The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data

David Hummels, Purdue University and NBER

Rasmus Jørgensen, University of Copenhagen

Jakob Munch, University of Copenhagen and IZA

Chong Xiang, Purdue University and NBER

September, 2013

Abstract: We estimate how offshoring (and exporting) affect wages by skill type. Our data match the population of Danish workers to the universe of private-sector Danish firms, whose trade flows are broken down by product and origin and destination countries. Our data reveal new stylized facts about offshoring activities at the firm level, and allow us to both condition our identification on within-job-spell changes and construct instruments for offshoring and exporting that are time varying and uncorrelated with the wage setting of the firm. We find that within job spells, (1) offshoring tends to increase the high-skilled wage and decrease the low-skilled wage; (2) exporting tends to increase the wages of all skill types; (3) the net wage effect of trade varies substantially across workers of the same skill type; and (4) conditional on skill, the wage effect of offshoring exhibits additional variation depending on task characteristics. We then construct worker cohorts prior to offshoring shocks and track cohort members consistently over time to capture the overall effect of offshoring, both in within-job-spell wages and displacement, on workers' present and future income streams.

Acknowledgements: We thank the Economic Policy Research Network for funding. For helpful comments we thank seminar participants at NBER, Harvard, Princeton, Michigan, UC Davis, UC Santa Cruz, Johns Hopkins, Boston College, Purdue, Clemson, Tennessee, EIIT, Copenhagen, NOITS, Nottingham, IFN Stockholm, Tubingen and EALE. We especially thank co-editor Marianne Bertrand and two anonymous referees, Pol Antras, Gene Grossman, Gordon Hanson, Marc Muendler, Nathan Nunn, and Steve Matusz.

I. Introduction

A key feature of global trade in the new century is the rapid growth of offshoring (Feenstra and Hanson 2003, Feenstra 2010) and trade in intermediate goods (Hummels, et al. 2001). How has offshoring affected workers' wages? The answer to this question is not theoretically obvious. At some level purchasing an input from a foreign source must replace a task previously done by a domestic worker, which would suggest displacement and lower wages (Feenstra and Hanson 1996, 1997). However the ability to use foreign inputs may lower a firm's costs and raise its productivity, allowing it to expand output and employment and raise wages (Grossman and Rossi-Hansberg 2007, 2008).[1] Nor is the causality easy to sort out empirically. The literature on heterogeneous firms (e.g. Bernard and Jensen 1999, Melitz 2003) suggests that high productivity firms are more likely to pay higher wages, export more and buy more imported inputs.

In this paper we employ matched worker-firm data from Denmark that is linked to firm-level data on imports and exports. Our worker-firm data cover the *universe* of private-sector Danish firms and the *population* of the Danish labor force during 1995-2006, allowing us to consistently track virtually every person in the Danish economy over time, regardless of his/her employment status or employer identity. Much of the literature has focused on how offshoring affects wages at the industry level, or how it affects the average wage bill of a firm. Our data allow us to assess whether a change in the extent of offshoring affects wages of a specific worker within a given job-spell (i.e. during that worker's tenure with a specific firm), and how these wage changes depend on the worker's characteristics, including education and occupation. Our estimates also provide evidence on the wage effects of exporting; even if wages are dampened by offshoring they may still rise with growing trade if exports boost labor demand. Finally, we assess the dynamic effects of offshoring following workers during and after exposure to an increase in imported inputs at their initial place of employment.

[1] See also Amiti and Konings (2007), Kasahara and Rodrigue (2008), Goldberg et al. (2010) and Bustos (2011).

Our trade data include detailed information on the inputs each firm imports (by HS-6 digit product and source country) and on firm sales (by HS-6 digit product and destination). In this period, the aggregate value of imports and exports by Danish manufacturing firms doubled, but there is substantial variation across firms in both the level of trade and changes in trade over time. Firms concentrate their import purchases and export sales in a narrow but stable set of goods that are largely unique to each firm. For example, 92 percent of import purchases by the typical firm are concentrated in just 5 inputs, and the typical input is purchased by a single Danish firm. Exporting behavior shows similar patterns.

These findings suggest an input-output structure that is highly specific to individual firms, and it allows us to solve a significant identification problem in relating wage change to offshoring at the firm level. The literature on heterogeneous firms shows that high productivity firms are systematically different from other firms: larger, more capital-intensive, and critically for this paper, more likely to pay higher wages and both export more and buy more imported inputs. To correct for simultaneity bias in estimating the impact of trade on wages, we need instruments that are correlated with a firm's decision to increase offshoring and/or exporting, but are not correlated with the firm's ability or wage setting.

We use shocks to Denmark's trading environment that are time varying and specific to each partner country x product being traded. These include transportation costs and world-wide shocks to export supply and import demand for the relevant partner country x product,[2] and contain rich variation across partner countries and across products. While these shocks are exogenous to Danish firms, their impact varies markedly across firms precisely because the firms have few or no inputs in common. That is, if only one Danish firm buys titanium hinges from Japan, idiosyncratic shocks to the supply or transport costs of those hinges affects just that one firm. Finally, the stability of sourcing patterns over time allows us to use pre-sample information about the inputs

[2] The former mainly exploit short-run fluctuations (e.g. yearly movements in oil and fuel prices), and the latter capture long-term shocks (see section V for details).

purchased and products exported when constructing our instruments. As a consequence, our estimates are unaffected by contemporaneous shocks to technology that affect both the types of inputs used and wage setting.

We begin by examining how exogenous shocks to trade are correlated with firm-level variables. Offshoring and exporting are positively correlated with firm sales, accounting profits and the average wage bill. Exporting is positively correlated with employment, but offshoring is associated with contractions in employment, primarily through a reduction in low skill workers. These correlation patterns are consistent with the pattern of wage changes within job spells. We find that for low-skilled workers, the wage elasticity of offshoring is about –0.022. Importantly, we find these results only if we instrument for offshoring. For high-skilled workers, offshoring has a wage elasticity of about +0.03 within job spells. These results suggest that offshoring tends to increase the skill premium within firms, which complements findings on offshoring and skill premium at the industry level (e.g. Feenstra and Hanson 1997, 1999).[3] On the exporting side, we find a low-skilled wage elasticity of about +0.05, and similar estimates for high-skilled wage elasticity.[4]

Since we estimate wage elasticities for both offshoring and exporting, we can characterize the net wage effects of trade (within job spells). These effects vary across workers of the same skill type, depending on how their employers change their exposure to trade. For example, we find that roughly half of low-skilled workers have positive net wage changes, despite the negative wage elasticity estimate for offshoring. These results complement recent theoretical and empirical work

---

[3] This literature typically examines the effects on the *relative* wage or demand for high-skilled labor. We show the effects on the *levels* of both low- and high-skilled wages. These elasticity estimates reflect the effects of both long-term and short-term shocks on wages since our instruments reflect both types of shocks (see note 2). They also capture the effects manifested through occupational changes within a given job spell.

[4] Specific kinds of correlated demand shocks might be an issue for our world-import-demand instruments for exports (see sub-section III.2). Therefore, while we can make a strong case for identifying the causal effects of offshoring on wages, the case for exports might be weaker, and the results for exports be viewed with more caution.

that emphasizes increased within-group inequality following trade liberalization (e.g. Goldberg and Pavcnik 2007, Helpman et al. 2010).

We then consider two extensions of our estimation framework. First, we assess how wage effects differ by task characteristics, conditional on skill type. We find that workers whose occupations involve routine tasks (as in Autor et al. 2003) experience larger wage drops with offshoring. In contrast, the occupations that intensively employ knowledge sets from mathematics, social science and languages systematically gain from offshoring shocks, while those that employ knowledge sets from natural sciences and engineering do not. Our results complement recent studies on wages and task characteristics. For example, Ebenstein et al. (2012) find that wage losses from offshoring are more pronounced for the workers who perform routine tasks. Ottaviano et al. (2012) find that offshoring pushes native U.S. workers towards more communication-intensive tasks and immigrant workers away from them. Relative to these studies, we focus on firm rather than industry-level changes, look at wage changes within job-spells and address endogeneity of both offshoring and exporting at the firm level.

Finally, offshoring can affect wages within job spells but can also lead to displacement, unemployment, and wage change for workers who re-attach to new firms and new industries. To capture the overall effects of offshoring we construct cohorts of all workers (of each skill type) employed by the firm in a year prior to an offshoring shock. We then track the average wage of this cohort to see the effect of offshoring on the entire cohort over a 5 year period. We find that unskilled worker cohorts suffer persistent average wage losses. For a firm that doubles its offshoring, its unskilled workers can expect a present discounted value of wage losses equal to 11.5 percent over 5 years, while its skilled workers have a more modest loss of 1.44 percent.

