I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16381

International Trade and Job Polarization: Evidence at the Worker Level

Wolfgang Keller
Hale Utar

AUGUST 2023

IZA Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16381

International Trade and Job Polarization: Evidence at the Worker Level

Wolfgang Keller
University of Colorado, CESifo, CEPR and NBER

Hale Utar
Grinnell College, IZA and CESIfo

AUGUST 2023

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

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

We employ employer-employee matched data from Denmark and utilize plausibly exogenous variation in the rise of import competition due to the dismantling of import quotas as China entered the World Trade Organization to show, first, that rising import competition has led to reduced employment in mid-wage occupations compensated by an increased likelihood of employment in both low-wage and high-wage occupations. Workers with higher education are more likely to move from mid- to high-wage occupations due to trade compared to moving from mid- to low-wage occupations. Employing task content information of detailed occupations, we also show that workers performing manual tasks are the ones most affected by import competition independently of the routine-task intensity of occupations. This implies that the effect of import competition is distinct from that of routine task-replacing technological change

JEL Classification: F14, F16, F66, J23, J24, J62

Keywords: job polarization, employer-employee matched data, import competition, job trajectories of individual workers, trade, technology, task, China, Denmark

Corresponding author:
Hale Utar
Department of Economics
Grinnell College
Grinnell
50112, IA
USA
E-mail: utarhale@grinnell.edu

* This study was sponsored by the Labor Market Dynamics and Growth Center at the University of Aarhus. Support of the Department of Economics and Business, Aarhus University and Statistics Denmark is acknowledged with appreciation. We thank Henning Bunzel for facilitating access to the confidential database of Statistics Denmark and for his support, Anna Salomons for sending us data, our scheduled discussants David Autor, Esther Ann Bøler, and Gabriel Ulyssea for their comments, and Susanto Basu, Nick Bloom, René Böheim, Dave Donaldson, Ben Faber, Kyle Handley, Jagadeesh Sivadasan, Casper Thorning as well as audiences at the AEA (San Francisco), UIBE Beijing, CEPR ERWIT, Cologne, Hong Kong University, JKU Linz, LSE, ZEW Mannheim, University of Michigan, CESifo Munich, Nankai, NBER SI CRIW, NBER Trade, EIIT Purdue, Singapore Management University, TIGN Montevideo, and DARES and ILO conference on Polarisation(s) in Labour Markets in Paris for helpful comments and suggestions. Kyle Butts,William Ridley, and Adam Solar provided valuable research assistance. The data source used for all figures and tables is Statistics Denmark.

1 Introduction

One of the most striking labor market phenomena to emerge in recent decades in many countries is the hollowing out of middle-income jobs combined with an increase in employment in both high- and low-wage occupations, a U-shaped pattern commonly referred to as job polarization.[1] In this paper, we ask if rising import competition from emerging economies, especially China, plays any role in this. The recent trade literature identifies competition with China as a significant factor in shaping the labor markets in developed economies (Autor, Dorn, Hanson 2016; McLaren 2022). This literature, however, does not study how occupational trajectories of workers are affected by rising competition with China. At the same time, the literature on job polarization does not answer whether and to what extent incumbent workers contribute to job polarization or whether this phenomenon is largely shaped by labor market entry and exit. Filling this gap, we employ an individual-level approach to examine if workers' changing occupational trajectories due to international trade contribute to job polarization using administrative, longitudinal employer-employee matched data from Denmark between 1990 and 2009.

Our analysis exploits the European Union-wide change in the product-level trade regime with China due to the dismantling of Multi-fiber Arrangement quotas as China entered the World Trade Organization (WTO).[2] Our difference-in-differences strategy compares occupation trajectories of workers whose firms domestically manufacture narrowly defined textile products that are subsequently subject to quota removals to trajectories of workers employed at other firms also manufacturing textile goods that are not affected by the quota removals. Exploiting quota information at the firm-product level together with the plausibly exogenous quota removal due to China's entry into the WTO provides an ideal quasi-natural experimental set-up to study the causal impact of trade exposure on workers' occupational trajectories.

To illustrate our approach, consider the employment changes between 2000 and 2009 of a constant set of workers shown in Figure 1. The employment share changes across occupations are presented for three sets of workers as of their sectoral affiliation in 1999, namely those who worked in the service sector, those who worked in the manufacturing sector, and the subset of manufacturing workers who were employed in textiles. Following the earlier literature (Autor 2010, Goos, Manning, Salomons 2014), we distill the U-shaped pattern of job polarization by distinguishing three sets of occupations, namely high-wage, mid-wage, and low-wage occupations. A common low-

[1] Early work includes Autor, Katz, and Kearney (2006, 2008), and Goos and Manning (2007). Autor (2010) focuses on the United States, and Goos, Manning, and Salomons (2014) provide evidence on 16 European countries. See Harrigan, Reshef, and Toubal (2016) for France. Figure A-1 shows the case of Denmark.

[2] Earlier literature employing this as a natural experiment includes Harrigan and Barrows (2009), Bloom, Draca, and van Reenen (2016), and Utar (2014, 2018).

wage occupation is a shop sales clerk, a typical mid-wage occupation is a machine operator, while a professional tends to be paid a high-wage.[3] Notice that for manufacturing workers the hollowing out of mid-wage jobs together with increases in employment in both low and high-wage occupations, that is, the U-shaped job polarization pattern, is present (and more pronounced for textile workers), whereas it is not present for workers employed in 1999 in the service sector. Because manufacturing goods are more tradable than services, while technology affects manufacturing and service sectors to a more similar degree, this is consistent with rising import competition playing a role for job polarization.

Figure 1: Decadal Changes in Employment Share for Workers from Different Sectors

Figure shows 2000-2009 employment share changes across occupations ranked by wage among workers who were employed in 1999 in the textile and clothing, manufacturing, and service sectors. The employment shares are constructed based on all workers in Denmark who were between 15 and 54 years old and employed in the respective sectors as of 1999.

Our first main finding is that import competition from China causes occupational transitions of workers leading to job polarization over the years 1999 to 2009. First, workers affected by import competition are pushed away from mid-wage occupations to a greater extent than workers not as

[3] A shop sales clerk's hourly wage is typically under 30 dollars, a machine operator makes around 40 dollars per hour, and a business professional makes around 55 dollars per hour. The classification of occupations into low, mid, and high wage groups is based on median hourly wages within each occupation, see Table 1.

affected, contributing to the hollowing out of the mid-wage jobs. Mid-wage workers affected by rising import competition also transition disproportionately to low-wage occupations, while others, though fewer, move into high-wage occupations. Import competition also facilitates low-wage workers' transition to high-wage occupations, which is in line with increased school enrollment among low-educated workers in response to import competition, as documented in Utar (2018). Stronger mid-wage losses combined with disproportionate transitions to either low- or high-wage occupations for workers subject to rising import competition yield a U-shaped job polarization pattern in the aggregate. Among the factors determining whether workers after leaving their mid-wage jobs move up or down in the occupational hierarchy is education. We show that college education is key for mid-wage workers to move up, and mid-wage workers with high-school education move disproportionately down in the occupational wage hierarchy.

We generalize these results by following the job trajectories of close to one million workers in the entire private sector economy by exploiting differences in the change of import penetration across workers' six-digit industries using an instrumental-variables approach. Rising import competition is an important factor driving job polarization for the entire economy.

Our second main result is to shed light on the key mechanism through which increased import competition with China causes job polarization. Employing task content information on the importance of individual tasks in narrowly defined occupations, we demonstrate that workers in manual task-intensive occupations are most negatively affected by import competition, whereas workers in non-manual (cognitive) task-intensive occupations are disproportionately less affected by job polarization induced import competition. We also show that the mechanism through which import competition affects workers is different from that of technological change because while the extent to which import competition leads to job polarization is increasing in the degree of an occupation's manual task intensity, it is independent from whether the task is routine or non-routine, which is key for the impact of technological change.[4] In other words, the polarizing impact of import competition and technological forces are distinct in the task space. Import competition and technological change contribute through different mechanisms to job polarization because while today's robots can replace many workers performing routine tasks, from a factor service trade perspective Chinese workers that perform manual tasks when the good is produced in China compete with Danish workers who can perform similar tasks when the good is produced in Denmark.

This paper relates to several different bodies of work. The first concerns the question of what explains job polarization. According to most accounts, job polarization is due to technological change, computer-controlled machinery replacing workers, especially those performing routine

[4] The concept of routine-biased technological change is due to Autor, Levy, and Murnane (2003), Autor, Katz, and Kearney (2006), and Goos and Manning (2007).

tasks, while the role of import competition is limited (Autor and Dorn 2013, Goos, Manning, and Salomons 2014, Michaels, Natraj, and van Reenen 2014). Even though research has increasingly given prominence to import competition from China for some major issues (Autor, Dorn, Hanson, and Song 2014, Pierce and Schott 2016), job polarization is not one of them. In particular, Autor, Dorn, and Hanson (2015) conclude that import competition has reduced employment opportunities for *all* US workers, a finding that rules out import competition as a cause of job polarization because it is difficult to generate U-shaped aggregate employment share changes when employment opportunities of all workers are affected negatively. Our contribution here is to show that at least in some advanced countries, rising import competition has triggered worker transitions that are consistent with the U-shaped pattern of job polarization.

Second, it has been challenging to separately identify the impacts of international openness and technological change in what is often referred to as globalization.[5] By comparing both import competition and technological change in the same analysis of regional labor outcomes, Autor, Dorn, and Hanson (2015) have recently documented some differences between the impacts of technological change and import competition. We extend this literature by shifting the focus from aggregate measures to the nature of tasks performed by individual workers. By showing that rising import competition leads more strongly to job polarization the more manual task-intensive an occupation is, irrespective of its routine task-intensity, we separate the mechanisms through which international openness and technological change operate in the context of job polarization. This also provides information for the recent literature seeking to isolate the labor market effects of automation technologies such as robots (Graetz and Michaels 2018, Bessen, Goos, Salomons, and van der Berge 2019, and Acemoglu and Restrepo 2020).

Third, our paper contributes to the recent literature that explores worker adjustment to increased import competition from China (Autor, Dorn, Hanson, and Song 2014, Utar 2018, Dauth, Findeisen, and Südekum 2021). This literature shows that increased trade in manufacturing goods with China led to a dramatic shock for workers in richer countries, causing long-term manufacturing earnings losses among workers impacted by the competition. While this literature shows that the recent increase in import competition played a significant role in displacing workers from the manufacturing sector, it does not address if and how workers' occupational transitions are impacted. Our paper is most closely related to Utar (2018), who employs the same trade liberalization to shed light on individual workers' responses as they adjust to the trade shock. Departing from Utar (2018) and the empirical literature cited above, we focus on occupational transitions of workers and contribute to the literature in at least two ways. One, we focus on job transitions of workers be-

[5] See Feenstra (2000); also, 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).

tween occupations that pay substantially different wages which, given substantial re-training costs, means that the transition is long-run, as opposed to the temporary earnings losses or unemployment emphasized elsewhere. Two, we describe the necessarily complex individual worker adjustments in a way that distills common patterns that have been observed in many countries.

The next 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. Section 3 moves on to present an overview of the administrative, micro-level data, with more details given in the Appendix. Section 4 introduces our empirical approach for studying worker-level impacts of the import quota liberalization, and we also discuss how challenges to identification are addressed. Next, we show that workers' job-to-job transitions in response to import competition lead to job polarization (Section 5), and that education is key for upward job transitions of workers who lose their mid-wage job. Section 6 summarizes the generalization of our findings for the entire private-sector Danish economy (with details in Section C). Section 7 demonstrates that import competition most strongly impacts 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 8 provides a concluding discussion, while the Appendix includes important additional results and information referred to throughout the paper.

2 Rising Import Competition in Denmark

Since the late 1990s, Denmark, like many other advanced economies, has experienced increased import competition from lower-wage countries. To examine the role of import competition in job polarization, we employ a concrete policy change as a quasi-natural experiment: the lifting of import quotas on China's textile and clothing products due to the country's entry into the WTO (December 2001).

The import quotas were part of the Multi-Fiber Agreement (MFA), which 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 industry in advanced countries. With the conclusion of multilateral trade negotiations in 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. Specifically, it was agreed that MFA quotas were to be abolished in four phases: in the years 1995, 1998, 2002, and 2005. According to the agreement, importing countries were able to decide which quotas to liberalize in each phase subject to certain conditions, and the EU liberalized mostly non-binding quotas vis-a-vis WTO countries in the first two phases.

An advantage of this policy change is that neither Denmark nor China was directly involved in negotiating the creation or removal of the import quotas. This is because negotiations took place at the level of the EU, where Denmark's influence as a relatively small country is limited. Also, since China was not a member of the WTO in 1995, it 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. The lifting of quotas led to a substantial surge of textile imports in Denmark from China which resulted in major impacts and restructuring at the firm level (Utar 2014). Between 2002 and 2010, the value of Chinese goods in Danish markets that were subject to quotas tripled and reached almost the level of the pre-shock total domestic industry value added. 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 product level information on domestic production of firms, we identify firms that were producing any 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 manufacturing firm.[6] Workers who in 1999 are employed in firms with a revenue share of zero are the control group, while workers employed in firms with positive revenue shares are treated at varying levels.[7] Additional information on this quota liberalization is given in Section B of the Appendix.

We complement this approach by employing changes in the penetration of Chinese imports for each of six-digit industries across Denmark's entire economy between 1999 and 2009 in an instrumental-variables approach. These results, with their underlying sample and approach, are described in Section C.

[6]To calculate the exposure, we consider all active MFA quotas imposed on China, including the quotas belonging to the 2005 liberalization, due to the overlap of firms producing goods subject to the first three phases and the last phase and resolved uncertainty around China's WTO accession. See Utar (2014) for firms' responses to the 2002 and 2005 removals.

[7]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, see below.

3 Worker- and Firm Data

This study is based on the Integrated Database for Labor Market Research (IDA) of Statistics Denmark, which contains administrative records on all individuals and firms in Denmark. The IDA database contains 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 (Bobbio and Bunzel 2018).

This database allows us to track and observe all job and non-job transitions of workers in our sample, including workers' movements into or out of the labor market, in and out of a specific industry, firm or occupation.

The worker information includes annual salary, hourly wage, years in the labor market, six-digit industry code, the unique firm identifier for the worker's employer, education level, demographic characteristics (age, gender and immigration status), and occupation. We also know the labor market attachment for each worker as of November of each year as employed, unemployed, or outside the labor market. Using the unique employee and employer identifications, the IDA data are merged with the firm-level accounting (FIRE), firm-product level production (VARES) databases as well as firm-level data on international transactions (UHDI) to measure exposure to import competition of firms and industries.

