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INTERNATIONAL TRADE AND JOB POLARIZATION: EVIDENCE AT THE WORKER-LEVEL

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ABSTRACT

This paper examines the role of international trade for job polarization– the decline in opportunities for mid-wage workers while those for high- and low-wage workers increase. With employer-employee matched data on virtually all workers and firms in Denmark between 1999 and 2009, we show that import competition has caused worker-level adjustments that lead to job polarization. When mid-wage workers adjust to the shock, highly educated and skilled workers end up in high-wage jobs whereas less educated workers end up in low-wage positions. We show that the specific tasks performed by a worker are central in determining trade's impact, and workers performing manual tasks are the ones most affected regardless of how routine or non-routine these tasks are. Trade lets foreign workers compete against domestic workers, in contrast to technical progress which pits man versus machine country by country. Quantitatively, we find that job polarization through trade-induced worker adjustments is at least as strong as through technical change and offshoring.

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1 Introduction

The rapid integration of emerging economies into world trade is the defining feature of the recent wave of globalization. In particular, China doubled its share of world merchandise exports during the 1990s before almost tripling it again during the first decade of the 21st century (World Bank 2016). During this globalization, labor markets in high-income countries have become polarized with employment hollowing out at mid-wage jobs at the same time when employment in low-wage and high-wage jobs has increased.[1] Using an aggregate approach, the available evidence does not find that international trade has contributed to job polarization. We revisit this question with an individual-level approach, examining whether workers' employment losses induced by import competition and the subsequent job-to-job transitions are a source of polarization.

Understanding job polarization is paramount, as policy makers need to know the reason for the loss of middle-class (mid-wage) jobs. Moreoever, job polarization may put the very functioning of society at risk if it means inequality that prevents winners and losers from agreeing on total welfare-increasing policies–including free trade. Using administrative, longitudinal data on the universe of Danish workers matched to firms between 1999 and 2009, we show that the adjustments of workers adversely affected by import competition have played a major role in the emergence of job polarization.

To estimate the effect of rising import competition we employ two complementary approaches. First, we exploit the removal of quotas on Chinese textile and clothing exports in a difference-in-differences strategy. This approach compares workers who manufacture narrowly defined textile products that are subsequently subject to quota removals to workers employed at other firms in the same industry that are not affected by the quota removals. Exploiting quota information at the product-level together with the plausibly exogenous quota removal due to China's entry into the World Trade Organization (WTO) provides an ideal quasi-natural experimental set-up to study the causal impact of trade exposure on workers' employment trajectories.

Second, we exploit differences in the change of import penetration for workers across the entire Danish private-sector economy. We augment Autor, Dorn, and Hanson's (2013) approach to address the possible endogeneity of a country's product-level imports from China with Chinese imports of the same products in other high-income countries with two additional instrumental variables, one based on transportation costs and the other based on distribution channels in international trade. Using this instrumental variable approach we show that rising import competition

[1] Figure A-1 shows the case of Denmark. The US is discussed in Autor, Katz, and Kearney (2006, 2008), Autor and Dorn (2013), while Goos and Manning (2007) and Spitz-Oener (2006), Dustmann, Ludsteck, and Schonberg (2009) analyze the UK and Germany, respectively; also, Goos, Manning, and Salomons (2014) study 16 European countries.

causes individual worker adjustments that lead to aggregate job polarization. In particular, mid-wage workers who lose their jobs due to import competition subsequently have a lower chance of obtaining another mid-wage job, whether in the shrinking manufacturing or in the expanding service sector.

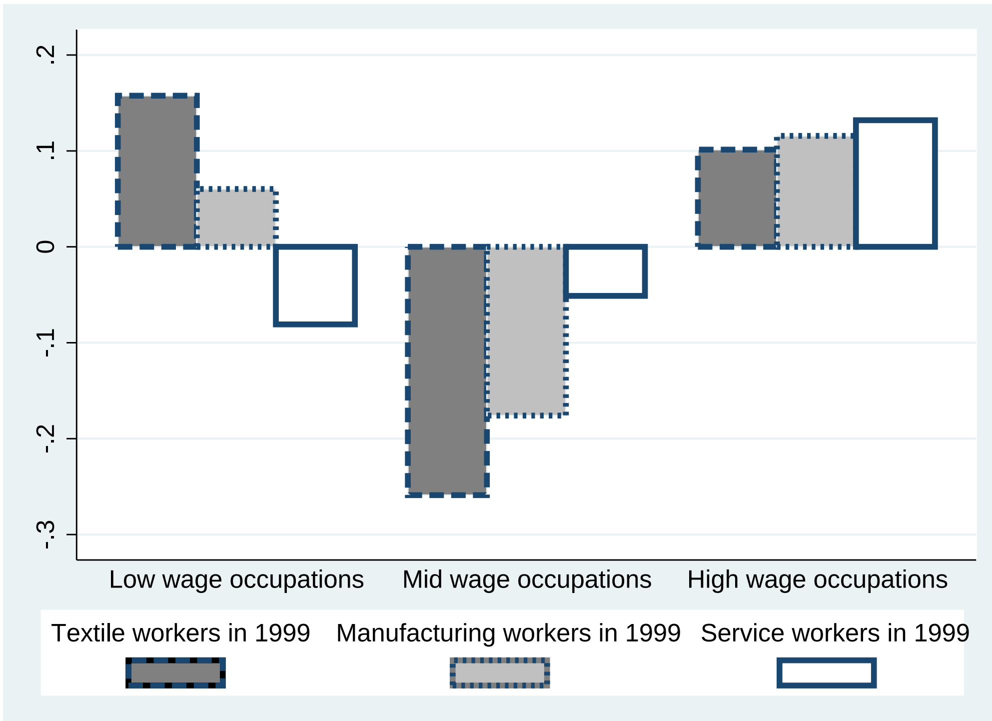

Figure 1: Employment Share Changes for Different Subsets of Denmark's 1999 Workforce, 2000-9

To illustrate our cohort approach, Figure 1 shows changing employment opportunities by wage levels (low, mid, and high) between 2000 and 2009 for three particular sets of workers: those employed in the textiles, manufacturing, and services sectors in 1999.[2] We see that employment share changes of workers who were initially employed in the service sector are increasing in wages, consistent with skill-biased technical change. In contrast, employment share changes of 1999 manufacturing workers exhibit the U-shaped pattern of job polarization, and by the end of 2009 close to one in five of the 1999 cohort of mid-wage manufacturing workers is either employed in low- or high-wage occupations. Furthermore, the textile sector, part of manufacturing, was especially affected by rising import competition due to quota removals, and it is here where we find

[2]Typical low-wage occupations include child care worker or shop sales person (hourly wage under 30 dollars), while a machine operator is representative for mid-wage jobs (around 40 dollars per hour), and a business professional is typical for high-wage occupations (55 dollars per hour). These three wage groups have been employed in the literature because three is the minimum to capture the U-shaped job polarization pattern. Our wage classification is similar to the literature (e.g., Autor and Dorn 2013, Goos, Manning, and Salomons 2014), and as shown in Table 1 below there are no changes in the wage ranking of major occupations over time.

the strongest evidence for the polarization pattern. This is initial evidence that import competition is a driver of job polarization because manufacturing is more exposed to trade competition and exhibits job polarization.

The paper goes on to show that import competition has a significant impact on individual workers' occupational movement leading to job polarization. First, workers affected by import competition lose middle-class employment disproportionately, and they also pick up more low-wage or high-wage jobs than those not affected. Second, in the pool of middle-class workers losing their job, more have to move down to low-wage jobs than can move up to reach high-wage jobs. High levels of education and skill are crucial for the upward move from a mid-wage to a high-wage jobs, whereas exposed mid-wage workers with low levels of education often end up accepting a low-wage position. Quantitatively, the impact of import competition on the hollowing-out of middle-class jobs is comparable to the effect of technical change. Moreover, import competition leads to worker adjustments that increase employment in both tails of the wage distribution, in contrast to technical change and offshoring.

Furthermore, by employing information on the importance of individual tasks in specific occupations, we highlight the key mechanism through which import competition causes occupational movement leading to job polarization. Workers performing manual tasks are most strongly affected by import competition, in contrast to workers performing cognitive tasks who are not affected. The impact of import competition is different from that of computer-related technical change because import competition impacts not only workers performing routine-manual, but also workers completing non-routine-manual tasks. Domestic workers executing manual tasks compete through international trade with foreign workers performing those same tasks, in contrast to technical change which heightens the competition between man and machine.

This paper makes a number of contributions. First, in contrast to existing research that examines aggregate employment shares we shed new light on job polarization by following individual movements in a cohort of workers.[3] The aggregate approach to job polarization, including Autor and Dorn (2013), Goos, Manning, and Salomons (2014), analyzes the economy over time, and the evolution of employment shares reflects both changes in the labor market as well as changes in the sample due to subsequent migration, sorting, and demographic responses. Aggregate analysis also picks up regional spillovers. In contrast, by following a cohort we typically observe no more than one job transition per worker, such as from an exposed mid-wage job to a low-wage job. Job polarization emerges as we combine the movements of multiple workers. An advantage of this micro approach is that we can narrow down the mechanisms underlying job polarization. By focusing on

[3]Other research employing individual-level data that does not center on job polarization includes Autor, Dorn, Hanson, and Song (2014), Utar (2018) and Traiberman (2019).

a given set of workers we can rule out entry, exit, and sorting as margins. As a consequence, the worker-level approach presents evidence on a source of job polarization that has not been isolated before. Because of this, our empirical results differ in some ways from research findings using the aggregate approach as we will discuss below.

A large literature finds that recent import competition from countries such as China has led to detrimental outcomes in labor markets of advanced countries (e.g., Autor, Dorn, and Hanson 2013, Pierce and Schott 2016).[4] This paper focuses on the role of trade for job polarization, for which there is little evidence to date (Autor and Dorn 2013, Michaels, Natraj, and van Reenen 2014). The finding of Autor, Dorn, and Hanson (2015) for the US that Chinese import competition has reduced employment opportunities similarly for workers at all levels of the wage distribution, low to high, is inconsistent with job polarization.[5] In contrast, building on administrative employer-employee matched data and plausibly exogenous variation we show that during the period 1999-2009, trade exposed workers moved away from mid-wage jobs towards the tails of the wage distribution in Denmark.. Both institutional and methodological factors are likely to explain the differences in results. Furthermore, our quasi-natural experiment is related to research on mass layoffs and job displacement (Jacobson, LaLonde, and Sullivan 1993, Polataev and Robinson 2008, and Sullivan and von Wachter 2009). One difference is that in our quota removal approach the definition of treatment is not based on actual job displacement but rather on each worker's ex-ante propensity to face rising import competition based on the product mix of the worker's firm.

Comparing the impacts of international openness and technological change on worker welfare is an important issue. A major challenge for separating openness from technology is that globalization clearly has aspects of both. For example, the recent increase in offshoring is unthinkable without a new level of coordination of production, distribution, and shipping resulting from new information technology (Autor 2010). By employing individual task information at a detailed occupation level, we can distinguish the impacts of import competition and routine-biased technical change (RBTC) on individual workers.[6] The result that import competition affects primarily workers performing manual tasks, which can be routine or non-routine, not only advances the literature on task-level causes of worker adjustment, but it also provides information for the literature seeking to isolate the labor market effects of automation technologies such as robots (Graetz and Michaels 2015, Bessen, Goos, Salomons, and van der Berge 2019, and Acemoglu and Restrepo 2020).

[4]Further, firms react by making new technology investments and shifting towards high-skilled workers (Utar and Torres-Ruiz 2013, Utar 2014, and Bloom, Draca, and van Reenen 2016).

[5]Also Lake and Millimet (2016) and Harrigan, Reshef, and Toubal (2017) conclude that trade does not cause job polarization.

[6]See Autor and Dorn (2013) and Goos, Manning, and Salomons (2014) that RBTC is a source of job polarization, among others. The concept of RBTC goes back to Autor, Levy, and Murnane (2003), Autor, Katz, and Kearney (2006), and Goos and Manning (2007).

In the remainder of the paper, the following section describes how the surge in imports from China to Denmark has generated an increased level of competition that can be exploited to study job polarization. We also present an overview of our administrative, micro-level data, with more details given in the Appendix. Section 3 introduces our empirical approach for studying worker-level impacts of the textile quota liberalization, and we also discuss how we address challenges with identification. Next we show that textile workers' job-to-job transitions in response to the import competition shock lead to job polarization (section 4), and we demonstrate that education and skill are key for upward rather than downward job transitions of workers who lose their middle-class job. We generalize our findings for the textile quota removals to Denmark's entire private-sector labor force in section 5, which also shows that the sectoral shift from manufacturing to services is key to obtaining the U-shaped job polarization pattern. Section 6 demonstrates that import competition impacts most strongly workers completing manual tasks; these need not be routine in nature, explaining why technical change does not mimic the impact of rising import competition on workers. Section 7 provides a concluding discussion, while the Appendix includes important supplemental information and additional results.

2 Rising Import Competition and Job Polarization in Denmark

2.1 Measuring Employment Polarization

For the period of 1999 to 2009, we distill the U-shaped pattern of employment changes into three occupational wage groups for our 1999 cohort of N = 900,329 workers, see Table 1. The table classifies occupations into the high-, mid-, and low-wage part of the distribution familiar from analyses of job polarization (Autor 2010, Goos, Manning, and Salomons 2014). These groups are based on the median wage paid in a full-time occupation in Denmark for the year 1999. The high-wage occupations comprise of managerial, professional, and technical occupations. Mid-wage occupations are clerks, craft and related trade workers, as well as plant and machine operators and assemblers. Finally, low-wage occupations include service workers, shop and market sales workers, as well as workers employed in elementary occupations. Notice that the three wage groups are quite stable over time.[7]

[7] Our breakdown of occupations into these three wage groups is similar to that of Goos, Manning, and Salomons (2014) in their study of sixteen European countries, including Denmark; their information is shown in Table E-1.

Table 1: Employment Groups by Occupational Wage

	Median Hourly Wage		Mean Hourly Wage		Employment Share		One-digit ISCO
	1999	2009	1999	2009	1999	2009	
High-Wage							
Legislators, Senior Officials, Managers	5.49	5.55	5.54	5.60	0.04	0.04	1
Professionals	5.30	5.36	5.35	5.41	0.14	0.17	2
Technicians, Associate Professionals	5.12	5.18	5.16	5.21	0.18	0.24	3
Mid-Wage							
Craft and Related Trade Workers	5.05	5.10	5.00	5.03	0.13	0.09	7
Plant and Machine Operators, Assemblers	5.01	5.09	5.10	5.02	0.09	0.06	8
Clerks	4.95	5.01	4.95	5.02	0.13	0.10	4
Low-Wage							
Elementary Occupations	4.92	4.96	4.93	4.96	0.12	0.10	9
Service Workers, Shop Sales Workers	4.84	4.94	4.85	4.93	0.17	0.19	5

Notes: Values are expressed in log 2000 Danish Kroner. Employment shares in percent. Elementary occupations are in sales, services, mining, construction, manufacturing, and transport. Does not include ISCO code 92 (Agricultural, fishery and related labourers). All hourly wages are calculated among workers with full-time jobs employed continuously with at least one year tenure. Employment shares are calculated using the number of employees and excluding army and agriculture as well as fishery occupations.

2.2 Quota Removals in Textile and Clothing

Since the late 1990s, Denmark, like many other advanced countries, has experienced increased import competition from lower-wage countries. To examine trade-induced job-to-job transition of workers leading to job polarization, we first employ a quasi-experiment that uses a concrete policy change, the lifting of textile quotas on China's exports due to the country's entry into the WTO (December 2001).[8] We also generalize the analysis to the entire private-sector labor force by employing an instrumental variables approach that exploits changes in import penetration due to the expansion of production capabilities in China in the early 2000s.

The textile quotas were part of the Multi-Fibre Agreement (MFA). It was established in 1974 as the cornerstone of a system of trade restrictions on developing countries' textile and clothing exports with the intention to protect this relatively labor-intensive sector in advanced countries. With the conclusion of multilateral trade negotiations in the year 1994, it was agreed to bring trade in textiles in line with the rules of other world trade at the time, and thus import quotas were to be removed.

[8] Our quasi-natural experimental strategy follows Utar (2018). For earlier work on these quota removals, see Harrigan and Barrows (2009), Utar (2014), and Bloom, Draca, and van Reenen (2016).

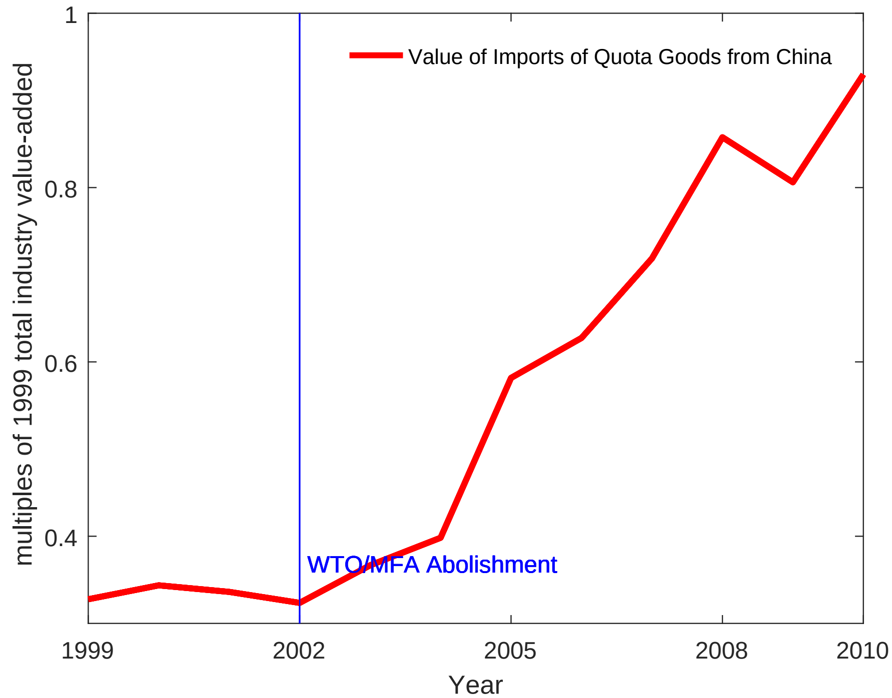

Figure 2: **Denmark's Imports of Quota Goods from China**

Notes: The figure shows the values of total imports of MFA quota goods from China, expressed in units of the 1999 total T&C value-added in Denmark.

Specifically, it was agreed that MFA quotas were to be abolished in four phases: in the years 1995, 1998, 2002, and 2005.

An advantage of this policy change is that neither Denmark nor China was directly involved in negotiating the creation or the removal of the textile quotas (as well as which goods would be covered in which of the four phases). This is in part because negotiations took place at the level of the EU, where Denmark's influence as a relatively small country is limited. Also, China did not influence the process because it was not a member of the WTO in 1995. Similarly, because it was not a member of the WTO, China did not benefit from the first two trade liberalization phases of 1995 and 1998. At the same time, China stood out in comparison to other countries subject to MFA quotas in terms of the number of binding quotas. While there was considerable uncertainty about the if, when, and how of China's entry into the WTO, China did become a member of the WTO in December 2001.

After joining the WTO, China benefited from the first three liberalization phases (1995, 1998, and 2002) in January 2002, and subsequently, from the fourth liberalization phase of 2005.[9]

The lifting of quotas led to a surge of Chinese textile imports in Denmark starting in the year

[9]Because any separate effects are difficult to distinguish as the uncertainty concerning China's quota-free access to the European market was fully resolved in December 2001, our analysis employs the entire period 2002 - 2009 as trade liberalization period (see Appendix B).

2002, as Figure 2 shows. Between 2002 and 2010, the value of quota goods tripled. This episode generates a plausibly exogenous increase in import competition.

To utilize this trade liberalization, we first match the import quotas imposed on China to their corresponding eight-digit Common Nomenclature (CN) goods, and using information on domestic production of firms we identify firms that were producing each of these quota-protected CN-8 digit goods in Denmark as of 1999. We then calculate a worker-level measure of exposure to import competition as the revenue shares of goods that are subject to the MFA quota removal for China for each textile and clothing firm. Workers who in 1999 are employed in firms with revenue share zero are the control group, while workers employed in firms with positive revenue shares are treated at varying levels.[10] Additional information on this quota liberalization is given in section B of the Appendix.

To summarize, the analysis follows the 1999 cohort of textile workers for a decade as they change jobs and switch firms, industries, or occupations, and as they become unemployed or move out of the labor force. In this way the analysis yields a worker-level picture of labor market adjustments throughout the entire economy. Our instrumental variable analysis based on the universe of private sector workers is described in section 5 below.

2.3 Worker- and Firm-Data

This study employs the Integrated Database for Labor Market Research of Statistics Denmark, which contains administrative records on individuals and firms in Denmark.[11] We start from annual information on all persons of age 15 to 70 residing in Denmark with a social security number, on all establishments with at least one employee in the last week of November of each year, as well as on all jobs that are active in that same week. Our economy-wide sample includes all workers who were between 18 and 50 years old in 1999 and employed in the private sector; this yields essentially the private-sector labor force of the year 1999.[12] These data are combined with the firm-level accounting and production databases using the employee-employer match as well as data on international transactions to measure exposure to import competition.[13] The size of our sample is N = 900,329 workers, indexed by i.

[10] As shown below, our results are similar when we use the indicator treatment variable definition of whether a firm produced any goods subject to the MFA China quota removal.

[11] See Bobbio and Bunzel (2018) for additional descriptions of this data.

[12] We have chosen this age limit so that workers do typically not retire during the sample period; our main results remain unchanged, however, if workers up to 65 years are added to the sample (see Appendix G.3).

[13] See Appendix Section E for further information on the data-sets.