Our paper is related to the literature on offshoring and wages, including older work that uses industry level data[5] and more recent work that employs firm-level or matched worker firm data[6]. Our paper is also related to the literature on exporting and skill premium.[7] We complement both bodies of work by employing matched worker-firm data with worker and firm characteristics including detailed trade data. This allows us to instrument for trade shocks, to separate wage changes for individual workers from changes in the composition of the workforce within a firm or industry, to analyze the distribution of changes within a skill type, and to analyze the overall effects of offshoring, combining wage changes within-job spells and wage changes due to displacement. More broadly, our paper fits into the literature on globalization and income inequality (as surveyed by Goldberg and Pavcnik 2007).

In what follows, section II describes our data and presents stylized facts about offshoring. Section III outlines a simple model to guide our empirical work and discusses our specification and our instruments for offshoring and exporting at the firm level. Section IV looks at changes in firm outcome variables. Section V estimates within job-spell wage effects by skill type and presents the net wage effects of trade. Section VI analyzes how offshoring effects vary across task characteristics and section VI analyzes the overall effects of offshoring on worker cohorts. Section VI concludes.

II. Data Description and Stylized Facts

In this section we explain the main features of the Danish labor market and the main sources of our data. We then discuss the new stylized facts about offshoring that our data reveal.

II.1. The Danish Labor Market

---

[5] The seminal contributions are Feenstra and Hanson (1997, 1999). Feenstra and Hanson (2003) survey earlier empirical work, most of which uses industry-level data; e.g. Hsieh and Woo (2005) examine how offshoring affects the relative high-skilled demand for Hong Kong.

[6] Harrison, McLaren and McMillan (2011) survey recent empirical work that uses firm-level or matched worker-firm data. Important examples include Amiti and Davis (2011), Martins and Opromolla (2009), and Krishna et al. (2011).

[7] Bernard and Jensen (1997), Schank et al. (2007), and Munch and Skaksen (2008) compare the wages or skill composition of exporting and non-exporting firms. Verhoogen (2008) and Frias et al. (2009) emphasize changes in demand for skilled labor for firms newly exposed to exporting.

Denmark is a good candidate country for studying the effect of labor demand shocks on wages. Botero et al. (2004) systematically examine labor market regulations in many countries. They classify Denmark as having one of the most flexible labor markets in the world, comparable to the US.[8] Unlike many continental European countries, employment protection is weak in Denmark, and Danish firms may adjust employment with relative ease. This labor market model has led to turnover rates and an average tenure which are in line with those of the Anglo-Saxon countries. In 1995 the average tenure in Denmark was the lowest in continental Europe at 7.9 years, similar to the level in UK (7.8 years) and lower than Germany (9.7 years). As compensation for high job turnover workers receive relatively generous unemployment benefits, but incentives to search for jobs during unemployment are reinforced through monitoring and sanction. Together these ingredients form what has been called the 'flexicurity' model.

The flexibility of the Danish labor market may seem surprising as over three quarters of all workers are union members. Decades ago the private labor market was dominated by the Standard-Rate system of bargaining which set wages at the industry level. However, the Danish labor market has undergone a process of decentralization so that by the start of our sample in 1995, only 16% of the private labor market was still covered by the Standard-Rate System. The majority of wage contracts are now negotiated at the worker-firm level. Decentralization has increased wage dispersion in the Danish labor market (Dahl et al. 2012), implying that wages better reflect worker and firm characteristics, such as individual workers' marginal productivity. Between 1980 and 2000, the 90/10 wage ratio in Denmark increased from 2.1 to 2.35, suggesting a mild rise in wage inequality. While the wage structure is still more compressed in Denmark than in the U.S., wage formation in Denmark has become significantly more flexible.

II.2. Data Sources

[8] There is evidence that even the most flexible labor markets have substantial frictions, such as specific human capital, search costs and wage bargaining (e.g. Manning 2011).

In this sub-section we outline our data sources and data construction. More details are in the Data Appendix. Our data on firms, workers and trade are drawn from several administrative registers in Statistics Denmark. Our firm data comes from the Firm Statistics Register, or FirmStat, which covers the universe of private sector Danish firms for the years 1995-2006. FirmStat associates each firm with a unique identifier, and provides annual data on many of the firm's activities, such as number of full-time employees and industry affiliation (six digit NACE code). We supplement FirmStat with additional data from other firm registers.

Our worker data is extracted from the Integrated Database for Labor Market Research, or IDA, which covers the entire Danish population aged 15-74 including the unemployed and those who do not participate in the labor force. The IDA associates each person with his/her unique identifier, and provides annual data on many of the individual's socio-economic characteristics, such as hourly wage, education, and occupation. IDA also records labor market status (employed, unemployed or out of the labor force) in week 48 each year. We focus on full-time workers. We measure the hourly wage rate as annual labor income plus mandatory pension fund payments divided by annual hours. We classify a worker as high-skilled if he/she has a tertiary education corresponding to the two highest categories (5 and 6) in the International Standard Classification of Education (ISCED). We classify all the other workers as low-skilled.

To match our firm data with our worker data we draw on the Firm-Integrated Database for Labor Market Research, or FIDA, which links every firm in FirmStat with every worker in IDA who is employed by that firm in week 48 of each year, including temporary workers. Using our matched worker-firm data, we can consistently track virtually every person in the Danish economy over time regardless of his/her employment status or employer identity. This allows us to condition our identification on the changes within a given worker-firm match (i.e. we control for job-spell fixed effects), and to track the effects of offshoring on the average income of a fixed cohort of workers over time. The high quality of the match results from two features of the data. One, the IDA and

FIDA are administrative data and the worker identifier used there remains unchanged throughout 1995-2006. Two, the Danish informal sector is almost non-existent, unlike in some developing countries such as Brazil and Mexico that have been previously used in matched worker-firm studies.

Our trade data comes from the Danish Foreign Trade Statistics Register. For each firm in each year 1990-2006 we have imports disaggregated by origin and product and exports disaggregated by destination and product. The Trade Statistics Register uses the same firm identifier as FirmStat and FIDA, so we match product-level trade data with our worker-firm data on an annual basis. Trade flows are recorded according to the eight-digit Combined Nomenclature, but we aggregate these flows to the roughly 5000 products in the six-digit Harmonized System (HS) to be compatible with the COMTRADE data used to construct our instruments. For each trade flow we observe its value in Danish Kroner (DKK) and weight in kilos. Compared with the official import statistics, our data account for 90-95% of all imports in every year.

After merging data on manufacturing workers, firms, and trade flows, we trim our sample in several ways to ensure the quality of our data. We drop worker-firm-year observations if the employment relationship, or job spell, lasts for a single year. We drop smaller firms (fewer than 50 employees and less than 0.6 million DKK in imports) which tend to have imputed balance sheet variables and to have missing intra-EU trade data (see the Data Appendix for more details).

We include firms in the sample only in the years in which they both import and export, a restriction that is necessary in order to implement our IV strategy (see section III.2). If a firm begins trading sometime within our sample years we treat its first year of trading as the pre-sample and focus our estimation on subsequent changes in importing and exporting behavior. In this way we focus on within-firm changes in the intensity of trade rather than on discrete changes from zero to positive foreign purchases.[9] That is, our estimates do not reflect wage changes occurring in the year that a firm transitions from no offshoring to positive offshoring. We do capture changes in wages resulting from continuous changes in offshoring subsequent to that initial transition.[10]

Our final sample has about 1.95 million worker-firm-year and 9,800 firm-year observations. This represents between 50% - 70% of all manufacturing employment in Denmark, depending on the year, and roughly 20% of all private sector employment. Table 1 contains summary statistics for the data in our sample.

II.3. Stylized Facts about Imports, Exports, and Offshoring

We begin by clarifying how we define offshoring and then provide a series of stylized facts about the foreign trade activities of Danish firms. In national and industry trade statistics, imports include both intermediate inputs for production and final goods for consumption. We are primarily interested in the extent to which firms are engaged in offshoring and the impact this has on workers employed by the firm. This raises the question of whether the firm-level imports we observe are final goods or inputs into production, and also whether these inputs are potentially substitutes for labor within the firms. We address these questions by distinguishing manufacturing from services firms, by comparing our approach to input-output tables, and by distinguishing narrow versus broad measures of offshoring in line with the literature.

Our data sample focuses on manufacturing firms,[11] but all Danish firms including those in service industries are required to report trade activity. The manufacturing firms in our sample

---

[9] Firms that discretely change their trade status have initial year offshoring and exporting values that are smaller than subsequent years. The share in total import of these entry years varies from 0%-5.2% for a given year, averaging 1.3% across all years. The year on year change for the first year is comparable in magnitude to that for subsequent years for offshoring, exports, and employment. Related, the summary statistics of the workers and firms in our estimation sample are similar to the full sample, with the firms in our estimation sample being somewhat larger and employing slightly more experienced workers with somewhat higher wages (see Table A2 and related discussions in the Appendix).