Table 1: Occupation Groups by Wage

	Median Hourly Wage		Mean Hourly Wage		Employment Share		One-digit ISCO
	1999	2009	1999	2009	1999	2009	
High-Wage							
Legislators, Senior Officials, Managers	5.488	5.550	5.538	5.604	0.037	0.039	1
Professionals	5.297	5.362	5.349	5.412	0.143	0.166	2
Technicians, Associate Professionals	5.116	5.177	5.160	5.211	0.182	0.237	3
Mid-Wage							
Craft and Related Trade Workers	5.053	5.098	5.002	5.034	0.126	0.090	7
Plant and Machine Operators, Assemblers	5.012	5.088	5.024	5.095	0.088	0.062	8
Clerks, Office Workers	4.949	5.013	4.945	5.023	0.132	0.102	4
Low-Wage							
Elementary Occupations	4.919	4.962	4.928	4.956	0.116	0.103	9
Service Workers, Shop Sales Workers	4.849	4.938	4.851	4.927	0.163	0.191	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 laborers). 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 military, agriculture and fishery occupations.

3.1 Classifying Occupations

We use the IDA database to obtain the wage ranking of occupations. Table 1 classifies occupations into the high-, mid-, and low-wage parts of the distribution, as in earlier analyses of job polarization (Autor 2010, Goos, Manning, and Salomons 2014).[8] We classify occupations based on the median hourly wage paid in a full-time occupation in Denmark for the year 1999. High-wage occupations are comprised of managerial, professional, and technical occupations. Mid-wage occupations are clerks, craft 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. It is good to note that our analysis concerns broad occupational movements of individuals rather than worker movement across finer occupations whose wage rankings may be sensitive to regional or short-run demand and supply conditions. Table 1 reports the corresponding median and mean hourly wages within the one-digit occupations that comprise the high-, mid- and low-wage groups both in 1999 and 2009. The wage ranking of the occupations does not change over the decade. This is true whether the ranking is measured in median or average hourly

[8] Following the job polarization literature, we focus on the non-agricultural occupations.

wages (Table 1).

3.2 Sample Characteristics

Table 2: Key Characteristics of the Sample

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

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.

Summary statistics for the quota experiment sample are shown in Table 2. The sample comprises all employees of the textile and clothing sector in the year 1999 who are between 17 and 57 years old as of 1999 (N = 10,487). Female workers account for more than half of all workers, more than one third of workers have vocational education, and the average labor market experience is almost 15 years. We see from Table 2 that mid-wage occupations in textiles are relatively important, with 66% of the 1999 textile workers holding mid-wage occupations. How different are these workers in comparison to an average worker in the economy? Summary statistics for the 1999 private sector cohort of workers are provided in the last two columns of Table 2 for comparison. We see that textile workers on average have more experience in the labor market and are less likely to be college educated. We employ the entire private sector cohort of workers of close to one million and conduct an economy-wide analysis based on an instrumental-variables approach to account for any composition effects that might arise from that.

Table B-1 in the Appendix shows worker characteristics in the textile sample depending on whether they were employed in 1999 in quota-producing textile manufacturing firms or not. Roughly half of the workers were employed at firms that manufactured products in Denmark 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 report 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, 37 percent of exposed workers are machine operators, as are 38 percent of the control group. Overall, the treatment and control groups are similar.

We will analyze worker-level employment responses to rising import competition. Key outcomes include the number of years of employment of worker i in mid-, high-, and low-wage occupations in periods before and after China's entry into the WTO, and they are denoted by MID^e_{is}, $HIGH^e_{is}$, and LOW^e_{is}, respectively. We also consider the possibility that workers may experience unemployment or leave the labor market for various reasons such as early retirement or going back to school. UE_{is} and OUT_{is} denote the number of years in period s where worker i's primary labor market status is unemployed or outside the labor market, respectively.[9] Descriptive statistics of these outcome variables are reported in Tables B-2 and C-7 in the Appendix.

3.3 Descriptive Evidence on Workers' Occupational Movement

If import competition leads 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 2 provides initial evidence 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 mid-wage occupations. 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 2 start at 100% and slope downward over time by construction. Importantly, since 2002 the rate at which exposed textile machine operators leave their occupation is higher than the rate at which other textile machine operators leave theirs. 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

[9] The primary labor market position of an individual in a given year is determined by Statistics Denmark based on the individual's labor market position as of November of that year. In the case of our economy-wide analysis, the variable MID^e_i 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. The variable MID^e_i 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. Analogously, we define LOW^e_i and $HIGH^e_i$ as the cumulative low-wage and high-wage employment of worker i from year 2000 to year 2009, respectively.

import competition.

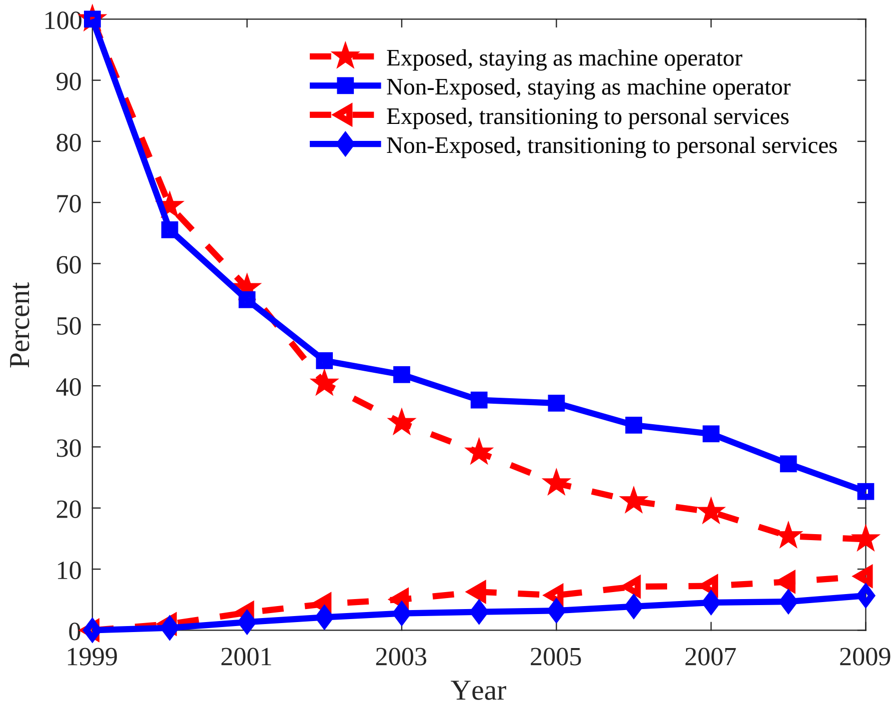


Figure 2: Machine Operators: Staying versus Switching to Low-wage Jobs, by Exposure

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.

Turning to increases in low-wage employment, the two lower lines in Figure 2 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 housekeeping, child care, elderly care, hairdressing, funeral arrangements, as well as protection of individuals and personal property. Figure 2 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.

4 Estimation Approach

In this section, we describe our estimation approach that exploits the drastic change in import competition due to the removal of import quotas for China as it entered the WTO. As the longitudinal structure of our data accommodates worker fixed effects, we employ a difference-in-differences estimation with two-way fixed effects. We aggregate the annual 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.

$$X_{is} = \alpha_0 + \alpha_1 \underbrace{Post_s \times Exposure_{ik}^{99}}_{\text{ImpComp}} + \alpha_2 Post_s + \delta_i + \varphi_{is}, \tag{1}$$

where $Exposure_{i(k)}^{99}$ 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, k, for which quotas will be removed with China's entry into the WTO:

$$Exposure_{ik}^{99} = \frac{\sum_{p \in Q} Rev_{ikp}^{99}}{TotRev_{ik}^{99}} \tag{2}$$

Here Rev_{ikp}^{99} denotes per-product revenue of firm k where worker i is employed as of 1999, Q denotes the set of quota products, p is an index for CN-8 digit products and $TotRev_{ik}^{99}$ is the total revenue of firm k as of 1999. This way, exposed workers employed at firms domestically producing quota products with a small share of revenue will be treated to a lesser degree than exposed workers whose firms more heavily rely 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 the textile workers over the post-shock years, 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' firm as of 1999. For ease of exposition, we denote the difference-in-differences term $Post_s \times Exposure_{ik}^{99}$ by $ImpComp_{is}$, mnemonic for import competition. We drop the subscript k for convenience as the cohort approach ensures that worker i uniquely identifies his or her firm, k, as of 1999.

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 outside of the labor market and in unemployment. We denote them as MID_{is}^{e}, $HIGH_{is}^{e}$, LOW_{is}^{e}, UE_{is}^{e}, and OUT_{is}^{e}.[10]

[10] 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 B-6. Notice that MID_{is}^{e}, $HIGH_{is}^{e}$, LOW_{is}^{e}, UE_{is}^{e}, and OUT_{is}^{e} are mutually exclusive but not exhaustive, as we do not rank military and agricultural occupations. There is also a small possibility that a worker's future occupation is not identified. However,

To focus on heterogeneity in workers' trade-induced employment paths depending on worker characteristics, we form a triple difference estimation equation where the difference-in-differences term $ImpComp_{is}$ is interacted with various characteristics of worker i as of 1999, denoted by C_i. The estimation equation is then:

$$X_{is} = \alpha_0 + \alpha_1 ImpComp_{is} + \alpha_2 Post_s + \alpha_3 ImpComp_{is} \times C_i + \alpha_4 Post_s \times C_i + \delta_i + \nu_{is}. \tag{3}$$

In this specification, $\alpha_1 + \alpha_3$ measures the impact of import competition on workers with characteristic C_i, α_4 captures any trend specific to the textile workers with this characteristic, while α_3 by itself gives the differential effect of import competition on workers with characteristic C_i.

Identification The inclusion of worker fixed effects implies that coefficients are estimated from within-worker variation over time. The influence of any observed or unobserved initial worker characteristic that may be correlated with a worker's future exposure to import competition or technological trend, including occupation, education, and unobserved ability, is absorbed by worker fixed effects.

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 the 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 these concerns, we conduct falsification tests for the period 1990-1999, during which heightened import competition due to the removal of import quotas on China was absent. Using data for our workers back to the year 1990, we run difference-in-differences specifications for various 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, we employ the two-period analysis with the years 1990-94 assumed to be the pre-shock and the years 1995-99 assumed to be the post-shock period. The analysis finds no evidence for significant effects. All our estimates on workers' labor market outcomes are close to zero and insignificant (Table B-3). We also conduct

as our estimates will show, these events are rare and do not affect our results.

this analysis with yearly data for the period 1990-1999 with similar findings (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.

The two-way fixed effects regression specification implies that our estimates are identified from within-worker changes controlling for aggregate changes such as the secular declining trend in labor-intensive manufacturing industries. Furthermore, we control for aggregate time trends that are specific to workers with certain characteristics (the term Post $\times$ C_i in equation (3)), such as susceptibility of workers' initial occupation to technical change. As yet another check on identification, we also perform an analysis in which the firms' exposure is randomly assigned. The coefficient estimates then are centered on zero, see Table B-5. This provides further evidence that our analysis identifies the causal impact of rising import competition.

5 Trade Liberalization and Occupational Movements

5.1 Exposure to Import Competition and the Emergence of Job Polarization

Table 3 shows results from estimating equation (1) for years of employment in mid-, high-, and low-wage occupations of worker i in period s, denoted by MID^e_{is}, $HIGH^e_{is}$, and LOW^e_{is}, respectively. We begin by studying the average impact of import competition before we turn to how the impact depends on workers' initial position on the occupational wage distribution.

First, column (1) shows that workers exposed to Chinese competition due to the dismantling of quotas spend less time in mid-wage occupations after the shock 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 increases the likelihood of employment in high-wage occupations (column (2)). The estimates in column (3) show that import competition also leads to an increase in employment in low-wage occupations. 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 provides evidence that import competition led to occupational transitions of workers that are consistent with job polarization. Import competition, via its effect on workers' occupations, is a source of inequality. Further, on average, we do not find that import competition increases the number of years unemployed or outside the labor market (columns (4) and (5)). This is consistent with

Utar (2018) who shows that increased import competition with China in Denmark mostly led to short-term unemployment spells between jobs rather than permanent unemployment or longer-term exits. Denmark implements active labor market policies facilitating and guiding job searches of unemployed workers and providing retraining opportunities, and this institutional context is likely to be important for comparing these results, for example, with U.S. workers' reactions to the China shock.

Table 3: Job Polarization due to Quota Removals: All Textile Workers

	(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: Estimation of equation (1) using OLS. Dependent variables are given at the top of the columns. Variables MID^e_{is}, $HIGH^e_{is}$, and LOW^e_{is} are defined as years of employment in mid-, high-, and low-wage occupations of worker i in period s. 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. Import Competition is defined as $Exposure^{99}_{ik} \times PostShock_s$ (equation (1)), where $Exposure^{99}_{ik}$ 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, k. 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 (645 clusters) are reported in parentheses. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

To assess the economic magnitudes of the impact of import competition, we compare workers at the 25th and the 75th percentile of exposure. This difference compares a textile worker who, as of 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 an employment decline in mid-wage occupations over the eight years of $-1.292 \times 0.284 = 0.367$ of a year or 4.4 months. Taking into account the average mid-wage employment of the control group over the post-shock years, which is 2.8 years, the 4.4 months amounts to a 13 percent reduction in mid-wage employment.

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 worker was employed at a firm in 1999 producing at least one quota product 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 discrete treatment, the coefficient estimate in the mid-wage employment equation is -0.337. This amounts to a reduction in employment in mid-wage occupations of 4 months (= 0.337×12), which is similar to the 4.4 months or 13 percent impact using the continuous treatment variable.[11]

Alternative Measures of Employment The employment variables so far do not distinguish full-time versus part-time jobs as long as they are held as a primary job. It is possible that trade competition reallocates workers disproportionately towards part-time jobs. Panel A of Table B-6 shows results for cumulative full-time employment in mid-, high-, and low-wage occupations. The estimates are very similar, indicating that workers experience a reduction in full-time employment in mid-wage occupations and moving from full-time to part-time jobs is not an important margin of adjustment. However, switching from mid-to low-wage jobs may not be easy, and it may be associated with spells of non-employment. In Panel B of Table B-6, we measure employment across the three types of occupations in total hours worked. The analysis of cumulative hours worked in low-wage jobs indicates that trade-induced increase in low-wage employment is associated with relatively short tenures in those jobs. In the final panel of Table B-6 we focus on cumulative earnings obtained in these jobs. In line with the finding of shorter tenures in low-wage occupations, we do not find that earnings obtained from low-wage occupations compensate significantly for the earnings losses associated with mid-wage occupations (Panel C of Table B-6).

To summarize, exposure to import competition due to removals of import quotas decreases workers' likelihood of being employed in mid-wage occupations, and it increases employment in either high- or low-wage occupations compared to workers not affected by rising import competition. Thus, import competition generates occupational mobility that leads to job polarization in the aggregate. These results are confirmed when the analysis is conducted on the economy-wide sample of more than 900,000 workers, see Table C-1 in the Appendix.

