In

[3]Heritage Foundation Index of Economic Freedom, https://www.heritage.org/index/about

[4]Bureau of Labor Statistics, U.S. Department of Labor. National Longitudinal Survey of Youth 1997 cohort, 1997-2013 (rounds 1-16). Produced by the National Opinion Research Center, the University of Chicago and distributed by the Center for Human Resource Research, The Ohio State University. Columbus, OH: 2015.

this calculation, I use wage observations starting from the age of 25 to reduce contribution of transitional/part-time jobs taken during college. I also use the variation of year-to-year changes in log-wages to identify the variance of wage shock σ_w and the frequency of occupation switches to identify switching costs ϕ.

Parameter(s)	**Identifying Moment**	**Data Source**
β_j	Average years of education by occupation	ACS-2015
θ_{NS}	St. dev. of wages (long-run)	NLSY-97
θ_S	Return to ability in professional occupations	NLSY-97
ρ	Return to ability in non-professional occupations	NLSY-97
$p_j, j = NS, S$	Average wage by occupation	NLSY-97
σ_γ	Average ability in professional occupations	NLSY-97
σ_ω	St.dev. of wage changes	NLSY-97
C	Occup. share of professionals	NLSY-97
ϕ	Frequency of occup. changes	NLSY-97

The model matches the US data almost perfectly which is not surprising as it is exactly identified. The coefficient estimates and their standard errors are reported in Table 4. The values of standard errors demonstrate that the empirical moments are able to identify the model's parameters with relatively high precision.

As expected, I find that talent is more scarce in skilled occupations with θ_S estimates varying around 2.6, while the shape parameter for skilled occupations is around $\theta_{NS} = 10.8$. It means that while the distribution of talent in the skilled occupation has a lower median, it has a higher mean and much higher variance. The correlation between skills equals to approximately 0.5. The positive correlation between talents ρ and lower θ_S leads workers with higher academic skills to skilled occupations where they are more likely to get a high draw of talent.

I also estimate the standard deviation of ability's measurement noise at $\sigma_\gamma = 1.29$. Given that the ability is a standard normal variable by assumption, the impact of noise on reported ASVAB is slightly higher than the effect of the true ability variation. Alternatively, I can intepret this finding as a lower correlation between the academic and productive talents as compared to the correlation between the productive talents.

Second-Stage Estimation. The second-stage calibration estimates four country-specific productivity parameters, including skill prices/productivities ($p_S, p_{NS}/A_s, A_{NS}$), disutility of professional occupations C and the incidence of occupational barriers q. I use six empirical moments to estimate the model's parameters.

I use PIAAC and representative national country samples to calculate average wages for skilled and non-skilled occupations. As before, average wages identify skill prices p_{NS}, p_S. I use the share of workers in professional occupations to estimate the disutility of professional occupations C. The share of workers in professional occupations monotonically decreases with respect to C (Figure 2).

Three moments help to estimate the incidence of occupational barriers q. Average ability of skilled workers as calculated from PISA decreases with q. Occupational barriers force individuals with high abilities and talents to take non-professional occupations while decreasing the threshold of moving to professional occupations for unconstrained individuals. Two moments specifically measure these effects: the 90th percentile of ability in non-professional occupations and the 10th percentile of ability in professional occupations. Figure 2 demonstrates that the ability at the 90th percentile experiences strong and monotonic growth in response to an increase in the incidence of occupational barriers.

The second-stage model includes the ability measurement error, though the level of noise in PISA is not necessarily the same as in the ASVAB used for the first-stage calibration. Straightforward approach would be to include the measurement noise in the list of country-specific parameters, but this approach entails reducing degrees of freedom and making the estimates less stable. Instead my baseline calibration uses the uniform level of ability measurement noise for all the countries. I calibrate the model for different level of measurement noise from 0 to 1.5 to find that the levels σ_γ from 0.4 to 0.6 result in convergence for all the countries in my sample. Taking this into account, I assume the standard deviation of measurement noise σ_γ to be 0.5 for all of my reported estimates. In the robustness section, I also describe calibration results for country-specific levels of measurement noise.

Parameter(s)	**Identifying Moment**	**Data Source**
β_j	Average years of education by occupation	PIAAC/Census
$A_j, j = NS, S$	Average wage by occupation	PIAAC/Census
C	Occupational share of skilled workers	PIAAC/Census
q	Average ability of skilled workers	PISA
-	Ability at 90% for non-professionals	PISA
-	Ability at 10% for professionals	PISA

The model achieves a good fit to the data despite having only six parameters for eight data moments. The squared error is less than 0.01 in 14 countries out of 19 used in the second-stage estimation. In remaining five countries the error is still less than 0.02. On average across all the moments and all the countries, the model explains approximately 80% of variation. Tables 5 and 6 report the model's fit for two selected countries with poor occupational sorting: Mexico and Brazil. For both countries the model almost perfectly matches the empirical moments.

5 Results

5.1 Incidence of Occupational Barriers

Consistent with large variation in ability sorting, I find a large cross-country variation in the proportion of individuals facing occupational barriers. Brazil and Mexico experience the highest proportion of constrained workers with 72% in Brazil and 67% in Mexico (Table 7). In contrast, I find very little occupational barriers in European countries where the proportion of constrained individuals q varies from 0% in Czech Republic and Belgium to 38% in Italy. Japan and the Republic of Korea, according to my estimation, have significant occupational barriers.

The incidence of occupational barriers is strongly correlated with my measures of occupational sorting. The correlation of q with the first single-dimensional measure is equal to -0.83 and the correlation with the multi-dimensional sorting measure is even higher in magnitude at -0.89[5] Finding high correlation is not surprising given that q is identified based on the average academic ability of students choosing professional occupations in PISA, and both sorting measures also use the academic skills in PISA. More interestingly, the incidence of occupational barriers q relates more to the initial measures of sorting (single- and multi-dimensional) than with the average ability used to identify it (for which the correlation is just -0.6). It suggests that the measurement of occupational barriers takes into account other factors affecting occupational sorting, such as the production technology.

