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Trade-induced Skill Polarization

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Trade-Induced Skill Polarization*

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Abstract

We study how wage gaps across skills and the skill distribution in an economy respond to trade integration. Using administrative data for Denmark (1995–2011), we find that trade has a negative effect on the wage gap between secondary and primary education and a positive effect on the wage gap between tertiary and secondary education. Using years of formal education as a measure of skills, we also show that trade affects skill distribution and induces *skill polarization*: trade has a positive effect on both the mean and the standard deviation of skills. Furthermore, we find that wage-gap changes induced by trade shocks explain about 21-30 percent of the overall effects of trade on the skill distribution.

Key words: skill polarization, skill distribution and trade integration.
JEL code: F16 - J24

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1 Introduction

The hollowing-out of the middle class is a recent phenomenon: mid-level jobs are disappearing (employment polarization), and wage inequality is increasing (wage polarization). The recent literature documents employment and 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 originates from exogenous demand shocks, such as the shocks that result from trade integration, which increase the relative *demand* for a particular type of labor. These existing theories assume that the skill supply is inelastic; however, this assumption raises concerns in a dynamic environment. For example, Acemoglu (2003) explains that when the supply of skills can respond to changing demands for skills, the economy will select a different point along the relevant 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 that we call "skill polarization". This type of polarization emphasizes that the skill distribution changes in response to exogenous shocks; 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. Although 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 and 1 percent of national GDP (Brookings Metropolitan Policy Program) to actively implement skill upgrading opportunities, especially in response to trade shocks.[2] In light of these policy efforts, the adjustments in the skill

[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 subgroup 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) emphasize that the off-shoring of tasks offers an explanation of the observed changes in the relative factor demands in response to trade.

[2]For example, some programs include vocational training, short-term programs, online degrees, adjustment payments and subsidies to formal education. The policy role is highlighted by Autor (2014) who writes that "$\cdots$ 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

supply can affect the whole skill distribution.

We adopt a systematic approach by answering three related questions. First, what impact do the exogenous demand shocks that result from trade have on wage gaps across skills? Second, what is the impact of these trade shocks on the skill distribution over time? Third, how much does the impact of trade on the skill distribution channel through wage-gap changes?

We study these 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 that range from free access to education and vocational training to unemployment benefits. Such institutions can make the skill supply elastic to certain extent in the long run and facilitate the adjustment of skill levels in response to trade-driven demand shocks.

The empirical analysis is conducted in two steps. The first step is to estimate the effects of trade on the wage gaps across skills and on the skill distribution, respectively. We use education as a proxy for skills and define wage gaps as the difference in the wages for workers with tertiary education relative to secondary education (high-skill wage gap) and the difference in wages for workers with secondary relative to primary schooling (low-skill wage gap), respectively. To remove endogeneity problems, we pursue an instrumental variable approach that identifies the effect of trade by exploiting changes in the world import and export for each product using U.N. COMTRADE data as in Hummels et al. (2014). In the second step, we explore whether any of the trade effect on the skill distribution goes through changing wage gaps. Specifically, we construct predicted changes in wage gaps due to trade from the first step (henceforth, exogenous trade-induced-wage-gap changes), and we then relate these exogenous changes to the skill distribution. The unit of analysis in both steps is at the level of relatively self-contained local labor markets (municipalities).[3] Accordingly, we assess how the predicted trade-induced-wage-gap changes affect the next period's skill distribution in these local labor markets – i.e., the average level and the variance of skills within the municipality.

demand for skills."

[3]Following Autor et al. (2013), we calculate the municipality exposure to trade by using national industry export and import sales and the share of employment for each industry in the municipality at the base year 1995. As in Foged and Peri (2016), the geographic units of analysis that we use to approximate local labor markets are municipalities, which has a broad definition that combines several of the old municipalities as local labor markets. Foged and Peri (2016) note that most worker mobility is observed across firms within a municipality, which confirms 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, 2018).

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 to be inelastic in the short run; thus, the contemporaneous trade shocks mainly causes a price effect captured by changes in relative wages of skills (Acemoglu, 2003), i.e., wage-gap changes, rather than changes in the skill supply. This is consistent with the notion that acquiring skills requires time. Third, although the skill supply is fixed in the short run, in a dynamic context (medium to long run), it is not fixed (Acemoglu, 2003). Under these assumptions, an exogenous increase in trade activities can lead to changes in the wage gaps, which can affect individuals' incentives to upgrade or maintain their 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. Our empirical analysis is guided by a simple three-period, partial equilibrium setting, with agents that are heterogeneous in their innate abilities. This model allows us to identify how exogenous changes in wage gaps affect individuals' incentives to upgrade their skills and how such individual-level decisions, when aggregated, affect the whole skill distribution.

Our main results for Denmark show that trade integration affects both wage gaps across skills and the skill distribution within the local labor markets. Specifically, we find that exogenous changes in trade have a negative effect on the wage gap between secondary and primary education and a positive effect on the wage gap between tertiary and secondary education. Furthermore, trade causes both the mean and the standard deviation of skills to increase and thus causes, what we define as, skill polarization. Finally, our empirical analysis indicates that changes in the wage gaps induced by trade integration explain a non-negligible share of the total trade effect on the skill distribution. Particularly, we estimate that changes in the wage gaps predicted from exogenous trade shocks can explain about 21-30 percent of the skill-distribution changes at the municipality level.

We make three main contributions to the literature. First, we study the effects of both exports and imports simutaneously on wage gaps across skills. At present, there is no consensus in the empirical literature on what effect globalization has on these wage gaps. On the one hand, for instance, Hummels et al. (2014) for Denmark and Greenland and Lopresti (2016) for the US find that imports have a negative influence on workers' wages, no matter their skill level. On the other hand, several studies within the trade literature report a positive impact of exports on high-skilled workers' wages (see, for example, Munch and Skaksen (2008) and Li (2018) for Denmark and China, respectively). We contribute to this literature by estimating simultaneously the effects of both export and import flows on wage gaps within the local labor market.

Our second contribution lies in the empirical examination of trade's impact on not only average skill level but also the *dispersion* of skills, i.e., the skill distribution. The existing literature provides some empirical explanations for cross-region differences in skill dispersion, such as state control over education (Stevenson and Baker, 1991), sorting and segregation (Friesen and Krauth, 2007), and school funding (Bénabou, 1996). No empirical paper to our knowledge has studied the impact of trade on skill dispersion.[4] However, the importance of understanding skill dispersion has been emphasized repeatedly in the literature. For instance, Hanushek and Woessmann (2008) provide a literature summary on the impact of skill dispersion on income inequality. Bombardini et al. (2012) study how skill dispersion affects a country's comparative advantage and thus trade flows. This paper complements the existing studies by empirically estimating the impact of trade on the skill distribution, including dispersion.

The third main contribution of this paper is getting granular to a specific channel through which exogenous trade shocks can affect skill distribution: wage-gap changes. Although several papers (e.g., Danziger, 2017; Davidson and Sly, 2014; Greenland and Lopresti, 2016; Li, 2018) investigate how the average skill level responds to trade shocks, none examines the channel of wage-gap changes through which trade affects skill acquisition. 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 who lived in municipalities that were more exposed to trade shocks. Another important advancement 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; 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 examining the effect of trade on the skill distribution through wage-gap changes, i.e., by exploring how trade-induced changes in the wage gaps across skills affect not only the average levels of skills but also the diversity of skills.