The welfare implications of import competition for a given worker depend on whether the worker falls or climbs in the occupational hierarchy. The following sheds more light on this by examining the occupational movements of workers who held mid-wage jobs as of the initial year (1999), followed by analogous analyses of occupational movements of textile workers who in 1999 had either low-wage or high-wage jobs.

[11] Instead of employing the share of revenue of a worker's firm that comes from import quota products in a reduced-form approach, we have also employed an instrumental variables approach based on this exposure variable, finding that it leads to similar results (see Table D-1).

5.2 Occupational Dynamics by Wage Group

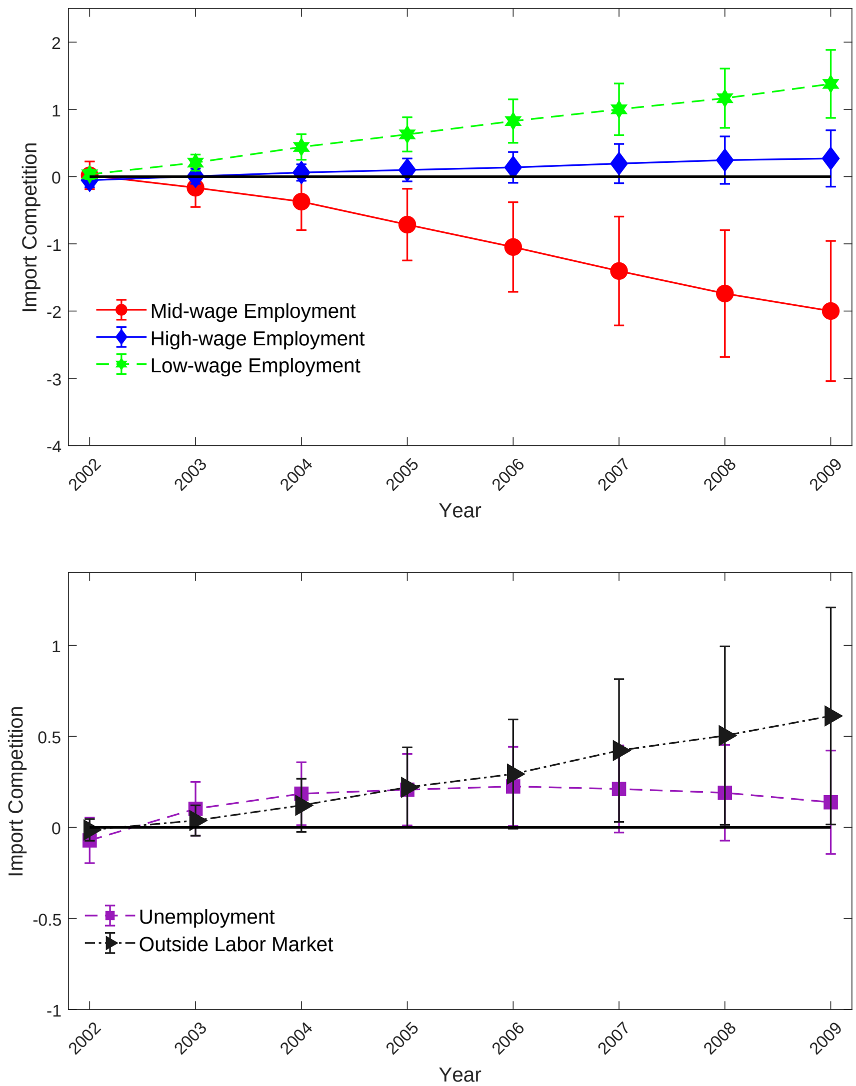


Figure 3: Import Competition and Labor Market Trajectories of Mid-Wage Textile Workers

Notes: Shown are difference-in-differences coefficients from estimating equation (1) with varying sample period ending from 2002 to 2009. Sample is all mid-wage textile workers as of the initial year 1999. The number of observations in every regression is N = 13,934. Dependent variables are given in the figure legend. All regressions include worker and time fixed effects. Robust 95% confidence intervals based on clustering at the firm level are shown.

There are about 7,000 workers who at the beginning of the sample period were employed in mid-wage occupations in the textile sector. Figure 3 shows how the trade shock affects the occupational trajectories of these workers over time. The figure also presents the dynamics of trade's impact on unemployment and labor force participation of these workers. Shown are separate estimates of equation (1) in which the end year of the post-period in the difference-in-differences analysis varies from the first year after the shock until the end of our sample period, 2009. The estimates underlying the figure are shown in the Appendix, Table B-7.

Figure 3 shows that while Chinese 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 employment reductions for these workers, the movements into high-wage employment is not significant. 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 negatively affected the typical job trajectory of a mid-wage worker, in line with the bulk of the evidence in the recent worker adjustment literature.

In addition, exit from the labor force due to import competition is somewhat important for mid-wage workers. Using the 25/75 percentile difference in exposure, the estimate of 0.61 (Figure 3 or Panel E of column 8 in Table B-7) indicates that the impact of import competition amounts to two months outside the labor market by the end of 2009. Considering the average time spent outside the labor market among mid-wage workers in the control group over the post-shock years, this translates to a 14 percent increase. Unemployment turns out to be less important over time for workers who were initially employed in mid-wage occupations.

We repeat the same analysis for workers who were employed in low-wage occupations before the dismantling of import quotas for China (see Figure 4). This group consists of about 1,250 workers. One difference to the occupational movements of mid-wage workers is that low-wage workers are more likely to lose their low-wage jobs at the onset of the rising competition, and the loss of low-wage jobs is compensated partially by mid-wage jobs initially. Both low-wage and mid-wage occupation coefficients are statistically significant in the first post-shock year. Notice that workers' annual outcomes are measured at the end of November each year, so the coefficient for 2002 measures workers' occupational response by the end of 2002. Interestingly, the mid-wage employment gain becomes indistinguishable from zero quickly, at the same time when we see a sustained increase in high-wage employment for these workers. The increased likelihood of moving from low- to high-wage jobs is consistent with Utar (2018) who shows a significant trade-induced increase in school enrollment among high-school educated workers.

The corresponding coefficient estimates are reported in Table B-8. Using the 75/25 percentile exposure of competition, the estimate of 1.8 indicates that import competition causes an increase in employment in high-wage occupations amounting to 6 months over the eight years for workers that start out in a low-wage job. This is substantial, considering the average high-wage employment of workers who were initially employed in low-wage occupations in the control group, and amounts to an 80 percent increase. By the end of the sample period in 2009, the main factor for the low-

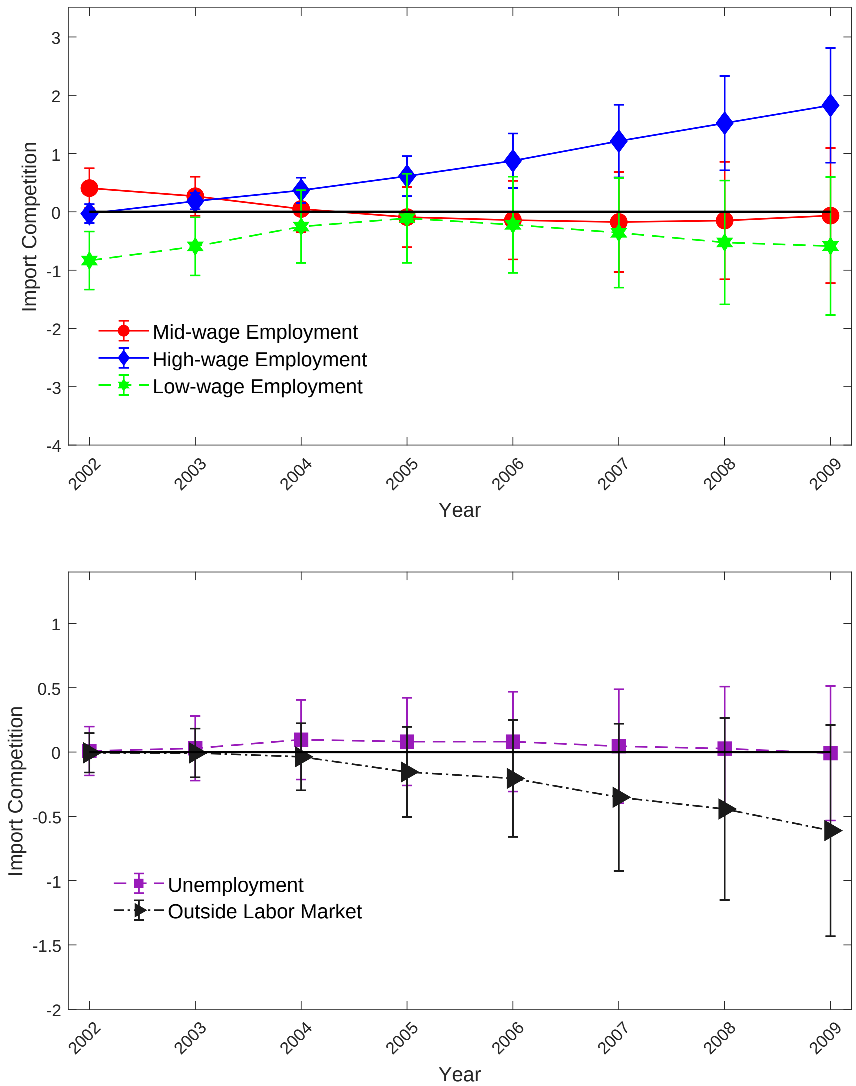


Figure 4: Import Competition and Labor Market Trajectories of Low-Wage Textile Workers

Notes: Shown are difference-in-differences coefficients from estimating equation (1) with varying sample period ending from 2002 to 2009. Sample is all low-wage textile workers as of the initial year 1999. The number of observations in every regression is N = 2,496. Dependent variables are given in the figure legend. All regressions include worker and time fixed effects. Robust 95% confidence intervals based on clustering at the firm level are shown.

wage textile workers' contribution to job polarization is that a disproportionate number of the trade-exposed low-wage workers succeed in transitioning to high-wage jobs.

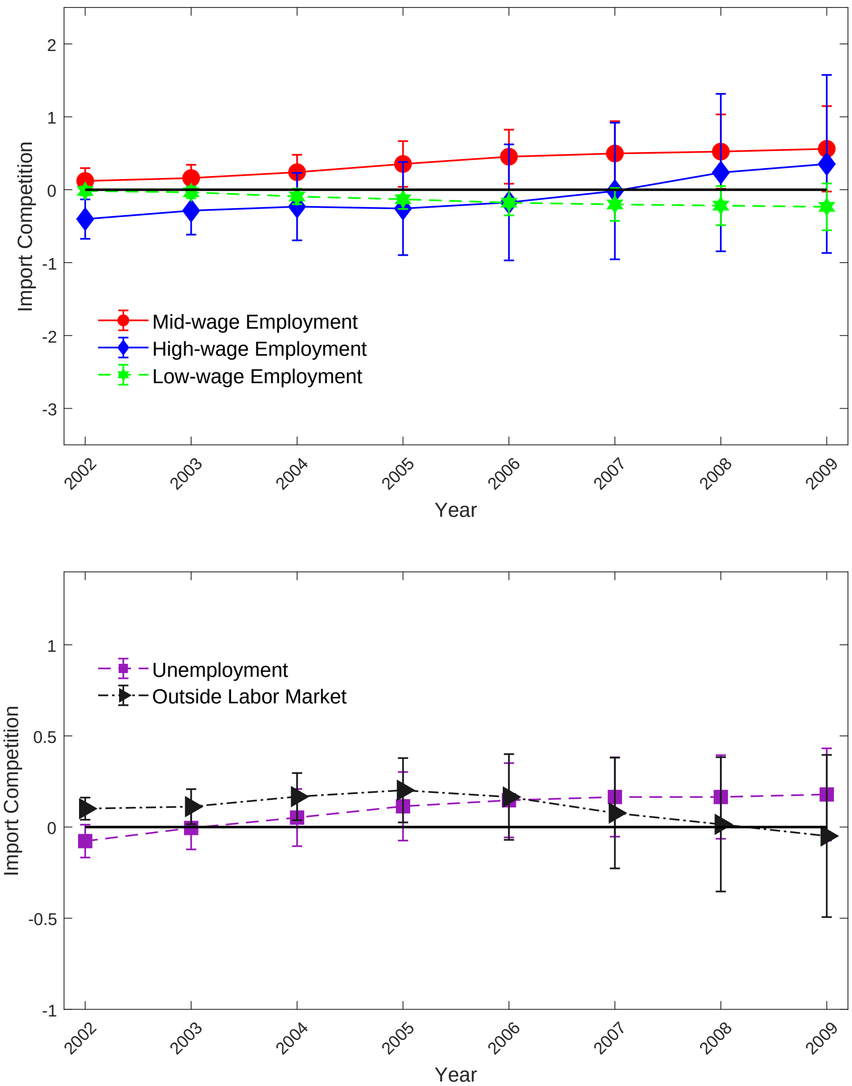


Figure 5: Import Competition and Labor Market Trajectories of High-Wage Textile Workers

Notes: Shown are difference-in-differences coefficients from estimating equation (1) with varying sample period ending from 2002 to 2009. Sample is all high-wage textile workers as of the initial year 1999. The number of observations in every regression is N = 4,294. Dependent variables are given in the figure legend. All regressions include worker and time fixed effects. Robust 95% confidence intervals based on clustering at the firm level are shown.

We also show the dynamic evolution of occupational mobility of 1999 high-wage workers (Figure 5, with regression results given in Table B-9). Although import competition causes a statistically significant decline in employment in high-wage occupations on impact, the point estimates turn positive over time. In other words, conditional on having a high-wage occupation at the onset of rising competition, import competition tends to increase high-wage employment in the long run so that the short-run negative employment impact is compensated for. Import competition also leads to a fall in the occupational hierarchy from high- to mid-wage occupations, but not toward low-wage occupations. Unemployment and exit from the labor market are not significant labor market positions in the long run. Overall, the contribution of workers who were initially located on the right tail of the occupational wage distribution to the emergent pattern of job polarization is limited to the non-negative long-run impact of import competition on high-wage employment.

Taking together, Figures 3, 4, and 5 indicate that the job polarization pattern noted for textile workers in the Introduction (Figure 1) is largely driven by the occupational movements of mid-wage workers, for whom rising import competition means a hollowing out of mid-wage employment opportunities that forces many of them to move down to low-wage occupations, while fewer manage to switch to high-wage occupations. According to our findings, the rise in low-wage employment associated with job polarization is largely driven by mid-wage workers moving down in the occupational hierarchy, whereas the rise of high-wage employment opportunities is due to a range of factors, the most interesting perhaps being that some of the exposed low-wage workers manage to move up into high-paying occupations.