There is little evidence on the prevalence of occupational or educational barriers across countries to compare with my estimates, but scarce available evidence is consistent with my results. In case of Mexico, Attanasio and Kaufman (2009) find that the expected private returns to education for Mexican households with below median income have no significant correlation with college enrollment decision. It implies that a significant portion of Mexican population (on the order of 30-70%) is credit-constrained in choosing college education and eventually accessing professional occupations. There are several estimates of the role of credit constraints in the US post-secondary education, but the estimates vary from no effect of credit constraints on educational choices (Kean and Wolpin, 2001) to less than 8% in (Carneiro and Heckman, 2002) and up to 50% in Brown, Scholz and Seshadri (2012) for the sample of households in Health and Retirement Survey.

5.2 Productivity Effects

With parameter estimates at hand, I proceed to evaluate the effects of occupational barriers on productivity. For each country, I calculate the percentage gain in output resulting from setting a proportion of constrained individuals q to zero. Given the lack of reliable estimates of the elasticity of substitution between skilled and unskilled workers (σ) I calculate and report

[5] The correlation is negative because occupational barriers reduce sorting.

productivity losses for a most common range of values of σ in the literature from 1.1 to 2.

In order to calculate the country's aggregate product I need to generalize my calculation to the whole country's labor force. In many developing countries, the labor force includes a large group of workers with no education beyond the middle school. These workers do not participate in PISA surveys and hence the distribution of academic talents for this workers is a priori unknown. In the output calculation, I assume that the distribution of talents among workers without high school education is identical to the observed population of high school graduates. This assumption leads to a more conservative estimation of productivity effects of occupational barriers, because it does not change the distribution of talents in the observed sample. In contrast, assuming that workers without high school education have lower talents would mean that the observed sample is more talented in countries with lower proportion of high school graduates.

I use the following approach to calculate the productivity losses. First, I estimate the aggregate output of a country accounting for workers with less than 8 years of education. Next, I use information on country's capital stock K from Penn Tables to calculate the country-specific interest-rate r_j. Finally, I calculate equilibrium skill prices, new equilibrium capital and output under an assumption of zero occupational barriers. Hence, my productivity losses incorporate effects from better sorting between occupations as well as dynamic effects resulting from higher capital and higher learning effort e.

The productivity gains are large for countries with significant occupational barriers. For Brazil, I predict that the output of high-school graduates would increase by 21-26% depending on the value of elasticity of substitution σ (Table 9). In Mexico the potential gain is around 14-17%. I estimate little to no gains in output for most European countries, excluding UK(10%), Greece (9%) and Italy (7%).

I find sizable potential gains for Asian countries in my sample. For Japan, the potential gains are estimated to be around 16% and for Korea it is around 14%. Both countries have a relatively small gap in average ability between professional and non-professional occupations, resulting in high estimated occupational barriers of approximately 40% in both countries.

Increasing the elasticity of substitution between occupational services has only a small positive effect on the potential productivity gains (Table 10). On one hand, a higher elasticity means a larger increase in the share of skilled occupations after removing the barriers. On another hand, a higher elasticity of substitution results in a smaller effect of human capital increase in skilled occupation on the aggregate productivity Y.

The magnitude of productivity effects depends both on the incidence of occupational barriers and on the country's technology A_{NS}, A_S. The role of technology is the most evident in the cases of Israel and Republic of Korea. According to my estimates, Israel has less occupational barriers than Korea, but higher potential productivity gains from removing them. The difference is explained by the fact that Israel is absolutely and relatively more productive in skilled labor. Hence resorting the workers towards skilled occupations produces larger productivity gains.

Almost all the productivity gains result from improvement in sorting. For example, for my preferred value of $\sigma = 1.3$, the share of skilled occupations in Brazil increases just by 4 percentage points from 22 to 26 percent. In contrast, the average talent of skilled workers increases by 56% due to higher sorting while the average talent of unskilled workers also increases by 2%. The average human capital increases proportionally to average talent due to higher learning effort and higher education.

The Role of Talent Correlation. How does the correlation of talents ρ affect my results? To answer this question, first, I re-estimate the distribution of skills based on the US data under the restriction that the correlation of skills is almost zero ($\rho = 0.05$). I then re-estimate the productivity losses with the resulting talent distributions parameters.

Fixing the correlation of talents at zero results in a bad model's fit during the first-stage calibration. Assuming low correlation of talents results in under-fitting the difference in average abilities between skilled and non-skilled workers and also to the underestimation of the proportion of skilled workers in the sample.

The model's fit for other countries during the second stage calibration also worsens. The estimation of measured productivity losses is then not reliable due to a poor model's fit. Ignoring the model's fit concerns, the magnitude of productivity losses goes down if one assumes a low talent correlation ($\rho = 0.05$). Overall, this exercise suggests that the value of talent correlation affects both the ability of the model to fit the data and the magnitude of measured productivity losses.

5.3 Inequality

In this model, occupational barriers have three effects on wage inequality. First, occupational barriers force relatively more productive workers to take non-professinal occupations and less productive workers taking professional occupations. The deteriation of sorting efficiency should lower the skill premium and wage inequality. The second effect comes from restricting the supply of skilled labor which increases the skill premium. The third effect is an increase in wage inequality within each occupation as workers in these occupations become more unequal in terms of general ability.

My quantitative analysis demonstrates that occupational barriers tend to increase wage inequality. Removing occupational barriers increases the wage premium by up to 12%. However, the increase in the share of skilled workers and the increase in the within-occupation inequality result in higher overall standard deviation of log-wages if occupational barriers are present. For example, in Brazil the standard deviation of log-wages in skilled occupations is 0.58 with occupational barriers and 0.5 without them. In Mexico, eliminating occupational barriers reduces the standard deviation of log-wages from 0.21 to 0.16 in non-skilled occupations and from 0.55 to 0.5 in skilled occupations. The same pattern holds in all other countries, but its magnitude varies depending on the initial incidence of occupational barriers. This result is similar to Costrell and Loury (2004), who find that increasing the noise in workers' ability measurement increases wage inequality if the production function is convex enough.

5.4 Robustness

In this section, I explore the robustness of my results with respect to an alternative model of frictions and to alternative calibration approaches.

Country-Specific Measurement Noise. The observed variation in ability distribution between individuals choosing professional and non-professional occupations can result not only from occupational barriers but also from the measurement noise. While PISA tests follow the standard protocol and theoretically should have similar noise levels, different school system and different culture can affect the informativeness of educational achievement scores. The variation in noise levels across countries can also translate in differences in observable ability distributions I use to calibrate the incidence of occupational barriers q. To address this concern, I estimate the model with country-specific ability measurement noise σ_γ.

