1 Introduction

The hollowing-out of the middle class is a recent phenomenon, according to which mid-level jobs are disappearing (employment polarization) and wage inequality is increasing (wage polarization). Recent literature documents employment and or wage polarization for developed economies, such as Goos and Manning (2007) for the UK, Goos et al. (2009) in the context of European economies, and Autor et al. (2003, 2006) for the US. Various theories posit different main drivers of this polarization phenomenon such as skill-biased technological changes (SBTC), routine-biased technological changes (RBTC), and the off-shoring of production tasks.[1] What weaves these theories into a common theme is that polarization stems from exogenous demand shocks, such as those resulting from trade integration, that increase the relative *demand* for a particular type of labor. These existing theories assume that the skill supply is inelastic; however, this assumption is only plausible in a static environment and not inconsequential in a dynamic one. For example, using the "supply side" of skills, Acemoglu (2003) explains that when the supply of skills can respond to changing demand for skills, the economy will select a different point along the relative demand curves.

Similar to Acemoglu (2003), we are also interested in the changing supply of skills in response to exogenous shocks. However, unlike Acemoglu (2003) we study how adjustments in the supply side of skills can lead to a different type of polarization which we call "skill polarization". This type of polarization highlights that the skill distribution changes in response to exogenous shocks such that it becomes polarized and mid-level skills begin to disappear. In part, the assumption of an inelastic supply of skills in the prior literature is rationalized by the idea that the acquisition of skills is a slow process and that, therefore, the skill distribution remains unchanged. One implication of this is that in the short-run any exogenous shock affecting the relative demand of skills causes a pure price effect captured by changes in the relative wages of skills. Whereas this assumption is plausible in the short-run, in a dynamic context the supply of skills is not necessarily inelastic. For example, many state-led programs in industrialized countries allocate between 0.11 to 1 percent of national GDP (Brookings Metropolitan Policy Program) to actively implement skill upgrad-

[1]For a review, see Katz and Autor (1999a). SBTC-based explanations posit that the demand for certain skills has increased over time primarily due to SBTC that complements only a sub-group of skills, which results in employment polarization. Moreover, Violante (2008) suggests that trade is an important determinant of not only the speed but also the direction of SBTC. RBTC à la Goos and Manning (2007) suggests that recent technical changes are biased toward replacing routine tasks, which causes job polarization. Grossman and Rossi-Hansberg (2008) highlight that the off-shoring of tasks offers an explanation of the observed changes in relative factor demands in response to trade.

ing opportunities[2], especially in response to trade shocks.[3] In light of these policy efforts, the adjustments in the skill supply can affect the whole skill distribution. In this paper we explore whether trade-induced exogenous changes to the relative prices of skills, i.e., wage gap shocks, can cause the hollowing-out of mid-level skills.

We adopt a systematic approach by answering three related questions: First, what impact do exogenous demand shocks resulting from trade have on wage gaps across skills? Second, what are the implications of exogenous changes in these wage gaps (induced by trade) for the skill distribution, and do they contribute to skill polarization over time? Finally, is a welfare state (such as Denmark) that promotes free education and a flexible labor market more prone to skill polarization relative to other states (such as Portugal) that lack such welfare policies and are characterized by rigid labor markets and less generous education policies?

We study the first two questions in the Danish case by using its employer-employee matched data because Denmark can be viewed as a context in which the skill supply responses constitute an upper bound for the effect in question. Denmark is characterized by a flexible labor market and is also a universalist welfare state that provides all of its citizens benefits ranging from free access to education and vocational training to unemployment benefits. Our hypothesis is that such domestic institutions should make the supply less inelastic in the long-run and facilitate the adjustment of skill levels in response to trade-driven demand shocks. To determine whether this is the case, we then extend our analysis by using Portuguese employer-employee matched data as a comparison to study the role of domestic institutions and answer our last research question.

The empirical analysis for each country is conducted in two steps. The first step is to estimate the effect of exogenous trade shocks on two types of wage gaps (upper- and lower-wage gaps), while controlling for other confounding factors. An upper-wage gap is defined as the ratio of wages between the 90th and the median percentiles (a measure that proxies for the wage gap associated with the right tail of worker skills), while a lower-wage gap is defined as the ratio of wages between the median and the 10th percentiles (a measure that proxies for the wage gap associated with the left tail of worker skills). We use the estimates from this step to construct predicted changes in wage gaps due to trade (henceforth exogenous trade-induced wage gap changes) – which are orthogonal to the skill distribution in the next

[2]Some examples include vocational training, short-term programs, online degrees, adjustment payments and subsidies.

[3]The policy role is highlighted by Autor (2014), who writes, "$\cdots$ it is critical to underscore that policy and governance has played and should continue to play a central role in shaping inequality even when a central cause of rising inequality is the changing supply and demand for skills."

step. While the unit of analysis in our first step is at the industry level, making our analysis comparable to the existing literature (e.g., Feenstra and Hanson, 2001), we aggregate the trade-induced wage gap changes at the level of relatively self-contained local labor markets (municipalities) in our second step.[4] To do so, we use the weights based on the share of each industry's sales in the total sales in each municipality.[5] In the second step, we assess how the predicted trade-induced wage gap changes from the first step affect next period's skill distribution in these local labor markets – i.e., the average level and the variance of skills within the municipality.[6]

Our empirical methodology is based on three key identification assumptions that are motivated by the existing literature. First, the exogenous international trade shock is a pure demand-shifter of skills (Katz and Autor, 1999b). Second, the supply of skills is assumed inelastic in the short-run, and thus the contemporaneous trade shocks mainly affects wage gaps (Acemoglu, 2003) rather than the skill supply. This is consistent with the notion that acquiring skills requires time. Third, even though the skill supply is fixed in the short run, in a dynamic context (medium-to-long run) it is not (Acemoglu, 2003). Under these assumptions, an exogenous increase in trade activity can lead to changes in the wage gap (due to changing demand of skills), which can affect individual's incentives to upgrade or maintain skill levels. These skill supply decisions at the individual level can translate into subsequent changes of the skill distribution when aggregated at a macro level. Furthermore, the responsiveness of skill distribution to exogenous shocks can depend on a country's labor market structure and institutional policies. We will shed light on this by comparing the Danish and Portuguese economy.

Our main results for Denmark show that trade integration has a non-linear effect on wage gaps across various skills and that such trade-induced wage gap changes significantly influence the skill distribution. Specifically, we find that the exogenous changes in trade have a negative effect on the lower-wage gap and a positive effect on the upper-wage gap. As a result, the predicted changes in these wage gaps increase the mean and the variance of the

[4]Our results, discussed later, are also consistent when the second step is estimated at the industry level (instead of municipality level). See the previous version of the paper (http://ftp.iza.org/dp10035.pdf).

[5]Note that our methodology is similar in spirit to Autor et al. (2013). While Autor et al. (2013) directly use the trade shocks at the industry level with the relevant weights to construct a local labor market exposure to trade, for the purpose of our study we first need to construct the exogenous trade-induced wage gap changes at the industry level (which we do in our first step) and then use the weights to construct the municipality-level exposure to these shocks (which we use in our second step).

[6]As in Foged and Peri (2016), the geographic units of analysis that we use to approximate local labor markets are municipalities. Foged and Peri (2016) note that most worker mobility is observed across firms within a municipality, confirming that municipalities, even in the long run, are rather self-contained labor markets. Our study is similar in spirit to the strand of the trade literature that investigates the impact of trade shocks on local labor markets (Autor et al., 2013; Li, 2016).

skill distribution, resulting in *skill polarization*. In contrast, for Portugal, we find that the exogenous changes in trade have a positive impact on both measures of wage gaps but that their impacts on the first two moments of the skill distribution are negligible. Therefore, our main results show that changes in trade-induced wage gaps improve the average level of skills but also make the skills more diverse in welfare states with flexible labor markets, such as those in Denmark, while the effects are less pronounced in frictional labor markets, such as those in Portugal.

To rationalize our empirical results from the second step of the analysis, we present a simple three-period, partial equilibrium setting, with agents that are heterogeneous in their innate abilities, to highlight how exogenous changes in wage gaps affect an individual's incentives to upgrade skills and how such individual-level decisions, when aggregated, affect the skill distribution. We also extend this framework to encompass the role of institutions by introducing labor market frictions. We then show that such frictions can mitigate the responsiveness of the skill distribution to exogenous changes in the wage gaps.

We make three main contributions to the literature. First, we study the effect of exogenous trade shocks on the changes in the wage gaps. At present, there is no consensus in the empirical literature on what effect globalization has on wage gaps. On the one hand, Feenstra and Hanson (2001) argue that the increased importation of intermediate products instead of final products can explain between 15 and 24 percent of the increased ratio of skilled to unskilled workers' wages. In contrast, Lawrence (2008) concludes that although increasing trade with developing countries may have contributed to growing wage dispersion over the 1995–2005 period, the impact seems to be small. On the other hand, Krugman (2008) argues that the difficulty of concluding what impact trade has had on wage gaps might be due to a lack of appropriate data. We contribute to this literature by estimating the effect of trade on wage gaps in Denmark and Portugal.

Our second contribution is studying how the distribution of skills responds to exogenous trade-induced wage gaps, which is sorely missing from the existing literature. In traditional trade models, the cross-country differences in average skill levels are typically assumed to be exogenous and, in turn, determine the patterns of trade. Bombardini et al. (2012) note that the cross-country differences in the diversity of skills are an important determinant of trade patterns in addition to average skill levels. Hence, most of the previous literature on trade assumes that the skill distribution (here, average and variance) is an exogenous driver of trade. Such an assumption is appealing and appropriate in a the short-run but highly restrictive for dynamic time-series analyses (see Acemoglu, 2003).

Although several papers (Danziger, 2017; Davidson and Sly, 2014) investigate how skill acquisition responds to trade shocks, a few studies address how the skill distribution changes accordingly. For example, Atkin (2012) studies how the onset of NAFTA, which resulted in new jobs in the Mexican manufacturing sector, affected the drop-out rates of students living in municipalities that were more exposed to trade shocks. Another important contribution in this context is from Blanchard and Olney (2017). They empirically find that educational attainment is affected by exogenously driven changes in the composition of a country's exports, and thus, they offer insights into how investment in human capital evolves with changing patterns of trade. Compared with these studies, we make an important contribution by studying the feedback effect of trade on the skill *distribution* by exploring how trade impacts not only the average levels of skills but also the diversity of skills. Therefore, we can study the issue of trade-induced skill polarization, which the aforementioned papers and the previous literature in this field have not fully explored.

Our last contribution is that we explore whether domestic education policies and labor market institutions interact with the effect of trade-induced wage gaps on the skill distribution. The existing literature alludes to the potential role that education and labor market policies can play in facilitating the adjustment of the skill composition to globalization. However, there are no analyses comparing the impact of trade on the skill distribution in economies such as Denmark, where the labor market is flexible and education policies are generous, and in economies such as Portugal, where education policies are less generous and the labor market is more frictional (Botero et al., 2004).

In Section 2, we present the institutional background for Denmark. Data and summary statistics are then discussed in Section 3. Our empirical strategy is explained in Section 4. We present our baseline results, additional robustness analyses and the comparison between Denmark and Portugal's results in Section 5. In Section 6, we provide a framework to rationalize our empirical results. We then conclude in Section 7. Proofs, figures, and tables are collected in appendices at the end of the paper.

2 Institutional Background

In this section, we explain the main features that define the trade patterns, labor market, and education policies in Denmark.

Denmark is a highly export-oriented economy. Traditionally, Danish trade has been limited to a few trading partners (in the 1990s approximately 10 countries, mostly EU members, accounted for 70 percent of Danish trade). Denmark has recently also begun to trade with emerging economies, such as the BRICs, East Asian countries, and Eastern European countries. Figure 1 illustrates that export value has exhibited a very steep and positive trend with respect to destination markets outside the developed world, such as China. Thus, despite the maturity of the Danish economy, the process of trade integration was still evolving over the period considered in our analysis. In terms of export composition, Denmark features large export shares within machinery and equipment, textiles, food and transport (OECD, 2013).

Following from the long-standing tradition of open trade, globalization is generally seen as a positive force in Denmark. Indeed, the flexibility of its labor market means that Denmark is in a better position than many other European countries to adapt to the changes in global market conditions brought about by the emergence of low-cost producer countries. Cornerstones of the Danish model are a high level of job to job mobility and generous social security policies. The absence of severance payment lowers hiring and firing costs, reduces matching frictions and makes it easier for firms to adjust the quality and size of their workforce. Moreover, although workers are not protected by stringent employment rules, they bear relatively low costs of changing employers and have easy access to unemployment or social assistance benefits and activation programs. In fact, the replacement rate is among the highest in the world (OECD, 2015). Another key feature of the Danish labor market is that its wage bargaining has recently become much more decentralized. Since the early 1980s, an increasing share of wage bargaining devolved to the individual-employee level, which increased the relevance of the employer and employee's role in the internal firm wage structure. As found in Eriksson and Westergaard-Nielsen (2009), within-firm wage variability in Denmark represents more than 80 percent of the total variability observed among all workers.

The Danish government generally provides abundant subsidies for individuals to undertake skill upgrading and education. Formal schooling is largely provided free at both the secondary and tertiary levels, and a monthly income transfer, i.e., *statens uddannelsesstøtte*, of approximately 700 dollars is provided to all Danish students during the entire course of their undergraduate and master's studies. Generous grants are also provided by the State to finance most of adult education and continuing educational programs.[7] As a result of these policies, the education level of the workforce is very high by international standards. In 2012, the population share having attained upper secondary education far exceeded the OECD average. The share having attained tertiary education is also above the OECD aver-

[7] In 2005 expenditures for adult education amounted to a total of DKK 5 billion, of which DKK 2.7 billion for educational activities and DKK 1.6 billion for special allowances (pub.uvm.dk/2007/lifelonglearning).

age (OECD, 2013). Furthermore two out of three adult Danes participate in formal and/or non-formal education. This participation rate is considerably above the average of 51 percent across 22 OECD countries and is in fact the joint highest with Finland and Sweden (OECD, 2013).

Because of these generous education policies, combined with a flexible labor market with limited matching frictions, the Danish workforce appears to be well equipped to adjust to changes in the wage gaps induced by trade. Such responses are therefore more likely to be reflected in changes in the distribution of skills, which is the subject of our study.

