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

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ABSTRACT

This paper examines the role of international trade for job polarization, where mid-wage occupations decline while employment opportunities of workers in both high- and low-wage occupations increase. With employer-employee matched data on virtually all workers and firms in Denmark between 1999 and 2009, we use instrumental-variables techniques and a quasi-natural trade liberalization experiment to show that import competition has been a significant cause of job polarization. Comparing import competition to other explanations of job polarization, import competition is quantitatively comparable to technical change as the most important alternative explanation of the hollowing out of middle-class jobs, and only import competition explains also the increase in employment opportunities in the high-and low-wage tails. Worker movement from exposed middle-class jobs up into high-wage or down into low-wage jobs is shaped by worker education and skill, and especially by task characteristics of the worker's occupation. We find that manual tasks are central for the impact of trade because foreign workers compete against domestic workers, in contrast to technical progress which pits man versus machine.

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1 Introduction

By increasing integration between economies globalization has led to a major increase in international trade. China, in particular, doubled its share of world merchandise exports during the 1990s before almost tripling it again during the first decade of the 21st century (World Bank 2016). During this globalization, labor markets in high-income countries became more polarized, with employment increases for high- and low-wage jobs at the expense of mid-wage jobs.[1] Figure 1 depicts the change between 1999 and 2009 in the share of employment accounted for by all non-farm occupations in Denmark and reveals a strong job polarization between the years 1999 and 2009.[2] This paper examines low-wage import competition as a source of job polarization, how it affects high-income countries' labor markets, and some of the policy issues this raises.

Understanding job polarization is paramount not only because the reason for the loss of middle-class jobs matters but also because job polarization means inequality, which may adversely affect the functioning of society.[3] In particular, if rising import competition creates inequality it may prevent the winners and losers to agree on policies that increase total welfare–not least free trade. Using administrative, longitudinal data on the universe of Danish workers matched to firms between 1999 and 2009, we show that import competition has been a statistically and economically significant cause of job polarization.

To estimate the effect of rising import competition we employ two complementary approaches. First, we define a worker's exposure to import competition according to the six-digit industry in which the worker is employed in the year 1999. Following Autor, Dorn, and Hanson (2013), the possible correlation of product-level imports with domestic taste or productivity shocks is addressed by instrumenting Denmark's imports from China with imports from China of the same products in other high-income countries. Key to this identification strategy is that the main reason for China's export growth during the 2000s is her rising supply capacity due to higher productivity and economic reforms , and as a consequence, China's export success in Denmark is similar to that in other high-income countries. We augment this approach by employing two measures of openness as additional instrumental variables, one based on transportation costs and the other based on pre-existing retail channels in international trade.

[1] For the case of the Unites States, see Autor, Katz, and Kearney (2006, 2008), Autor and Dorn (2013); United Kingdom: Goos and Manning (2007); Germany: Spitz-Oener (2006), Dustmann, Ludsteck, and Schonberg (2009); and across 16 European countries, see Goos, Manning, and Salomons (2014).

[2] The figure shows smoothed employment share changes for all non-agricultural occupations at the three digit occupation level that are ranked from low to high according to 1999 hourly wages. The extent of job polarization in Denmark during the early 2000s was comparable to that in the U.S., see for example Autor and Dorn (2013).

[3] We refer to positions in mid-wage occupations synonymously as middle-class jobs.

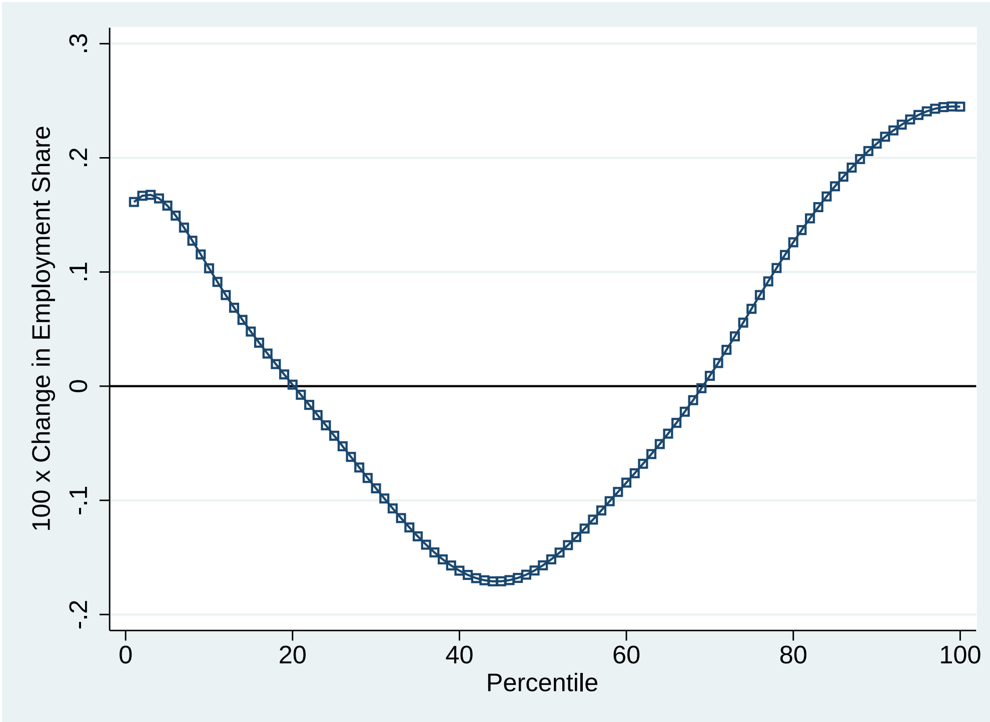

Figure 1: Job Polarization in Denmark 1999-2009; smoothed

Second, we exploit the removal of quotas on Chinese textile exports as China entered the World Trade Organization (WTO) in a difference-in-difference strategy.[4] This approach compares workers who domestically manufacture narrowly defined products that are subsequently subject to quota removals to workers employed at other textile-manufacturing firms that are not affected by the quota removals. This trade liberalization is a quasi-natural experiment that complements our instrumental-variables results for Denmark's entire economy.[5]

Figure 2 shows employment share changes between 2000 and 2009 across high-, mid-, and low-wage occupations. A typical low-wage occupation is a child care worker or a shop sales person (hourly wage of 29 and 28 dollars respectively), while a machine operator is representative for mid-wage jobs (35-45 dollars per hour depending on type of machines), and a business professional is typical for high-wage occupations (55 dollars per hour). These three wage groups have been employed in the literature on job polarization because they are the minimum to capture the job polarization pattern of Figure 1.[6] The figure shows changing employment opportunities for

[4]We use "textiles" for short; these are goods in the textiles and clothing industries.

[5]Our quasi-natural experimental strategy follows Utar (2018). Earlier work on the effect of trade liberalization employing the WTO textile quota removal includes Harrigan and Barrows (2009), Brambilla, Khandelwal, and Schott (2010), Khandelwal, Schott, and Wei (2013), Utar (2014), and Bloom, Draca, and van Reenen (2016).

[6]Our classification of occupations into wage groups for Denmark is similar to that in the literature (e.g., Autor and Dorn 2013), Denmark is similar to other advanced countries (see Goos, Manning, and Salomons 2014), and as shown

three subsets of workers, those who in year 1999 were employed in the service sector, in the manufacturing sector, and in textiles (a part of manufacturing).[7]

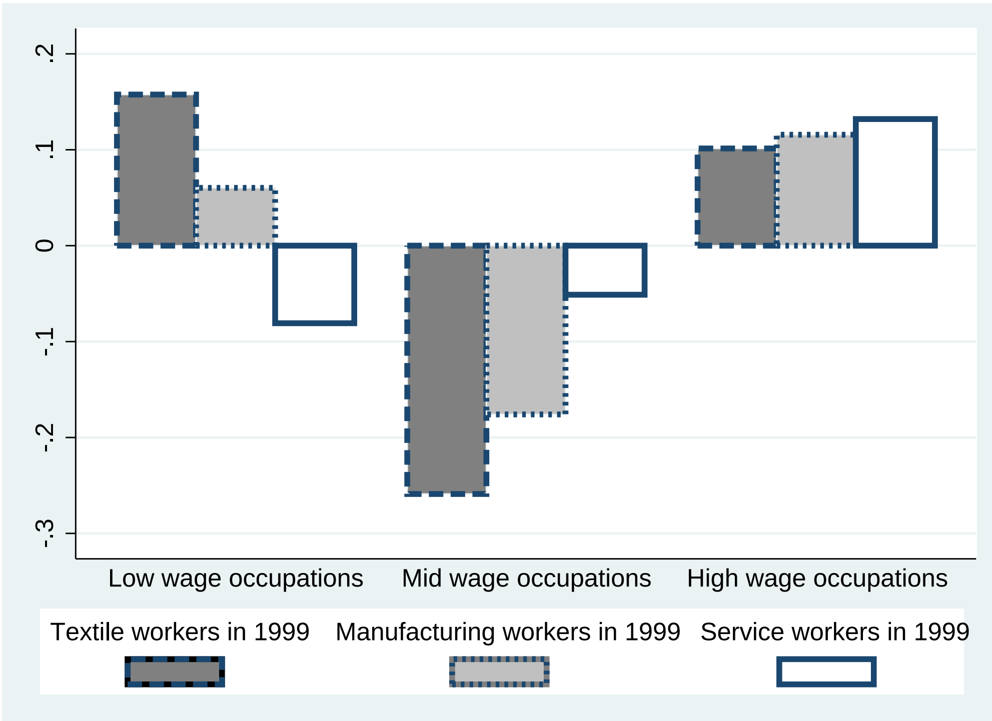

Figure 2: Changes in Employment Share for Different Subsets of the 1999 Cohort of Danish Workers, 2000-2009

We see that employment share changes of service sector workers are increasing in the wage, consistent with skill-biased technical change. In contrast, employment share changes of 1999 manufacturing workers exhibit the pattern of job polarization, and by the end of 2009 close to one in five of the cohort of mid-wage manufacturing workers are either employed in low- or high-wage occupations. Furthermore, the textile sector was especially strongly affected by rising import competition due to quota removals, and it is here where we find the strongest evidence for the U-shaped polarization pattern.

This is preliminary evidence for import competition affecting job polarization because the former is more concentrated in manufacturing in comparison to technical change whose impact is more diffused across many sectors of the economy. Below, we show that import competition is significant in explaining job polarization in Denmark by employing plausibly exogenous variation that

in Table 1 below there are no changes in the wage ranking of major occupations over time.

[7] We took all workers in those sectors who were between 18 and 50 years old–young enough not to reach retirement age over the next ten years.

controls for omitted variables, alternative explanations, and other possible confounders. Moreover, quantitatively rising import competition had a comparable impact on the hollowing-out of middle-class jobs as technical change, at the same time when import competition also led to higher low-wage and high-wage employment. We also show that middle-class workers exposed to job losses due to import competition are much more likely to move down into low-wage employment if they have at most high school education, while the chance of moving up into high-wage jobs (and not into unemployment or non-employment) is significantly higher for college-educated workers.

Furthermore, we focus on worker task as the unit of analysis to analyze how import competition affects employment opportunities to generate job polarization.[8] Employing individual O*NET tasks and information at the four-digit level occupation level, we find that it is workers performing manual tasks who are most strongly affected by import competition whereas workers performing cognitive tasks are not affected.[9] We refer to the importance of manual activities as Manual Task Intensity (MTI). The impact of import competition is distinct from that of technical change because the former affects not only workers performing manual routine but also by workers performing manual non-routine tasks. In a nutshell, our results follow because in international trade, foreign workers compete against domestic workers, in contrast to technical progress which pits man versus machine.

The large literature on the labor market impact of import competition, in particular from China, has established that regions specialized in import-competing manufacturing industries experience a rise in unemployment and industries exposed to Chinese import competition see greater employment loss (Autor, Dorn, and Hanson 2013, Pierce and Schott 2016, Utar and Torres-Ruiz 2013).[10] This paper shifts the focus to job polarization, where early work has found little evidence that international trade is important (Autor and Dorn 2013, Michaels, Natraj, and van Reenen 2014). More recently, Autor, Dorn, and Hanson (2015) present evidence for the U.S. that Chinese import competition has reduced employment opportunities for a broad range of occupations from low- to high-paying ones, which is inconsistent with job polarization.[11] Revisiting the issue, we show that rising import competition can be a cause of job polarization. Variation in institutional setting as well as research design help to explain these differences in findings, as will be discussed below. Our paper is related as well to work on job displacement (Jacobson, LaLonde, and Sullivan 1993, Polataev and Robinson 2008, Sullivan and van Wachter 2009). A key difference is that our treat-

[8] See Autor (2013) for a discussion of the so-called task approach.

[9] O*NET stands for Occupational Information Network.

[10] Also, firms exposed to import competition make new technology investments and shift towards a more highly-skilled labor force (Bloom, Draca, and van Reenen 2016, Utar 2014). Autor, Dorn, and Hanson (2016) present a useful survey.

[11] Also Lake and Millimet (2016) and Harrigan, Reshef, and Toubal (2017) find little evidence that trade causes job polarization in the U.S. and France respectively.

ment definition is not based on job loss as such but derived from firms' susceptibility to exposure to increased import competition with China based on their manufactured products.

A question of perennial interest is the relative importance of international openness versus technology for labor market outcomes. In the 1980s a hotly debated question was the cause of the rise of the skill premium (relative wage of skilled to unskilled worker), with technological change and trade being leading explanations.[12] A key challenge for separating the factors openness and technology is that globalization has clearly aspects of both-for example, the increase in offshoring is largely unthinkable without the new coordination possibilities due to advances in information technology (Autor 2010). Fast forward to the 2000s, our analysis distinguishes the impacts of import competition and routine-biased technical change (RBTC) on job polarization (for evidence that RBTC has caused job polarization, see Autor and Dorn 2013, Goos, Manning, and Salomons 2014).[13] Our finding that import competition affects primarily workers performing manual tasks which may or may not be routine in nature not only advances the literature on the task-level causes of job polarization but also contributes to the literature on the future of work and the race between man and machine (Graetz and Michaels 2018, Acemoglu and Restrepo 2018).

While in the past analyses of job polarization have often focused on changes in regional or national employment shares, we study job polarization by analyzing the individual occupational movements of the cohort of the 1999 Danish workers over time. Individual workers typically contribute to the movement from mid-wage to low-wage or from mid-wage to high-wage occupations, and both have to be present in the sample to obtain job polarization. On the other hand, if one were to employ the aggregate approach in studying the impact of trade on job polarization, the change in employment shares would not only reflect the impact of import competition on exposed workers but also subsequent migration, industry sorting, and demographic responses, which can be challenging to quantify. As a result the two approaches complement each other. In addition, for the most part we follow the literature on job polarization by studying occupational movements between three broad wage groups (low-, middle-, and high-wage occupations; see Figure 2). Other research employing individual-level data includes Autor, Dorn, Hanson, and Song (2014) who emphasize sectoral switching cost as a barrier to adjustment, as well as Utar (2018) and Traiberman (2019) who shift the focus towards costs of adjustment between different occupations.

In the remainder of the paper, the following section describes the changing pattern of import competition in Denmark, and how it guides our empirical strategy to study job polarization. We also discuss our worker, firm, and sectoral data for the Danish economy. Section 3 shows that rising

[12]Technological change is often thought to have been more important, see the discussion in Feenstra (2000).