Table 2: Key Characteristics of the Sample

	Mean	Standard Deviation
Panel A. Economy-wide Sample Worker Characteristics, 1999 (N = 900,329)		
Age	34.093	8.852
Female	0.339	0.473
Immigrant	0.045	0.208
Education		
- College	0.176	0.381
- Vocational	0.436	0.496
- High School	0.377	0.485
Experience	12.868	6.205
History of Unemployment	1.025	1.716
Log Hourly Wage	5.032	0.448
High Wage Occupation	0.265	0.441
Mid Wage Occupation	0.509	0.500
Low Wage Occupation	0.194	0.395
Union Membership	0.762	0.426
Panel B. Quasi-experiment Sample Worker Characteristics, 1999 (N = 10,487)		
Age	39.663	10.358
Female	0.569	0.495
Immigrant	0.061	0.240
Education		
- College	0.123	0.329
- Vocational	0.352	0.478
- High School	0.509	0.500
Experience	14.729	5.783
History of Unemployment	1.292	1.828
Log Hourly Wage	4.964	0.374
High Wage Occupation	0.205	0.404
Mid Wage Occupation	0.664	0.472
Low Wage Occupation	0.119	0.324
Union Membership	0.822	0.383

Notes: Variables Female, Immigrant, Union Membership, High Wage, Mid Wage and Low Wage Occupations, as well as College, Vocational, High School are indicator variables. Age, Experience, and History of Unemployment measured in years. High School stands for at most completed high school education; History of Unemployment is the summation of unemployment spells of worker *i* until 1999. Log Hourly Wage in units of 2000 Danish Kroner.

Panel A of Table 2 summarizes worker characteristics as of 1999. Panel B of Table 2 shows summary statistics for our quasi-experiment sample, workers who were employed in 1999 in Denmark's textile and clothing industries (N = 10,487). The worker information includes annual salary, hourly wage, industry code of primary employment, education level, demographic characteristics (age, gender and immigration status), labor market experience (years in the labor market, spells of unemployment) and occupation of primary employment.[14]

Our economy-wide sample is defined as all workers employed in firms operating in the non-agricultural private sector for which Statistics Denmark collects firm-level balance sheet data.[15] In the year 1999 these workers were employed in a wide range of industries, including mining, manufacturing, wholesale and retail trade, hotels and restaurants, transport, storage and communication, as well as real estate, renting and business activities (see Figure C-1). Exposure to import competition is determined by the worker's six-digit industry of employment in the year 1999, denoted as $\Delta ImpPent_i^J$, where J indexes the six-digit industry of worker i.

We distinguish three levels of education, which are at most college, vocational education, and high school education. In Denmark vocational education is provided by technical high schools (after 9 years of mandatory schooling) and involves several years of training with both formal schooling and apprenticeships. In our sample, the percentage of workers with college education is 18%, 44% of workers have vocational training, and the remaining 38% workers have at most high school education. This is quite similar to Denmark as a whole, where these percentages are 25%, 43%, and 32%, respectively. As one would expect, the three education levels are disproportionately represented in our three wage groups, with 55 percent of the workers in low-wage occupations but only 14 percent of the workers in high-wage occupations having at most a high school degree.

Summary statistics for the sample of textile workers are shown in Panel B of Table 2. It comprises of all employees of the textile and clothing sector who are of working age throughout the sample period (N = 10,487).[16] There are a number of differences between the textile workers and the private-sector cohorts of 1999. One of them is that compared to the economy as a whole, as typical of manufacturing in general, mid-wage occupations in textiles are relatively important, with 66% of textile workers holding mid-wage occupations in 1999.

Table B-1 in the Appendix shows textile worker characteristics depending on whether they were employed in quota producing textile manufacturing firms or not (discrete exposure). Roughly half of the workers were employed at firms that manufactured products subject to quota removals for China (exposed in Table B-1). The average age of both treated and untreated workers is the same at 40. We also see that both sets of workers have between 14 and 15 years of labor market experience. Average annual earnings are quite similar in 1999 for exposed and control workers. Also notice that 37 percent of exposed workers are machine operators, as are 38 percent of the control group.

[14] Information on worker occupation is of unusually high quality in Denmark in part it matters for earnings. Occupation codes are generally given at the four-digit ISCO-88 classification with more than four hundred occupations.

[15] Our sample does not include workers in public administration, education, and health sectors, the bulk of which in Denmark is publicly owned. Including those does not yield important additional insights.

[16] Since this sample is smaller we employ less conservative age limits. The sample includes all workers who in 1999 are between 17 and 57 years old.

We will analyze worker-level employment responses to rising import competition. Key outcomes include the years of employment of worker i in mid-, high-, and low-wage occupations (see Table 1 for the list of these occupations). In our economy-wide analysis, the variable MID_i^e is defined as the sum of all years from 2000 to 2009 that worker i has held a primary job in mid-level wage occupations.[17] Analogously, we define LOW_i^e and $HIGH_i^e$ as the cumulative low-wage and high-wage employment of worker i from year 2000 to year and 2009, respectively (see Table 1 for these occupations). In the case of the quota removal liberalization, we employ the panel versions of these outcome variables, for example, average mid-wage employment in 1999-2001 versus in 2002-2009.[18]

One might ask whether Denmark's labor market is suitable to studying occupational movements of individual workers in response rising import competition. We show this to be the case in the Appendix, see section D.

2.4 Descriptive Evidence from the Movements of Textile Workers

If import competition has led to job polarization, mid-wage employment reductions and low-wage employment increases must be relatively pronounced for workers employed in firms that are affected by the post-2002 quota removal. Figure 3 provides initial evidence on this by comparing the job transitions of treated (exposed) and control (non-exposed) machine operators and assemblers (ISCO 82; machine operators for short). Consider first the hollowing out of middle-class jobs. Because our sample starts with the universe of machine operators in 1999 and does not include machine operators that enter this occupation after 1999, the two upper lines in Figure 3 start at 100% and necessarily slope downward over time. The chief observation is that the rate at which machine operators leave their occupation in exposed firms is higher than the rate at which they leave it in non-exposed firms. By 2009 only about 15% of the exposed machine operators are in that same occupation, in contrast to 23% of the machine operators that are not exposed to rising import competition.

Turning to increases in low-wage employment, the two lower lines in Figure 3 give the cumulative probabilities of 1999 machine operators to work in personal and protective services (ISCO 51). This is a low-wage occupation that includes the organization and provision of travel services, housekeeping, child care, hairdressing, funeral arrangements, as well as protection of individu-

[17]The variable MID_i^e ranges from a maximum of 10 years–a worker who has been employed in mid-wage occupations in every year, 2000 to 2009, to a minimum of 0 for a worker who never had a spell in mid-wage jobs. See Table C-1 in the Appendix for the summary statistics of the outcome variables.

[18]Descriptive statistics of the outcome variables for the quasi-experiment and for the economy-wide sample are reported in Table B-2 and Table C-1 in the Appendix, respectively.

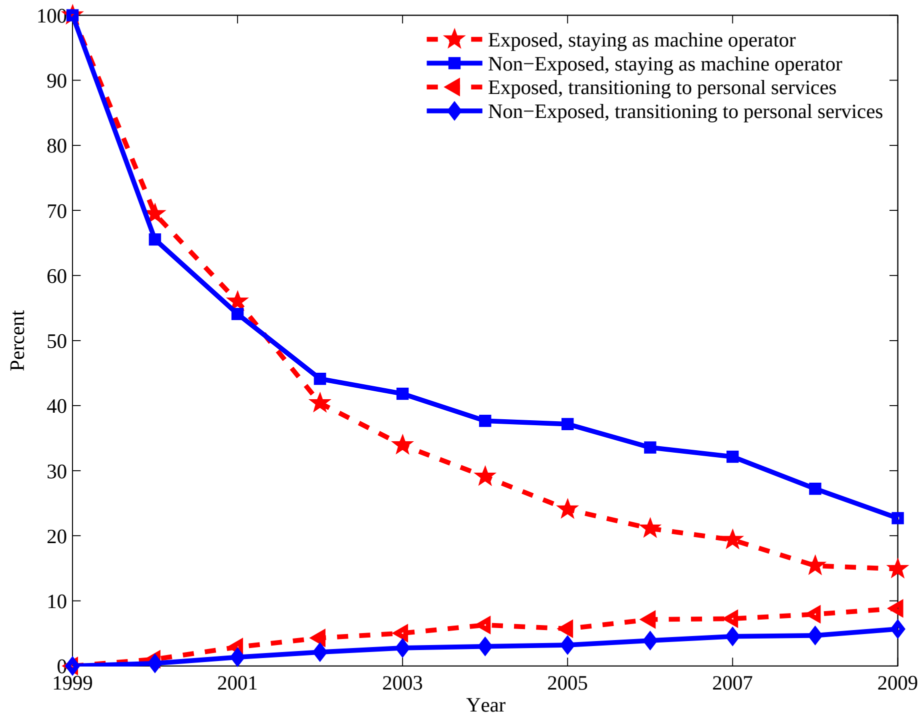

Figure 3: Machine Operators: Staying versus Switching to Low-wage Jobs, by Exposure

Notes: Shown are probabilities of 1999 machine operators, a mid-wage occupation, to stay in that occupation, and their probabilities to move into personal service occupations, which are low-wage occupations, by worker exposure.

als and personal property. Figure 3 shows that the movement of exposed machine operators into personal and protective service jobs is more pronounced than for non-exposed machine operators. By the year 2009, almost one in ten of the exposed machine operators is a personal and protective service worker, compared to only about one in fifteen of the non-exposed machine operators. Consistent with job polarization, workers exposed to rising import competition move relatively strongly from mid-wage into low-wage occupations.[19]

3 Estimation Approach

This section describes our estimation approach for the textile quasi-experiment and discusses how we address challenges with identification. The difference-in-differences framework exploits the drastic change in import competition as China entered the WTO (first full year: 2002) and the longitudinal structure of the data accommodates worker fixed effects. We aggregate the annual

[19] A similar figure for high-wage occupations (not shown) indicates that exposed workers move also more strongly than non-exposed workers into high-wage occupations.

data into pre- and post-shock periods to address the concerns noted in Bertrand, Duflo, and Mullainathan (2004): X_{is} is the outcome in period s (pre- versus post-period) for worker i. The years of the pre-liberalization period are 1999 to 2001, and the years of the post-liberalization period are 2002 to 2009. The estimation equation is given by:

$$X_{is} = \alpha_0 + \alpha_1 Post_s x Exposure_{i,99} + \alpha_2 Post_s + \delta_i + \varphi_{is}, \tag{1}$$

where $Exposure_{i,99}$ is the degree to which a worker i is exposed to rising import competition due to the dismantling of import quotas, measured as the revenue share of eight-digit products of worker $i's$ firm for which quotas will be removed with China's entry into the WTO. This way, exposed workers employed at firms domestically producing quota products with a small share of revenue will be given less weight than exposed workers whose workplaces concentrate heavily on domestic MFA good production. The variable $Post_s$ is an indicator variable for the post-liberalization period (years 2002-2009) that captures the influence of aggregate trends affecting all workers, while δ_i denotes worker fixed effects.

The error term φ_{is} in equation (1) is assumed to be mean zero, and we allow for correlation within groups of workers employed by the same firm by clustering standard errors by the workers' 1999 firm.[20] For ease of exposition, we denote the difference-in-differences term $Post_s x Exposure_{i,99}$ by $ImpComp_{is}$, mnemonic for import competition.

The outcome variables X_{is} are five mutually exclusive labor market positions of workers, namely the years of employment in mid-, high-, and low-wage occupations, as well as the years in the outside of the labor market and in unemployment. We denote them as MID^e_{is}, $HIGH^e_{is}$, LOW^e_{is}, UE^e_{is}, and OUT^e_{is}.[21]

Given our focus on mechanisms determining workers' employment paths, we form an estimation equation where the difference-in-differences term $ImpComp_{is}$ is interacted with various characteristics of worker i in the year 1999, denoted by C_i. The estimation equation is then:

$$\begin{aligned} X_{is} = \alpha_0 + \alpha_1 ImpComp_{is} + \alpha_2 ImpComp_{is} x C_i + \alpha_3 Post_s + \\ \alpha_4 Post_s x C_i + \delta_i + \nu_{is}. \end{aligned} \tag{2}$$

In this specification, α_2 measures the differential effect of rising import competition on workers

[20] To examine evolution over time, we also estimate equation (1) with different endpoints from 2002 to 2009.

[21] Alternatively, we measure employment in mid-, high-, and low-wage occupations in terms of full-time years of employment, in terms of the total hours worked, and in terms of earnings in these positions, see Table F-1.

with characteristic C_i.

Identification The inclusion of worker fixed effects implies that the coefficient α_1 is estimated from within-worker variation over time. This has the advantage that the influence of any observed or unobserved worker characteristic as of year 1999 that may be correlated with a worker's future exposure to competition, including occupation, education, (unobserved) ability, or specific technology trend, is eliminated.

The coefficient α_1 in equation (1) is the well-known linear difference-in-differences estimator, which gives the treatment effect under the standard identification assumption that in the absence of treatment the workers would have followed parallel trends. This assumption would not hold, for example, if removal of quotas for other developing countries in 1995 and 1998 (MFA quota removal Phase I and II, respectively) had led to increased competition and differential trends between treated (exposed) and control workers. Furthermore, the second half of the 1990s is also a period of increased trade integration with Eastern European countries as part of the European integration process.

To address this we conduct a falsification exercise for the period 1990-1999, during which rising import competition due to the removal of import quotas on China was absent (placebo test). Using data for our workers back to the year 1990, we run difference-in-differences specifications for five labor market outcomes without changing the definition of treatment (a worker's firm's 1999 revenue share of MFA quota products). In this placebo analysis, the years 1990-94 are assumed to be the pre- and the years 1995-99 are assumed to be the post-shock period. The analysis finds no evidence for significant effects. For example, our estimates for hours worked before 1995 are close to zero and insignificant, as they are after 1995 (Table B-4). We conclude from this placebo analysis that there is no evidence that the MFA removal phases I and II, the enlargement of the European Union with the Eastern European Countries, or any other factor generated differential pre-trends that would preclude estimating consistent effects for the period 1999-2009.

What about other threats to identification? The inclusion of worker and time fixed effects implies that our estimates are identified from within-worker changes controlling for aggregate changes for all textile workers. Furthermore, we control for aggregate time trends that are specific to workers with certain characteristics (the term Post x C_i in equation (2)), such as susceptibility of workers' initial occupation to technical change. Nevertheless, as another general check on identification and our firm-level treatment criterion we also perform an analysis in which the textile and clothing firms are assigned randomly as exposed. The coefficient estimates we obtain from this exercise are centered on zero, implying no effect (see Table B-6). This provides further evidence that we identify causal impacts of rising import competition.

4 Import Competition and Occupational Movement of Textile Workers

4.1 Quota Removals and Adjustment Consistent with Job Polarization

The following analysis encompasses all 1999 textile workers who are of working age until the year 2009. The years following the first removal of Multi-fibre Arrangement quotas on China in January 2002, are times of surging Chinese imports in the Danish textile and clothing industry.

Table 3 shows the results from estimating equation (1) for employment in mid-, high-, and low-wage employment of worker i in period s, denoted by MID^e_{is} , $HIGH^e_{is}$, and LOW^e_{is}, respectively.

Table 3: Job Polarization due to Quota Removal

	(1)	(2)	(3)	(4)	(5)
	MID^e_{is}	$HIGH^e_{is}$	LOW^e_{is}	UE^e_{is}	OUT^e_{is}
Import Competition	-1.292***	0.788***	0.665***	0.084	0.175
	(0.382)	(0.285)	(0.220)	(0.127)	(0.236)
	[-0.337***]	[0.207**]	[0.168***]	[0.022]	[0.008]
Worker Fixed Effects	✓	✓	✓	✓	✓
Time Fixed Effects	✓	✓	✓	✓	✓
N	20,974	20,974	20,974	20,974	20,974

Notes: Dependent variable given at the top of the column. Variables UE^e_{is} and OUT^e_{is} are defined as years of unemployment and outside of the labor force of worker i in period s. Estimation of equation (1) using OLS. Import Competition is defined as $Exposure_i xPostShock_s$ (equation (1)), where $Exposure_i$ is the manufacturing revenue share of eight-digit goods that were subject to removal of quotas for China in 1999 of worker i's employer. Results from employing a discrete treatment definition (revenue share larger than 0 Yes/No) are given in square brackets. Robust standard errors clustered at the level of the workers' initial firm are reported in parentheses. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

First, column (1) shows that workers exposed to rising Chinese competition due to the dismantling of quotas for China have less mid-wage employment than non-exposed workers, with a coefficient of about -1.3. This means that import competition has been a factor in the hollowing out of mid-wage jobs in Denmark. Second, import competition has also led exposed workers to have more high-wage employment, as shown in column (2) of Table 3. The estimates in column (3) show that import competition has also led to an increase in low-wage employment, as shown in column (3).

The size of the coefficients in the high- and low-wage employment regressions are comparable in size and roughly half as large in absolute value as the coefficient in the mid-wage regression of column (1). This indicates that import competition leads to job-to-job transitions of workers that are consistent with job polarization. Further, over this decade import competition does not have a significant impact on unemployment and labor market exit (columns (4) and (5)).

To asses the economic magnitudes of the impact of import competition we compare workers at the 25th and the 75th percentile of exposure. The 75/25 percentile difference compares a textile worker who in 1999 is employed at a firm with 28.4% of revenue in domestically produced quota goods with another textile worker whose firm in 1999 does not produce any quota product. The result in column (1) shows that the competition from China causes a decline in mid-wage occupations over the eight years of -1.292 times 0.284 = 0.367 of a year, or 4.4 months.

Alternatively, we can compare the effect of import competition to the typical levels of employment in particular jobs in the sample. For mid-wage jobs, the coefficient in column (1) implies that import competition leads to a 17% decline compared to the sample average of mid-wage employment. Furthermore, exposed workers have on average about 28 percent higher low-wage employment than non-exposed workers, and exposed workers have on average also about 23 percent more high-wage employment compared to non-exposed workers.

While the revenue share of quota-exposed products captures the intensity of import competition faced by workers, the results are similar when Import Competition is defined as an indicator variable, equal to one if the firm has any eight-digit products that will be subject to heightened import competition after China's entry into the WTO, and zero otherwise (results reported in square brackets, Table 3). For example, with the indicator treatment definition the coefficient in the mid-wage employment equation of -0.337 amounts to a reduction in mid-wage employment of 4 months, which is similar to the 4.4 months impact using the continuous treatment variable.

We now consider full-time and hours worked as well as earnings as outcome variables (see Table F-1). Our employment variables so far do not distinguish full-time versus part-time jobs as long as they are held as a primary job, and it is possible that trade competition reallocates workers disproportionately towards part-time jobs. However, results that only focus on full-time jobs are quite similar, see Panel A, indicating moving from full-time to part-time jobs is not an important margin of adjustment.[22] The analysis of hours worked in low-wage jobs indicates that trade-induced low-wage employment increases come with relatively short tenure (Panel B of Table F-1). In line with this, we do not find significant earnings gains in these low-wage occupations (Panel

[22] Utar (2018) shows trade exposure causes shorter employment spells in Denmark disrupted frequently by unemployment spells but does not increase workers' likelihood to move to part-time jobs.

C).

To summarize, based on the adjustments of individual workers the textile quota trade liberalization led to lower mid-wage employment at the same when both high-wage and low-wage employment increased. Thus, the impact of import competition on Danish textile workers is consistent with job polarization.

The welfare implications of rising import competition for a given worker depend on whether the worker falls (or not) in the occupational wage distribution. The following sheds more light on this, as well as key mechanisms, by examining the occupational movements of specifically those workers who held mid-wage jobs at the beginning of the sample period (year 1999).

4.2 The Occupational Dynamics of Mid-Wage Workers

There were about 7,000 textile workers who at the beginning of the sample period were employed in mid-wage occupations. Figure 4 shows how the import shock affects the labor market position of these workers over time. Shown are estimates for versions of equation (1) in which the length of the post-period in the difference-in-differences analysis is varied from the year 2002 to the eight-year period of years 2002-2009. The figure also shows the dynamics of trade's impact on unemployment and labor force participation of these workers. The estimates underlying the figure are shown in the Appendix, Table F-2.

Figure 4 shows that while rising import competition leads to a substantial reduction in mid-wage employment for these workers, the trade-induced increase in low-wage employment is on average larger than the increase in high-wage employment. In fact, despite mid-wage reductions for these workers, there is no significant movement into high-wage jobs.[23]

In addition, exit from the labor force due to import competition is quite important, amounting to a difference of roughly two months between treated and control workers. Unemployment turns out to be less important, although in the short term, until the year 2004, import competition causes more unemployment than labor market exit.[24]

The fact that exposed mid-wage textile workers are more likely to switch into low- rather than high-paying jobs provides evidence that import competition has affected these workers negatively

[23]This implies that the more symmetric impact of import competition on high- and low-wage employment shown in Table 3 is due to workers who were initially in high- or low-wage occupations.

[24]We also find that rising import competition generates a downward push into mid-wage occupations for 1999 high-wage workers. Further, there is limited evidence that 1999 low-wage workers are induced to become unemployed or exit the labor force. While upward movements due to import competitionfrom 1999 low-wage positions are rare, they are significant from low- into high-wage occupations. On these movements, see Tables F-3 and F-4.