5.3 Education Affecting the Direction of Occupational Movements

This section examines the influence of education in shaping trade-induced occupational movements of workers. We distinguish workers who were employed in mid-wage occupations by their highest attained education level as of 1999 and estimate equation (3). Results are shown in Table 4 which presents the coefficient estimates for α_1 (the difference-in-differences coefficient) and α_3 (the triple-difference coefficient) of equation (3) while for brevity, estimates of α_2 and α_4 are not reported.

We distinguish three groups of workers: with at least some college education, vocational education, and at most a high-school degree. In Denmark, like in many other European countries, mid-level education corresponds to vocational education which is provided in technical schools with both formal schooling and apprenticeship components. First, we focus on the role of college education in the occupational movement of mid-wage workers. Column 1 of Table 4 addresses whether the extent to which workers lose their mid-wage occupations depends on their education. Column (1) of Panel A shows that import competition causes a significant employment reduction in mid-wage occupations regardless of whether workers are college educated or not.

While the extent to which import competition causes mid-wage employment loss does not vary significantly for college-educated workers, having a college education plays a critical role in determining whether a mid-wage worker can move into high-wage employment, see column (2), Panel A. Indeed, the upward movement from mid-wage occupations is entirely driven by workers with at least some college education. The triple difference coefficient estimate, 1.88, together with close to zero and insignificant difference-in-differences coefficient, 0.13, imply that the import competition increases high-wage employment for them, by ($1.88 \times 12 \times 0.284 =$) 6.4 months over the eight post-shock years which translates to a 95 percent increase.[12] At the same time, having a college education also significantly decreases the likelihood of moving to low-wage jobs relative to other exposed mid-wage workers by about half (column 3, Panel A).

In addition to playing a significant role in determining upwards versus downward occupational movements, having a college education also reduces transitions to unemployment or exit from the labor market due to import competition (see columns (4) and (5) of Panel A).

Panel B of Table 4 explores if import competition has any disproportionate impact on mid-wage workers with at most high school education. Are workers with the least education more likely to lose their mid-wage jobs? We find that the answer to this question is no (Panel B of column (1)). On the other hand, a low level of education significantly decreases a worker's chance to move up from mid-wage to high-wage occupations. Column 2 of Panel B shows that import competition does not increase mid-wage workers' chance to move up if workers are high-school educated (0.73 + (-0.75) = -0.02).

In Panel C, we focus on vocational education, an important institution in Europe. Since vocation-specific education can have a differing impact on job transitions of workers depending on the type of vocation, we distinguish manufacturing-specific (e.g., weaving machine operators or industrial cabinet makers) from service vocations (e.g., decorators). All triple difference point estimates in Panel C take the opposite signs for manufacturing- versus service-specific vocational education, confirming this hypothesis.[13] The point estimates in column (1) show larger mid-wage employment losses for workers with manufacturing-specific vocational education (-2.06-1.00 = -3.06) than for workers with service-specific vocational education (-2.06 + 0.87 = -1.19) or even high-school educated workers (-2.02+0.06 = -1.94). At the same time, there is a substantial amount of uncertainty for these estimates, preventing us from concluding any significant disproportionate impact of import competition on manufacturing or service-oriented vocationally educated workers.

[12] We use the 75/25 percentile difference in exposure, which is 0.284 and the average high-wage employment over 2002-2009 of mid-wage workers in the control group, which is 6.7 months.

[13] We adjust equation (3) by controlling for separate aggregate trends for manufacturing and service-specific vocational training.

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

	(1) MID^e_{is}	(2) $HIGH^e_{is}$	(3) LOW^e_{is}	(4) UE^e_{is}	(5) OUT^e_{is}
Panel A.					
ImpComp	-1.991***	0.131	1.439***	0.173	0.680**
	(0.540)	(0.189)	(0.263)	(0.146)	(0.310)
ImpComp x College	-0.099	1.878**	-0.864*	-0.517*	-0.952*
	(0.937)	(0.806)	(0.450)	(0.279)	(0.533)
Panel B.					
ImpComp	-2.020***	0.731**	0.924***	0.106	0.622*
	(0.594)	(0.358)	(0.284)	(0.198)	(0.322)
ImpComp x High School Ed	0.064	-0.755**	0.757**	0.047	-0.049
	(0.538)	(0.337)	(0.336)	(0.204)	(0.403)
Panel C.					
ImpComp	-2.060***	0.242	1.587***	0.068	0.516
	(0.575)	(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 all panels:					
Worker FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Educ. Indicators x Time FEs	✓	✓	✓	✓	✓

Notes: Dependent variables are given at the top of the columns. Estimation of equation (3) adjusted for two instead of one initial characteristic by OLS. Sample is all textile workers in mid-wage occupations as of the initial year 1999. The number of observations in every regression is N = 13,934. The variable ImpComp denotes $Exposure^{99}_{ik} xPostShock_s$ where $Exposure^{99}_{ik}$ is defined as the revenue share of 8-digit CN goods that were subject to removal of quotas for China in 1999 of worker i's employer, k. Robust standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10 %, 5%, and 1% levels, respectively.

Results in column (2) of Panel C show that vocational education is not an essential factor in helping mid-wage workers to move up in the occupational wage hierarchy. College education appears to be a must for import competition to create opportunities for mid-wage workers to move up. Moreover, import competition pushes mid-wage workers down in the occupational hierarchy even if they have vocational education (column 3). At the same time, if oriented toward services, vocational education helps to decrease the extent to which mid-wage workers move down in the occupational wage hierarchy.

Another important finding is seen from columns (4)-(5). Trade-induced unemployment and non-employment are concentrated among mid-wage workers with manufacturing-specific vocational education. This result is in line with the findings of the recent adjustment cost literature and speaks to the specificity of occupations in the manufacturing sector (Utar 2018, Traiberman 2019). Overall, the findings are consistent with the idea that vocational education does not typically provide the more general skills necessary for upward movements on the job ladder. On the other hand, service-focused vocational education decreases a worker's extent of moving down in the wage hierarchy, and also increases employment in comparison to manufacturing-specific vocational education.

We also explore the role of education for the occupational movement of high- and low-wage workers due to import competition. These results, shown in Tables B-10 and B-11, respectively, confirm the importance of education for shaping import competition-induced movements in the occupational wage hierarchy. To sum up, there is strong evidence that education influences the way exposed textile workers' transitions across broad wage groups yield the job polarization pattern in the aggregate.

5.4 Job Polarization and Movements across Sectors

In this section, we examine the sectoral dimension of trade-induced job polarization, and in particular, we explore the role of a trade-induced shift from mid-wage jobs abundant manufacturing towards services. To do that, we now track workers' movements not only in terms of their occupations (high-, low-, and mid-wage) but also in terms of sectors. Table 5 shows these results. Panel A focuses on mid-wage workers as of 1999 and shows the impact of import competition on mid-, high, and low-wage occupations across manufacturing and services. For example, the dependent variables for row 1 in Panel A are the number of years in employment in mid-, high-, and low-wage occupations in the manufacturing sector, respectively in columns (1) through (3).

Column 1 of Panel A shows that the entire trade-induced reduction in mid-wage employment is driven by employment loss in the manufacturing sector. The coefficient estimate of -2.706 together with the 75/25 percentile exposure of competition implies more than nine months of reduction in mid-wage manufacturing employment among mid-wage workers. Indeed, import competition raises employment in mid-wage service occupations for these workers, but this increase is not sufficient to recover the loss of mid-wage employment in the manufacturing sector. Column 2 shows that mid-wage workers exposed to import competition have significantly higher likelihood of moving to high-wage occupations in services but not in high-wage occupations in manufacturing. Finally, column 3 of Panel A shows that import competition pushes mid-wage workers towards low-wage occupations both in manufacturing and services, though quantitatively, import competition pushes mid-wage workers more strongly toward low-wage occupations in the service sector.

By distinguishing typical high-wage (finance, business, wholesale) versus low-wage service industries (retail, personal), in Table B-12 in the Appendix we show that mid-wage workers move to low-wage occupations both in finance, business, and wholesale industries but also in traditionally low-wage industries such as retail and personal services (see Table B-12 in the Appendix). When they move up to high-wage occupations in the service sector, these occupations tend to be in high-wage industries (column 2, Panel A of Table B-12).

Panel B focuses on trade-induced movements of high-wage workers as of 1999. We know from Figure 5 that high-wage workers are not immune from employment loss, but over time they recover from the high-wage employment loss. Here we see that while the loss of high-wage employment is driven by the loss of manufacturing jobs, the recovery is driven entirely by the gain in high-wage employment in the service sector (column 2 of Panel B in Table 5), typically in Finance/Business/Wholesale services (Panel B of Table B-12).

Finally, in panel C, we focus on low-wage workers as of the year 1999. For these workers, too, import competition causes them to move away from their initial occupations in the manufacturing sector towards high-wage occupations in the service sector.

In sum, while import competition indiscriminately causes employment losses for all workers across the occupational wage distribution in the manufacturing sector, it also pushes them towards the tails of the distribution, especially in services. This is in line with large employment losses documented in the manufacturing sector in response to the China trade shock. At the same time, these results also show that import competition contributes to economy-wide job polarization, and sectoral displacement is an important mechanism for trade-induced job polarization.

Table 5: Occupational Movements of Workers by Sector

	(1) MID^e_{is}	(2) $HIGH^e_{is}$	(3) LOW^e_{is}
Panel A. Sample: Mid-wage Workers (N = 13,934)			
1. Manufacturing			
	-2.706***	-0.070	0.260**
	(0.562)	(0.151)	(0.125)
2. Services			
	0.808***	0.364**	1.160***
	(0.273)	(0.159)	(0.234)
Panel B. Sample: High-wage Workers (N = 4,294)			
1. Manufacturing			
	-0.177	-2.407***	-0.074
	(0.194)	(0.772)	(0.057)
2. Services			
	0.727***	2.650***	-0.155
	(0.231)	(0.463)	(0.143)
Panel C. Sample: Low-wage Workers (N = 2,496)			
1. Manufacturing			
	-0.381	0.216	-1.150**
	(0.477)	(0.225)	(0.544)
2. Services			
	0.246	1.632***	0.501
	(0.298)	(0.467)	(0.447)

Notes: Dependent variables are mid-, high-, and low-wage employment respectively in columns (1)-(3) within particular industries given in the panel headings. The table shows the coefficient on ImpComp, defined as $Exposure^{99}_{ik} \times PostShock_s$ (equation (1)) by OLS. The estimation samples are all 1999 textile workers in mid-wage occupations, in high-wage occupations, and in low-wage occupations, respectively in Panel A, B, and C. Robust standard errors clustered at the (initial) firm-level are reported in parentheses. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

6 Rising Import Competition and Job Polarization in Denmark's Entire Private-Sector Economy

By exploiting the dismantling of import quotas on China's textile and clothing exports to the EU, the previous analysis has shown that the mobility of workers between occupations due to rising import competition has contributed to a pattern of job polarization in Denmark. We have also shown that education is key for determining the direction, up or down, that affected mid-wage workers take in the wage distribution. Furthermore, our findings indicate that movements from the manufacturing sector toward services has played an important role in the emergence of the job polarization pattern.

A natural question is the extent to which these results for textile workers generalize to Denmark's entire economy. To this end, we employ an instrumental variable approach based on the plausibly exogenous increase in China's domestic productivity to study the impact of rising import competition across rather disaggregated six-digit industries for Denmark's entire private-sector economy (see Section C). We find broad similarities to our results for textile workers. Rising import competition has induced occupational movements in Denmark's labor force that have contributed to job polarization (Table C-1), the level of a worker's education has helped to determine the direction of worker movement (Table C-4), and the sectoral shift towards services matters for job polarization in Denmark's entire labor force (Table C-5) as it does for textile workers. Moreover, we provide evidence that the impact of rising import competition for job polarization is not spuriously capturing the effect of technological change or offshoring (Table C-6). Furthermore, in our setting rising import competition has quantitatively a comparably large effect on the hollowing-out of mid-wage employment as routine-biased technical change, see Section C for these results.

7 Trade versus Technology: Worker Adjustment and Tasks

Routine tasks are characteristic of many mid-skilled, mid-wage jobs, such as book-keeping, clerical, or assembly line work. Because the task contents of these occupations follow precise, well-defined procedures that can be codified in computer software and performed by machines, the recent technological change has been so far emphasized as the driver of job polarization. In this section, we examine the extent to which the impact of rising import competition can be separated from the effects of technical change in causing shrinking mid-wage jobs.

We employ information on individual tasks from the Occupational Information Network (O*NET) database and match the occupation-level task content data with our worker-level data at the four-digit occupation level (ISCO) based on workers' four-digit occupations as of 1999. We separately focus on four main types of tasks, namely routine, non-routine, manual, and cognitive (non-manual) tasks. These four task categories allow us to span a two-dimensional task space to achieve a deeper understanding of the relationship between import competition and technology in generating job polarization.

In the following, we estimate triple difference regressions with two-way fixed effects (as in equation 3) where the characteristic C_i is the importance of a particular task in the worker's four-digit occupation and the dependent variable is the years of employment in mid-wage occupations. To ensure that our findings are robust, we employ multiple O*NET variables that are associated with each type of task as commonly employed in the literature (Autor, Levy, Murnane 2003; Crino 2010; Hummels, Jørgensen, Munch, and Xiang 2014). Each task characteristics variable is a continuous variable showing the intensity of that particular task in a given occupation. Table 6 reports the results for tasks that heavily involve manual activities.[14]

We see that workers who perform tasks in which *Repetitive Motions* are important disproportionately suffer from employment losses in mid-wage occupations due to import competition (column (1)).[15] Quantitatively, the impact of import competition on losing mid-wage jobs is almost three times as large for workers that perform repetitive motions compared to other workers. Another manual task is *Manual Dexterity*. Results in column (2) show that workers performing tasks where manual dexterity is important, have significantly lower mid-wage occupation employment due to 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.

To sum up, import competition has an especially negative effect on mid-wage employment if the worker's occupation is intensive in repetitive motions, manual or finger dexterity, or if the pace of work is determined by the speed of machines. It is worth noting 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 for mid-wage employment, on

[14]Recently the European Commission also started an O*NET like program called European Skills, Competences, Qualifications and Occupations (ESCO). We prefer to utilize O*NET which is sponsored by the U.S. Department of Labor/Employment and Training Administration in part because the eight European countries do not include Denmark.