[13]See Autor, Levy, and Murnane (2003), Autor, Katz, and Kearney (2006), and Goos and Manning (2007) on RBTC. A framework accounting for job polarization in the United States between 1950 and 2007 based on structural change is presented in Barany and Siegel (2018).

import competition has caused job polarization in the entire Danish private-sector economy, and that it has been quantitatively as important as technical change. We confirm the economy-wide instrumental-variables results with a quasi-natural experiment– the liberalization of textile trade through quota removals– in section 4, and find both worker education and skill to be important in determining the upward versus downward movements as middle-class jobs are threatened by import competition. We also document the special importance of manual tasks in the exposure of workers to import competition, and how it differs from the impact of routine-biased technical change. Section 5 provides a concluding discussion. A number of additional results are presented in the Online Appendix.

2 Import Competition and Polarization Pattern

2.1 The Rise of Import competition

To see how the rise of low-wage countries in the global economy can lead to job polarization in a high-wage country (Home), consider a framework in which Home has one traded and one non-traded goods sector. Traded goods production requires intensively manual tasks that are performed by workers with moderate skill levels, who are paid mid-level wages in the labor market. An increase in productivity in the traded goods sector abroad raises foreign competitiveness and exports. At Home there is an increase in the level of import competition together with a reduction in the relative demand for mid-level wage workers performing manual tasks. Transitions from mid-level to other jobs will be shaped by the extent of wage adjustments as well as any worker- or occupation- specific adjustment costs. We ask whether import competition has led to the mid-wage employment declines as well as the increases in low- and high-wage employment that define job polarization.

The paper examines the impact of import competition on employment changes using two complementary approaches. First, we study changes in import penetration from China across six hundred industries that are differentially exposed to import competition.[14] These are in manufacturing and non-manufacturing. Examining job polarization by following workers throughout the entire economy has the advantage that the effects of globalization will not be missed even if they materialize outside of manufacturing. Second, we employ the exogenous shock of the dismantling of quotas on Chinese textile imports in conjunction with China's WTO accession. While the aggregate implications of the quota removal are limited it allows us to investigate the effect of trade liberalization on

[14] For work employing differential trade exposure at the regional, industry, or occupation-level, see, e.g., Autor, Dorn, and Hanson (2013), Dix-Carneiro and Kovak (2015), and Ebenstein, Harrison, McMillan, and Phillips (2014).

job polarization in a quasi-experimental setting when unobservable heterogeneity across workers is addressed by individual fixed effects.

Turning to our first approach, the change in import penetration from China is defined as:

$$\Delta ImpComp_j = \frac{M^{CH}_{j,2009} - M^{CH}_{j,1999}}{C_{j,1999}}. \quad (1)$$

Here, $M^{CH}_{j,t}$ denotes Denmark's imports from China in product 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 product category (NACE) j. We address potential endogeneity by instrumenting the numerator of (1) with changes in imports from China in eight other high-income countries.[15] A key requirement for this strategy is that Chinese export success is explained by China's increased supply capacity, which affects high-income countries' imports from China similarly, and that Chinese import growth is not driven by product-level demand shocks that are common to all high-income countries (see Brandt, Hsieh, and Zhu 2008, Autor, Dorn, and Hanson 2013).

Because Denmark is a relatively small market for Chinese exports, the likelihood that they target a particular Danish product is small. To address possible sorting in anticipation of import changes, our instrumental variables approach utilizes consumption levels of the year 1996. We employ two additional instrumental variables at the six-digit industry level: geography-based transportation costs and a measure of the importance of retail channels. These variables are the log average of the distance from Denmark's import partners using the 1996 imports as weights, and the ratio of the number of retail trading firms over the total number of importing firms in 1996.

Figure 3 shows the change in Chinese import penetration between 1999 and 2009 across manufacturing industries versus the share of workers in middle-class jobs in 1999. Products belonging to the same two-digit industry are given labels with the same color and shape. We see that the relationship between import penetration and the share of mid-level workers varies widely within a two-digit industry. For example, metal forming and steam generator products are both part of the fabricated metal products industry, they both have about 50% mid-wage worker, and yet the change in import penetration for steam generator products was much lower than for metal forming products. What may account for these stark within-industry differences?

Despite these similarities, the tasks performed by mid-level workers in the occupations belonging

[15] The high-income countries are Australia, Finland, Germany, Japan, Netherlands, New Zealand, Switzerland, and USA. To construct the variable in equation (1) we employ international trade data and business statistics data from Statistics Denmark; the instrumental variable is based on information from the United Nation's COMTRADE and Eurostat. See section A.5 in the Online Appendix for details.

to the same two-digit industry can in fact be quite different, and so can be worker exposure to import competition. Take "Fibre-preparing-, spinning-, and winding-machine operators" (textile machine operators for short) and "Industrial robot operators", for example, both four-digit occupations of the International Standard Classification of Occupations (ISCO).[16]

Workers in both occupations make typically mid-level wages, and yet textile machine operators are more negatively affected by rising import competition compared to industrial robot operators; the latter might actually experience improved employment prospects due to skill upgrading, because Denmark is among the countries with the highest recent increase in robotization (Graetz and Michaels (2015). Our analysis addresses these important differences in within-industry exposure by including up to more than four hundred occupational fixed effects.

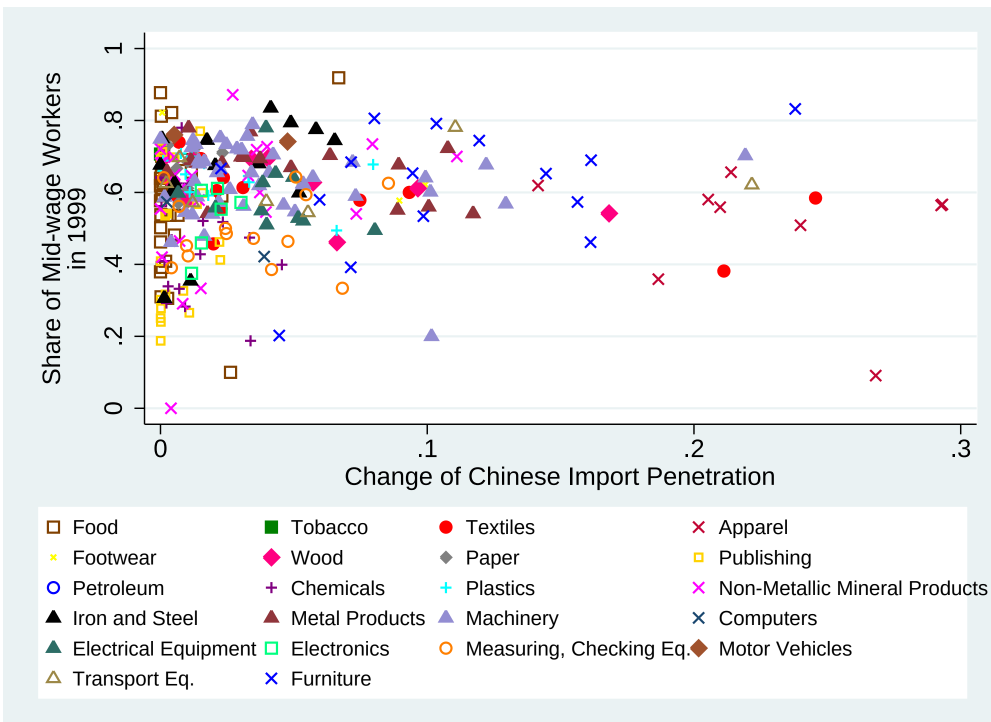

Figure 3: Mid-wage Workers and Import Competition from China

Furthermore, we exploit the employer-employee link to capture technology differences in more than six hundred economic activities proxied by the share of information-technology educated workers. In addition, we account for product quality using the wage share of vocationally educated workers in the total wage bill. We also include two-digit industry fixed effects to avoid capturing differences in growth of Chinese imports across industries due to broad technological differences.

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

As a result, we are not capturing Chinese import growth due to the potentially disproportional effect of a decline in the costs of offshoring or automatization across industries.

In our second approach we exploit a specific policy change, the removal of Multi-fibre Arrangement (MFA) quotas, to define exposure at the worker level. The entry of China in December 2001 into the WTO meant the removal of binding quantitative restrictions on China's exports to countries of the European Union (EU); it led to a strong surge in textile imports in Denmark during the years 2002 to 2009, and prices declined (Utar 2014). This increase in import competition is plausibly exogenous because Denmark did not play a major part in negotiating the creation of the quotas or their removal since it was managed at the EU level and finalized in the year 1995. Moreover, the sheer magnitude of the increase in imports after the quota removal was unexpected, and in part driven by the allocative efficiency gains in China (Khandelwal, Schott, and Wei 2013).

There were two so-called phases of MFA textile quota removals after China joined the WTO, namely in the years 2002 and 2005.[17] Because any separate effects are difficult to distinguish our analysis employs the entire period 2002 - 2009 as trade liberalization period.[18]

We implement this approach by identifying all firms that in 1999 produced narrowly defined goods in Denmark – e.g., "Shawls and scarves of silk or silk waste" – that are subject to the MFA quota removal for China. This is our treated group of firms. The control group of firms with similar characteristics can be constructed because within product categories the quotas did not protect all goods. We then utilize the employer-employee link provided by Statistics Denmark to obtain two sets of workers: a treatment and a control set. In the year 1999, about half of the textile and clothing workers are exposed to rising import competition in this sense.

A key identification requirement is that treated and not treated workers are not subject to differential trends before the trade liberalization. The placebo results for 1990-99 reported in the Appendix show no evidence for significantly different pre-trends, see Table A-4. In sum, the MFA removal setting affords us a way to strengthen the instrumental variables analysis with evidence from a quasi-natural experiment. Additional information on the MFA quota system and its removal is given in section B of the Appendix.

[17]The extent of the surge in imports in textiles from China in 2005 led to a temporary suspension of the removal of a few quota categories until 2008.

[18]While some of the most significant quota removals came only in the year 2005, the evidence in Table A-5 in the Appendix suggests that overall, major firm responses to rising import competition started in the year 2002. This was partly due to the overlap of firms exposed to the 2002 and the 2005 quota removals for China.

2.2 Offshoring, Technical Change, and Task Information by Occupation

Our analysis of occupation-level drivers of polarization employs information from the O*NET data base, version 14. It reports information of the prevalence of certain tasks by occupation based on data from the US Bureau of Labor Statistics. See Section A.6 for more information. We also employ the composite task measure RTI (Routine Task Intensity) based on the Directory of Occupational Titles of the U.S. Department of Labor due to Autor, Levy, and Murnance (2003). The RTI index is a composite based on the prevalence of several types of activities performed in a specific occupation, indexed by o:

$$RTI_o = ln(Routine_o) - ln(Abstract_o) - ln(Manual_o). \tag{2}$$

Here, *Routine* is the routine score of the occupation, *Abstract* is its abstract score, and *Manual* is the manual score of a specific occupation.

For offshoring, we employ two different measures that capture the offshorability of workers in different occupations. Blinder and Krueger's (2013) index focuses on whether tasks in a particular occupation is intensive in tasks that are difficult to offshore because they involve personal interaction and face-to-face communication, while Goos, Manning, and Salomons (2014) offshorability index is constructed from data on actual instances of offshoring by European companies.

2.3 Characteristics of the Danish Labor Market

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

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

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

2.4 Worker- and Firm Information

This study employs the Integrated Database for Labor Market Research of Statistics Denmark, which contains administrative records on individuals and firms in Denmark.[19] We have annual information on all persons of age 15 to 70 residing in Denmark with a social security number, information on all establishments with at least one employee in the last week of November of each year, as well as information on all jobs that are active in that same week. These data files have been complemented with firm-level data and international transactions to assess exposure to import competition, as well as information on domestic production which we employ in the quota removal analysis.

Table 1: Ranking of Occupations by Wage

	Median Hourly Wage		Mean Hourly Wage		Employment Share		Corresponding Major ISCO
	1999	2009	1999	2009	1999	2009	
High-Wage							
Legislators, Senior Officials, Managers	5.488	5.550	5.538	5.604	0.038	0.039	1
Professionals	5.297	5.362	5.349	5.412	0.145	0.168	2
Technicians, Associate Professionals	5.116	5.177	5.160	5.211	0.184	0.239	3
Mid-Wage							
Craft and Related Trade Workers	5.053	5.098	5.002	5.034	0.128	0.091	7
Plant and Machine Operators, Assemblers	5.012	5.088	5.095	5.024	0.089	0.062	8
Clerks	4.949	5.013	4.945	5.023	0.134	0.103	4
Low-Wage							
Elementary Occupations	4.919	4.962	4.928	4.956	0.117	0.104	9
Service Workers, Shop Sales Workers	4.849	4.938	4.851	4.927	0.165	0.193	5

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

[19] See Bunzel (2008) and Timmermans (2010) for additional descriptions of this data.

The worker information includes annual salary, hourly wage, industry code of primary employment, education level, demographic characteristics (age, gender and immigration status), and occupation of primary employment.[20] Information on worker occupation is of high quality in Denmark in part because occupational codes influence earnings, and both employers and workers (as well as their labor unions) pay close attention to them. As noted above, occupation codes are generally given at the four-digit level of the ISCO-88 classification which yields more than four hundred detailed occupations.

Table 1 reports occupational wages for our 1999 cohort of N = 900,329 workers between 1999 and 2009, as well as the employment share across major occupational groups. The table classifies occupations into the high-, mid-, and low-wage part of the distribution familiar from analyses of job polarization. These groups are based on the median wage paid in an occupation in Denmark for the year 1999.[21] The high-wage occupations comprise of managerial, professional, and technical occupations. Mid-wage occupations are clerks, craft and related trade workers, as well as plant and machine operators and assemblers. Finally, low-wage occupations include service workers, shop and market sales workers, as well as workers employed in elementary occupations.

The employment share of mid-wage occupations fell by around ten percentage points between 1999 and 2009, in line with the hollowing out of middle class jobs. Furthermore, the three wage groups are quite stable over time. For example, in 1999 high-wage earning technicians and associate professionals (ISCO 3) make 16.7 percent more than mid-wage earning clerks (ISCO 4), while the corresponding figure for 2009 is 16.4 percent. Similarly, the gap between middle- and low-wage jobs does not change dramatically either. In 1999, a typical clerk makes 9.4 percent more than the typical low-wage service and shop sales worker (ISCO 5), while in the year 2009 this difference is similar at 9.6 percent.

Our breakdown of occupations into three major wage groups is also similar to that of Goos, Manning, and Salomons (2014) in their study of sixteen European countries, including Denmark, based on 1993 wages, see Table A-2.

The sample includes all workers who were between 18 and 50 years old in 1999 and employed in a firm operating in the non-agricultural private sector for which Statistics Denmark collects firm-level balance sheet data. These workers were employed in a wide range of industries, including mining, manufacturing, wholesale and retail trade, hotels and restaurants, transport, storage and communication, as well as real estate, renting and business activities. The sectoral breakdown

[20] Employment status is based on the last week in November of each year. 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.

[21] We rank occupations at the one-digit level for full-time workers (see Table 1)

of the sample in 1999 is shown in Figure 7 in the Appendix. As in most high-income countries, the sectoral composition of the economy during this time changed from manufacturing (from just above one third of the sample in 1999 to 20% by 2009) towards services.

By holding constant this sample of workers we can construct a worker-level exposure variable that is based on workers' employment as of the initial year. This has the advantage that it is not endogenous to the workers' subsequent job changes. Our results are also not affected by factors that lead to entry or exit of workers, including domestic and international migration.[22] Regarding the other sample constraints, workers between 18 and 50 workers are typically active in the labor market throughout the sample period, while firm-level accounting information is needed to construct a number of important control variables.[23] Descriptive statistics for the sample are reported in Table 2.