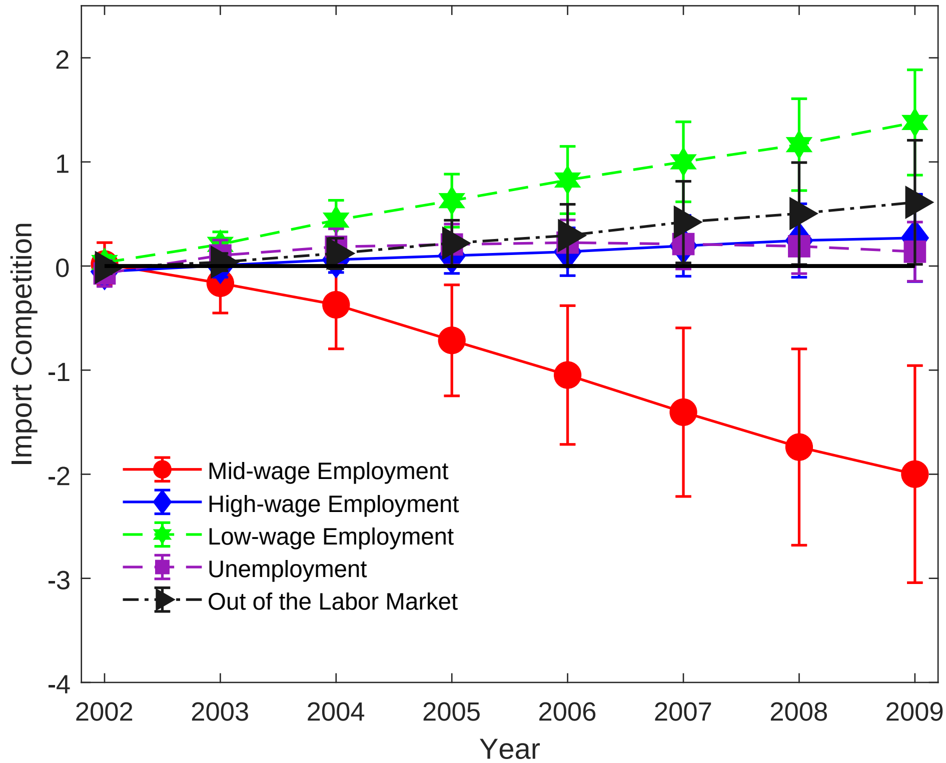

Figure 4: Import Competition and Labor Market Trajectories of Mid-Wage Textile Workers

Notes: Shown are coefficients from estimating equation (1) with varying sample period end from 2002 to 2009. Robust 95% confidence intervals based on clustering on 1999 firm.

overall. This contributes to increased inequality in the economy.

4.3 Determinants of the Direction of Occupational Movements

4.3.1 Education

This section examines the influence of education and skill in shaping occupational movements of workers in response to rising import competition. Our sample is all textile workers who were holding mid-wage jobs in the year 1999. We begin by distinguishing workers by their highest attained education level as of 1999. Results are shown in Panel A of Table 4. In this panel, the reference category is workers with at most high-school education.

First, we consider the extent to which these middle-wage workers continue to be employed in mid-wage occupations. This is related to the upper two lines shown in Figure 3 above. Column

(1) shows that the extent to which import competition causes mid-wage employment loss does not vary significantly by a worker's level of education.

In contrast, education does play a major role for upward versus downward occupational movements, as we show now. First, even though exposed workers with the lowest level of education (high school) lose mid-wage employment, they fail to gain high-wage employment compared to workers not exposed to rising import competition (column (2)). Second, import competition leads to an increase in low-wage employment of such workers (column (3)). Taken together, import competition from China pushes low-educated workers from middle-class jobs to low-wage jobs.

Mid-wage workers affected by trade who switch into high-wage employment are often college-educated, as shown in column (2). Despite this, some college-educated workers help to account for trade-induced low-wage employment (1.68 + (-1.11) = 0.57, see column (3)). This indicates that a high level of education is not as unambiguously beneficial for a worker's occupational movement as a low level of education is detrimental. College education does, however, tend to reduce the chance that a worker becomes unemployed or moves outside of the labor market (not significant, see columns (4) and (5)). The finding that mid-wage workers with college education adjust comparatively well means that worker adjustments in response to import competition open up a new dimension of inequality.

There is little evidence that vocational education prevents workers from exiting the labor force or becoming unemployed (Panel A, columns (4), (5)). A benefit of vocational education is that such workers are less likely than high school educated workers to be pushed into low-wage jobs by import competition; at the same time, vocational training does not give as much protection from this downward move as college education (column (3)). Similarly, while vocational education is preferred to high school education for moving into high-wage jobs when import competition increases, vocationally trained workers do not move into high-wage jobs as well as college educated workers (column (2)).

Overall, the findings are consistent with the idea that vocational education can be effective for a worker to avoid falling in the occupational wage distribution while it does not typically provide the more general skills necessary for upward movements in response to a negative trade shock.

Table 4: Trade-induced Occupational Movements of Mid-wage Workers: The Role of Education

	(1) MID_{is}^{e}	(2) $HIGH_{is}^{e}$	(3) LOW_{is}^{e}	(4) UE_{is}^{e}	(5) OUT_{is}^{e}
Panel A.					
ImpComp	-1.956***	-0.024	1.681***	0.154	0.573
	(0.585)	(0.17)	(0.316)	(0.155)	(0.372)
ImpComp x College	-0.133	2.033**	-1.105**	-0.498*	-0.845
	(0.985)	(0.835)	(0.49)	(0.298)	(0.56)
ImpComp x Vocational	-0.111	0.451	-0.713**	0.126	0.299
	(0.566)	(0.316)	(0.361)	(0.202)	(0.424)
Panel B.					
ImpComp	-2.060***	0.242	1.587***	0.068	0.516
	(0.576)	(0.215)	(0.294)	(0.170)	(0.355)
ImpComp x Manuf Voc Ed	-1.003	-0.173	-0.580	0.682**	1.445**
	(0.897)	(0.369)	(0.435)	(0.289)	(0.655)
ImpComp x Service Voc Ed	0.867	0.226	-0.708*	-0.026	-0.326
	(0.671)	(0.431)	(0.396)	(0.211)	(0.428)
For both panels:					
Worker FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Educ. Indicators x Time FEs	✓	✓	✓	✓	✓
N	13,934	13,934	13,934	13,934	13,934

Notes: Dependent variable at top of column. Estimation of equation (2) adjusted for two instead of one initial characteristic by OLS. The variable ImpComp denotes $Exposure_i xPostShock_s$ where $Exposure_i$ is defined as the revenue share of 8-digit Combined Nomenclature goods that were subject to removal of quotas for China in 1999 of worker i's employer. Robust standard errors clustered at the initial (1999) firm-level are reported in parentheses. *, **, and *** indicate significance at the 10 %, 5% and 1% levels respectively.

To shed more light on the role of specific skills provided by vocational training, we distinguish manufacturing-specific (such as textile operator or industrial cabinet maker) from service-specific (such as decorator) vocational education. Results are shown in Panel B of Table 4.

First, a service-oriented vocational training tends to reduce mid-wage employment losses, while a manufacturing-specific vocational education if anything increases them (column (1); not significant). One reason for this is likely that the trade shock adversely affects many mid-wage workers in manufacturing. Furthermore, service orientation tends to increase the chance that a worker moves into a high-wage job by more than manufacturing orientation does. Correspondingly, service-specific vocational education improves the chance that a worker can avoid having to work in a low-wage job compared to manufacturing orientation.

However, the main advantage of a service-oriented vocational education is that such workers avoid the trade-induced unemployment that workers with manufacturing-oriented vocational education experience, and they are also less likely to exit from the labor market (columns (4) and (5), respectively). This is related to finding that rising import competition accelerates the sectoral shift from manufacturing to services (e.g., Utar 2018). Thus, while a service-oriented vocational training has the benefit to increase the chance of upwards- versus downward occupational movements, the two right-most columns in Table 4 show that there are also important advantages for worker adjustment at the extensive margin (unemployment and labor market exit).

In sum, there is strong evidence that education shapes the way a particular exposed middle class worker contributes to the aggregate pattern of job polarization.[25] These education results, especially the importance of high education for high-wage employment gains, are broadly confirmed by findings for the entire private-sector labor force, see Table G-5.

4.3.2 Skills

In the following we employ a worker's hourly wage as an indicator of how skills (beyond formal education) affect occupational transitions of 1999 mid-wage workers. Specifically, the analysis contrasts the impact of import competition on workers with particularly low and particularly high wages, defined as in the lowest versus the highest quintile of the hourly wage distribution, respectively. Results are shown in Table 5. The reference category in these regressions is workers with wage levels close to the average (central 60 percent of the wage distribution).

[25]This analysis has been in terms of 1999 levels of education; for evidence that international trade can provide incentives for human capital accumulation, see Blanchard and Olney (2017) and Utar (2018).

Table 5: The Role of Skill for Moving Up and Down in the Occupational Hierarchy

	(1) Mid-Wage Emp.	(2) High-Wage Emp.	(3) Low-Wage Emp.	(4) Unemploy-ment	(5) Labor Market Exit
ImpComp	-2.046***	0.240	1.395***	0.214	0.473
	(0.603)	(0.25)	(0.311)	(0.152)	(0.336)
ImpComp x Low Wage	1.491**	-0.195	-0.462	-0.622**	-0.095
	(0.667)	(0.385)	(0.458)	(0.287)	(0.531)
ImpComp x High Wage	-0.597	2.117***	-0.670	-0.069	-1.032**
	(1.079)	(0.747)	(0.542)	(0.281)	(0.474)
Worker FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Time x Wage Quintile FEs	✓	✓	✓	✓	✓
N	13,934	13,934	13,934	13,934	13,934

Notes: Dependent variable at top of column. Sample is all mid-wage textile workers. Estimation of equation (2) adjusted for two instead of one initial characteristic by OLS. Low (High) Wage: indicator variable equal to one if worker belongs to lowest (highest) quintile of the hourly wage distribution of 1999 mid-wage workers. Robust standard errors clustered at the 1999 firm level in parentheses. *, **, and *** indicate significance at the 10 %, 5% and 1% levels respectively.

First, we find evidence that workers with relatively low wages are less likely to lose their job compared to other middle-class workers exposed to import competition (column (1)). Thus, while different levels of education are not associated with varying probabilities to lose middle-class jobs (as shown in Table 4), wage differences are.

Next, we see that it is exposed middle-wage workers commanding a relatively high wage who have the best chance of moving up into high-wage employment (column (2)). Because these high-earning workers are more likely to have college education, this is in line with our findings in Table 4. In contrast, workers who command low wages are not disproportionately likely to shift downward into low-wage jobs compared to exposed workers with average skill levels, and neither are highly skilled workers significantly less likely to fall down to a low-wage job (see column (3)).

We also find that workers who receive relatively low wages are less likely to become unemployed than workers that are paid more (column (4)), and that workers receiving relatively high wages move out of the labor force to a lesser extent than workers receiving lower wages (column (5)). While the former differs from what we found for workers with the lowest level of education, the latter is in line with our findings for college-educated workers (see Table 4).

These results show that mid-wage job loss is more common on the low end of the wage distribution, whereas workers with higher skills are more likely to move up in the job distribution. Overall, we see that workers in the middle of the wage distribution face a substantial trade-induced risk of moving down in the hierarchy of jobs.

4.3.3 Movements of Textile Workers across Sectors

Before turning to the analysis of Denmark's entire private-sector labor force, this section examines the sectoral dimension of trade-induced job polarization. We focus on workers who in 1999 were employed in mid-wage occupations and track their movements not only in terms of occupation (high-, low-, and mid-wage) but also in terms of major industries. These results are shown in Table 6.[26] We see, first, that the response among the adversely affected mid-wage textile workers who remain in manufacturing is asymmetric: workers move into low-wage jobs but not high-wage jobs.

Second, trade exposed mid-wage workers strongly move into the service sector in terms of employment. Among the textile workers that are induced to shift to the service sector, some stay in mid-wage jobs. Trade exposure also causes a significant increase in high-wage employment in the service sector (Panel C, column (2)); for these workers the trade shock becomes a blessing in disguise. However, trade exposure leads to substantially more low-wage employment than high-wage employment in the service sector. This indicates that overall, shifting to the service sector is a relatively bad welfare outcome for these workers on average. Nevertheless, new low-wage employment is generally distributed across the entire spectrum of services, from finance and business to retail and personal services (Panel C.2 and C.3., column (3)). New high-wage employment opportunities for the mid-wage workers exist mostly in high-wage industries such as finance, business and wholesale services.[27]

[26] We show analogous results for workers initially holding high-wage and low-wage occupations in Tables F-5 and F-6.

[27] The dependent variables in Panel C.1 in Table 6 are occupations in finance (banks, insurance, mortgage), leasing, renting, various other business services and wholesale industries. The dependent variables in Panel C.2 in Tables 6 include occupations in retail (supermarkets, grocery stores, other retail shops), hotels, restaurants, industrial or coin laundries, dry cleaners, hairdressing salons and other personal services. Notice that these high-wage (Finance, Business, Wholesale) and low-wage (Retail, Personal) service industries are mutually exclusive but not exhaustive categories within the service sector. That is, they are not covering the entire service sector.

Table 6: Movements of Mid-wage Textile Workers by Wage Group and Sector

	(1) Mid-Wage Emp.	(2) High-Wage Emp.	(3) Low-Wage Emp.
Panel A.	All Industries		
	-1.999***	0.270	1.379***
	(0.532)	(0.214)	(0.258)
Panel B.	Manufacturing		
	-2.706***	-0.070	0.260**
	(0.562)	(0.151)	(0.125)
Panel C.	Services		
	0.808***	0.364**	1.160***
	(0.273)	(0.159)	(0.234)
Panel C.1.	Finance, Business, Wholesale		
	0.667***	0.218**	0.313***
	(0.235)	(0.110)	(0.0913)
Panel C.2.	Retail, Personal		
	-0.038	0.041	0.133**
	(0.059)	(0.026)	(0.060)

Notes: Dependent variable at top of column. Table shows the coefficient on ImpComp, defined as $Exposure_i xPostShock_s$ (equation (1)) by OLS. The number of observations in every regression is N = 13,934. All regressions include worker and time fixed effects. Robust standard errors clustered at the (initial) firm-level are reported in parentheses. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

5 Analysis for Denmark's Private Sector Labor Force

5.1 Import Competition as a Source of Economy-wide Job Polarization

Our analysis of Denmark's private sector sample of workers exploits the rise of imports from China in the early 2000s by studying the impact of changes in import penetration from China across six hundred industries –manufacturing and non-manufacturing– that are differentially exposed to import competition. This section generalizes the previous analysis of 1999 textile and clothing workers. Our economy-wide import shock is defined as the change in imports from China between the years 2009 and 1999 over 1999 absorption in a given six-digit (NACE) industry j, and it is denoted by $\Delta ImpPent_j$.[28] When we use $\Delta ImpPent_j$ in worker-level equations, we denote it as $\Delta ImpPent_i^J$.

Figure C-2 in the Appendix shows the change in Chinese import penetration between 1999 and 2009 across six-digit manufacturing industries versus the share of workers in middle-class jobs in 1999. Products belonging to the same two-digit industry are given labels with the same color and shape. We see that the relationship between import penetration and the share of mid-level workers varies strongly even within two-digit industries. To control for broad technological differences between industries our analysis will include two-digit industry fixed effects. Further, to address the potential endogeneity of imports from China we employ an instrumental-variables approach. See section C in the Appendix for further description of this approach as well as our data sources.

In the case of mid-wage employment, our estimation equation is given by

$$MID_i^e = \alpha_0 + \alpha_1 \Delta ImpPent_i^J + Z_i^W + Z_i^F + Z_i^J + \varepsilon_i. \tag{3}$$

The variable MID_i^e is defined as the sum of all years of mid-wage employment of worker i during the years 2000 to 2009, while Z_i^W, Z_i^F, and Z_i^J denote worker-, firm, and six-digit industry-level variables. Because firms can be important in formulating the response to import competition, we include the most salient firm characteristics in this context, which are size, quality (proxied by average wage), and the frequency at which workers separate from their firms. In addition to two-digit industry fixed effects, technological change controls include two-digit occupation fixed effects and the share of workers at each six-digit industry with information technology (IT) education. Importantly, we also control for pre-trends at the six-digit level. The full list of our control variables is listed in the notes to Table 7 as well as in Tables E-4 and G-2.

We address potential endogeneity by instrumenting the change in Chinese import penetration in worker i's six-digit industry, j, $\Delta ImpPent_i^J$, with three variables: (1) Chinese six-digit imports in eight other high-income countries over Denmark's absorption as of 1996; (2) the weighted average distance to the source countries of Denmark's six-digit industry imports in 1996; and (3) the fraction of retail trade firms in 1996 of all importing firms in worker i's six-digit industry. Chinese imports in other high-income countries is a suitable instrument because Chinese economic reforms and productivity growth have increased China's supply and raised her exports to all high-income countries, not only to Denmark.[29] The second and third instrumental variables can be seen

[28] Absorption is defined as production plus exports minus imports.

[29] On economic reform and productivity gains in China, see Brandt, Hsieh, and Zhu (2008). The approach adopted

as structural measures of openness. If the distance to Denmark's sources of imports in an industry tends to be high, all else equal this is a sign that transport costs are low in this industry. Also, a high share of retail trade firms in a product-line proxies for the pre-existing strength of distribution channels, and any given productivity improvement in China will have a relatively strong impact in that product line. See sections C and G in the Appendix for additional information.

First-stage coefficients are shown in Table G-2 (bottom). Notice that each instrumental variable has the expected sign and is individually significant. The robust Kleibergen-Paap (K-P) F-statistic is about 13, with a p-value below 0.0002, indicating that the instruments have power. Furthermore, notice that in the mid-wage regression the Hansen J overidentification test statistic is only 0.197 (p-value of 0.906), which provides evidence that the instruments are valid.

Table 7 shows the key second-stage result on $\Delta ImpPent_i^J$ from estimating equation (3).[30] The negative coefficient of about -5.4 indicates that an increase in Chinese import penetration has a negative impact on the mid-wage employment of workers in Denmark. Hence, we confirm the hollowing out of middle class jobs due to the textile quota liberalization above for the entire labor force.

Next, we estimate equations analogous to (3) which have years of high-wage and low-wage employment as dependent variables. We are interested in whether import competition from China has caused employment increases in the high- and low-wage tails of the worker distribution. Mid-wage employment losses are only one part of the job polarization pattern, and without an increase in both high- and low-wage employment one cannot conclude that import competition has caused worker adjustments leading to job polarization. Results are shown in Table 7, columns (2) and (3).

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here is similar to Haskel, Pereira, and Slaughter (2007) and Autor, Dorn, and Hanson (2013).

[30] For OLS and results with the step by step inclusion of regression variables, see Table G-1. Results for all variables are reported in Table G-2.

Table 7: **Import Competition and Employment by Wage Group**

	(1) Mid-wage Emp. MID_i^e	(2) High-wage Emp. $HIGH_i^e$	(3) Low-wage Emp. LOW_i^e
Δ ImpPent	-5.441**	2.436**	2.413**
	(2.287)	(1.087)	(1.181)
Demographic Characteristics	✓	✓	✓
Education Characteristics	✓	✓	✓
Log Hourly Wage	✓	✓	✓
Labor Market History	✓	✓	✓
Union Membership	✓	✓	✓
Unemployment Ins. Indicator	✓	✓	✓
Firm Characteristics	✓	✓	✓
Product Characteristics	✓	✓	✓
Occupation Fixed Effects (Two-digit ISCO)	✓	✓	✓
Industry Fixed Effects (Two-digit NACE)	✓	✓	✓
Number of Clusters	170	170	170
Number of Observations	900,329	900,329	900,329
First-Stage F-test	12.575	12.575	12.575
First-Stage F-test p-value	0.000	0.000	0.000
Hansen Overidentification J-statistic	0.197	4.542	0.247
Hansen OverID J-statistic p-value	0.906	0.103	0.884

Notes: Dependent variable is years of employment in mid-, high-, and low-wage occupations between 2000 and 2009, given at top of column. Estimation by two stage least squares, with second-stage coefficients shown. Demographic variables are age as well as indicators for gender and immigration status. Education indicator variables: At least some college, vocational education, and at most high school. Wage is the logarithm of *i*'s average hourly wage. Labor market history variables: the sum of the fraction of unemployment in each year since 1980, the number of years of labor market experience before 1999, and number of years squared. Union and unemployment insurance (UI): indicator variables for membership status in year 1999. Firm variables: size, measured by the number of full-time equivalent employees, quality, measured by the log of average hourly wage paid, and strength of firm-worker relationship, measured by the separation rate between years 1998 and 1999. Product-level variables: size, measured by the log number of employees in 1999, information technology (IT) skills, as the share of workers with IT education, and importance of lower-level technical skills, measured by the wage share of vocationally trained workers, all in 1999. Further product-level variables: the percentage change in employment over years 1993-1999 as a pre-trend control, average annual growth of energy usage, and retail employment growth where worker *i*'s manufactured product is sold. Excluded instrumental variables at the six-digit product level: the change in Chinese import penetration in eight high-income countries, the log average distance of each product's import sources, using 1996 imports as weights, and the share of trade firms importing directly in 1996. Robust standard errors clustered at the 3-digit industry level in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

Results for the employment effect of rising import competition on high-wage employment are shown in column (2). The coefficient of 2.4 indicates that, on average, workers exposed to rising Chinese import competition have more employment in high-wage jobs than virtually identical workers employed at similar firms not exposed to rising import competition. Turning to the impact of rising import competition on low-wage employment, we find that, on average, trade-exposed workers have disproportionately more employment in low-wage jobs, and the coefficient turns out to be 2.4 as well (column (3)). The results in Table 7 show that rising import competition from China has led to a hollowing out of mid-wage employment at the same time when it had the effect of increasing low-wage and high-wage employment. Taken together, these findings mean that not only for textile workers but also for Denmark's labor force as a whole, the rise in import competition from China has led to job-to-job transitions consistent with job polarization.

It is useful to compare our findings with what is known about the United States. In particular, Autor, Dorn, and Hanson (2015) report that rising import competition has *not* led to the partly positive, partly negative employment changes characteristic of job polarization. Instead, Autor, Dorn, and Hanson (2015) emphasize that there are negative employment effects for virtually all workers.[31]

Reconciling labor market outcomes between the U.S. and Denmark, as between any other two countries, must remain speculative as countries have different institutions, workers, and geography (Traiberman 2019). One factor that might help to explain the differences though is that Autor, Dorn, and Hanson (2015) adopt an aggregate approach by exploiting regional variation across commuting zones whereas we shed light on the causes of job polarization by exploiting individual, worker-level information. For example, Autor, Dorn, and Hanson's (2015) approach reflects entry and exit of workers from the sample because these authors study cross-sections of regions, not longitudinal data on workers as employed here. Furhtermore, in our cohort approach, exposed and not exposed workers are compared irrespective of where they move, and there is no sample attrition. In contrast, Autor, Dorn, and Hanson's (2015) analysis is, for example, affected by differences in migration behavior for workers with more or less skills.[32]

Differences in the institutional setting such as labor market policies in Denmark versus the United

[31] Similarly, Lake and Millimet (2016) do not find evidence for job polarization explained by import competition in the U.S. using a local labor market approach.