A recent paper by Keller and Utar (2016) also contributes to this line of work by using Danish data and complements our work. They show that import competition from China explains both the decrease in middle-wage and the increase in low- and high-wage employment in Denmark from 1999 to 2009, which is consistent with our findings. 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, emphasizes the adjustment of the skill supply and the skill polarization due to both export and import shocks that are not

[4] There are a few theoretical papers modeling the impact of trade on skill distribution, for instance, Abdel-Rahman (2005) and Blanchard and Willmann (2016).

limited to only China. The skill polarization identified in our paper is especially relevant for European economies that are suffering from economic polarization. It provides a new perspective and complements the job and wage polarization found in other studies.

In Section 2, we provide a simple theoretical framework that guides our empirical analysis. In Section 3, we present the institutional background for Denmark. The data and summary statistics are then discussed in Section 4. Our empirical strategy is explained in Section 5. We discuss our baseline results and additional analyses in Section 6. We then conclude in Section 7. The proofs, figures, and tables are collected in appendices at the end of the paper.

2 Theoretical Intuition

In this section, we introduce a tractable partial equilibrium framework that links exogenous wage-gap shocks to the skill choices made by heterogeneous individuals. Different from our later empirical analysis where wage-gap shocks are induced by exogenous trade shocks, here we do not model the origins of wage-gap shocks to keep the theoretical framework simple.[5]

What this simple theoretical framework will do is to provide an economic intuition for how exogenous changes in wage gaps affect skill distribution, i.e., both the *mean* and *variance* of a nation's skill distribution. Past literature has focused mostly on how college wage premiums affect individuals' decision to attend colleges (e.g., Willis and Rosen, 1979; Averett and Burton, 1996), however, to our knowledge, no previous theory exists to analyze how wage-gap changes affect the distribution of skill supply in an economy. Understanding a country's trend of skill distribution is important, as we mentioned in the introduction—the distribution can shape the country's economic inequality, growth, and trade patterns. This theoretical framework sheds light on the distributional effect. The predictions from this section will also provide a guidance to our empirical hypotheses on the mean and the standard deviation of Danish skill distribution in the next section.

2.1 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

[5] More specifically, we do not model how trade affect factor prices or skill upgrading; there already exists an extensive literature (e.g., Stolper and Samuelson, 1941; Dornbusch et al., 1980; Abdel-Rahman, 2005; Costinot and Vogel, 2010; Bustos, 2011; Blanchard and Willmann, 2016; Blanchard and Olney, 2017).

remains constant over an individual'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}. $I_{it} = 1$ if individual i decides to upgrade skills today and will earn a higher wage $w(s_{it} + \bar{e})$ next period, which corresponds to her new skill level at that time, $s_{it} + \bar{e}$; otherwise, $I_{it} = 0$ and she will continue to earn the same wage, $w(s_{it})$ next period, based on her current skill level, s_{it}. Moreover, acquiring skills that are one level higher requires a fixed amount of credits, $\bar{e}$, and has an opportunity cost in terms of the time spent upgrading skills and thus reduced labor income. This opportunity cost increases with the required units of credits and decreases with the innate ability of the individual and is assumed to be $\frac{\bar{e}}{a_i}$.

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., $W \equiv \sum_{t=1}^{3} w(s_{it}) p_t (1 - I_{it} \frac{\bar{e}}{a_i})$.[6] 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 function of skills ($\frac{dw}{ds} > 0$).[7] Finally, we assume that inflation is nonnegative (i.e., $p_1 \leq p_2 \leq p_3$).

In this setup, ability thresholds, A_1 and A_2 (assuming $\underline{a} < A_1 < \frac{\underline{a}+\bar{a}}{2} < A_2 < \bar{a}$), exist such that the whole population is divided into workers who acquire no new skills (low-skilled

[6]We make this assumption for simplicity to present closed-form solutions for the analysis below, and incomplete financial market is not the focus of this paper.

[7]We do not explicitly assume whether wages are concave or convex in skills (i.e., $\frac{d^2w}{ds^2} < 0$ or $\frac{d^2w}{ds^2} > 0$, respectively). This assumption is not crucial and may depend on the definition of skills (education, experience, and tenure) and regulations specific to the regional setting. In particular, while Lemieux (2006) and Acemoglu and Autor (2011) document the "convexification" of wages in years of schooling in recent years, Dustmann and Meghir (2005) show that the wages of workers who have higher skills are concave in seniority and tenure, but it is not the case for low-skilled workers. We therefore do not make any explicit assumption.

workers), workers who acquire skills that are one level higher (medium-skilled workers), and workers who acquire total skills that are two levels higher (high-skilled workers):

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

where $\Delta_1 \equiv w(\underline{s}+\bar{e}) - w(\underline{s})$ is the wage gap of medium-to-low-skilled workers, $\Delta_2 \equiv w(\underline{s}+2\bar{e}) - w(\underline{s}+\bar{e})$ is the wage gap of high-to-medium-skilled workers.[8] If an individual's ability is less than the lower threshold ($a_i \leq A_1$), her lifetime utility is maximized by not upgrading her 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 of the first two periods).

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. Detailed solutions and proofs are provided in the online appendix. On the one hand, an increase in Δ_1 decreases A_1 while increasing A_2. The intuition is that 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. That is, 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 will now only upgrade their skills once. Consequently, when we assume the individual ability has a uniform distribution and A_2 is more sensitive to an increase in Δ_1 than A_1 is (i.e., $|\frac{\partial A_1}{\partial \Delta_1}| < |\frac{\partial A_2}{\partial \Delta_1}|_{\Delta_2}|$), both the skill mean and variance will decrease. That is, under these assumptions and denoting the skill mean by $E(s)$ and the skill variance by $Var(s)$ we have:

- An increase in Δ_1 decreases $E(s)$ and $Var(s)$.

On the other hand, an increase in Δ_2 (conditional on zero changes to Δ_1) does not affect A_1 but decreases A_2, i.e., $\frac{\partial A_2}{\partial \Delta_2}|_{\Delta_1} < 0$. Since the return from acquiring skills twice increases, A_2 decreases, and more medium-ability individuals will acquire skills twice, while low-ability workers are unaffected. This results in a higher aggregate mean and a more diverse skill distribution:

- An increase in Δ_2 increases $E(s)$ and $Var(s)$.

[8]Note that the 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 the wage gaps from our empirical setup, e.g., $log(\Delta_2) \equiv log(w_{tertiary}/w_{secondary}) \equiv log(w_{tertiary}) - log(w_{secondary})$.

In our empirical results below, trade shocks induce a decrease in Δ_1 and an increase in Δ_2; hence, according to the above theory, a country's skill mean and variance will both increase. We now investigate the above predictions by using register data from Denmark.

3 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 trade-oriented economy (OECD, 2013). 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). Since the early 2000s, Denmark has also begun to trade with emerging economies, such as the BRICs, East Asian, and Eastern European countries. Thus, despite the maturity of the Danish economy, the process of trade integration was still evolving over the period considered in our analysis.

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 caused 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 payments lowers hiring and firing costs, reduces 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, 2013).

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.[9] As a result of these policies, the education level of the workforce is very high by international standards. In 2012, the population share that has attained upper secondary education far exceeded the OECD average. So is the share that has attained tertiary education. Furthermore, two out of three adult Danes participate in formal and/or nonformal education, which is considerably above the average of 51 percent across 22 OECD countries and is in fact the highest jointly with Finland and Sweden (OECD, 2013).

Because of these generous education policies, combined with a flexible labor market with limited 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.