A key outcome variable in our analysis is employment of worker i in mid-wage occupations (see Table 1), defined as

$$MID_i^e = \sum_{t=2000}^{2009} Emp_{it}^m, \tag{3}$$

where Emp_{it}^m is an indicator variable that takes the value of one if worker i has held a primary job in mid-level wage occupations in year $t \in T$, $T = \{2000, ..., 2009\}$. The variable MID_i^e ranges from a maximum of 10 years for a 1999 mid-wage worker who has been employed in mid-wage occupations throughout the years 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 between the years 2000 and 2009, respectively. Panel A of Table 2 shows, for example, that workers have about 3.6 years of mid-wage employment between the years 2000 and 2009. In addition to mid-, high-, and low-wage employment, Panel A of Table 2 shows summary statistics on non-employment (unemployment and time spent outside of the labor force).

[22] For example, as a result of the increase in refugees in Denmark starting in the mid-1990s, the employment share of Non-European Union immigrants increased from 2.5 to 4.5 % until the mid-2000s; see Foged and Peri (2016) for a study of the impact of refugees on native worker outcomes in Denmark.

[23] Sectors that are not included as initial employment of workers in the sample are mainly public administration, education, health, and a wide range of small personal and social service providers. Education and health sectors in Denmark are to a large extent publicly owned. We have also employed a larger sample including the public sector with about 1.5 million observations, finding that this does not yield important additional insights.

Table 2: Key Characteristics of the Sample

	Mean	Standard Deviation
Panel A. Cumulative Labor Market Outcome, Years 2000 - 2009		
Employment in High Wage Jobs	2.638	3.689
Employment in Mid Wage Jobs	3.581	3.755
Employment in Low Wage Jobs	1.281	2.457
Unemployment	0.393	0.985
Outside of the Labor Force	0.542	1.410
Panel B. Worker Characteristics, 1999		
Age	34.093	8.852
Female	0.339	0.473
Immigrant	0.045	0.208
Education		
- College	0.176	0.381
- Vocational	0.436	0.496
- High School	0.377	0.485
Experience	12.868	6.205
History of Unemployment	1.025	1.716
Log Hourly Wage	5.032	0.448
High Wage Occupation	0.265	0.441
Mid Wage Occupation	0.509	0.500
Low Wage Occupation	0.194	0.395
Union Membership	0.762	0.426

Notes: N = 900,329 workers. Variables in Panel A are measured in years. In Panel B, variables Female, Immigrant, Union Membership, High Wage, Mid Wage and Low Wage Occupations, as well as College, Vocational, High School are indicator variables. Age, Experience, and History of Unemployment measured in years. High School stands for at most completed high school education; History of Unemployment is the summation of unemployment spells of worker *i* until 1999. Log Hourly Wage in units of 2000 Danish Kroner.

Panel B shows worker characteristics as of the year 1999. We distinguish three levels of education, college, vocational education, and at most high school education. In Denmark vocational education is provided by the technical high schools (after 9 years of mandatory schooling) and involves several years of training with both schooling and apprenticeships. In our sample, percentage of workers with college education is 18%, 44% of workers have vocational training, and the remaining 38% workers have at most high school education. This is quite similar to Denmark as a whole, where these percentages are 25%, 43%, and 32%, respectively. As one would expect, the three education levels are disproportionately represented in our three wage groups, with 55 percent of the workers in low-wage occupations but only 14 percent of the workers in high-wage occupations having at most a high school degree.

Summary statistics for the sample of textile workers are shown in Table 3. It comprises of all employees of the textile and clothing sector who are of working age throughout the sample period, about 10.5 thousand workers.[24] There are a number of differences between the textile workers and the private-sector labor force in Denmark. One of them is that compared to the economy as a whole, as typical of manufacturing in general, mid-wage occupations are relatively more important (66% of textile workers hold mid-wage occupations in 1999).

Table 3: Summary Statistics: Sample of Textile Workers

	Mean	Standard Deviation
Panel A. Labor Market Outcomes in 2002 - 2009		
Employment in High Wage Jobs	1.366	2.498
Employment in Mid Wage Jobs	2.545	2.840
Employment in Low Wage Jobs	1.010	1.985
Unemployment	0.501	1.019
Outside of the Labor Force	1.096	2.013
Panel B. Worker Characteristics in 1999		
Age	39.663	10.358
Female	0.569	0.495
Immigrant	0.061	0.240
Education		
- College	0.123	0.329
- Vocational	0.352	0.478
- High School	0.509	0.500
Experience	14.729	5.783
History of Unemployment	1.292	1.828
Log Hourly Wage	4.964	0.374
High Wage Occupation	0.205	0.404
Mid Wage Occupation	0.664	0.472
Low Wage Occupation	0.119	0.324
Union Membership	0.822	0.383

Notes: N = 10,487 workers. Variables in Panel A are cumulative and measured in years. In Panel B, 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.

If import competition has led to job polarization, mid-wage employment reductions and low-wage employment increases must be relatively pronounced for workers who are employed in firms that

[24] Since this sample is smaller we employ less conservative age limits. The sample includes all workers who in 1999 are between 17 and 57 years old. This ensures that they will typically be active in the labor market between 2002 and 2009.

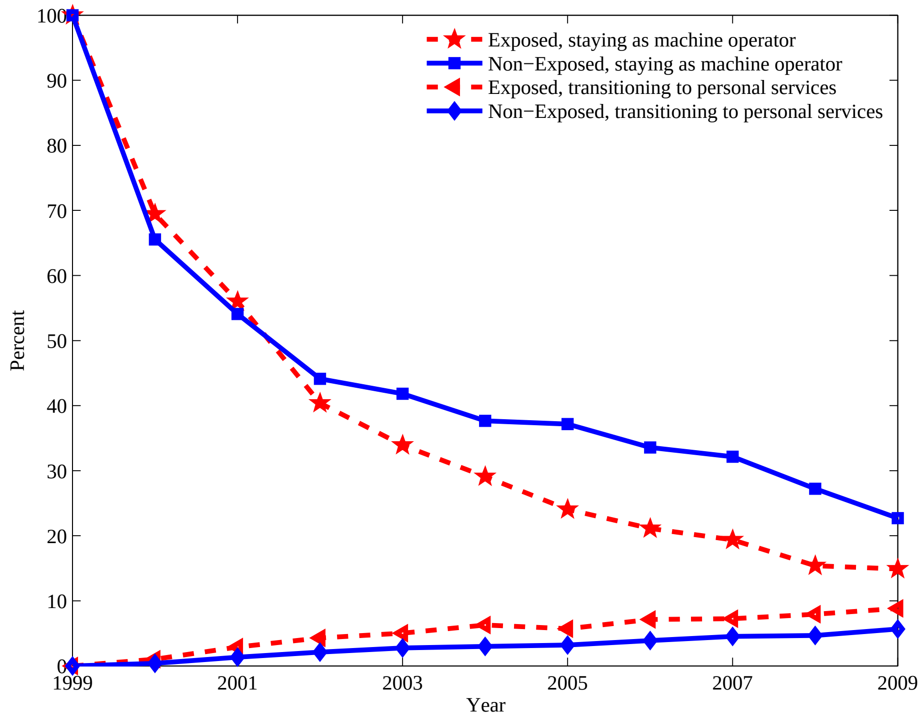

Figure 4: The Probabilities of Machine Operators to Stay in their Occupation, and to Switch to Personal Service Occupations, by Exposure

subsequently are affected by the quota removal. Figure 4 provides initial evidence on this by comparing the job transitions of treated and untreated machine operators and assemblers (ISCO 82; machine operators for short). Consider first the hollowing out of middle-class jobs. Because our sample starts with the universe of machine operators in 1999 and does not include machine operators that enter this occupation after 1999, the two upper lines in Figure 4 start at 100% and necessarily slope downward over time. The chief observation is that the rate at which machine operators leave their occupation in exposed firms is higher than the rate at which they leave it in non-exposed firms. By 2009 only about 15% of the exposed machine operators are in that same occupation, in contrast to 23% of the machine operators that are not exposed to rising import competition.

Turning to increases in low-wage employment, the two lower lines in Figure 4 give the cumulative probabilities of 1999 machine operators to work in personal and protective services (ISCO 51). This is a low-wage occupation that includes the organization and provision of travel services, housekeeping, child care, hairdressing, funeral arrangements, as well as protection of individuals and personal property. Figure 4 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 in the personal and protective service occupation, 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.[25]

Employment trajectories of the mid-wage workers are typically one-directional, either up to high- or down to low-wage jobs. In our economy-wide sample with more than 900,000 observations, more than 95% of the mid-wage workers either stay in that wage category or move either up or down for any amount of time during 2000-2009. It will therefore be critical for welfare reasons to examine the factors that determine the direction of the move, upwards or downwards. We will turn to this below.

3 Import Competition Leads to Job Polarization

This section examines whether rising import competition has been a significant cause of job polarization in Denmark. We first show the effect of import competition on mid-level wage jobs before examining whether there was positive employment growth in both the higher and lower tails of the wage distribution.

3.1 Chinese Imports and the Hollowing-Out of Middle Class Jobs

To shed new light on the factors that influence the relationship between import competition and changes in mid-wage employment we proceed in steps and estimate several versions of the following equation

$$Mid_i^e = \alpha_0 + \alpha_1 \Delta ImpComp_j + Z_i^W + Z_i^F + Z_i^N + \varepsilon_i, \tag{4}$$

where Z_i^W are worker- , Z_i^F are firm-, and Z_i^N are product-level variables (product-level variables are at the 6-digit industry level). The change in Chinese import penetration, $\Delta ImpComp_j$, is instrumented as described in section 2.1.

The first specification employs Chinese import competition, captured by $\Delta ImpComp_j$, solely together with two-digit industry fixed effects. At the bottom of Table 4 the robust first-stage F-statistic of about 12.5 (p-value of virtually 0) shows that the instrumental variables are predictive

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

of the change in Chinese import competition. First-stage coefficients are significant and of the expected sign; they are shown in the Online Appendix, Table A-7. The second stage coefficient is negative, see Table 4, column 1. While the focus is on the coefficient on import competition, all coefficients are shown in the Online Appendix, Table A-7.

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

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

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

Notice that the strength and performance of the instrumental variables does not change much with the inclusion of worker, firm, and product-level variables. In particular, the first-stage F-statistic is similar, and the over-identification tests show no evidence that the instrumental variables are not valid. The final column in Table 4 shows OLS results for comparison. The Chinese imports variable has a negative point estimate but it is close to zero. This is consistent with the hypothesis that import demand from China is positively correlated with industry demand shocks, and failing to account for this correlation the OLS estimate is upwardly biased.

Table 4: Import Competition and the Decline in Mid-Wage Employment

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

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

3.2 Import Competition and the Tails of the Wage Distribution

This section asks whether rising import competition has caused employment increases in the high- and low-wage tails of the worker distribution. Mid-wage employment losses are only one part of the job polarization pattern, and without an increase in both high- and low-wage employment one cannot conclude that import competition has caused job polarization.

Table 5: **Import Competition and the Tails of the Wage Distribution**

	(1) Mid-wage Emp.	(2) High-wage Emp.	(3) Low-wage Emp.
Δ Import Competition	-5.441**	2.436**	2.413**
	(2.287)	(1.087)	(1.181)
Demographic Characteristics	✓	✓	✓
Education Characteristics	✓	✓	✓
Log Hourly Wage	✓	✓	✓
Labor Market History	✓	✓	✓
Occupation Fixed Effects	✓	✓	✓
Union and Unemployment Ins. Indicators	✓	✓	✓
Firm Characteristics	✓	✓	✓
Product Characteristics	✓	✓	✓
Industry Fixed Effects	✓	✓	✓
Number of Clusters	170	170	170
Number of Observations	900,329	900,329	900,329
First-Stage F-test	12.575	12.575	12.575
First-Stage F-test [p-value]	0.000	0.000	0.000

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. All specifications include demographic (gender, age, immigration status), education, hourly wage, labor market history (unemployment history, linear and square terms of experience), union and unemployment insurance memberships, firm (size, wage, separation rate), as well as 6-digit industry covariates as described in Table 4. Robust standard errors clustered at the 3-digit industry level in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

Column 1 in Table 5 repeats the result for mid-wage employment from Table 4. Results for the employment effect of rising import competition for high-wage employment are shown in column 2. The coefficient is positive with a point estimate of 2.4, indicating that, on average, workers exposed to rising Chinese import competition have more employment in high-wage jobs than virtually identical workers employed at similar firms not exposed to rising import competition. In column 3 we show evidence on the impact of rising import competition on low-wage employment, defined as the years of employment in low-wage occupations during 2000-2009. On average, workers exposed to rising import competition from China have disproportionately more employment in low-wage jobs, and the coefficient turns out to be 2.4 as well.

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.[26] The coefficient in column 2 translates on average into 0.09 years *more* of high-wage employment. The difference to zero in the sum of the regression coefficients in Table 5 is accounted for by unemployment and years spent outside the labor force; they will be discussed below.

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

This is the first main result of the paper: Rising import competition explains part of the reductions in middle-class jobs and increases in high- and low-wage positions characteristic of job polarization.

It is interesting to examine some of the coefficients of the other included variables in the specifications of Table 5; they are shown in Table A-7 in the Appendix. Specifically, the coefficient on the indicator for women in the high-wage employment regression is about 0.77, consistent with women being more successful in moving into high-wage employment than men. This is in line with the gender difference in the United States 1979-2007 (Autor 2010, Figure 4). Furthermore, the coefficient on union membership in the mid-wage employment regression is positive at about 0.56, which means that the hollowing-out of middle-class employment has been slower for workers who are members of a labor union. This finding mirrors Firpo, Fortin, and Lemieux (2011) who emphasize the importance of deunionization in the pattern of U.S. wage polarization.

The following discussion examines a number of additional aspects.

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

3.2.1 The Dynamics of the Import Effect

For this analysis we have estimated equation 4 with different years as sample endpoints, beginning with the year 2000 until the year 2009. Two-stage least squares point estimates of the impact of import competition on workers' cumulative employment in high-, mid-, and low-wage occupations as well as on unemployment and labor force exit are shown in Figure 5 (standard errors are shown in Table A-9 in the Appendix) . For example, the downward trending line in Figure 5 is the impact of rising import competition on mid-wage employment; for the year 2009 as the sample endpoint, the point estimate is -5.4, as in Table 5, first row.