[32] Migration might be one reason why in particular our results for high-wage employment are different. Autor, Dorn, and Hanson (2015) find that in trade-exposed commuting zones the employment share of higher skilled managerial, professional, and technical jobs falls, whereas we find that import competition increases high-wage employment. Individuals employed in high-wage occupations tend to be highly skilled, and as such they are relatively able to adjust to negative labor demand shocks. If skilled workers move disproprtionately towards less exposed commuting zones as well, their employment share in exposed regions will fall. In line with that, Bound and Holzer (2000) as well as Malamud and Wozniak (2012) find that less educated workers migrate less in response to negative labor market shocks than highly educated workers.

States may also play a role. For example, due to active labor market policies and transfer insurance policies Danish workers suffered much lower losses in personal income than their U.S. counterparts (Utar 2018 and Autor, Dorn, Hanson, and Song 2014, respectively). Along the same lines, we find that prime-age Danish workers exited the labor force to a lower degree (Figure 5) than workers in the U.S. according to the non-employment response to import competition documented by Autor, Dorn, and Hanson (2015).[33]

To assess economic magnitudes we compare two workers, one at the 10th and the other at the 90th percentile of exposure to import competition. The difference in the change in Chinese import penetration for these workers is 0.037. With a coefficient of about -5.4 in column (1), a highly exposed worker has typically just under 0.2 years of mid-wage employment *less* than the typical not exposed worker.[34] The coefficient in column (2) translates on average into 0.09 years *more* of high-wage employment. The difference to zero in the sum of the regression coefficients in Table 7 is accounted for by unemployment and years spent outside the labor force; they will be discussed below.

To put these coefficients in perspective, a worker with a poor unemployment history usually has 0.4 years less mid-wage employment between 2000 and 2009 than a worker with a good unemployment record, and a 47 years old worker has typically 0.8 years less mid-wage employment than a 22 years old worker. A worker employed in a large firm with 200 employees has 0.02 years more high-wage employment over ten years than a worker employed in a smaller firm with ten employees. These figures suggest that rising import competition has sizable effects on the occupational movements of workers.

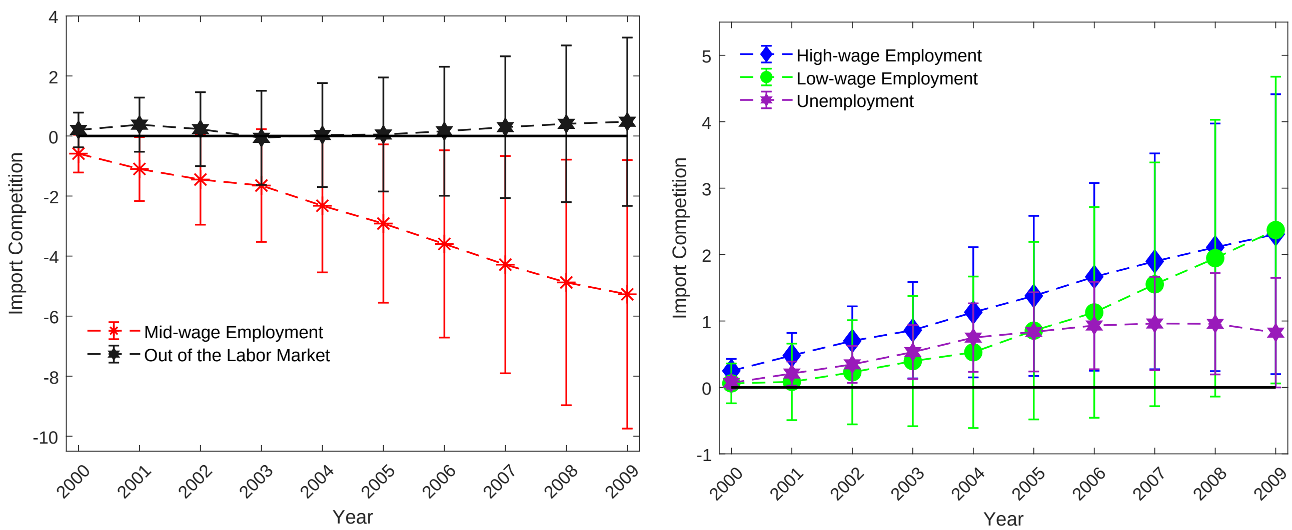
Some of the coefficients of other variables in the specifications of Table 7 are interesting. In particular, the coefficient on the indicator for women in the high-wage employment regression is about 0.77, consistent with women being more successful in moving into high-wage employment than men (see Appendix, Table G-2). This is in line with Autor's (2010) finding on the gender difference in the United States. Furthermore, the coefficient on union membership in the mid-wage employment regression is positive, which means that the hollowing-out of middle-class employment has been slower for workers who are members of a labor union. This finding mirrors Firpo, Fortin, and Lemieux (2018) who emphasize the importance of deunionization for U.S. wage polarization.

[33] Keller and Utar (2018) show that institutional differences also matter for the market work-family work choice.

[34] Evaluated at the 90th vs. 10th percentile exposure difference for manufacturing workers, the effect is 0.43 years.

5.2 Dynamics and Sectoral Adjustments

In this section we estimate equation (3) with different years as sample endpoints, from the year 2000 to the year 2009, to gauge the dynamic impact of import competition. Two-stage least squares point estimates of the impact of import competition on workers' employment in high-, mid-, and low-wage occupations as well as on unemployment and labor force exit are shown in Figure 5 (the full results are shown in Table G-4 in the Appendix) . For example, the downward trending line in Figure 5a is the impact of import competition from China on mid-wage employment; for the year 2009 as the sample endpoint, the point estimate is -5.4, the same as in Table 7, first row.



(a) Mid-wage employment loss

(b) Gains in the tails

Figure 5: The Dynamic Effect of Import Competition on Workers' Labor Market Status

Notes: Estimation of equation (3) with varying endpoint. Estimation by two-stage least squares (second-stage coefficients shown). Shown are robust 95 % confidence intervals based on clustering at the three-digit industry level.

Figure 5 makes several important points. First, there is only one series that is consistently in negative territory, namely mid-wage employment. The point estimates for the four other labor market outcomes, in contrast, are positive or virtually zero. This provides evidence that the employment increases in low- and high-wage occupations due to import competition are the flip sides of the mid-wage employment decrease. Second, the effect of import competition on mid-wage employment is negative already in the year 2000, the effect on impact, and the coefficient gets larger (in absolute value) year after year in an almost linear fashion. This is consistent with rising import competition destroying mid-wage jobs in Denmark over the medium- to long-run.

Third, import competition's impact on high-wage and low-wage employment is rising over time.

Also, trade's impact on unemployment is stronger than its effect on low-wage employment, a result that is only reversed after the year 2005 (Figure 5b). A plausible interpretation is that before the year 2005 workers prefer becoming unemployed to entering the low-wage part of the economy, and only as time goes by do workers accept the necessity of taking up low-wage employment. Finally, the figure shows that movements outside of the labor force do not play a major role (Figure 5a).

Overall, we see from Figure 5 that polarized employment trajectories are a long-run outcome of import competition, while unemployment is a transitory station of workers dealing with exposure to rising import competition. The results are also generally similar to the corresponding findings for textile workers using our quasi-experimental approach, see Figure 4.[35]

Like other high-income countries, Denmark's economy has shifted from manufacturing to services sectors in recent decades. At the same time, there is evidence that import competition caused polarized employment trajectories for manufacturing workers (Figure 1). We thus ask whether job polarization driven by rising import competition is related to the structural shift from manufacturing to services. To assess the importance of structural change we distinguish jobs in different sectors, specifically in manufacturing versus services. Table 8 reports two-stage least squares results on the impact of rising import competition separately by type of occupation and by sector.[36]

We see that the decline of mid-wage employment caused by rising import competition is concentrated in manufacturing (Table 8, Part A, column (2)). In the services sector, in contrast, trade-exposed workers tend to have actually more mid-wage employment than non-exposed workers (not significant; column (3)). Import competition reduces employment opportunities first and foremost for manufacturing workers, not generally mid-wage workers. Next, the increase in high-wage employment through import competition is distributed more broadly across sectors (Panel B), with point estimates for import competition of about 1.8 and 1.3 for manufacturing and services, respectively.[37]

Rising import competition from China also reduces low-wage manufacturing employment (Panel C, column (2)). That is, there is no trade-induced job polarization for manufacturing on its own. Polarization only emerges when worker movements through the entire economy are incorporated into the analysis. The overall increase in low-wage employment is mostly due to low-wage employment increases in the service sector (column (3), Panel C.). Our finding of import competition-

[35] One difference is that the impact of import competition on high- and low-wage employment in the economy as a whole is comparable in size, whereas for 1999 textile workers the shift towards low-wage employment is stronger than that towards high-wage employment.

[36] All specifications include the full set of variables of Table 7. Furthermore, there is evidence that the excluded instruments have power, with the p-value of the robust first-stage F-statistic always being less than 0.0001.

[37] This is in line with recent findings that import competition forces firms to downsize at the same time when they shift their demand towards workers with relatively high skills (Utar 2014).

induced increases in low-wage service employment confirms the transitions from machine operator to personal and protective service occupations shown in Figure 3 above.[38]

Table 8: Import Competition, Job Polarization, and Sectoral Change

	(1)	(2)	(3)
Panel A.	Mid-Wage Employment 2000-2009		
	All	Manufacturing	Services
Δ ImpPent	-5.441**	-7.074*	1.100
	(2.287)	(3.613)	(1.497)
Panel B.	High-Wage Employment 2000-2009		
	All	Manufacturing	Services
Δ ImpPent	2.436**	1.777	1.326
	(1.087)	(1.983)	(1.761)
Panel C.	Low-Wage Employment 2000-2009		
	All	Manufacturing	Services
Δ ImpPent	2.413**	-2.017*	4.366***
	(1.181)	(1.077)	(1.343)

Notes: Dependent variable at top of each column in every panel. Shown are second-stage results from separate instrumental-variables estimations, with N = 900,329. Manufacturing is years of employment 2000-2009 in the manufacturing industry, Services is years of employment in the service sector. Specifications include all variables described in Notes to Table 7. Robust standard errors clustered at the 3-digit industry level in parentheses. *, ** and *** indicate significance at 10%, 5%, and 1% level respectively.

Furthermore, by stripping out part-time employment and examining hours worked instead of years of employment, we confirm that the polarizing effect of rising import competition is mostly due to changes in full-time employment, while changes in hours and part-time work play only minor roles (see Table G-3 in the Appendix). We also find that the impact of imports is more strongly due to employment polarization rather than wage polarization, although wage changes do not offset the polarizing effect of import competition.

[38] Autor and Dorn (2013) argue that routine-biased technical change is the main source of low-wage service employment growth in the US.

5.3 Technical Change and Offshoring as Alternative Explanations

We now employ measures of technical change and offshoring to examine the impact of import competition along with these important alternative forces. First, an influential measure in the literature is the routine task intensity index (RTI), capturing an occupation's susceptibility to routine-biased technical change (see Autor and Dorn, 2013, Goos, Manning, and Salomons, 2014).[39] The RTI index captures the impact of computers at the work place because they substitute for workers performing easily programmable and routine-intensive tasks. Second, to examine the influence of offshoring on employment changes, we employ an index of the offshorability of a task due to Goos, Manning, and Salomons (2014).[40]

As the measures of technical change and offshoring vary at the two-digit occupation level, we drop our two-digit occupation fixed effects for more aggregate occupation variables.[41] Furthermore, the sample now is somewhat smaller than before because RTI and offshoring measures are not available for our entire sample. Even with these changes the impact of rising import competition on middle-class employment is similarly estimated, with a coefficient of -5.47 versus -5.44 before (Table 9, column (1), and Table 7, column (1), respectively).

We begin by adding the offshoring variable to our specification. It enters with a negative sign, indicating that workers in occupations that are more easily offshorable experience mid-wage employment reductions compared to other workers during the sample period (column (2)). This provides evidence that offshoring contributes to the hollowing out of middle-class jobs. At the same time, the impact of rising import competition is largely unchanged as the offshoring variable is added.

Next, we add RTI, the measure of routine-biased technical change, to our specification. We estimate a negative coefficient, indicating that, consistent with earlier evidence, workers completing tasks that are routine-intensive have less mid-wage employment than other workers (column (3)). Note that the introduction of RTI reduces the size of the offshoring coefficient (and it ceases to be significantly different from zero) while the import competition coefficient is largely unchanged.

To quantify the effects we employ standardized coefficients, shown in square brackets.[42] We find that the impacts of technical change and import competition on middle-class jobs are similar (co-

[39] One might prefer a direct measure of technology adoption, see, e.g., Graetz and Michaels (2015) and Bessen, Goos, Salomons, and van der Berge (2019). The RTI measure is based on Autor, Levy, and Murnane (2003) and Autor, Katz, and Kearney (2006, 2008). It is derived from Dictionary of Occupational Titles data of the US Bureau of Labor Statistics. See Autor (2013) for an overview.

[40] We have also employed the offshorability index of Blinder and Krueger, which yields similar results. Results are available upon request.

[41] We employ indicator variables for working in a high-, mid-, and low-wage occupation in the year 1999, as well as a measure of each four-digit's occupation's propensity to interact with computers (O*NET activity question 4.A.3.b.1).

[42] The variables are normalized to have mean 0 and a standard deviation of 1.

efficients of -0.046 and -0.045, respectively). This provides evidence that the impacts of import competition and technical change on the hollowing out of middle class jobs are comparable in magnitude.

Turning to employment changes in the high-wage tail, we ask whether workers exposed to rising import competition have more employment in high-wage occupations once we account for the influence of technical change and offshoring. The point estimate of the import competition variable is 3.5, which is somewhat larger than without RTI and offshoring variables (column (4)). The coefficient for offshoring is negative in our high-wage employment equation: workers who in 1999 have a relatively offshorable job do not on average experience gains in high-wage employment (conditional on import competition and technical change). The RTI coefficient is positive, indicating that workers completing routine-intensive tasks disproportionately contribute to more employment in high-wage occupations.

Results for low-wage employment are shown in column (5). The coefficient on import competition is positive and quantitatively similar to before. We also find that offshoring contributes to the increase in low-wage employment, however, technical change does not: the RTI coefficient is not significantly different from zero (column (5)).

Thus, offshoring accounts for neither mid-wage employment reductions nor high-wage employment increases (columns (3) and (4)) in Table 9), while technical change does not induce worker adjustments that lead to growth in low-wage employment (column (5)). Consequently, only import competition explains the gains in the both end of the wage distribution. This differs from evidence on the role of trade for job polarization in the existing, more aggregate analyses.[43]

So far our approach in this section was to add well-known measures to the regression that capture aspects of technical change and offshoring at the two-digit occupational level. It may however be that the susceptibility of occupations to generate employment changes in line with job polarization, whether due to technical change or other factors, depends on more finely defined task characteristics. To address this possibility, in the final three columns of Table 9 we present two-stage least squares results for the impact of import competition on mid-, high-, and low-wage employment that control for four-digit occupational fixed effects. These 400+ fixed effects capture arbitrary forces

[43] See Michaels, Natraj, and van Reenen (2014). Much of the existing work on job polarization examines changes in employment shares by wage group, not years of employment of workers, and in principle it is possible that our RTI coefficients translate into increases in employment shares for both high- and low-wage occupation groups. At the same time, this is unlikely because in absolute value the coefficient in the mid-wage regression is considerably smaller than the coefficient in the high-wage regression.

Table 9: Alternative Explanations for Job Polarization

	Mid-wage Emp.	Mid-wage Emp.	Mid-wage Emp.	High-wage Emp.	Low-wage Emp.	Mid-wage Emp.	High-wage Emp.	Low-wage Emp.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
						w/ Occupational Fixed Effects		
Δ ImpPent	-5.469**	-5.742**	-5.520**	3.542***	2.104*	-5.089**	2.767**	2.045**
	(2.303)	(2.345)	(2.359)	(1.355)	(1.123)	(2.149)	(1.062)	(0.966)
	[-0.044]	[-0.046]	[-0.045]	[0.029]	[0.026]	[-0.041]	[0.023]	[0.026]
Offshoring		-0.088**	-0.043	-0.205***	0.140***			
		(0.037)	(0.028)	(0.020)	(0.017)			
		[-0.027]	[-0.013]	[-0.065]	[0.068]			
Routine Task Intensity			-0.180***	0.425***	-0.026			
			(0.054)	(0.035)	(0.036)			
			[-0.046]	[0.111]	[-0.010]			
Four-Digit Occupation FEs						✓	✓	✓
N	786,090	786,090	786,090	786,090	786,090	786,090	786,090	786,090
First-stage F-test [p-value]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Notes: Estimation by two stage least squares. Robust standard errors that are clustered at the 3-digit industry level are reported in parentheses. Beta coefficients are reported in square brackets. All specifications include demographic (gender, age, immigration status), education, wage, labor market history (unemployment history, linear and square terms of experience), union and unemployment insurance memberships, firm variables (size, wage, separation rate), as well as product-level control variables as described under Table 7. All specifications also include two-digit industry fixed effects. In all regressions, initial occupations are controlled for by occupation indicators as high-, mid-, and low-wage occupations and the occupations' likelihood of interacting with computers. Offshoring is the offshorability of worker *i*'s two digit occupation class, due to Goos, Manning and Salomons (2014). "Routine Task Intensity" follows Autor, Levy and Murnane (2003) and Autor and Dorn (2013) and captures the routine task intensity of worker *i*'s two digit occupation code. The sources of the offshoring and routine task intensity variables is Goos, Manning and Salomons (2014). The number of observations drops because there are no routine task intensity or offshoring measures for some of the Danish occupation codes. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

in the susceptibility of workers' occupations to contribute to the pattern of job polarization.[44] As columns (6), (7), and (8) show, the results with four-digit occupational fixed effects are broadly similar to those without (compare with Table 7). Thus, we have ruled out the possibility that our results are driven by omitted variables operating at the detailed occupational level.

Overall, we have seen that individual-level worker responses to rising import competition are consistent with the pattern of job polarization in the early 2000s, while responses to technical change and offshoring are less so.[45] This may help to explain why international economic factors in particular are a source of discontent in a substantial part of the labor force.

6 Trade vs Technology: Tasks and Worker Adjustment

We return to our quasi-natural experiment to study which occupations are particularly vulnerable to the impact of rising import competition, and the extent to which this contrasts with the effects of technical change. Complementing our analysis with aggregate task measures such as the Routine Task Index (RTI) in the previous section, we now employ information on individual tasks from the O*NET data base. While an advantage of the RTI is that by combining several task dimensions in a certain way the measure provides a quite robust metric, a disadvantage is that RTI's aggregate nature poses a challenge for understanding the role of sub-components of the index.[46]

Ideally, work employing individual O*NET variables is based on a broad agreement on which O*NET variables are indicative of which types of tasks. In this respect we broadly follow earlier work, see Autor, Levy, Murnane (2003), Blinder (2009), Blinder and Krueger (2013), Crino (2010), Hummels, Jørgensen, Munch, and Xiang (2014), and Firpo, Fortin, and Lemieux (2011).[47] In the following we estimate triple difference-in-difference regressions (equation 2) where the characteristic C_i is the importance of a particular task in the worker's occupation based on specific O*NET variables. Moreover, to ensure that our findings are robust we employ multiple O*NET question for each type of task. Table 10 reports the results for tasks that heavily involve manual activities.[48]

We see that trade exposed workers who perform tasks in which *Repetitive Motions* are important

[44] With four-digit occupation fixed effects, our measures of offshoring and technical change are not identified anymore, and we have dropped these variables.

[45] A concern with this conclusion might be that it our results are due to the fact that our trade variable is defined as the *change* in import penetration (and instrumented), while the technical change and offshoring variables are not. At the same time, we do not think that this is the case because when employing a simple treatment indicator (and OLS) in our quasi-natural experiment, results are similar (available upon request).

[46] From the definition of the RTI, a higher routine-ness of a task is equivalent to a lower manual-ness in exactly the same way; as will become clear, we believe that separating these two dimensions is important.

[47] An alternative approach to using O*NET variables is to employ firm-level data on computer adoption or automation expenses, e.g., Doms and Lewis (2006) and Bessen, Goos, Salomons, and van der Berge (2019). It is worth

Table 10: The Impact of Import Competition on Workers Performing Manual Tasks

	Routine Manual				Non-routine Manual		
Task	Repetitive Motions	Manual Dexterity	Finger Dexterity	PDSE	Grossbody Coordination	Multi-limb Coordination	Response Orientation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Imp Comp	-0.558*	-0.989***	-0.871**	-0.503	-1.251***	-1.050***	-1.044***
	(0.304)	(0.331)	(0.346)	(0.309)	(0.375)	(0.346)	(0.353)
ImpComp x Task	-0.967***	-1.286***	-1.340***	-1.129***	-1.279***	-1.374***	-1.242***
	(0.347)	(0.319)	(0.368)	(0.291)	(0.298)	(0.295)	(0.297)
Worker Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Time Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Time x Task Fixed Effects	✓	✓	✓	✓	✓	✓	✓
N	18,462	19,980	18,700	19,870	19,900	20,106	18,428

Notes: The dependent variable in all columns is the period average of worker *i*'s mid-wage employment. In each regression a specific task variable is indicated in the column heading. Sample is all 1999 textile and clothing workers. Estimation of equation 2 by OLS. PDSE stands for Pace of work is Determined by the Speed of the Equipment. *, **, and *** indicate significance at the 10 %, 5% and 1% levels respectively.

suffer significantly higher mid-wage employment losses.[49] Quantitatively, the impact of import competition on losing middle-class employment is almost three times as large compared to other workers. Another manual task is *Manual Dexterity*. We see that workers performing tasks where manual dexterity is important have significantly lower mid-wage employment due to rising import competition than the average exposed worker. Similar results are found for *Finger Dexterity* and for tasks where the pace of work is determined by the speed of the equipment (*PDSE*), see columns (3) and (4), respectively.

We conclude that workers performing manual tasks have disproportionately less mid-wage employment compared to other trade exposed workers. Notice that when repetitive motions are important, or the pace of work is determined by the speed of machines, typically those tasks have a relatively high degree of routine-ness, making these trade-exposed workers disproportionately affected by routine-biased technical change as well.