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

Table 6: 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: Estimation of equation 3 by OLS. The dependent variable in all columns is the years of employment in mid-wage occupations. In each regression, a specific task variable employed in that regression is indicated in the column heading. The estimation sample is all 1999 textile and clothing workers. PDSE stands for Pace of work is Determined by the Speed of the Equipment. Robust standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10 %, 5% and 1% levels respectively.

the right side of Table 6 we show results for manual tasks that have a relatively low level of routine-ness. Take *Gross Body Coordination*, for example, which involves the coordination of simultaneous movements of different parts of the body. 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 highly repetitive and programmable, *Gross Body Coordination* can be seen as a non-routine manual task (Acemoglu and Autor 2010). 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 Chinese import competition do. Results for *Multi-limb Coordination* are similar (column (6)). Another non-routine-manual task is *Response Orientation*, which involves behavioral and physiological responses to a novel or potentially threatening stimulus (focusing attention, turning head and body to it, arousal of activating and nervous system). Workers in jobs for which such tasks are important have disproportionately lower employment in mid-wage occupations compared to other trade-exposed workers (column (7)).

Comparing the left and the right sides of Table 6, it is evident that the degree to which import competition with China has a negative effect on mid-wage employment is similarly strong across workers performing non-routine-manual tasks and routine-manual tasks.[16] The key finding is that workers in occupations intensively performing manual tasks are most vulnerable to the hollowing out of mid-wage occupations due to import competition.

If workers performing manual tasks disproportionately experience decreased mid-wage employment, it should also be the case that workers performing non-manual (cognitive) tasks experience these effects comparatively less. Moreover, does the impact differ depending on how routine or non-routine these cognitive tasks are? This is examined in Table 7. We expect there to be some correlation between jobs intensive in 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 high level of cognitive skill, but it is a rather structured, routine task. The first routine cognitive task in our analysis is *Evaluating Information to Determine Compliance with Standards*.

We find that workers with occupations where *Evaluating Information* is important experience disproportionately less mid-wage employment reductions than the typical worker due to import competition (column (1)). In fact, there are virtually no mid-wage employment reductions for workers

[16] These results are based on all 1999 textile workers so that we can fully utilize the task content variation across all occupations, though if we restrict the sample to mid-wage workers only, results are similar (see Table B-13).

in these cognitive but also routine-intensive jobs. A similar result is obtained for another routine-cognitive task, workers with occupations who frequently repeat the same task such as checking entries in a ledger, see column (2).

On the right side of Table 7 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 decreased 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.[17]

Table 7: 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: Estimation of equation (3) by OLS. The dependent variable in all columns is the years of employment in mid-wage occupations. In each regression, the specific task variable is indicated in the column heading. The estimation sample is all 1999 textile and clothing workers. Regressions include worker and time fixed effects as well as the interaction between time fixed effects and the task variable. Robust standard errors clustered at the firm level are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

Overall, workers whose occupations are intensive in manual tasks are central to the import competition-

[17] We find broadly similar results for the smaller sample of 1999 textile workers who are employed in mid-wage occupations, see Table B-14.

induced hollowing out of mid-wage employment that is a hallmark of job polarization. The finding that manual task intensity matters for the impact of import competition regardless of the routine-ness of these manual tasks is important because it establishes that the impact of rising import competition is independent from that of technology. Our results with the economy-wide sample in Table C-6 also complement earlier findings that task routine-ness contributes to job polarization because it accelerates routine-biased technical change. However, if job polarization would depend only on the routine-ness of tasks, there would be no disproportionate mid-wage employment loss for workers completing non-routine manual tasks (as seen from Table 6, right side), and there would be significant mid-wage employment losses for workers performing routine cognitive tasks (compare with Table 7, left side).

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

8 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 examine the impact of the removal of quantitative restrictions on China's textile exports following China's entry into the WTO in 2002 because this trade policy change provides a unique quasi-natural experiment where industry shocks play a limited role. Import competition leads to a significant negative effect on mid-wage jobs at the same time that exposure to import competition increases employment in both high- and low-wage jobs. We also generalize this finding by employing an instrumental-variables approach for virtually the entire private-sector labor force of Denmark. Furthermore, by comparing the impact of import competition from China side-by-side with that of other factors we show that, quantitatively, import competition has a similarly large effect on the hollowing-out of mid-wage employment as routine-biased technical change over 1999-2009. By showing that import competition from China leads to job polarization, we add a major labor market outcome as a consequence of globalization which brings with it both misfortune and opportunity.

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, regardless of how routine or non-routine these tasks are.

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 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.

References

[1] **Acemoglu, Daron, and David Autor** 2010. “Skills, Tasks and Technologies: Implications for Employment and Earnings”, Chapter 12 in the Handbook of Labor Economics, Volume 4, Orley Ashenfelter and David E. Card (eds.), Amsterdam: Elsevier.

[2] **Acemoglu, Daron, and Pascual Restrepo** 2020. “Robots and Jobs: Evidence from US Labor Markets”, *Journal of Political Economy*, 128(6): 2188–2244.

[3] **Autor, David** 2010. “The Polarization of Job Opportunities in the U.S. Labor Market: Implications for Employment and Earnings”, Center for American Progress and The Hamilton Project.

[4] **Autor, David, and David Dorn** 2013. “The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market”, *American Economic Review*, 103(5): 1553-1597.

[5] **Autor, David, David Dorn, and Gordon Hanson.** 2013. “The China Syndrome: Local Labor Market Effects of Import Competition in the United States”, *American Economic Review*, 103(6): 2121-2168.

[6] **Autor, David, David Dorn, and Gordon Hanson.** 2015. “Untangling Trade and Technology: Evidence from Local Labor Markets”, *Economic Journal*, 125(584): 621-646.

[7] **Autor, David, David Dorn, and Gordon Hanson.** 2016. “The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade”, *Annual Review of Economics*, 8:205–40.

[8] **Autor, David, David Dorn, Gordon Hanson and Jae Song.** 2014. “Trade Adjustment: Worker Level Evidence”, *The Quarterly Journal of Economics*, 129: 1799-1860.

[9] **Autor, David, Lawrance F. Katz, and Melissa S. Kearney** 2006. “The Polarization of the U.S. Labor Market”, *American Economic Review: Papers and Proceedings*, 96(2), 189-193.

[10] **Autor, David, Lawrance F. Katz, and Melissa S. Kearney** 2008. “Trends in U.S. Wage Inequality: Revising the Revisionists”, *The Review of Economics and Statistics*, 90(2), 300-323.

[11] **Autor, David, Levy, Frank, and Richard Murnane** 2003. “The Skill-Content of Recent Technological Change: An Empirical Investigation”, *Quarterly Journal of Economics*, 118, 1279-1333.

[12] **Bertrand, Marianne, Esther Duflo and Sendhil Mullainathan** 2004. “How Much Should We Trust Differences-in-Differences Estimates?”, *The Quarterly Journal of Economics*, No:119(1): 249-275.

[13] **Bessen, James, Maarten Goos, Anna Salomons, and Wiljan van der Berge** 2019. “Automatic Reaction - What Happens to Workers at Firms that Automate?”, Boston University working paper, February.

[14] **Bloom, Nicholas, Mirko Draca, and John Van Reenen** 2016. “Trade induced technical change? The impact of Chinese imports on innovation and information technology”, *Review of Economic Studies*, 83: 87-117.

[15] **Bobbio, Emmanuele and Henning Bunzel** 2018. “The Danish Matched Employer-Employee Data”, Aarhus University, Economics Working Papers 2018-3.

[16] **Crino, Rosario** 2010. “Service Offshoring and White-Collar Employment”, *Review of Economic Studies*, 77(2):595-632

[17] **Dauth, Wolfgang, Sebastian Findeisen, and Jens Suedekum** 2021. “Adjusting to Globalization in Germany”, *Journal of Labor Economics*, 39:1, 263-302.

[18] **Feenstra, Robert C.** (2000), "Introduction", in The Impact of International Trade on Wages, R. C. Feenstra (editor), National Bureau of Economic Research, pp. 1-11.

[19] **Goos, Maarten, and Alan Manning** 2007. "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain", *The Review of Economics and Statistics*, 89(1), 118-133.

[20] **Goos, Maarten, Alan Manning, and Anna Salomons** 2014. "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring", *American Economic Review*, 104(8), 2509-2526.

[21] **Graetz, Georg, and Guy Michaels** 2018 "Robots at Work", *Review of Economics and Statistics*, 100(5): 753-768.

[22] **Harrigan, James, and Geoffrey Barrows** 2009. "Testing the Theory of Trade Policy: Evidence from the Abrupt End of the Multifiber Arrangement", *The Review of Economics and Statistics*, 91(2), 282-294.

[23] **Harrigan, James, Ariell Reshef, and Farid Toubal** 2016. "The March of the Techies: Technology, Trade, and Job Polarization in France, 1994-2007", NBER Working Paper No. 22110.

[24] **Hummels, David, Rasmus Jorgensen, Jacob Munch, and Chong Xiang** 2014. "The Wage Effects of Offshoring: Evidence From Danish Matched Worker-Firm Data", *American Economic Review*, 104(6): 1597-1629.

[25] **McLaren, John.** 2022. "Trade Shocks and Labor-Market Adjustment". *Oxford Research Encyclopedia of Economics and Finance*, Forthcoming, Available at SSRN

[26] **Michaels, Guy, Ashwini Natraj, and John Van Reenen** 2014. "Has ICT Polarized Skill Demand? Evidence From Eleven Countries Over Twenty-Five Years", *The Review of Economics and Statistics*, 96(1), 60-77.

[27] **Pierce, Justin R. and Peter K. Schott.** 2016. "The Surprisingly Swift Decline of U.S. Manufacturing Employment", *American Economic Review*, 106(7): 1632-62.

[28] **Statistics Denmark** 2015. Integrated Database for Labor Market Research (IDA) Database. Provided and maintained by ECONAU/LMDG and Statistics Denmark.

[29] **Traiberman, Sharon** 2019. "Occupations and Import Competition: Evidence from Denmark", *American Economic Review*, 109 (12): 4260-4301.

[30] **Utar, Hale** 2014. "When the Floodgates Open: "Northern" Firms' Response to Removal of Trade Quotas on Chinese Goods", *American Economic Journal: Applied Economics*, 6(4): 226-250.

[31] **Utar, Hale** 2018. "Workers beneath the Floodgates: Impact of Low-Wage Import Competition and Workers' Adjustment", *The Review of Economics and Statistics*, 100(4): 631-647.

Online Appendix:

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

Wolfgang Keller
Hâle Utar

Contents (Appendix)

A Measuring Employment Polarization

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. This figure is constructed by using IDA database to calculate the change between 1999 and 2009 in the share of employment accounted for by three-digit ISCO occupations encompassing all of the non-farm employment in Denmark. Occupations are ranked by the mean log wage of workers in each occupation in 1999.

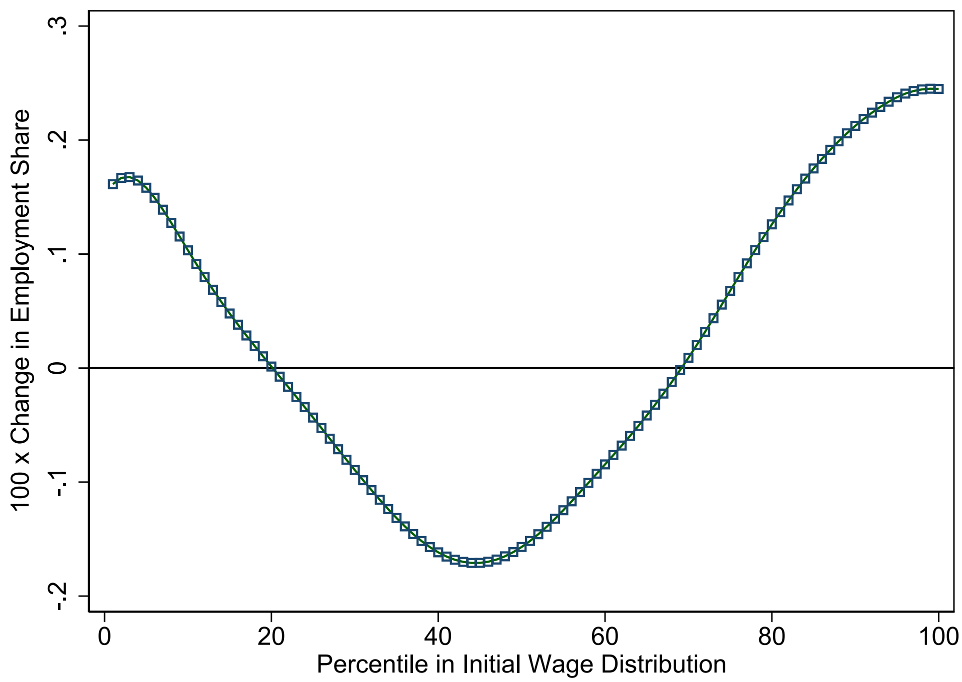


Figure A-1: Job Polarization in Denmark 1999-2009

Notes: Smoothed employment share changes (Lowess; bandwidth = 0.75) for all non-agricultural occupations at the three-digit level ranked according to their 1999 hourly wage.

A.1 Danish Occupation Classification

In Denmark, occupation codes are administratively collected. They are important for collective wage bargaining and unemployment insurance purposes, and the extent of mis-classification is small.[18]

[18]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.

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.

A.2 Classification of Occupations by Wage across European Countries

The study by Goos, Manning, and Salomons (2014) use 1993 wages across European countries (including Denmark) to classify occupations into high-, mid-, and low-wage bins. Their classification, shown in Table A-1, is consistent with ours shown in Table 1.

Table A-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).

B Removal of Textile Import Quotas on China as a Quasi-natural Experiment

B.1 Overview

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.

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 (Utar 2014). 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.

By the year 2009, Chinese textile and clothing exports to Denmark relative to domestic value added had almost tripled. 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 in Denmark at firms subject to the quota removals faced increased import competition from China starting in the year 2002.[19] We use the

[19] 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).

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 (see Table 3).

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	0.257	0.000
Age	39.560	39.757
Immigrant	0.052	0.069
College	0.134	0.114
Vocational Ed.	0.355	0.349
Union Membership	0.841	0.803
UI Membership	0.920	0.900
Labor Market Experience	14.909	14.564
Log Annual Salary	12.103	12.085
Machine Operator	0.367	0.385
Mid-wage Occupation	0.634	0.692
High-wage Occupation	0.236	0.176
Low-wage Occupation	0.124	0.115

Notes: Variables Immigrant, Union Membership, UI Membership, High Wage, Mid Wage and Low Wage Occupations, as well as College, Vocational Education are indicator variables. Immigrant includes both first and second generation immigrants. 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 for the analysis of the textile trade liberalization.

Table B-2: Key Outcome Variables for the Textile Quota Removal

	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, $HIGH_{is}^{hrs}$	1.096	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
Earnings in High Wage Jobs, $HIGH_{is}^{wage}$	1.480	4.786	20,974
Earnings in Mid Wage Jobs, MID_{is}^{wage}	2.729	5.000	20,974
Earnings 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 the worker's own 1996-1999 average annual hours worked and wage, respectively.