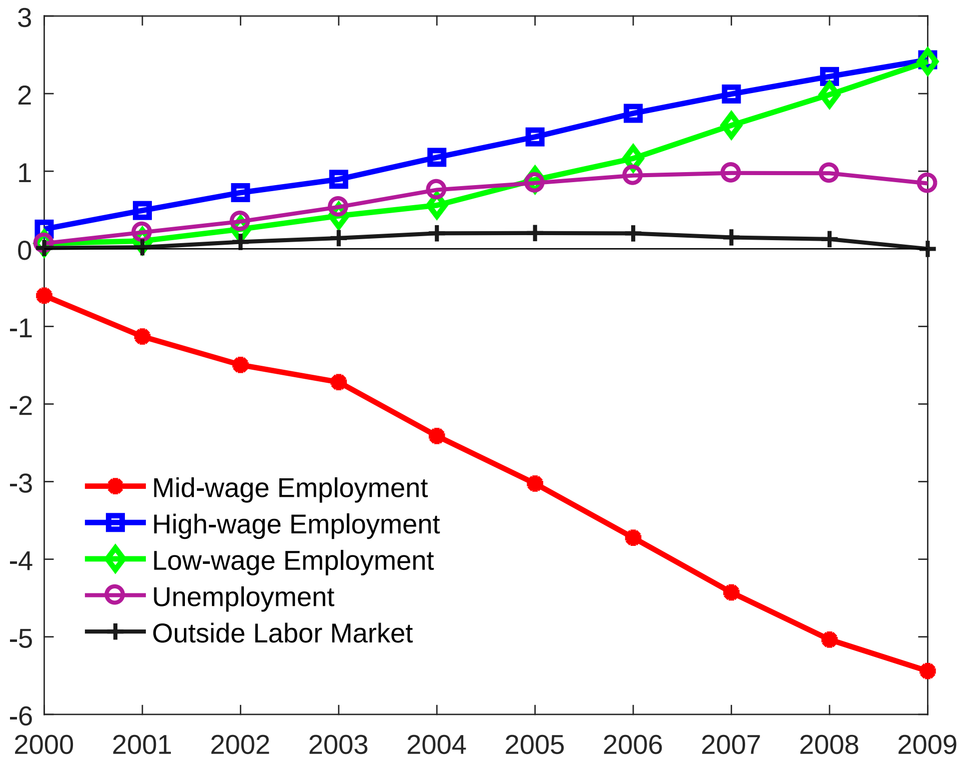

Figure 5: The Dynamic Effects of Import Competition on Labor Market Status

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

Third, import competition's impact on high-wage and low-wage employment is rising over time. Also, trade's impact on unemployment is stronger than its effect on low-wage employment, a result that is only reversed after the year 2005. 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 workers arrange themselves with the necessity of taking up low-wage jobs. Finally, the figure shows that movements outside of the labor force play not a major role for our results.

Overall, we see from Figure 5 that polarized employment trajectories are a long-run outcome of the import competition shock, while unemployment is a transitory station of workers dealing with exposure to rising import competition.

3.2.2 The Role of Sectoral Change

Like other high-income countries, Denmark's economy has shifted from manufacturing to services sectors in recent decades. At the same time, there is evidence that import competition caused polarized employment trajectories for manufacturing workers (Figure 2). It is thus important to ask whether job polarization driven by rising import competition is related to the structural shift from manufacturing to services. In that case, workers would not only face major occupational change but also the challenge of switching broad sectors.

In the analysis above we have distinguished a worker's employment in high-, mid-, and low-wage occupations. To assess the importance of structural change we will decompose the workers' employment further by sector, specifically manufacturing versus services. Table 6 reports two-stage least squares results on the impact of rising import competition separately by type of occupation and by sector. All specifications include the full set of variables that were present in Table 5. Furthermore, there is evidence that the excluded instruments have power in each of the specifications; the p-value of the robust first-stage F-statistic is always less than 0.0001.

Table 6: Channels of Job Polarization Due to Trade

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

Notes: The number of observations is 900,329 in each cell. Estimation by two stage least squares. Robust standard errors clustered at the 3-digit industry level in parentheses. All specifications include demographic (gender, age, immigration status), education, hourly wage, labor market history (unemployment history, linear and square terms of experience), union and unemployment insurance memberships, firm (size, wage, separation rate), as well as product-level variables as described under Table 4. All specifications also include two digit occupation fixed effects and two-digit industry fixed effects. $^{\circ}$, * and ** indicate significance at the 10 %, 5% and 1% levels respectively.

Panel A of Table 6 shows that the decline of mid-wage employment caused by rising import competition is concentrated in manufacturing (column 2). In contrast, exposed workers tend to have actually more mid-wage service employment than non-exposed workers, although the difference is not significant at standard levels (column 3). Import competition reduces employment opportunities first and foremost for manufacturing workers, not generally for mid-wage workers.

Next, the increase in high-wage employment through import competition is distributed more broadly across sectors (Panel B), with point estimates for import competition of about 1.8 and 1.3 for manufacturing and services, respectively (not significant). These results are in line with recent findings that import competition forces firms to downsize at the same time when they shift their demand towards worker having relatively high skills (Utar 2014).

At the lower end of the wage distribution rising import competition from China 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 we incorporate worker movements through the entire economy into the analysis. The overall increase in low-wage employment (column 1, Panel C.) is mostly due to low-wage employment increases in the service sector (column 3, Panel C.). Our finding of import competition-induced increases in low-wage service employment confirms the transitions from machine operator to personal and protective service occupations shown in Figure 4 above. The growth in low-wage service employment is also in line with Autor and Dorn's (2013) findings of job polarization driven by routine-biased technical change in the United States, which underlines the importance of analyzing import competition and technical change side by side (see next section).

For now it is useful to compare our findings on trade with what we know about the United States. In particular, Autor, Dorn, and Hanson (2015; ADH for short) find that rising import competition has *not* led to partly positive, partly negative employment changes characteristic of job polarization but instead to negative employment effects for virtually all workers.[27] Reconciling labor market outcomes between the U.S. and Denmark is speculative, as noted by Traiberman (2019), as these countries have different institutions, workers, and geography; however, an important factor here is likely that ADH exploit regional variation across commuting zones whereas we identify the impact of trade from longitudinal information on workers.

For example, ADH find that in trade-exposed commuting zones the employment share of higher skilled managerial, professional, and technical jobs falls over time. In contrast, we estimate a positive impact of trade on employment in such high-wage occupations (Table 6, Panel B). Individuals employed in high-wage occupations tend to be highly skilled, and as such they are relatively able to adjust to negative labor demand shocks. If skilled workers move disproportionately away from exposed commuting zones as a result of the trade shock their employment share in exposed regions will tend to fall.[28] By focusing on regions ADH's analysis reflects such effects. In contrast, our longitudinal worker-level analysis compares individual exposed and not exposed workers irrespective of where they move, and therefore results can be different.

Differences in the institutional setting such as labor market policies in Denmark versus the United States can also play a role. For example, due to active labor market policies and income transfer and insurance policies Danish workers suffered much lower losses in personal income than their U.S.

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

[28] Bound and Holzer (2000) as well as Malamud and Wozniak (2012) find that less educated workers adjust less in terms of migration to negative labor market shocks than highly educated workers. Migration is only one of several possible adjustment margins.

counterparts (Utar 2018 and Autor, Dorn, Hanson, and Song 2014, respectively), and similarly we find that prime age Danish workers exited the labor force to a lesser degree (Figure 5) in comparison to the non-employment response to import competition documented for the U.S. in ADH.

The following summarizes supplementary findings on job polarization in several dimensions, see Table A-8 in the Appendix. By stripping out part-time employment and examining hours worked instead of years of employment, we confirm that the polarizing effect of rising import competition is mostly due to changes in full-time employment, with changes in hours and part-time work playing only minor roles. We also find that the impact of imports is more strongly due to employment rather than wage polarization, although wage changes do not offset the polarizing employment effects of import competition.

The key finding so far is that rising import competition can explain job polarization. The following analysis compares import competition with other potential causes of job polarization, in particular technical change.

3.3 Technical Change and Offshoring as Alternative Explanations

This section employs measures of technical change and offshoring to examine the impact of import competition along with these alternative forces.

A well-known measure in the literature is the routine task intensity index (RTI), which captures an occupation's susceptibility to routine-biased technical change (Autor, Levy, and Murnane 2003).[29] The following table shows also results for the Goos, Manning, and Salomons (2014) offshorability index, with similar results for the Blinder and Krueger measure reported in the Appendix.[30]

Because the RTI and offshoring measures vary at the two-digit occupation level, in order to identify the roles of technical change and offshoring we drop our two-digit occupation fixed effects for more aggregate occupation variables.[31] Furthermore, the RTI and offshoring measures are not available for the entire sample of about 900,000 workers but rather closer to 800,000 workers. However, the impact of rising import competition on middle-class employment with these changes is estimated to be similar, with a coefficient of -5.47 versus -5.44 before (Table 7, column 1, and Table 5,

[29] Autor (2013) recommends to use as far as possible off-the-shelf measures in task analysis. The RTI index is a measure based on Dictionary of Occupational Titles (DOT) data, a precursor to the O*NET data base, using 1980 data; it has been employed in Autor, Levy, and Murnane (2003), Autor and Dorn (2013), and Autor, Dorn, and Hanson (2013) among others. Below we will also employ information on individual tasks.

[30] See Table A-10 in the Online Appendix.

[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).

respectively).

We begin by adding offshoring to our specification. Offshoring 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 is consistent with offshoring contributing to the hollowing out of middle-class jobs. At the same time, the impact of rising import competition is largely unchanged by the introduction of the offshoring variable.

Next, we add RTI, the measure of routine-biased technical change, to our specification. It comes in with a negative coefficient, indicating that workers performing tasks that are routine-intensive have less mid-wage employment than other workers (column 3). Consistent with earlier evidence, this result reflects the impact of computers at the work place because they substitute for workers performing easily programmable and routine-intensive tasks. 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.

Furthermore, reporting standardized coefficients based on variables with mean zero and standard deviation of one in hard brackets, we find that the impacts of technical change and import competition on mid-wage employment are very similar (coefficients of -0.046 and -0.045, respectively). This provides evidence that the impacts of import competition and technical change on the hollowing out of middle class jobs are comparable in magnitude. One might be concerned that it matters for these results that import competition is instrumented while RTI and offshoring are not, however, we do not believe that this is of first-order importance since we obtain similar findings using OLS for estimating the impact of import competition in a quasi-experimental setting.

Next, we ask whether workers exposed to rising import competition have more employment in high-wage occupations once we account for technical change and offshoring. The point estimate of the import competition variable is 3.5, which is somewhat larger than without adding the RTI and offshoring variables. The coefficient for offshoring is negative in the high-wage employment equation, indicating that offshoring does not explain the employment increases in the high-wage tail needed for job polarization (conditional on import competition and technical change). The RTI coefficient is positive, indicating that workers performing routine-intensive tasks disproportionately contribute to more employment in high-wage occupations.

Results for low-wage employment are shown in column 5. The coefficient on import competition is positive and quantitatively similar to the result without accounting for offshoring and technical change. We also find that offshoring contributes to the increase in low-wage employment, however technical change does not because the RTI coefficient is not significantly different from zero

Table 7: Alternative Explanations for Job Polarization

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

Notes: Estimation by two stage least squares. Robust standard errors that are clustered at the 3-digit industry level are reported in parentheses. Beta coefficients are reported in square brackets. All specifications include demographic (gender, age, immigration status), education, wage, labor market history (unemployment history, linear and square terms of experience), union and unemployment insurance memberships, firm variables (size, wage, separation rate), as well as product-level control variables as described under Table 4. 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.

(column 5).

With offshoring neither accounting for mid-wage reductions nor high-wage increases and technical change not explaining the growth of low-wage employment, rising import competition is the only factor that can explain the U-shaped pattern of employment changes across occupational wage levels that defines job polarization.[32]

The final three columns of Table 7 present two-stage least squares results for the impact of rising import competition on mid-, high-, and low-wage employment that control for four-digit occupational fixed effects. These fixed effects capture arbitrary forces in the susceptability of workers to be affected by import competition which if omitted may affect our estimation results. Given these approximately 400 additional fixed effects, our measures of offshoring and technical change are not identified anymore. As columns 6, 7, and 8 show, the results with four-digit occupational fixed effects are broadly similar to those with more aggregate occupational fixed effects (compare with Table 5), and there is little evidence that our results are driven by omitted variables operating at the detailed occupational level.

The second key result of the paper is that the impact of rising import competition is comparable to routine-biased technical change in hollowing out middle class jobs, and at least during the first decade of the twenty-first century in Denmark, import competition is the only factor leading also to increases in both the high and the low tails of the wage distribution. We also find that only international openness–including import competition and offshoring– but to a lesser degree technical change can explain workers' downward movements in the occupational hierarchy. This may help to explain why international economic factors in particular are a source of discontent in large parts of the labor force.

4 The Anatomy of Job Polarization

4.1 Trade Liberalization in Textiles: Evidence from a Quasi-Natural Experiment

We now examine polarization in the setting of the removal of quantitative restrictions on China's textile exports. Our analysis encompasses all 1999 textile workers who are of working age until

[32] Recall that much of the existing work on job polarization examines changes in employment shares by wage group, not years of employment of workers. In principle, it is possible that our RTI coefficients in columns 3 and 5 translate into increases in employment shares for both high- and low-wage occupation groups. It is unlikely though because in absolute value the coefficient in the mid-wage regression is considerably smaller than the coefficient in the high-wage regression.

the year 2009. These years, following the first removal of the Multi-fibre Arrangement quotas for China in January 2002, are times of surging Chinese import competition in the Danish textile and clothing industry.

The exposure of a worker to Chinese import competition is defined as the 1999 share of revenue, three years prior to the new Chinese competition, that worker i's firm derived from domestically produced goods that are subject to the removal of quotas for China. The focus on the discrete policy change in 2002 lends itself to a difference-in-difference strategy where outcomes are averaged before and after the year 2002 (periods 1999-2001 and 2002-2009, respectively). Furthermore, as detailed in the Appendix, the removal of quotas on Chinese goods can be treated as plausibly exogenous. Our baseline estimation strategy is difference-in-differences OLS with worker fixed effects. A cross-sectional estimation strategy with an extensive set of covariates for the year 1999 leads to similar results (see Table A-11 in the Appendix).

The difference-in-difference specification is given by:

$$MID^{e}_{is} = \beta_0 + \beta_1 Exposure_i x PostShock_s + \beta_2 PostShock_s + \delta_i + \varepsilon_{is}. \tag{5}$$

In equation (5) s identifies the pre- and post-liberalization periods (years 1999-2001 and 2002-2009, respectively), MID^{e}_{is} is years of mid-wage employment in period s, $Exposure_i$ is the degree to which a worker i is exposed to rising import competition due to the removal of quotas, measured as the revenue share of products of worker $i's$ firm for which quotas will be removed with China's entry into the WTO. $PostShock_s$ is an indicator variable for the post-liberalization period of 2002-2009, and δ_i denotes for worker fixed effects.

$Post_s$ captures the influence of aggregate trends in the industry and in the labor market affecting all workers. All time-invariant differences across workers, such as gender, occupation, age, education, and wage in the year 1999, as well as across the workers' firms, such as their organizational and technological structure as of 1999 are captured by worker fixed effects, δ_i. Of key interest is the estimate of β_1 which measures the impact of import competition.[33] It reveals whether exposed textile workers have different outcomes in the quota removal period compared to virtually identical non-exposed textile workers, relative to the period in which competition from quota products was absent (years 1999 - 2001).

To study the potential heterogeneous impact of import competition on occupational mobility, we employ the following specification:

[33] We will refer the coefficient estimate β_1 as Import Competition in the regression results.

$$Y_{is}^{e} = \beta_0 + \beta_1 Exposure_i x PostShock_s + \beta_2 PostShock_s + \beta_3 Exposure_i x PostShock_s x Char_i + \beta_4 PostShock_s x Char_i + \delta_i + \varepsilon_{is}, \tag{6}$$

In equation (6) $Char_i$ denotes a characteristics of worker i, such as the task he or she performs. Of primary interest is the estimate of β_3 which measures the impact of import competition on workers with certain characteristics, relative to workers who do not have these characteristics.