In order to disentangle the roles of routine versus manual tasks in the loss of middle-class jobs, on the right side of Table 10 we show results for manual tasks that are less routine. Take *Gross Body Coordination*, for example, which involves the coordination of simultaneous movements of different parts of the body.[50] Because this task is based on movements of individual limbs as well as the body, and helped by physical fitness, it is classified as (broadly) manual. At the same time, because the movements require coordination of different body parts these tasks are unlikely to be very repetitive and programmable, and we classify *Gross Body Coordination* as a non-routine manual task.

The result in column (5) shows that workers employed in occupations for which gross body coordination is important experience about twice the mid-wage employment reductions that other workers exposed to rising import competition do. Results for *Multi-limb Coordination* are similar (column (6)). Another non-routine-manual task is *Response Orientation*, which involves the characteristic behavioural and physiological responses to a novel or potentially threatening stimulus (focusing attention, turning head and body to it, arousal of activating and nervous system). Exposed workers in jobs for which such tasks are important have disproportionately lower mid-wage employment compared to other trade-exposed workers (column (7)).

keeping in mind that import competition and technology adoption also interact, see Utar (2014).

[48] Notice that while occupations requiring Repetitive Motions tend to be the same that require *Manual Dexterity*, the match is not perfect and as a result the interpretation of the omitted category varies somewhat across columns.

[49] *Repetitive Motions*, short for *Spend time making repetitive motions*, is O*NET question 4.C.2.d.1.i; Table E-2 lists all O*NET questions used in the following analysis.

[50] According to www.oxfordreference.com, gross body coordination is defined as coordination of simultaneous movements of different parts of the body which are involved in whole-body actions. It is an important component of physical fitness; Oxford Reference Link

Comparing the left and the right sides of Table 10, the degree to which trade-exposed workers performing non-routine manual tasks experience mid-wage employment reductions is similar to the extent to which routine-manual task content exacerbates mid-wage employment reductions.[51] The key finding is that workers in occupations intensively performing manual tasks are most vulnerable to the hollowing out of middle-class jobs. Furthermore, we see from Table 10 that this holds whether these manual tasks are routine or not routine in nature.

Table 11: Exposure to Import Competition and Cognitive Tasks

	Routine Cognitive		Non-routine Cognitive		
Task	Evaluating Information	Repeating Same Task	Developing Strategies	Inductive Reasoning	Mathematical Reasoning
	(1)	(2)	(3)	(4)	(5)
Imp Comp	-0.884**	-1.147***	-0.753**	-0.737**	-0.953***
	(0.363)	(0.380)	(0.344)	(0.344)	(0.340)
ImpComp x Task	0.779**	1.087***	0.635*	0.706**	1.045***
	(0.328)	(0.168)	(0.357)	(0.350)	(0.289)
N	20,728	19,972	18,516	19,606	20,132

Notes: The dependent variable in all columns is worker *i*'s period-average of mid-wage employment. In each regression a specific task variable is indicated in the column heading. Sample is all 1999 textile and clothing workers. Estimation of equation 2 by OLS. Regressions include worker and time fixed effects as well as the interaction between time fixed effect and Task variable. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

If trade-exposed workers performing manual tasks are prone to mid-wage employment reduction, it should also be the case that workers performing non-manual tasks experience these effects comparatively less. This is examined in Table 11. Non-manual tasks are taken to be cognitive tasks. We expect there to be some correlation between jobs intensively using cognitive tasks and jobs held by workers with relatively high skill levels. At the same time, the overlap is not perfect; moreover, some cognitive tasks are more routine in nature than others. For example, ensuring that an individual tax return complies with the tax codes of a particular country involves a relatively

[51] Similar results are found for 1999 mid-wage workers, see Table F-7. In addition, we have confirmed that manual task intensity influences the extent to which workers move up into high-wage or down into low-wage occupations; results are available upon request.

high level of cognitive skill but it is a rather structured, routine task. The first routine cognitive task in our analysis is *Evaluating Information*.[52]

We find that workers with jobs where *Evaluating Information* is important experience smaller mid-wage employment reductions than the typical exposed worker (column (1)). In fact, there are virtually no mid-wage employment reductions for workers in these routine-cognitive intensive jobs. A similar result is obtained for another routine-cognitive task, workers with occupations who frequently repeat the same task (e.g., checking entries in a ledger), see column (2).

On the right side of Table 11 we report results for several non-routine cognitive tasks. There is, first, *Developing Strategies* (short for Developing Objectives and Strategies). Trade-exposed workers for which this task is important do not experience large if any mid-wage employment losses (column (3)). The same is true for workers intensively using *Inductive Reasoning* or *Mathematical Reasoning*, see columns (4) and (5), respectively.

To summarize, workers completing cognitive tasks do not experience lower mid-wage employment the way other exposed workers do, and moreover, there is little difference in the outcome of workers executing cognitive tasks that are routine, versus workers who perform cognitive tasks that are not routine in nature.[53]

Overall, workers who perform intensively manual tasks are central to the trade-induced hollowing out of middle-class jobs characteristic of job polarization. The finding that manual task intensity matters for job polarization is important. It complements earlier results that task routine-ness contributes to job polarization because it accelerates routine-biased technical change. However, if workers' movements' contributing to job polarization would depend only on the routine-ness of tasks, there would be no disproportionate mid-wage employment reduction for workers completing non-routine manual tasks (but see Table 10, right side). Furthermore, there would be sizable mid-wage employment losses for workers performing routine cognitive tasks (but see Table 11, left side).

Manual task intensity matters for the impact of trade because in terms of task content, rising import competition pits Danish against Chinese workers. Despite recent advances the ability of computerized machines to complete non-routine tasks is still limited compared to that of humans, and thus it is not surprising that competition between workers in different countries has bite.

The previous analysis has shown that although both rising low-wage import competition and tech-

[52] Short for the O*NET question of *Evaluating Information to Determine Compliance with Standards*.

[53] We find broadly similar results for the subset of 1999 textile workers who are employed in mid-wage occupations, see Table F-8. Results tend to be somewhat stronger for all 1999 textile workers, which may be due to the fact that the number of workers completing cognitive tasks in high-wage occupations is substantial.

nical change are key aspects of globalization, a task-level analysis of adjustment at the individual worker-level goes some way to separate their distinct effects on the hollowing-out of middle-class jobs that is an essential part of job polarization.

7 Conclusions

This paper has used administrative matched employer-employee data for Denmark to examine the role of heightened import competition with low-wage countries for generating the U-shaped employment pattern known as job polarization. We first show that rising import competition has led to job polarization by studying the impact of the removal of quantitative trade restrictions on China's textile exports following China's entry into the WTO in 2002. This trade policy change provides a quasi-natural experiment where occupational sorting and industry shocks play a limited role. Treatment is defined by the detailed product portfolio of each worker's firm several years before the trade liberalization.

We then employ an instrumental-variables approach using variation in trade exposure together with information on virtually the entire private-sector labor force of Denmark in 1999 to show that the recent increase in low-wage import competition has led to a significant hollowing-out of mid-wage jobs at the same time that it caused both low- and high-wage employment to grow. With the finding that import competition from China has led to job polarization we add a major labor market outcome as a consequence of globalization to those identified in earlier work.

By comparing the impact of import competition side-by-side with that of other factors we show that, quantitatively, rising import competition has had a similarly large effect on the hollowing-out of middle-class employment as routine-biased technical change. Furthermore, the loss in mid-wage jobs due to import competition is accompanied by both high- and low-wage employment gains, in contrast to technical progress, which does not trigger worker movements to low-wage jobs in our analysis. Import competition can explain the increased likelihood of employment in low-wage jobs, which may be a reason why trade openness is a source of discontent for many workers.

We also examine the task content of different occupations and show that workers performing manual intensive tasks are those who contribute most to trade-induced job polarization, whereas workers completing cognitive intensive tasks are not. Thus, while computer-aided machines affect worker outcomes depending on whether tasks are routine or non-routine, the impact on workers from greater goods market competition turns on the manual versus cognitive task dimension.

By highlighting the continuing importance of humans for manual-intensive tasks, our worker-level analysis of the impact of import competition provides useful information for other research as well. For example, recent work by Acemoglu and Restrepo (2020) on the future of labor shows that the endogenous introduction of new tasks in which humans have a comparative advantage over machines limits the extent to which employment and the share of labor in total compensation will fall. An important extension that may influence these dynamics would seem to be the impact of greater international openness because that will increase the extent to which workers in different countries compete with each other.

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Appendix:

"International Trade and Job Polarization: Evidence at the Worker Level"

Wolfgang Keller and Hale Utar

June 2, 2020

Contents (Appendix)

A Job Polarization in Denmark

Figure A-1 depicts the change between 1999 and 2009 in the share of Danish employment by wage levels, revealing a strong trend towards job polarization.

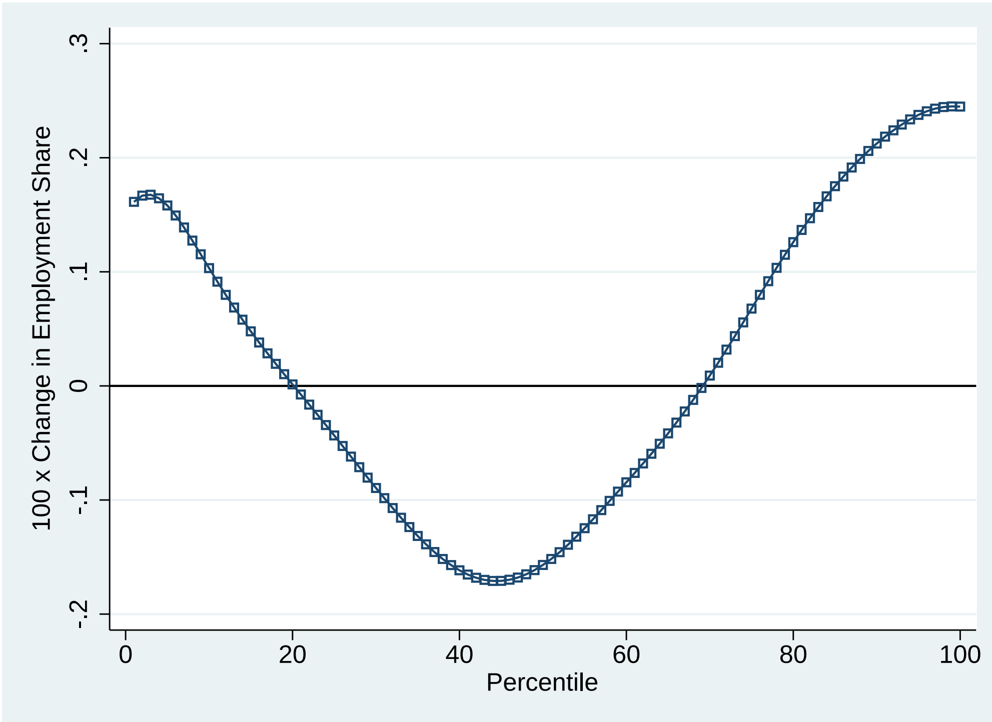

Figure A-1: Job Polarization in Denmark 1999-2009

Notes: Smoothed employment share changes for all non-agricultural occupations at the three-digit level ranked according to their 1999 hourly wage.

B Textile Quota Removal Quasi-Experiment

B.1 Background

The original purpose of the Multi-Fibre Arrangement (MFA) of 1974 was to provide comprehensive protection against competition from low-wage country exports of textiles and clothing through quantitative restrictions. As one of the smaller members of the EU, the coverage of quotas was not strongly influenced by Denmark, and since 1993 the quotas were also managed at the EU level. Negotiations at the WTO to remove these quotas concluded in the year 1995, at a time when China was not part of the WTO yet, and liberalizations for specified products were to take place in four phases (1995, 1998, 2002, and 2005). Once China entered the WTO in the year 2002, it benefited from the first three liberalization phases, and in the year 2005 it participated in the fourth.[54] Since neither Denmark nor China had a major influence on either creation or removal of these quotas this trade liberalization is plausibly exogenous and can be seen as a quasi-natural experiment.

While the textile and clothing quotas covered a wide range of products ranging from bed linens over synthetic filament yarns to shirts, their coverage within each broad product category varied, making it important to utilize MFA quotas at a detailed product-level. For example, "Shawls and scarves of silk or silk waste" were part of a quota restriction for China while "Shawls and scarves of wool and fine animal hair" were not. Coverage of these quotas was determined throughout the 1960s and 1970s.

Most of the quotas for China had more than 90% filling rates. Using transaction-level import data it can be confirmed that that the MFA quotas were binding for China. Both the 2002 and the 2005 quota lifting caused a surge of MFA goods from China into Denmark, accompanied by a decline in unit prices of these goods.[55] By the year 2009 Chinese textile and clothing exports to Denmark, relative to domestic value added had almost tripled (see Figure 2). It has also been shown that the quota removal for China led to an extra efficiency gain in China due to prior mismanagement of quotas by the Chinese government and the decline in prices was a result of entry of more efficient Chinese producers into the export market (Khandelwal, Schott, and Wei, 2013).

As a consequence, virtually all workers employed at firms subject to the quota removals faced increased import competition from China starting in the year 2002.[56] We use the revenue share of firms in quota goods in 1999 as our main measure of exposure to import competition. As an alternative treatment measure we employ an indicator variable which is equal to one if the revenue share is positive, and zero otherwise; results with either treatment variable are similar.

[54] Due to the surge of Chinese imports in the first few months of 2005, the EU renegotiated a few of the quotas with China, with the result that they agreed on an extension on certain products until 2008 (the so-called "Bra War"). Including or excluding those products fully liberalized in 2008 from the treatment definition does not affect the results in this paper.

[55] A number of countries used some discretion in the sequencing of the liberalization by leaving the most important quotas to the last, the 2005 phase of quota removal. We discuss the relationship between the 2005 and earlier quota removal phases below.

[56] As Phase I and II removals did not cover China which had the highest number of binding quotas, the first two removals did not trigger more competition in the industry (Utar 2014).

Summary statistics for the sample of 1999 textile workers depending on whether they were employed in a quota-producing firm or not are shown in Table B-1.

Table B-1: Worker Characteristics in 1999 by Treatment Status

	Exposed (N=5,015)	Control (N=5,472)
Exposure	0.26	0
Age	39.56	39.76
Immigrant	0.05	0.07
College	0.13	0.11
Vocational Ed.	0.35	0.35
Union Membership	0.84	0.80
UI Membership	0.92	0.90
Labor Market Experience	14.91	14.56
Log Annual Salary	12.10	12.09
Machine Operator	0.37	0.38
Mid-wage Occupation	0.63	0.69
High-wage Occupation	0.24	0.18
Low-wage Occupation	0.12	0.11

Notes: Variables Immigrant, Union Membership, UI Membership, High Wage, Mid Wage and Low Wage Occupations, as well as College, Vocational Education are indicator variables. Age, and Experience, and History of Unemployment measured in years. Log Annual Salary in units of 2000 Danish Kroner. Exposure is defined as the revenue share of domestically produced MFA goods for worker *i*'s firm in 1999.

Table B-2 provides descriptive statistics on the outcome variables used in the quasi-experiment.

Table B-2: Key Outcome Variables for the Quasi-Experiment

	Mean	Standard Deviation	N
Panel A. Labor Market Outcomes			
Employment in High Wage Jobs, $HIGH_{is}^{e}$	0.963	1.961	20,974
Employment in Mid Wage Jobs, MID_{is}^{e}	2.150	2.232	20,974
Employment in Low Wage Jobs, LOW_{is}^{e}	0.662	1.546	20,974
Unemployment, UE_{is}^{e}	0.309	0.794	20,974
Outside of the Labor Force, OUT_{is}^{e}	0.585	1.528	20,974
Full-time Employment in High Wage Jobs, $HIGH_{is}^{fte}$	0.930	1.924	20,974
Full-time Employment in Mid Wage Jobs, MID_{is}^{fte}	2.061	2.213	20,974
Full-time Employment in Low Wage Jobs, LOW_{is}^{fte}	0.594	1.468	20,974
Hours in High Wage Jobs, $HIGH_{is}^{hrs}$	1.036	2.788	20,720
Hours in Mid Wage Jobs, MID_{is}^{hrs}	2.371	3.058	20,720
Hours in Low Wage Jobs, LOW_{is}^{hrs}	0.715	2.232	20,720
Wages in High Wage Jobs, $HIGH_{is}^{wage}$	2.729	5.00	20,974
Wages in Mid Wage Jobs, MID_{is}^{wage}	1.480	4.786	20,974
Wages in Low Wage Jobs, LOW_{is}^{wage}	0.857	3.427	20,974

Notes: Employment variables are measured in years. All hours and wage variables are normalized by workers' own 1996-1999 average annual hours worked and wage, respectively.

B.2 The 2002 vs 2005 Sequencing of Quota Liberalizations

A concern with the MFA quota liberalizations might be that the fourth liberalization phase of 2005 might have been more important than the liberalization phases before because the liberalization of key products was intentionally kept to the last possible moment. Furthermore, due to a surge of Chinese imports in the first few months of 2005 at EU ports in response to the fourth phase of the quota removal, the EU retained a few of the quota categories until 2008.

Our approach of employing the entire period 2002 to 2009 as the treatment period is designed to address these issues. First, by extending beyond 2008 it covers the liberalization of products for which the EU went temporarily back on its 2005 commitments. Second, by design our approach of employing all years from 2002 to 2009 as treatment period addresses the fact that the 2002 and the 2005 liberalization effects are hard to disentangle. This is partly due to the overlap of firms exposed to the 2002 and the 2005 quota removals for China, so that the firms that manufacture Phase III quota products are largely the same as those that produce Phase IV quota products. Furthermore, while there was considerable uncertainty about the if, how, and when regarding China's entry into the WTO, and hence the 2002 liberalizations, there was no additional uncertainty regarding the fourth liberalization phase of 2005 because it was part of the negotiations completed in 1995. Forward-looking agents concerned with Chinese import competition would have responded to the fourth liberalization phase of 2005 starting in the year 2002.

To shed some more light on the periods of liberalization, post-2002 and post-2005, the following summarizes the firm-level analysis conducted in Utar (2014). $MFAQ2_j$ is an indicator variable that takes 1 if firm j produces a quota good as of year 1999 which is subject to the 2002 removal for China. Similarly, $MFAQ5_j$ takes 1 if firm j produces a quota good as of year 1999 which is subject to the 2005 removal for China. The following equation is estimated for the period 1999-2007:

$$\ln Y_{jt} = \alpha_0 + \alpha_1 MFAQ2_j x Post2002_t + \alpha_2 MFAQ5_j x Post2005_t + \delta_j + \tau_t + \varepsilon_{jt} \tag{B-1}$$

In equation B-1 Y_{jt} denotes the firm-level outcome variable, indicator variables $Post2002_t$ and $Post2005_t$ take 1 on and after the respective removal years, δ_j denotes firm fixed effects and τ_t denotes year fixed effects. Results are reported in Table B-3. They show that while the reduction in firm-level revenue to the 2005 removal was relatively strong, the employment response was stronger to the 2002 quota removal (columns (3) and (4)). Column (5) shows employment among less educated workers dropped 16% annually in response to the 2002 removal even controlling for the impact of the 2005 removal. The impact of the 2002 removal on workers with vocational education in textile production was even stronger. The annual reduction is estimated to be 20% (column (6)). The finding that the employment reduction is especially strong on production workers is an indication that the employment reaction to the 2002 removal is not due to voluntary separations but firm lay-offs.

Overall, there is little evidence from this analysis that the 2002 liberalization phase is less important than the 2005 liberalization for employment outcomes, and the preferred approach is to define the entire period 2002-2009 as the treatment period.

Table B-3: The 2002 versus 2005 Quota Removals: Firm-level Evidence

	(1) Log Sales	(2) Log Value Added	(3) Log Employment	(4) Log Full-time Equivalent Number of Employees	(5) Log Employees w/ High School Education	(6) Log Employees w/ Textile Production Education
MFAQ2xPost2002	-0.075	-0.081	-0.123***	-0.146**	-0.164***	-0.201***
	(0.064)	(0.061)	(0.059)	(0.057)	(0.053)	(0.046)
MFAQ5xPost2005	-0.158***	-0.187***	-0.081	-0.125**	-0.152***	-0.049
	(0.059)	(0.067)	(0.054)	(0.059)	(0.046)	(0.037)
Firm FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
N	4,555	4,536	4,503	4,545	4134	4,134

The estimation sample includes yearly observations of textile and clothing firms over 1999-2007. The definition of dependent variables, given in column headings, follows Utar (2014). Robust standard errors are clustered at the firm level. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

B.3 Differential Pre-Trends for the 1999 Cohort of Textile Workers?

A key identification condition for our difference-in-differences approach is that there are no differential pre-trends for the set of treated versus not treated workers. First, in order to limit anticipation effects of the upcoming trade liberalization, especially the dropping of quota products, treatment is determined by the product mix of firms in the year 1999, three years before China's WTO entry. Second, we perform a placebo analysis by examining any difference between treatment and control group of workers during the years 1990-1999, a time during which no surge in Chinese import competition was present, and reassuringly, the placebo analysis yields no significant effects. See Table B-4 for the placebo analysis with an annual sample, and Table B-5 for the placebo analysis based on data aggregated into two-periods (pre- and post-1995).