4 Data

Information about firms and workers is collected from three databases/registers at the Danish official statistical institute (Denmark Statistics), namely, 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 1995 to 2011.[10] Moreover, we drop the firms with only 1 employee to exclude self-employment. We next provide further details about how we process the data in each database.

IDA is a longitudinal employer-employee register that contains information on the age, gender, nationality, place of residence, work, education, labor market status, occupation, and annual wage of each individual aged 15-74 years between 1995 and 2011.[11] 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 the individuals who are employed full-time every year from 1995 to 2011. The individual information in *IDA* is used to estimate our measures of wage gaps and skills, which is explained in the next section.[12] Then, we

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

[10]We use 1993 as a pre-sample year in the construction of our instrumental variables as explained in the next section.

[11]Unlike Hummels et al. (2012), which is concerned with labor's response in implementing training programs for workers displaced due to offshoring, we do not have access to information on nonformal education. Our measure of skills is based only on formal schooling.

[12]To address outliers, the top and bottom 1 percent of wage earners in each year are excluded. However,

aggregate these measures to the municipality level for the purpose of our empirical analysis. As in Foged and Peri (2016), we consider the 98 Danish municipalities as local labor markets.

Our second database is the Firm Statistics Register (henceforth, FirmStat), which covers the universe of private-sector firms from 1995 to 2011. It provides each firm's industry affiliation, which is measured as the 4-digit level classification of the Danish Industrial Activities.

The last database that we use is the *Foreign Trade Statistics Register*. It contains data on export and import sales at the firm level for the same period as *FirmStat*. Exports and imports are recorded in Danish kroner (DKK) according to the 8-digit Combined Nomenclature as long as the transaction is worth at least $7,500$ DKK or involves goods that weigh at least $1,000$ kg.[13] To construct our instruments, as explained in the next section, we aggregate these flows at the 4-digit level of the Combined Nomenclature and merge them with the U.N. COMTRADE data.[14] Moreover, we map 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. Following Autor et al. (2013), we then calculate a municipality's exposure to trade by using national industry export and import sales and the share of employment for each industry in the municipality in the base year 1995.

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics of our main variables for our sample period from 1995 to 2011. The first row reports the average wage gap between secondary and primary education at the municipality level (denoted by Δ_1), whereas the second row reports the average wage gap between tertiary and secondary education at the municipality level (denoted by Δ_2). Similar to Li (2018), we estimate the wage gaps at the municipality level by estimating the following individual-level wage regression:[15]

$$lnw_{imt} = \alpha_{mt} + \Delta_{1mt} Secondary_{it} + \Delta_{2mt} Tertiary_{it} + \varepsilon_{imt} \tag{2}$$

the inclusion of the top and bottom earners in our analysis does not affect our man findings, as shown in Table A1 of the online appendix.

[13] $7,500$ DKK is equivalent to approximately $1,000$ euros at the time of this writing. Since the introduction of the euro, the Danish Central Bank has adopted a fixed exchange rate policy vis-a-vis the euro.

[14] 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.

[15] We also use alternative specifications for this regression to estimate Δ_1 and Δ_2, such as including additional individual controls: age, gender, work experience, and etc. The main findings of this paper remain when we use the alternatively estimated Δ_1 and Δ_2, as shown in Table A1 of the online appendix.

where w_{imt} is the real wage earned by individual i residing in municipality m in year t.[16] Notice that a large majority of workers (82 percent) in our sample lives and works in the same municipality. $Secondary_{it}$ is the dummy variable equal to 1 if individual i who lives in municipality m has secondary education or above at time t. $Tertiary_{it}$ is the dummy variable equal to 1 if individual i has tertiary education or above and lives in municipality m at time t. The coefficients Δ_{1mt} and Δ_{2mt} measure the return to secondary relative to primary education and the return to tertiary relative to secondary education, respectively, and they are allowed to be municipality and year specific.[17] For the sake of simplicity, we henceforth denote the municipality wage gap between secondary and primary education by Δ_1 and the municipality wage gap between tertiary and secondary education by Δ_2. In the sample period considered in the analysis, the average wage gap between secondary and primary education is 18 percent, whereas the average wage gap between tertiary and secondary education is 41 percent.

Our main skill variables are represented by the mean and the standard deviation of the years of education in each municipality. In our sample period, the mean and standard deviation are 11.4 and 2.1, respectively, on average over the years. We also conduct empirical analyses by using the shares of primary-, secondary- and tertiary-educated workers.

Finally, the main measures of trade activity at the municipality level are based on the export and import values apportioned to each municipality using the base year's industry share of employment (Autor et al., 2013; Pierce and Schott, 2016). We elaborate more on its calculation in the next section. Table 1 shows that on average, Danish municipalities have a slightly larger exposure to imports than exports.

To provide preliminary insights into the correlations of interest, we plot in Figure 1 the correlation between the change in the log of trade variables between 1995 and 2011 at the municipality level and the change in Δ_1 and Δ_2 over the same period. We can see that trade and the high-skill wage gap (Δ_2) are positively associated, whereas trade and the low-skill wage gap (Δ_1) are negatively associated. We then plot in Figure 2 the correlation between the change in the log of trade variables between 1995 and 2011 at the municipality level and the change in the mean and standard deviation of years of education over the same period. These scatter plots show that trade, especially when measured in terms of exports, is positively associated with both the mean and the standard deviation of skills at

[16] The wage variable is represented by annual gross wages. Annual wages are in real terms and adjusted for possible unemployment spells during the year. Given that we do not observe working hours for the whole period, we only consider full-time employees.

[17] The predicted wage for individual i in municipality m with primary education is α_{mt}, secondary education is $\alpha_{mt} + \Delta_{1mt}$, and tertiary education is $\alpha_{mt} + \Delta_{1mt} + \Delta_{2mt}$. As a result, the wage gap between secondary and primary education is Δ_{1mt}, and between tertiary and secondary education, it is Δ_{2mt}.

the municipality level.

Overall, this descriptive evidence suggests that the municipalities with higher exposure to trade are associated with an increase (decrease) in the return to tertiary (secondary) education and also positively associated with a change in the distribution of skills. In the next sections, we examine whether these relationships hold in a more rigorous empirical specification in which we address potential endogeneity issues. Moreover, we analyze how much of the changes in the skill distribution due to trade is mediated through changes in the wage gaps across skills.

5 Methodology

We now present our empirical strategy. We first estimate at the municipality level the impact of exogenous trade shocks on the wage gaps and the skill distribution, respectively. We then examine how much the impact of trade shocks on the skill distribution goes through the channel of wage-gap changes.

5.1 The Impact of Trade on Wage Gaps and Skill Distribution

For the impact of trade on the wage gaps, we use the following municipality-level specification:

$$\Delta_{mt} = \alpha + \beta_1 Export_{mt} + \beta_2 Import_{mt} + \gamma_m + \gamma_t + \epsilon_{mt} \tag{3}$$

where the dependent variable Δ_{mt} is either the wage gap between secondary and primary education (Δ_{mt}=Δ_1) or the wage gap between tertiary and secondary education (Δ_{mt}=Δ_2). Both of these wage gap variables are estimated at the municipality and year level from equation (2). The variable $Export_{mt}$ ($Import_{mt}$) is the log of municipality export (import) exposure measure, which is constructed by apportioning national industry-level export (import) values to each municipality m at time t by using the municipality's 1995 share of industry employment. The above specifications are completed with a full set of municipality-fixed effects, denoted by γ_m, and time fixed effects, denoted by γ_t.