[10] We experimented with using a balanced panel of only those firms with positive imports and exports in the sample in all years and obtained qualitatively similar results. The main difference is that we lose about 40% of our observations in the balanced-panel sample and cannot fit the log-exports regression as well in the first-stage IV (see Tables A3-A4 and related discussions in the Appendix). We also experimented with incorporating firms that offshore but do not export, and got similar results for the wage effects of offshoring.

account for 21% of total Danish imports and they supply 50% of Danish exports, with service industry firms comprising the remainder. Service firms are distinctive in that they report re-selling, with no value-added by the firm, a large fraction of their import purchases. We call this fraction the "retail share". For the manufacturing firms the median retail share is 2.9%, whereas for the service firms the median retail share is 35.5% (or 86.4% if we exclude those service firms who do not report inputs in this category).[12] This gives us confidence that the manufacturing v. service industry distinction is useful for identifying imports used as production inputs by Danish firms, rather than imports purchased for direct consumption by Danish consumers. We have also done spot checks of particular manufacturing firms, and confirmed that the import product categories make sense as likely input purchases given the goods they are making.[13]

A second concern is that manufacturing firms are purchasing foreign inputs but these inputs may not substitute for labor within the firm. We define "broad offshoring" to be the total value of imports by a given manufacturing firm in a given year. This total could include raw materials, which represent 7.8% of manufacturing firms' imports[14], or manufactured inputs that the firm would be unlikely to produce itself. In the literature Feenstra and Hanson (1999) define "narrow offshoring" as purchases of inputs belonging to the same industry as that of producing firms.[15] The idea is that the closer the inputs are to the final outputs, the more likely it is that labor within the firm could have produced those inputs.

We apply this idea more specifically to individual firms, defining narrow offshoring to be the sum of imports in the same HS4 category as goods sold by the firm (either domestically or in

---

[11] We base this distinction on the industry classification of the firms, and drop firms whose classification switches between manufacturing and service industries.

[12] The "retail share" variable is available only from 2003 onwards so we cannot use it as an additional control in our manufacturing firm panel. The service firms who report no inputs in this category likely correspond to firms that sell no goods at all.

[13] For example, we examined import purchases by the largest five firms selling in HS 9021 "Orthopedic appliances, artificial body parts, and hearing aids." The largest single input, representing one third of imports, was HS 8518 "Microphones, loud speaker and sound amplifiers".

[14] We define raw materials as imports in HS categories 01-15, 25-27, 31 and 41.

[15] That is, imports of computer microchips by the electronics industry would be classified as narrow offshoring, but those same imports by the automobile industry would not.

exports). Table 2 shows that our narrow offshoring measure captures 71% of a firm's imports.[16] Imports of raw materials are then counted in broad offshoring, but are omitted from narrow offshoring. A related concern is that imports of machinery may capture access to foreign technology, which may affect labor demand and wages through a different channel.[17] Machinery and machinery parts combined represent nearly 17% of imports, but as we show in the appendix, this is primarily machinery parts and not finished machines. Finished machines account for a small share of imports, and are excluded from narrow offshoring for all firms except those firms producing machines themselves.

We can now characterize the trading activities of the firms in our sample. During our sample period 1995-2006, both imports and exports more than doubled. The regional pattern of trade has been largely stable over this period. European partners dominate Danish trade, providing 85% of imports (and buying 75% of exports) in contrast to 6% of imports (and 9% of exports) from North America. Asia as a source of imports has grown in significance (its share going from 5% to 8.5%) but remains a small portion of the total. Narrow offshoring (not pictured) grew slightly faster than broad offshoring, and had a similar regional composition.

Table 1 reports the importance of trade at the firm level. Narrow offshoring represents 12% of gross output and 27% of total (imported plus domestic) material purchases for the average firm. Broad offshoring represents 19% of gross output, and 43% of total material purchases for the average firm. Exports are 45 percent of gross output for the average firm. The standard deviations indicate that these values all vary significantly across firm-years in our sample. Our data also exhibit substantial time series variation in trade for a given firm. For narrow offshoring, 55 percent of the firm-year observations are either 30 percent above or 30 percent below the firm

[16] 87% of all imports are in the same HS2 category as sales and offshoring measures based on HS2 categories yields similar results.

[17] Papers relevant to this point include Hanson and Harrison (1999), Caselli and Coleman (2001), Amiti and Konings (2008), Verhoogen (2008) and Bustos (2011).

mean. The rich variation in within-firm changes for both offshoring and exports will be key to identifying their effects on wages.

We distinguish inputs both by exporting country and HS-6 digit product code. The firms in our sample buy many foreign inputs (roughly 2000 firms importing 13500 distinct origin-HS6 inputs in a typical year), with the median firm reporting purchases in 20 distinct exporter-HS6 categories. However, these purchases are concentrated in just a few key inputs. Table 2 reveals that the top 2 exporter-HS6 categories comprise 67.9% of imports for the median firm, and the top 5 exporter-HS6 categories account for 92.1% of median firm imports. The pattern is similar for exports, with the median firm reporting 19 distinct importer-HS6 export categories, 51.3% of which comes from the top 2 categories and 77.7% from the top 5 categories.

In the literature it is common to use industry level input-output tables to provide information on the types of inputs a firm is likely to import. We do not follow this approach[18] because, even within industries, Danish firms have relatively few inputs and relatively few outputs in common. In a typical year we have roughly 2000 firms importing 13,500 distinct origin-HS6 inputs. For each of these inputs we calculate the number of Danish manufacturers that import that input and examine the distribution. For the median product, just 1 firm out of 2000 buys the input, while a product in the 90th percentile has 3 purchasers. The distribution of the number of firms who export the same product to the same destination country tells a similar story: the median is 1 firm and the 90th percentile 3 sellers. This highly specific input-output structure implies that a given shock to foreign buyers and sellers will have markedly different impacts across Danish firms. This feature of our data allows us to construct instrument variables for offshoring and exports, and we revisit this point in sub-section III.3.

[18] Input purchases in our data are highly specific to individual firms and so are poorly represented using industry aggregates. Further, IO tables provide industry-time variation in input use, but since we employ industry-time fixed effects to control for demand shocks our estimates require the use of firm-time variation in inputs. See the Data Appendix for more details and more discussions.

III. Framework, Specification, and Instruments

The literature has identified many channels through which importing and exporting could potentially affect the activities of the firm. Rather than focusing on one specific channel, we outline a production function framework to help us interpret how changes in import use and export sales affect labor demand and wages. We then describe the resulting specification, and our instrumental variables approach to estimation.

III.1. Framework and Specification

Let *j* index firms and *t* index years. We assume that firm j faces an upward-sloping supply curve for both unskilled and skilled labor. This is due to frictions in the labor market that may arise for a number of reasons. It takes time and effort for workers to change jobs because information about the labor market is imperfect or because jobs are differentiated in terms of commuting distances or other non-monetary aspects. Bargaining, wage setting mechanisms such as efficiency wages, and the accumulation of firm-specific human capital also create rents in the employment relationship. See Manning (2011) for a recent review of theory and empirics for imperfect labor markets.[19] We briefly explore how human capital specificity is related to the variation of the wage effects of offshoring in section VI.

To motivate labor demand consider the production function for firm *j* in year *t*:

$$(1) \qquad Y_{jt} = A_{jt} K_{jt}^{\alpha} H_{jt}^{\beta} C_{jt}^{1-\alpha-\beta}, \quad \text{where } C_{jt} = \left(L_{jt}^{\theta} + M_{jt}^{\theta}\right)^{1/\theta}, \text{ and } \theta = \frac{\sigma - 1}{\sigma}.$$

In equation (1), Y_{jt} is output, A_{jt} is productivity, K_{jt} is capital and H_{jt} is skilled labor. C_{jt} is a CES composite input using unskilled labor, L_{jt}, and imported inputs, M_{jt}, and $\sigma > 0$ is the substitution elasticity for unskilled labor and imported inputs.[20] Imported inputs correspond to offshoring in

[19] In a trade context several theoretical papers with imperfections in the labor market have recently emerged. The imperfections modeled include rent sharing (Amiti and Davis 2012), efficiency wages (Davis and Harrigan 2011), fair wages (Egger and Kreickemeier 2009) and search costs (Helpman et al. 2010).