I find that accounting for country-specific measurement noise has a relatively minor effect on estimated incidence of occupational barriers. The incidence goes down slightly for Latin American countries, Japan, Korea and Greece, but goes up to 10-20% for other European countries. The magnitude of productivity effects goes down for most countries, but remains comparable to baseline estimates. Chile is an exception, where instead of previously high estimated barriers the new calibration attributes previous empirical patterns to the measurement noise. The calibrated measurement error varies a lot across countries with $\sigma_\gamma = 1.36$ in Mexico and $\sigma_\gamma = 0.07$ in Slovenia. This variation indicates rather poor identification of model's parameters.

Model of Wage Distortions. In the alternative model of labor frictions I assume that workers face idiosyncratic wage shocks in form of discrimination taxes. This setup is similar to the setup used by Hsieh et al (2018), but the group identity, which determines the size of the distortion in their model, is not observed in my case. Instead all the workers a priori face random shocks which distort the relationship between wages and productivities. The wage equals to:

$$w'_{ij} = p_j h_{ij} \exp(-\tau\gamma t_{ij})$$

In this expression t_{ij} is a random variable distributed according to a generalized Pareto distribution with a shape parameter 2, scale 1 and location at zero. If this variable takes a high value, the wage paid to the worker in occupation j is drastically reduced, forcing to shift to another occupation. This wage shock can represent taste-based discrimination of workers or the outcomes of some unobserved bargaining process. The parameter $\tau \geq 0$ measures the impact of the random distortion t on wages.

Table 11 reports the parameter estimates for the wage distortions model. The model achieves a good though imperfect fit to empirical moments despite overidentification (4 parameters for

6 empirical moments). It passes the Hansen's overidentification test for 11 countries out of 22 in my sample, which is only slightly less than the preferred model of occupational barriers. For remaining countries the error remains relatively small.

The alternative model of wage distortions produces very similar estimates for potential productivity gains compared to the occupational barriers model. For most countries with poor occupational sorting on ability, such as Brazil and Mexico, the predicted productivity losses are slightly higher. In contrast to the baseline model of occupational barriers, the wage distortion model predicts significant productivity gains from eliminating sorting frictions even for European countries. For example, it predicts the potential GDP gain of 13% for UK, 12% for Greece and 7% for Italy (Table 10). The increase in predicted losses happens because the wage distortions model can capture all the transitory wage shocks, which can also affect the occupational sorting.

6 Conclusion

This paper studies the role of academic skills in occupational choice. It constructs two measures of occupational sorting from PISA 2015 microdata which measure the statistical dependency between academic skills and expected future occupations for 52 developed and developing countries. I show that both measures are highly mutually consistent. The measures of occupational sorting for students also highly correlate with similar measures constructed for working adults.

The data indicates a strong cross-country variation in the role of academic skills and non-cognitive abilities in occupational choice. In countries with lowest role of skill, including most Latin American countries in the sample, I observe almost no connection between students' performance on educational achievement tests and skill intensity of students' expected occupations. Overall, academic skills affect the occupational choice much more in developed countries and in countries with relatively low levels of inequality.

To estimate the implications of sorting patterns for cross-country productivity variation, I construct and estimate a macroeconomic model of occupational choice. The model follows the general framework of Lee (2016) and Hsieh et al (2018), but workers face a random barrier preventing them from taking professional occupations instead of group-based distortion taxes. The model allows me to estimate both the incidence of occupational barriers across countries and potential productivity gains from eliminating these barriers.

The first finding of my calibration exercise is that the difference in students sorting patterns across future occupations implies very high magnitude of occupational barriers in several countries in my sample. For example, the data is consistent with approximately 70% of high school students being unable to pursue professional occupations in Brazil. My second finding is that occupational barriers have significant but not drastic effects on aggregate productivity. Countries with highest occupational barriers can increase their GDP by about 20-25% by removing the barriers. Given that the US in 2015 had 3.6 higher GDP per capita by PPP compared to Brazil, occupational barriers make a moderate contribution into explaining cross-country productivity differences.

It is unlikely that the measurement noise in educational achievements tests explains the observed sorting patterns. OECD uses standardized procedures to conduct educational testing across countries. I also find that students in countries with lower role of skills in occupational choice spend similar time on finishing the test and skip only slightly more answers as compared to students in countries with most efficient sorting. The model's calibration with country-specific measurement noise also results in similar estimates of occupational barriers while reducing the estimation efficiency.

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A Validity of Occupational Sorting Measures

In this section, I present the analysisi of validity of occupational sorting measures. There are two validity concerns which I need to address in this section. My first concern is that occupational sorting measures in some countries are significantly lower due to more noise in ability measurement. It can happen if, for example, students' in these countries systematically apply less effort on the PISA test. My second concern is that the cross-country variation in occupational sorting measures is driven by the accuracy of future job reporting. For example, one can imagine a scenario in which both countries A and B have same rules for job assignments based on skills, but students in country A perfectly predict their future occupations, while the predictions of students from country B are more random. In this scenario countries would differ in occupational sorting if we measure it based on students' reports, but would have the same occupational sorting based on actual occupations. Finally, I check whether the observed pattern of occupational sorting remains the same if I correlate skills not with the uniformly calculated occupational prestige, but with the country-specific average income of expected occupation. Overall, I find that the measurement noise for cognitive skills has little explanatory power for my measures, and the sorting measures based on students' data correlate with similar measures for working adults, supporting the validity of my approach. In the last part of this section, I also consider the correlation between my measures of occupational sorting and different institutional and economic variables potentially affecting sorting. this analysis shows meaningful correlations with other well-established measures of socio-economic development.

A.1 Skill Measurement Noise

First, I study the role of noise in the measurement of academic skills. First, the systematic variation in measurement noise can come from the variation in students' effort. Zamarro, Hitt and Mendez (2016) suggest that the variation in students' effort explains at least one third of cross-country variation in country average PISA scores. This might be problematic for my sorting measures, because if some students put less effort, their scores do not reflect their academic skills.

To measure the effort, I use the average time taken by students to complete a cognitive test and the number of skipped answers. I consider an answer to be skipped if it's not answered or answered in less than two seconds, assuming that two seconds is not enough for a thoughtful answer. My analysis does not reveal any systematic relationship between the average number of skipped answers and the measures of occupational sorting. The average time to complete the cognitive part also tends to be higher in countries with weaker sorting on skills. This is the opposite of what one should expect if one tries to explain lower occupational sorting measures through the lack of effort in answering cognitive questions.