However, $Export_{mt}$ and $Import_{mt}$ could be endogenous, as unobserved municipality-specific shocks could be correlated with both the wage gap variables and trade. For instance, municipalities that are becoming more open to trade may experience concurrent shocks to local productivity or factor demand and supply that affect the wage gaps. In order to address the reverse causality and the endogeneity issues due to omitted factors, we pursue an instrumental variable approach that identifies exogenous trade shocks at the municipality level to instrument $Export_{mt}$ and $Import_{mt}$.

We construct the municipality trade shocks in two steps. First, we calculate changes in the world import and export for each product using U.N. COMTRADE data following the approach employed in Hummels et al. (2014) and aggregate the product-level world import and export changes to the 4-digit level of Danish industry classification by using the pre-sample (1993) share of export and import sales for each product at the industry level. More specifically, the export shock variable in industry j at time t is calculated as follows:

$$ExportShock_{jt} = \sum_{c=1}^{C} \sum_{p=1}^{P} \frac{exp_{jcp\_1993}}{exp_{j\_1993}} I_{cpt} \tag{4}$$

whereas the import shock variable in industry j at time t is calculated as

$$ImportShock_{jt} = \sum_{c=1}^{C} \sum_{p=1}^{P} \frac{imp_{jcp\_1993}}{imp_{j\_1993}} E_{cpt} \tag{5}$$

where I_{cpt} (E_{cpt}) is each country c's total purchases (sales) of product p from (to) the world market less purchases from (sales to) Denmark at time t (Hummels et al., 2014). They are exogenous to Denmark and vary across countries and products. The variable exp_{jcp_1993} (imp_{jcp_1993}) represents industry j's Danish export (import) value of product p to (from) country c in the pre-sample year (which is 1993 in our case), and exp_{j_1993} (imp_{j_1993}) denotes the total Danish export (import) value in each industry j.

In the second step, we apportion the industry-level $ExportShock_{jt}$ and $ImportShock_{jt}$ to each municipality by using the pre-sample (1993) share of industry employment in the municipality. The resulting municipality-level trade shocks are then used to instrument our $Export_{mt}$ and $Import_{mt}$, respectively, in equation (3). Note that these employment shares are exogenous to the changes in the level or type of technology over time that might affect both trade and wage gaps at the municipality level, as in Autor et al. (2013) and Pierce and Schott (2016). The results from regression (3) allow us to establish the impact of trade on wage gaps within a Danish municipality.

Using a similar specification, we quantify the impact of trade on the skill distribution by examining the first two moments of workers' skills at each municipality, i.e., the average years of education at municipality m, denoted by $\bar{skill}_{mt}$, and the standard deviation of years of education, denoted by $\sigma(skill_{mt})$. The standard deviation of years of education can also be regarded as a measure of skill diversity. Specifically, we estimate the following equations at the municipality level:

$$\bar{skill}_{mt} = \alpha + \beta_1 Export_{mt-1} + \beta_2 Import_{mt-1} + \gamma_m + \gamma_t + \epsilon_{mt} \tag{6}$$

$$\sigma(skill_{mt}) = \alpha + \beta_1 Export_{mt-1} + \beta_2 Import_{mt-1} + \gamma_m + \gamma_t + \epsilon_{mt} \tag{7}$$

where the key explanatory variables, $Export_{mt-1}$ and $Import_{mt-1}$, are lagged, which is consistent with the notion that skill distribution changes take time and cannot occur simultaneously with the current demand shocks due to trade. To identify the effect of municipality exposure to exports and imports, we employ the same instrumental variable approach used in equations (3)-(5).

5.2 The Impact of Trade on Skill Distribution via Wage-gap Changes

Once we have established the impact of trade on wage gaps on the one hand and the impact of trade on skill distribution on the other hand, we estimate the impact of trade on the skill distribution through the trade-induced-wage-gap changes at the municipality level. We use the predicted wage gap changes at the municipality level from Equation (3), i.e., changes in the wage gap due to the exogenous trade shocks, as the main explanatory variables to quantify the impact of trade on the skill distribution that is mediated by the changes in wage gaps. Specifically, we estimate the following specifications at the municipality level:

$$\bar{skill}_{mt} = \alpha + \delta_{ave} \hat{\Delta}_{mt-1} + \eta_m + \eta_t + \epsilon_{mt} \tag{8}$$

$$\sigma(skill_{mt}) = \alpha + \delta_{disp} \hat{\Delta}_{mt-1} + \eta_m + \eta_t + \epsilon_{mt} \tag{9}$$

where the vector $\hat{\Delta}_{mt-1}$ includes both wage gaps, Δ_1 and Δ_2, that are predicted from equation (3) in the previous section. Note that the predicted wage gaps are lagged, which is consistent with the specification used to identify the effects of trade on the skill distribution. In the baseline, we lag the wage gap variables by one year; in the robustness check reported in the online appendix, we also lag them by either two or three years. The standard errors are sequentially bootstrapped together with Equation (3).

6 Empirical Results

In this section, we first discuss in detail the effects of trade on the wage gaps and the skill distribution in the Danish local labor markets, respectively. We next present the effects of trade on the skill distribution mediated through the wage-gap changes. We then discuss whether other alternative mechanisms explain these results and show that they are not fully explained by alternative explanations, such as workers' sorting across municipalities or demographic changes of the workforce composition within the local labor market. We also conduct various robustness checks and show that our main findings are robust.

6.1 Results on the Impact of Trade on Wage Gaps and Skill Distribution

In Table 2, we first estimate the impact of both exports and imports on the wage gap between secondary and primary education (Δ_1) in column (1) and on the wage gap between tertiary and secondary education (Δ_2) in column (2), respectively. Using our instrumental variable approach to address endogeneity concerns and after controlling for municipality and year fixed effects, we find that a 10 percent increase in the municipality exposure to exports triggers a 3 percentage point decrease in Δ_1 and a 12 percentage point increase in Δ_2.[18] The 12 percentage point increase in Δ_2 result is consistent with Munch and Skaksen (2008) and Li (2018), who also find a positive impact of exports on high-skilled workers' wages for Denmark and China, respectively. However, the municipality exposure to imports does not affect the wage gap between tertiary and secondary education, but it does negatively influence the wage gap between secondary and primary education. A 10 percent increase in imports implies a 6 percentage point decrease in the wage gap between secondary and primary education. This last result confirms a long standing finding within the trade literature that imports have a negative influence on wages, especially for relatively low-skilled workers (e.g., Hummels et al. (2014)).

Table 2 also reports the impact of trade on the skill distribution in columns (3) and (4). Trade has a positive effect on both the mean and the standard deviation of years of education. In particular, a 10 percent increase in the export variable at time $t-1$ increases the mean (the standard deviation) years of education by 0.98 (0.36) at time t, which corresponds to an 8 (17) percent increase. A 10 percent increase in the import variable at time $t-1$ increases the mean years of education by 1.01 at time t, i.e., a 9 percent increase.

[18]Since the dependent variables are themselves estimates, the regressions in columns (1) and (2) of Table 2 are weighted by the inverse of their standard errors.

We then examine the impact of exports and imports on the share of workers with primary, secondary and tertiary education in columns (5)-(7), respectively. There is suggestive evidence that trade reduces the share of workers with secondary education and simultaneously increases the shares of workers with the lowest and the highest educational level. The effect is especially strong for the share of workers with a tertiary education. A 10 percent increase in the municipality exposure to exports (imports) increases the share of tertiary-educated workers within the municipality by 0.02 (0.04). This corresponds to a 13 (25) percent increase. Combining these results presented in columns (3)-(7) suggests that trade shifts the Danish skill distribution to the right and makes it polarized.