[20] We have skilled and unskilled labor entering asymmetrically to illustrate the difference between labor types that are substitutes for or complements to imported inputs. We explore generalizations in the theory

our data. Let ψ_{jt} be a reduced-form representation for the demand for firm *j*'s output (e.g. if the output market is perfectly competitive ψ_{jt} is the price for firm j's output).[21] Using equation (1) we can derive the demand for unskilled labor by firm *j* in year *t*,

$$\text{(2)} \qquad \psi_{jt}\frac{\partial Y_{jt}}{\partial L_{jt}} = \psi_{jt}(1-\alpha-\beta)A_{jt}K_{jt}^{\alpha}H_{jt}^{\beta}C_{jt}^{\frac{1}{\sigma}-\alpha-\beta}L_{jt}^{-\frac{1}{\sigma}}.$$

Equation (2) says that if $1/\sigma-(\alpha+\beta)<0$ (i.e. if unskilled labor and imported inputs are close substitutes), an increase in imported inputs lowers unskilled labor demand. Given an upward-sloping labor supply curve facing the firm, this reduces the unskilled-labor wage.[22] Equation (2) also illustrates an important endogeneity issue in estimating the effect of offshoring on wages. An increase in either firm productivity A_{jt} or output demand ψ_{jt} will raise the demand for unskilled labor (and its wage), but it will also raise the demand for imported inputs. Variation in productivity and output demand across firms or within firms over time will induce a positive correlation in the data between imported materials and unskilled labor demand. We address this problem by using instruments to identify exogenous shifts in offshoring, and by using instrumented shocks to exports to capture movements in ψ_{jt}.

We show in the Appendix that the upward-sloping labor supply curve and equations (1) and (2) imply that

$$\text{(3)} \qquad \begin{aligned} \ln w_{ijt} &= b_{L,M}\ln M_{jt} + b_{M1}S_i \ln M_{jt} + b_{L,X}\ln\psi_{jt} + b_{X1}S_{it}\ln\psi_{jt} \\ &\quad + x_{it}\beta + b_K K_{jt} + b_h H_{jt} + \ln A_{jt} + \eta_{ij} + \varepsilon_{ijt}, \end{aligned}$$

appendix. We could also include domestic materials purchased from other Danish firms as part of the composite input, but this changes none of the conclusions.

[21] If firm j faces a downward sloping demand curve for its output, then ψ_{jt} is the marginal revenue. For our empirical exercises we can be agnostic about the structure of firm j's output market, though we will treat an exogenous rise in firm j's exports as a positive demand shift for firm j's output.

[22] When labor and imported inputs are poor substitutes, however, demand for unskilled labor could actually increase. In our empirical work we allow for the possibility that labor of different types could be substitutes or complements for foreign materials. See also note 17.

where i indexes workers. In equation (3), w_{ijt} is the wage of worker i employed by firm j in year t, S_i is a dummy variable that equals 1 if worker i is high-skilled, and η_{ij} is unobserved ability specific to the worker-firm match (Abowd et al. 1999). $b_{L,M}$ is the elasticity of unskilled wage with respect to offshoring, and $b_{H,M} = b_{L,M} + b_{M1}$ is the elasticity of high-skilled wage with respect to offshoring (see the Appendix for an explicit representation of $b_{L,M}$). We also allow shocks to output demand $\ln \psi_{jt}$ to have different effects across skilled and unskilled worker types in (3).

To implement (3) in the data, we add the following. We incorporate year-by-industry and region fixed effects ($\varphi_{IND,t}$ and φ_R) to control for those respective components of A_{jt} and ψ_{jt}. We use job-spell fixed effects to absorb η_{ij}. The job spell fixed effects also absorb the components of A_{jt} and ψ_{jt} that are worker-firm specific. Time varying shocks to worker productivity are captured by including a vector x_{it} of worker-level characteristics, such as experience, union status and marital status, that change over time. To capture time varying shocks to ψ_{jt} we use X_{jt}, the value of firm j's exports in year t.

Firms may have time varying shocks to productivity that are correlated with both offshoring and exporting activities and with worker wages. Accordingly, we will instrument for both offshoring and exporting as discussed in the next sub-section. Finally, we include a vector z_{it} of firm-control variables (output, employment, capital, the skilled worker share of employment). These modifications yield the following estimating equation

$$(4) \qquad \begin{aligned} \ln w_{ijt} &= b_{L,M} \ln M_{jt} + b_{M1} S_{it} \ln M_{jt} + b_{L,X} \ln X_{jt} + b_{X1} S_{it} \ln X_{jt} \\ &\quad + x_{it}\beta_1 + z_{jt}\beta_2 + \alpha_{ij} + \varphi_{IND,t} + \varphi_R + \varepsilon_{ijt}. \end{aligned}$$

Because it incorporates a vector of firm controls, the estimation of equation (4) corresponds to the direct effect of offshoring on wages, holding these firm variables constant. The trade literature suggests that offshoring may raise productivity or lower production costs and as a result increase firm output and inputs of all types.[23] We show in the theory appendix that the wage response inclusive of this productivity effect can be estimated by simply eliminating the firm controls from equation (4)

$$
\text{(5)} \qquad \begin{aligned} \ln w_{ijt} &= b^{*}_{L,M} \ln M_{jt} + b^{*}_{M1} S_{it} \ln M_{jt} + b^{*}_{L,X} \ln X_{jt} + b^{*}_{X1} S_{it} \ln X_{jt} \\ &\quad + x_{it}\beta_1 + \alpha_{ij} + \varphi_{IND,t} + \varphi_R + \varepsilon_{ijt}. \end{aligned}
$$

By comparing the coefficient estimates of regressions (4) and (5) we can determine whether the productivity effect boosts labor demand and wages.[24] Note that this same reasoning explains why we use levels of offshoring and exports as opposed to measures that are scaled by firm size. Time invariant differences in firm size are absorbed in the fixed effects, but changes in firm size over time may be the result of changing imports and exports. If we scale trade variables by firm size we eliminate a channel through which trade can affect wages and employment over time. Instead we estimate regressions with and without firm size as a control variable.

It is useful to compare the identification assumption of (4) and (5) with the literature that examines firm- and worker-specific components of wages using matched worker-firm data (e.g. Abowd and Kramarz 1999). Because that literature uses worker fixed effects and firm fixed effects, the identification is based on the workers who switch employers, and so requires the assumption that worker mobility is random conditional on *worker and firm fixed effects* (and other observable worker and firm controls). Krishna et al. (2011) show that this assumption is at odds with data, and that worker mobility is systematically correlated with time-invariant but worker-firm match-specific factors (i.e. job-spell fixed effects). Because we control for job-spell fixed effects in (4) and (5), we have addressed Krishna et al. (2011)'s critique. Equations (4) and (5) require the weaker

[23] We can then think of the direct effect of offshoring on labor demand as a move along a given isoquant, and the indirect or "productivity" effect of offshoring as a move to a higher isoquant. We are grateful to Gene Grossman for pointing out this distinction.

[24] This comparison requires the assumption that our excluded instruments are uncorrelated with the residuals in the wage equation regardless of whether the wage equation includes additional firm control variables.

identification assumption that worker mobility is random conditional on *job-spell fixed effects* (and other observable worker and firm controls). We return to this issue in Section VII.

III.2. Instruments

In our empirical specifications we will relate time varying labor market outcomes to time varying firm-level measures of trade. The identification challenge we face is that firm-level shocks to demand or productivity will affect both trade and wage setting. To address this problem, we construct instruments that are correlated with the value of imports and exports for a firm-year but are uncorrelated with changes in the firm's productivity and wage structure. The offshoring instruments are world export supply and transport costs. The exports instruments are world import demand and transport costs.[25]

World export supply WES_{ckt} is country *c*'s total supply of product *k* to the world market, minus its supply to Denmark, in period *t*. These data are constructed from COMTRADE bilateral trade data at the HS6 level. *WES* captures changes in comparative advantage for the exporting country, arising from changes in production price, product quality, or variety.[26] Similarly, world import demand WID_{ckt} is country *c*'s total purchases of product *k* from the world market (less purchases from Denmark) at time *t*. A rise in *WID* could result from shocks to demand (either consumer tastes or industrial uses of particular products) or reflect a loss of comparative advantage by *c* in product *k*.

Changes in transport costs capture shocks to the delivered price of particular inputs purchased by Denmark. To get transportation costs we first estimate cost functions using US imports data following Hummels (2007). We then use the estimated coefficients plus pre-sample

[25] Other studies of offshoring exploit variation in tariff or changes in tariff due to a liberalization episode. In our context, tariffs have little explanatory power in the first stage because the bulk of Danish imports arrive duty free from Europe and there are few changes to the tariff structure in this period. We had exchange rates as an additional instrument in the working paper version and obtained very similar results.

[26] In the Appendix we derive an expression relating import values explicitly to WES and transport costs (plus other variables) using our framework in section III.1. Using an IV strategy similar to our WES, Autor, Dorn and Hanson (2011) instrument U.S. imports from China by Chinese exports to other high-income, non-U.S. countries.

information on the destination, bulk, and modal use for Danish imports to construct *c*-*k*-*t* varying cost measures, tc_{ckt}. Full details on this estimation are in the Data Appendix, but the key source of variation is an interaction between distance, modal use, and oil prices. In our sample period real oil prices fell from $20 to $11 per barrel between 1995 and 1998, and then rose sharply to $45 per barrel in 2005 (see Figure A1 of the Appendix). These fuel prices have an especially strong effect on goods air shipped long distances and a very weak effect on goods moved short distances via train. This implies that changes over time in fuel prices affect the level of costs, the relative cost of employing air v. ocean v. land transport and the relative cost of distant versus proximate partners.