3 Data

Information about firms and workers is collected from three databases/registers at the Danish official statistical institute (Denmark Statistics): the "Integrated Database for Labor Market Research" (*IDA*), the "Accounting Statistics Registers" (*FirmStat*), and the "Foreign Trade Statistics Register" (*Udenrigshandelsstatistikken*). From the population of all firms, we only retain private firms that are included in all three databases over the period from 1993 to 2012. Moreover, we drop firms with only 1 employee to exclude self-employment. We now provide further details about how we process the data in each database.

IDA is a longitudinal employer-employee register, containing information on the age, gender, nationality, place of residence, work, education, labor market status, occupation, and annual wage of each individual aged 15-74 between 1980 and 2012. The information is updated once a year in week 48. Apart from deaths and permanent migration, there is no attrition in the data. From this register, we only keep individuals who are employed full time every year in the period from 1993 to 2012. The individual information in *IDA* is used to estimate our individual skill measure, which will be explained in the next section. Then, we use the individual skill measure to calculate the first two moments of skill distribution for each Danish municipality, for the purpose of our empirical analysis. Individual-level variables in *IDA* are also used to measure a number of workforce characteristics at the municipality level: the share of workers with secondary and post-secondary education; the percentage of male employees; and the average age and work experience. Because we can track people throughout the study period, we can also establish the average tenure of all employees. To address outliers, the top and bottom 1 percent of wage earners in each year are excluded.

Our second database is Firm Statistics Register (FirmStat henceforth), which covers the universe of private-sector firms over the years 1993-2012. It provides the annual value of capital stock, firm productivity and industry affiliation.[8] We also aggregate the firm-level data at the 4-digit level classification of the Danish Industrial Activities.[9]

The last database that we use is the *Foreign Trade Statistics Register*. It contains data on export (and import) sales and the number of exported products at the firm level for the same period as *FirmStat*. This data are available both by specific destination and at an aggregated level. Exports are recorded in Danish kroner (DKK) according to the 8-digit Combined Nomenclature as long as the transaction is worth at least 7500 DKK or involves goods that weigh at least 1000 kg.[10] To construct our instruments, as explained in the next section, we aggregate these flows at the 4-digit level and merge them with the U.N. COMTRADE data.[11] Moreover, as we did for all the other variables included in the empirical analysis, we calculate export (and import) sales at the 4-digit level classification of the Danish Industrial Activities.[12]

3.1 Descriptive Statistics

Table 1 presents the descriptive statistics of our main variables for our sample period of 1993–2012. The first row reports the cross-industry average ratio between the 90th and 50th percentiles of the within-industry wage distribution (denoted by Δ_2), whereas the second row reports the cross-industry average ratio between the 50th and 10th percentiles of the within-industry wage distribution (denoted by Δ_1). Assuming that wages are monotonic in

[8] Capital stock comprises the sum of the values (in Danish kroner) of land, buildings, machines, equipment and inventory. Firm productivity, which is the most important predictor of a firm's export behavior, according to recent trade theory, is calculated as turnover per employee in logarithmic scale (i.e., labor productivity). We deflate all monetary values using the World Bank's GDP deflator with 2005 as the base year.

[9] Consistent with the literature on the "servization of manufacturing" (Bernard et al., 2017; Bernard and Fort, 2015) we find in our sample period a substantial number of non-retail firms that report their core activity being in services despite simultaneously trading goods (approximately 1,500, on average, over the sample period or, equivalently, approximately 7 percent of all exporting firms). Most of these firms are companies that no longer undertake goods production but are still involved in design, R&D and engineering processes, the supervision of third-party production and branding, marketing and distribution. These businesses have many of the same capabilities and activities as traditional manufacturing firms but no longer directly control the assembly and processing activities in-house. As we will discuss later in the robustness checks section, our main results do not change when we exclude those firms (and the industries in which they operate) from the sample and focus our analysis on the manufacturing sector only.

[10] 7500 DKK is equivalent to approximately 1000 euros at the time of writing. Since the introduction of the euro, the Danish Central Bank has adopted a fixed exchange rate policy vis-a-vis the euro.

[11] The first 6-digits of the Combined Nomenclature in the *Foreign Trade Statistics Register* are the same as the product classification in the COMTRADE data, i.e., the HS classification. However, we use the 4-digit level aggregation to considerably improve consistency over time.

[12] We map international export and import data at the 6-digit product level to the 4-digit industry level by merging the *Foreign Trade Statistics Register* with *FirmStat*, where for each firm, we observe the industry code.

skills (Blanchard and Willmann, 2016), we can interpret Δ_2 as the wage gap associated with the upper skill levels and Δ_1 as the wage gap for the lower skill levels. In other words, Δ_2 is a proxy for the return on the highest skills relative to median skills and Δ_1 is the proxy for the return on median skills relative to the lowest skills.

An important observation is that the wage gap for the higher skills is smaller than the wage gap for the lower skills ($\Delta_1 > \Delta_2$). This is in line with the decreasing marginal return to skills. As skills increase, wages increase but at a decreasing rate. We also plot the evolution of Δ_1 and Δ_2 over time in the first panel of Figure 2. It shows that Δ_2 (in the range of 1.5) is indeed always smaller than Δ_1 (in the range of 1.8). In addition, the wage gap for the higher skills is increasing over time, while the wage gap for lower skills exhibits a negative trend.

Our measure of trade activity in the main analysis is based on overall export value, although in a robustness check, we also consider import value. In an additional specification, we also make a distinction between exports to developed (north) and developing (south) countries. Table 1 reveals that Denmark has a higher value of exports to northern than to southern countries, which is consistent with the notion that most Danish trade is within the EU. On average, Denmark also has a larger import than export value.

In the empirical analysis, we also consider a number of industry-level characteristics. The main descriptive statistics for those characteristics are also reported in Table 1. Specifically, these control variables include average firm capital intensity and average firm productivity as proxies for industry technology, the average share of male or foreign workers, and a host of workforce composition characteristics.

Our main skill variable is a multidimensional index drawn from Portela (2001) (definition 1), which is based on the interaction of years of education, experience and unobserved ability, as explained in the next section. We also conduct empirical analyses using five additional measures of skills. The first alternative is based on years of education only (definition 2). The next three measures (definitions 3-5) are all estimated from the additive "two-way" worker-firm effects model (Abowd et al., 1999), as explained in the robustness check section. These variables represent a host of proxies for workers' skills acquired formally at school and informally in the labor market. Since the additive model requires additional assumptions that may be restrictive, we also provide the results when using a skill measure based on a job-spell fixed effects model (definition 6).

The second panel of Figure 2 reports the developments of the first two moments of skills over time, where skills are measured using definition 1. It shows that both the average and standard deviation of skills have been increasing steeply for Denmark. Similar patterns are observed if we consider the other definitions of skills.

4 Methodology

Two challenges complicate our effort to empirically study our research questions. First, individuals' skill, our variable of interest, is generally very difficult to measure. Second, reverse causality between our measures of wage gaps, trade, and skill distribution could pose a threat to identification. We organize this section into two parts highlighting how we address the aforementioned challenges. The first part describes our measure of skills. The second part discusses our two-step empirical strategy to study the effect of trade on wage gaps and how such trade-induced wage gap changes affect the distribution of skills, i.e., the mean (average) and variance (diversity) of skills.

4.1 Skill Measures

Our baseline skill measure is drawn from Portela (2001) and is a multidimensional index of workers' human capital. Specifically, this index is constructed at the worker level by combining information on employees' years of education, work experience, and unobserved ability as follows:

$$\begin{aligned} skill_{it} = mschool_t \times \left(0.5 + \frac{e^{(school_{it} - mschool_t)/sschool_t}}{1 + e^{(school_{it} - mschool_t)/sschool_t}}\right) \\ \times \left(0.5 + \frac{e^{(exp_{it} - mexp_t)/sexp_t}}{1 + e^{(exp_{it} - mexp_t)/sexp_t}} | school_{it}\right) \\ \times \left(0.5 + \frac{e^{(effect_{it} - meffect_t)/seffect_t}}{1 + e^{(effect_{it} - meffect_t)/seffect_t}} | school_{it}, exp_{it}\right) \end{aligned}$$

where i is the index for individual workers, t is for year, e is natural exponential function. $school_{it}$, exp_{it}, and $effect_{it}$ are the years of education, work experience, and unobserved ability for worker i at year t, respectively. The variables $mschool_t$, $mexp_t$, and $meffect_t$ are the mean of workers' years of education, work experience, and unobserved ability at year t in the economy, respectively, and $sschool_t$, $sexp_t$, and $seffect_t$ are the corresponding standard deviations. Note that unobserved ability is measured by the individual fixed effects estimated from gender-specific wage equations, in which we control for workers' education, age, experience, tenure, their squares, and firm fixed effects (Abowd et al., 1999).[13]

The skill measure, $skill_{it}$, is measured in the following way according to the above equation. We first assume that all workers start off with the average level of education in the economy, $mschool_t$. This average is then adjusted by $(0.5 + \frac{e^{(school_{it}-mschool_t)/sschool_t}}{1+e^{(school_{it}-mschool_t)/sschool_t}})$ to take into account worker i's ranking in the distribution of schooling received by all workers in the economy. This correction is computed using the cumulative logistic distribution. The second adjustment to worker i's skill measure is her work experience conditional on her education. That is, we consider worker i's relative position in the distribution of work experience only among individuals with the same education level. This correction reflects the fact that individuals with the same education level may have different skills as a result of different work experiences. Finally, we use a similar procedure to correct for worker i's unobserved ability conditional on schooling and work experience. These three adjustments allow us to measure the skills for worker i at year t, $skill_{it}$, which we later use to calculate the average and standard deviation of skills at the year-municipality level.

To understand our baseline measure of individual skills, first notice that each adjustment can range from 0.5 to 1.5. An adjustment greater than 1 depicts above-average schooling, work experience, or ability, and vice versa. Conditioning on schooling allows us to adjust the skill measure with experience and ability. For instance, imagine two individuals: i) one who acquired a Ph.D. in 6 years; ii) another one who took 4 years for the same degree and gained 2 years of work experience after graduation. If we simply use their education level as a skill measure, then the two individuals will appear to have exactly the same skill level. Our experience-adjusted skill measure, however, discounts the first individual's skills for the lack of work experience. Therefore, the statistical moments of our skill measure will likely capture the municipality's skill distribution better than those based on education only. Nevertheless we will also provide the main results by using among others a skill measure based on years of education in the robustness checks.

4.2 Empirical Strategy

We now present our empirical strategy in two steps. Specifically, we answer two main questions here: First, what is the impact of exogenous demand shocks due to trade on wage gaps over time? Second, what implications do such demand shocks affecting wages have for the skill distribution? In the first step, we first estimate the trade shocks' impact on wage gaps at the industry level, and then use relevant weights to construct the local labor market

[13]See section 5.2.2 below for more details on this econometric model.

exposure to trade-induced wage gap changes (which we use as our exogenous shock in the second step). This is similar to the approach of Autor et al. (2013), who construct exogenous trade shocks at the industry level and aggregate the shocks at the local labor market level using the relevant weights to construct the local labor market exposure to trade shocks. In the second step, we estimate the impact of the above wage gap changes on the local labor market skill distribution.

We prefer the two-step empirical approach for three reasons. First, under the identification assumptions detailed in the introduction, exogenous trade shocks can affect wage gaps in the short run through skill demand changes, but the resulting wage-gap changes cannot affect the skill supply in the short run because the skill supply is inelastic. However, the wage-gap changes can affect the skill supply in a dynamic context in a longer time horizon (Acemoglu, 2003). Two-step regressions allow us to distinguish between the timing of trade-induced wage-gap changes and the subsequent skill supply adjustments. Second, the two-step strategy allows us to identify a rather unexplored channel (i.e.; the one of wage-gap changes) through which trade can affect the skill distribution. This helps us to interpret and theorize our empirical results. Third, the first step itself addresses an interesting question, i.e., to what extent the demand shocks from trade can affect wage gaps. It also allows us to compare our results from the first step with those of existing papers.[14]

4.2.1 The First Step: The Impact of Trade on Wage Gaps

For the first step, we use the following industry-level specification:

$$\Delta_{jt} = \alpha + \beta' X_{jt} + \gamma trade_{jt} + \delta_j + \delta_t + \epsilon_{jt} \tag{1}$$

where the dependent variable is wage gaps and can take one of two measures. One is the ratio of the 50th to the 10th percentile of the wage distribution ($\frac{w50_{jt}}{w10_{jt}} = \Delta_{1jt}$) at industry level j at year t, as a proxy for the medium-to-low-skill wage gap (i.e., lower wage gap). The other is the ratio of the 90th to the 50th percentile of the wage distribution ($\frac{w90_{jt}}{w50_{jt}} = \Delta_{2jt}$) at industry level j at year t, as a proxy for the high-to-medium-skill wage gap (i.e., upper wage gap). Hence, we run two separate regressions for the upper wage gaps and the lower wage gaps, as we intend to examine the possible differential impact of trade on two types of wage gaps. The variable $trade_{jt}$ is total export value for industry j at year t.[15]

[14]For instance, Acemoglu (2003) exploit differences in demand shocks induced by trade as one of the possible explanations to cross-country differences in skill premia.

[15]In an alternative specification implemented in the robustness checks section, we measure the industry-level export value separately for "north" and "south" destinations. "North" includes countries in North

The vector X_{jt} includes productivity (measured as sales per employee), capital intensity, and workforce composition characteristics (such as the shares of college-educated, foreign-born, or male workers, as well as workers' average age), for each industry j at year t. The above specifications are completed with a full set of industry fixed effects, denoted by δ_j, and time fixed effects, denoted by δ_t. Most of these control variables are motivated by the technology- and trade-augmented model of labor demand and supply developed by Katz and Murphy (1992), as in our empirical specification both the supply and demand of labor may change because of non-trade factors. More specifically, the variables of industry productivity, capital intensity, and time trends control for the effect of SBTC and labor demand changes, while the variables of workforce composition characteristics control for labor supply changes.[16] Furthermore, by including the share of foreign workers in X_{jt}, we also control for the impact of immigration on our measures of wage gaps. Finally, productivity, capital intensity, and industry dummies also help us control for the effects due to industry size.