Table B-4: Potential Pre-Trends: A Placebo Analysis for 1990-99

	(1) Earnings	(2) Income	(3) Hours	(4) HourlyWage	(5) Unemployment
Exposure x Y90	-0.166	-0.061	-0.053	-0.012	-0.159
	(0.136)	(0.134)	(0.067)	(0.059)	(0.389)
Exposure x Y91	-0.14	-0.046	-0.049	0.021	-0.193
	(0.121)	(0.134)	(0.068)	(0.054)	(0.401)
Exposure x Y92	-0.053	0.016	-0.01	0.025	-0.353
	(0.116)	(0.123)	(0.06)	(0.052)	(0.383)
Exposure x Y93	-0.043	0.069	0.031	-0.007	-0.018
	(0.106)	(0.103)	(0.067)	(0.046)	(0.416)
Exposure x Y94	-0.039	0.078	0.039	-0.04	-0.341
	(0.086)	(0.089)	(0.063)	(0.044)	(0.361)
Exposure x Y95	-0.055	0.058	0.036	-0.039	-0.398
	(0.083)	(0.077)	(0.063)	(0.036)	(0.374)
Exposure x Y96	-0.057	0.058	0.009	-0.026	-0.387
	(0.076)	(0.061)	(0.06)	(0.034)	(0.400)
Exposure x Y97	-0.06	-0.027	0.034	-0.038	-0.292
	(0.068)	(0.051)	(0.056)	(0.033)	(0.326)
Exposure x Y98	-0.082	-0.042	-0.001	-0.036	-0.400
	(0.062)	(0.036)	(0.058)	(0.038)	(0.353)
N	87,976	100,455	85,509	83,509	101,246

Notes: The dependent variable in all regressions is expressed in logarithm. Results shown for interaction variables of Exposure with annual year indicators, 1990 to 1999 (omitted category: 1999). Unemployment is an index variable showing the percentage of time spent as unemployed, 1 is added to this variable before taking logarithm. All regressions include worker and year fixed effects. Exposure is degree to which a worker is exposed to rising import competition due to quota removal, measured as the revenue share of products of a worker's firm for which quotas will be removed with China's WTO entry.

Table B-5: Potential Pre-Trends: A Placebo Analysis for 1990-99–Two Period Analysis

	(1) Earnings	(2) Income	(3) Hours	(4) HourlyWage	(5) Unemployment
Exposure x Post 1995	0.050	-0.046	0.039	-0.013	-0.0173
	(0.079)	(0.084)	(0.039)	(0.037)	(0.319)
N	19,454	20,254	18,556	18,556	20,402

Notes: Analysis conducted with data aggregated into two periods, pre-1995 and post-1995. The dependent variable in all regressions is expressed in logarithm. Unemployment is an index variable showing the percentage of time spent as unemployed, 1 is added to this variable before taking logarithm. All regressions include worker and year fixed effects. Exposure is the degree to which a worker is exposed to rising import competition due to the removal of quotas, measured as the revenue share of products of a worker's firm for which quotas are removed with China's WTO entry.

B.4 Randomization Test–Placebo Assignment of Exposure

For this exercise we randomly assign quota goods producing status for the textile firms. Using this (random) exposure status we run equation (1) with our sample, repeating this exercise 100 times. The averages of the results from this exercise are presented in Table B-6.

Table B-6: The Impact of Import Competition with Random Exposure

	(1) Mid-Wage Emp.	(2) High-Wage Emp.	(3) Low-Wage Emp.	(4) Unemploy-ment	(5) Labor Market Exit
ImpComp (Random Exposure)	0.001	-0.021	0.001	0.004	0.003
	(0.202)	(0.077)	(0.066)	(0.017)	(0.052)
N	20,974	20,974	20,974	20,974	20,974
Worker FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓

Notes: Textile firms are randomly assigned as quota-goods producing firms, or not, in 100 bootstrap samples. Using the random exposure assignment, table shows averages from estimating equation (1) for five outcome variables, given at top of column. Standard errors calculated from the 100 bootstrap samples.

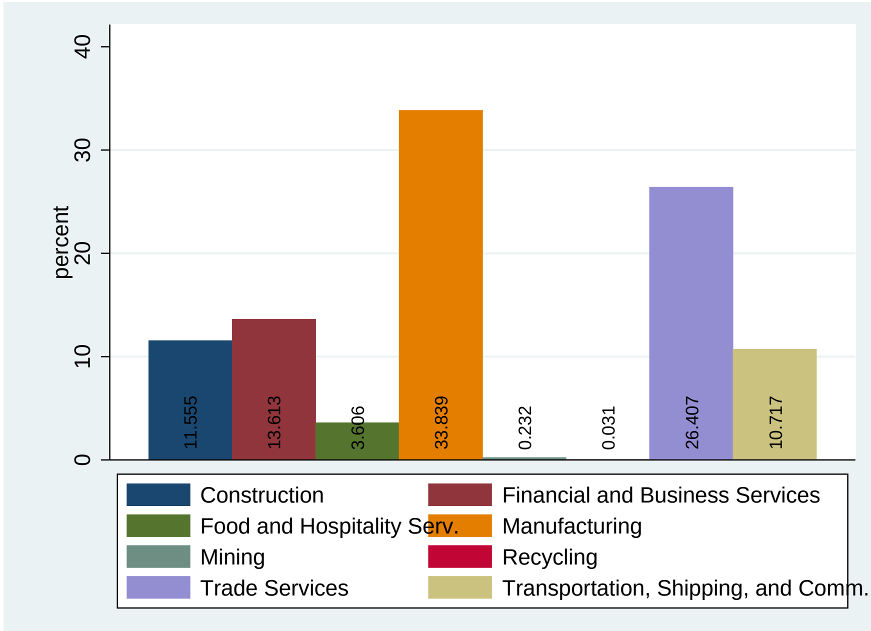

Figure C-1: Industry Affiliation of Workers in 1999

C Economy-wide Changes in Import Penetration

C.1 Characteristics of the Economy-wide Sample

There are N = 900,329 workers in our economy-wide sample. Figure C-1 provides information on the sectoral distribution of these workers in the year 1999. Manufacturing accounts for a relatively large fraction of our labor force because the sample excludes much of Denmark's publicly-owned sector given that there, information to compute key control variables is not fully available. We have ascertained that adding public-sector workers does not lead to major additional insights.

Table C-1 provides summary statistics on the outcome variables used in the private sector analysis. See Table B-2 for the descriptive statistics on the outcome variables for the textile sample.

Table C-1: Key Outcome Variables

	Mean	Standard Deviation	N
Panel A. Cumulative Labor Market Outcome, Years 2000 - 2009			
Employment in High Wage Jobs, $HIGH^e$	2.638	3.689	900,329
Employment in Mid Wage Jobs, MID^e	3.581	3.755	900,329
Employment in Low Wage Jobs, LOW^e	1.281	2.457	900,329
Unemployment, UE	0.393	0.985	900,329
Outside of the Labor Force, OUT	0.542	1.410	900,329
Full-time Employment in High Wage Jobs, $HIGH^{fte}$	2.532	3.617	900,329
Full-time Employment in Mid Wage Jobs, MID^{fte}	3.403	3.701	900,329
Full-time Employment in Low Wage Jobs, LOW^{fte}	1.100	2.295	900,329
Hours in High Wage Jobs, $HIGH^{hrs}$	3.124	5.410	879,614
Hours in Mid Wage Jobs, MID^{hrs}	4.039	4.968	879,614
Hours in Low Wage Jobs, LOW^{hrs}	1.445	3.587	879,614
Wages in High Wage Jobs, $HIGH^{wage}$	5.281	24.260	900,329
Wages in Mid Wage Jobs, MID^{wage}	5.339	11.141	900,329
Wages in Low Wage Jobs, LOW^{wage}	2.087	16.000	900,329

Notes: Employment variables are measured in years. All hours and wage variables are normalized by workers' own 1996-1999 average annual hours worked and wage, respectively.

C.2 Cross-Industry Variation in Import Penetration: Empirical Specification

Recall that in the case of mid-wage employment as the dependent variable, the estimation equation in our economy-wide analysis is as follows:

$$Mid_i^e = \alpha_0 + \alpha_1 \Delta ImpPent_i^J + Z_i^W + Z_i^F + Z_i^J + \varepsilon_i, \tag{C-1}$$

where Mid_i^e is the sum of years that worker i is employed in mid-wage occupations in the years 2000 to 2009, and Z_i^W, Z_i^F , and Z_i^J are worker-, firm, and six-digit industry-level variables.

Figure C-2 shows the change in Chinese import penetration between 1999 and 2009 across manufacturing industries versus the share of workers in mid-wage jobs in 1999. Products belonging to the same two-digit industry are given labels with the same color and shape. We see that the relationship between import penetration and the share of mid-level workers varies widely, even within a two-digit industry.

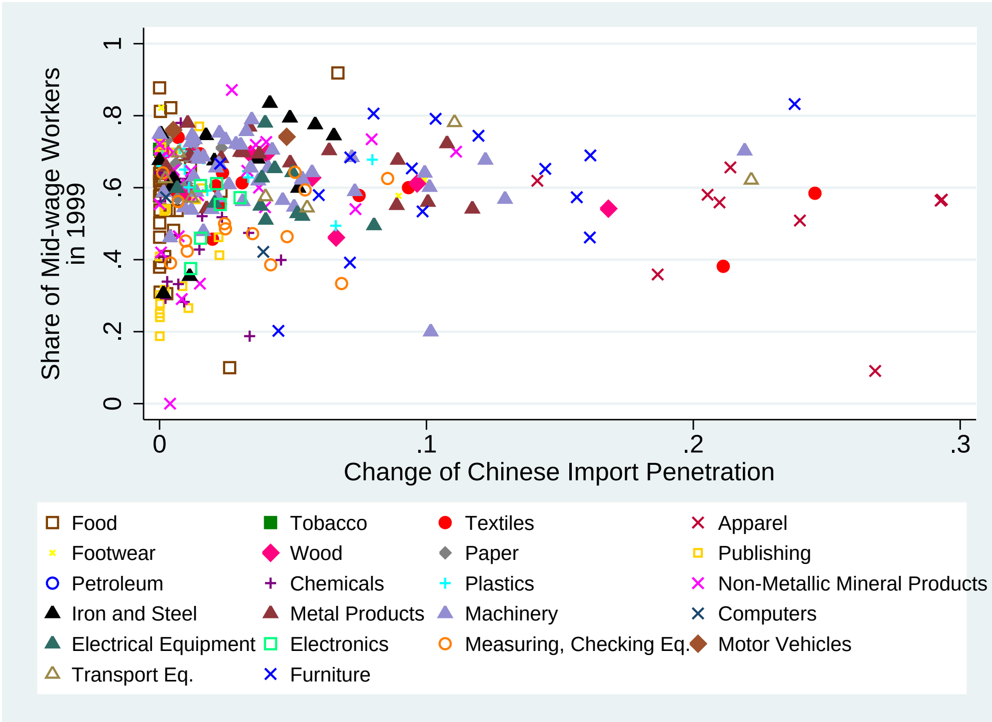

Figure C-2: Mid-wage Workers and Import Competition from China

The relatively disaggregated six-digit industry approach is important because, for example, even though metal forming and steam generator products are both part of the fabricated metal products industry, they both have about 50% mid-wage worker, and yet the change in import penetration over the sample period for steam generator products was much lower than for metal forming products.

The differences in import exposure is because despite some similarities, the tasks performed by mid-level workers in the occupations belonging to the same two-digit industry can in fact be quite different, and so can be worker exposure to import competition. Take "Fibre-preparing-, spinning-, and winding-machine operators" (textile machine operators for short) and "Industrial robot operators", for example, both four-digit occupations of the International Standard Classification of Occupations (ISCO).[57]

Workers in both occupations make typically mid-level wages, and yet textile machine operators are more negatively affected by rising import competition compared to industrial robot operators; the latter might actually experience improved employment prospects due to skill upgrading, be-

[57]These are ISCO classes 8261 and 8170, respectively. Other examples of four-digit occupations include silk-screen textile printers, textile pattern makers, tailors, bleaching machine operators, stock clerks, data entry operators, bookkeepers, accountants, secretaries, and sewing machine operators.

cause Denmark is among the countries with the highest recent increase in robotization (Graetz and Michaels (2018). Our analysis addresses these important differences in within-industry exposure by including more than four hundred occupational fixed effects.

Furthermore, we exploit the employer-employee link to capture technology differences in more than six hundred economic activities proxied by the share of information-technology educated workers. In addition, we account for product quality using the wage share of vocationally educated workers in the total wage bill. We also include two-digit industry fixed effects to avoid capturing differences in growth of Chinese imports across industries due to broad technological differences. As a result, we are not capturing Chinese import growth due to the potentially disproportional effect of a decline in the costs of offshoring or automation across industries.

C.3 Instrumental Variables

We address the potential endogeneity of changes in import penetration with an instrumental-variables approach. First, imports from China in eight other high-income countries are employed as an instrumental variable of the following form:

$$\Delta HIP_j^{CH} = \frac{OM_{j,2009}^{CH} - OM_{j,1999}^{CH}}{C_{j,1996}} \, ,$$

where $OM_{j,t}^{CH}$ is the total value of imports in the corresponding industry j in the eight high-income countries at year t. The countries are Australia, Finland, Germany, Japan, the Netherlands, New Zealand, Switzerland, and the United States. Changing the set of these high-income countries does not have a major effect on our results.[58]

We employ two additional instrumental variables that can be viewed as structural measures of market openness in the pre-trade shock period. One is the logarithm of the weighted average distance to the source countries of the goods Denmark imported in worker i's 1999 industry of employment (at the six-digit level). The weights for these distances are the import value shares in the year 1996. All else equal, high distance is indicative of low transport costs.

Our third instrumental variable is the fraction of retail trade firms among all firms that import in worker i's six-digit industry in the year 1996. The presence of retail firms in international trade is an indicator of already established distribution channels for foreign goods to reach the domestic markets and enhance the competition. With a higher share of retail firms in import, it becomes

[58] Here, we employ 1996 instead of 1999 consumption levels in order to reduce possible industry sorting.

comparatively easy for foreign goods to reach consumers in a country, thereby making the industry relatively vulnerable to exogenous supply shocks in China.

C.3.1 Sources and Construction of Instrumental Variables

We construct our measure of Chinese import competition by developing a mapping between the international trade data at the eight-digit product level from Denmark's UHDI database and Denmark's six-digit industry classification, DB93 (DB stands for *Dansk Branchekode*). Our mapping follows the match between Combined Nomenclature (CN) and Classification of Products by Activity (CPA) of Eurostat's RAMON database. We adapt this according to Danish industrial production using the VARES database. The mapping between trade (CN and Harmonized System, HS) and production data (DB93) is created separately for the three CN/HS versions, CN/HS-1996, CN/HS-1999 and CN/HS-2009. To construct Danish consumption figures at the six-digit DB93 level, we employ data on exports and imports from UHDI together with manufacturing revenue obtained from FIRE.

The information on distance to construct the second instrumental variable comes from the CEPII database http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=8, while information on the share of retail firms at the six-digit industry level comes from the FIRE and UHDI databases.

D Characteristics of the Danish Labor Market

Work on Denmark's labor market such as Bagger, Christensen, and Mortensen (2014), Hummels, Jorgenson, Munch, and Xiang (2014), Groes, Kircher, and Manovskii (2015), and Traiberman (2019) indicates that the country is a good candidate for examining job polarization. In contrast to many continental European economies there are few barriers to worker movements between jobs in Denmark. Turnover as well as average worker tenure is comparable to the Anglo-Saxon labor market model (in 1995, average tenure in Denmark was 7.9 years, comparable to 7.8 in the UK). Hiring and firing costs are low in Denmark. This is confirmed by more recent international comparisons: for example, in the 2013 Global Competitiveness report, Denmark and the US are similarly ranked as 6th and 9th respectively in terms of flexibility of hiring and firing regulations.

The flexibility in terms of firing and hiring practices is combined with a high level of publicly provided social protection. Most Danish workers participate in centralized wage bargaining, which tends to reduce the importance of wages in the labor market adjustment process. However, in recent years decentralization in wage determination has increased wage dispersion (Eriksson and

Westergaard-Nielsen 2009). While we find that shifts in employment between different occupations are central to explaining polarization in the Danish labor market, exploring hourly wage and earnings effects we find that our findings are consistent results documented in Hummels, Jorgenson, Munch, and Xiang (2014).

E Data Sources and Definitions

Our main database is the Integrated Database for Labour Market Research (abbreviated IDA), which is compiled from person (IDA-*personer*), establishment (IDA-*arbejdssteder*), and job files (IDA-*ansættelser*) by Statistics Denmark. We supplement this database with the domestic production dataset (abbreviated VARES), a dataset on business statistics (abbreviated FIRE), and the dataset on customs transactions (abbreviation UHDI). These datasets are accessed through the servers sponsored by the Labor Market Development and Growth (LDMG) project and University of Aarhus. Information on import quotas for the European Union textile and clothing sector comes from the *Système Intégré de Gestion de Licenses* (abbreviated SIGL) database, which is available online at http://trade.ec.europa.eu/sigl/index.html. Information on the task content of occupations employed in this paper comes from the U.S. Bureau of Labor Statistics O*NET database, version 14. Below we provide a brief description of this data. More detailed information regarding the Danish data is at http://www.dst.dk/da/Statistik/dokumentation/Times .

E.1 Data Sets

Integrated Database for Labor Market Research (IDA)

The IDA Database is the main source of information on workers. It provides a snapshot of the labor market for each year at the end of November. There is demographic and education information on every resident in Denmark between the age of 15 and 74 with a unique personal identification number. Compiled from separate establishment and job files, it provides the labor market status of each individual, as well as the annual salary and hourly wage, occupational position, and industry code of their primary employment. Employment status is based on the last week in November of each year.[59] We describe the information on industry, education, and occupation in greater detail below.

Production Database (VARES)

[59] Thus our results will not be influenced by short-term unemployment spells or training during a year as long as the worker has a primary employment in the last week of November of each year.

The database is part of the industrial commodity production statistics (abbreviated PRODCOM) collected by Statistics Denmark. Production is reported following the Combined Nomenclature (CN) classification at the eight-digit level for all firms with ten or more employees. We employ the VARES database to identify firms that manufacture domestically in Denmark products subject to rising competition due to the removal of import quotas (the Multi-fiber Arrangement) on Chinese goods after 2001. While some manufacturing firms have less than ten employees, such firms typically outsource their production, and consequently we can identify virtually all firms that domestically produce quota products using VARES. The reporting unit is the "Kind of Activity Unit" (KAU), which is the sum of a company's workplaces in the same main industry. Reporting units provide as well their company identification code, allowing us to match the eight-digit production information with other firm-level information.

Business and accounting statistics (FIRE)

This dataset by Statistics Denmark compiles business and accounting data, as well as tax reports, value-added tax (VAT) reports, and information from incorporated companies. It is employed in this paper to create the pre-trend variable in the firm's product category as well as other measures at the six-digit industry level. The information covers virtually all firms for most sectors, including manufacturing, construction, retail, mining, as well as hospitality, transportation, telecommunication, real estate, rental, information technology, R&D and other business services.[60]

International trade data (UHDI)

The data comes from Denmark's customs records together with monthly reports to Statistics Denmark from about 8,000 firms in Denmark in which their trade with other countries of the European Union (EU) is reported. This is supplemented with information on EU trade from VAT returns, which are mandatory for virtually all firms in Denmark. Thus the data-set covers the entire universe of trading firms. The information of each record gives shipment date, value, and weight, and if applicable the shipment's quantity. It also provides information on the eight-digit product classification according to the Combined Nomenclature system, as well as a unique firm identifier. Statistics Denmark aggregates this data into annual information for each triplet of product-firm-country.

Textile quota data (SIGL)

The *Système Intégré de Gestion de Licenses* (SIGL) database provides categories of textile and clothing products that are subject to trade quotas in the European Union for a particular year.

[60] Firms must satisfy certain minimum sizes: at least 0.5 full-time equivalent employment, as well as certain minimum sales, between 150,000 and 200,000 Danish Kroner in manufacturing and 500,000 Danish Kroner in wholesale trade. 1 Danish Kroner is about 0.15 $ US in 2019.

We employ this data to identify firms in Denmark that will be affected by the quota removals on Chinese exports following that country's entry into the WTO. The quota categories are administrative descriptions of quota products that do not follow standard statistical product classifications. The quotas have a varying degree of coverage; for example, the quota category "Gloves, mittens and mitts, knitted or crocheted" covers nine products at the eight-digit CN level, while the category "Woven fabrics of synthetic filament yarn obtained from strip or the like of polyethylene or polypropylene, less than 3 m wide" corresponds to a single eight-digit CN product. Quota categories include both textile and clothing products. A given category does not necessarily cover a technologically or materially homogeneous group of products, nor does it have to be comprehensive. For example, ramie bedspreads are covered by the quota restriction for China while cotton bedspreads are not, and "Brasseries of all types of textile material" is covered, in contrast to "Corselettes of all types of textile materials". The source of the match between quota categories and eight-digit products is Utar (2014).

E.2 Industry Classifications

The IDA database provides industry codes for each wage earner based on administrative sources rather than surveys. For persons who work at a specific workplace, typically a firm, the personal industry code is equal to the industry code of the workplace following the Danish Industrial Classification (detailed below). If a person does not have a specific workplace, for example the person works from home or performs duties at several different locations, such as day care providers, the personal industry code is assigned according to the person's work performed. Similarly if a person's workplace is not a particular physical location, for example a nurse employed by the municipality to provide care for elderly people in their residences, the person's workplace (employer) is the municipality while the person's personal industry code is defined by the work performed, in this case the "nursing homes" industry.

We employ the Danish Industrial Classification (*Dansk Branchekode*; abbreviated DB) at the six-digit level. Throughout the sample period three different systems apply, DB93, DB03 and DB07. DB93 is a six-digit nomenclature that follows the NACE Rev. 1 classification (NACE stands for Nomenclature Générale des Activités Économiques dans la Communaté Européenne). Denmark's DB03 classification was introduced in the year 2003 and it follows the NACE Rev. 1.1 system. In 2008 DB03 was replaced with DB07, which follows NACE Rev. 2. The first four digits of the Danish Industrial Classifications are identical to the corresponding NACE system. We employ concordances provided by Statistics Denmark to record economic activity consistently.

E.3 Education

The *IDA-personer* files specify for each individual the level of the highest completed education or professional training (*Erhvervskompetancegivende uddannelse*). We generally distinguish three education levels, which are college education, vocational education (or, training) and at most a high school degree.

In general, vocational education in Denmark follows a mandatory duration of nine years of schooling. Vocational education tends to be between 2.5 and 5 years long and contains periods of formal schooling and apprenticeships. Becoming a welder (*Svejser*), for example, requires three years of vocational education, in which three blocks of schooling are distributed over the period that otherwise consists of an apprenticeship. Other examples are a metal worker with a vehicle body focus (*Karrosserismed*), which requires four years of vocational training with six schooling periods throughout the apprenticeship period, or a metal worker specializing in alloy (*Klejnsmed*), which takes a total of 4.5 years including four longer schooling periods.