Table 8: Job Polarization due to Quota Removal

	(1)	(2)	(3)
	MID_{is}^{e}	$HIGH_{is}^{e}$	LOW_{is}^{e}
Import Competition	-1.292***	0.788***	0.665***
	(0.382)	(0.285)	(0.220)
Worker Fixed Effects	✓	✓	✓
Period Fixed Effects	✓	✓	✓
N	20,974	20,974	20,974

Notes: Dependent variable given at the top of the column. Estimation by OLS. Robust standard errors clustered at the firm-level are reported in parentheses. Import Competition is defined as $Exposure_i x PostShock_s$ (equation (4)), where $Exposure_i$ is a continuous trade exposure variable defined as the manufacturing revenue share of 8-digit Combined Nomenclature goods that were subject to removal of quotas for China in 1999 of worker i's employer. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

Column (1) shows that workers exposed to Chinese competition from former quota products have on average less mid-wage employment than non-exposed workers, with a coefficient of about -1.3. Exposed workers have also on average more high-wage employment than non-exposed workers, consistent with a higher rate of worker transitions from mid- to high-wage employment for exposed workers (column 2). At the same time, workers at firms producing quota products have also on average disproportionately higher low-wage employment, as shown in column (3) of Table 8.

While the revenue share of quota-exposed products captures the intensity of new import competition faced by each worker, the results–not reported in Table 8– are similar when Import Competition is defined as an indicator variable, equal to one if the firm has any 8-digit products that will be subject to heightened import competition after China's entry into the WTO, and zero otherwise.[34]

[34] Specifically, the coefficient in the mid-wage employment equation is -0.337 while the coefficients in the high- and

To asses the economic magnitudes of the impact of import competition we compare workers at the 25th and the 75th percentile of exposure.[35] The results in column (1) shows that the competition from China causes a decline in mid-wage occupations over the eight years of -1.292 0.284 = 0.367 of a year or 4.4 months. A decline of mid-wage employment for exposed textile workers of 0.367 years is larger than the just under 0.2 that we found above for the typical Danish (private-sector) worker. This confirms the relatively strong impact of rising import competition in the textile sector, and it is also in line with the differences in mid-wage employment share changes shown in Figure 2. Furthermore, exposure to import competition leads to a 17% decline compared to the sample average mid-wage employment. Exposed workers have on average about 28 percent higher low-wage employment than non-exposed workers, and exposed workers have on average also about 23 percent more high-wage employment compared to non-exposed workers.

To summarize, the evidence from the MFA quota trade liberalization confirms the earlier results for the entire private-sector economy that rising import competition has led to job polarization. This is important because the impact of rising import competition in the quota liberalization is straightforward to estimate, involving nothing more than a set of OLS regressions. The following section employs the quota removal experiment to better understand the mechanisms that lead to import competition-induced job polarization.

The Occupational Dynamics of Middle-Class Workers The following section examines the roles of worker education, skill, and task in determining the up- versus downward occupational movements of workers who were at the beginning of the sample period employed in middle-class jobs. In 1999, there were about 7,000 such workers in the textile and clothing industry.

Figure 6 shows how rising import competition has affected the labor market position of these workers over time. We see estimates for different versions of equation 5 in which the length of the post-period in the difference-in-difference analysis is varied from the year 2002 to the eight-year period of years 2002-2009. The coefficients are shown together with standard errors in Table A-12 in the Appendix.[36] Figure 6 also shows the dynamics of trade's impact on unemployment and labor force exit of these workers.

The figure shows that while these workers experience a substantial reduction in mid-wage employment through rising import competition, the trade-induced increase in low-wage employment is

low-wage employment equations are 0.207 and 0.168, respectively (all coefficients significant at a 5 percent or lower level). Exposure to import competition in former quota products tends to raise unemployment and exit from the labor force as well, though not significantly so.

[35] The 75/25 percentile difference compares a textile worker who in 1999 is employed at a firm with 28.4% of revenue in domestically produced quota goods with another textile worker whose firm in 1999 does not produce any quota product.

[36] Tables A-13 and A-14 show analogous results for initial low- and high-wage workers.

larger than the increase in high-wage employment. In fact, despite mid-wage reductions for these workers there is no significant movement into high-wage jobs.[37]

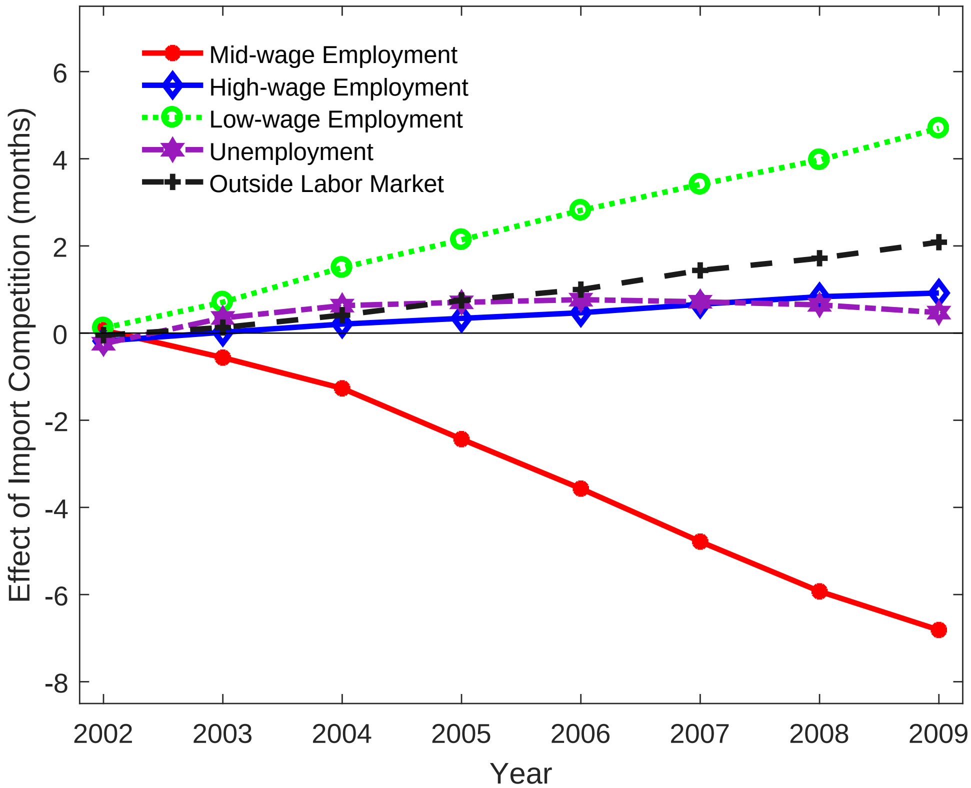

Figure 6: Import Competition and Labor Market Trajectories of Middle-Class Textile Workers

In addition, exit from the labor force due to import competition is more important for middle-class textile workers than in the private sector labor force as a whole, whereas unemployment for middle-class textile workers is a less important outcome than in the economy as a whole (compare Figures 6 and 5).[38]

Overall, while the impact of rising import competition on middle-class textile workers is broadly

[37]This implies that the more symmetric impact of import competition on high- and low-wage employment shown in Table 8 is due to workers who were initially in high- or low-wage occupations. Indeed, there are a number of trade-exposed workers who initially held low-wage jobs that disproportionately pick up employment in high-wage occupations.

[38]We also find evidence that rising import competition generates a sustained downward push into mid-wage occupations for workers who in 1999 have high-wage occupations; otherwise, the quota liberalization does not have significant effects by 2009. For workers who in 1999 have low-wage jobs there is limited evidence that the rise in import competition pushes them out of the labor force or into unemployment by 2009. Upward movements from low-wage to mid-wage jobs driven by trde are rare as well, however, there is a significant movement of workers from low- into high-wage occupations as the result of rising import competition; see Section D.1 in the Appendix.

similar to that on the entire (private-sector) labor force, the fact that exposed middle-class textile workers are more likely to switch into low-rather than high-paying jobs indicates that rising import competition has affected middle-class textile workers overall more negatively than other exposed Danish workers. This is in line with the descriptive evidence of Figure 2 and underlines the severity of the trade shock in the textiles and clothing sector.

4.2 Education and Skill as Determinants of the Direction of Occupational Movements

This section examines the influence of education and skill in shaping occupational movements of workers in response to rising import competition. The sample includes all 1999 textile workers who held middle-class jobs. We begin by distinguishing workers by the 1999 level of education. Results are shown in Table 9.

First, consider the extent to which these middle-wage workers continue to be employed in mid-wage occupations. Column 1 shows that regardless of workers' education, import competition causes lower subsequent mid-wage employment, and the extent to which this happens does not vary significantly among mid-wage workers. The largest negative interaction point estimate of -1.2 is for workers with manufacturing-oriented vocational training (such as machine operators), though it is not significant at standard levels.

Education does play a major role for upward vs. downward occupational movements, however. We see that if the middle-wage worker is college educated, import competition has a significant positive impact on his or her probability of upward movement into high-wage jobs, while if the middle-wage worker has at most high school education the chance of moving into high-wage jobs is zero (column 2, Panel A. and Panel D., respectively).[39]

Results for downward movements of middle-wage workers into low-wage employment are also strongly affected by worker education. For a relatively low level of education the extent to which an exposed middle-class worker moves downward into low-wage employment is almost doubled. At the same time, his or her chance of moving up into high-wage jobs is significantly reduced with a low level of education (column 3, Panel D. and Panel A., respectively).

[39] Also notice that college-educated workers exposed to rising import competition are less likely to move into unemployment and outside the labor force than other workers (Panel A., columns 4 and 5).

Table 9: Occupational Movements in Response to Trade Shocks: The Role of Education

	(1) Mid-Wage Employment	(2) High-Wage Employment	(3) Low-Wage Employment	(4) Unemployment	(5) Labor Force Exit
Panel A.					
Import Competition	-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.					
Import Competition	-1.939***	0.197	1.577***	0.0610	0.462
	(0.569)	(0.212)	(0.298)	(0.171)	(0.365)
ImpComp x Voc Training	-0.128	0.231	-0.609*	0.218	0.410
	(0.536)	(0.310)	(0.343)	(0.197)	(0.406)
Panel C.					
Import Competition	-1.861***	0.297	1.430***	0.0604	0.435
	(0.547)	(0.232)	(0.272)	(0.157)	(0.317)
ImpComp x Manuf Voc Training	-1.202	-0.228	-0.423	0.690**	1.526**
	(0.905)	(0.373)	(0.421)	(0.280)	(0.640)
Panel D.					
Import Comp	-2.020***	0.731**	0.924***	0.106	0.622*
	(0.593)	(0.358)	(0.284)	(0.198)	(0.322)
ImpComp x High School	0.064	-0.755**	0.757**	0.047	-0.049
	(0.538)	(0.337)	(0.336)	(0.204)	(0.403)

Notes: Dependent variable at top of column. Estimation by OLS. The number of observations in every regression is 13,934. All regressions include worker and period fixed effects. Robust standard errors clustered at the firm-level are reported in parentheses. Import Competition (and ImpComp for short) denote $Exposure_i xPostShock_s$ (equation (4)), where $Exposure_i$ is a continuous trade exposure variable defined as the manufacturing revenue share of 8-digit Combined Nomenclature goods that were subject to removal of quotas for China in 1999 of worker i's employer. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

Table 9 also shows results for vocationally trained workers, see Panel B. Comparing the upward and downward movements in response to the import shock for vocationally trained and college-educated workers, there are both similarities and differences. For one, vocationally-trained workers, just like college-educated workers, have a lower chance to be pushed from middle-class to low-wage jobs than other exposed workers (column 3, Panels B. and A., respectively). At the same time, vocational training, in contrast to college education, does not lead to trade-induced transitions to high-wage employment (column 2). This asymmetry is consistent with the idea that specific forms of vocational training can be effective for a worker to avoid downward movements in the occupational wage distribution at the same time when generally it does not provide the more general skills necessary for upward movements in response to a negative trade shock.

Results for the subset of manufacturing-oriented vocationally trained workers (such as welders) in Panel C. are also interesting. Generally, manufacturing-oriented training leads to worse outcomes than other vocational training (although the difference is not always significant). To an extent this is a reflection of the structural decline in the number of manufacturing jobs. In line with this argument, exposed workers with a manufacturing-oriented vocational training are particularly likely to become unemployed or exit the labor force (columns 4 and 5, Panel C.).

These results are broadly confirmed by findings for the entire private-sector labor force, see section D.5 in the Appendix.

In sum, there is strong evidence that education shapes the way a particular exposed middle class worker contributes to the overall pattern of job polarization in the economy.[40]

In the next section we employ a worker's hourly wage as an indicator of how his or her skill affects occupational transitions. Specifically, the analysis contrasts the impact of import competition on workers with particularly low and particularly high wages, defined as in the lowest versus the highest quintile of the wage distribution, respectively. Results are shown in Table 10.[41]

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

Next, we see that it is the exposed middle-class workers commanding a relatively high wage who are moving up into high-wage employment (column 4). Because these high-earning workers are more likely to have college education, this result is in line with our findings in Table 9. In contrast, workers making low wages (likely with low levels of education) are not more likely to shift downward into low-wage jobs compared to other exposed workers (column 5), and neither are workers making high wages–who tend to have relatively high education levels–significantly less likely to

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

[41]We show results on all five wage quintiles in Table A-16 in the Appendix.

Table 10: The Role of Individual Skill for Worker Transitions leading to Polarization

	Mid-Wage Emp.		High-Wage Emp.		Low-Wage Emp.		Unemployment		Outside of Labor Market	
ImpComp	-2.176***	-1.819***	0.382	0.185	1.404***	1.331***	0.251*	0.078	0.495	0.548*
	(0.601)	(0.524)	(0.271)	(0.202)	(0.295)	(0.265)	(0.145)	(0.152)	(0.345)	(0.289)
ImpComp x Low Wage	1.621**		-0.337		-0.470		-0.658**		-0.117	
	(0.696)		(0.408)		(0.454)		(0.286)		(0.536)	
ImpComp x High Wage		-0.823		2.171***		-0.605		0.0677		-1.107**
		(1.109)		(0.755)		(0.531)		(0.284)		(0.479)
N	13,934	13,934	13,934	13,934	13,934	13,934	13,934	13,934	13,934	13,934
Worker Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Period Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Period x Quintile Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Estimation of equation by OLS. Low (High) Wage: indicator that worker is in the lowest (highest) quintile of the hourly wage distribution of 1999 mid-wage workers. Sample is all mid-wage textile workers (N = 13,934). All regressions include worker, period, and period by quintile fixed effects. Robust standard errors clustered at the firm level in parentheses. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

move down to low-wage occupations (column 6).

Finally, we see that workers receiving relatively high wages do not shift out of the labor force while workers with relatively low wages are significantly less likely to be unemployed compared to other exposed middle-class workers (columns 10 and 9, respectively). While the former is in line with our findings for college-educated workers in Table 9, the latter differs from what we found for workers with the lowest level of education. Overall, these results indicate that education and skill are two complementary factors that determine whether exposed middle-class workers move upward or downward in response to a trade shock.

We have also examined the occupational transitions of textile workers in their sectoral dimension. Exposed middle-class textile workers leave manufacturing for low-wage but not high-wage jobs in manufacturing, and they strongly move to employment in the services sector. While some workers stay in middle-class positions trade exposure also leads to new service employment in both low-wage service positions industries (retail, but also low-wage jobs in finance, business) and high-wage service positions (finance, business, but not retail). These results are shown in Table A-15 in the Appendix.[42]

4.3 Trade versus Technology in Job Polarization: A Worker-Task Analysis

The following analysis employs information on individual tasks of the O*NET data base to shed new light on factors that make workers employed in different occupations more or less prone to job polarization. Compared to aggregate task measures –such as the Routine Task Index– this allows to separate the role of sub-components, in particular manual versus routine tasks. Our analysis broadly follows earlier work in relating O*NET variables to task groups (Autor, Levy, Murnane 2003, Blinder 2009, Blinder and Krueger 2013, Crino 2010, and Firpo, Fortin, and Lemieux 2011). To ensure that findings are robust we employ multiple O*NET question for each task group.[43]

Analogous to the analysis of education above (Table 9), we interact the importance of a particular task in the worker's occupation with the degree to which this worker is exposed to rising import competition after China's WTO entry and estimate a triple difference in difference equation with individual fixed effects (equation 6). Table 11 reports the results for tasks that heavily involve manual activities.