One possible threat to the identification of γ is that the variable $trade_{jt}$ is likely to be endogenous in regression (1). To obtain an unbiased estimate of the parameter γ, we instrument the export value variable with exogenous trade shocks at the industry level in a 2SLS estimation. Exogenous trade shocks are constructed first by calculating changes in the world import demand for each product using U.N. COMTRADE data following the IV approach employed in Hummels et al. (2014) and then aggregating the product-level world import demand changes to the 4-digit level of Danish industry classification. We denote our IV as m_{jt}. Specifically, the instrument is constructed jointly for total exports as follows:

$$m_{jt} = \sum_{c=1}^{C} \sum_{p=1}^{P} \frac{exp_{jcp\_baseyear}}{exp_{j\_baseyear}} I_{cpt} \tag{2}$$

where I_{cpt} is each country c's total purchases of product p from the world market (less

America, Oceania, and Western and Southern Europe (excluding the new EU members of the 2004 enlargement). All other countries in the world are considered in the category "south." In addition, we also use import value instead of export value as an alternative measure.

[16] For instance, if technological change follows a linear trend, then the effect of SBTC will be absorbed by our time fixed effects. However, if technology disproportionately changes the productivity of high-skilled workers over time, then such effects should be captured by industry productivity. Moreover, the role of machinery in providing better technology, which favors skilled workers, should be captured by controlling for industry-level capital intensity. In our robustness checks, we also use expenditures on research and development (R& D) at the industry level relative to total expenditures to divide the sample into high- and low-tech industries. Examining the low-tech industries in isolation will help us to further separate the impact of SBTC from that of trade.

purchases from Denmark) at time t (Hummels et al., 2014). They are exogenous to Denmark and vary across countries and products. The variable $exp_{jcp\_baseyear}$ represents industry j's export value of product p to destination c in the base year (which is 1993 in our case), and $exp_{j\_baseyear}$ denotes the world total export value in each industry j. The weights, $\frac{exp_{jcp\_baseyear}}{exp_{j\_baseyear}}$, are the base-year (1993) export shares, which are constant and industry-specific. Hence, they are exogenous to changes in the level or type of technology over time that might affect both exports and wage gaps at the industry level. Overall, m_{jt} is not endogenous with the dependent variable, Danish wage gaps.

The results from regression (1) allow us to establish the overall impact of trade on wage gaps within Danish industries. To further explore whether Denmark's trade with different destinations is driving the result, in an additional analysis, we predict the impact of export value for different export destinations on our measures of wage gaps, i.e., trading with northern or southern countries (Costinot and Vogel, 2010). We can then interpret the overall effect of trade on the wage gap, γ, as a combination of effects from trading with both types of countries.

4.2.2 The Second Step: The Impact on the Skill Distribution

In the second step, we estimate the impact of exogenous trade-induced wage-gap changes on the skill distribution at the municipality level.[17] We use the predicted wage gap changes at the industry level from Equation 1, i.e., changes in the wage gap due to the exogenous trade shocks, to calculate the average wage gap changes weighted by industry shares for each municipality m. The industry weights are constructed as the share of each industry's sales in the total sales at the municipality level. Then, to quantify the impact on skill distribution, we examine the first two moments of individual skills at each municipality: the average individual skill level at municipality m, denoted by $\bar{skill}_{mt}$, and the standard deviation of skills, denoted by $\sigma(skill_{mt})$. The latter can also be regarded as a measure of skill diversity. We estimate the following specifications at the municipality level[18]:

$$\bar{skill}_{mt} = \alpha + \beta \bar{skill}_{mt-1} + \gamma' X_{mt-1} + \delta_{ave} \hat{\Delta_{mt-1}} + \eta_m + \eta_t + \epsilon_{mt} \tag{3}$$

$$\sigma(skill_{mt}) = \alpha + \beta\sigma(skill_{mt-1}) + \gamma' X_{mt-1} + \delta_{disp} \hat{\Delta_{mt-1}} + \eta_m + \eta_t + \epsilon_{mt} \tag{4}$$

[17] We use the municipality in which a firm is located as a reference point.

[18] As in Foged and Peri (2016), we consider the broad municipality definition that combines several of the old municipalities as local labor markets.

where the first two moments of the skill distribution at municipality m are based on the skill variable described in the Section 4.1. The key explanatory variable ($\hat{\Delta_{mt-1}}$) is calculated as the weighted average of $\gamma^{iv}\hat{trade}_{jt-1}$, with γ^{iv} estimated from Equation (1) using the IV approach. Due to collinearity issues, we cannot include predicted changes in the lower wage gap, $\Delta_{1,mt-1}$, and the upper wage gap, $\Delta_{2,mt-1}$, at the same time in a regression; we have to include them separately. Furthermore, the wage gaps $\hat{\Delta_{mt-1}}$ are lagged consistently with our identification assumption according to which skill distribution changes take time and cannot happen simultaneously with current trade-induced wage-gap changes. In the baseline, we lag the wage gap variable by one year (as the results reported in Section 5.1). In the robustness checks, we also lag it by either two or three years (see Section 5.2.5).

The vector of industry characteristics in weighted averages at the municipality level (X_{mt-1}) is also lagged by one year to attenuate simultaneity issues; it includes productivity, capital intensity, average workers' age, and the shares of male and foreign-born workers. These variables, again, control for skill distribution changes due for example to SBTC, and immigration. Finally, we include both municipality fixed effects, η_m, and time fixed effects, η_t. Since the first two moments of the skill distribution are stock variables, we also include the lagged value of the dependent variable to control for autocorrelation. We estimate Equations (3) and (4) by using the system GMM estimator suggested by Blundell and Bond (1998), in which all the explanatory variables described above except the year fixed effects are considered endogenous.[19] The standard errors are clustered at the municipality level and sequentially bootstrapped with Equation 1. Finally, the coefficients in Equations 3 and 4 are weighted by the number of employed individuals at the municipality level, as in Foged and Peri (2016).

5 Results

Our main results can be summarized as follows. First, the wage gap associated with the medium-to-low (high-to-medium) skills is negatively (positively) affected by trade. Second, an increase in different types of wage gaps has different effects on the distribution of skills: (1) An increase in medium-to-low wage gap results in lower average skills and a more homogeneous skill distribution; (2) an increase in the high-to-medium wage gap results in higher average skills and a more heterogeneous skill distribution. Interpreting our results from the first and second steps allows us to conclude that trade integration increases the overall mean

[19] We restrict the number of instruments of the endogenous variables by setting the maximum lag to 5 periods. Moreover, the year dummies are only to be considered as instruments in the level equations.

and standard deviation of the skill distribution in Denmark. The increased variation of the skill distribution suggests skill polarization.

In the following section, we first discuss in detail the baseline results and then present a host of robustness checks that allow us to corroborate our main findings. We then extend the analysis to Portugal to investigate whether our findings of the impact of trade on the skill distribution also apply in a context characterized by a highly regulated labor market and less generous education policies compared to the Danish case. This comparison allows us to shed light on the interaction between domestic institutions and international trade in influencing the skill distribution.

5.1 Baseline Results

The estimated coefficients from the first and second steps of our econometric specification are presented in the first and second panels of Table 2, respectively. The results from our first step show that an increase in trade value causes the wage gap for high-to-medium-skill workers (Δ_2) to increase and the wage gap for medium-to-low-skill workers (Δ_1) to decrease. Specifically, the first panel of the table shows that a one-standard-deviation increase in the export value causes an approximately 1 (8) percent increase (decrease) in Δ_2 (Δ_1). These numbers are obtained by using the averages of $\frac{w90}{w50}$ (i.e., Δ_2) and $\frac{w50}{w10}$ (i.e., Δ_1) and the standard deviation of the log of the export value from Table 1.

The results from our second step show that the effect of the trade-induced wage gap on the skill distribution in the local labor market is significant. In particular, the second panel of the table shows that a one-standard-deviation increase in the predicted wage gap $\hat{\Delta}_2$ ($\hat{\Delta}_1$) leads to a 27 percent increase (3 percent decrease) in the mean of skills and a 77 (15) percent increase (decrease) in the standard deviation of skill, when we estimate the second step with standard OLS.[20] We obtain more conservative results if we estimate the second step by using the system GMM estimator, which treats the main explanatory variables in equations 3-4 as endogenous. According to the results reported in the third panel of Table 2, a one-standard-deviation increase in the predicted wage gap, $\hat{\Delta}_2$ ($\hat{\Delta}_1$), leads to a 15 percent increase (2 percent decrease) in the mean of skills and a 25 (5) percent increase (decrease) in the standard deviation of skill.

Combining the findings from the first and second steps reveals that changes in the wage gaps due to trade (Δ_1 and Δ_2) have a uni-directional effect on the skill distribution in the

[20]These numbers are obtained by using the averages of the mean and standard deviation of skills and by increasing $\hat{\Delta}_2$ and $\hat{\Delta}_1$ by one standard deviation.

local labor market. In particular, since the predicted Δ_1 decreases and Δ_2 increases, they together cause the average and variance of skills to increase. As a result, the Danish skill distribution shifts to the right and becomes more dispersed. Moreover, qualitatively similar results [not presented in the paper for brevity but available in a previous version of this study[21]] are obtained if we estimate the second step at an industry level (instead of using municipality as the unit of analysis). This suggests that our reported effects are on average consistent across industries. Additionally, our results are confirmed by running a simple one-step model, in which we estimate the direct impact of our export shocks on the the two moments of the skill distribution.[22]

We rationalize these results using a simple conceptual framework, which is presented more formally in Section 6. Here, briefly, the intuition is that while a decrease in Δ_1 reduces the marginal return for the low-skill population to acquire medium skills, it also reduces the marginal cost (in terms of the opportunity cost of losing current wages while upgrading skills) for the medium-skill workers to acquire higher skills. Moreover, an increase in Δ_2 further increases the return for the medium-skill population to acquire higher skills, without affecting the low-skill population. Therefore, overall, the lower-skill population is discouraged from upgrading skills, while the medium skill population is encouraged to upgrade their skills. The above induces higher average skill levels, if the proportion of upgraders dominates the proportion of discouraged workers. In addition, skills in both tails become more abundant than before, resulting in skill polarization, i.e., the variance in skills increases.

A recent paper by Keller and Utar (2016) also contributes to this line of work by using Danish data and complements our work from two aspects.[23] First, their paper's analysis focuses on job polarization due to import competition from China and the change of demand for jobs with different wage levels. Our paper, by contrast, highlights skill polarization due to both export and import (see section 5.2.3) shocks, which are not only limited to China, and the adjustment of skill supply. The skill polarization highlighted in our paper is especially relevant for European economies that are suffering from a hollowing-out of mid-level skills. While the popular press typically suggests an aging population as the explanation for this phenomenon, our paper provides a new explanation for this recent polarization causing the vanishing of mid-level skills (Business Insider, 2016).[24] Second, our study supplements the

[21] http://ftp.iza.org/dp10035.pdf

[22] Specifically we estimate Equations (3) and (4) with a system GMM approach by replacing the predicted wage gap variables with the instrument m_{jt-1}. In this one-step specification, the estimated coefficients on the export shocks are both positive and statistically significant.

[23] Using a different empirical specification, Keller and Utar (2016) show that import competition from China explains both the decrease in middle-wage and the increase in low- and high-wage employment in Denmark during the period 1999–2009, which is in line with our findings.

[24] http://nordic.businessinsider.com/sweden-and-denmark-have-daunting-skills-gaps—and-risk-losing-

main results for Denmark by considering the experience of Portugal, another small open economy with a completely different institutional framework over the same period of time. This comparison helps us to shed light on the role of institutions and educational policies in affecting the impact of trade on skill distribution.

5.2 Robustness Checks

5.2.1 Alternative Mechanisms

We interpret our baseline findings as trade-induced wage gap changes affecting the incentives to upgrade skills such that the skill distribution becomes more polarized. However, the changes in the skill distribution we observed in our baseline results may also be due to two alternative mechanisms such as migration between municipalities or inflows and outflows from the labor market.

First, changes in the wage gap (due to trade shocks) may encourage skill-specific labor reallocation across municipalities. However, Foged and Peri (2016) document that most worker mobility in Denmark takes place across firms within a municipality, confirming that municipalities, even in the long run, are rather self-contained labor markets. Moreover, we regress the share of workers moving into or out of a given municipality on the lagged predicted wage gaps. We do not find any statistically significant association between labor flows and wage gap changes, as reported in the first panel of Table 3. This result further confirms that the changes in the distribution of skills are not driven by migration across municipalities.

Second, trade-induced wage gap changes may affect the age composition of the workforce such that we observe skill polarization. Since we control for detailed workforce composition characteristics at the municipality level in all of our specifications, this potential channel is less of a concern. However, it is nevertheless useful to demonstrate that the impact of trade-induced wage gap changes on the skill distribution is not driven by adjustments at the extensive margin to provide further confidence in the interpretation of our results. According to the age composition channel, older (younger) workers who are relatively less (more) skilled may decide to retire (enter the labor market) earlier as a result of the changes to the wage gaps induced by trade reported in the first-step estimation. This could affect the age composition and as a result the skill composition of the workforce at the municipality level. To test this potential channel, we regress the share of workers younger than 35 and that of workers older than 55 on the lagged predicted wage gap changes at the municipality

their-competitiveness-as-a-result-2016-10.

level (we also remove the age controls from the specification). We report the results in the lower panel of Table 3. The age composition channel does not seem to exhaustively explain the coefficients in our baseline estimates in Table 2. While the share of workers younger than 35 is only marginally correlated with the predicted wage gap changes, the share of workers older than 55 is not significantly affected by wage gap changes. Hence, age composition is not a key driver of our baseline results.

5.2.2 Alternative Measures of Skills

In this section, as part of our robustness checks, we use five alternative measures of skills to run the regressions in the second step of our empirical analyses. The results are reported in Table 4. The first alternative measure (i.e., skill definition 2) simply relies on the workers' years of education, as in Blanchard and Olney (2017). However, the main limitation of this measure is that it only captures those skills acquired through formal schooling and, contrary to skill definition 1, it is not adjusted for the quality of skills.