If a worker decides to complete a vocational education and later on go to university, the university entrance requirements can be earned through a longer version of the vocational education program. This generally takes five years. Otherwise it is necessary to complete a general high school degree before going to university. College education can also be applied in the sense that it is vocation- or profession-oriented (this distinguishes college from university education in Denmark). We have classified any education that includes college education, however applied it may be, as college education. The distinction whether an educational title contains college-level education is made by Statistics Denmark.

To distinguish different forms of vocational training in parts of the analysis we have examined the roughly 3,000 education titles and classified them broadly into service versus manufacturing orientation. Those with a service focus include pharmacy technicians, farming machine mechanics, office workers, orthopedic technicians, and decorators, while vocational training with a manufacturing focus includes welders, toolmakers, and industrial cabinet makers, for example. We leave out education titles specific to transportation, such as truck driver or skipper, as well as certain educations specific to agriculture and fishing (e.g. farmer, fisherman). In our entire private-sector sample there are 235,180, or 26% whose highest education is vocational training with a service focus (training for a service vocation). The number of workers with manufacturing-oriented vocational education is 80,250 (9% of all workers).

E.4 Occupation Classifications

The information on worker occupation in the IDA database is provided in terms of the Danish version of the United Nation's occupational classification system, called DISCO; here, ISCO stands for International Standard Classification of Occupations. The Danish classification follows the four-digit ISCO-88 system between the years 1999 and 2002, and from 2003 on the Danish system employs a six-digit classification, where the first four digits are identical to the international ISCO system.

In Denmark, occupation codes are administratively collected in Denmark, and the extent of misclassification is small. If an individual's occupation cannot be determined or cannot be classified under a certain ISCO category, it is coded as unknown (code 9999). This occurs for 7% of all workers in 1999. We remove these workers from the sample, however, including these workers with a separate occupation category does not change our main results.

Table 1 in the text gives our classification into low-, mid-, and high-wage occupations. A comparison with the following information for European countries from Goos, Manning, and Salomons (2014) indicates that it is similar.

Table E-1: Three Wage Groups across European Countries

	ISCO-88
High-Wage Occupations	
Corporate Managers	12
Physical, mathematical and engineering science professionals	21
Life science and health professional	22
Other professionals	24
Managers of small enterprises	13
Physical, Mathematical and Engineering Associate Professionals	31
Other Associate Professionals	34
Life Science and Health Associate Professionals	32
Mid-Wage Occupations	
Drivers and Mobile Plant Operators	83
Stationary plant and related operators	81
Metal, machinery and related trade work	72
Precision, handcraft, craft printing and related trade workers	73
Office clerks	41
Customer service clerks	42
Extraction and building trade workers	71
Machine operators and assemblers	82
Other craft and related trade workers	74
Low-Wage Occupations	
Personal and protective service workers	51
Laborers in mining, construction, manufacturing and transport	93
Models, salespersons and demonstrators	52
Sales and services elementary occupations	91

Notes: Occupations are ranked according to the 1993 mean European wage. Excluded occupations are: Legislators and senior officials (11), Teaching professionals (23), Teaching associate professionals (33), Market-oriented skilled agricultural and fishery workers (61), Subsistence agricultural and fishery workers (62), Agricultural, fishery and related labourers (92) and Armed forces (01). Source is Goos, Manning, and Salomons (2014).

E.5 Task and Offshoring Data

For the analysis in section 6, we employ occupational characteristics provided in the O*NET database of June 2009. The O*NET database provides information on the importance and/or the level of activity in a particular task. We broadly follow the literature in relating O*NET variables to task groups, in particular Autor, Levy, Murnane (2003), Blinder (2009), Blinder and Krueger

(2013), Crino (2010), and Firpo, Fortin, and Lemieux (2011). Table E-2 lists the O*NET question numbers employed in this paper.

The variables are ordinal, with increasing value indicating the importance of the corresponding activity. Variables are standardized for the regression analysis. We also invert the original variable "Structured versus Unstructured Work" so that its value increases with greater importance of structured work (as opposed to unstructured work). The variable "Importance of Repeating Same Tasks" contains both mental and physical components; the underlying question asks "How important is repeating the same physical activities (e.g., key entry) or mental activities (e.g., checking entries in a ledger) over and over, without stopping, to performing this job?". Although a routine cognitive task may also have a significant physical routine associated with it, we classify this variable as a routine cognitive task.

The O*NET information is reported according to the Standard Occupational Classification (SOC) of the year 2000. We map this to our occupation data following the ISCO-88 system using the crosswalks provided at the National Crosswalk center (SOC 2009, SOC 2006, SOC 2000, ISCO-88): see ftp://ftp//ftp.xwalkcenter.org/DOWNLOAD/xwalks/.

The routine task intensity (RTI) index is due to Autor, Levy, Murnane (2003) and mapped into the two-digit digit ISCO occupational classification by Goos, Manning, and Salomons (2014). The offshoring variables also vary across two-digit ISCO occupations. Both the Blinder and Krueger (2013) as well as the Goos, Manning, and Salomons (2014) indices are meant to capture the offshorability of a worker based on the tasks that he or she performs, with Goos, Manning, and Salomon's (2014) index being based on actual instances of offshoring by European countries. Table 7 in the paper employs the Goos, Manning, and Salomons (2014) variable; employing the Blinder and Krueger (2013) variable yields broadly similar results. The source of both the RTI variable as well as the two offshoring indices is Goos, Manning, and Salomons (2014).[61] The offshoring variables are defined for the particular occupational classification employed by Goos, Manning, and Salomons (2014). Table E-1 provides the list of two-digit occupational classes for which these

[61] We thank Anna Salomons for sending us the data.

authors construct their offshoring and RTI variables.

Table E-2: O*NET Questions Employed in the Paper

Question	Title	Type
Panel A.	ROUTINE MANUAL TASKS	
4.C.2.d.1.i	Spend time making repetitive motions	Context
4.C.3.d.3	Pace Determined by Speed of Equipment	Context
1.A.2.a.2	Manual Dexterity	Abilities
1.A.2.a.3	Finger Dexterity	Abilities
Panel B.	ROUTINE COGNITIVE TASKS	
4.A.2.a.3	Evaluating Information to Determine Compliance with Standards	Activities
4.C.3.b.7	Importance of Repeating Same Tasks	Context
Panel C.	NON-ROUTINE MANUAL TASKS	
1.A.2.b.2	Multilimb Coordination	Abilities
1.A.3.c.3	Gross Body Coordination	Abilities
1.A.2.b.3	Response orientation	Abilities
Panel D.	NON-ROUTINE COGNITIVE TASKS	
1.A.1.c.1	Mathematical Reasoning	Abilities
1.A.1.b.5	Inductive Reasoning	Abilities
4.A.2.b.1	Making Decisions and Solving Problems	Activities
4.A.2.b.4	Developing Objectives and Strategies	Activities
Panel E.	INFORMATION TECHNOLOGY INVOLVED TASKS	
4.A.3.b.1	Interacting with computers	Activities

E.6 Variable Definitions, Sources, and Summary Statistics

Table E-3 gives definitions as well as sources for all our variables, respectively.

Table E-4: Variable Statistics

Variable Name	Mean	Standard Deviation	Source
Female	0.339	0.473	IDA-*personer*
Immigrant	0.045	0.208	IDA-*personer*
Age	34.093	8.852	IDA-*personer*
College	0.176	0.381	IDA
Vocational	0.436	0.496	IDA
High School	0.377	0.485	IDA
Unemployment History	1.025	1.716	IDA-*personer*
Log Hourly Wage	5.032	0.448	IDA-*ansættelser*
Union Membership	0.762	0.426	Income registers
UI Membership	0.807	0.395	Income registers
Experience	12.868	6.205	IDA-*personer*
Experience squared	204.097	148.870	IDA-*personer*
Separation Rate	0.297	0.225	IDA-*arbejdssteder*
Log Firm Wage	5.121	0.247	IDA-*arbejdssteder*
Firm Size	231.863	668.347	IDA-*arbejdssteder*
Industry Vocational Labor Share	0.461	0.144	IDA
Industry IT Investment	0.005	0.014	IDA
Industry Pre-Trend	0.278	0.713	IDA
Industry Size	8.713	1.250	IDA
Retail Demand Change	0.097	0.195	FIRE
Energy Growth	-0.075	0.105	FIRE
Δ ImpPent	0.011	0.030	UHDI, FIRE
ΔHIP^{CH}	1.240	4.196	FIRE, EUROSTAT, COMTRADE
Log distance to import source	2.465	3.456	CEPII, UHDI
Share of retail firms in import	0.020	0.052	UHDI, FIRE

Table E-3: Variable definitions

Variable Name	Variable definition
Female	Equal to 1 if worker is female, 0 otherwise
Immigrant	Equal to 1 if worker is first or second generation immigrant, 0 otherwise
Age	Worker's age in years as of 1999
College	Equal to 1 if worker attended a college as of 1999, 0 otherwise
Vocational	Equal to 1 if highest attained education of worker is vocational school as of 1999, 0 otherwise
High School	Equal to 1 if highest attained education of worker is a general high school as of 1999, 0 otherwise
Unemployment History	Summation of unemployment spells of worker i until 1999 (expressed in years)
Log Hourly Wage	Log of hourly wage of worker in 1999
Union Membership	Equal to 1 if worker is a member of a union in 1999, 0 otherwise
UI Membership	Equal to 1 if worker is a member of Unemployment Insurance (UI) as of 1999, 0 otherwise
Experience	Number of years worker i is in the labor market as of 1999
Experience^2	Square of Experience
Separation Rate	The share of workers who are not employed in the firm (of worker i) from 1998 to 1999
Log Firm Wage	Logarithm of average hourly wage paid in the firm (of worker i) in 1999
Firm Size	The full-time equivalent number of employees in the firm (of worker i) in 1999
Industry Vocational Labor Share	The wage share of workers with vocational school education over the total wage payment in the four-digit industry (of worker i) in 1999
Industry IT Investment	The share of workers with IT education in the 6-digit industry (of worker i) in 1999
Industry Pre-Trend	The percentage change between 1993-1999 in the total number of employees in workers' 6-digit industry in 1999
Industry Size	The logarithm of the number of workers employed in worker i's six digit industry in 1999
Retail Demand Change	The percentage of employment changes over 2000-2008 in the corresponding retail/wholesale sector of the six-digit manufacturing industry of worker
Energy Growth	The average annual growth in energy expenditure in the four-digit industry over 2000-2008
Intermediate Goods Share	The number of products that are classified according to Classification by Broad Economic Categories (BEC) Rev. 4 as 'intermediate goods' over the total number of products in worker i's six digit industry in 1999

F Textile Quota Liberalization: Additional Results

The following table reports results on the trade adjustment of the 1999 textile workers for full-time employment, hours worked, and earnings.

Table F-1: Trade Impact on Full-time Employment, Hours, and Earnings

	(1)	(2)	(3)
Panel A.	**Full-time Employment**		
	MID_{is}^{fte}	$HIGH_{is}^{fte}$	LOW_{is}^{fte}
Import Comp	-1.319***	0.742***	0.629***
	(0.373)	(0.278)	(0.206)
Worker FE	✓	✓	✓
Time FE	✓	✓	✓
Observations	20,974	20,974	20,974
Panel B.	**Hours worked**		
	MID_{is}^{hrs}	$HIGH_{is}^{hrs}$	LOW_{is}^{hrs}
Import Comp	-1.832***	0.829**	0.281
	(0.431)	(0.405)	(0.295)
Worker FE	✓	✓	✓
Time FE	✓	✓	✓
Observations	20,720	20,720	20,720
Panel C.	**Earnings**		
	MID_{is}^{wage}	$HIGH_{is}^{wage}$	LOW_{is}^{wage}
Import Comp	-2.126***	1.578**	0.242
	(0.565)	(0.759)	(0.364)
Worker FE	✓	✓	✓
Time FE	✓	✓	✓
Observations	20,974	20,974	20,974

Notes: Dependent variables given in panel headings. Hours worked and earnings variables are measured in worker *i*'s own initial (1996-1999 average) annual hours worked and annual earnings, respectively. Robust standard errors clustered at the 1999 firm level in parentheses. °, *, and ** indicate significance at the 10 %, 5% and 1% levels respectively.

F.1 The Gradual Impact of Import Competition on Textile Workers

The following results describe the movements of the 1999 mid-wage textile workers. First, Table F-2 provides the coefficients and standard errors behind Figure 4 in the text.

Table F-2: The Dynamic Impact on Mid-wage Textile Workers

	(1) **2002**	(2) **2003**	(3) **2004**	(4) **2005**	(5) **2006**	(6) **2007**	(7) **2008**	(8) **2009**
Panel A.	Years in Mid-wage employment, MID^e_{is}							
Import Comp	0.019	-0.165	-0.372*	-0.714***	-1.047***	-1.404***	-1.739***	-1.999***
	(0.105)	(0.146)	(0.216)	(0.272)	(0.340)	(0.413)	(0.481)	(0.532)
Panel B.	Years in High-wage employment, $HIGH^e_{is}$							
Import Comp	-0.054	0.0055	0.061	0.099	0.137	0.194	0.245	0.270
	(0.054)	(0.058)	(0.063)	(0.087)	(0.117)	(0.149)	(0.180)	(0.214)
Panel C.	Years in Low-wage employment, LOW^e_{is}							
Import Comp	0.034	0.208***	0.441***	0.628***	0.826***	1.001***	1.166***	1.379***
	(0.036)	(0.061)	(0.097)	(0.130)	(0.165)	(0.196)	(0.225)	(0.258)
Panel D.	Years in unemployment, UE^e_{is}							
Import Comp	-0.0714	0.102	0.185**	0.207**	0.225**	0.211*	0.190	0.138
	(0.064)	(0.075)	(0.088)	(0.100)	(0.111)	(0.122)	(0.134)	(0.145)
Panel E.	Years outside the labor market, OUT^e_{is}							
Import Comp	-0.014	0.038	0.121	0.220**	0.293*	0.422**	0.504**	0.612**
	(0.030)	(0.043)	(0.075)	(0.112)	(0.153)	(0.200)	(0.250)	(0.304)
Worker FEs	✓	✓	✓	✓	✓	✓	✓	✓
Period FEs	✓	✓	✓	✓	✓	✓	✓	✓
N	13,934	13,934	13,934	13,934	13,934	13,934	13,934	13,934

Notes: Given at top of column is last year of sample period. Estimation of equation (1) by OLS for each end year starting with 2002. The sample includes all 1999 mid-wage textile workers. Robust standard errors clustered at the 1999 firm level in parentheses. *, ** and *** indicate significance at the 10%, 5%, and 1% levels respectively.

Next, Table F-3 presents the evolution of the impact of rising import competition on textile workers who in 1999 are employed in high-wage occupations. Note that even when we end the analysis in the year 2002–which may be seen as the impact effect of the increase in competition–there is a significantly negative effect on high-wage employment.

Table F-3: The Dynamic Impact on High-wage Textile Workers

	(1) **2002**	(2) **2003**	(3) **2004**	(4) **2005**	(5) **2006**	(6) **2007**	(7) **2008**	(8) **2009**
Panel A.	Years Mid-wage employment, MID^e_{is}							
Import Comp	0.120	0.160*	0.240**	0.353**	0.453**	0.497**	0.523**	0.561*
	(0.0898)	(0.0930)	(0.122)	(0.160)	(0.189)	(0.226)	(0.260)	(0.299)
Panel B.	Years High-wage employment, $HIGH^e_{is}$							
Import Comp	-0.403***	-0.287*	-0.232	-0.258	-0.174	-0.0180	0.235	0.353
	(0.138)	(0.168)	(0.236)	(0.326)	(0.406)	(0.478)	(0.551)	(0.623)
Panel C.	Years Low-wage employment, LOW^e_{is}							
Import Comp	-0.017	-0.036	-0.093*	-0.131*	-0.178**	-0.202*	-0.218	-0.235
	(0.031)	(0.041)	(0.054)	(0.069)	(0.089)	(0.115)	(0.137)	(0.164)
Panel D.	Years in unemployment, UE^e_{is}							
Import Comp	-0.077*	-0.005	0.052	0.114	0.147	0.165	0.165	0.179
	(0.046)	(0.060)	(0.080)	(0.096)	(0.104)	(0.111)	(0.117)	(0.129)
Panel E.	Years outside the labor market, OUT^e_{is}							
Import Comp	0.101***	0.112**	0.167**	0.202**	0.165	0.077	0.015	-0.049
	(0.032)	(0.049)	(0.066)	(0.090)	(0.120)	(0.155)	(0.188)	(0.227)
Worker	✓	✓	✓	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓	✓	✓	✓
N	4,294	4,294	4,294	4,294	4,294	4,294	4,294	4,294

Notes: Given at top of column is last year of sample period. Estimation of equation (1) by OLS for each end year starting with 2002. The sample includes all 1999 high-wage textile workers. Robust standard errors clustered at the 1999 firm level in parentheses. *, ** and *** indicate significance at the 10%, 5%, and 1% levels respectively.

Finally, Table F-4 presents the evolution of the impact of rising import competition on textile workers who in 1999 are employed in low-wage occupations. Note that for these workers, rising import competition has a positive impact on high-wage employment: exposed low-wage workers have significantly higher high-wage employment than virtually identical low-wage textile workers that are not exposed to rising import competition (Panel B). These are workers that succeed in moving up by two broad wage categories. Their number, however, is relatively small.

Table F-4: The Dynamic Impact on Low-wage Textile Workers

	(1) **2002**	(2) **2003**	(3) **2004**	(4) **2005**	(5) **2006**	(6) **2007**	(7) **2008**	(8) **2009**
Panel A.	Years Mid-wage employment							
Import Comp	0.407**	0.268	0.0494	-0.0902	-0.142	-0.174	-0.149	-0.064
	(0.174)	(0.171)	(0.202)	(0.263)	(0.344)	(0.437)	(0.513)	(0.591)
Panel B.	Years High-wage employment							
Import Comp	-0.03	0.184**	0.369***	0.613***	0.876***	1.214***	1.522***	1.828***
	(0.0827)	(0.0713)	(0.111)	(0.175)	(0.239)	(0.317)	(0.413)	(0.502)
Panel C.	Years Low-wage employment							
Import Comp	-0.835***	-0.593**	-0.252	-0.110	-0.221	-0.358	-0.525	-0.587
	(0.254)	(0.254)	(0.318)	(0.390)	(0.421)	(0.480)	(0.542)	(0.603)
Panel D.	Years in unemployment							
Import Comp	0.008	0.029	0.096	0.081	0.081	0.045	0.027	-0.009
	(0.0973)	(0.128)	(0.158)	(0.174)	(0.198)	(0.226)	(0.246)	(0.267)
Panel E.	Years outside the labor market							
Import Comp	-0.006	-0.007	-0.037	-0.155	-0.205	-0.352	-0.443	-0.611
	(0.078)	(0.097)	(0.133)	(0.179)	(0.232)	(0.292)	(0.361)	(0.419)
Worker FEs	✓	✓	✓	✓	✓	✓	✓	✓
Period FEs	✓	✓	✓	✓	✓	✓	✓	✓
N	2,496	2,496	2,496	2,496	2,496	2,497	2,498	2,499

Notes: Given at top of column is last year of sample period. Estimation of equation (1) by OLS for each end year starting with 2002. The sample includes all 1999 low-wage textile workers. Robust standard errors clustered at the 1999 firm level in parentheses. *, ** and *** indicate significance at the 10%, 5%, and 1% levels respectively.

F.2 Trade-induced Between-Sector Movements of Textile Workers

The following set of results complements our discussion of the trade-induced sectoral switching of mid-wage textile workers in the paper. Results on the sectoral switching of high-wage and low-wage textile workers due to rising import competition are presented in Table F-5 and Table F-6. In addition to analyzing trade induced employment in the service sector as a whole, we also study the employment effect in service industries that are considered relatively high-wage industries. The dependent variables in Panel C.1 in Tables 6, F-5 and F-6 are occupations in finance (banks, insurance, mortgage), leasing, renting, various other business services and wholesale industries. The dependent variables in Panel C.2 in Tables 6, F-5, and F-6 include occupations in retail (supermarkets, grocery stores, other retail shops), hotels, restaurants, industrial or coin laundries, dry cleaners, hairdressing salons and other personal services. Notice that these high-wage (finance, business, wholesale) and low-wage (Retail, Personal) service industries are mutually exclusive but not exhaustive categories within the service sector. That is, they are not covering the entire service sector.

Table F-5: Occupational Movement of **High-Wage Workers** due to Trade–Sectoral Analysis

	(1) Mid-Wage Emp	(2) High-Wage Emp	(3) Low-Wage Emp
Panel A.	All Industries		
	0.561*	0.353	-0.235
	(0.299)	(0.623)	(0.164)
Panel B.	Manufacturing		
	-0.177	-2.407***	-0.0738
	(0.194)	(0.772)	(0.0574)
Panel C.	Services		
	0.727***	2.650***	-0.155
	(0.231)	(0.463)	(0.143)
Panel C.1.	Finance, Business, Wholesale		
	0.516***	1.538***	0.028
	(0.151)	(0.367)	(0.046)
Panel C.2.	Retail, Personal		
	0.040	-0.027	-0.036
	(0.059)	(0.090)	(0.057)

Notes: Dependent variable at top of column. Sample is all 1999 high-wage textile workers (N = 4,294). Shown is coefficient on ImpComp, defined as $Exposure_i xPostShock_s$, see equation (1). *, ** and *** indicate significance at the 10%, 5%, and 1% levels respectively.

Table F-6: Occupational Movement of **Low-Wage Workers** due to Trade–Sectoral Analysis

	(1) Mid-Wage Emp	(2) High-Wage Emp	(3) Low-Wage Emp
Panel A.	All Industries		
	-0.0642	1.828***	-0.587
	(0.591)	(0.502)	(0.603)
Panel B.	Manufacturing		
	-0.381	0.216	-1.150**
	(0.477)	(0.225)	(0.544)
Panel C.	Services		
	0.246	1.632***	0.501
	(0.298)	(0.467)	(0.447)
Panel C.1.	Finance, Business, Wholesale		
	0.160	0.851***	0.341
	(0.170)	(0.288)	(0.226)
Panel C.2.	Retail, Personal		
	-0.0022	0.116	-0.065
	(0.125)	(0.108)	(0.158)

Notes: Dependent variable at top of column. Sample is all 1999 low-wage textile workers (N = 2,496). Shown is coefficient on ImpComp, defined as $Exposure_i xPostShock_s$, see equation (1). *, ** and *** indicate significance at the 10%, 5%, and 1% levels respectively.