The instruments have country-product-time variation. To get a single value for each firm-year we aggregate as follows. Let I_{ckt} represent instrument $I \in (tc, WES)$ for exporting country *c*, selling HS 6 product *k*, at time *t*, and let s_{jck} represent the share of *c*-*k* in total materials imports for firm *j* in the pre-sample year (1994).[27] Then to construct a time varying instrument for firm *j* we have $I_{jt} = \sum_{c,k} s_{jck} I_{ckt}$. The idea behind this strategy is the following. For some reason firm *j* sources a particular input *k* from country *c*. Firm *j* may have a long standing business relationship with a firm in *c*, or the inputs that *c* makes might be a particularly good fit for firm *j*. For example, manufacturers of air pumps require German pressure gauges, which are of no use to producers of artificial knees who instead require Japanese titanium hinges. That relationship is set in the pre-sample and is fairly consistent over time. Table 2 reports that 64.4 percent of *c*-*k* import flows purchased by firms in-sample also appeared in the pre-sample (conversely, roughly one-third of in-sample import purchases were not represented in the pre-sample).

Over time there are shocks to the desirability of purchasing input *k* from country *c*. Transportation costs become more favourable or country *c* experiences changes in its production

[27] Some of our firms either enter or begin offshoring within sample. For these firms we use sourcing patterns in their first year of offshoring and employ data from year 2 and onwards for the wage and firm outcome regressions.

costs, variety or quality that are exogenous to firm *j*, and these are reflected in changing export supply to the world as a whole. Because firm *j* uses input *k* from country *c* more than other firms it disproportionately benefits from these changes. Recall from Section II.3 that firms have very few inputs in common and that in most cases, firm *j* is the *only* firm that buys input *k* from country *c*. Since these shocks vary across-k across-c, their impacts vary across firm j, even within the same industry. Our strategy for instrumenting exports is similar, only focused on world import demand (country c's total imports of product k at time t from the world less Denmark) and transport costs on Danish exports, and using the firm's pre-sample share of exports to *c-k*.

To summarize, we instrument for offshoring (exporting) using the weighted averages of world export supply (world import demand), and transport costs. The shocks are external to Denmark and they vary across partner country x product. The weights are pre-sample import (export) shares, and they differ significantly across firms. Following Wooldridge (2002), we instrument for the interaction between high-skill and offshoring (exports) using the interactions between high-skill and the instruments for offshoring (exports).

We can now discuss threats to identification. We need instruments that are correlated with offshoring (or exporting) and orthogonal to changes in within-job-spell wage setting by the firm. We first consider possible problems with the instruments I_{ckt} themselves, and then consider possible problems with the firm share weighting s_{jck}.

Shocks to transport costs may affect both the cost of inputs and the ability to export from Denmark. If we only included instrumented offshoring in equations (4) and (5), this would be problematic, but since we also include instrumented exporting by the firm, we are capturing this channel. Oil price shocks figure prominently in our transport cost measure and this can have an overall effect on the macroeconomy and labor demand. Recall however that our wage regressions also control for region and industry x time fixed effects. These controls should absorb shocks to demand via oil prices (e.g. changes in industry prices in response to oil shocks).

Similarly, suppose a rise in world export supply for a particular *c-k* input is due not only to supply shocks but also reflects shocks to demand around the world and in Denmark. For example, rising exports of computer memory chips likely reflects growth in both supply and demand for electronics. If the firm using that memory chip input produces a good that experiences that same demand shock it may be correlated with wage setting. We deal with this issue in three ways. One, by incorporating industry by time fixed effects and firm outputs, we control for time varying shocks to demand for particular industries and firms within Denmark. Two, by incorporating firm exports, we control for time-varying demand shocks outside of Denmark. Three, in section V we experiment with dropping the industries that one may consider especially susceptible to demand shocks in this period (e.g. computers, construction supplies), in a manner similar to Autor et al. (2012).

The problem of correlated domestic and foreign demand shocks is potentially more of a concern for our exporting instruments, especially if these demand shocks are firm-year specific, wide-spread, and not adequately captured by firm output. In this sense, our case for identifying the causal effects of exports on wages is weaker than for offshoring,[28] and the our results for exports merit more caution in interpretation.

An additional possibility is that shocks originating with Danish firms could affect product prices in the markets of their foreign suppliers or foreign customers. This could be an issue for a large country like the US, but Denmark is a small country of less than six million people and represents a small share of trade, both in the aggregate and for individual partners and products. For the median exporter-product, Denmark represents 0.79 percent of purchases and for the median importer-product, Denmark represents 0.73 percent of sales.[29] This suggests that individual Danish firms are unlikely to exert a large influence over the trade volumes of Denmark's

[28] To the extent that demand shocks are not completely purged from our estimation they are likely to bias our results against finding negative wage effects of offshoring. This is because rising demand for a firm's product implies rising offshoring and rising wages.

[29] For each exporter c - HS 6 product k - time t we compute Denmark's share of purchases (conditional on the share being positive). The median is calculated over all c-k-t.

trade partners. In addition, in section V we experiment with dropping any c-k-t trade flow where Denmark has a greater than 1 percent share and obtain similar results.

A second set of concerns relate to the share-weighting of the instruments for each input. One might worry that there are differences in the types of technology used by firms, and differences in technology affect wage setting and the types of inputs purchased. Recall that all our wage regressions are within job spells so that time invariant differences across firms in technology and input use are absorbed into the fixed effects. It might be that there are changes over time in the level or the type of technology (and therefore both imports and wages), but this is precisely why we use pre-sample data on input use, in order to prevent technological change from impacting input use and wages.

IV. Preliminary Analyses: The effect of trade on firm outcomes

In this section we describe firm outcome variables and their correlation with importing and exporting behavior in Table 3. The first column reports the result of simple regressions at the firm level using all manufacturing firms in Denmark. The dependent variable is a firm j, year t characteristic (employment, output, average wage bill, etc.) and the explanatory variable is an indicator for whether the firm is engaged in offshoring (according to our narrow definition). Offshoring firms are different in almost every respect – they have higher sales, more employment, a larger capital/worker ratio, are more profitable and pay a higher average wage.

Some of this may reflect time invariant differences across firms, and our identification will work off within firm changes. The second column restricts the sample to only those firms engaged in offshoring and repeats these regressions with firm fixed effects in order to relate within-firm changes in outcomes to changes in offshoring over time. Rising offshoring is positively correlated with rising employment, sales, capital per worker, average wage bills and accounting profits. This is the heart of the identification problem. It may be that growth in offshoring causes these firms to be larger, more profitable, and able to pay higher wages. Or it may be that all these outcomes are jointly determined as a result of time-varying shocks to the firm's productivity or demand for their products. If so, the positive correlations between offshoring and firm outcomes (e.g. employment) could be driven by simultaneity bias.

We repeat this exercise, this time using predicted values for our trade variables. That is, we regress offshoring and exports on the instruments discussed previously, construct predicted values, and correlate these with firm outcomes. (We discuss the first stage in greater depth below). In column three we report the coefficients from firm outcome regressions in which we include only predicted imports. As in the preceding columns, an exogenous increase in imports leads to a sharp rise in sales, accounting profits, capital per worker and average wage bill. However, we now see a steep decline in employment, with an elasticity of -0.10, which occurs primarily through reducing the numbers of low-skill workers. The rising share of high skill workers suggests that the large increase in average wage bill per worker is driven by compositional changes within the firm. We will use within job-spell wage regressions to account for compositional changes in our main estimation.

In columns four and five we report coefficients from including predicted imports and predicted exports together as explanatory variables. The coefficients on imports are similar to what we had in column three, though the employment effects are now larger. Rising exports lead to increases in all firm outcome variables.

In this table we can see many of the key features of our simple model in section III. When we correlate firm outcomes with indicators for importing status, or with within-firm changes in the extent of importing, we find that "better" firms import and that importing is correlated with increases in employment. However, when we isolate exogenous shocks to the importing decision that are uncorrelated with firm's productivity in levels or in changes then we see a very different picture. Exogenous increases in importing improve sales and profitability outcomes for the firm, but lead to contractions in employment and a shift away from low-skill labor.

Does the rise in imported materials represent increased offshoring by the firm, or something else? Consider three reasons that a firm might increase foreign purchases. One, the firm may be expanding sales due to rising productivity and/or increased demand for its goods and require more inputs of all types, including imported inputs. Two, the firm might be substituting foreign inputs for inputs previously purchased from another Danish firm. Three, the firm might be substituting foreign inputs for inputs previously produced within the firm, that is to say, offshoring. Our IV strategy rules out the first possibility and the estimated employment effects rule out the second possibility. Put another way, switching from a domestic to a foreign supplier may well have important benefits for the firm in terms of sales and profitability, but it should not have a negative effect on employment within the firm. We should only observe a reduction in employment if the firm is substituting foreign inputs for its own labor.