The next three definitions of skills are based on workers' wages. Because such measures reflect not only skills but also an individual's unobserved characteristics and firm-level wage policies, we estimate an additive "two-way" worker-firm effects model and decompose wages into the following four components using the methodology developed in Abowd et al. (1999) for each gender separately (AKM model, henceforth): i) a systematic component related to observable worker characteristics (age, work experience, tenure and years of education), ii) an unobservable time-invariant component at the worker level, iii) firm fixed effects, and iv) a residual. Similar to Iranzo et al. (2008) and Irarrazabal et al. (2013), we use the predicted wages due to the observable characteristics (i.e., the systematic component above) as a comprehensive measure of both formal and informal skills for our skill definition 3. For skill definitions 4 and 5, we calculate the skill measure by excluding age and both age and tenure, respectively, from the systematic component of wages. This is done to take into account those cases in which age or tenure do not exactly reflect the upgrading of the skills acquired in the labor market but rather a mechanical improvement of wages related to seniority. Buhai et al. (2014) document, for example, that there are significant returns to seniority in Denmark.

The last alternative skill measure (skill definition 6) is based on the systematic part of the wage regression estimated with job-spell fixed effects. This wage regression model is less restrictive than the AKM model, because it does not require the conditional exogenous mobility assumption (Krishna et al., 2014).[25]

[25]The inclusion of time-invariant match effects in the wage regression accounts for the endogenous assign-

By using these alternative measures of skills to calculate the first two moments of the skill distribution at the municipality level, we find that the effects of the trade-induced wage gap changes on the skill distribution, as presented in Table 4, are very similar (i.e., in terms of sign, statistical significance and magnitude) to our baseline results in Table 2. According to the results reported for skill definition 2, for example, a one-standard-deviation increase in the predicted wage gap, $\hat{\Delta}_2$ ($\hat{\Delta}_1$), leads to a 11 percent increase (1.6 percent decrease) in the mean of skills and a 20 (2.5) percent increase (decrease) in the standard deviation of skill.

5.2.3 Alternative Measures of Trade Activity

In this section, we assess the sensitivity of our main results to alternative measures of trade activity. First, we investigate whether the effects of trade on the wage gaps are heterogeneous across destination markets. To do so, we distinguish between exports to the developed economies (north) and those to developing countries (south). Table 5 includes the results. Our benchmark results appear to be driven by trade with the south, as the impact of trade with the north on wage gaps is not statistically significant. The results show that Δ_2 increases and that Δ_1 decreases with exports to the south, which is consistent with the Samuelson-Stolper hypothesis (Costinot and Vogel, 2010). The second step shows that the effects of trade with the south on the skill distribution are qualitatively consistent with our baseline results, i.e., the wage gap changes induced by trade with the south shift the skill distribution to the right and increase skill dispersion in local labor markets.

In the next sensitivity exercise, we replace the export value in the baseline with the import value as a measure of trade activity. To do so, we re-calculate our instrument by examining changes in the world export supply to all countries for each product (minus Denmark's export value) gathered from U.N. COMTRADE data. Our assumption is that a measure based on the rest of the world's export supply can be safely assumed to be exogenous to Danish import activities. The results based on this alternative measure of trade are reported in Table 6. The estimates are similar to our baseline findings, i.e., the import value affects the wage gaps, and the impact on the first two moments of the skill distribution at the municipality level is statistically significant and in the same direction as our baseline results.

ment of workers to firms due to the component of match-specific ability that is time invariant. Thus, in estimating the wage regression with job-spell fixed effects, we assume that worker mobility is random conditional on time-invariant match-specific worker ability and time-varying worker and firm characteristics. This is a less restrictive assumption that the one required by the AKM model, i.e. exogenous mobility conditional on observables. The main limitation of the job-spell fixed effects model is that it does not allow to separately identify individual fixed effects, which are an important component of our main skill definition.

Specifically, a one-standard-deviation increase in the predicted change in the trade-induced wage gap $\hat{\Delta}_2$ ($\hat{\Delta}_1$) leads to a 10 percent increase (3 percent decrease) in the skill mean, as well as a 20 percent increase (8 percent decrease) in the standard deviation of skills in local labor markets. The qualitative impact of the import value on the skill distribution is similar to that estimated using the export value and reveals that trade increases skill polarization in Denmark.

Next, we investigate whether the impact of trade on the skill distribution depends on the type of product exported. Blanchard and Olney (2017) show that the composition of trade plays a crucial role in affecting the incentives for acquiring education. They find that growth in less-skill-intensive exports depresses average educational attainment, while growth in highly skill-intensive exports increases schooling. The estimated coefficient on total exports may conceal these opposing effects on the acquisition of skills. Hence, we construct the export value separately for high- and low-skill-intensive industries. To do so, we distinguish between industries with R&D expenditures above the country average (regarded as high-tech industries) and those with below-average R&D expenditures (defined as low-tech industries). Information on R&D expenditures at the 3-digit NACE industry level is retrieved from the OECD database. Estimating our baseline model separately for the two types of industries also allows us to further tease out the impact of trade from that of SBTC. Table 7 and Table 8 present the results for trade activity for high-tech and low-tech industries, respectively.

Unlike the evidence reported in Blanchard and Olney (2017), we do not find substantially different patterns across these two groups of sectors. Our results are consistent with the baseline evidence reported in Table 2. The mean and standard deviation of skills in local labor markets are positively affected by the predicted change in wage gap in both types of sectors. However, the magnitude involved in the effects of $\hat{\Delta}_2$ on the skill moments is much larger when we focus on the high-tech industries compared to the baseline result. A one-standard-deviation increase in the predicted wage gap, $\hat{\Delta}_2$ ($\hat{\Delta}_1$), triggers a 19 percent increase (4 percent decrease) in the skill mean and a 38 percent increase (7 percent decrease) in the standard deviation of skills.

Finally, we also investigate whether our baseline results change when we focus on the manufacturing sector only (Table 9), as in Blanchard and Olney (2017). These results are also similar to our baseline results in Table 2.

5.2.4 Alternative IV Strategies

One of the main assumptions behind our identification strategy is that changes in non-Danish imports from non-Danish markets are orthogonal to industry-specific shocks occurring in Denmark. We deem this assumption plausible because Denmark is a small economy of fewer than 6 million people and represents a small share of trade. However, to further remove any possible correlation between the instrument and the residual in Equation 1, we exclude those countries that share similar business cycles to Denmark, as higher imports from these markets may be correlated with the error term in Equations (1) and (3), if their imports are triggered by demand shocks correlated with those occurring in Denmark. Hence, we exclude Germany, Sweden, and the United States while estimating Equation 2. The results are reported in Table 10 and are also consistent with those obtained in the baseline analysis.

Next, as an additional check, we re-estimate our baseline specification while excluding industries in which demand or technology shocks are more likely to be correlated across countries. Following Colantone et al. (2015), these industries are: the manufacture of coke, refined petroleum products and nuclear fuel (NACE 23); the manufacture of rubber and plastic products (NACE 25); the manufacture of radio, television and communication equipment and apparatus (NACE 32); air transport (NACE 62); and post and telecommunications (NACE 64). The result is reported in Table 11, and it confirms the robustness of our baseline results.

We also follow Autor et al. (2013) in excluding an alternative group of seven industries that have experienced substantial fluctuations over the sample period across countries, due to technological innovations, housing booms, and the rapid growth of emerging economies. These industries are the manufacture of textiles and manufacture of wearing apparel (NACE 17); the dressing and dyeing of fur (NACE 18); the tanning and dressing of leather and the manufacture of luggage, handbags, saddlery, harness and footwear (NACE 19); the manufacture of other non-metallic mineral products (NACE 26); the manufacture of basic metals (NACE 27); the manufacture of fabricated metal products, except machinery and equipment (NACE 28); and the manufacture of office machinery and computers (NACE 30). The result is reported in Table 12, and it also confirms the robustness of our baseline results.

5.2.5 Additional lags

We now check whether our results are sensitive to the specification of the first-year lag in the second step of our regressions. We therefore run these regressions by including either a two-year or a three-year lag instead of a one-year lag to allow more time for the skill distribution to adjust to changes in the trade-induced wage gap. The findings from this last check are reported in Table 13. The coefficients estimated on the two- or three-year lag are slightly larger in magnitudes. This suggests that the effect is becoming stronger when we increase the number of lagged years and it is consistent with the notion that skill investment does not happen instantaneously.

5.3 The Role of institutions: The Case of Portugal

Thus far, our empirical analysis focuses on the Danish case. Our results show that trade-induced wage gap changes result in higher average skills and higher variance of skills, leading to skill polarization in Denmark. These findings may be due to certain Danish institutions, i.e., a flexible labor market and generous education policies, which enable workers to easily adjust their skills in response to changes in wage gaps. Such effects of trade on the skill distribution may be eliminated or become weaker in a different setting where workers face higher adjustment costs, i.e., a frictional labor market and/or costly education. To investigate whether this is the case, we extend our datasets and analyses to Portugal.

For the purpose of our paper, Portugal provides a good comparison to Denmark for the following two reasons. First, both countries are small, highly export-oriented with a few trading partners, and have similar export composition. Second, they are extremely different in terms of labor market institutions and education policies. On the one hand, as described in the previous section, Denmark provides abundant subsidies for individuals to upgrade skills. The support takes the form not only of formal schooling but also comprehensive active labor market policies intended to keep the skills of the workforce updated. Denmark also has an extremely flexible labor market, which reduces the frictions hindering labor reallocation across firms. On the other hand, by contrast, Portugal is characterized by one of the most rigid labor markets in the world (Botero et al., 2004), with less-generous education policies and less emphasis on lifelong learning opportunities.

Specifically, wage-setting in the Portuguese labor market is highly regulated, consisting of mandatory minimum wages and the widespread use of (centralized) collective wage bargaining at the sector level (Card et al., 2016). Roughly 90 percent of private sector jobs are covered by sector-wide collective agreements negotiated by employer associations and trade unions (Addison et al., 2016), where almost all minimum working conditions (e.g., wage floors for each category of workers, overtime pay and normal working hours) are set.

Furthermore, Portugal still lags behind EU targets set for 2020 regarding educational attainment and early school-leaving rates. Over 60 percent of the population aged 25-64 has an education level lower than upper-secondary education, which ranks as the third-largest share in the OECD area (OECD, 2015). In addition, the public resources available to support students acquiring higher education are scant relative to Denmark.[26] The *numerus clausus* system in Portuguese public universities only allows a fixed number of students to be admitted every year on a competitive basis, while private institutions that charge higher tuition fees are left as the only alternative for those who cannot obtain a spot in a public university. As a result, Portugal has the highest association between students' socio-economic background and their educational attainment among the OECD countries (OECD, 2015).

Finally, Portuguese active labor market policies (ALMPs) are characterized by a lower level of vocational training for the unemployed than the corresponding Danish policies. Although public expenditures on ALMPs increased at the beginning of the financial crisis and peaked in 2008 at 0.63 percent of GDP, they have declined in subsequent years and have been below those of Denmark (and other Nordic countries), where expenditures on ALMPs have been above 1 percent of GDP since 2009 (ILO, 2014). The scarce resources for retraining the unemployed also contribute to Portugal's longer unemployment duration compared to other countries (Blanchard and Portugal, 2001; OECD, 2015).

Due to the institutional differences and trade similarities between the two economies, we expect the effects of trade-induced wage gap changes on the skill distribution to be stronger for Denmark than for Portugal. The comparison between these two economies enables us to examine whether the impact of trade integration on the skill distribution is mediated by flexible labor market and generous education policies.

We conduct the same empirical analysis described above using "Quadros de Pessoal" *(QP)*, a matched employer-employee dataset for Portugal. The *QP* dataset is comparable to the IDA dataset for Denmark in its structure and content (Buhai et al., 2014). It is an annual, mandatory employment survey administered by the Portuguese Ministry of Employment and covers all firms (with at least one wage earner) and their establishments and employees. The analysis of the Portuguese case is thus based on all active firms in the dataset over the period 1993–2012.[27] Individual-level data files are used to estimate measures of wage gaps, workforce characteristics (e.g., the share of workers with secondary and tertiary education, the share of male employees, workers' average age, and work experience), and firm characteristics (e.g., labor productivity and location). They are comparable to those used for Denmark.[28]

[26] Tuition fees vary between 950 and 1250 euros per academic year for full-time students enrolled in bachelor's or master's programs in public higher education institutions. For PhD degrees, the average tuition fee amounts to approximately 3000 euros per academic year.

[27] The year 2001 is missing, as no data were collected at the worker level in this year by the Portuguese Ministry of Employment.

[28] The QP dataset provides very detailed information on earnings, by including the base wage (gross pay for

Similar to Denmark, the measures of wage gap changes are aggregated but at the 3-digit industry-level[29], whereas the first two moments of the skill distribution are further aggregated at the municipality level using the weighted average of the municipal industry mix.[30] Trade information at the industry level is obtained from Statistics Portugal and merged with the QP dataset. Finally, following the Danish case, we construct the relevant instruments for Portuguese trade shocks by industry based on information from U.N. COMTRADE at the product level. The link between 3-digit industries, the relevant 4-digit products exported, and the destination countries is provided by Statistics Portugal. Firm-level characteristics (such as labor productivity) are also aggregated at the industry (municipality) level for the first- (second-) stage regression.

The results for Portugal are presented in Table 14. We find that trade has a significant and positive effect on both wage gap measures (Δ_1 and Δ_2), and that the magnitudes observed are comparable to those estimated for the Danish case. A one-standard-deviation increase in the export value implies an approximately 8.5 (4.3) percent increase in Δ_2 (Δ_1). Estimates from the second step, however, show that the average level of skills is not affected as much as that in Danish case: A one-standard-deviation increase in the predicted wage gap, $\hat{\Delta}_2$, leads to a mere 0.6 percent increase in the skill mean and a mere 0.2 percent increase in the standard deviation of skills at the municipality level. Moreover, the impact of $\hat{\Delta}_1$ on the skill mean is statistically insignificant, while a one-standard-deviation increase in $\hat{\Delta}_1$ decreases the standard deviation of skills only by 0.4 percent.