The noise in skill measurement also results from measuring skills based on only a small set of questions. To measure this noise, I use the variation in plausible scores for each of the three tested academic subjects. I find a weak negative correlation between my measures of occupational sorting and the dispersion of plausible values for mathematics and a weak positive correlation for the reading plausible values dispersion. Overall, there is no evidence that the noise in skill measurement drives the cross-country variation of occupational sorting measures.

A.2 Students vs Adults

Do sorting measures for students reflect the sorting of working adults? The observed variation in my measures can result from misreporting future occupations. Indeed, it might be hard to know your opportunities and preferences in fifteen years from now when you are a fifteen-year old. While my data does not provide a direct way to measure discrepancies between expected and reported occupations, I use two indirect approaches to address this concern. First, I construct the measures of occupational sorting based on working adults to see whether sorting inefficiencies indicated by students' expectations reflect actual labor market sorting patterns. Second, I calculate country-level percentages of students who are uncertain in their future occupations and correlate it with my occupational sorting measures.

I use the data on skills and occupations of working adults from the Programme for the International Assessment of Adult Competencies (PIAAC) to construct the measure of occupational sorting for working adults. This dataset provides the data on occupations, earnings and literacy and numeracy skills of adult workers. PIAAC covers mostly OECD countries but it contains fifteen countries which are present also in the PISA sample.

On the first calculation step, I recode the PIAAC reported ISCO-8 occupation code of working adults into the occupational prestige index (ISEI) by using *ISCOISEI* routine for Stata[6]. Then I calculate the percentile of each worker in the country's distribution of occupational prestige to obtain a measure of job allocation. The conversion to percentiles pursues the same goal as the conversion done for the PISA measures: it produces a measure of job assignment which is free from cross-country differences in occupational distributions.

On the second step, I construct the index of ability, which is equal to the first principal component of numeracy and literacy skills in PIAAC. The actual measure of occupational sorting is the Spearman rank correlation between the ability and the occupational prestige score. I compare the resulting variable with the sorting measures calculated from the PISA dataset. Table 2 describes the pairwise correlations between the PISA-based misallocation measures and the PIAAC-based measure for adult workers.

There is a strong and positive correlation between the previously constructed measures based on PISA and the measures for working adults constructed from the PIAAC data. The Pearson correlation coefficient is 0.53 and it is significant at 5%. The correlation between the single-dimensional measure for working adults and the multi-dimensional measure for students is also positive, but is relatively weak and not statistically significant for this sample size. Overall, these calculations suggest that the perceived returns to skill actually measure some characteristics of actual labor market assignments, whether they result from employment or educational decisions.

The indirect way to measure the reporting noise in occupations is to use the percentage of uncertain answers in each country. The percentage of uncertain answers reflects the quality of information students have about occupations, which determines the level of noise. The percentage of uncertain answers has a positive and statistically significant, but weak correlation with my occupational sorting measures. The Pearson correlation is equal to 0.38 for the first single-dimensional measure and 0.31 for the second multi-dimensional measure (Cramer V).

A.3 Does Occupational Prestige Measure Future Incomes?

My first occupational sorting measure uses the occupational prestige index of occupation as a proxy for skill intensity. The occupational prestige index might not be an equally good measure of skill intensity for all countries in my sample. For example, skill requirements for engineers might higher than the skill requirement for doctors in Mexico with the reverse order in the US.

To address this concern, I construct a different proxy of skill intensity. The alternative proxy uses country-specific average incomes by occupation, calculated based on reported parents

[6]Written by J. Hendrickx, https://ideas.repec.org/e/phe38.html

incomes from PISA. For occupation j in country i this variable equals to the average incomes of those students' families from country i, in which the parent with the highest occupational prestige score has an occupation j. Family income levels in PISA 2015 are given in six country-specific intervals. Suppose, a student reports the highest income level (6) and the student's father is a doctor and the mother is a primary school teacher. In this case the income level of family is attributed to the occupation of a doctor as this occupation has the highest occupational prestige score among the two. This calculation does not account for the income generated by the second-highest occupational code, but the error should be small as long as there is either a strong marital sorting or low employment levels of mothers.

The income-based single-dimensional sorting measure equals to the correlation between the student's percentile by skill and the student's percentile by average income of expected occupation. The data allows me to calculate the measure only for 15 countries. For this limited sample of countries, the correlation between the old occupational prestige-based and the new income-based sorting measures equals to 0.8. It implies that using the occupational prestige score as a uniform proxy for income in different countries does not introduce significant distortion into my results.

A.4 Correlates of Skill Misallocation

There are several institutional and economic variables which might affect occupational sorting according to the literature. In this subsection, I explore the correlations between these variables and my measures of occupational sorting. If these theories are true, one would expect to see significant correlations between the corresponding institutional and economic variables and properly measured occupational sorting. And if my sorting measures of are indeed valid, they should capture the same correlations. I study several potential determinants of occupational sorting:

Inequality and Social Mobility. Income inequality as measured by the Gini coefficient has a very strong and negative correlation with both measures of occupational sorting. In other words, in more unequal countries skills do nor predict occupations as well as in mroe equal countries. The correlation coefficient is equal to -0.69 for the first measure and -0.82 for the second. In both cases the coefficient is significant at 1% level despite a small sample size of 43 countries. The correlation also holds on the more uniform subset of European countries.

The observed positive correlation between inequality and occupational sorting suggests that the trade-off between inequality of opportunities and inequality of outcomes (described by Benabou, 2000) is either weak or non-existent in my sample. In other words, more equal countries have lower inequality of opportunities. This finding is consistent with the labor matching model of Costrell and Loury (2004), who find that under some (plausible) assumptions a decrease in quality of information on skill leads to skill misallocation and higher wage inequality.

Intergenerational elasticity of incomes from Corak (2013) also correlates with my occupational sorting measures, but these correlations can follow from the known correlation between the intergenerational income elasticity and the income inequality (Corak, 2006). The Inequality of Opportunities index (IoP), which is produced by Brunori (2016) for selected European countries, measures the variance in incomes explained by observable uncontrollable circumstances (such as parental education, parental occupations and gender). My calculations do not show any significant correlation between the IoP index and the occupational sorting measures. However, the low significance can be explained by the low sample size (of only 15 countries).