[42] Results by sector for 1999 high- and low-wage workers are shown in Tables **??** and **??**, respectively.

[43] By using O*NET questions our analysis employs variation in tasks by occupation for the United States. Recently, a similar task survey has been conducted for a number of European countries (European Skills/Competences, Qualifications and Occupations (ESCO); first full version published on July 28, 2017). We prefer to utilize O*NET because ESCO does not include Denmark, and matching our 1988 occupational codes (ISCO-88) to the ESCO data using a 2008 classification (ISCO-08) would introduce considerable error.

Table 11: 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)
N	18,462	19,980	18,700	19,870	19,900	20,106	18,428
R-squared	0.696	0.701	0.697	0.699	0.695	0.700	0.697
Worker Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Period Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Period x Task Fixed Effects	✓	✓	✓	✓	✓	✓	✓

Notes: The dependent variable in all columns is years in mid-wage employment between 2000 and 2009. Sample is all 1999 textile and clothing workers. Estimation is by OLS. Regressions include worker and period fixed effects as well as the interaction between the period fixed effect and Task variable. In each regression a specific task variable is indicated in the column heading. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

The results show that workers exposed to rising import competition who perform tasks in which *Repetitive Motions* are important suffer significantly higher mid-wage employment losses.[44] Quantitatively, the impact of import competition on losing middle-class employment is almost three times as large compared to other workers. Another manual task is *Manual Dexterity*. We see that workers performing tasks where manual dexterity is important have significantly lower mid-wage employment due to rising import competition than the average exposed worker. Similar results are found for *Finger Dexterity* and for tasks where the pace of work is determined by the speed of the equipment (*PDSE*), see columns (3) and (4), respectively.

We conclude that workers performing manual tasks have disproportionately less mid-wage employment compared to other workers exposed to rising import competition. Notice that when repetitive motions are important, or the pace of work is determined by the speed of machines, typically those tasks have a relatively high degree of routine-ness, making these trade-exposed workers disproportionately affected by routine-biased technical change as well.[45]

In order to disentangle the roles routine versus manual tasks in workers' losing middle-class jobs, on the right side of Table 11 we show results for manual tasks that are much less routine. Take *Gross Body Coordination*, for example, which involves the coordination of simultaneous movements of different parts of the body.[46] Because this task is based on movements of individual limbs as well as the body, and helped by physical fitness, it is classified (broadly) manual. At the same time, because the movements require coordination of different body parts these tasks are unlikely to be very repetitive and programmable. Thus we classify *Gross Body Coordination* as a non-routine manual task, as in Autor, Levy, and Murnane (2003).

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

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

[45] See also Firpo, Fortin and Lemieux (2011) and Hummels, Jørgensen, Munch, and Xiang (2014) for similar classifications based on O*NET questions.

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

Comparing the left and the right sides of Table 11, the degree to which trade-exposed workers performing non-routine manual tasks experience mid-wage employment reductions is similar to the extent to which routine-manual task content exacerbates mid-wage employment reductions. Similar results are found for 1999 mid-wage workers, see Table A-17.[47] The key finding is that workers in occupations intensively performing manual tasks are most vulnerable to the hollowing out of middle-class jobs. We refer to this as Manual Task Intensity (MTI).[48] Furthermore, we see from Table 11 that this holds whether these manual tasks are routine or not routine in nature.

Table 12: 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)
Observations	20,728	19,972	18,516	19,606	20,132
R-squared	0.699	0.700	0.693	0.692	0.699

Notes: The dependent variable in all columns is years in mid-wage employment between 2000 and 2009. Sample is all 1999 textile and clothing workers. Estimation is by OLS. Regressions include worker and period fixed effects as well as the interaction between the period fixed effect and Task variable. In each regression a specific task variable is indicated in the column heading. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

If workers performing manual tasks are prone to mid-wage employment reductions through rising import competition, it should be the case that workers performing non-manual tasks experience these effects comparatively less. This is examined in Table 12. Non-manual tasks are taken to be cognitive tasks. We expect there to be some correlation between jobs intensively using cognitive tasks and jobs held by workers with relatively high skill levels. At the same time, the overlap

[47] In addition, we have confirmed that manual task intensity influences the extent to which workers move up into high-wage or down into low-wage occupations; results are available upon request.

[48] Manual Task Intensity is conceptually different from Routine Task Intensity (RTI; Autor, Levy, and Murnane 2003) in that it is based on a single (not several) task characteristic(s).

is not perfect, and 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*, short for the O*NET question of *Evaluating Information to Determine Compliance with Standards*, with results shown in column 1 of Table 12.

We find that workers employed in jobs where *Evaluating Information* is important are experiencing smaller mid-wage employment reductions than the typical exposed worker (column 1). In fact, there are virtually no mid-wage employment reductions for workers in these routine-cognitive intensive jobs. A similar result is obtained for set of another routine-cognitive tasks, those for which repeating the same task (e.g., checking entries in a ledger) is important, see column 2.

On the right side of Table 12 we report results for several non-routine cognitive tasks. There is, first, Developing Objectives and Strategies (*Developing Strategies*). Exposed workers for which this task is important do not experience large if any mid-wage employment losses due to rising import competition (column 3). The same is true for workers intensively using *Inductive Reasoning*, see column 4. The last column of Table 12 shows results for workers whose job requires intensively to perform *Mathematical Reasoning*. We see that such workers do not experience mid-wage employment reductions as a result of rising import competition. To summarize, workers performing cognitive tasks do not experience lower mid-wage employment the way other exposed workers do, and moreover, there is little difference in the outcome of workers performing cognitive tasks that are routine, versus workers who perform cognitive tasks that are not routine in nature.[49]

Overall, workers who perform intensively manual tasks are central to the trade-induced hollowing out of middle-class jobs characteristic of job polarization. The finding that Manual Task Intensity (MTI) matters for job polarization is the third key result of this paper. It complements earlier findings that task routine-ness contributes to job polarization because it accelerates routine-biased technical change. However, if workers' movements' contributing to job polarization would depend only on the routine-ness of tasks, there would be no disproportionate mid-wage employment reduction for workers performing non-routine manual tasks (but see Table 11, right side). Furthermore, there would be a disproportionate mid-wage employment effect for workers performing routine cognitive tasks (but see Table 12, left side).

The main reason why the manual task intensity matters for the impact of trade is that in terms of task content, rising import competition pits Danish against Chinese workers. Despite recent

[49]We find broadly similar results for the subset of 1999 textile workers who are employed in mid-wage occupations, see Table A-18. Results tend to be somewhat stronger for all 1999 textile workers, which may be due to the fact that the number of workers performing cognitive tasks in high-wage occupations is substantial.

technology advances the ability of robots to perform non-routine tasks is still limited compared to that of humans, and thus it is not surprising that competition between workers in different countries has bite.

Given the well-documented role of routine-biased technical change for job polarization, it may be surprising that mid-wage employment reductions of workers performing routine-cognitive tasks are relatively low (Table 12, left side). One possible explanation is that typical skill levels in China are still lower than in Denmark, so that the international competition in that part of the task space is more moderate.[50]

The previous analysis has shown that although both rising import competition and technical change are key aspects of globalization, it is possible to separate their distinct effects in the context of the hollowing-out of middle-class jobs characteristic of job polarization.

5 Conclusions

This paper has used administrative matched employer-employee data for Denmark between 1999 and 2009 to examine the role of rising import competition for generating the U-shaped employment response across the occupational wage distribution known as job polarization. Employing a widely-used instrumental-variables approach to generate variation in trade exposure together with information on virtually the entire private-sector labor of Denmark in 1999, we first find that rising import competition from China has led to a significant hollowing-out of mid-wage jobs at the same time that it led to growth in both low- and high-wage employment. With our finding that rising import competition has contributed to job polarization we add a major labor market outcome to others identified in earlier work.

Second, by comparing the impact of import competition side-by-side to that of other factors that can explain job polarization we show that, quantitatively, rising import competition has had a similarly large on hollowing-out middle-class employment as had routine-biased technical change. Furthermore, import competition also explains part of the increase in low-wage and high-wage employment, while technical change does not. Import competition and offshoring can both explain the increased likelihood of employment in low-wage jobs in our setting, which may be a reason why trade openness is a particular source of discontent for many workers.

We confirm the finding that rising import competition has led to job polarization by studying the

[50] Another possibility may be that it is generally harder to embody elements of cognitive knowledge in goods that are traded internationally, compared to the ease of embodying manual tasks. Answering these interesting questions goes beyond the scope of this paper.

impact of the removal of quantitative trade restrictions on Chinas textile exports following Chinas entry into the WTO in 2002. This adds evidence from a quasi-natural experiment where occupational sorting and industry shocks are rather limited and treatment is defined by the detailed product portfolio of each workers firm years before the trade liberalization.

Finally, we shift our focus to the task content of different occupations to show that workers performing manual intensive tasks are those who contribute most to generating trade-induced job polarization, whereas workers performing cognitive intensive tasks are not. Thus, while computers and communication technology improvements 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.

Our finding that rising import competition matters for job polarization because humans remain important for performing manual-intensive tasks provides useful information for other literatures as well. For example, recent work by Acemoglu and Restrepo (2018) 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 labor share fall. An important extension that may influence these dynamics would seem to be studying the ongoing impact of greater international openness which allows workers in different countries to compete more strongly with each other.

References

[1] **Daron Acemoglu Pascual Restrepo** 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment", *American Economic Review*, vol 108(6):1488-1542.

[2] **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.

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

[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, Gordon Hanson and Jae Song.** 2014. "Trade Adjustment: Worker Level Evidence", *The Quarterly Journal of Economics*, 129: 1799-1860.

[8] **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.

[9] **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.

[10] **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.

[11] **Bagger, Jesper, Bent Jesper Christensen, and Dale T. Mortensen** 2014. "Wage and labor productivity dispersion: The roles of total factor productivity, labor quality, capital intensity, and rent sharing.", Working paper.

[12] **Barany, Sofia, and Christian Siegel** 2018. "Job Polarization and Structural Change", *American Economic Journal: Macroeconomics*, Vol. 10, No. 1, pp. 57-89.

[13] **Bernard, Andrew B., Bradford J. Jensen and Peter K. Schott** 2006. "Survival of the best fit: Exposure to low-wage countries and the (uneven) growth of U.S. manufacturing plants", *Journal of International Economics*, Elsevier, vol. 68(1), 219-237.

[14] **Bjørnskov, Christian, Ioana Neamtu, and Niels Westergård-Nielsen** 2012. "Growing Inequality And Its Impacts In Denmark", GINI Country Report for Denmark.

[15] **Blanchard, Emily, and Will Olney** 2017. "Globalization and Human Capital Investment: Export Composition Drives Educational Attainment", *Journal of International Economics* 106: 165-183.

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

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

[18] **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.

[19] **Bound, John, and Harry T. Holzer** 2010. "Demand Shifts, Population Adjustments, and Labor Market Outcomes during the 1980s", *Journal of Labor Economics* Vol. 18, No. 1, pp. 20-54.

[20] **Brambilla, Irene, Amit Khandelwal and Peter Schott** 2010. "China's Experience Under the Multifiber Arrangement (MFA) and the Agreement on Textile and Clothing (ATC)", Robert Feenstra and Shang-Jin Wei (Eds), China's Growing Role in World Trade, NBER, Cambridge: MA.

[21] **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.

[22] **Bunzel, Henning** 2008. "The LMDG Data Sets", mimeo, Univeristy of Aarhus.

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

[24] **Dix-Carneiro, Rafael, and Brian Kovak** 2015. "Trade Reform and Regional Dynamics: Evidence From 25 Years of Brazilian Matched Employer-Employee Data", NBER Working Paper No. 20908.

[25] **Dustmann, Christian, Johannes Ludsteck, and Uta Schonberg** 2009. "Revisiting the German Wage Structure", *The Quarterly Journal of Economics*, 124, 843-881.

[26] **Ebenstein, Avraham, Ann Harrison, Margaret McMillan and Shannon Phillips** 2014. "Estimating the Impact of Trade and Offshoring on American Workers using the Current Population Surveys", *The Review of Economics and Statistics*, 96(3): 581-595.

[27] **Eriksson, Tor and Niels Westergaard-Nielsen** 2009. "Wage and Labor Mobility in Denmark, 1980-2000", in *The Structure of Wages: An International Comparison*, (Eds.) Edward P. Lazear and Kathryn L. Shaw, Chicago: University of Chicago Press and National Bureau of Economic Research.

[28] **Feenstra, Robert C.** (2000), "Introduction", The Impact of International Trade on Wages, R. C. Feenstra (editor), University of Chicago Press for the NBER, pp. 1-11.

[29] **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).

[30] **Foged, Mette and Giovanni Peri** 2016. "Immigrants' Effect on Native Workers: New Analysis on Longitudinal Data", *American Economic Journal: Applied Economics*, 8(2): 1-34.

[31] **Goldberg, Pinelopi and Nina Pavcnik** 2007. "Distributional Effects of Globalization in Developing Countries, *Journal of Economic Literature*, 45(1), pp. 39-82.

[32] **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.

[33] **Goos, Maarten, Alan Manning, and Anna Salomons** 2009. "Job Polarization in Europe", *American Economic Review: Papers and Proceedings*, 99(2), 58-63.

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

[35] **Graetz, Georg and Guy Michaels** 2015 "Robots at Work", Center for Economic Performance Discussion Paper No. 1335.

[36] **Groes, Fane, Philipp Kircher, and Iorii Manovskii** 2015. "The U-Shapes of Occupational Mobility", *Review of Economic Studies*, 82(2): 659-692.

[37] **Hakobyan, Shushanik and John McLaren** 2016. "Looking for Local Labor-Market Effects of NAFTA", *The Review of Economics and Statistics*.

[38] **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.

[39] **Harrigan, James, Ariell Reshef, and Farid Toubal** 2015. "The March of the Techies: Technology, Trade, and Job Polarization in France, 1994-2007", presented at NBER ITI Winter Meeting 2015.

[40] **Harrison Ann, John McLaren, Margaret McMillan** 2011. "Recent Perspectives on Trade and Inequality", *Annual Review of Economics*, Vol 3, pp 261-289.

[41] **Haskel, Jonathan E., Sonia C. Pereira, and Matthew J. Slaughter** 2007. "Does Inward Foreign Direct Investment Boost The Productivity Of Domestic Firms?", *The Review of Economics and Statistics*, August 2007, 89(3): 482-496.

[42] **Holzer, Harry** 2015. "Job Market Polarization and U.S. Worker Skills: A Tale of Two Middles", *Economic Studies*, The Brookings Institution.

[43] **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.

[44] **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.

[45] **Koopman, Robert, Zhi Wang, and Shang-Jin Wei** 2014. "Tracing Value-Added and Double Counting in Gross Exports", *American Economic Review*, 104(2): 459-94.

[46] **Lake, James, and Daniel L. Millimet** 2016. "Good Jobs, Bad Jobs: Whats Trade Got To Do With It?", IZA Discussion Paper 9814, March.