B.2 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 set of manufactured products 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-3 for the placebo analysis based on data aggregated into two-periods (pre- versus post-1995), and Table B-4 for the placebo analysis with data and coefficients at an annual frequency.[20]

Table B-3: Potential Pre-Trends: A Placebo Analysis for 1990-99 with Two Periods

	(1) Earnings	(2) Income	(3) Hours	(4) HourlyWage	(5) Unemployment
Exposure x Post 1995	0.050	-0.046	0.039	-0.013	-0.173
	(0.079)	(0.085)	(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 period fixed effects. Robust standard errors clustered by 1999 firm in parentheses. 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 as defined in Equation 2.

[20] The placebo analysis back to 1990 loses a small number of observations as some of the workers are too young to be in the labor market in the early years, but that does not have a major effect on our results since the sample average age is forty as of 1999.

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

	(1) Earnings	(2) Income	(3) Hours	(4) HourlyWage	(5) Unemployment
Exposure × Y90	-0.166	-0.061	-0.053	-0.012	-0.159
	(0.136)	(0.134)	(0.067)	(0.059)	(0.389)
Exposure × Y91	-0.140	-0.046	-0.049	0.021	-0.193
	(0.121)	(0.134)	(0.068)	(0.054)	(0.401)
Exposure × Y92	-0.053	0.016	-0.010	0.025	-0.353
	(0.116)	(0.123)	(0.06)	(0.052)	(0.383)
Exposure × Y93	-0.043	0.069	0.031	-0.007	-0.018
	(0.106)	(0.103)	(0.067)	(0.046)	(0.416)
Exposure × Y94	-0.039	0.078	0.039	-0.04	-0.341
	(0.086)	(0.089)	(0.063)	(0.044)	(0.361)
Exposure × Y95	-0.055	0.058	0.036	-0.039	-0.398
	(0.083)	(0.077)	(0.063)	(0.036)	(0.374)
Exposure × Y96	-0.057	0.058	0.009	-0.026	-0.387
	(0.076)	(0.061)	(0.06)	(0.034)	(0.400)
Exposure × Y97	-0.060	-0.027	0.034	-0.038	-0.292
	(0.068)	(0.051)	(0.056)	(0.033)	(0.326)
Exposure × 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	83,509	83,509	101,246
Worker FEs	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓

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. Robust standard errors clustered by 1999 firm in parentheses. 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 as defined in Equation 2. Yxx indicates a fixed effect for year 19xx.

B.3 Placebo Assignment of Exposure

As an additional check on identification, we assign the treatment status of textile firms randomly. We do so 100 times and run equation (1) with each of the simulation samples. The average of the results from this procedure are reported in Table B-5.

Table B-5: The Impact of Import Competition with Random Exposure

	(1) MID_{is}^{e}	(2) $HIGH_{is}^{e}$	(3) LOW_{is}^{e}	(4) UE_{is}^{e}	(5) OUT_{is}^{e}
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.

We see that when exposure is randomly assigned, average coefficients are close to zero, as they should be. This provides additional support that we estimate the causal effect of the textile quota removal.

B.4 Employment Opportunities Measured by Full-time Employment, Earnings and Hours

Table B-6 reports results for the 1999 textile workers in response to the removal of import quotas on China in terms of their full-time employment, hours worked, and earnings.

Table B-6: Alternative Measures of Employment by Occupations Ranked by Wage

	(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 units of worker i's own 1996-1999 average annual hours worked and annual earnings, respectively. Robust standard errors clustered at the (1999) firm level are in parentheses. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

B.5 Dynamic Effects by Broad Wage Group

First, Table B-7 provides the coefficients and standard errors that underlie Figure 3; see the text for the discussion.

Table B-7: The Dynamics of Occupational Movements of 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	0.005	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	-0.071	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 firm level are in parentheses. *, ** and *** indicate significance at the 10%, 5%, and 1% levels respectively.

Second, Table B-8 presents the evolution of the impact of rising import competition on textile workers who in 1999 are employed in low-wage occupations. This accompanies Figure 4 in the text. 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 wage groups. However, the number of workers in this group is relatively small.

Table B-8: The Dynamics of Occupational Movements of 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	0.049	-0.090	-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	-0.030	0.184**	0.369***	0.613***	0.876***	1.214***	1.522***	1.828***
	(0.083)	(0.071)	(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
	(0.097)	(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 firm level are in parentheses. *, ** and *** indicate significance at the 10%, 5%, and 1% levels respectively.

Finally, Table B-9 presents the coefficient estimates for those textile workers that were in 1999 employed in high-wage occupations. These regression coefficients are supplemental to Figure 5 in the text.

Table B-9: Occupational Movements of 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	-0.018	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 firm level are in parentheses. *, ** and *** indicate significance at the 10%, 5%, and 1% levels respectively.

B.6 Responses to Rising Import Competition and Education

This section presents results on the effect of education on the occupational movements of high-wage and low-wage textile workers in response to rising import competition; they are given in Tables B-10 and B-11, respectively, and they complement Table 4 in the text on the role of education for mid-wage textile workers's mobility across high-, mid-, and low-wage jobs.

Table B-10: Education and Occupational Movements of High-Wage Workers

	(1)	(2)	(3)	(4)	(5)
	MID^e_{is}	$HIGH^e_{is}$	LOW^e_{is}	UE^e_{is}	OUT^e_{is}
Panel A.					
ImpComp	0.048	0.865	-0.506**	0.155	0.179
	(0.419)	(0.630)	(0.205)	(0.168)	(0.295)
ImpComp x College	1.335**	-1.357	0.707***	0.059	-0.580
	(0.658)	(0.957)	(0.252)	(0.266)	(0.412)
Panel B.					
ImpComp	0.565*	-0.218	-0.055	0.275**	0.003
	(0.327)	(0.735)	(0.171)	(0.132)	(0.251)
ImpComp x High School Ed	-0.057	2.208*	-0.710*	-0.400	-0.120
	(0.740)	(1.232)	(0.367)	(0.311)	(0.560)
Panel C.					
ImpComp	0.984***	0.678	-0.229	0.087	-0.341
	(0.351)	(0.691)	(0.195)	(0.169)	(0.287)
ImpComp x Manuf Voc Ed	-1.436*	-2.987**	0.869*	0.560	1.410**
	(0.794)	(1.369)	(0.490)	(0.343)	(0.658)
ImpComp x Service Voc Ed	-1.235*	0.006	-0.345	0.176	0.575
	(0.631)	(0.875)	(0.324)	(0.266)	(0.554)
For all panels:					
Worker FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Educ. Indicators x Time FEs	✓	✓	✓	✓	✓

Notes: Dependent variable at top of column. Estimation of equation (3) by OLS. Panel C regressions follow equation (3) adjusted for two characteristics. Sample is all textile workers in high-wage occupations as of the year 1999. The number of observations in every regression is N = 4,294. The variable ImpComp denotes $Exposure^{99}_{ik} \times PostShock_s$ where $Exposure^{99}_{ik}$ is defined as the revenue share of 8-digit CN goods that were subject to removal of quotas for China in 1999 of worker i's employer, k. 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.

Table B-11: Education and Occupational Movements of Low-Wage Workers

	(1) MID^e_{is}	(2) $HIGH^e_{is}$	(3) LOW^e_{is}	(4) UE^e_{is}	(5) OUT^e_{is}
Panel A.					
ImpComp	0.102	1.687***	-0.679	-0.020	-0.592
	(0.599)	(0.497)	(0.601)	(0.279)	(0.436)
ImpComp x College	4.015**	2.847	2.242	0.332	0.027
	(2.023)	(2.119)	(2.378)	(0.842)	(1.059)
Panel B.					
ImpComp	0.332	2.283***	-1.771**	0.325	-0.396
	(0.776)	(0.651)	(0.891)	(0.256)	(0.599)
ImpComp x High School Ed	-0.775	-0.821	2.080**	-0.550	-0.324
	(0.818)	(0.787)	(0.938)	(0.421)	(0.787)
Panel C.					
ImpComp	-0.761	1.713***	0.110	-0.157	-0.517
	(0.656)	(0.617)	(0.651)	(0.341)	(0.521)
ImpComp x Manuf Voc Ed	4.907**	-1.415	-1.719	1.486*	1.202
	(2.236)	(1.969)	(2.602)	(0.844)	(1.620)
ImpComp x Service Voc Ed	-0.527	0.189	0.368	-0.365***	-0.501*
	(0.382)	(0.333)	(0.526)	(0.124)	(0.299)
For all panels:					
Worker FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Educ. Indicators x Time FEs	✓	✓	✓	✓	✓

Notes: Dependent variable at top of column. Estimation of equation (3) by OLS. Panel C regressions follow equation (3) adjusted for two characteristics. Sample is all textile workers in low-wage occupations as of the year 1999. The number of observations in every regression is N = 2,496. The variable ImpComp denotes $Exposure^{99}_{ik} \times PostShock_s$ where $Exposure^{99}_{ik}$ is defined as the revenue share of 8-digit CN goods that were subject to removal of quotas for China in 1999 of worker i's employer, k. 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.

B.7 Sectoral Shifts to the Service Sector and Job Polarization

This section provides more information on the nature of the shift of exposed textile workers to the services sector by distinguishing different service industries. It complements the analysis surrounding Table 5 in the text.

Table B-12: Occupational Movements by Wage Group and Sector

	(1)	(2)	(3)
	MID^e_{is}	$HIGH^e_{is}$	LOW^e_{is}
Panel A. Sample: Mid-wage Workers (N = 13,934)			
1. Finance, Business, Wholesale			
	0.667***	0.218**	0.313***
	(0.235)	(0.110)	(0.0913)
2. Retail, Personal			
	-0.038	0.041	0.133**
	(0.059)	(0.026)	(0.060)
Panel B. Sample: High-wage Workers (N = 4,294)			
1. Finance, Business, Wholesale			
	0.516***	1.538***	0.028
	(0.151)	(0.367)	(0.046)
2. Retail, Personal			
	0.040	-0.027	-0.036
	(0.059)	(0.090)	(0.057)
Panel C. Sample: Low-wage Workers (N = 2,496)			
1. Finance, Business, Wholesale			
	0.160	0.851***	0.341
	(0.170)	(0.288)	(0.226)
2. Retail, Personal			
	-0.002	0.116	-0.065
	(0.125)	(0.108)	(0.158)

Notes: Dependent variables are mid-, high-, and low-wage employment respectively in columns (1)-(3) within particular industries given at panel headings. Table shows the coefficient on ImpComp, defined as $Exposure^{99}_{ik} \times PostShock_s$ (equation (1)) by OLS. Sample is all 1999 textile workers in mid-wage occupations, in high-wage occupations, and in low-wage occupations, respectively in Panel A, B, and C. Robust standard errors clustered at the (initial) firm-level are reported in parentheses. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

B.8 Occupational Movements and Tasks of Mid-wage Textile Workers

Section 7 in the text provides information on the role of tasks for the occupational movements of workers. Here we complement this analysis by focusing on 1999 textile workers who were employed in mid-wage occupations instead of all 1999 textile workers. The analysis for manual tasks is given in Table B-13, while results for cognitive tasks are shown in Table B-14. Notice that workers completing manual tasks are more negatively affected by rising import competition, and this is the case whether the task is routine or not routine.

Table B-13: 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. Robust standard errors clustered at the (initial) firm-level are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

Table B-14: 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***	-1.683***	-1.208*	-1.390*	-1.337***
	(0.595)	(0.516)	(0.698)	(0.772)	(0.492)
ImpComp x Task	0.301	1.096***	0.559	0.606	1.057**
	(0.544)	(0.181)	(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. Robust standard errors clustered at the (initial) firm-level are reported in parentheses. *, ** and *** indicate significance at the 10%, 5%, and 1% levels respectively.

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

C Generalizing the Results Using the Universe of Private Sector Workers

Do the findings on textile workers generalize for the entire economy? Here we address this point by examining labor market trajectories of Denmark's entire 1999 private-sector cohort. The sample characteristics as of 1999 are summarized in Table 2, it includes all workers who were between 18 and 50 years old and employed in the Danish private sector as of 1999.[21] The size of our sample is N = 900,329 workers, indexed by i. By holding constant this sample of workers we can construct a worker-level exposure variable that is based on workers' six-digit industry of employment as of 1999, the initial year. This has the advantage that it is not endogenous to the workers' subsequent job changes.

[21] As before, we track and observe all job transitions of workers in our sample, including their movements to or out of public sectors.

C.1 Rising Import Competition Captured by Cross-Industry Variation

The analysis of the entire private sector exploits the plausibly exogenous 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. Our economy-wide import shock is defined as the change in imports from China between the years 2009 and 1999 over 1999 absorption–production plus imports minus exports– in a given six-digit (NACE) industry j, and it is denoted by $\Delta ImpPent_j$.

$$\Delta ImpPent_j = \frac{M^{CH}_{j,2009} - M^{CH}_{j,1999}}{C_{j,1999}}. \tag{C-1}$$

Here, $M^{CH}_{j,t}$ denotes Denmark's imports from China in industry j and year $t = \{1999, 2009\}$, and $C_{j,1999}$ is Denmark's consumption in initial year $t = 1999$, equal to production minus exports plus imports in the six-digit industry j.

Exposure to import competition for each worker is determined by the worker's six-digit industry of employment as of the year 1999, denoted as $\Delta ImpPent^J_i$, where j indexes the six-digit industry of worker i.

Figure C-1 shows the change in Chinese import penetration between 1999 and 2009 across six-digit 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 strongly even within two-digit sectors.

Distinguishing more than six hundred industries is important because, for example, even though metal forming and steam generator products are both part of the fabricated metal products industry, and they both have about 50% mid-wage workers, yet the change in import penetration over the sample period for steam generator products was much lower than for metal forming products. Our approach also allows us to control for two-digit industry fixed effects to avoid capturing differences in the growth of Chinese imports across industries due to, e.g., rising automation or offshoring based on technological differences.