V. The effect of trade on worker wages within job-spells.

Having established that imported materials are likely to substitute for labor within the firms, we now present the results of our main estimation. Our empirical strategy is to relate changes in individual worker's wages to exogenous changes in importing and exporting activity by the firms that employ them, after controlling for worker-firm "job-spell" fixed effects and time varying characteristics of the worker. We estimate equations (4) and (5) basing identification on within-firm, over-time variation in imports and exports and include only those workers staying in the firm. Including firm variables controls for changes in labor demand arising from a productivity effect, that is, the measured wage elasticity is net of the productivity effect. Excluding these variables allows for time-varying changes to firm outcome variables as a result of the import and export shocks and so produces the wage elasticity estimate inclusive of the productivity effect.

In equations (4) and (5), we have 4 endogenous variables, (narrow) offshoring and exports, and the interaction of each with the high skill dummy. Following Wooldridge (2002), we include the full set of instruments in the first-stage regressions for each endogenous variable. For each endogenous variable we estimate both with and without firm controls, for a total of 8 first stage regressions. In each case, the regression is fitting predicted offshoring at the worker-firm-year level (following, e.g., Angrist and Pischke 2009), and includes job-spell fixed effects. We report the results in Table 4, clustering the standard errors at the firm-year level. In the offshoring regressions, changes in world export supply and transportation costs have the predicted sign and are significantly correlated with growth in imports for the firm. We see similar patterns on the exporting side.[30] In Table 5 we estimate within-job spell wage regressions in which we pool over all workers. The dependent variable is the log hourly wage rate of worker i employed by firm j in year t, and we again cluster standard errors at the firm-year level. We provide fixed effect, and fixed effect-IV estimates both with and without additional firm controls. In the fixed effect specifications we exploit only within worker-firm variation but ignore the potential simultaneity problem where unobserved firm productivities drive both wages and offshoring. In contrast, the fixed effect-IV specification includes job-spell fixed effects and corrects for this simultaneity bias.

In the fixed effect specification we find very small wage effects from both importing and exporting. In contrast, when we instrument we find effects that are roughly 10 times larger in magnitude. Offshoring lowers an unskilled worker's wage (elasticity -0.022), so that being in a firm that doubles its offshoring has an effect similar in magnitude to losing 1.5 year's experience on the job. In contrast, offshoring raises a skilled workers wage (elasticity 0.03). These results suggest that offshoring tends to raise the skill premium within the firm. In the theory section we noted that running these regressions with firm controls is equivalent to a move along an isoquant while

[30] We also experiment with having the instruments enter the regressions by themselves and by sub-groups (e.g. only the import-based instruments in the offshoring regression, etc.), and obtain similar coefficient estimates for the instruments.

omitting firm controls allows for the possibility of a productivity effect -- that output and capital will rise in response to an offshoring shock and boost the demand for labor. We see evidence weakly consistent with this conjecture in that wage gains for skilled workers are smaller when we control for the productivity effect. Though these differences are small they are consistent with the idea that offshoring produces both labor substitution and productivity responses, with the former clearly dominating.

Turning to the export interactions, we see that rising exports are a rising tide that lifts all boats, with a low skill wage elasticity of .049 to .053, and no significant difference for high skill labor. This is consistent with a view that offshoring and exporting shocks represent very different changes within the firm. Offshoring induces input substitution toward skilled labor and away from unskilled labor while exporting increases input use across the board.

We also explore the response of total labor income to offshoring and exports, as workers might increase or decrease their hours depending on how strong the income effect (higher wages lead to higher income, more leisure and less hours) is relative to the substitution effect (higher wages lead to more hours and less leisure). Columns (5)-(6) of Table 5 report these results. We find similar coefficient patterns on offshoring for both high and low skilled workers, but smaller magnitudes in both cases. The primary difference from the wage regressions is the large positive interaction between exports and high skilled workers.[31]

The coefficient estimates in Table 5 alone are not sufficient for calculating the net wage effects of trade, because firms are engaged in both importing and exporting, and as we discussed in sub-section II.3, both are rising fast. Given the conflicting signs on offshoring and exports, the net wage effect for an unskilled worker depends on whether exports or offshoring are rising faster within their firm.

[31] One reason for the larger income response of skilled workers could be that skilled workers have more flexibility in setting their hours (e.g. Dahl et al. 2012).

To see an example of these effects, consider the following shock to oil prices. Between 1998 and 2000 crude oil prices rose 210% while jet fuel prices rose 52%. Using the fitted transport cost functions described in the Appendix, and the fitted values for the first stage estimation in Table 4, we calculate that the average firm would decrease offshoring by 16% and decrease exports by 10%, *ceteris paribus*. Using the point estimates in Table 5, this translates to a 0.17% (-16% x (-0.0228) – 10% x 0.0531) decline in wages for unskilled workers and a 1.02% decline in wages for skilled workers. However, the impact of the oil price change varies considerably depending on what the firm is trading and with whom. For the firm with a cost shock one standard deviation above the mean, offshoring declines by 28%, while exporting declines by only 16%. For a firm with this profile, the unskilled wage would fall by 0.21% and the skilled wage by 1.71%.

Of course, oil prices are just one factor that moves trade and we employ several instruments. Table 6 considers the full distribution of changes in trade that occur in our sample, and the corresponding change in wages. In Panel A of Table 6 we divide firm-years into bins on the basis of year on year percentage changes in offshoring (down) and exports (across) for that firm. We then report, in each bin, the share of the low skill workforce (in normal font), and the median wage changes (in boldface) experienced by the workers as predicted using the coefficient estimates of Table 5. Consider the bin in the top right corner. This corresponds to firm-years where imports are at least 30 percent below the previous year, and where exports are at least 30 percent above the previous year. That bin represents 2.2 percent of the low skill workforce and given the estimates in Table 5, we predict that these workers will experience a median wage increase of 6.6 percent relative to the previous year. In contrast, the bottom left corner represents firm-years with rapidly rising imports and rapidly falling exports. That is 1.5 percent of the low skill workforce and the median predicted wage loss is 6.15 percent relative to the previous year.

Overall, the median wage change for unskilled workers is close to 0, with 56 percent of low skill workers experiencing wage losses and 44 percent wage gains. Just over 10 percent of workers have wage losses greater than 2%, and 12 percent of workers have wage gains greater than 2%. Panel B of Table 6 reports predicted wage changes for high-skilled workers. The majority (55%) of high skilled workers have positive predicted wage changes, as both offshoring and exporting tend to increase high skilled wage. 26 percent of skilled workers have predicted wage gains above 1.9% and 13 percent have wage losses of 2% or more.

Summarizing, Table 6 shows that even within the same skill type, there is substantial variation in the net wage effects of trade, as employers change both their offshoring and exporting over time. These results complement recent theoretical and empirical findings that emphasize an increase in within-group inequality following trade liberalization (e.g. Goldberg and Pavcnik 2007, Helpman et al. 2010).

Table 7 reports a set of robustness checks. For each check we estimate two regressions, one with firm controls and one without (corresponding to equations (4) and (5), respectively). First, we employ only those job spells lasting at least 7 years, which is close to the average job duration in Denmark (7.9 years). This cuts our sample in half, but gives us more observations per job spell to identify trade shocks. We find results that are similar to those in Table 5. These results confirm that the source of our identification is within-job-spell changes, and that having long job spells in the data is important for the identification strategy to work.

It may seem puzzling that although most of Danish trade is with other high income countries, offshoring tends to reduce the wage of low skilled workers.[32] To investigate whether our results are driven by Danish trade with low income countries, we restrict our sample to only include Danish trade with high income partners. We find a similar sign pattern for offshoring. The estimated wage elasticities with respect to exports are now quite different, with high skill workers

[32] Burstein and Vogel (2011) show that North-North trade can increase skill premium if productivity is complementary with skill, and their results also hold for North-North offshoring. To see this, consider the following simple extension of their framework. There are two countries with the same factor composition but different productivities for tasks. A firm offshores a task if the foreign country is more productive in the task, which reduces the range of less productive tasks performed in the economy. If productivity and skilled labor are complementary, this will raise the relative demand for high-skilled labor and the skill premium.

enjoying a larger wage gain than low skill workers. Ideally, we would run a similar specification for Danish trade with low income partners. Unfortunately, these trade flows tend to be small and exhibit much fluctuation, and so they are less compatible with the use of pre-sample shares in our IV estimation.