Abstracting from institutional and labor market frictions, one would expect the increasing wage gaps in Portugal (as we find in the first step) to encourage both the medium and the low skill workers to upgrade their skills, and thus to increase the municipality skill mean and leave the skill standard deviation change ambiguous. However, this is not the case. Despite significant changes to wage gaps for Portugal, their estimated impact on the skill distribution is much lower than the one reported in the Danish case. Given how similar these two countries are except for their labor market structure and education policies, our results suggest that institutional factors and labor market frictions may affect how a country's skill

normal hours of work), regular benefits and overtime pay. Since it is mandatory for the employer to provide and make this information available to the public for each establishment, this reinforces the reliability and accuracy of the wage data. We construct our monthly wage measure based on both workers' base earnings and any regular wage supplements, after excluding outliers (the top and bottom 1 percent of each year's wage earners).

[29]The Portuguese Classification of Economic Activities (CAE, comparable to NACE) underwent several changes over the period considered. To perform the empirical analysis over the same period covered by the Danish data (1993–2012), we standardize all industry classifications according to the earlier versions of NACE rev. 1.1, which is more aggregated than later versions (NACE rev. 2). This corresponds to approximately 80 (3-digit) industries every year.

[30]The Portuguese Classification of local labor markets includes approximately 300 municipalities.

distribution responds to trade shocks. A rigid labor market and less-generous education policies can attenuate responses of the skill distribution, as in the Portuguese case. This finding is explained through our conceptual framework below in Section 6, where we incorporate a reduced form of labor market frictions to study the interaction between domestic institutions and the impact of trade on skill distribution.

6 Theoretical Intuition

Our empirical results highlight three important findings. First, international trade has significant effects on the wage gaps for skilled and unskilled workers. In particular, in Denmark, international trade decreases the wage gap of medium-to-low-skill workers, while it increases the wage gap of high-to-medium skill workers. Second, changes in the trade-induced wage gaps have a significant effect on the Danish skill distribution. Specifically, the predicted trade-induced wage gaps increase both the mean and variance of skills in Denmark, which results in skill polarization. That is, the extreme skills at both tails become more abundant. Third, comparing results for Denmark and Portugal sheds light on the importance of labor market frictions and education policies in affecting the impact of trade on the skill distribution. In this section, we explain the last two results using a tractable partial equilibrium framework that links the skill choices by heterogeneous individuals to exogenous wage gap shocks, while the first result can already be rationalized by existing trade theories, such as those by Costinot and Vogel (2010).[31]

6.1 A Three-Period Skill Upgrading Example

A country is populated by a continuum of heterogeneous agents with unit mass. Each individual i has a unique level of inherent ability, a_i, which is bounded, $0 < \underline{a} \leq a_i \leq \bar{a}$, and remains constant over one's life span. Ability, a, is distributed continuously with a cumulative distribution function denoted by $F(a)$ with the corresponding density function denoted by $f(a)$.

Each individual lives three periods, and each period is of length one. In each period t, individual i decides to acquire skills that are one level higher or continue working with her existing skills. We denote this decision using an indicator function I_{it}, where $I_{it} = 1$ if

[31] While favoring a simple theoretical intuition, we do not explicitly model the origins of wage gap shocks. In the empirical analysis, we focus on changes in wage gaps that are induced by trade integration, because trade integration is one of the primary sources of factor price changes. Therefore, the model builds on the exogenous change in wage-gaps and its effect on the skill distribution.

individual i decides to upgrade skills; otherwise, $I_{it} = 0$. If $I_{it} = 0$, the individual continues to earn wages, $w(s_{it})$, based on her current skill level, s_{it}. If $I_{it} = 1$, then in the next period, she will earn a higher wage, $w(s_{it} + \bar{e})$, corresponding to her new skill level. However, acquiring skills that are one level higher requires a fixed amount of credits, $\bar{e}$, and has an opportunity cost in terms of the wages not earned during the time spent upgrading skills. This opportunity cost increases with the required units of credits and decreases with the innate ability of the individual. More succinctly, the opportunity cost of skill upgrading for individual i is simply $\frac{\bar{e}}{a_i}$.

Each individual maximizes her lifetime utility based on consumption, c_{it}. We assume that each individual can perfectly smooth her consumption over her lifetime, financed by her lifetime income, W; i.e., $W \equiv \sum_{t=1}^{3} w(s_{it})p_t(1 - I_{it}\frac{\bar{e}}{a_i})$.[32] We write individual i's skill choice problem as follows:

$$V_i = \max_{I_{it}} U(c_{i1}) + \beta U(c_{i2}) + \beta^2 U(c_{i3})$$

s.t.

$$\sum_{t=1}^{3} c_{it}p_t = \sum_{t=1}^{3} w(s_{it})p_t(1 - I_{it}\frac{\bar{e}}{a_i}), \quad s_{it} = \underline{s} + \sum_{k=1}^{t-1} \bar{e}I_{ik}.$$

where $U(c_{it})$ denotes the utility from consumption, p_t is the price in each period, $\underline{s}$ is the lowest skill level that each individual is born with in the first period, and skill upgrading is simply an additive process to the previous skill level via earning a fixed credit, $\bar{e}$. We assume that the wage is an increasing and concave function of skills ($\frac{dw}{ds} > 0$, $\frac{d^2w}{ds^2} < 0$).[33] Finally, we assume that inflation is non-negative (i.e., $p_1 \leq p_2 \leq p_3$).

In the this setup, ability thresholds, A_1 and A_2 (where $\underline{a} < A_1 < A_2 < \bar{a}$), exist such that the whole population is divided into those who acquire no new skills (low-skill workers), those who acquire skills that are one level higher (medium-skill workers), and those who acquire total skills that are two levels higher (high-skill workers):

$$A_1 = \frac{w(\underline{s})p_1\bar{e}}{(p_2 + p_3)\Delta_1}, \quad A_2 = \frac{[w(\underline{s}) + \Delta_1]p_2\bar{e}}{p_3\Delta_2} \tag{5}$$

[32] Relaxing this assumption requires non-zero consumption, c_{it}, in each period. Qualitatively, the analysis remains unchanged, and therefore, we make this assumption for simplicity to present closed-form solutions for the analysis below.

[33] These assumptions imply that there is always a positive return for upgrading skills in terms of wages and that the marginal benefit of upgrading skills decreases. This is closer to what we observe in the data, where the median annual earnings of full-time, year-round wage and salary workers for ages $25 - 34$ by educational attainment in the USA in 2012 shows an approximate wage differential of $\$18,000$ for high school and college education versus $\$12,000$ for college and university education. See, for example, http://nces.ed.gov/fastfacts/display.asp?id=77.

where $\Delta_1 \equiv w(\underline{s} + \bar{e}) - w(\underline{s})$ is the wage gap of medium-to-low-skill workers, $\Delta_2 \equiv w(\underline{s} + 2\bar{e}) - w(\underline{s} + \bar{e})$ is the wage gap of high-to-medium-skill workers, and $\Delta_1 > \Delta_2$.[34]

If an individual's ability is less than the lower threshold ($a_i \leq A_1$), her lifetime utility is maximized by not upgrading skills. If an individual's ability is between the two thresholds ($A_1 < a_i \leq A_2$), her lifetime utility is maximized by upgrading skills once in the first period. If an individual's ability is above the higher threshold ($a_i > A_2$), her lifetime utility is maximized by upgrading skills twice (once in each period). We provide detailed solutions in the Appendix A. Without loss of generality, we assume that A_1 is below the medium ability while A_2 is above the medium ability. That is, $\bar{a} + \underline{a} < 2A_2$ and $\bar{a} + \underline{a} > 2A_1$.

Using this framework, it is straightforward to show how exogenous changes in the wage gaps, Δ_1 and Δ_2, affect the ability threshold levels, A_1 and A_2, and thus the skill distribution. In particular, an increase in Δ_1 decreases A_1 ($\frac{\partial A_1}{\partial \Delta_1} < 0$) while increasing A_2 ($\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}|) > 0$. An increase in Δ_2 does not affect A_1 but decreases A_2 ($\frac{\partial A_2}{\partial \Delta_2}|_{\Delta_1}|) < 0$. The detailed mathematical proofs are in Appendix A. These changes in thresholds in response to wage gap changes have implications for the overall skill distribution as follows.

We denote the skill mean by $E(s)$ and the skill variance by $Var(s)$ and assume that ability is uniformly distributed. We find the following:

- If $|\frac{\partial A_1}{\partial \Delta_1}| < |\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}|$, an increase in Δ_1 decreases $E(s)$ and $Var(s)$.
- An increase in Δ_2 increases $E(s)$ and $Var(s)$.

When Δ_1 increases, the return to acquiring skills for the low-ability individuals increases, while the opportunity cost of acquiring skills for the medium-ability individuals increases. As a result, thresholds A_1 and A_2 move further apart. Some low-ability individuals who would never have upgraded their skills now will upgrade their skills once, while some medium-ability individuals who would have upgraded their skills twice now will only upgrade their skills once. Consequently, conditional on ability having a uniform distribution, the mean and variance will be affected: If the increase in A_2 is larger than the decrease in A_1, then both the skill mean and variance will decrease. In our empirical results, trade shocks induce a decrease in Δ_1; hence, according to the above theory, both the skill mean and variance will increase.

In the case of an increase in Δ_2, the return from acquiring skills twice increases, A_2 decreases, and hence, more medium-ability individuals would acquire skills twice, while low-

[34]Note that wage level in our theoretical setup corresponds to the logged wage level in our empirical setup. In particular, the wage gaps, Δ_1 and Δ_2, are log-transformations of wage gaps from our empirical setup, e.g., $log(\Delta_2) \equiv log(w_{90}/w_{50}) \equiv log(w_{90}) - log(w_{50})$.

ability workers are unaffected. This results in a higher aggregate mean and a more diverse skill distribution. The above predictions are consistent with our empirical results for Denmark, where we report a higher skill mean and skill variance (i.e., skill polarization) due to exogenous changes in the trade-induced wage gaps.

6.2 An Extension with Domestic Institutions

Thus far, the labor market in the model is assumed to be fully flexible in the sense that as long as an individual upgrades skills, she will find a job that pays the skill-matching wage each period. Now, we extend the model by assuming that the labor market is rigid due to uncertainty in finding a job with the skill-matching wage after skill upgrading. Such uncertainty could be viewed as a reduced form of a regulated labor market that limits turnover rates. We denote by θ the probability of finding a job with the skill-matching wage and by $(1-\theta)$ the probability of having a wage that corresponds to skills one level lower than the acquired skills. The smaller θ is, the more rigid the labor market.[35]

Under this additional assumption and assuming a risk-neutral agent, the new ability thresholds, A_1 and A_2, are now also a function of the labor market friction (θ) and are as follows:

$$A_1 = \frac{w(\underline{s})p_1\bar{e}}{\theta(p_2+p_3)\Delta_1}, \quad A_2 = \frac{[w(\underline{s})+\theta\Delta_1]p_2\bar{e}}{p_3[\theta\Delta_2+(1-\theta)\Delta_1]} \tag{6}$$

For simplicity, we restrict the range of θ such that the skill upgrading decision is monotonic. This is similar to assuming that $A_1 < A_2$ to facilitate comparison across the two versions of the model.[36] Intuitively, the labor market friction (θ) affects the return to and the opportunity cost of skill upgrading. In the case of a frictionless market, the return to skill upgrading is higher but the opportunity cost is either the same or lower. The labor market friction, however, entails that when Δ_1 increases, A_1 decreases; however, A_2 increases for a large θ and decreases for a small θ, leaving the effect of Δ_1 on the skill distribution ambiguous and conditional on the size of θ. The intuition is that the uncertainty in skill-wage matching simultaneously reduces the return to and the opportunity cost of skill upgrading. It is then the relative reduction in these two components in the skill upgrading decision that determines whether A_2 increases, decreases or remains unchanged and, thus, determines the changes in the skill distribution.[37]

[35]See the mathematical details in Appendix A.

[36]For $A_1 < A_2$ to hold, θ needs to satisfy a certain condition. We prove that the condition is consistent with $0 < \theta \leq 1$. See Appendix A for details.

[37]Let $\bar{\epsilon}$ be a cutoff of θ such that when $\theta = \bar{\epsilon}$, the reduction in the return to and cost of upgrading is equal,

In a frictional labor market, when Δ_2 increases, A_2 decreases; hence, the implication for the skill distribution remains the same as before when $\theta = 1$, i.e., a higher skill mean and variance, except the effect is smaller. To summarize, when the labor market is rigid, i.e., when $\theta < 1$, we have the following.

Denote the mean by $E(s)$ and the variance by $Var(s)$, and assuming that ability is uniformly distributed and $0 < \theta < 1$:

- An increase in Δ_1 has an ambiguous effect on the $E(s)$ and $Var(s)$ of skills.
- An increase in Δ_2 increases both the $E(s)$ and $Var(s)$ of skills but with a smaller magnitude relative to when $\theta = 1$.

The first implication above is that the distributional effects on skills depend not only on the on the relative changes in A_1 and A_2 (as in the frictionless environment) but also on the size of θ, as discussed above. It is therefore an empirical question to study the distributional effects of Δ_1 on the skill distribution in a frictional labor market.

The second implication above is that the effect of Δ_2 on A_2 is always smaller in a frictional labor market than in a flexible labor market. In summary, in the presence of frictions in the labor market, we are agnostic about the distributional effects on skills when Δ_1 changes but are certain that the effects are expected to be much less pronounced when Δ_2 changes. These conclusions are consistent with our empirical results for Portugal relative to those for Denmark.

7 Conclusion

Our paper shows that exogenous changes in wage gaps induced by trade significantly affect average skill levels and the variation in skills in a flexible labor market, such as Denmark, but these moments are less affected in a frictional labor market, such as Portugal. As a result we conclude that economies such as Denmark in which supply adjusts easily to exogenous demand shocks reveal skill polarization. We present a simple theoretical intuition on the link between changes in wage gaps and individual skill-upgrading decisions. We show that the exogenous changes in the wage gaps affect the opportunity cost of and returns to skill upgrading, which translates into significant effects on the skill distribution in a flexible labor market. However, the above effects are smaller for a frictional labor market.

and therefore, $|\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}| = 0$; above $\bar{\epsilon}$, the reduction in the return to is more than the reduction in the cost of upgrading, and therefore, $|\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}| > 0$; and below $\bar{\epsilon}$, the reduction in the cost of is more than the reduction in the return to upgrading, and therefore, $|\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}| < 0$. See Appendix A.