6.2 Results on the Impact of Trade via Wage-gap Changes

The previous section shows that trade can influence both wage gaps and the skill distribution. We now explore whether changes in the wage gaps induced by trade at time $t-1$ contributes to explain the impact of trade on skills at time t by estimating equations (8) and (9). Columns (1) and (2) of Table 3 show that a 10 percentage point increase in the predicted wage gap between secondary and primary education ($\hat{\Delta}_1$) decreases the mean (standard deviation) of years of education within the municipality by 0.038 (0.060), which corresponds to approximately a 0.3 (3) percent decrease. The effect of the wage gap between tertiary and secondary education ($\hat{\Delta}_2$) is, however, positive and larger: a 10 percentage point increase in $\hat{\Delta}_2$ raises the mean (standard deviation) of years of education within the municipality by 0.106 (0.089), which corresponds to an approximately 1 (4) percent increase. It is also worth noting that the directions of these changes are consistent with the predictions by the theory in section 2.

Combining the findings reported in columns (1) and (2) of Tables 2 and 3, we find that the predicted changes in the wage gaps due to trade ($\hat{\Delta}_1$ and $\hat{\Delta}_2$) have a unidirectional effect on the skill distribution in the local labor market. In particular, since the $\hat{\Delta}_1$ decreases and $\hat{\Delta}_2$ increases on average in response to trade shocks in the data, they together cause the mean and the variance of skills to increase. As a result, the Danish skill distribution shifts to the right and becomes polarized.

To put all of these results into perspective, we interpret our coefficients as follows. Given that a 10 percent increase in exports raises $\hat{\Delta}_2$ by 12 percentage points (row 1 and column 2 of Table 2) and the mean (standard deviation) of years of education by 8 (17) percent (row 2 and column 3 (4) of Table 2), we can infer that the export-induced changes in $\hat{\Delta}_2$ explain approximately 14 (30) percent of the total effect of exports on the mean (standard deviation) of skills.[19] Similar calculations show that the export-induced (import-induced) changes in $\hat{\Delta}_1$ explain approximately 5 (2.3) percent of the total effect of exports (imports) on the mean of skills.[20] Overall, the combined effect of the wage-gap changes can explain about 21 percent of the total effect of trade on the mean of skills and 30 percent of the effect on the standard deviation of skills.

Table 3's columns (3)-(5) report the effects of the trade-induced-wage-gap changes at time $t-1$ on the share of primary-, secondary- and tertiary-educated workers within the local labor market at time t. A 10 percentage point increase in $\hat{\Delta}_1$ triggers an increase in the share of workers with secondary education by 0.007 and a decrease in the share of workers with primary education by 0.001. These effects correspond to a 1.2 percent increase and a 0.4 percent decrease, respectively. This is consistent with the theoretical prediction in section 2 that the skill-upgrading-ability-thresholds A_1 and A_2 will move farther apart given an increase in Δ_1. More specifically, in the theory, although an increase in Δ_1 raises the marginal return for the low-skilled population to acquire medium skills (i.e., a secondary education), it also raises the marginal cost (in terms of the opportunity cost of losing current wages while upgrading skills) for medium-skilled workers to acquire higher skills (i.e., a tertiary education).

We also find that an increase in $\hat{\Delta}_2$ at time $t-1$ of 10 percentage points raises the municipality share of tertiary-educated workers at time t by 0.002, which corresponds to a 1.3 percent increase. This is also consistent with the theoretical prediction that only ability threshold A_2 will decrease given an increase in Δ_2. In particular, an increase in Δ_2 increases the return for the medium-skilled population to acquire higher skills, without affecting the low-skilled population.

Overall, since $\hat{\Delta}_1$ decreases and $\hat{\Delta}_2$ increases with trade integration in the Danish data, its skill distribution responds to them by shifting to the right and becoming polarized. More specifically, the lower-skilled population is discouraged from upgrading skills, while the medium-skilled population is encouraged to upgrade their skills, which induces a higher mean of skill supplies when the proportion of upgraders dominates the proportion of discouraged workers. Meanwhile, the skills in both tails become more abundant than before, which results in skill polarization, i.e., the variance in skills increases.

[19] We perform the following calculations. A 12 percentage point increase in predicted Δ_2 raises the mean (standard deviation) of skills by $0.128 = 0.12 \times 1.067$ ($0.106 = 0.12 \times 0.889$), which corresponds to a 1.12 (5.06) percent increase in the mean (standard deviation) of skills. This means that the effect of export-induced-$\hat{\Delta}_2$-changes on the mean (standard deviation) of skills explains $0.0112/0.08 \times 100 = 14$($0.0506/0.17 \times 100 = 30$) percent of the total effect of exports on the mean (standard deviation) of skills.

[20] We do not perform these calculations for the skill standard deviation response to $\hat{\Delta}_1$ changes because the effect is statistically insignificant to begin with.

6.3 Alternative Mechanisms

So far, we interpret the previous findings reported in Table 3 as that trade-induced-wage-gap changes affect the incentives to upgrade skills such that the skill distribution becomes polarized. However, the skill distribution changes that we observe in the data may also be a result of alternative mechanisms such as skill-specific sorting of workers across municipalities and/or labor market inflows and outflows.

First, changes in the wage gaps (due to trade shocks) may encourage skill-specific labor reallocation (sorting) across municipalities. However, Foged and Peri (2016) document that most worker mobility in Denmark occurs across firms within a municipality, which confirms that municipalities, even in the long run, are rather self-contained labor markets. Nevertheless, we estimate equations (8) and (9) by confining data sample to only stayers – the workers who remain in the same municipality over the entire sample period.[21] Table 4 presents qualitatively similar results to those in Table 3. An increase in $\hat{\Delta}_2$ at time $t-1$ still statistically significantly increases the mean and the standard deviation of the years of education and the share of tertiary educated workers at time t, while the impact of an increase in $\hat{\Delta}_1$ is still negative but no longer significant.

In Table 5's top two panels, we also regress the shares of differently educated workers who move into or out of a given municipality on the lagged predicted wage gaps and find statistically insignificant results. This implies that there is no strong association between labor flows and wage-gap changes. These results further confirm that the changes in the distribution of skills reported in the baseline analysis 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. The intuition is that if older (younger) workers are relatively less (more) skilled, they may decide to retire (enter the labor market) earlier as a result of the changes to the wage gaps induced by trade reported in our estimation. This could affect the age composition of the workforce 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 31 years and the share of workers older than 45 years on the lagged predicted wage gap changes at the municipality level. The results are reported in the last panel of Table 5. Although the share of workers younger than 31 years is positively correlated with $\hat{\Delta}_2$, the share of workers older than 45 years is not significantly affected by wage-gap changes. Therefore, the age composition is not a key driver of our baseline results.

[21] On average about 60 percent of workers stay in the same municipality for the entire sample period.

6.4 Robustness

In additional results reported in the online appendix, we assess the robustness of our estimation in equations (8) and (9). Since the first two moments of the skill distribution are based on skill stocks rather than flow variables, we include their lagged values in an alternative specification to control for autocorrelation. We then estimate the dynamic versions of equations (8) and (9) by using the system GMM estimator suggested by Blundell and Bond (1998), in which all the explanatory variables except the year fixed effects are considered to be endogenous.[22] The first two columns of Table A-1 of the online appendix show that the coefficients estimated on the predicted wage gaps are similar to the coefficients reported in the baseline analysis, although they are smaller in magnitude.