[47] **Malamud, Ofer, and Abigail Wozniak** 2012. "The Impact of College on Migration: Evidence from the Vietnam Generation", *Journal of Human Resources*, Volume 47, Number 4, pp. 913-950.

[48] **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.

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

[50] **Polataev, Maxim, and Chris Robinson** 2008. "Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984-2000", *Journal of Labor Economics*, vol. 26, issue 3, 387-420.

[51] **Spitz-Oener, Alexandra** 2006. "Technical Change, Job Tasks and Rising Educational Demand: Looking Outside the Wage Structure", *Journal of Labor Economics*, 24, 235-270.

[52] **Timmermans, Bram** 2010. "The Danish Integrated Database for Labor Market Research: Towards Demystification for the English Speaking Audience", DRUID Working Papers 10-16.

[53] **Traiberman, Sharon** 2019. "Occupations and Import Competition: Evidence from Denmark", working paper.

[54] **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.

[55] **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.

[56] **Utar, Hale, and Luis Torres Ruiz.** 2013. "International Competition and Industrial Evolution: Evidence from the Impact of Chinese Competition on Mexican Maquiladoras", *Journal of Development Economics*, 105: 267-287.

[57] **World Bank** 2016. World Development Indicators databese, merchandise exports.

Online Appendix:

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

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July 24, 2019

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A Data Sources and Definitions

The main database employed in this study 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 can be accessed at http://www.dst.dk/da/Statistik/dokumentation/Times .

A.1 Data Sets

Integrated Database for Labor Market Research (IDA)

The IDA Database is the main source of information on workers. It provides a snapshot of the labor market for each year at the end of November. It contains 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. 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 typically outsource their production, and consequently we can identify virtually all firms that domestically produce quota products using VARES. The reporting unit is the "Kind of Activity Unit" (KAU), which is the sum of a company's workplaces in the same main industry. Reporting units provide as well their company identification code, allowing us to match the eight-digit production information with other firm-level information.

Business and accounting statistics (FIRE)

This dataset by Statistics Denmark compiles business and accounting data, as well as tax reports, value-added tax (VAT) reports, and information from incorporated companies. It is employed in this paper to create the pre-trend variable in the firm's product category as well as other measures at the six-digit industry level. The information covers virtually all firms for most sectors, including manufacturing, construction, retail, mining, as well as hospitality, transportation, telecommunication, real estate, rental, information technology, R&D and other business services.[51]

International trade data (UHDI)

The data comes from Denmark's customs records together with monthly reports to Statistics Denmark from about 8,000 firms in Denmark in which their trade with other countries of the European Union (EU) is reported. This is supplemented with information on EU trade from VAT returns, which are mandatory for virtually all firms in Denmark. Thus the data-set covers the entire universe of trading firms. The information of each record gives shipment date, value, and weight, and if applicable the shipment's quantity. It also provides information on the 8-digit product classification according to the Combined Nomenclature (CN) 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 8-digit CN level, while the category "Woven fabrics of synthetic filament yarn obtained from strip or the like of polyethylene or polypropylene, less than 3 m wide" corresponds to a single 8-digit CN product. Quota categories include both

[51] 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.

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).

A.2 *Industry Classifications*

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

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

A.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). Among the service-oriented vocational training titles we separately identify those that focus on information technology (IT) education. 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); of these, about 3% (n = 6,452) are workers with IT-oriented vocational education. The number of workers with manufacturing-oriented vocational education is 80,250 (9% of all workers).

A.4 *Occupation Classifications*

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

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

A.5 *Chinese Import Competition and Instrumental Variables Approach*

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

Imports from China in eight other high-income countries are employed as an instrumental variable of the following form:

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

where $OM_{j,t}^{CH}$ is the total value of imports in the corresponding industry j in the eight high-income countries at year t. The countries are Australia, Finland, Germany, Japan, the Netherlands, New Zealand, Switzerland, and the United States. Data for the European countries comes from Eurostat and is available in the eight-digit CN classification. Data for the non-European countries comes from the United Nation's COMTRADE database in the six-digit Harmonized System classification. We match the international trade data of all eight high-income countries to the six-digit DB93 classification of Denmark via our CN/HS-DB mapping.

We employ two additional instrumental variables, that can be viewed as structural measures of

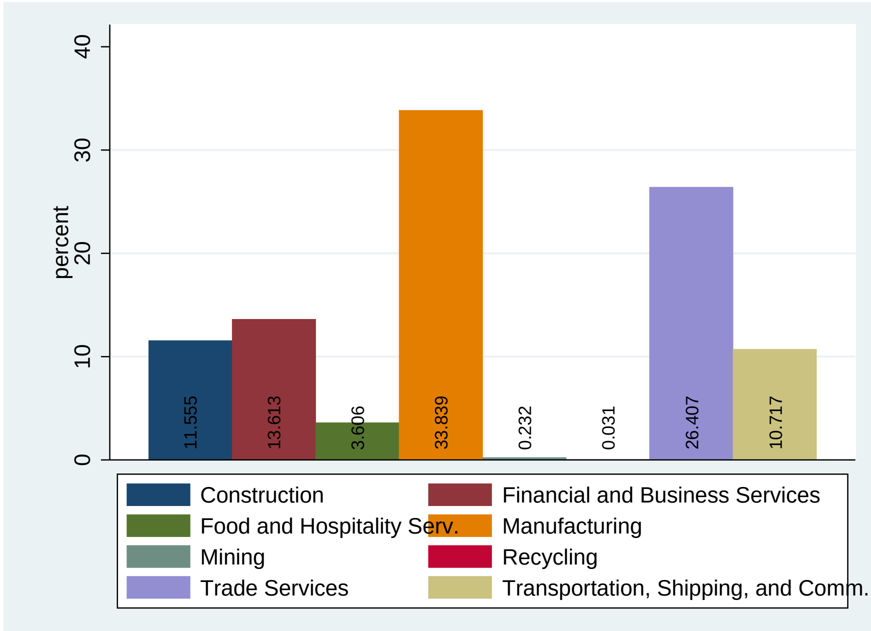

Figure A-1: Industry Affiliation of Workers in 1999

market openness in the pre-trade shock period. They are, first, the logarithm of the weighted average distance to the source countries of the goods Denmark imported in 1996 in worker i's initial industry of employment. Employing bilateral distance data from CEPII http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=8, we weight these distances by the import value shares at the six-digit industry level. The second measure is the fraction of retail trade firms in all importing firms in worker i's six-digit industry in the year 1996. When retail and wholesale firms are present it is comparatively easy for imported goods to reach consumers, thereby making the industry more vulnerable to exogenous supply shocks in China. The data comes from the FIRE database.

Figure A-1 provides information on the sectoral distribution of our entire private-sector sample (N = 900,329).

A.6 *Task and Offshoring Data*

For the worker task analysis in section 4.3, we employ occupational characteristics provided in the O*NET database of June 2009. The O*NET database provides information on the importance and/or the level of activity in a particular task. We broadly follow the literature in relating O*NET variables to task groups, in particular Autor, Levy, Murnane (2003), Blinder (2009), Blinder and Krueger (2013), Crino (2010), and Firpo, Fortin, and Lemieux (2011). Table A-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?". Since 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) variable is due to Autor, Levy, Murnane (2003) and mapped into the two-digit digit ISCO occupational classification by Goos, Manning, and Salomons (2014). The offshoring variables also vary across two-digit ISCO occupations. Both the Blinder and Krueger (2013) as well as the Goos, Manning, and Salomons (2014) indices are meant to capture the offshorability of a worker based on the tasks that he or she performs, with Goos, Manning, and Salomon's (2014) index being based on actual instances of offshoring by European countries. Table 7 in the paper employs the Goos, Manning, and Salomons (2014) variable, while results for the Blinder and Krueger (2013) are shown in Table A-10. The source of both the RTI variable as well as the two offshoring indices is Goos, Manning, and Salomons (2014).[52] The offshoring variables are defined for the particular occupational classification employed by Goos, Manning, and Salomons (2014). Table A-2 provides the list of two-digit occupational classes for which these

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

authors construct their offshoring and RTI variables.

Table A-1: O*NET Questions Employed in the Paper

O*NET Q No	Title	Type
Panel A.	ROUTINE MANUAL TASKS	
4.C.2.d.1.i	Spend time making repetitive motions	Context
4.C.3.d.3	Pace Determined by Speed of Equipment	Context
1.A.2.a.2	Manual Dexterity	Abilities
1.A.2.a.3	Finger Dexterity	Abilities
Panel B.	ROUTINE COGNITIVE TASKS	
4.A.2.a.3	Evaluating Information to Determine Compliance with Standards	Activities
4.C.3.b.7	Importance of Repeating Same Tasks	Context
Panel C.	NON-ROUTINE MANUAL TASKS	
1.A.2.b.2	Multilimb Coordination	Abilities
1.A.3.c.3	Gross Body Coordination	Abilities
1.A.2.b.3	Response orientation	Abilities
Panel D.	NON-ROUTINE COGNITIVE TASKS	
1.A.1.c.1	Mathematical Reasoning	Abilities
1.A.1.b.5	Inductive Reasoning	Abilities
4.A.2.b.1	Making Decisions and Solving Problems	Activities
4.A.2.b.4	Developing Objectives and Strategies	Activities
Panel E.	INFORMATION TECHNOLOGY INVOLVED TASKS	
4.A.3.b.1	Interacting with computers	Activities

Table A-2: High-, Mid-, and Low Wage Occupations across European Countries (Goos, Manning, and Salomons (2014))

	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
Middling 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).

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

Table A-3: Variable definitions

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

B Rising Import Competition through Removal of Import Quotas for China

The original purpose of the Multi-Fibre Arrangement (MFA) of the year 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 benefited from the fourth liberalization. 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. This experiment has been employed by Brambilla, Khandelwal, and Schott (2008) for the United States, and Bloom, Draca, and van Reenen (2016) for a set of European countries, among other work. Our analysis in this respect builds on Utar (2014).

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 and negotiations about the MFA were held at the EU level.

Most of the quotas for China had more than 90% filling rates. Using transaction-level import data it can be confirmed that that the MFA quotas were binding for China. Both the 2002 and the 2005 quota lifting caused a substantial 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 were a result of entry of more efficient Chinese producers into the export market (Khandelwal, Schott, and Wei 2013).

As a consequence, virtually all workers employed at firms subject to the quota removals faced increased import competition from China starting in the year 2002. We use the revenue share of firms in quota goods in 1999 as our measure of exposure to import competition.

A key identification condition 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, we choose the year 1999, three years before China's WTO entry, to determine whether a firm was producing a product that would be subject to a quota removal. Second, we have performed 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 A-4.

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

	(1)	(2)	(3)	(4)
	Earnings	Hours	HourlyWage	Unemployment
Exposure x 91	0.026	0.004	0.032*	-0.034
	(0.067)	(0.056)	(0.019)	(0.267)
Exposure x 92	0.113	0.043	0.037	-0.194
	(0.073)	(0.056)	(0.028)	(0.308)
Exposure x 93	0.123	0.084	0.004	0.141
	(0.078)	(0.060)	(0.034)	(0.365)
Exposure x 94	0.127	0.092	-0.028	-0.182
	(0.090)	(0.057)	(0.042)	(0.299)
Exposure x 95	0.112	0.089	-0.028	-0.182
	(0.093)	(0.057)	(0.045)	(0.350)
Exposure x 96	0.109	0.062	-0.014	-0.228
	(0.096)	(0.056)	(0.046)	(0.382)
Exposure x 97	0.106	0.087	-0.026	-0.132
	(0.108)	(0.061)	(0.046)	(0.332)
Exposure x 98	0.084	0.052	-0.024	-0.241
	(0.120)	(0.060)	(0.052)	(0.353)
Exposure x 99	0.166	0.053	0.012	0.159
	(0.136)	(0.067)	(0.059)	(0.389)
N	87,976	83,509	83,509	101,246

Notes: The dependent variable in all regressions is expressed in logarithm. Results shown for interaction variables of Exposure with separate year indicators, 1991 to 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. Sample period: 1990-1999. 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 worker's firm for which quotas will be removed with China's entry into the WTO. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

Furthermore, there is the question whether the trade liberalization was partially reversed in some countries. In particular, due to a surge of Chinese imports in the first few months of 2005 at EU ports in response to the fourth phase of the quota removal, the EU retained a few of the quota categories until 2008. Another concern is that the fourth liberalization phase of 2005 might have been more important than the third liberalization phase of 2002 because the liberalization of key products was intentionally kept to the last possible moment.

Our approach of employing the entire period 2002 to 2009 as the treatment period is designed to address these issues. First, by extending beyond 2008 it covers the liberalization of products where the EU went temporarily back on its 2005 commitments. Second, our approach reflects the fact that the 2002 and the 2005 liberalization effects are hard to disentangle. Specifically, given necessary votes in the U.S. Congress, while there was considerable uncertainty about China's entry into the WTO in 2002 there was no new uncertainty around the fourth liberalization phase in 2005, and with forward-looking agents the impact of the fourth liberalization would be felt starting in 2002.

To shed some more light on the periods of liberalization, post-2002 and post-2005, the following summarizes the firm-level analysis conducted in Table D-6 in the Online Appendix of Utar (2014). $MFAQ2_j$ is an indicator variable that takes 1 if firm j produces a quota good as of year 1999 which is subject to the 2002 removal for China. Similarly, $MFAQ5_j$ takes 1 if firm j produces a quota good as of year 1999 which is subject to the 2005 removal for China. We then estimate the following equation over the period 1999-2007:

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

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

Overall, there is little evidence from this analysis that the 2002 liberalization phase is less important

Table A-5: The 2002 versus 2005 Quota Removals: Evidence from Firm-level Analysis

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

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

than the 2005 liberalization for employment outcomes. The preferred approach is to define the entire period 2002-2009 as the treatment period.

C Supplementary Information and Analysis

C.1 Descriptive Statistics and Data Sources: Private-Sector Sample

Table A-6: 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
ΔIP^{CH}	0.011	0.030	UHDI, FIRE
ΔHIP^{CH}	1.240	4.196	FIRE, EUROSTAT, COMTRADE
Log distance to import source	2.465	3.456	CEPII, UHDI
Share of retail firms in import	0.020	0.052	UHDI, FIRE

Table A-7 gives the full two-stage least squares results that are summarized in Table 5 of the paper. First-stage results on the excluded instruments are shown at the bottom of Table A-7.

Table A-7: Import Competition and Job Polarization

Dep. Var.	$HIGH^e$ (1)	MID^e (2)	LOW^e (3)
ΔIP^{CH}	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***
	(5.035)	(4.401)	(2.209)
Industry Pre-Trend	-0.013	0.008	-0.003
	(0.014)	(0.018)	(0.012)

Continued on next page

Table A-7 – *Continued from previous page*

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

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

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

Table A-8: Import Competition and Full-time Employment, Hours, and Earnings

	(1)	(2)	(3)
Panel A.	Mid-Wage Emp.	High-Wage Emp.	Low-Wage Emp.
		Full-time Employment	
Δ Import Comp	-5.167**	2.411**	2.005*
	(2.244)	(1.087)	(1.126)
N	900,329	900,329	900,329
Panel B.	Mid-wage Hours	High-wage Hours	Low-wage Hours
Δ Import Comp	-5.925**	2.279**	2.315*
	(2.526)	(1.103)	(1.393)
N	879,614	879,614	879,614
Panel C.	Mid-wage Earnings	High-wage Earnings	Low-wage Earnings
Δ Import Comp	-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 in 2000-2009 in Panel A., hours worked in 2000-2009 relative to 1999 in Panel B., and labor earnings in 2000-2009 relative to 1999 in Panel C. Estimation by two stage least squares. 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 A-8 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 5.