Educational Institutions. High tuition costs of higher education and borrowing constraints can prevent some students from getting skilled occupations despite high ability. I use the government expenditures per tertiary student (UNESCO) as a percentage of GDP per capita to proxy for tuition costs. My analysis still suggests no significant correlation between the government expenditures and the sorting measures (Table 2).

I also consider the opportunity that the students' occupational expectations become less noisy closer to the graduation. As all students report their occupational choice at the age of 15, the difference in high school graduation age implies that some students are much closer to the moment of implementing their occupational decisions. It is then natural to assume that students which are closer to graduation, are going to report more deliberate choices. The average graduation age by country (also from UNESCO) accounts for this factor.

The data shows an opposite pattern: countries with a higher graduation age demonstrate a stronger link between skills and occupational choice. This link, however, does not hold on the subsample of European countries, suggesting that the correlation might be just a statistical artifact.

Labor Institutions. Hiring an employee with a right skillset is in the best interest of private firms. Hence the institutions which restrict firms in their ability to hire, promote or fire workers might negatively affect the efficiency of sorting. Here I consider the public ownership of employers which can limit the role of profit incentives and lower the efficiency of sorting. I also consider labor union density rate and collective barganing coverage of unions, because labor unions restrict firms' compensation and employment decisions.

I do not find support for the idea that unions or public ownership negatively affect occupational sorting. On the opposite, many European countries score high on occupational sorting measures despite powerful labor unions and high public employment. Both measures of occupational sorting strongly and positively correlate with the percentage of public employment and the collective bargaining coverage, but weakly with the union density rate. The potential explanation for the observed positive correlation is that both unions and the proportion of public employment have a very weak effect on occupational sorting of students. Despite restricting occupational mobility and wages they do not prevent individuals from choosing occupations at the start of the career. At the same time, both unionization rates and collective bargaining correlate with occupational sorting through other omitted factors such as the Gini coefficient.

Productivity (and other macroeconomic variables). In Porzio (2017) the industries with a higher technological distance to frontier can have more polarized inter-firm distribution of skill. It happens due to complementarity between worker's and manager's human capital under the assumption that more advanced technologies are more intensive in terms of manager's talent. I use log GDP per capita and Total Factor Productivity (TFP), as calculated from Penn World Tables 9.0 to proxy for the technological distance to frontier. I also include two characteristics of financial sector development (stock market capitalization and the domestic credit to private sector, World Bank), as the financial sector can increase the return to ability through better matching capital with ability. I also expect the rate of economic growth to correlate with sorting if cognitive and non-cognitive skills matter more in adopting new technologies in contrast to manual and specific skills (Hanushek et al, 2017).

Both sorting measures have small correlation with the level of economic development as measured by GDP per capita. On average, rich countries tend to have stronger sorting on skill, but due to the small coefficient magnitude and the small sample size the connection is not statistically significant even at 5%. Two measures of financial sector development also do not have any statistically significant correlation with sorting measures.

Sorting measures tend to be lower in countries experiencing rapid economic growth in last 10 years. The correlation is marginally significant at 5% for the first measure and marginally insignificant for the second. The direction of correlation contrasts with Hanushek et al (2017), who observe a strong positive correlation between economic growth and returns to skills for adult workers.

Political Institutions. Murphy, Schleifer and Vishny (1991) and Acemoglu (1995) explain how a higher productivity of rent-seeking activities results in an inefficient occupational choice. Additionally, the elite can use the restriction on social mobility to limit de facto political power of other classes in the sense of Acemoglu and Robinson (2008). I use the variable of Control of Corruption and Constraint on Executive to control for rent-seeking opportunities. The variables of Democracy and Polity, Political Competition and Executive Recruitment describe the political inclusiveness to test for the second hypothesis. All the variables, except for World Bank's Control of corruption, come from Polity IV dataset.[7]

The connection between the political institutions and the sorting on academic skills is relatively weak. All correlations have expected positive signs, but only the democracy index is significant at 5%. While these results do not show a significant role of political institutions, the institutions can still matter either for sorting in executive positions or for sorting between different majors.

Business Institutions. According to Acemoglu, Antras and Helpman (2007) and Cole, Greenwood and Sanchez (2016), contracting institutions complement advanced technologies. If more advanced technologies also involve higher returns to skill, the quality of institutions should positively correlate with the strength of sorting on ability. I use the contract enforcement cost and the Distance to Frontier variable from the "Doing Business" database[8] of World Bank to measure the quality of contracting institutions.

According to my calculations, the quality of contracting institutions does correlate with higher occupational sorting, though the correlation is relatively weak. Higher contract enforcement costs correspond to lower sorting measures with statistical significance at 1% for the first measure (rank correlation between skill and occupational prestige) and significance at 5% for the second multi-dimensional measure.

Trade Openness. In the famous anti-utopia of Young (1958) competition with foreign producers forces United Kingdom to transition to a more meritocratic system. This reasoning finds more theoretical support in Itshoki, Helpman and Redding (2010) who predict that opening a country to trade should result in better inter-firm sorting of workers. Table 2 uses three different variables to explore this hypothesis: the proportion of trade (export plus import) relative to GDP, the costs to import and export from World Bank and the applied weighted average tariff (World Bank).

Table 2 demonstrates a strong correlation between the trade openness and the sorting measures. The share of foreign trade (sum of export and import) in GDP positively correlates with both measures, but is significant only at 5%. One of the reasons for low significance is a large variation in the share due to large variation in country sizes. The residual from the regression of trade share on log population is statistically significant at 1% for both measures. Both average trade costs per container and the applied weighted average tariff on all goods relate to lower sorting measures and are highly statistically significant. The correlation holds both on the whole sample and on the sub-sample of European countries.

Summing up, both measures of occupational sorting demonstrate strong and positive correlation with trade openness measures and strong and negative correlation with Gini coefficients. It implies that the theoretical explanation of occupational sorting patterns should also generate higher inequality in countries with weaker sorting. The strength of occupational sorting based

[7]Polity IV Annual Time-Series 1800-2017, Center for Systemic Peace, http://www.systemicpeace.org/inscrdata.html.

[8]Doing Business, The World Bank (http://www.doingbusiness.org).

on skills tends to be higher in countries with good political and business institutions.