In the next robustness check, we make two modifications, respectively, and re-estimate the wage gaps from equation (2). First, we reinstate the top and bottom 1 percent earners back to our sample; the results are reported in columns (3) and (4) of Table A-1. Second, we include additional individual control variables, such as age and gender, to the original equation (2); the results are reported in columns (5) and (6). These results are consistent with those in our baseline, and thus the key findings remain robust.

We then test the robustness of our identification strategy for the exogenous trade shocks with three alternative approaches, respectively. First, we exclude countries that share similar business cycles to Denmark, i.e., Germany, Sweden, and the United States, in the instrument calculation of the industry level trade shocks in equations (4) and (5). In the second approach, we exclude industries in which demand or technology shocks are more likely to be correlated across countries.[23] Third, we follow Autor et al. (2013) by excluding an alternative group of seven industries that experienced substantial fluctuations over the sample period across countries due to technological innovations, housing booms, and the rapid growth of emerging economies.[24] The results from these three robustness tests are reported in Table A-2 of the online appendix, and they confirm the robustness of our baseline results in terms

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

[23] 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 apparatuses (NACE 32), air transportation (NACE 62), and post and telecommunications (NACE 64).

[24] These industries are the manufacture of textiles and the 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 nonmetallic 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).

of calculating exogenous trade shocks.

Finally, we check whether our baseline results reported in Table 3 are sensitive to the use of the one-year lag on the predicted wage gaps. We re-estimate equations (8) and (9) 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 trade-induced changes in the wage gaps. The findings are reported in Table A-3 of the online appendix. The coefficients estimated on the two- or three-year lag are slightly larger in magnitude, especially in response to $\hat{\Delta}_2$ changes. This suggests that the effect becomes stronger given more time for skill adjustments and confirms our assumption that skill supply adjustments lag trade-induced-wage-gap changes.

6.5 Extensions: Results by Age Group and by Industry

Up to this point, we have established the robustness of our baseline results. We now extend our baseline results in two dimensions. First, we re-estimate equations (8) and (9) by including in the sample only workers from one of the following age groups: i) young workers, i.e., workers younger than 31 years; ii) middle-aged workers, i.e., workers older than 30 and younger than 45; and iii) old workers, i.e., workers older than 45. The results are reported in Table 6. They show that the effects of the trade-induced-wage-gap changes on the skill distribution separately estimated for each subgroup are similar in terms of sign to our baseline results in Table 3. Most of the significant effects concentrate at the first two age groups. Furthermore, the coefficients estimated on the predicted wage gap between tertiary and secondary education are larger in magnitude for the group of middle-aged workers compared to those reported for the youngest group. A 10 percentage points increase in Δ_2 raises the mean and standard deviation of years of education within the municipality by approximately 1.32 and 4.85 percent, respectively, for middle aged workers, whereas by 1.09 and 2.19 percent, respectively for young workers.

Second, we investigate whether the impact of trade on the skill distribution through wage-gap changes 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 high-skill-intensive exports increases schooling. Our estimated coefficients reported in the baseline analysis conceal these opposing effects on the acquisition of skills. Here, we extend Blanchard and Olney (2017) to focus on the channel of trade-induced-wage-gap changes. We reconstruct the trade variables used in Equation (3) separately for high- and low-skill-intensive industries, re-estimate the municipality wage-gap changes triggered by each type of industry's trade shocks, and re-estimate the impact of these predicted changes on the overall distribution of skills at the municipality level. To distinguish the two types of industries, we use R&D expenditure data and define the industries with R&D expenditures above the country average as high-skill-intensive ones, while the other industries as less-skill-intensive ones. Information on R&D expenditures at the 3-digit NACE industry level is retrieved from the OECD database.

Columns (1) and (2) of Table 7 present the results from the predicted wage-gap changes that themselves are estimated from trade shocks within high-skill-intensive industries, whereas columns (3) and (4) report the coefficients estimated on the predicted wage-gap changes triggered by trade shocks to the other industries. We find that the skill distribution effect through the channel of trade-induced-wage-gap changes is slightly larger in high-skill-intensive industries than in the less-skill-intensive industries. Since, trade shocks still decrease $\hat{\Delta}_1$ and increase $\hat{\Delta}_2$ here, the mean and standard deviation of skills in local labor markets are still positively affected by the predicted changes in wage gaps in both types of industries, especially in the high-skill-intensive ones. More specifically, a 10 percentage point increase in $\hat{\Delta}_2$ triggers a 1.28 percent increase in the mean of years of education and a 5.22 percent increase in the standard deviation of the years of education within an municipality on average for the high-skill-intensive industries. The corresponding effects within less-skill-intensive industries feature smaller magnitudes.

In columns (5) and (6) of the same table, we also investigate whether our baseline results change when we focus on the changes in predicted wage gaps induced from trade shocks only to the manufacturing sector, as in Blanchard and Olney (2017). These results are similar to our baseline results presented in the first two columns of Table 3.

7 Conclusion

Our paper shows that trade integration has a negative effect on the wage gap between secondary and primary education, a positive effect on the wage gap between tertiary and secondary education, and a positive effect on both the mean and the standard deviation of skills, which causes *skill polarization*. Furthermore, our empirical analysis emphasizes that trade-induced changes in the wage gaps explain a nonnegligible portion of the overall impact of trade on the skill distribution. This is consistent with the predictions from our simple theoretical framework that models how the wage-gap changes affect individual skill-upgrading decisions. The intuition is that the exogenous changes in 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 with generous education provisions.

This study informs policymakers about how exogenous demand shocks such as trade integration can affect the skill distribution, in particular, through wage-gap changes. Since a country's skill distribution can further affect economic growth and inequality down the road, it is crucial to understand the distribution changes and to take them into account in policy designs.