Our trade variables exploit year on year variation relative to the firm mean and we further explore whether they represent more permanent or transitory shocks. We follow Bertrand (2004) and replace our WES/WID instruments with their 3-year moving averages.[33] We find very similar wage effects to those in Table 5. These results suggest that our WES/WID instruments capture permanent shocks, similar to Autor et al (2012). Our transport-cost instrument, on the other hand, exploits annual fluctuations in oil and fuel prices and captures short-run shocks. Finally, in our threats to identification section we described two potential problems. First, one might worry that our world export supply instrument is capturing shocks to world demand for products as well as supply. During our sample period, many high income countries, including Denmark, experienced booms in the technology and housing sectors. Following Autor et al. (2012) we drop the industries that include computers, steel, flat glass and cement. This does not change the sign pattern of coefficients, though it makes the wage losses for unskilled workers and the wage gains for skilled workers larger.

Table 7 suggests that our basic findings in Table 5 are robust to alternative specifications.[34] Below, we apply our estimation framework to explore particular occupations or task characteristics.

---

[33] As in Bertrand (2004) we use contemporaneous and 2-year-moving-average values for the first and last 2 years of data.

[34] We have also experimented with the following alternatives, and obtained similar results. See the Data Appendix for more details. (1) break low-skilled workers into medium-skilled and very low-skilled. They have similar wage elasticity estimates; (2) use the top 2 categories or top 5 categories of pre-sample trade flows; (3) employ only the job spells longer than 5 years; (4) define narrow offshoring as imports within the same HS2 categories as sales; (5) use broad offshoring instead of narrow offshoring; (6) dropping the trade flows where which Denmark accounts for over 1%, 10% or 25% of trade with that partner and product; and (7) adding Danish trade to WES and WID.

VI. Wage Effects by Occupation and Task Characteristics

Our data identify the occupation of each worker, which allows us to examine whether occupations having particular task characteristics are especially affected by trade. Conceptually, our approach is the same as that laid out in Section III, in which workers of different types may be substitutes or complements for foreign materials. Instead of only grouping workers by educational attainment, we also group them by the characteristics of the particular tasks they do. That is, we augment equation (4) with the interaction between an occupational characteristic (OCC) and offshoring to see whether offshoring effects on wages are different across task characteristics within a skill type. For estimation we use fixed effects-IV similar to Table 5, where we also instrument for the additional OCC x offshoring interaction. To get a clean identification, we drop the workers who switch occupations during job spells.

We obtain occupational characteristics data from O*NET version 13, 2008 (see the Data Appendix for more details). For categories of task characteristics we first follow Autor et al. (2003) and consider routine and non-routine tasks. For each category we pick the O*NET characteristics that most closely match the ones used in Autor et al. (2003) and compute the principal component.[35] We normalize the principal components to have mean 0 and standard deviation 1.

We report the results in Table 8. The workers with average routineness scores (Z = 0) are little affected by offshoring (the coefficients of offshoring and offshoring x high-skill are both insignificant).[36] Conditional on skill type, workers with above-the-average routineness (Z > 0) suffer larger wage losses (the coefficient of offshoring x Z is negative and significant). In contrast, non-routine tasks interact positively with offshoring. The non-routine category is a composite of mathematics and other characteristics (see the Appendix for the list). When we drop math characteristics as a component of the non-routine category, we find that the remaining aspects of

---

[35] Autor et al. (2003) use historical task data. Examples of routine tasks are manual dexterity and finger dexterity, and of non-routine tasks, mathematics and thinking creatively. Details in the Data Appendix.

[36] The negative interaction between offshoring and the high skill indicator do not contradict Table 5 because educational attainment is negatively correlated (-0.54) with routine-ness.

non-routine tasks interact negatively with offshoring. In other words, it is mathematics and not non-routineness more generally that drives the positive interaction with offshoring.

These results motivate us to examine tasks that intensively employ characteristics corresponding to other broad categories of college education: communication and language, social sciences and natural sciences.[37] High-skilled workers (high skill = 1) whose jobs require social-science skills 1 standard deviation above the mean (Z = 1) see an additional wage elasticity of 3.8 percent, for a total of 5.2 percent. Put another way, there is a "social-science premium" : college-educated workers with strong social-science skills enjoy larger wage increases from offshoring than other college-educated workers. Similarly, the "communication premium" is 4.5 percent, implying that for a college educated (high skill = 1) director or chief executive (communication = 2, or 2 standard deviations above average), the wage elasticity is 2x4.5% = 9.0% with respect to offshoring. Natural sciences, however, have little interaction with offshoring.

Finally, as we discussed in section III, firms could face upward-sloping labor supply curves for a variety of reasons including specific human capital, search costs, or bargaining. We explore whether differences in specific human capital across workers lead to differences in the wage effects of offshoring. We follow Parent (2000) and measure industry-specific experience for worker i as the number of years worker i has worked in a given industry,[38] and interact i's industry experience with offshoring. We report the results in the last column of Table 8. The industry-experience-offshoring interaction term has a negative coefficient but it is small in magnitude and insignificant. We leave it to future research to distinguish which of these mechanisms is at work.

VII. Worker Mobility and Cohort-based Analysis

[37] Examples of social sciences are economics and accounting. Natural sciences include engineering and technology. Examples of communication tasks include persuasion and negotiation. Details in the Appendix.
[38] We trace the workers' industry affiliations back to 1988. We do not make use of occupation-specific experience (e.g. Kambourov and Manovskii 2009) because data on occupations are non-existent or of poor quality before 1995. We do not pursue hypotheses related to wage-bargaining and search costs because we lack relevant measures.

In sections V and VI we examine the wage effects of offshoring within job-spells, that is, for the workers who remain employed within the same firm. In this section, we extend the analysis to include the entire cohort of workers employed in a firm prior to an offshoring shock, and we follow this cohort of workers for five years. This approach, which we adapt from Walker (2012), has two benefits. First, it enables us to examine wage and income effects for all workers, including changes occurring within the firm, earnings losses associated with unemployment and earnings changes related to change of firm, industry or occupation. We can then calculate the effect of offshoring on expected future income stream for all workers. Second the cohort-approach allows us to examine concerns about sample selection that arise when employing within-job-spell wage regressions or when focusing only on workers who are displaced.

To elaborate, in sections V and VI we find that offshoring tends to increase skill premium (i.e. the relative wage of skilled workers), and our regressions assume that worker mobility is random conditional on job-spell fixed effects (plus other observable worker and firm controls). Suppose instead that there are *time-varying and individual-specific* shocks to worker productivity that happen to correspond to the offshoring event. If there is a systematic relationship between these time varying shocks and the sample of workers who remain employed within the firm, and if high- and low-skilled workers have opposite selection patterns (i.e. the high-skilled workers with positive shocks stay but the low-skilled workers with positive shocks leave), then selection could imply a positive relationship between offshoring and skill premium.

We can gauge the importance of selection in our data by examining the pattern of worker mobility in response to offshoring shocks. For ease of display, we define a positive offshoring shock as an increase in predicted offshoring of more than 10% between year t and t+1[39]. We then show the year t-2 characteristics of the entire set of workers employed by the firms with positive offshoring shocks, and compare them with the year t-2 characteristics of those who leave in year t.

[39] Predicted values obtained using instruments as before. Similar results hold when we use a 20 or 30% threshold.

Table 9 shows that the average low-skilled leaver is younger and less experienced, and has a 3.7 percent lower wage than the average low-skilled worker, and that similar patterns hold for high-skilled workers. These results suggest that there is indeed selection (conditional on observables) in our data, and that such selection is unlikely to drive a positive correlation between offshoring and skill premium.

Table 9, however, does not address selection conditional on unobservables. By examining the evolution of wages and earnings for an entire cohort of workers, stayers and leavers, our cohort-based analysis addresses these selection issues.

Consider all the low-skilled workers employed by firm j in a base year v (e.g. v = 1995). Call them cohort jv, and consider the average wage for the cohort. Suppose that in year v+1 (e.g. v+1 = 1996) firm j increases offshoring for exogenous reasons. Some fraction of the cohort-jv workers remain employed with firm j in year v+1, while other workers are displaced. Displaced workers may be unemployed or re-attach to the labor force in a new firm. Both stayers and leavers figure into the cohort average wage in v+1. By fixing the composition of the cohort prior to the offshoring shock, and by consistently tracking this same group of workers for five years, we capture the overall effects of offshoring on the time path of the cohort-average wage.

We use the same firm sample as in sections II-VI and include all workers employed in the base year.[40] Since offshoring is not a discrete event in our data and firms are subject to multiple shocks (changes in the extent of offshoring) over time, we define multiple cohorts for each firm, corresponding to the set of workers employed in the firm in each base year v. For each firm j by base year v (v is 1995-2001) we form two cohorts, all the high-skilled workers and all the low-skilled workers employed with j in v. In total there are 9000 such cohorts.

[40] To ensure that the cohort members do not enter the retirement age of 61 we impose the additional restriction that the workers' ages are 20-54 in one of the base years 1995-2001. This reduces the sample by 9.6%. In our sample workers do not exit unless they die or emigrate outside of Denmark. In the rare cases of exits (0.8% of the observations) we set the outcome variables to zero.