Table A-9: The Dynamics of the Impact of Import Competition on Labor Market Status

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

Notes: Year on top of column indicates last year of sample. Dependent variable given in each panel. Each cell gives results on the variable Import Competition for a separate regression; N = 900,329. Estimation by two stage least squares. Robust standard errors clustered at the 3-digit industry level in parentheses. All specifications include demographic (gender, age (linear and square terms), immigration status, interaction between gender and age), education, hourly wage, labor market history (unemployment history, linear and square terms of experience), union and unemployment insurance memberships, firm (size, wage, separation rate), as well as product-level covariates as described in Table 4. All specifications also include two digit occupation fixed effects and two-digit industry fixed effects. $^{\circ}$, * and ** indicate significance at the 10 %, 5% and 1% levels respectively.

C.2 Results for an Alternative Offshoring Measure

Table A-10 shows results employing the alternative offshoring measure due to Blinder and Krueger (2013). The pattern of the results is broadly similar to employing the Goos, Manning, and Salomons (2014) measure, see Table 7. One difference is that using the Blinder and Krueger (2013) variable, offshoring remains significant in the mid-wage employment equation once the RTI variable is included. Also, the coefficient for import competition in the low-wage equation is not significant anymore, although it is comparable in magnitude to the earlier results (coefficients of 1.7 and 2.1, respectively).

Table A-10: Results for Blinder and Krueger (2013) Offshoring Measure

	(1) Mid-wage Emp.	(2) Mid-wage Emp.	(3) Mid-wage Emp.	(4) High-wage Emp.	(5) Low-wage Emp.
Δ Imports from China	-5.469**	-5.539**	-5.431**	4.117***	1.727
	(2.303)	(2.288)	(2.322)	(1.442)	(1.106)
	[-0.044]	[-0.045]	[-0.044]	[0.034]	[0.022]
Offshoring		-0.107***	-0.069**	-0.128***	0.111***
		(0.040)	(0.034)	(0.022)	(0.016)
		[-0.029]	[-0.019]	[-0.035]	[0.047]
Routine Task Intensity			-0.180***	0.373***	0.003
			(0.055)	(0.038)	(0.039)
			[-0.046]	[0.097]	[0.001]
N	786,090	786,090	786,090	786,090	786,090
First-stage F-test [p-value]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

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 4. 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 (from O*NET). "Offshoring" is the offshorability of worker *i*'s two digit occupation class, due to Blinder and Krueger (2013). "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 is below N = 900,329 because there are no routine task intensity or offshoring measures for some of the Danish occupation codes. $^{\circ}$, * and ** indicate significance at the 10 %, 5% and 1% levels respectively.

D Supplemental Results for the Textile Quota Liberalization

We present alternative and robustness analysis for the quasi-experimental setting of the removal of quantitative restrictions on China's textile exports. The first set of results is, instead of for the difference-in-difference specification (equation 5), based on a cross-sectional specification analogous to the instrumental variables results of section 3. There are N = 10,487 1999 textile workers. Since the beginning of the quota removal was in year 2002, our cumulative variables are now defined over the period 2002-2009. As in equation 4 in the main paper, in addition to fixed effects for the workers' 1999 occupation by broad wage group we control for a detailed set of worker and firm characteristics as of the initial year 1999. Table A-11 presents these results. In the regression with cumulative mid-wage employment as dependent variable, the coefficient is about -1.5, implying that exposed textile workers have typically about half a year less mid-wage employment than not exposed workers (Table A-11, column 2). The results show that on average, Chinese import competition also raises high- and low-wage employment (Panel A, columns 1 and 3); the implied difference between exposed and not-exposed workers is about three months of employment each.

Table A-11: Quasi-Experimental Evidence using A Cross-sectional Approach

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A.	High-wage Emp.	Mid-wage Emp.	Low-wage Emp.	High-wage Emp.	Mid-wage Emp.	Low-wage Emp.
Import Competition	0.692**	-1.513**	0.746**	0.570*	-1.387**	0.796**
	(0.252)	(0.344)	(0.205)	(0.239)	(0.373)	(0.201)
Four-digit occupation FEs				✓	✓	✓
N	10,487	10,487	10,487	10,487	10,487	10,487

Notes: Estimation by OLS. Robust standard errors clustered at the (initial) firm-level are reported in parentheses. Cumulative worker-level dependent variables are defined over 2002-2009. Import Competition is a continuous trade exposure variable defined as the revenue share of 8-digit Combined Nomenclature goods that were subject to removal of quotas for China in 1999 of worker *i*'s employer. All specifications include demographic (gender, age, immigration status), education, hourly wage, labor market history (unemployment history, linear and square terms of experience), union and unemployment insurance memberships, and firm variables (size, wage, separation rate). In addition, all specifications include two-digit occupation fixed effects in columns 1 to 3 and four-digit occupation fixed effects in columns 4 to 6. $^{\circ}$, * and ** indicate significance at the 10 %, 5% and 1% levels respectively.

In the specifications on the right side of Table A-11 we have replaced two-digit with four-digit occupational fixed effects to address possible differences in the degree to which workers are affected by import competition at the detailed occupation level. Given the broad similarity of the results, such effects are not of major importance for our results.

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

Describing the movements of 1999 mid-wage textile workers, Table A-12 provides the coefficients and standard errors behind Figure 6 in the text.

Table A-12: The Dynamic Impact on Mid-wage Textile Workers

	(1) **2002**	(2) **2003**	(3) **2004**	(4) **2005**	(5) **2006**	(6) **2007**	(7) **2008**	(8) **2009**
Panel A.	Years in Mid-wage employment							
Import Comp	0.0192	-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							
Import Comp	-0.0536	0.00548	0.0607	0.0992	0.137	0.194	0.245	0.270
	(0.0537)	(0.0575)	(0.0625)	(0.0868)	(0.117)	(0.149)	(0.180)	(0.214)
Panel C.	Years in Low-wage employment							
Import Comp	0.0337	0.208***	0.441***	0.628***	0.826***	1.001***	1.166***	1.379***
	(0.0358)	(0.0612)	(0.0971)	(0.130)	(0.165)	(0.196)	(0.225)	(0.258)
Panel D.	Years in unemployment							
Import Comp	-0.0714	0.102	0.185**	0.207**	0.225**	0.211*	0.190	0.138
	(0.0637)	(0.0753)	(0.0881)	(0.100)	(0.111)	(0.122)	(0.134)	(0.145)
Panel E.	Years outside the labor market							
Import Comp	-0.0139	0.0377	0.121	0.220**	0.293*	0.422**	0.504**	0.612**
	(0.0303)	(0.0425)	(0.0746)	(0.112)	(0.153)	(0.200)	(0.250)	(0.304)
N	13,934	13,934	13,934	13,934	13,934	13,934	13,934	13,934
Worker FEs	✓	✓	✓	✓	✓	✓	✓	✓
Period FEs	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Given at top of column is last year of sample period. Estimation by OLS. The sample contains all 1999 mid-wage textile workers. All regressions include worker and period fixed effects. Robust standard errors clustered at the firm level in parentheses. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

Table A-13 presents evolution of rising import competition on textile workers who in 1999 are employed in high-wage occupations. It is interesting to note that when we end the analysis in the year 2002–which may be seen as an on-impact effect–import competition has a significantly negative effect on high-wage employment.

Table A-13: The Dynamic Impact on High-wage Textile Workers

	(1) **2002**	(2) **2003**	(3) **2004**	(4) **2005**	(5) **2006**	(6) **2007**	(7) **2008**	(8) **2009**
Panel A.	Years Mid-wage employment							
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							
Import Comp	-0.403***	-0.287*	-0.232	-0.258	-0.174	-0.0180	0.235	0.353
	(0.138)	(0.168)	(0.236)	(0.326)	(0.406)	(0.478)	(0.551)	(0.623)
Panel C.	Years Low-wage employment							
Import Comp	-0.0167	-0.0356	-0.0925*	-0.131*	-0.178**	-0.202*	-0.218	-0.235
	(0.0314)	(0.0407)	(0.0541)	(0.0685)	(0.0885)	(0.115)	(0.137)	(0.164)
Panel D.	Years in unemployment							
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							
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)
N	4,294	4,294	4,294	4,294	4,294	4,294	4,294	4,294
Worker	✓	✓	✓	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Given at top of column is last year of sample period. Estimation by OLS. The sample contains all 1999 high-wage textile workers. All regressions include worker and time fixed effects. Robust standard errors clustered at the firm level in parentheses. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

Table A-14 presents analogously the evolution of rising import competition on textile workers who in 1999 are employed in low-wage occupations. Note that rising import competition has a positive impact on high-wage employment: exposed low-wage workers have significantly higher high-wage employment than virtually identical low-wage textile workers that are not exposed to rising import competition (Panel B). These are workers that succeed in moving up by two broad wage categories. Their number, however, is relatively small.

Table A-14: The Dynamic Impact on Low-wage Textile Workers

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

Notes: Given at top of column is last year of sample period. Estimation by OLS. The sample contains all 1999 low-wage textile workers. All regressions include worker and period fixed effects. Robust standard errors clustered at the firm level in parentheses. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

D.2 Sectoral Switching by 1999 Mid-wage Textile Workers

The following set of results complements our discussion of the trade-induced sectoral switching of mid-wage textile workers in section 4.2 of the paper.

Table A-15: Occupational Movements of Mid-wage Textile Workers by Sector

	(1) Mid-Wage Emp.	(2) High-Wage Emp.	(3) Low-Wage Emp.
Panel A.	All Industries		
	-1.999***	0.270	1.379***
	(0.532)	(0.214)	(0.258)
Panel B.	Manufacturing		
	-2.706***	-0.0701	0.260**
	(0.562)	(0.151)	(0.125)
Panel C.	Services		
	0.808***	0.364**	0.260**
	(0.273)	(0.159)	(0.125)
Panel C.1.	Finance, Business		
	0.667***	0.218**	0.313***
	(0.235)	(0.110)	(0.0913)
Panel C.2.	Retail, Personal		
	-0.038	0.041	0.133**
	(0.059)	(0.026)	(0.060)

Notes: Dependent variable at top of column. Estimation shows the coefficient on Import Competition, defined as $Exposure_i xPostShock_s$ (equation (4)) by OLS. The number of observations in every regression is N = 13,934. All regressions include worker and period fixed effects. Robust standard errors clustered at the firm-level are reported in parentheses. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

Results on the sectoral switching of high-wage and low-wage textile workers due to rising import competition are available from the authors upon request.

D.3 Individual Skill as a Determinant of Up vs. Down Movements

The following Table A-16 expands on the wage effects by quintile shown in Table 10 in the text.

Table A-16: Wage Quintiles

	(1)	(2)	(3)	(4)	(5)
Panel A.	Mid-wage Employment				
ImpComp	-2.176***	-2.118***	-2.002***	-1.774***	-1.819***
	(0.601)	(0.555)	(0.541)	(0.532)	(0.524)
ImpComp x Q1	1.621**				
	(0.696)				
ImpComp x Q2		0.869			
		(0.698)			
ImpComp x Q3			0.091		
			(0.621)		
ImpComp x Q4				-0.339	
				(0.812)	
ImpComp x Q5					-0.823
					(1.109)
Panel B.	High-wage Employment				
ImpComp	0.382	0.351	0.229	0.267	0.185
	(0.271)	(0.237)	(0.209)	(0.229)	(0.202)
ImpComp x Q1	-0.337				
	(0.408)				
ImpComp x Q2		-0.104			
		(0.284)			
ImpComp x Q3			0.183		
			(0.342)		
ImpComp x Q4				-0.014	
				(0.378)	
ImpComp x Q5					2.171***
					(0.755)
Panel C.	Low-wage Employment				
ImpComp	1.404***	1.396***	1.428***	1.268***	1.331***
	(0.295)	(0.289)	(0.284)	(0.251)	(0.265)
ImpComp x Q1	-0.470				
	(0.454)				
ImpComp x Q2		-0.356			
		(0.497)			
ImpComp x Q3			-0.264		
			(0.472)		
ImpComp x Q4				0.316	
				(0.612)	
ImpComp x Q5					-0.605
					(0.531)

Notes: Dependent variable given in each of the Panels of the table. Q1 is a quintile indicator for the worker to be in the first quintile of the hourly wage distribution of all 1999 mid-wage textile workers (N = 13,394). Q2 to Q5 are quintiles two to five. Estimation of equation by OLS. All regressions include worker, period, and period by quintile fixed effects. Robust standard errors clustered at the firm level in parentheses. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

D.4 The Relationship between Trade Exposure and Tasks for Mid-Wage Textile Workers

This section provides complementary analysis to section 4.3 of the paper. The only difference is that the sample below excludes workers who in 1999 were employed in high- or low-wage occupations. The analysis for manual tasks is given in Table A-17, while results for cognitive tasks are shown in Table A-18. Notice that workers performing manual tasks are more strongly affected by rising import competition, and this is the case whether the task is routine or not routine.

Table A-17: 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 years of mid-wage employment, 2000 to 2009. All regressions include worker and period fixed effects as well as the interaction between the period fixed effect and Task variable. In each regression a specific task variable is indicated in the column heading. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

Table A-18: Import Competition and Cognitive Tasks: Mid-wage Workers

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

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

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

D.5 Job Polarization and Education: Results for Denmark's Private-Sector Labor Force

This section provides evidence on the role of education in determining occupational movements after a trade shock for the entire private-sector labor force of Denmark; it complements results for the textile workers shown in section 4.2.

We include two interaction variables between exposure to trade and education, ΔIP^{CH}*College and ΔIP^{CH}*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).[53]

Table A-19: Worker Education and Job Polarization through Import Competition

	(1) High-wage Emp.	(2) Mid-wage Emp.	(3) Low-wage Emp.
ΔIP^{CH}	2.82**	-4.38**	1.24
	(1.22)	(2.23)	(1.27)
ΔIP^{CH}*HighSchool	-2.91**	-0.58	1.74*
	(1.33)	(1.45)	(1.03)
ΔIP^{CH}*College	4.53**	-4.05	2.45*
	(2.29)	(3.27)	(1.33)
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. Robust standard errors clustered at the 3-digit industry level are reported in parentheses. 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 4 notes. All specifications also include two-digit occupation and industry fixed effects. Regressions in columns (1)-(3) also include base year (1999) hourly wage. *, ** and *** indicate significance at the 10 %, 5% and 1% levels respectively.

We see that the chance of a trade-exposed worker to be in a high-paying occupation is increasing in the worker's level of education (Table A-19, column 1). Vocationally trained workers is the

[53]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 4, column 5).

omitted category, and the probability that an at most high school educated exposed worker has significantly more high-wage employment is zero. This is what we found as well for low-educated textile workers, see Table 9. Furthermore, college-educated workers exposed to rising import comeptition are more likely to increase their high-wage employment compared to exposed workers with lower levels of education (column 1).

Interestingly, trade-exposed workers with vocational education have significantly more high-wage employment than non-exposed workers with such education, whereas for the subset of mid-wage textile workers this was not the case (see Table 9). 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 found above for textile workers.

Finally, both low and high levels of education are associated with higher levels of trade-induced low-wage employment, see column 3. The finding for low education levels mirrors our findings for textile workers, see Table 9, while the finding for college educated workers does not. The reason for the higher low-wage employment for college-educated workers might have to do with life cycle and work versus family choices, as emphasized by Keller and Utar (2018).[54]

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