C.2 Import Competition as a Source of Economy-wide Job Polarization

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

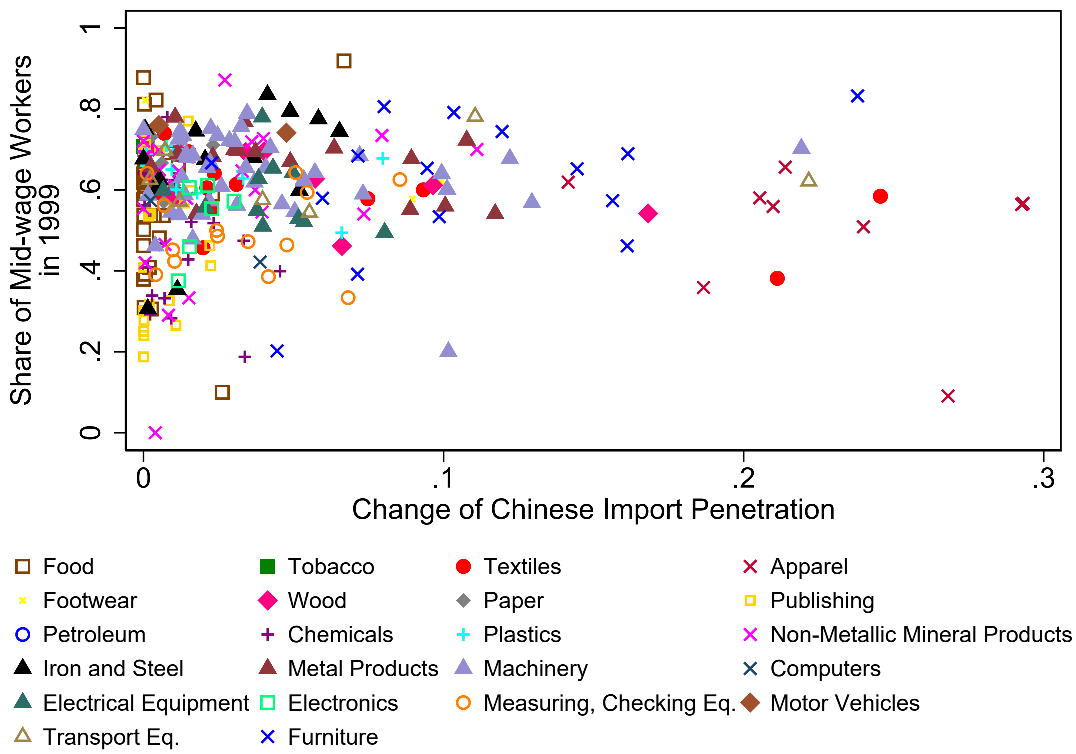


Figure C-1: Mid-wage Workers and Import Competition from China

Notes: Shown is the change in Chinese import penetration between 1999 and 2009 across six-digit manufacturing industries, plotted against the share of workers in mid-wage jobs in 1999. The import penetration rate data are truncated at 0 and 0.5 for scaling purposes. Products belonging to the same two-digit industry are given labels with the same color and shape.

$$MID_i^e = \alpha_0 + \alpha_1 \Delta ImpPent_i^J + Z_i^W + Z_i^F + Z_i^J + \varepsilon_i. \quad \text{(C-2)}$$

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.[22]

Firm and industry characteristics are derived from workers' employment as of 1999. Because firms can be important for affecting a worker's 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 (separation rate). Since technological change is a potentially important driver of job polarization, in addition to two-digit industry fixed effects, we control for technological change effects by including two-digit occupation fixed effects and the share of workers with information technology (IT) education at the six-digit industry level. Importantly, we also employ the growth of employment for 1993-99 as a pre-trend control at the six-digit level. The full list of our control variables is listed in the Notes to Table C-1 as well as in Table C-2, and in addition, sources are given in Table E-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 the 1999-2009 change in Chinese imports in eight other high-income countries over Denmark's absorption as of 1996:

$$\Delta HIP_j^{CH} = \frac{OM_{j,2009}^{CH} - OM_{j,1999}^{CH}}{C_{j,1996}}, \quad \text{(C-3)}$$

where $OM_{j,t}^{CH}$ is the total value of imports in the corresponding six-digit industry j in eight high-income countries at year t.[23] To address possible sorting in anticipation of import changes, our instrumental variables approach utilizes consumption levels from the year 1996. Chinese imports growth 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 (Amiti and Freund 2010; Brandt, Hsieh, and Zhu 2008).[24] We strengthen this approach using two structural measures of openness. First, there is a measure

[22]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. 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. Table C-7 provides summary statistics on the outcome variables used in this analysis.

[23]They are Australia, Finland, Germany, Japan, the Netherlands, New Zealand, Switzerland, and the United States.

[24]The approach adopted here is similar to Autor, Dorn, and Hanson (2013).

of transportation costs, denoted as $Open_j^{Dist}$, which is the log of the weighted sum of bilateral distances to the import source countries, where the weights are the import source countries' shares of industry imports as of 1996:

$$Open_j^{Dist} = log \sum_c \{\omega_c^j \times d_{DNK,c}\}, \tag{C-4}$$

where $d_{DNK,c}$ is the distance between Denmark and country c and ω_c^j is industry j's import share from import source country c in 1996. If industry j has relatively low-transport cost, $Open_j^{Dist}$ will be relatively high because import shares are less skewed towards sources that are relatively nearby. Since an industry's exposure to a given supply shock in China is expected to increase with lower transportation costs, we expect a positive relationship between $\Delta ImpPent_j$ and $Open_j^{Dist}$. This is plausibly exogenous because transportation costs are strongly determined by geography and lagged import shares are employed.

Second, we employ a measure of market entry costs, denoted as $Open_j^{DC}$. It is the fraction of retail trade firms in 1996 of all importing firms in worker i's six-digit industry. A high share of internationally active retail trade firms within a six-digit industry proxies for the pre-existing strength of distribution channels, and any given productivity improvement in China is expected to have a relatively strong impact on that industry. The exclusion restriction, conditional on the two-digit industry and occupation fixed effects, pre-trends, and other controls, is that the more established international distribution channels in worker i's industry do not affect workers other than making them more prone to rising import competition. To provide additional support for the excludability of the two instruments, we implement a simple test by adding the two instruments into equation C-2 and instrument $\Delta ImpPent_i^J$ using our first instrument (imports into other advanced countries). The t values for the estimated openness coefficients are -0.02 and 0.39 for $Open_j^{DC}$ and $Open_j^{Dist}$, respectively. We then test the null hypothesis that the coefficients of the openness instruments are zero. In other words, we ask if there is any extra explanatory power from the two openness instruments once we employ imports from other advanced countries as an instrumental variable. We cannot reject the hypothesis that the coefficients are jointly zero at or below conventional statistical levels.

First-stage coefficients are shown in Table C-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 C-1 shows second-stage results from estimating equation (C-2). The negative coefficient of -5.4 shows that an increase in Chinese import penetration has a significant negative impact on mid-wage employment of workers in Denmark. This generalizes the hollowing out of mid-wage jobs through rising import competition that we have seen above for the textile workers to the entire private-sector labor force.

Next, we are interested in whether import competition from China also leads to employment increases in the high- and low-wage tails of the job distribution. The effect of import competition on high-wage employment is shown in column (2). Workers exposed to rising Chinese import competition, on average, have significantly 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 Chinese 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 C-1 show that heightened import competition from China has led to a hollowing out of mid-wage employment at the same time 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 occupational movements consistent with job polarization. The results in columns (4) and (5) show that to a limited extent, import competition leads to unemployment; at the same time, import competition with China is not a significant factor in Denmark in causing workers to exit the labor market altogether. This finding suggests that Denmark's active labor market policies might have been relatively successful, in line with Utar (2018).

It is useful to compare our findings with results for the United States. In particular, Autor, Dorn, and Hanson (2015) report that import competition has *not* led to the partly positive, partly negative employment changes that is characteristic of job polarization, but instead Autor, Dorn, and Hanson (2015) document negative employment effects for virtually all workers. One reason for this difference might be active labor market policies that provide more re-training opportunities for Danish compared to US workers. Another factor that might help to explain the differences is that Autor, Dorn, and Hanson (2015) exploit regional variation across commuting zones, whereas we analyze a cohort of workers so that our results are not affected by changes in the composition of the sample which would typically occur when employing cross-regional analysis over time.

Table C-1: **Import Competition and Job Polarization–Economy-wide Evidence**

	(1) MID_i^e	(2) $HIGH_i^e$	(3) LOW_i^e	(4) UE_i^e	(5) OUT_i^e
Δ ImpPent	-5.441**	2.436**	2.413**	0.843**	-0.001
	(2.287)	(1.087)	(1.181)	(0.425)	(0.389)
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	170	170
Number of Observations	900,329	900,329	900,329	900,329	900,329
First-Stage F-test	12.575	12.575	12.575	12.575	12.575
First-Stage F-test p-value	0.000	0.000	0.000	0.000	0.000
Hansen Overidentification J-statistic	0.197	4.542	0.247	0.324	0.438
Hansen OverID J-statistic p-value	0.906	0.103	0.884	0.850	0.803

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.

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.[25] The coefficient in column (2) translates on average into 0.09 years *more* of high-wage employment.

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 import competition has sizable effects on the occupational movements of workers. The difference to zero in the sum of the regression coefficients of the first three columns of Table C-1 is largely accounted for by unemployment and years spent outside the labor force.

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

C.3 Full Instrumental Variables Estimation Results

Table C-2 gives the full two-stage least squares results that are summarized in Table C-1. First-stage coefficients on the excluded instruments are shown at the bottom of Table C-2.

Table C-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
	(0.399)	(0.386)	(0.377)
Industry IT Investment	10.240**	-5.967	-7.090***

Continued on next page

Table C-2 – *Continued from previous page*

Dep. Var.	$HIGH^e$ (1)	MID^e (2)	LOW^e (3)
	(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_j^{CH}	0.002***		
	(0.0005)		
$Open_j^{Dist}$	0.015***		
	(0.005)		
$Open_j^{DC}$	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.

C.4 Alternative Measures of Employment and Earnings

Table C-3 shows evidence on the impact of rising import competition when we measure employment effects by years of full-time employment, hours worked, as well as earnings by broad wage group for our private-sector sample.

Table C-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 C-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 C-1. The results show that full-time years of employment results are not very different from our baseline results that include part-time employment. Moreover, changes in hours worked are broadly similar to the impact of rising import competition on years of employment. Results in Panel C indicate that there is a stronger movement towards the high- and low-wage tails of the distribution in terms of employment polarization than for wage polarization, although earnings effects do not offset the employment effects we estimate.

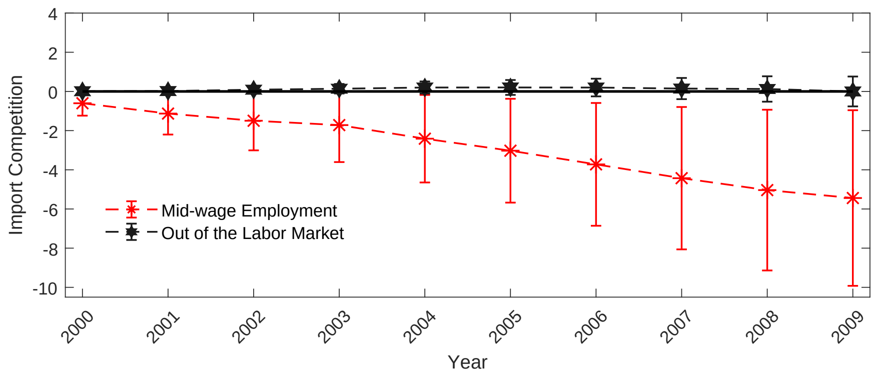
C.5 The Dynamics of Occupational Movements

In this section we estimate equation (C-2) with different years as sample endpoints, from 2000 to 2009, to gauge the dynamic impact of rising import competition on Denmark's entire private-sector labor force. 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 C-2. For example, the downward trending line in Figure C-2a 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 coefficient given in Table C-1, first row, column (1).

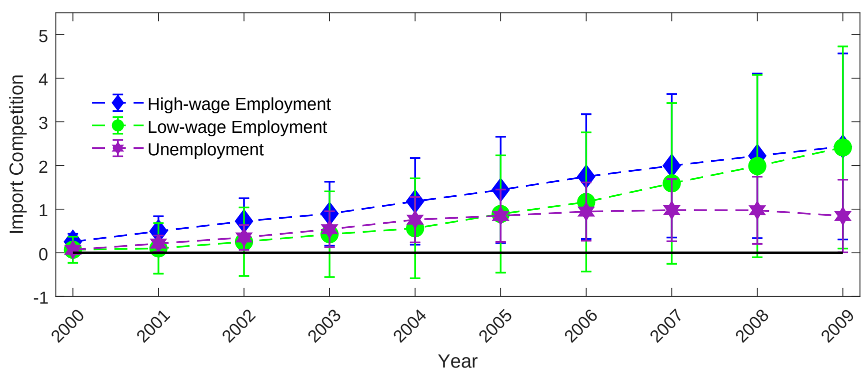
Figure C-2 shows that there is only one series that is consistently in negative territory, namely mid-wage employment. In contrast, the point estimates for the other four labor market outcomes are positive or close to zero. This means that the employment increases in low- and high-wage occupations due to import competition are the flip sides of the mid-wage employment decrease. The effect of import competition on mid-wage employment is negative already in 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 over the medium- to long run.

Focusing on Figure C-2b, import competition's impact on high-wage and low-wage employment is rising over time. At the same time, trade-induced unemployment is stronger in early years than trade-induced low-wage employment, a result that changes only reversed after the year 2005 (Figure C-2b). 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 in any year (Figure C-2a).

Overall, we see from Figure C-2 that polarized employment trajectories are a long-run outcome of import competition, while unemployment is a transitory station of workers dealing with exposure



(a) Mid-wage Employment and Labor Market Exit



(b) High-wage and Low-wage Employment as well as Unemployment

Figure C-2: The Dynamic Effects of Import Competition on Labor Market Status

Notes: Estimation of equation (C-2) with varying year endpoint. Estimation by two-stage least squares (second-stage coefficients shown), with N = 900,329. Shown are robust 95 % confidence intervals based on clustering at the three-digit industry level.

to import competition. The results are also generally similar to the corresponding findings for the textile trade liberalization, see Figure 3.

C.6 The Role of Education – Economy-wide Results

To examine the role of education for occupational movements in our private-sector sample, 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).[26]

Table C-4: 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
	(1.214)	(2.245)	(1.253)
Δ ImpPent*HighSchool	-2.706**	-0.039	1.227
	(1.269)	(1.368)	(0.915)
Δ ImpPent*College	4.437*	-3.288	1.883
	(2.297)	(3.261)	(1.283)
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 C-2. 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 employment of a trade-exposed worker in a high-wage paying occupation is increasing in the worker's level of education (Table C-4, column (1)). This is similar to our finding for

[26] 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 C-2).

low-educated textile workers (Table 4). Furthermore, college-educated workers exposed to rising import competition experience particularly high increases in high-wage employment compared to exposed workers with lower levels of education (column (1)).

Interestingly, import competition-exposed workers with vocational education have significantly more high-wage employment than non-exposed workers with such education, which was not the case for 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, there is no monotonic relationship between education level and the impact of rising import competition on low-wage employment, see column (3).