This study informs policymakers about how exogenous demand shocks such as trade integration can affect the skill distribution through skill supply responses. The population aging faced by many developed economies is often the primary culprit for the looming concern about the hollowing-out of mid-level skills. Our paper informs policymakers that the supply-side responses (in economies with flexible labor markets and generous education policies) to exogenous demand shocks (such as those brought by trade integration) are also an important driver and should be accounted for when designing policies.

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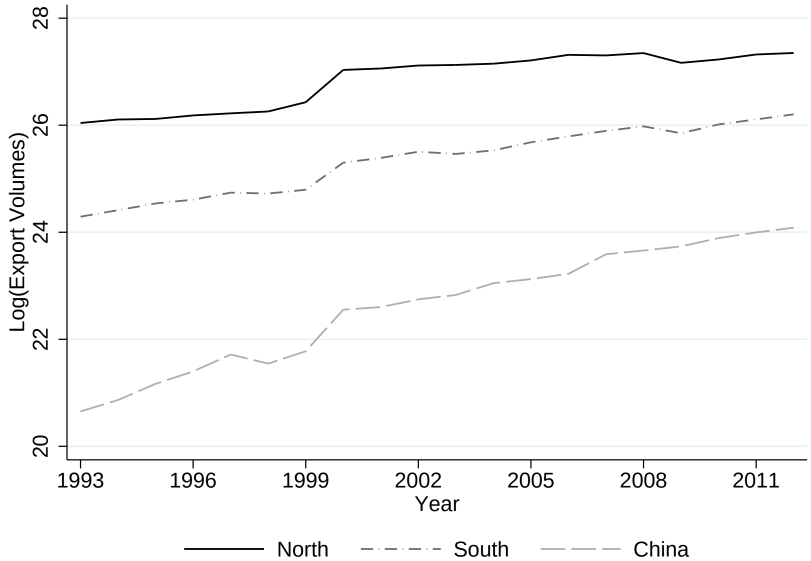
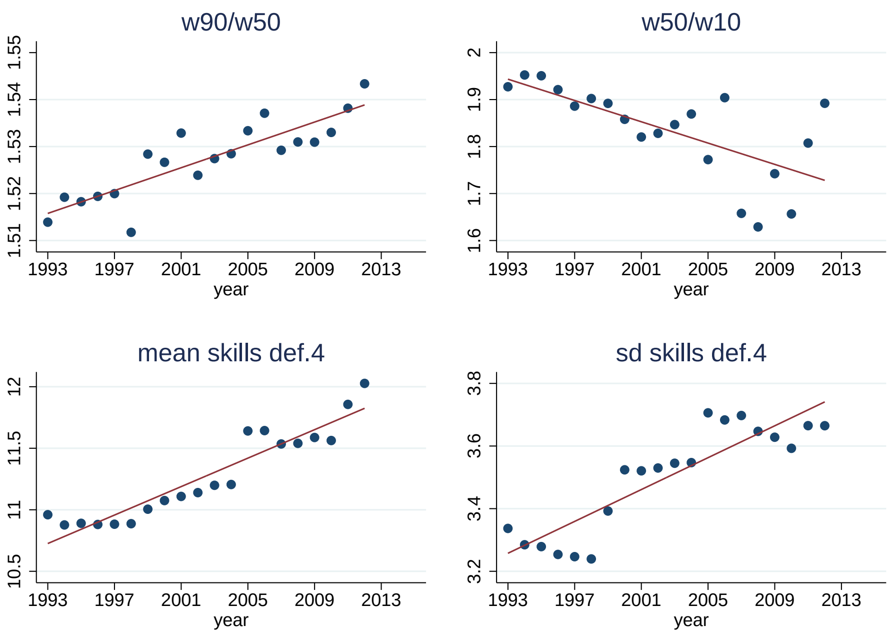
Figure 1: Destination of Danish Export



Note: Amount in Danish Kroner (DKK). North includes countries in North America, Oceania, and Western and Southern Europe (excluding the new EU members of the 2004 enlargement). All other countries in the world are considered in the category of South. Source: Statistics Denmark.

Figure 2: Wage Gap and Skills over Time



Note: The first two panels plot the average wage gap for $\frac{w90}{w50}$ and $\frac{w50}{w10}$ against time, respectively. The last two panels plot the first two moments of the skill distribution against time based on skill definition 2, which is simply years of education.

Table 1: Descriptive Statistics

Industry-level variables	**Definition**	**Mean**	**Sd**
Wage gaps			
w90/w50	ratio of the 90th to 50th percentile of the wage distribution at the industry level	1.544	0.201
w50/w10	ratio of the 50th to 10th percentile of the wage distribution at the industry level	1.802	0.300
Trade variables:			
Export	Log of real export volumes	16.377	6.481
Export North	Log of real export volumes to developed countries	15.780	6.855
Export South	Log of real export volumes to non developed countries	13.908	6.898
Import	Log of real import volumes	17.540	5.254
Control variables			
Productivity	log of average total sales per employee	6.647	6.745
Capital intensity	log of average capital stock per employee	6.116	6.300
Male	average share of male employees	0.660	0.194
Foreign	average share of foreign employees	0.051	0.044
Age	average employees' age	40.809	4.061
Work experience	average work experience	14.548	3.920
Tenure	average tenure	5.677	2.183
N			8,566
Municipality-level variables			
Skill variables			
Skill definition 1-mean	Continuous skill variable based on Portela et al. (2001)	11.321	0.691
Skill definition 1-sd		3.718	0.336
Skill definition 2-mean	Continuous skill variable based on years of formal education	11.432	0.654
Skill definition 2-sd		3.614	0.407
Skill definition 3-mean	Continuous skill variable estimated from AKM, systematic component	1.576	0.076
Skill definition 3-sd		0.200	0.015
Skill definition 4-mean	Continuous skill variable estimated from AKM, systematic component without age	0.621	0.079
Skill definition 4-sd		0.234	0.014
Skill definition 5-mean	Continuous skill variable estimated from AKM, systematic component without age and tenure	0.576	0.079
Skill definition 5-sd		0.223	0.016
Skill definition 6-mean	Continuous skill variable estimated from match fixed effects model	12.240	0.154
Skill definition 6-sd		0.430	0.036
N			1,862

Note: All descriptive statistics are calculated as averages over the period 1993–2012.

Table 2: Effects of Trade Activity on the Wage Gap and Skill Distribution

Step 1	w90/w50	w50/w10		
Export	0.003***	-0.018***		
	(0.000)	(0.001)		
F stat	30746.35	30746.35		
N	8,566	8,566		
R-sq	0.142	0.227		
		OLS		
Step 2, skill definition 1	Mean	SD	Mean	SD
Predicted w90/w50, one-year lag	10.030***	9.550***		
	(0.262)	(0.237)		
Predicted w50/w10, one-year lag			-1.726***	-1.643***
			(0.057)	(0.043)
N	1,764	1764	1764	1764
R-sq	0.887	0.768	0.887	0.768
		GMM		
Step 2, skill definition 1	Mean	SD	Mean	SD
Predicted w90/w50, first-year lag	5.812***	3.146***		
	(0.333)	(0.225)		
Predicted w50/w10, first-year lag			-1.000***	-0.541***
			(0.059)	(0.044)
N	1,764	1,764	1,764	1,764
Wald Wald chi-sq	57070.748	40520.625	57070.748	40520.625

Notes: Skill definition 1 is based on the multidimensional index of workers' human capital. In the first step, export is instrumented with world import demand (see Equation 2), and standard errors are clustered at the industry level. The first step includes the following control variables: industry sales per employee, industry capital intensity, industry workforce composition characteristics, and year and 2-digit industry dummies. The second step includes the lag of the dependent variable and the following control variables averaged at the municipality level: the lag of sales per employee average, capital intensity and workforce composition characteristics, plus year and municipality dummies. The second step is estimated by using either OLS (second panel) or the system GMM estimator (third panel), and the standard errors are clustered at the municipality level and sequentially bootstrapped with step 1, 200 replications. Estimates in the second step are weighted by the number of employed individuals at the municipality level. Significance levels: ***1%, **5%, *10%.

Table 3: Effects of Trade-Induced Wage Gaps on Workforce Composition

	Share of workers moving into the municipality		Share of workers moving out of the municipality	
Predicted w90/w50, first-year lag	0.639		-0.328	
	(1.305)		(0.874)	
Predicted w50/w10, first-year lag		-1.221		1.077
		(1.529)		(1.330)
N	1,764	1,764	1,764	1,764
Wald chi-sq	30400.188	19756.005	20456.176	16789.789
	Share of workers younger than 35		Share of workers older than 55	
Predicted w90/w50, first-year lag	0.255*		-0.026	
	(0.144)		(0.044)	
Predicted w50/w10, first-year lag		-0.118*		0.015
		(0.066)		(0.020)
N	1,764	1,764	1,764	1,764
Wald chi-sq	40700.345	41659.345	10345.677	11345.906

Notes: The specifications of the first and second steps are the same as those reported in Table 2, with the only exception being the second step in the second panel, where we exclude workers' average age from the set of control variables. The second step is estimated by using the system GMM estimator, and the standard errors are clustered at the municipality level and sequentially bootstrapped with step 1, 200 replications. Estimates in the second step are weighted by the number of employed individuals at the municipality level. Significance levels: ***1%, **5%, *10%.

Table 4: Effects of Trade-Induced Wage Gaps on the Skill Distribution: Alternative Skill definitions

Step 2, skill definition 2	Mean	SD	Mean	SD
Predicted w90/w50, first-year lag	2.633***	0.940***		
	(0.366)	(0.185)		
Predicted w50/w10, first-year lag			-0.453***	-0.162***
			(0.074)	(0.050)
N	1,764	1,764	1,764	1,764
Wald chi-sq	57070.748	40520.625	57070.748	40520.625
Step 2, skill definition 3	Mean	SD	Mean	SD
Predicted w90/w50, first-year lag	0.526***	0.094***		
	(0.025)	(0.013)		
Predicted w50/w10, first-year lag			-0.091***	-0.016***
			(0.004)	(0.003)
N	1,764	1,764	1,764	1,764
Wald chi-sq	10456.765	9843.345	10456.765	9843.345
Step 2, skill definition 4	Mean	SD	Mean	SD
Predicted w90/w50, first-year lag	0.481***	0.170***		
	(0.024)	(0.011)		
Predicted w50/w10, first-year lag			-0.083***	-0.029***
			(0.004)	(0.002)
N	1,764	1,764	1,764	1,764
Wald chi-sq	10456.765	9843.345	10456.765	9843.345
Step 2, skill definition 5	Mean	SD	Mean	SD
Predicted w90/w50, first-year lag	0.484***	0.193***		
	(0.020)	(0.011)		
Predicted w50/w10, first-year lag			-0.083***	-0.033***
			(0.003)	(0.002)
N	1,764	1,764	1,764	1,764
Wald chi-sq	10456.765	9843.345	10456.765	9843.345
Step 2, skill definition 6	Mean	SD	Mean	SD
Predicted w90/w50, first-year lag	0.619***	0.350***		
	(0.039)	(0.020)		
Predicted w50/w10, first-year lag			-0.107***	-0.060***
			(0.006)	(0.003)
N	1,764	1,764	1,764	1,764
Wald chi-sq	11009.342	9987.673	11009.342	9987.673

Notes: Skill definition 2 is based on years of education. Skill definition 3 is based on the systematic component of the two-way fixed effects wage regression. Skill definitions 4 and 5 are based on the systematic component of the two-way fixed effects wage regression, without age and without age and tenure, respectively. Skill definition 6 is based on the whole systematic component of the wage regression with spell fixed effects. In first step, standard errors are clustered at the industry level. The second step is estimated by using the system GMM estimator, and the standard errors are clustered at the municipality level and sequentially bootstrapped with step 1, 200 replications. Estimates in the second step are weighted by the number of employed individuals at the municipality level. The specifications of the first and second steps are the same as those reported in Table 2. Significance levels: ***1%, **5%, *10%.

Table 5: Effects of Trade Activity on the Wage Gap and Skill Distribution: The Role of Export Destination

Step 1	w90/w50	w50/w10		
Export North	0.001	-0.001		
	(0.001)	(0.002)		
Export South	0.006***	-0.011***		
	(0.000)	(0.001)		
F stat	3834.16	3834.155		
N	8,566	8566		
R-sq	0.159	0.408		
Step 2, skill definition 1	Mean	SD	Mean	SD
Predicted w90/w50, first-year lag	4.532***	2.418***		
	(0.332)	(0.249)		
Predicted w50/w10, first-year lag			-0.969***	-0.473***
			(0.050)	(0.040)
N	1,764	1,764	1,764	1,764
Wald chi-sq	55189.003	30897.122	55189.003	30897.122

Notes: Skill definition 1 is based on the multidimensional index of workers' human capital. In the first step, export north and export south are instrumented with world import demand separately for north and south, and standard errors are clustered at the industry level. The second step is estimated by using the system GMM estimator, and the standard errors are clustered at the municipality level and sequentially bootstrapped with step 1, 200 replications. Estimates in the second step are weighted by the number of employed individuals at the municipality level. The specifications for the first and second steps are the same as those reported in Table 2. Significance levels: ***1%, **5%, *10%.

Table 6: Effects of Trade Activity on the Wage Gap and Skill Distribution: The Role of Imports

Step 1	w90/w50	w50/w10		
Import	0.004***	-0.008***		
	(0.000)	(0.001)		
F stat	31199.44	31199.44		
N	8,566	8,566		
R-sq	0.154	0.399		
Step 2, skill definition 1	Mean	SD	Mean	SD
Predicted w90/w50, first-year lag	3.974***	2.515***		
	(0.120)	(0.005)		
Predicted w50/w10, first-year lag			-1.538***	-0.812**
			(0.095)	(0.004)
N	1,764	1,764	1,764	1,764
Wald chi-sq	56899.144	38987.489	56899.144	38987.489

Notes: skill definition 1 is based on the multidimensional index of workers' human capital. In the first step, import is instrumented with world export supply (see the equivalent of Equation 2, where import volumes are replaced with export volumes), and standard errors are clustered at the industry level. The second step is estimated by using the system GMM estimator, and the standard errors are clustered at the municipality level and sequentially bootstrapped with step 1, 200 replications. Estimates in the second step are weighted by the number of employed individuals at the municipality level. The specifications of the first and second steps are the same as those reported in Table 2. Significance levels: ***1%, **5%, *10%.