B Calculation of Empirical Moments

I use the combination of several datasets to calculate the empirical moments used in the calibration. The data on average academic skills comes from PISA dataset. I use PIAAC for the data on occupational structure, average wages and average years of education. Due to lack of data in PIAAC I use the 5% 2010 Census for the Brazil, 10% 2010 Population and Housing Census for Mexico and 2015 American Community Survey (1%) for the USA. All the international data are downloaded from the I-Pums International[9]. Below I describe the calculation steps for each of the samples.

PISA. My sample for the calculation of the average ability includes all the high school students with non-missing data on reading and numeracy skills. I exclude observations in which students expect to take future jobs of engineer, doctor or lawyer without expecting to obtain higher education, because I assume that these professions require at least college education in all the countries in my sample. The plausible value of academic ability equals to the first principal components of reading and mathematics plausible values. The ability variable equals to the average across ten plausible values of ability. I consider all occupations with the occupational prestige score equal or higher than 50 to be skilled (professionals).

PIAAC. I use the data from the Programme for the International Assessment of Adult Competencies (PIAAC) to calculate occupational shares and average log-wages. I limit the sample to employees having paid work. I also require that workers have finished high school to make the sample of working adults consistent with the PISA sample. I take earnings per hour in 2013 US dollars expressed through the purchasing power parity (earnhrpppw variable). The earnings are winsorized at 1% from both lower and upper end to remove outliers. Workers are considered to be professionals (skilled) if the occupational prestige index of their actual main occupation is equal or higher than 50. To calculate the average log-wage and the occupational shares I use weighting according to the final sample weight (spfwt0) and the statistical routines specifically developed for the PIAAC data (piaactab and piaacdes procedures for Stata).

Census data (Brazil, Mexico, USA). The sample includes only workers with at least high school education in ages from 24 to 50 years old (prime age adults). Workers have to be paid employees, who are not disabled and work at least 30 hours per week on average on their main job during the last month (Mexico and Brazil) or last year (USA). For Mexico and Brazil the wage calculation starts from the income earned during the last month expressed in 2010 US dollars by PPP. I divide this number by 4.35 (weeks in a month) multiplied by the number of hours worked per week. For USA the wage equals to the income from wages divided by the estimated number of hours worked in last year. The number of hours worked in last year is equal to 40 multiplied by the number of weeks worked. I winsorize log-wages at 1% to remove outliers. All the empirical moments are weighted by the final sample weight.

[9]Minnesota Population Center. Integrated Public Use Microdata Series, International: Version 7.0 [dataset]. Minneapolis, MN: IPUMS, 2018. https://doi.org/10.18128/D020.V7.1

C Tables

Table 1: Correlations between the occupational sorting measures

	ρ(PIAAC)	Cramer V(PISA)	ρ (PISA)
ρ(PIAAC)	1		
Cramer V(PISA)	0.337	1	
ρ(PISA)	0.533^{**}	0.872^{***}	1

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

Table 2: Proximate Causes of Occupational Sorting

	Rank	Rank, Europe	Cramer V	CramerV, Europe
	b	b	b	b
Inequality and Social Mobility				
Gini coefficient	-.693***	-.246	-.821***	-.505**
Education Gini coefficient	-.546***	-.172	-.548***	-.284
Intergen. income elasticity	-.315	.318	-.592**	-.632
Inequality of Opportunity	.367	.367	-.011	-.011
Educational Systems				
Average high school graduation age	.449***	-.0621	.574***	.2
Gov. spending per tert. student	-.0626	-.0605	.148	.0765
Labor Institutions				
Public employment(% of total)	.489**	.017	.747***	.528*
Union density rate	.0031	-.45*	.29	.0224
Coll. bargaining coverage	.356*	-.123	.517**	.0741
Productivity and Economic Factors				
Log GDP per capita	-.0383	.0584	-.273	-.14
Econ. growth (2005-2014)	-.33*	-.132	-.18	.117
TFP	-.0548	-.173	.0217	-5.9e-04
Stock market(% of GDP)	-.171	.0988	-.0783	1.3e-04
Domestic credit to private sector	.0737	-.236	-.0183	-.351
Political Institutions				
Polity	.339	.562	.234	.278
Democracy	.441*	.542	.322	.257
Constraint on Chief Executive	.402	.619	.305	.365
Executive Recruitment	.204	.619	.113	.365
Political Competition	.329	.181	.227	-.0533
Control of Corruption	-.243	.0434	-.29*	-.152
Business Institutions				
Distance to Frontier(WB)	.283*	-.34	.297*	-.074
Contract enforcement cost	-.378**	-.0325	-.373**	-.213
Bankruptcy recov. rate	.235	-.12	.29*	.0477
Trade Openness				
Trade(% of GDP)	.295*	.375*	.352*	.44*
Trade costs (USD per container)	-.645***	-.537**	-.659***	-.415*
Applied weighted average tariff	-.432**	-.339	-.493***	-.176

* indicates significance at 5% level, ** 1% level and *** at 0.1% level.

Table 3: Parameter Estimates and Model Fit for the USA

Parameter	θ_{NS}	θ_{SC}	ρ	σ_ϵ	C
Value	10.75	2.60	0.49	1.29	6.74
St. error	(0.92)	(0.06)	(0.05)	(0.12)	(0.64)

Moment	**Model**	**Data**
Occup. share skilled	0.35	0.35
Aver. logwage unskilled	2.81	2.81
Aver. logwage skilled	3.15	3.16
Aver. abil. skilled	0.46	0.46
Returns (unsk)	0.06	0.06
Returns(skilled)	0.10	0.10
Std(logwage) LR	0.38	0.38
Std(logwage) SR	0.33	0.33
Switch rate	0.10	0.10

Table 4: Parameter Estimates and Model Fit for Mexico

Parameter	p_{SC}	p_{NS}	C	q
Value	2.80	2.38	0.65	0.58
St. error	(0.03)	(0.10)	(0.04)	(0.06)

Moment	**Model**	**Data**
Occup. share skilled	0.24	0.23
Aver. logwage unskilled	1.16	1.17
Aver. logwage skilled	1.95	1.95
Aver. abil. skilled	0.25	0.25
Std(logwage)	0.59	0.70

Table 5: Parameter Estimates and Model Fit for Brazil

Parameter	p_{SC}	p_{NS}	C	q
Value	3.25	3.11	0.55	0.66
St. error	(0.02)	(0.07)	(0.04)	(0.03)

Moment	**Model**	**Data**
Occup. share skilled	0.22	0.22
Aver. logwage unskilled	1.28	1.28
Aver. logwage skilled	2.07	2.07
Aver. abil. skilled	0.20	0.20
Std(logwage)	0.56	0.78