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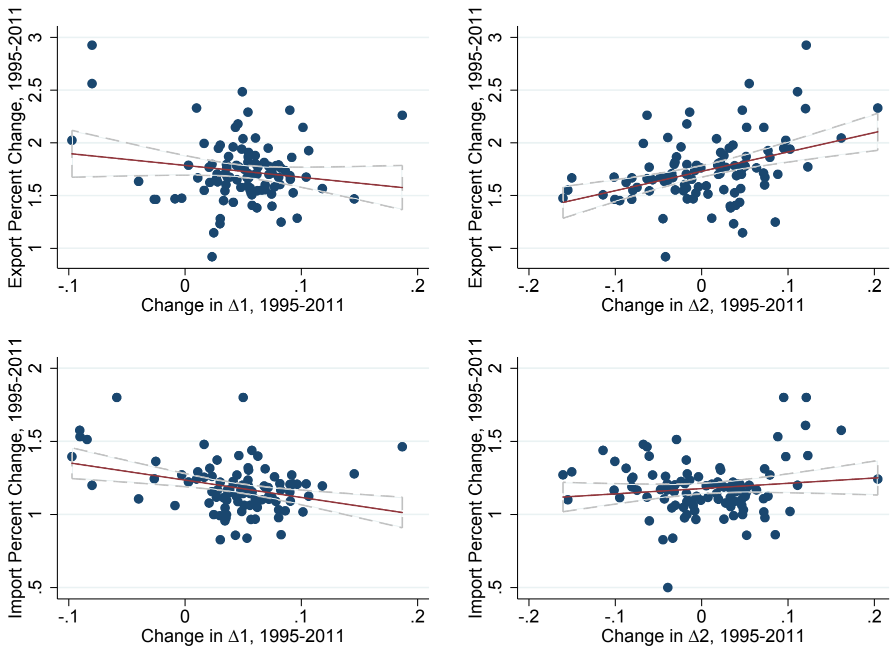
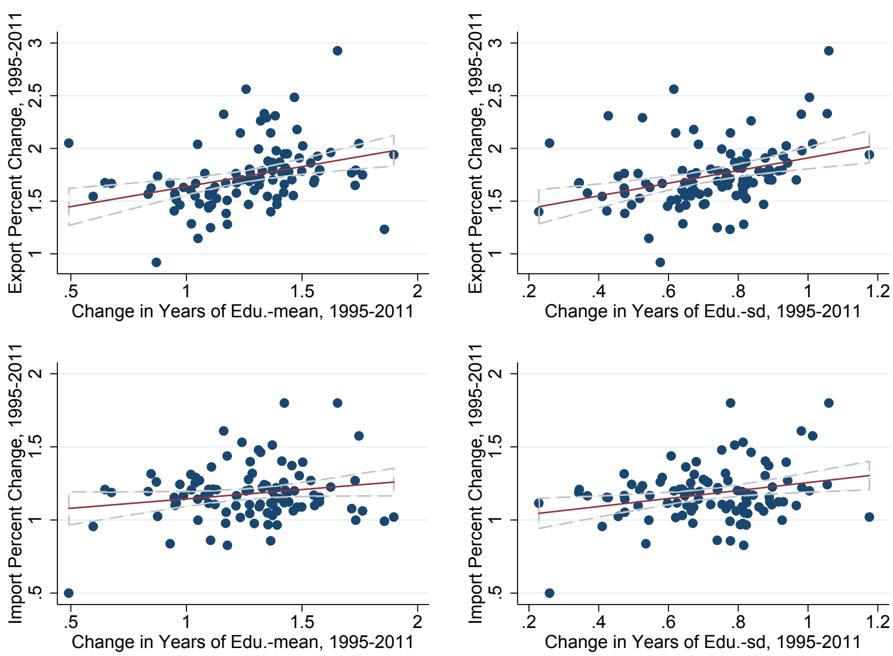
Figure 1: Trade and Wage Gaps



Note: The change in the log of exports (imports) at the municipality level between 1995 and 2011 is reported on the vertical axis in the first (second) panel. The change in the wage gap between secondary and primary (tertiary and secondary) education is reported on the horizontal axis in the left (right) panel. The band shows the 95 percent confidence interval.

Figure 2: Trade and Skills



Note: The change in the log of exports (imports) at the municipality level between 1995 and 2011 is reported on the vertical axis in the first (second) panel. The change in the average years (standard deviation) of education at the municipality level is reported on the horizontal axis in the left (right) panel. The band shows the 95 percent confidence interval.

Table 1: Descriptive Statistics

	Definition	Mean	Sd
Wage Gaps:			
Δ_1	average wage gap between secondary and primary education at the municipality level	0.179	0.038
Δ_2	average wage gap between tertiary and secondary education at the municipality level	0.406	0.076
Skill variables:			
Years of Education -mean	average years of education at the municipality level	11.395	0.637
Year of Education -sd	standard deviation of years of education at the municipality level	2.125	0.329
Share of Primary Edu.	share of workers with primary education at the municipality level	0.277	0.075
Share of Secondary Edu.	share of workers with secondary education at the municipality level	0.565	0.052
Share of Tertiary Edu.	share of workers with tertiary education at the municipality level	0.158	0.099
Trade variables:			
Export	log of export values at the municipality level weighted by the 1995 employment share for each industry	17.650	0.674
Import	log of import values at the municipality level weighted by the 1995 employment share for each industry	18.055	0.808
N			1,666

Note: All descriptive statistics are calculated as averages over the period 1995–2011.

Table 2: Trade, Wage Gaps and Skills

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ_1	Δ_2	**Years of Education-mean**	**Years of Education-sd**	**Share of Primary**	**Share of Secondary**	**Share of Tertiary**
Export	-0.003***	0.012***					
	(0.001)	(0.003)					
Import	-0.006**	0.005					
	(0.003)	(0.004)					
Export, one-year lag			0.098**	0.036**	0.012	-0.019	0.002**
			(0.044)	(0.016)	(0.008)	(0.012)	(0.001)
Import, one-year lag			0.101*	0.051	0.003*	-0.012*	0.004**
			(0.055)	(0.038)	(0.002)	(0.007)	(0.002)
Municipality Fixed Effects	yes	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes	yes
Mean Y	0.179	0.406	11.395	2.125	0.277	0.565	0.158
N	1,666	1,666	1,568	1,568	1,568	1,568	1,568
R-sq	0.697	0.767	0.771	0.811	0.831	0.792	0.823
First Stage F-stats on Instruments	106.31; 20.05	106.31; 20.05	98.13; 31.34	98.13; 31.34	98.13; 31.34	98.13; 31.34	98.13; 31.34
First Stage- Export IV Coeff.	0.607*** (0.064)	0.607*** (0.064)	0.598*** (0.059)	0.598*** (0.059)	0.598*** (0.059)	0.598*** (0.059)	0.598*** (0.059)
First Stage- Import IV Coeff.	0.191*** (0.045)	0.191*** (0.045)	0.211*** (0.062)	0.211*** (0.062)	0.211*** (0.062)	0.211*** (0.062)	0.211*** (0.062)

Note: The dependent variable in column 1(2) is the average wage gap between secondary (tertiary) and primary (secondary) education at the municipality level. The dependent variable in column 3 is the average years of education at the municipality level. The dependent variable in column 4 is the average standard deviation of the year of education at the municipality level. The dependent variable in column 5 is the share of workers with primary education at the municipality level. The dependent variable in column 6 is the share of workers with secondary education at the municipality level. The dependent variable in column 7 is the share of workers with tertiary education at the municipality level. Danish export (Import) is instrumented with world import (export) (see Equation 4). In columns 1 and 2, the standard errors are weighted by the inverse of the standard errors of the dependent variable. Significance levels: ***1%, **5%, and *10%.

Table 3: Trade-Induced Wage Gaps and Skills

	(1)	(2)	(3)	(4)	(5)
	Years of Education-mean	**Years of Education-sd**	**Share of Primary**	**Share of Secondary**	**Share of Tertiary**
Predicted Δ_1, one-year lag	-0.384*	-0.604	-0.014*	0.072**	-0.008
	(0.201)	(0.406)	(0.008)	(0.035)	(0.005)
Predicted Δ_2, one-year lag	1.067**	0.889**	-0.013	-0.080	0.023**
	(0.522)	(0.395)	(0.011)	(0.051)	(0.010)
Municipality Fixed Effects	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes
Mean Y	11.395	2.125	0.277	0.565	0.158
N	1,568	1,568	1,568	1,568	1,568
R-sq	0.771	0.811	0.831	0.792	0.823

Note: The dependent variable in column 1 is the average years of education at the municipality level. The dependent variable in column 2 is the average standard deviation of the year of education at the municipality level. The dependent variable in column 3 is the share of workers with primary education at the municipality level. The dependent variable in column 4 is the share of workers with secondary education at the municipality level. The dependent variable in column 5 is the share of workers with tertiary education at the municipality level. The explanatory variables Δ_1 and Δ_2 are estimated from equation (3) using our instrumental variable approach. The standard errors are clustered at the municipality level and sequentially bootstrapped with equation (3), 200 replications. Significance levels: ***1%, **5%, and *10%.