Table 7: Effects of Trade Activity on the Wage Gap and Skill Distribution: High-Tech Sectors

Step 1	w90/w50	w50/w10		
Export	0.009**	-0.022***		
	(0.000)	(0.003)		
F stat	1285.377	1285.377		
N	1,313	1,313		
R-sq	0.255	0.472		
Step 2, skill definition 1	Mean	SD	Mean	SD
Predicted w90/w50, first-year lag	7.195***	4.665***		
	(0.057)	(0.040)		
Predicted w50/w10, first-year lag			-1.986***	-0.695***
			(0.027)	(0.019)
N	1,764	1,764	1,764	1,764
Wald chi-sq	57854.120	37954.003	57854.120	37954.003

Notes: High-Tech sectors are those with R&D expenditures above the overall economy average. Skill definition 1 is based on the multidimensional index of workers' human capital. In the first step, export is instrumented with world import demand (see Equation 2), and standard errors are clustered at the industry level. The second step is estimated by using the system GMM estimator, and the standard errors are clustered at the municipality level and sequentially bootstrapped with step 1, 200 replications. Estimates in the second step are weighted by the number of employed individuals at the municipality level. The specifications of the first and second steps are the same as those reported in Table 2. Significance levels: ***1%, **5%, *10%. Significance levels: ***1%, **5%, *10%.

Table 8: Effects of Trade Activity on the Wage Gap and Skill Distribution: Low-Tech Sectors

Step 1	w90/w50	w50/w10		
Export	0.003***	-0.016***		
	(0.001)	(0.004)		
F stat	2820.041	2820.041		
N	6,157	6,157		
R-sq	0.131	0.238		
Step 2, skill definition 1	Mean	SD	Mean	SD
Predicted w90/w50, first-year lag	1.420***	0.385***		
	(0.076)	(0.058)		
Predicted w50/w10, first-year lag			-0.255***	-0.069***
			(0.015)	(0.010)
N	1,764	1,764	1,764	1,764
Wald chi-sq	51677.087	38000.765	51677.087	38000.765

Notes: Low-Tech sectors are those with R&D expenditures below the overall economy average. Skill definition 1 is based on the multidimensional index of workers' human capital. In the first step, export is instrumented with world import demand (see Equation 2), and standard errors are clustered at the industry level. The second step is estimated by using the system GMM estimator, and the standard errors are clustered at the municipality level and sequentially bootstrapped with step 1, 200 replications. Estimates in the second step are weighted by the number of employed individuals at the municipality level. The specifications of the first and second steps are the same as those reported in Table 2. Significance levels: ***1%, **5%, *10%. Significance levels: ***1%, **5%, *10%.

Table 9: Effects of Trade Activity on the Wage Gap and Skill Distribution: Manufacturing Sectors

Step 1	w90/w50	w50/w10		
Export	0.004***	-0.067***		
	(0.000)	(0.004)		
F stat	7753.62	7753.62		
N	3,379	3,379		
R-sq	0.054	0.271		
Step 2, skill definition 1	Mean	SD	Mean	SD
Predicted w90/w50, first-year lag	4.316***	3.255***		
	(0.514)	(0.366)		
Predicted w50/w10, first-year lag			-0.735***	-0.390***
			(0.031)	(0.020)
N	1,764	1,764	1,764	1,764
Wald chi-sq	53456.591	37654.998	53456.591	37654.998

Notes: Skill definition 1 is based on the multidimensional index of workers' human capital. In the first step, export is instrumented with world import demand (see Equation 2), and standard errors are clustered at the industry level. The second step is estimated by using the system GMM estimator, and the standard errors are clustered at the municipality level and sequentially bootstrapped with step 1, 200 replications. The first step is estimated within the manufacturing sector only. Estimates in the second step are weighted by the number of employed individuals at the municipality level. The specifications of the first and second steps are the same as those reported in Table 2. Significance levels: ***1%, **5%, *10%.

Table 10: Robustness Check for the Instrumental Variable: The Role of Correlated Business Cycles across Countries

Step 1	w90/w50	w50/w10		
Export	0.005***	-0.021***		
	(0.000)	(0.001)		
F stat	34768.76	34768.76		
N	8,566	8,566		
R-sq	0.134	0.224		
Step 2, skill definition 1	Mean	SD	Mean	SD
Predicted w90/w50, first-year lag	7.956***	4.479***		
	(0.323)	(0.244)		
Predicted w50/w10, first-year lag			-1.725***	-1.042***
			(0.051)	(0.045)
N	1,764	1,764	1,764	1,764
Wald chi-sq	55200.644	39533.112	55200.644	39533.112

Notes: Skill definition 1 is based on the multidimensional index of workers' human capital. In the first step, export is instrumented with world import demand calculated by excluding Germany, Sweden and the United States from Equation 2. In the first step, standard errors are clustered at the industry level. The second step is estimated by using the system GMM estimator, and the standard errors are clustered at the municipality level and sequentially bootstrapped with step 1, 200 replications. Estimates in the second step are weighted by the number of employed individuals at the municipality level. The specifications of the first and second steps are the same as those reported in Table 2. Significance levels: ***1%, **5%, *10%.

Table 11: Robustness Check for the Instrumental Variable: The Role of Correlated Technology or Demand Shocks (Colantone et al., 2015)

Step 1	w90/w50	w50/w10		
Export	0.003***	-0.019***		
	(0.000)	(0.001)		
F stat	29370.04	29370.04		
N	7,415	7,415		
R-sq	0.158	0.412		
Step 2, skill definition 1	Mean	SD	Mean	SD
Predicted w90/w50, first-year lag	5.676***	3.949***		
	(0.373)	(0.272)		
Predicted w50/w10, first-year lag			-1.082***	-0.670***
			(0.053)	(0.043)
N	1,764	1,764	1,764	1,764
Wald chi-sq	54665.578	40100.334	54665.578	40100.334

Notes: Skill definition 1 is based on the multidimensional index of workers' human capital. In the first step, export is instrumented with world import demand calculated by excluding from Equation 2 the following industries: the manufacture of coke, refined petroleum products and nuclear fuel (NACE 23); the manufacture of rubber and plastic products (NACE 25); the manufacture of radio, television and communication equipment and apparatus (NACE 32); air transport (NACE 62); and post and telecommunications (NACE 64). In first step, standard errors are clustered at the industry level. In the second step, standard errors are clustered at the municipality level and sequentially bootstrapped with step 1, 200 replications. Estimates in the second step are weighted by the number of employed individuals at the municipality level. The specifications of the first and second steps are the same as those reported in Table 2. Significance levels: ***1%, **5%, *10%.

Table 12: Robustness Check for Instrumental Variable: The Role of Correlated Technology or Demand Shocks (Autor et al., 2013)

Step 1	w90/w50	w50/w10		
Export	0.003***	-0.017***		
	(0.000)	(0.001)		
F stat	27887.92	27887.92		
N	6,866	6,866		
R-sq	0.1644956	0.4136645		
Step 2, skill definition 1	Mean	SD	Mean	SD
Predicted w90/w50, first-year lag	5.107***	3.169***		
	(0.328)	(0.285)		
Predicted w50/w10, first-year lag			-1.071***	-0.519***
			(0.055)	(0.046)
N	1,764	1,764	1,764	1,764
Wald chi-sq	54665.578	40100.334	54665.578	40100.334

Notes: Skill definition 1 is based on the multidimensional index of workers' human capital. In the first step, export is instrumented with world import demand calculated by excluding from Equation 2 the following industries: the manufacture of textiles and manufacture of wearing apparel (NACE 17); the dressing and dyeing of fur (NACE 18); the tanning and dressing of leather; the manufacture of luggage, handbags, saddlery, harness and footwear (NACE 19); the manufacture of other non-metallic mineral products (NACE 26); the manufacture of basic metals (NACE 27); the manufacture of fabricated metal products, except machinery and equipment (NACE 28); and the manufacture of office machinery and computers (NACE 30). In first step, standard errors are clustered at the industry level. The second step is estimated by using the system GMM estimator, and the standard errors are clustered at the municipality level and sequentially bootstrapped with step 1, 200 replications. Estimates in the second step are weighted by the number of employed individuals at the municipality level. The specifications of the first and second steps are the same as those reported in Table 2. Significance levels: ***1%, **5%, *10%.

Table 13: Effects of Trade-Induced Wage Gaps on the Skill Distribution: Two- and Three-Year Lags

Step 2, skill definition 1	Mean	SD	Mean	SD
Predicted w90/w50, two-year lag	6.298***	3.454***		
	(0.332)	(0.240)		
Predicted w50/w10, two-year lag			-1.084***	-0.594***
			(0.063)	(0.042)
N	1,666	1,666	1,666	1,666
Wald chi-sq	40144.561	28756.008	40144.561	28756.008
Step 2, skill definition 1	Mean	SD	Mean	SD
Predicted w90/w50, three-year lag	6.780***	3.751***		
	(0.325)	(0.268)		
Predicted w50/w10, three-year lag			-1.167***	-0.645***
			(0.064)	(0.045)
N	1,568	1,568	1,568	1,568
Wald chi-sq	39000.732	22756.128	39000.732	22756.128

Notes: Skill definition 1 is based on the whole systematic component of the two-way fixed effects wage regression. The second step is estimated by using the system GMM estimator, and the standard errors are clustered at the municipality level and sequentially bootstrapped with step 1, 200 replications. Estimates in the second step are weighted by the number of employed individuals at the municipality level. The specifications of the first and second steps are the same as those reported in Table 2. Significance levels: ***1%, **5%, *10%.

Table 14: Effects of Trade Activity on the Wage Gap and Skill Distribution: The Case of Portugal

Step 1	w90/w50	w50/w10		
Export	0.036***	0.020***		
	(0.004)	(0.004)		
F stat	256.5	256.5		
N	1,126	1,126		
R-sq	0.561	0.595		
Step 2, skill definition 1	Mean	SD	Mean	SD
Predicted w90/w50, first-year lag	0.165***	0.023***		
	(0.024)	(0.005)		
Predicted w50/w10, first-year lag			-0.297	-0.042***
			(0.199)	(0.010)
N	4,218	4,218	4,218	4,218
Wald chi-sq	120345.876	100344.367	120345.876	100344.367

Notes: Skill definition 1 is based on the multidimensional index of workers' human capital. In the first step, export is instrumented with world import demand (see Equation 2), and standard errors are clustered at the industry level. The first step includes the following control variables: industry sales per employee, industry workforce composition characteristics, and year and 2-digit industry dummies. The second step includes the lag of the dependent variable and the following control variables averaged at the municipality level and lagged one period: sales per employee average, workforce composition characteristics, and year and municipality dummies. The second step is estimated by using the system GMM estimator, and the standard errors are clustered at the municipality level and sequentially bootstrapped with step 1, 200 replications. Estimates in the second step are weighted by the number of employed individuals at the municipality level. Significance levels: ***1%, **5%, *10%.

A Appendix: Theoretical Solutions

In this section, we present a general model of the skill upgrading decision. $\theta = 1$ corresponds to a frictionless environment, while $0 < \theta < 1$ corresponds to the frictional environment.

Since individuals can perfectly smooth their consumption over time, it is easy to show that their lifetime utility, V_i, is an increasing function of their lifetime income, $W_i \equiv \sum_{t=1}^{3} w(s_{it})p_t(1 - I_{it}\frac{\bar{e}}{a_i})$. Hence, we examine the following three cases.

Case 1: No skill upgrading: $I_{it} = 0$ ***for*** $t = 1, 2, 3$

The first case is if the individual decides not to obtain additional skills. Her lifetime income is:

$$W^1 = w(\underline{s})(p_1 + p_2 + p_3) \tag{7}$$

Case 2: Upgrade skills once: $I_{i1} = 1$ ***and*** $I_{it} = 0$ ***for*** $t = 2, 3$

The second case is if the individual upgrades her skills once in her lifetime. Her lifetime income is:

$$W^2 = w(\underline{s})p_1(1 - \frac{\bar{e}}{a_i}) + [\theta w(\underline{s} + \bar{e}) + (1 - \theta)w(\underline{s})]p_2 + [\theta w(\underline{s} + \bar{e}) + (1 - \theta)w(\underline{s})]p_3 \tag{8}$$

Case 3: Upgrade skills twice: $I_{it} = 1$ ***for*** $t = 1, 2$ ***and*** $I_{i3} = 0$

The third case is if the individual upgrades her skills twice in her lifetime. Her lifetime income is:

$$W^3 = w(\underline{s})p_1(1 - \frac{\bar{e}}{a_i}) + [\theta w(\underline{s} + \bar{e}) + (1 - \theta)w(\underline{s})]p_2(1 - \frac{\bar{e}}{a_i}) + [\theta w(\underline{s} + 2\bar{e}) + (1 - \theta)w(\underline{s} + \bar{e})]p_3 \tag{9}$$

We solve for the ability thresholds, $A_1 = \frac{w(\underline{s})p_1\bar{e}}{\theta(p_2+p_3)\Delta_1}$ and $A_2 = \frac{[w(\underline{s})+\theta\Delta_1]p_2\bar{e}}{p_3[\theta\Delta_2+(1-\theta)\Delta_1]}$, such that when an individual i's ability $a_i \leq A_1$, they have $W^1 \geq W^2$, and when an individual $i's$ $a_i \geq A_2$, the individual has $W^3 \geq W^2$; when an individual i's ability $A_1 \leq a_i \leq A_2$, the individual has $W^2 \geq W^3$ and $W^2 \geq W^1$.