F.3 The Relationship between Trade Exposure and Tasks for Mid-Wage Textile Workers

This section provides complementary analysis to section 6 of the paper. The only difference is that the sample below excludes workers who in 1999 were employed in high- or low-wage occupations. The analysis for manual tasks is given in Table F-7, while results for cognitive tasks are shown in Table F-8.[62] Notice that workers completing manual tasks are more strongly affected by rising import competition, and this is the case whether the task is routine or not routine.

Table F-7: Import Competition and Manual Tasks: Mid-wage Workers

	Routine Manual				Non-routine Manual		
	Repetitive Motions	Manual Dexterity	Finger Dexterity	PDSE	Grossbody Coordination	Multilimb Coordination	Response Orientation
Imp Comp	-0.621	-1.243***	-1.156**	-0.599	-1.818***	-1.489***	-1.430***
	(0.605)	(0.472)	(0.494)	(0.535)	(0.509)	(0.486)	(0.487)
ImpComp x Task	-1.021*	-1.428***	-1.439***	-1.181***	-1.604***	-1.388***	-1.327***
	(0.550)	(0.392)	(0.545)	(0.352)	(0.409)	(0.337)	(0.370)
Observations	12,446	13,452	12,414	13,546	13,614	13,566	12,446
R-squared	0.627	0.626	0.626	0.627	0.625	0.626	0.628

Notes: The dependent variable in all regressions is the period average mid-wage employment. PDSE stands for pace determined by speed of equipment. All regressions include worker and period fixed effects as well as the interaction between the period fixed effect and Task variable. In each regression a specific task variable is indicated in the column heading. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

[62] Notice that in each column the interpretation of the omitted category is somewhat different. This is because while occupations requiring, e.g., *Repetitive Motions* tend to be the same that require *Manual Dexterity*, they are not perfectly correlated.

Table F-8: Import Competition and Cognitive Tasks: Mid-wage Workers

	Routine Cognitive		Non-routine Cognitive		
	Evaluating	Repeating	Developing	Inductive	Math
	(1)	(2)	(3)	(4)	(5)
Imp Comp	-1.761***	-1.732***	-1.208*	-1.390*	-1.337***
	(0.595)	(0.491)	(0.698)	(0.772)	(0.492)
ImpComp x Task	0.301	0.880***	0.559	0.606	1.057**
	(0.544)	(0.329)	(0.643)	(0.729)	(0.438)
Observations	13,714	13,664	12,510	13,556	13,608
R-squared	0.623	0.626	0.625	0.623	0.624

Notes: The dependent variable in all regressions is the period-average mid-wage employment. All regressions include worker and period fixed effects as well as the interaction between the period fixed effect and Task variable. In each regression a specific task variable is indicated in the column heading. *, ** and *** indicate significance at the 10%, 5%, and 1% levels respectively.

The results show that workers performing cognitive tasks tend to be affected less by rising import competition compared to other workers, although in contrast to the larger sample of all textile workers not always significantly so.

G Additional Results for Economy-wide Sample

Table G-1 shows results on the impact of changes in import penetration on mid-wage employment for Denmark's private-sector labor force when regression variables are introduced step by step. The first specification employs Chinese import competition, captured by $\Delta ImpPent_j$, solely together with two-digit industry fixed effects. The second stage coefficient is negative, see Table G-1, column (1). While the focus is on the coefficient on import competition, all coefficients are shown in Table G-2.

The import competition coefficient falls in absolute value with the inclusion of age, gender, immigration status and education variables, while worker characteristics (experience, unemployment history, hourly wage, and the worker's two-digit occupation) reduce the coefficient further (columns (2) and (3), respectively). This indicates that part of the estimated middle-class employment losses are due to the composition of the workforce in the part of the economy that is relatively exposed to Chinese import competition.

The specification underlying column (3) in Table G-1 compares workers with similar demographic and education characteristics, wages and employment experiences, occupations, and industry characteristics, some of whom are employed in producing six-digit product categories exposed to rising import competition while others are not. It does not account for firm effects, which have been shown to be important for the impact of rising import competition (Utar 2014, Bloom, Draca, and van Reenen 2016). In the present context including the most salient firm characteristics –size, quality, and the extent to which workers separate from their firms–does not change the import competition estimate much (column (4)).

Middle-class employment is likely affected by the rate at which new information and communication technologies are adopted. We therefore include the share of information technology-educated workers for each of the roughly 600 six-digit industries in the regression, as well as the wage share of vocationally trained workers. The import competition coefficient is now estimated at about -5.4 (column (5)), which is less than half the size of the point estimate in column (1). Failing to account for detailed worker-, firm-, and product characteristics would overestimate the impact on import competition on employment in middle class jobs.

Notice that the strength and performance of the instrumental variables does not change much with the inclusion of worker, firm, and six-digit industry-level variables. In particular, the first-stage F-statistic is similar, and the over-identification tests show no evidence that the instrumental variables are not valid. The final column in Table G-1 shows OLS results for comparison. The Chinese

Table G-1: Import Competition and the Decline in Mid-Wage Employment

	(1)	(2)	(3)	(4)	(5)	(6)
	IV	IV	IV	IV	IV	OLS
Δ ImpPent	-12.070*	-9.892**	-6.934**	-7.099**	-5.441**	-0.0900
	(6.119)	(4.760)	(3.197)	(2.913)	(2.287)	(0.665)
Demographic Characteristics	no	yes	yes	yes	yes	yes
Education Characteristics	no	yes	yes	yes	yes	yes
Log Hourly Wage	no	no	yes	yes	yes	yes
Labor Market History	no	no	yes	yes	yes	yes
Occupation (Two Digit ISCO) FEs	no	no	yes	yes	yes	yes
Union and Unemployment Insurance Membership	no	no	yes	yes	yes	yes
Firm Characteristics	no	no	no	yes	yes	yes
Product Characteristics	no	no	no	no	yes	yes
Industry (Two Digit NACE) FEs	✓	✓	✓	✓	✓	✓
N	900,329	900,329	900,329	900,329	900,329	900,329
Number of Clusters	170	170	170	170	170	170
Kleibergen-Paap F-test of excl. instr	12.56	12.57	12.57	12.40	12.58	
Hansen J overidentification test	0.743	0.767	0.463	0.103	0.197	
Hansen J P-value	0.690	0.681	0.793	0.950	0.906	

Notes: Dependent variable is years in mid-wage occupations, 2000-2009. Estimation method is given at top of column. Demographic variables are age, age-squared, as well as indicators for gender, immigration status, and an interaction term between a female indicator and age. Education indicator variables distinguish: At least some college, vocational education, manufacturing-specific vocational education, and at most high school. Wage is the logarithm of *i*'s average hourly wage. Labor market history variables: the sum of the fraction of unemployment in each year since 1980, the number of years of labor market experience before 1999, and number of years squared. Union and unemployment insurance (UI): indicator variables for membership status in year 1999. Firm variables: size, measured by the number of full-time equivalent employees, quality, measured by the log of average hourly wage paid, and strength of firm-worker relationship, measured by the separation rate between years 1998 and 1999. Product-level (6-digit industry) variables: size, measured by the log number of employees in 1999, information technology (IT) skills, as the share of workers with IT education, and importance of lower-level technical skills, measured by the wage share of vocationally trained workers, all in 1999; the percentage change in employment over years 1993-1999; average annual growth of energy usage, and retail employment growth where worker *i*'s manufactured product is sold, both over years 2000-2008. Excluded instrumental variables: the change in Chinese import penetration in eight high-income countries, the log average distance of each product's import sources, using 1996 imports as weights, and the share of trade firms importing directly in 1996, all at the six-digit industry level. Robust standard errors clustered at the 3-digit industry level in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

imports variable has a negative point estimate but it is close to zero. This is consistent with the hypothesis that import demand from China is positively correlated with industry demand shocks, and failing to account for this correlation the OLS estimate is upwardly biased.

Table G-2 gives the full two-stage least squares results that are summarized in Table 7 of the paper. First-stage results on the excluded instruments are shown at the bottom of Table G-2.

Table G-2: Import Competition and Job Polarization

Dep. Var.	(1) *HIGH*^{e}	(2) *MID*^{e}	(3) *LOW*^{e}
Δ ImpPent	2.436**	-5.441**	2.413**
	(1.087)	(2.287)	(1.181)
Female	0.768***	-0.608***	0.272**
	(0.108)	(0.109)	(0.126)
Immigrant	-0.561***	-0.058	0.041
	(0.031)	(0.038)	(0.040)
Age	-0.017*	-0.071***	-0.016
	(0.010)	(0.020)	(0.016)
College	1.677***	-0.407***	-0.244***
	(0.058)	(0.065)	(0.041)
Vocational	0.128***	0.422***	0.047
	(0.030)	(0.077)	(0.055)
High School	0.112***	0.150***	0.070***
	(0.033)	(0.035)	(0.027)
Manufacturing Specific Vocational Ed.	-0.010	0.217***	-0.173***
	(0.027)	(0.062)	(0.035)
Female x Age	-0.025***	0.022***	-0.004
	(0.003)	(0.003)	(0.005)
Age-square	-0.000	0.001**	0.000
	(0.000)	(0.000)	(0.000)
Unemployment History	-0.117***	-0.131***	0.033***
	(0.008)	(0.011)	(0.006)
Log Hourly Wage	0.339***	-0.290***	-0.195***
	(0.067)	(0.050)	(0.074)
Union Membership	0.020	0.559***	0.152***
	(0.036)	(0.057)	(0.037)
UI Membership	-0.315***	0.506***	0.323***
	(0.091)	(0.029)	(0.061)
Experience	0.007	0.029**	0.026***
	(0.006)	(0.012)	(0.010)
Experience squared	0.000*	0.002**	-0.001
	(0.000)	(0.001)	(0.000)
Separation Rate	0.041	-0.713***	-0.046
	(0.047)	(0.062)	(0.052)
Log Firm Wage	0.662***	-0.010	-0.123*
	(0.085)	(0.095)	(0.065)
Firm Size	0.000***	-0.000**	0.000*
	(0.000)	(0.000)	(0.000)
Industry Vocational Labor Share	-1.125***	1.697***	-0.164

Continued on next page

Table G-2 – *Continued from previous page*

Dep. Var.	$HIGH^e$ (1)	MID^e (2)	LOW^e (3)
	(0.399)	(0.386)	(0.377)
Industry IT Investment	10.240**	-5.967	-7.090***
	(5.035)	(4.401)	(2.209)
Industry Pre-Trend	-0.013	0.008	-0.003
	(0.014)	(0.018)	(0.012)
Industry Size	0.024	0.061**	0.054**
	(0.018)	(0.025)	(0.022)
Retail Demand Change	0.062	-0.023	0.019
	(0.054)	(0.083)	(0.052)
Energy Growth	1.124**	-0.612	0.045
	(0.496)	(0.482)	(0.216)
Two-digit Occupation Fixed Effects	✓	✓	✓
Two-digit Industry Fixed Effects	✓	✓	✓
N	900,329	900,329	900,329
K-P F-test statistic	12.58	12.58	12.58
P-value of K-P test statistic	0.000	0.000	0.000
Hansen J overidentification test	4.542	0.197	0.247
Hansen J P-value	0.103	0.906	0.884
Number of Clusters	170	170	170
First Stage Coefficients for all specifications			
ΔHIP^{CH}	0.002***		
	(0.0005)		
Log distance to import source	0.015***		
	(0.005)		
Share of retail firms in import	0.113*		
	(0.068)		

Robust standard errors, clustered at the 3-digit industry level, are reported in parentheses.
*, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

Beyond the findings discussed in the text, it is worth noting that older workers are not only less likely to be in (shrinking) mid-wage employment but they are also somewhat less likely to be in high-wage jobs during 2000-2009. Also, the pattern of coefficients for the Industry IT Investment variable, namely increasing with the level of education, is in line with skill-biased technical change.

Table G-3 shows results on full-time employment, hours worked, and earnings in the case of our economy-wide sample.

Table G-3: Import Competition and Full-time Employment, Hours, and Earnings

	(1)	(2)	(3)
Panel A.		**Full-time Employment**	
	MID^{fte}	$HIGH^{fte}$	LOW^{fte}
Δ ImpPent	-5.167**	2.411**	2.005*
	(2.244)	(1.087)	(1.126)
N	900,329	900,329	900,329
Panel B.		**Hours worked**	
	MID^{hrs}	$HIGH^{hrs}$	LOW^{hrs}
Δ ImpPent	-5.925**	2.279**	2.315*
	(2.526)	(1.103)	(1.393)
N	879,614	879,614	879,614
Panel C.		**Earnings**	
	MID^{wage}	$HIGH^{wage}$	LOW^{wage}
Δ ImpPent	-6.188*	5.135	1.981
	(3.325)	(4.880)	(1.942)
N	900,329	900,329	900,329

Notes: Dependent variables are years of full-time employment across mid-, high, and low-occupations in 2000-2009 in Panel A. They are total hours worked in 2000-2009 across mid-, high, and low-occupations in Panel B., and labor earnings in 2000-2009 in Panel C. Total hours worked and labor earnings variables are measured in worker *i*'s own initial annual hours worked and initial annual wage, respectively. Estimation by two stage least squares, with second-stage coefficients shown. Robust standard errors clustered at the 3-digit industry level in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

Each entry in Table G-3 is the point estimate and standard error for the import competition variable. The estimation employs the same set of right-hand side variables as in Table 7.

Table G-4 presents results from instrumental-variables estimations with samples that vary from two years (2000-2001) to ten years (2000-2009) of length.

Table G-4: The Dynamic Impact of Import Competition on Labor Market Status

Year	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Years in mid-wage occupations, MID^e										
Δ ImpPent	-0.603*	-1.130**	-1.496*	-1.718*	-2.412**	-3.025**	-3.723**	-4.428**	-5.036**	-5.441**
	(0.322)	(0.545)	(0.769)	(0.960)	(1.136)	(1.348)	(1.594)	(1.848)	(2.086)	(2.280)
Panel B. Years in high-wage occupations, $HIGH^e$										
Δ ImpPent	0.254***	0.494***	0.724***	0.896**	1.179**	1.442**	1.746**	1.995**	2.221**	2.436**
	(0.0925)	(0.174)	(0.267)	(0.373)	(0.504)	(0.619)	(0.727)	(0.836)	(0.959)	(1.084)
Panel C. Years in low-wage occupations, LOW^e										
Δ ImpPent	0.0697	0.101	0.253	0.425	0.561	0.889	1.165	1.591*	1.987*	2.413**
	(0.153)	(0.294)	(0.400)	(0.499)	(0.582)	(0.683)	(0.810)	(0.937)	(1.063)	(1.177)
Panel D. Years in unemployment, UE^e										
Δ ImpPent	0.0692	0.212**	0.352**	0.539***	0.760***	0.848***	0.945***	0.977***	0.974**	0.843**
	(0.0451)	(0.0934)	(0.144)	(0.209)	(0.265)	(0.306)	(0.339)	(0.363)	(0.392)	(0.424)
Panel E. Years outside the labor market, OUT^e										
Δ ImpPent	0.011	0.020	0.089	0.138	0.200	0.203	0.199	0.147	0.125	-0.001
	(0.035)	(0.056)	(0.087)	(0.124)	(0.158)	(0.193)	(0.230)	(0.275)	(0.330)	(0.387)

Notes: Year on top of column indicates last year of sample. Dependent variable given in each panel. Each cell gives results on the variable Import Competition for a separate regression; N = 900,329. Estimation by two stage least squares. Robust standard errors clustered at the 3-digit industry level in parentheses. All specifications include demographic (gender, age (linear and square terms), immigration status, interaction between gender and age), education, hourly wage, labor market history (unemployment history, linear and square terms of experience), union and unemployment insurance memberships, firm (size, wage, separation rate), as well as product-level covariates as described in Table G-1. All specifications also include two digit occupation fixed effects and two-digit industry fixed effects. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

G.1 The Role of Education: Results for Denmark's Private-Sector Labor Force

Complementing the results in the text, this section provides evidence on the role of education in affecting trade-induced occupational movements in Denmark's private-sector labor force.

We include two interaction variables between exposure to trade and education, $\Delta ImpPent$*College and $\Delta ImpPent$*HighSchool. As a consequence, the linear Chinese import competition variable captures the impact of trade exposure on vocationally trained workers (vocational training is the omitted category).[63]

Table G-5: Education and Job Polarization through Import Competition

	(1) High-wage Emp.	(2) Mid-wage Emp.	(3) Low-wage Emp.
Δ ImpPent	2.871**	-4.897**	1.589
	(1.210)	(2.239)	(1.249)
Δ ImpPent*HighSchool	-2.706**	-0.039	1.227
	(1.266)	(1.368)	(0.913)
Δ ImpPent*College	4.437*	3.288	1.883
	(2.290)	(3.251)	(1.279)
N	900,329	900,329	900,329

Notes: Dependent variable at top of column. HighSchool is indicator for at most high school education; College is an indicator for college education. Vocational education is the omitted category. Estimation by two stage least squares. All specifications include demographic (gender, age, immigration status), education, labor market history (unemployment history, linear and square terms of experience), union and unemployment insurance memberships, firm variables (size, wage, separation rate), as well as product-level control variables as described in Table G-1 notes. Specifications also include two-digit occupation and industry fixed effects, as well as 1999 hourly wage. Robust standard errors clustered at the 3-digit industry level are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

We see that the chance of a trade-exposed worker to be in a high-paying occupation is increasing in the worker's level of education (Table G-5, column (1)). Vocationally trained workers is the omitted category, and the probability that an at most high school educated exposed worker has

[63] All specifications include indicator variables for the three education levels, two-digit industry and occupation fixed effects, as well as the other covariates of our baseline specification (Table G-1, column (5)).

significantly more high-wage employment is zero. This is what we found as well for low-educated textile workers, see Table 4. Furthermore, college-educated workers exposed to rising import competition are more likely to increase their high-wage employment compared to exposed workers with lower levels of education (column (1)).

Interestingly, trade-exposed workers with vocational education have significantly more high-wage employment than non-exposed workers with such education, which was not the case for the subset of mid-wage textile workers (see Table 4). At the same time, vocational training does not shield these workers from having lower mid-wage employment compared to non-exposed workers (column (2)), which is similar to what we find for textile workers.

Finally, both low and high levels of education are associated with higher levels of trade-induced low-wage employment, see column (3). The finding for low education levels mirrors our findings for textile workers, see Table 4, while the finding for college educated workers does not. The reason for the higher low-wage employment for college-educated workers might have to do with life cycle and work- versus family choices, as emphasized by Keller and Utar (2018).[64]

[64] When we distinguish workers who have vocational training with a manufacturing focus from workers who have vocational training with a service focus, we find that the former are less likely to have lower mid-wage employment compared to other exposed workers, while the latter (and especially workers with an focus on IT training) have a higher chance to increase their high-wage employment.

G.2 Import Competition and the Role of Intermediate Goods

Table G-6: The Role of Intermediate Goods Trade

	(1) MID^e	(2) $HIGH^e$	(3) LOW^e	(4) UE^e	(5) OUT^e
Δ ImpPent	-7.586**	3.507**	2.248	1.233**	0.123
	(3.231)	(1.488)	(1.44)	(0.574)	(0.508)
Δ ImpPent x Intermediate Goods Share	11.100**	-5.677**	1.416	-2.345*	-1.593
	(5.219)	(2.735)	(2.191)	(1.294)	(1.117)
Intermediate Goods Share	-0.175	0.072	0.020	0.012	-0.057*
	(0.0152)	(0.079)	(0.09)	(0.032)	(0.029)
Number of Clusters	170	170	170	170	170
Demographic Characteristics	✓	✓	✓	✓	✓
Education Characteristics	✓	✓	✓	✓	✓
Log Hourly Wage	✓	✓	✓	✓	✓
Labor Market History	✓	✓	✓	✓	✓
Two Digit Occupation FEs	✓	✓	✓	✓	✓
Union and UI Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Product Characteristics	✓	✓	✓	✓	✓
Two Digit Industry FEs	✓	✓	✓	✓	✓
Observations	900,329	900,329	900,329	900,329	900,329

Notes: Dependent variable at top of column. UE^e stands for unemployment, OUT^e for years outside of the labor force. Estimation by two stage least squares, second-stage coefficients shown. First-stage F p-value less than 0.0001. Specifications include all worker, firm and product-level covariates as in Table G-2. All specifications also include two-digit industry fixed effects. Robust standard errors clustered at the three-digit industry level in parentheses. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

G.3 Results for Workers Eighteen to Sixty-five Years Old

Table G-7: Adjustment by Workers Eighteen to Sixty-five Years Old

	(1) MID^e	(2) $HIGH^e$	(3) LOW^e	(4) UE^e	(5) OUT^e
Δ ImpPent	-4.777**	2.598**	2.075**	0.903**	-0.414
	(2.046)	(1.018)	(1.038)	(0.432)	(0.474)
Number of Clusters	170	170	170	170	170
Demographic Charactersitics	✓	✓	✓	✓	✓
Education Charactersitics	✓	✓	✓	✓	✓
Log Hourly Wage	✓	✓	✓	✓	✓
Labor Market History	✓	✓	✓	✓	✓
Two Digit Occupation FEs	✓	✓	✓	✓	✓
Union and UI Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Product Charactersitics	✓	✓	✓	✓	✓
Two Digit Industry FEs	✓	✓	✓	✓	✓
N	1,115,835	1,115,835	1,115,835	1,115,835	1,115,835

Notes: Dependent variable at top of column. UE^e stands for unemployment, OUT^e for years outside of the labor force. Estimation by two stage least squares. The Kleibergen-Paap (first-stage) F-statistics is 12.78 (p-value = 0.000) for all columns. Robust standard errors clustered at the three-digit industry level in parentheses. All specifications include all worker, firm and product-level covariates as in Table G-2. All specifications also include two-digit industry fixed effects. *, ** and *** indicate significance at the 10 %, 5%, and 1% levels, respectively.