Table 4: Trade-Induced Wage Gaps and Skills for the Sample of "Stayers"

	(1)	(2)	(3)	(4)	(5)
	Years of Education-mean	**Years of Education-sd**	**Share of Primary**	**Share of Secondary**	**Share of Tertiary**
Predicted Δ_1, one-year lag	-0.247	-0.102	-0.011	0.023*	-0.012
	(0.182)	(0.081)	(0.007)	(0.013)	(0.011)
Predicted Δ_2, one-year lag	1.274*	0.711*	-0.004	-0.008	0.012*
	(0.759)	(0.381)	(0.012)	(0.007)	(0.006)
Municipality Fixed Effects	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes
Mean Y	11.331	2.013	0.261	0.599	0.139
N	1,568	1,568	1,568	1,568	1,568
R-sq	0.771	0.811	0.831	0.792	0.823

Note: The dependent variable in column 1 is the average years of education at the municipality level. The dependent variable in column 2 is the average standard deviation of the year of education at the municipality level. The dependent variable in column 3 is the share of workers with primary education at the municipality level. The dependent variable in column 4 is the share of workers with secondary education at the municipality level. The dependent variable in column 5 is the share of workers with tertiary education at the municipality level. The explanatory variables Δ_1 and Δ_2 are estimated from equation (3) using our instrumental variable approach. The sample includes only "stayers", i.e., the workers who remain in the same municipality over the whole sample period. The standard errors are clustered at the municipality level and sequentially bootstrapped with equation (3), 200 replications. Significance levels: ***1%, **5%, and *10%.

Table 5: Trade-Induced Wage Gaps, Sorting across Municipalities and Workforce Composition

	(1)	(2)	(3)
	Share of workers with primary education moving in the municipality	**Share of workers with secondary education moving in the municipality**	**Share of workers with tertiary education moving in the municipality**
Predicted Δ_1, one-year lag	-0.042	-0.159*	-0.055
	(0.103)	(0.085)	(0.038)
Predicted Δ_2, one-year lag	-0.002	0.005	0.009*
	(0.015)	(0.016)	(0.004)
Municipality Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	yes	yes
Mean Y	0.007	0.018	0.013
N	1,568	1,568	1,568
R-sq	0.692	0.697	0.723
	(4)	**(5)**	**(6)**
	Share of workers with primary education moving out the municipality	**Share of workers with secondary education moving out the municipality**	**Share of workers with tertiary education moving out the municipality**
Predicted Δ_1, one-year lag	0.764	1.334	0.647
	(0.654)	(1.027)	(0.514)
Predicted Δ_2, one-year lag	0.435	0.993	-0.435
	(0.345)	(0.623)	(0.501)
Municipality Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	yes	yes
Mean Y	0.011	0.026	0.015
N	1,568	1,568	1,568
R-sq	0.658	0.648	0.569
	(7)	**(8)**	
	Share of workers younger than 31	**Share of workers older than 45**	
Predicted Δ_1, one-year lag	-0.042	-0.173	
	(0.035)	(0.102)	
Predicted Δ_2, one-year lag	0.111*	0.075	
	(0.059)	(0.034)	
Municipality Fixed Effects	yes	yes	
Year Fixed Effects	yes	yes	
Mean Y	0.247	0.383	
N	1,568	1,568	
R-sq	0.880	0.841	

Note: The dependent variable in columns 1-3 is the share of differently educated workers who move into the municipality. The dependent variable in columns 4-6 is the share of differently educated workers who move out of the municipality. The dependent variable in column 7 is the share of workers younger than 31 years in the municipality. The dependent variable in column 8 is the share of workers older than 45 years in the municipality. The explanatory variables Δ_1 and Δ_2 are estimated from equation (3) using our instrumental variable approach. The standard errors are clustered at the municipality level and sequentially bootstrapped with equation (3), 200 replications. Significance levels: ***1%, **5%, and *10%.

Table 6: Trade-Induced Wage Gaps and Skills, Results by Age Group

	(1)	(2)	(3)	(4)	(5)	(6)
	Workers younger than 31		Workers older than 30 and younger than 46		Workers older than 45	
	Years of Education-mean	Years of Education-sd	Years of Education-mean	Years of Education-sd	Years of Education-mean	Years of Education-sd
Predicted Δ_1, one-year lag	-0.074	-0.101*	-0.452	-0.838*	-0.245	-0.201
	(0.066)	(0.060)	(0.333)	(0.435)	(0.235)	(0.137)
Predicted Δ_2, one-year lag	1.266**	0.501*	1.505**	0.976**	1.033*	1.009
	(0.489)	(0.275)	(0.642)	(0.330)	(0.579)	(0.756)
Municipality Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Mean Y	11.569	2.279	11.364	2.013	10.943	1.816
N	1,568	1,568	1,568	1,568	1,568	1,568
R-sq	0.823	0.801	0.817	0.811	0.798	0.805

Note: The dependent variable in columns 1, 3 and 5 is the average years of education at the municipality level. The dependent variable in columns 2, 4 and 6 is the average standard deviation of the year of education at the municipality level. Columns 1 and 2 are estimated by including only workers younger than 31 years in the sample. Columns 3 and 4 are estimated by including only workers older than 30 and younger than 46 years in the sample. Columns 5 and 6 are estimated by including only workers older than 45 years in the sample. The explanatory variables Δ_1 and Δ_2 are estimated from equation (3) using our instrumental variable approach. The standard errors are clustered at the municipality level and sequentially bootstrapped with equation (3), 200 replications. Significance levels: ***1%, **5%, and *10%.

Table 7: Trade-Induced Wage Gaps and Skills, Results by Industry

	(1)	(2)	(3)	(4)	(5)	(6)
	High-Skill-Intensive Sectors		**Less-Skill-Intensive Sectors**		**Manufacturing**	
	Years of Education-mean	**Years of Education-sd**	**Years of Education-mean**	**Years of Education-sd**	**Years of Education-mean**	**Years of Education-sd**
Predicted Δ_1, one-year lag	-0.595	-0.790	-0.211*	-0.547	-0.415*	-0.587
	(0.365)	(0.512)	(0.121)	(0.323)	(0.225)	(0.356)
Predicted Δ_2, one-year lag	1.454**	1.109**	1.023**	0.802*	1.016**	1.019**
	(0.530)	(0.464)	(0.505)	(0.464)	(0.456)	(0.503)
Municipality Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Mean Y	11.395	2.125	11.395	2.125	11.395	2.125
N	1,568	1,568	1,568	1,568	1,568	1,568
R-sq	0.807	0.801	0.817	0.811	0.817	0.811

Note: The dependent variable in columns 1, 3 and 5 is the average years of education at the municipality level. The dependent variable in columns 2, 4 and 6 is the average standard deviation of the year of education at the municipality level. In columns 1 and 2, the explanatory variables Δ_1 and Δ_2 are estimated from equation (3) using our instrumental variable approach and by including only high-skill-intensive sectors in the calculation of the trade variables. In columns 3 and 4, the explanatory variables Δ_1 and Δ_2 are estimated from equation (3) using our instrumental variable approach and by excluding the high-skill-intensive sectors in the calculation of the trade variables. High-skill-intensive sectors are the sectors with R&D expenditures above the overall economy average. In columns 5 and 6, the explanatory variables Δ_1 and Δ_2 are estimated from equation (3) using our instrumental variable approach and by excluding service sectors in the calculation of the trade variables. The standard errors are clustered at the municipality level and sequentially bootstrapped with equation (3), 200 replications. Significance levels: ***1%, **5%, and *10%.