The effect of changes in Δ_1 and Δ_2 on the thresholds can be summarized as follows:

$$\frac{\partial A_1}{\partial \Delta_1} = -\frac{w(\underline{s})p_1\bar{e}}{\theta(p_2 + p_3)\Delta_1^2} < 0 \tag{10}$$

$$\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2} = \frac{p_2\bar{e}[\theta^2\Delta_2 - (1 - \theta)w(\underline{s})]}{p_3[\theta\Delta_2 + (1 - \theta)\Delta_1]^2} \tag{11}$$

$$\frac{\partial A_2}{\partial \Delta_2}|_{\Delta_1} = -\frac{\theta[w(\underline{s}) + \theta\Delta_1]p_2\bar{e}}{p_3[\theta\Delta_2 + (1 - \theta)\Delta_1]^2} < 0 \tag{12}$$

Moreover, changes in θ affecting the above differentials can be summarized as follows:

$$\begin{aligned}
\frac{\partial\left(\frac{\partial A_1}{\partial \Delta_1}\right)}{\partial\theta} &= \frac{w(\underline{s})p_1\bar{e}}{\theta^2(p_2+p_3)\Delta_1^2} > 0 && (13)\\
\frac{\partial\left(\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}\right)}{\partial\theta} &= \frac{p_2\bar{e}[w(\underline{s})(2\Delta_2-\Delta_1)+\theta w(\underline{s})(\Delta_1-\Delta_2)]}{p_3[\theta\Delta_2+(1-\theta)\Delta_1]^3} && (14)\\
\frac{\partial\left(\frac{\partial A_2}{\partial \Delta_2}|_{\Delta_1}\right)}{\partial\theta} &= -\frac{p_2\bar{e}[w(\underline{s})\Delta_1+w(\underline{s})\theta(\Delta_1-\Delta_2)+2\theta\Delta_1^2]}{p_3[\theta\Delta_2+(1-\theta)\Delta_1]^3} < 0 && (15)
\end{aligned}$$

Finally, assuming a uniform distribution of ability, the first two moments are computed using the following expressions. Moreover, the movement of thresholds in response to changes in Δs affects these moments, and we provide the corresponding implications below.

(1) Mean ($E(s)$):

$$\begin{aligned}
E(s) &= \underline{s}\frac{A_1-\underline{a}}{\bar{a}-\underline{a}} + (\underline{s}+\bar{e})\frac{A_2-A_1}{\bar{a}-\underline{a}} + (\underline{s}+2\bar{e})\frac{\bar{a}-A_2}{\bar{a}-\underline{a}}\\
&= \underline{s} + \frac{2\bar{a}-A_1-A_2}{\bar{a}-\underline{a}}\bar{e}
\end{aligned}$$

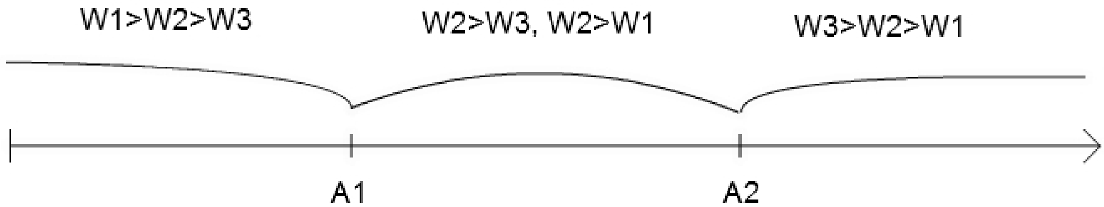
(2) Variance ($Var(s)$):

$$\begin{aligned}
Var(s) &= \sum[s_i-E(s)]^2\\
&= \frac{A_1-\underline{a}}{\bar{a}-\underline{a}}(\frac{2\bar{a}-A_1-A_2}{\bar{a}-\underline{a}}\bar{e})^2 + \frac{A_2-A_1}{\bar{a}-\underline{a}}(\frac{\bar{a}+\underline{a}-A_1-A_2}{\bar{a}-\underline{a}}\bar{e})^2 + \frac{\bar{a}-A_2}{\bar{a}-\underline{a}}(\frac{2\underline{a}-A_1-A_2}{\bar{a}-\underline{a}}\bar{e})^2\\
&= \frac{\bar{e}^2}{(\bar{a}-\underline{a})^3}\{(A_1-\underline{a})(2\bar{a}-A_1-A_2)^2 + (A_2-A_1)(\bar{a}+\underline{a}-A_1-A_2)^2\\
&+ (\bar{a}-A_2)(2\underline{a}-A_1-A_2)^2\}\\
&= \frac{\bar{e}^2}{(\bar{a}-\underline{a})^3}\{(A_1-\underline{a})(2\bar{a}-A_1-A_2)^2 + [\bar{a}-\underline{a}-(A_1-\underline{a})-(\bar{a}-A_2)](\bar{a}+\underline{a}-A_1-A_2)^2\\
&+ (\bar{a}-A_2)(2\underline{a}-A_1-A_2)^2\}\\
&= \frac{\bar{e}^2}{(\bar{a}-\underline{a})^3}\{(A_1-\underline{a})[(2\bar{a}-A_1-A_2)^2-(\bar{a}+\underline{a}-A_1-A_2)^2] + [\bar{a}-\underline{a}](\bar{a}+\underline{a}-A_1-A_2)^2\\
&+ (\bar{a}-A_2)[(2\underline{a}-A_1-A_2)^2-(\bar{a}+\underline{a}-A_1-A_2)^2]\}\\
&= \frac{\bar{e}^2}{(\bar{a}-\underline{a})^2}\{(A_1-\underline{a})(3\bar{a}+\underline{a}-2A_1-2A_2) + (\bar{a}-A_2)(2A_1+2A_2-\bar{a}-3\underline{a})\\
&+ (\bar{a}+\underline{a}-A_1-A_2)^2\}\\
&= \frac{\bar{e}^2}{(\bar{a}-\underline{a})^2}\{(A_1-\underline{a})(3\bar{a}+\underline{a}-2A_1-2A_2) - \bar{a}\underline{a} + (A_1-\underline{a})^2 + A_2(\bar{a}+\underline{a}-A_2)\}
\end{aligned}$$

A.1 Flexible Market ($\theta = 1$)

Replacing $\theta = 1$, $a_i \leq \frac{w(\underline{s})p_1\bar{e}}{(p_2+p_3)[w(\underline{s}+\bar{e})-w(\underline{s})]} \equiv A_1$ and $a_i \geq \frac{w(\underline{s}+\bar{e})p_2\bar{e}}{p_3[w(\underline{s}+2\bar{e})-w(\underline{s}+\bar{e})]} \equiv A_2$. Assuming $\frac{d^2w}{ds^2} < 0$ and positive inflation (i.e., $p_1 \leq p_2 \leq p_3$), we have $A_1 < A_2$. Hence, we can draw Figure 3.

Figure 3: Ability Thresholds and the Skill Upgrading Decision



Note: The above illustration depicts the ability-specific thresholds and the associated ranking of wealth given zero, one or two skill upgrades. This illustration highlights that those individuals whose ability is below A_1 do not upgrade their skills, those above the A_2 level of ability upgrade their skills twice in their lifetime, and those in between A_1 and A_2 upgrade their skills only once.

$$\frac{\partial A_1}{\partial \Delta_1} < 0 \tag{16}$$

$$\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2} > 0 \tag{17}$$

$$\frac{\partial A_2}{\partial \Delta_2}|_{\Delta_1} < 0 \tag{18}$$

Implications for the Overall Skill Distribution:

- If $|\frac{\partial A_1}{\partial \Delta_1}| < |\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}|$, an increase in Δ_1 decreases the mean ($E(s)$) and variation ($Var(s)$) of skills. (1) Mean: When Δ_1 increases, A_1 decreases and A_2 increases. Since $|\frac{\partial A_1}{\partial \Delta_1}| < |\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}|$, the decrease in A_1 is smaller than the increase in A_2. Hence, $E(s) = \underline{s} + \frac{2\bar{a}-A_1-A_2}{\bar{a}-\underline{a}}\bar{e}$ decreases. (2) Variance: Since $\bar{a} + \underline{a} < 2A_2$, $\bar{a} + \underline{a} > 2A_1$, and $\underline{a} < A_1 < A_2 < \bar{a}$, we have $3\bar{a} + \underline{a} - 2A_1 - 2A_2 > \bar{a} + \underline{a} - 2A_1 > 0$. When Δ_1 increases, A_1 decreases and A_2 increases. Assuming that $|\frac{\partial A_1}{\partial \Delta_1}| < |\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}|$, we have that both $(A_1 - \underline{a})$ and $(3\bar{a} + \underline{a} - 2A_1 - 2A_2)$ decrease. The last term in $Var(s)$ is $A_2(\bar{a} + \underline{a} - A_2)$. Its value changes by $\bar{a} + \underline{a} - 2A_2 < 0$ when A_2 increases by 1. Hence, $Var(s)$ is $A_2(\bar{a}+\underline{a}-A_2)$ and also decreases when A_2 increases. Therefore, we prove that $Var(s)$ decreases when Δ_1 increases.

- An increase in Δ_2 increases both the mean ($E(s)$) and the variation ($Var(s)$) of skills. (1) Mean: When Δ_2 increases, A_2 decreases while A_1 does not change. Hence, $E(s) = \underline{s} + \frac{2\bar{a}-A_1-A_2}{\bar{a}-\underline{a}}\bar{e}$ increases.
  (2) Variance: When A_2 decreases, we have that both $3\bar{a} + \underline{a} - 2A_1 - 2A_2$ and $A_2(\bar{a} + \underline{a} - A_2)$ increases. Therefore, we prove that $Var(s)$ increases when Δ_2 increases.

A.2 Frictional Markets ($0 < \theta < 1$)

Before proving the implications for the skill distribution of changes in Δ_1 and Δ_2, we first establish the condition for θ under which $A_1 < A_2$. To have $A_1 < A_2$, we need $X\theta^2 + Y\theta + Z > 0$, where

$$\begin{aligned} X &= (p_2 + p_3)p_2\bar{e}\Delta_1^2 > 0 \\ Y &= \bar{e}w(\underline{s})[(p_2 + p_3)p_2\Delta_1 + (\Delta_1 - \Delta_2)p_1p_3] > 0 \\ Z &= -\bar{e}w(\underline{s})p_1p_3\Delta_1 < 0 \end{aligned} \tag{19}$$

Given the quadratic nature of the equation $X\theta^2 + Y\theta + Z$, it is easy to see that the equation's lowest point is achieved at $\theta = \frac{-Y}{2X} < 0$. That is, for any $0 < \theta \leq 1$, $X\theta^2 + Y\theta + Z$ monotonically increases along θ. Then, we solve for the positive θ^* that equalizes $X\theta^2 + Y\theta + Z$ to 0:

$$\theta^* = \frac{-Y + \sqrt{Y^2 - 4XZ}}{2X} > 0 \tag{20}$$

where $-4XZ > 0$, and thus, $Y^2 - 4XZ > Y^2 > 0$. Hence, we have $\frac{-Y+\sqrt{Y^2-4XZ}}{2X} > 0$. Assuming that $\frac{d^2w}{ds^2} < 0$ and positive inflation (i.e., $p_1 \leq p_2 \leq p_3$), when $\theta = 1$ in the baseline mode,l we have $A_1 < A_2$, and thus, $X\theta^2 + Y\theta + Z > 0$. Therefore, $X\theta^2 + Y\theta + Z$ monotonically increases for the positive $\theta \in [\theta^*, 1]$.

We have proven that $\frac{-Y+\sqrt{Y^2-4XZ}}{2X} < 1$. Hence, we have shown that to have $A_1 < A_2$, we need $0 < \frac{-Y+\sqrt{Y^2-4XZ}}{2X} = \theta^* < \theta \leq 1$, and this condition is consistent with θ being a probability between 0 and 1.

Restricting $\theta \in [\theta^*, 1]$, we can now study the distributional effects of changes in wage gaps.

Recall that we cannot assign a positive or negative value to $\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}$ unless we have additional conditions stating whether θ is above or below some cutoff denoted by $\bar{\epsilon}$ while restricting the cutoff to lie in the range where $A_1 < A_2$, only, i.e., $\theta^* < \bar{\epsilon}$. To find $\theta = \bar{\epsilon}$, we need the numerator of $\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2} = 0$, which implies that $[\theta^2\Delta_2 - (1-\theta)w(\underline{s})] = 0$. Solving for the quadratic equation in θ, $\bar{\epsilon} = \frac{-w(\underline{s}) \pm \sqrt{w^2(\underline{s}) + 4\Delta_2 w(\underline{s})}}{2\Delta_2}$.

Then, for $\theta \in [\theta^*, \bar{\epsilon}]$, we have $\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2} < 0$, and for $\theta \in [\bar{\epsilon}, 1]$, we have $\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2} > 0$.

Implications for the Overall Skill Distribution:

- An increase in Δ_1 has an ambiguous effect on $E(s)$ and $Var(s)$. Depending on the relationship between $|\frac{\partial A_1}{\partial \Delta_1}|$ and $|\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}|$ and the magnitude of θ, various cases are possible, and therefore, the ultimate effect is at best ambiguous.

$$Mean = \begin{cases} \text{Decreases if } |\frac{\partial A_1}{\partial \Delta_1}| < |\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}| \text{ \& } \theta \in [\bar{\epsilon}, 1] \\ \text{Increases if } |\frac{\partial A_1}{\partial \Delta_1}| > |\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}| \text{ \& } \theta \in [\bar{\epsilon}, 1] \\ \text{Unchanged if } |\frac{\partial A_1}{\partial \Delta_1}| = |\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}| \text{ \& } \theta \in [\bar{\epsilon}, 1] \\ \text{Increases if } \theta \in [\theta^*, \bar{\epsilon}] \end{cases}$$

$$Variance = \begin{cases} \text{Decreases if } |\frac{\partial A_1}{\partial \Delta_1}| < |\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}| \text{ \& } \theta \in [\bar{\epsilon}, 1] \\ \text{Ambiguous otherwise} \end{cases}$$

- An increase in Δ_2 increases both the $E(s)$ and $Var(s)$ of skills but by a smaller magnitude relative to the case when $\theta = 1$. (1) Mean: When Δ_2 increases, A_2 decreases while A_1 does not change. Hence, $E(s) = \underline{s} + \frac{2\bar{a} - A_1 - A_2}{\bar{a} - \underline{a}}\bar{e}$ increases. Moreover, $\frac{\partial\left(\frac{\partial A_2}{\partial \Delta_2}|_{\Delta_1}\right)}{\partial \theta} < 0$, meaning than in absolute terms, the effect increases as θ increases.
  (2) Variance: When A_2 decreases, we have that both $3\bar{a} + \underline{a} - 2A_1 - 2A_2$ and $A_2(\bar{a} + \underline{a} - A_2)$ increases. Therefore, we prove that $Var(s)$ increases when Δ_2 increases. Moreover, $\frac{\partial\left(\frac{\partial A_2}{\partial \Delta_2}|_{\Delta_1}\right)}{\partial \theta} < 0$, meaning that in absolute terms, the effect increases as θ increases.