Table 6: Occupational Barriers and Potential Productivity Gains

Country	Error	A_{NS}	A_S	q	GDP gain(perc.)	Capital gain
Brazil	0.00	0.95	0.44	0.73	19.39	19.40
Chile	0.00	0.90	0.66	0.53	16.27	16.26
Mexico	0.00	0.99	0.35	0.68	13.14	13.13
Belgium	0.00	0.97	0.78	0.00	0.00	-0.00
Czech	0.04	0.83	0.57	0.00	0.01	0.01
Denmark	0.01	0.98	0.89	0.08	2.34	2.35
France	0.01	1.01	0.67	0.06	1.46	1.46
Greece	0.01	0.91	0.56	0.32	6.23	6.23
Italy	0.00	1.14	0.55	0.40	6.45	6.45
Netherlands	0.00	0.89	0.89	0.20	5.42	5.43
Norway	0.00	0.96	0.82	0.24	5.48	5.48
Poland	0.00	0.86	0.69	0.35	8.60	8.59
Slovakia	0.02	0.87	0.59	0.09	1.77	1.79
Slovenia	0.00	0.79	0.74	0.04	0.84	0.84
UK	0.00	0.84	0.91	0.29	7.40	7.40
Israel	0.00	0.61	0.94	0.33	12.02	12.03
Japan	0.01	0.87	0.81	0.47	14.91	14.91
Korea	0.00	1.02	0.60	0.52	12.09	12.10
New Zealand	0.00	0.88	0.91	0.17	4.32	4.31

Table 7: Effects on Inequality

Country	Premium		Std. of logwage, unsk		Std. of logwage, sk	
Country	Barriers	No barriers	Barriers	No barriers	Barriers	No barriers
Brazil	2.23	2.38	0.20	0.16	0.58	0.50
Chile	2.34	2.48	0.20	0.16	0.55	0.51
Mexico	2.10	2.39	0.21	0.16	0.54	0.50
Belgium	1.31	1.31	0.16	0.16	0.55	0.55
Czech	1.58	1.58	0.17	0.17	0.54	0.54
Denmark	1.35	1.39	0.17	0.16	0.55	0.55
France	1.48	1.51	0.17	0.16	0.53	0.53
Greece	1.50	1.61	0.18	0.16	0.55	0.53
Italy	1.53	1.67	0.19	0.16	0.57	0.53
Netherlands	1.46	1.52	0.18	0.15	0.57	0.55
Norway	1.33	1.41	0.18	0.16	0.57	0.55
Poland	1.71	1.82	0.19	0.16	0.55	0.53
Slovakia	1.59	1.63	0.17	0.17	0.54	0.54
Slovenia	1.60	1.61	0.16	0.16	0.54	0.54
UK	1.67	1.73	0.18	0.16	0.57	0.53
Israel	1.88	1.95	0.19	0.15	0.58	0.54
Japan	1.69	1.85	0.20	0.16	0.56	0.52
Korea	1.63	1.82	0.20	0.16	0.54	0.51
New Zealand	1.58	1.64	0.18	0.16	0.55	0.54

Table 8: Occupational Barriers and Potential Productivity Gains, country-specific measurement noise

Country	Error	A_{NS}	A_S	σ_ϵ	q	GDP gain(perc.)	Capital gain
Brazil	0.01	0.96	0.43	1.71	0.67	18.42	18.42
Chile	0.00	0.91	0.60	1.91	0.01	0.11	0.13
Mexico	0.01	0.99	0.34	2.07	0.53	9.08	9.11
Belgium	0.01	0.96	0.80	0.17	0.18	4.33	4.33
Czech	0.01	0.87	0.52	0.30	0.18	3.04	3.07
Denmark	0.01	0.95	0.92	0.11	0.19	5.49	5.49
France	0.01	1.01	0.67	0.12	0.23	4.93	4.93
Greece	0.01	0.88	0.57	1.06	0.13	2.86	2.85
Italy	0.00	1.14	0.52	1.21	0.19	2.65	2.65
Netherlands	0.00	0.87	0.90	0.40	0.20	5.99	5.99
Norway	0.00	0.95	0.83	0.45	0.24	6.06	6.05
Poland	0.01	0.87	0.67	0.68	0.23	5.20	5.19
Slovakia	0.01	0.87	0.60	0.15	0.39	9.35	9.35
Slovenia	0.00	0.79	0.73	0.43	0.09	2.37	2.37
UK	0.00	0.84	0.89	1.14	0.10	2.84	2.82
Israel	0.01	0.61	0.92	0.97	0.26	9.35	9.38
Japan	0.00	0.87	0.76	1.59	0.01	0.16	0.16
Korea	0.01	1.00	0.62	0.44	0.52	14.29	14.28
New Zealand	0.00	0.88	0.90	0.70	0.08	2.52	2.53

Table 9: Potential Productivity Gains from Eliminating Occupational Barriers

σ	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2.0
					Americas					
Brazil	20.85	21.50	22.15	22.72	23.24	23.84	24.36	24.88	25.37	25.85
Chile	16.50	16.77	17.06	17.35	17.61	17.82	18.07	18.31	18.48	18.70
Mexico	14.21	14.63	14.99	15.33	15.68	16.00	16.33	16.63	16.94	17.22
					Europe					
Belgium	1.74	1.75	1.72	1.72	1.70	1.71	1.69	1.69	1.68	1.67
Czech	2.74	2.74	2.74	2.72	2.71	2.72	2.68	2.69	2.67	2.68
Denmark	3.14	3.11	3.10	3.10	3.07	3.07	3.05	3.04	3.03	3.02
France	0.46	0.46	0.46	0.46	0.45	0.46	0.44	0.45	0.46	0.46
Greece	9.24	9.24	9.26	9.26	9.26	9.30	9.31	9.32	9.33	9.33
Italy	7.38	7.40	7.42	7.44	7.46	7.46	7.46	7.48	7.49	7.51
Netherlands	6.45	6.43	6.42	6.41	6.39	6.38	6.36	6.36	6.34	6.34
Norway	6.68	6.64	6.61	6.59	6.56	6.53	6.51	6.47	6.45	6.45
Poland	12.58	12.67	12.76	12.86	12.93	13.02	13.09	13.13	13.19	13.26
Slovakia	7.06	7.05	7.08	7.08	7.08	7.10	7.10	7.10	7.11	7.13
Slovenia	2.14	2.14	2.13	2.14	2.14	2.14	2.14	2.13	2.11	2.11
UK	10.27	10.29	10.31	10.34	10.37	10.38	10.39	10.42	10.44	10.47
					Other					
Israel	14.25	14.31	14.39	14.46	14.50	14.58	14.62	14.71	14.74	14.78
Japan	18.62	18.77	18.90	19.01	19.13	19.24	19.35	19.44	19.53	19.63
Korea	14.74	14.89	15.03	15.17	15.29	15.40	15.52	15.64	15.75	15.85
New Zealand	5.32	5.34	5.32	5.33	5.32	5.30	5.31	5.30	5.30	5.29