C.7 Job Polarization and Sectoral Change

This section asks whether economy-wide job polarization driven by import competition, as shown in Table C-1, is related to workers' movement from manufacturing to services. To assess the importance of structural change, we distinguish high-, mid-, and low-wage jobs in manufacturing versus services. Table C-5 reports two-stage least squares results on the impact of import competition separately by type of occupation and by sector.[27]

We see that the decline of mid-wage employment caused by import competition is driven by job losses in manufacturing (Table C-5, Part A, column (2)). 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.[28]

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 from manufacturing to services 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.), confirming the transitions from machine operator to personal service occupations shown in Figure 2 above. These results broadly generalize our findings from the textile trade liberalization to the entire private-sector labor market.

[27] All specifications include the full set of variables of Table C-1. 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.

[28] Coefficients for Manufacturing and Services do not sum to the All coefficient because Manufacturing and Services do not account for all labor market positions; excluded are Agriculture and Mining as well as labor market exit and unemployment, which are of relatively small importance, as also indicated by the coefficient estimates in Table C-5.

Table C-5: 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)
For All Panels			
N	900,329	900,329	900,329
First-stage F-test [p-value]	[0.000]	[0.000]	[0.000]

Notes: Dependent variable at top of each column in every panel. Shown are second-stage results from separate instrumental-variables estimations. 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 C-1. Robust standard errors clustered at the 3-digit industry level in parentheses. *, ** and *** indicate significance at 10%, 5%, and 1% level respectively.

C.8 Technical Change and Offshoring as Alternative Explanations

This section considers the roles of technical change and offshoring alongside of import competition by employing measures of routine task intensity (RTI) and offshoring from Goos, Manning, and Salomons (2014).[29] The routine task intensity captures an occupation's susceptibility to routine-biased technical change (see Autor and Dorn 2013, Goos, Manning, and Salomons 2014).[30] The

[29] So far our analysis has controlled for technical change and offshoring via two-digit occupation fixed effects.

[30] 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

RTI measure captures the impact of computers at the workplace because they substitute for workers performing easily programmable and routine-intensive tasks. To examine the influence of offshoring on employment changes, we employ a measure of the offshorability of an occupation due to Goos, Manning, and Salomons (2014). We match these measures with each worker's occupation as of 1999 to examine workers employment trajectories depending on their susceptibility to technical change and offshoring. As the measures of technical change and offshoring vary at the two-digit occupation level, we replace our two-digit occupation fixed effects with other occupational variables.[31]

Table C-6 show these results. The sample now is somewhat smaller than before because RTI and offshoring measures are not available for all workers. Even with these changes, the impact of rising import competition on mid-wage employment is similarly estimated, with a coefficient of -5.48 versus -5.44 before (Table C-6, column (1), and Table C-1, 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 mid-wage jobs. At the same time, the impact of 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 workers completing tasks that are routine-intensive have less mid-wage employment than other workers (column (3)). This is consistent with existing evidence showing that routine-biased technological change has caused lower employment opportunities of mid-wage workers. 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.[32] We find that the impacts of technical change and import competition on mid-wage occupations are similar (coefficients of -0.040 and -0.044, respectively). This provides evidence that the impacts of import competition and technical change on the hollowing out of mid-wage jobs are comparable in magnitude.

Turning to employment changes in high-wage occupations, the point estimate of the import com-

overview.

[31] 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).

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

Table C-6: 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/ Four-digit Fixed Effects		
Δ ImpPent	-5.479**	-5.771**	-5.524**	3.193**	2.374*	-5.021**	2.512**	2.242**
	(2.404)	(2.444)	(2.464)	(1.376)	(1.267)	(2.212)	(1.052)	(1.086)
	[-0.043]	[-0.046]	[-0.044]	[0.026]	[0.029]	[-0.040]	[0.020]	[0.027]
Offshoring		-0.088**	-0.048*	-0.197***	0.137***			
		(0.036)	(0.028)	(0.020)	(0.017)			
		[-0.027]	[-0.015]	[-0.062]	[0.064]			
Routine Task Intensity			-0.153***	0.396***	-0.041			
			(0.053)	(0.037)	(0.036)			
			[-0.040]	[0.107]	[-0.017]			
Four-Digit Occupation FEs						✓	✓	✓
N	837,815	837,815	837,815	837,815	837,815	837,815	837,815	837,815
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 C-1. 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.

petition variable is 3.2 (column (4)). The coefficient for offshoring is negative in our high-wage employment equation: workers who in 1999 have a relatively offshorable occupation do not, on average, experience an increase in high-wage employment (conditional on import competition and technical change). The RTI coefficient is positive, indicating that workers completing routine-intensive tasks disproportionately move up in the occupational hierarchy compared to workers not completing routine-intensive tasks.

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)). This indicates that while technological change contributes to the hollowing out of mid-wage employment as well as to employment increases in the high-wage tail, it does not help to explain the increase in low-wage employment.

To summarize, workers susceptible to offshoring do not account for high-wage employment increases (column (4) in Table C-6), while technical change does not induce workers disproportionately to take up low-wage employment (column (5)) in our context. Consequently, only import competition explains gains in both tails of the wage distribution. Care should be taken to not overemphasize these findings, however. One reason for this is that our measure of rising import competition is instrumented and at the six-digit level, whereas our offshoring and technological change measures are two-digit and uninstrumented variables from the literature.

In the final three columns of Table C-6, 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 more than 400 fixed effects capture arbitrary influences of the susceptibility of workers' occupations to contribute to the pattern of job polarization.[33] As columns (6), (7), and (8) show, the results with four-digit occupational fixed effects are broadly similar to those without shown in Table C-1. 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 increased import competition from China are consistent with the pattern of job polarization in the early 2000s, while responses to technical change and offshoring are less so. At the same time only workers susceptible to a trade shock, whether in the form of offshoring or import competition, experience a significant increase in the low-wage employment (column 5, Table C-6). This may help to explain why international economic factors in particular are a source of discontent in a substantial part of the labor force.

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

C.9 Outcome Variables in the Economy-wide Analysis

Table C-7 provides summary statistics on the outcome variables used in the private sector analysis.

Table C-7: Key Outcome Variables in the Economy-wide Analysis

	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
Earnings in High Wage Jobs, $HIGH^{wage}$	5.281	24.260	900,329
Earnings in Mid Wage Jobs, MID^{wage}	5.339	11.141	900,329
Earnings 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 a worker's own 1996-1999 average annual hours worked and wage, respectively.

D Alternative Estimation Approaches for Textile Trade Liberalization

Table D-1 compares results for our quasi-natural experiment and instrumental-variables approaches for the textile workers sample. In column (1) we replicate our quasi-natural experiment in the same regression framework we use in Section C by relating the exposure to competition to the cumulative employment of workers over 2002-2009 in a cross-sectional analysis. Hence we replace the worker fixed effects with detailed demographic, labor market, education and occupation information of workers and initial firm characteristics. The point estimates are a bit larger but similar to our estimates based on our default approach with worker fixed effects. In column (2) we replace the firm-level exposure variable with the change in import penetration across six-digit industries (equation (C-1)). While the growth in the Chinese penetration is expected to be mostly driven by the removals of the MFA quotas, not necessarily all variation is expected to be exogenous to domestic industry conditions. Column (2) uses OLS and potential endogeneity is not taken cared of. Next, we instrument the change of import penetration of column (2) with the same instrumental variables that we employ in Section C (column (3)). Finally, we employ the firm-level exposure variable to instrument for the change in Chinese import penetration across six-digit industries to isolate the variation driven by the abolishment of the import quotas (column (4)). The results in column (4) are similar to our main results. Table D-1 suggests that using the instrumental-variables approach in the case of the textile trade liberalization would lead to similar results as our difference-in-differences approach with worker fixed effects in the text.

Table D-1: Comparing Reduced-Form and IV Estimators

Specification	**OLS**	**OLS**	**IV (Industry)**	**IV (Firm)**
	(1)	(2)	(3)	(4)
Panel A. Years in mid-wage occupations, MID^e				
$Exposure_{ik}^{99}$	-1.536***			
	(0.342)			
$\Delta ImpPent_{ij}$		-1.702***	-1.851***	-3.217***
		(0.382)	(0.532)	(0.788)
Panel B. Years in high-wage occupations, $HIGH^e$				
$Exposure_{ik}^{99}$	0.758***			
	(0.271)			
$\Delta ImpPent_{ij}$		1.237***	1.262***	1.589***
		(0.345)	(0.368)	(0.529)
Panel C. Years in low-wage occupations, LOW^e				
$Exposure_{ik}^{99}$	0.791***			
	(0.211)			
$\Delta ImpPent_{ij}$		0.063	0.150	1.657***
		((0.267))	(0.358)	(0.522)
Panel D. Years in unemployment, UE^e				
$Exposure_{ik}^{99}$	0.324***			
	(0.106)			
$\Delta ImpPent_{ij}$		-0.006	-0.118	0.678***
		(0.146)	(0.187)	(0.251)
Panel E. Years outside the labor market, OUT^e				
$Exposure_{ik}^{99}$	0.209			
	(0.154)			
$\Delta ImpPent_{ij}$		-0.063	-0.213	0.438
		(0.209)	(0.232)	(0.331)
First-stage F-stat (K-P)			234.091	113.610

Notes: N = 10,487. All specifications include demographic (gender, age, immigration status, occupation, education, hourly wage, labor market history (unemployment history, linear and square terms of experience), union and unemployment insurance memberships, firm (size, wage, separation rate) characteristics. Sample is all 1999 textile and clothing workers. Estimation by OLS in columns (1)-(2) and by 2SLS in columns (3)-(4). In column (3) the same instruments are employed as in the entire private-sector sample (Section C). In column (4), $Exposure_{ik}^{99}$ is used to instrument $\Delta ImpPent_{ij}$. Robust, clustered standard errors in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

E Data Sources and Definitions

Our main source 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 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.[34] We describe the information on industry, education, and occupation in greater detail below.

Production Database (VARES)

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

[34] 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.

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 industry 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.[35]

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 dataset 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. 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

[35] 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.

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 daycare 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*/the General Industrial Classification of Economic Activities within the European Communities). 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 Task and Offshoring Data

For the analysis in Section 7, 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) and Firpo, Fortin, and Lemieux (2011). Table E-1 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 that we employ is based on 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).[36] The offshoring variables are defined for the particular occupational classification employed by Goos, Manning, and Salomons (2014). Table A-1 provides the list of two-digit occupational classes for

[36] We thank Anna Salomons for providing the data.

which these authors construct their offshoring and RTI variables.

Table E-1: 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.4	Developing Objectives and Strategies	Activities

E.5 Variable Definitions, Sources, and Summary Statistics

Tables E-2 and E-3 give data sources and definitions for control variables used in Section C, respectively.

Table E-2: 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
$Open_j^{Dist}$	2.465	3.456	CEPII, UHDI
$Open_j^{DC}$	0.020	0.052	UHDI, FIRE

Table E-3: Variable definitions

Variable Name	**Variable definition**
Age	Worker's age in years as of 1999
Age^2	Square of Worker's age as of 1999
College	Equal to 1 if worker attended a college as of 1999, 0 otherwise
Energy Growth	The average annual growth in energy expenditure in the four-digit industry over 2000-2008
Experience	Number of years worker *i* is in the labor market as of 1999
$Experience^2$	Square of Experience
Female	Equal to 1 if worker is female, 0 otherwise
Firm Size	The full-time equivalent number of employees in the firm (of worker *i*) in 1999
High School	Equal to 1 if highest attained education of worker is a general high school as of 1999, 0 otherwise
Immigrant	Equal to 1 if worker is first or second generation immigrant, 0 otherwise
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
Log Firm Wage	Logarithm of average hourly wage paid in the firm (of worker *i*) in 1999
Log Hourly Wage	Log of hourly wage of worker 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
Separation Rate	The share of workers who are not employed in the firm (of worker *i*) from 1998 to 1999
Unemployment History	Summation of unemployment spells of worker *i* until 1999 (expressed in years)
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
Vocational	Equal to 1 if highest attained education of worker is vocational school as of 1999, 0 otherwise

Appendix Bibliography

[1] **Amiti Mary, Caroline Freund.** 2010. “The anatomy of China’s export growth.”, In China’s Growing Role in World Trade, ed. R Feenstra, S-J Wei, pp. 56–61. Cambridge: NBER

[2] **Autor, David** 2013. “The “task approach” to labor markets: an overview”, *Journal for Labour Market Research*, 46(3): 185-199.

[3] **Autor, David, and David Dorn** 2013. “The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market”, *American Economic Review*, 103(5): 1553-1597.

[4] **Autor, David, David Dorn, and Gordon Hanson.** 2013. “The China Syndrome: Local Labor Market Effects of Import Competition in the United States”, *American Economic Review*, 103(6): 2121-2168.

[5] **Autor, David, David Dorn, and Gordon Hanson.** 2015. “Untangling Trade and Technology: Evidence from Local Labor Markets”, *Economic Journal*, 125(584): 621-646.

[6] **Autor, David, Levy, Frank, and Richard Murnane** 2003. “The Skill-Content of Recent Technological Change: An Empirical Investigation”, *Quarterly Journal of Economics*, 118, 1279-1333.

[7] **Blinder, Alan** 2009. “How Many U.S. Jobs Might Be Offshorable?”, *World Economics*, 10(2):41-78.

[8] **Blinder, Alan, and Alan Krueger** 2013. “Alternative Measures of Offshorability: A Survey Approach”, *Journal of Labor Economics*, 31(2): S97-S128.

[9] **Brandt, Loren, Chang-Tai Hsieh, and Xiaodong Zhu** 2008. “Growth and Structural Transformation in China.” In *China’s Great Economic Transformation*, edited by Loren Brandt and Thomas G. Rawski, 683-728. Cambridge University Press.

[10] **Firpo, Sergio, Nicole Fortin, and Thomas Lemieux** 2011. “Occupational Tasks and Changes in the Wage Structure”, IZA Discussion Paper 5542, Institute for the Study of Labor (IZA).

[11] **Goos, Maarten, Alan Manning, and Anna Salomons** 2014. “Explaining Job Polarization: Routine-Biased Technological Change and Offshoring”, *American Economic Review*, 104(8), 2509-2526.

[12] **Khandelwal, Amit, Peter Schott and Shang-Jin Wei** 2013. “Trade Liberalization and Embedded Institutional Reform: Evidence from Chinese Exporters”, *American Economic Review*, Vol. 103(6): 2169-2195.

[13] **Statistics Denmark** 2015. Integrated Database for Labor Market Research (IDA) Database. Provided and maintained by ECONAU/LMDG and Statistics Denmark.

[14] **Utar, Hale** 2014. “When the Floodgates Open: ”Northern” Firms’ Response to Removal of Trade Quotas on Chinese Goods”, *American Economic Journal: Applied Economics*, 6(4): 226-250.

[15] **Utar, Hale** 2018. “Workers beneath the Floodgates: Impact of Low-Wage Import Competition and Workers’ Adjustment”, *The Review of Economics and Statistics*, 100(4): 631-647.