Table 10: Potential Productivity Gains for the Wage Distortions Model

Country	Error	A_{NS}	A_S	σ_ϵ	q	GDP gain(perc.)
Brazil	0.02	0.51	0.11	0.50	1.31	28.89
Chile	0.00	0.51	0.29	0.50	0.54	22.80
Mexico	0.00	0.77	0.03	0.50	1.14	18.45
Belgium	0.02	0.76	0.48	0.50	0.03	5.33
Czech	0.02	0.52	0.07	0.50	0.03	3.92
Denmark	0.00	0.74	0.73	0.50	0.02	3.95
France	0.04	1.09	0.18	0.50	0.09	7.21
Greece	0.02	0.66	0.09	0.50	0.30	12.30
Italy	0.01	1.63	0.09	0.50	0.15	6.80
Netherlands	0.00	0.55	0.67	0.50	0.03	5.58
Norway	0.00	0.73	0.52	0.50	0.05	6.64
Poland	0.01	0.52	0.22	0.50	0.13	10.46
Slovakia	0.01	0.47	0.13	0.50	0.04	5.42
Slovenia	0.00	0.35	0.27	0.50	0.01	2.94
UK	0.00	0.38	0.90	0.50	0.14	13.40
Israel	0.00	0.09	1.05	0.50	0.17	17.99
Japan	0.00	0.42	0.60	0.50	0.32	18.92
Korea	0.00	0.90	0.19	0.50	0.54	17.03
NewZealand	0.00	0.50	0.77	0.50	0.02	5.04

D Figures

Figure 1: Sensitivity of Empirical Moments to Model's Parameters, USA

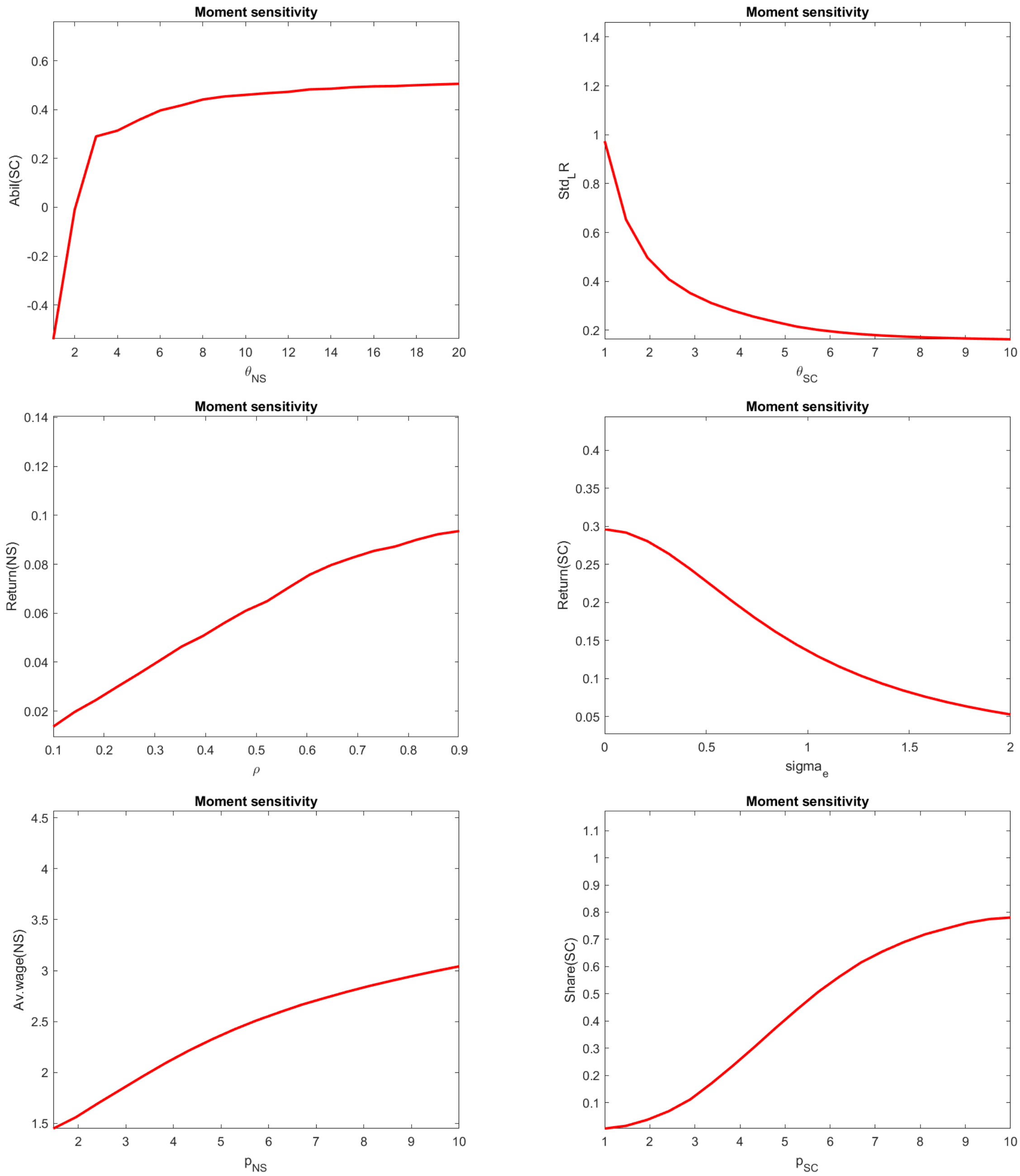

Figure 2: Sensitivity of Empirical Moments to Parameters in the Model with Barriers (Mexico)