For each cohort constructed from firm j for base year v, its offshoring shock in year v+1 is the percentage change in the predicted offshoring of firm j between v and v+1, $\Delta \log OFF_{v+1}^{j} = \log(OFF_{v+1}^{j} / OFF_{v}^{j})$, a continuous variable. We calculate the predicted values of offshoring using our first-stage IV regressions from section V, and we use predicted values to ensure that the shocks are exogenous to the firms and workers. The cohort-outcome variables we examine are cohort-average wages, earnings and gross earnings. Wages and earnings are defined as in the previous sections. Gross earnings are the sum of earnings, unemployment insurance benefits and social assistance.[41]

Using these data we estimate

(6) $$\Delta \log y_{vt}^{j} = \alpha_v + \alpha_t + (\Delta x_{vt}^{j})\beta + \sum_{k=1}^{5} \delta_k (\Delta \log OFF_{v+1}^{j}) D_{k+v} + \varepsilon_{vt},$$

where y_{vt}^{j} is the outcome variable of a firm j cohort with base year v at time t, where t=v+1,..,v+5. α_v represents cohort fixed effects, α_t year fixed effects, and x_{vt}^{j} the vector of control variables. In equation (6) we define Δy_{vt}^{j} and Δx_{vt}^{j} as changes relative to the base year in order to match the expression for the offshoring shock. The control variables x_{vt} include the change in cohort-average experience, and the percentage change in the predicted exports of firm j, calculated from the first-stage IV regressions of section V. D_{k+v} are dummies for the *k*th years after base year v, where k = 1,…,5. The coefficients of interest in equation (6) are the δ_k's; δ_1 is the contemporaneous effect of the offshoring shock, δ_2 is the 1-year-post-shock effect, etc. Finally we weight the regressions by the number of cohort members, and we cluster standard errors by firm-j-year-t, given that a single firm j has multiple cohorts.

We estimate regression (6) separately for low-skilled and high-skilled cohorts, and report the estimates of the δ_k's in Table 10. The first column shows the results for the cohort-average

[41] We set to zero the hourly wages and earnings of non-employed workers since they are unobserved.

wages for low-skilled workers. In the year of the offshoring shock, the elasticity of cohort wages with respect to offshoring is -0.0274. This means that for an average low-skilled worker, the overall effect (including both wage and displacement) of being employed by a firm that doubles offshoring for exogenous reasons is a 2.74% loss in income in the year of the offshoring shock. This result is consistent with our findings in section V that offshoring tends to reduce low-skilled workers' wages within job spells.

In addition, Table 10 shows that the negative effect of offshoring persists over time: it becomes larger in magnitude 1 year post-shock (elasticity -0.0394) and remains negative until 4 years post-shock (elasticity -0.011). In order to summarize the accumulated wage losses for low-skilled workers, Table 10 computes the present discounted value (PDV) of the wage changes over the five-year window using a 4% discount value, as well as the t-statistics of the PDV. To interpret the PDV of -0.1155, suppose a firm doubles offshoring. Then the PDV suggests that the average low-skilled workers of the firm can expect a total loss of 11.55% of their pre-offshoring wages in the course of 5 years.

Turning to high-skilled workers, offshoring tends to increase their wages within job spells (as we show in section V), but if they get displaced after offshoring their wages are likely to drop. This means that the overall effect of offshoring can be either positive or negative for the cohort-average wages of high-skilled workers. The second column of Table 10 reports the overall effect of offshoring on high-skilled workers. In the year of the offshoring shock, the overall effect is -0.0097, suggesting that the wage losses suffered by displaced workers dominate the within-job-spell wage effect. The overall effect of offshoring becomes larger in magnitude (elasticity -0.0126) 1 year post-shock, remains negative (but insignificant) for two more years, and then turns positive (elasticity +0.015) 4 years post-shock. The PDV for cohort-average wages for high-skilled workers is a small (and insignificant) -0.0144.

The third-sixth columns report the overall effects of offshoring where we measure income using cohort-average earnings and gross earnings for low-skilled and high-skilled workers. For low-skilled workers these overall effects are qualitatively similar to the overall effects for cohort-average wages but they are smaller in magnitudes.[42] The PDVs for cohort-average earnings and gross earnings are -0.0415 and -0.0404, respectively. For high-skilled workers, however, these overall effects tend to be positive. The PDVs for cohort-average earnings and gross earnings are 0.0492 and 0.0457, respectively.

The last two columns of Table 10 show the effect of a base year offshoring shock on average log earnings for the first-year leavers (i.e. the workers who leave in the year of the offshoring shock). It is clear that the first-year leavers suffer large and persistent earnings losses when hit by offshoring shocks, and this holds for both high and low skilled workers. Figure 1 displays the size of the earnings changes for the first-year leavers, using the earnings effects for all workers as the benchmark for comparison.

Why are wage effects larger in magnitude for first-year leavers than for all workers? It may be that the first-year leavers are a selected sample.[43] Alternatively, it may be that offshoring leads to the loss of specific human capital. In related work, Hummels et al. (2011), we use the framework of Jacobson et al. (1993) to show, conditional on worker fixed effects, large earnings losses for mass-layoff workers displaced due to offshoring. These losses are considerably larger than the losses for other mass-layoff workers, suggesting that specific human capital losses may be especially important in the case of offshoring. Further, in Hummels et al (2012) we focus on transitions to new employment after displacement, and show that the mass-layoff workers

[42] One may wonder why the first-year effects on the low-skilled workers' earnings are insignificant, given our findings in Table 5 that offshoring reduces low-skilled workers' earnings within job spells. This is likely because Table 10 is based on a different specification than Table 5 (e.g. regression (6) does not control for job-spell fixed effects but regressions (4) and (5) do).

[43] Selection could matter because firms use the occasion of offshoring to lay off high wage workers (which is not consistent with Table 9) or to lay off low-productivity workers who were collecting rents. In either case, we would expect that first-year leavers experience especially large wage losses.

displaced due to offshoring take longer to reattach to the workforce than other mass-layoff workers, suggesting that search costs may play an especially important role for these workers.

VIII. Conclusions

We employ a unique matched worker-firm dataset from Denmark to measure how offshoring shocks affect wages at the worker level. Our data reveal new stylized facts about offshoring activities at the firm level. Because we observe the specific products and source countries for imported inputs purchased by Danish firms we can construct instruments for offshoring decisions that are time varying and uncorrelated with the wage setting and productivity of the firm. In addition, because we can consistently track virtually every person in the Danish economy over time, we can condition our identification on variation within specific worker-firm matches (i.e. job spells).

Our key findings are these. One, controlling for the endogeneity of trade events is critical. Instrumental variables estimates of the effect of imports and exports on wages yield much larger effects than those that ignore endogeneity. Two, offshoring has considerably different wage effects across educational groups, raising skilled labor wages (elasticity +0.03) and lowering unskilled labor wages (elasticity -0.022). These estimates likely reflect the causal effects of offshoring on wages. We also find that export has similar wage effects across education groups (elasticity +0.05), with the caveat that these estimates likely have a weaker causal interpretation than the estimates for offshoring. Three, the net effect of trade on wages depends on the wage elasticity estimates and how firms change exposure to trade, and this exhibits substantial variation across workers of the same skill type. For example, 26% (12%) of high skilled (low skilled) workers have net wage changes above 2% per year while 13% (10%) of high skilled (low-skilled) workers have annual changes below –2%.

We then extend our estimation framework in two ways. First, exploring occupational characteristics allows us to identify several additional and unique relationships. Conditional on skill type, routine tasks suffer wage losses from offshoring. Occupations that intensively employ knowledge sets from math, social science and languages gain from offshoring shocks, while those that employ knowledge sets from natural sciences and engineering are no more or less insulated from offshoring shocks than the average manufacturing worker. These results suggest that not all degrees are created equal.

Finally, we construct worker cohorts prior to offshoring shocks and track cohort members consistently over time. Since we fix the cohort compositions by construction we are able to capture the overall effect, both in within-job-spell wages and displacement, on workers' present and future income streams when their employer increases offshoring for exogenous reasons. Our results imply that if a firm doubles offshoring, an average low-skilled worker of this firm can expect a net loss between 4.04% and 11.55% in the present-discounted value (PDV) of his/her income in the next five years, while an average high-skilled worker sees a more modest change between -1.44% and +4.92% for his/her 5-year PDV. When we focus on the (admittedly selected) sub-sample of workers who leave the firm in the first year of the offshoring shock, we find very large earnings losses. For both high and low skilled workers employed in firms who double offshoring, the 5-year PDV of earnings losses accumulates to over 50 percent of their pre-displacement earnings.

References

Abowd, J., Kramarz, F., 1999. "The Analysis of Labor Markets using Matched Employer-Employee Data", in "Handbook of Labor Economics", edited by Orley Ashenfelter and David Card, North-Holland.

Abowd, J., Kramarz, F., Margolis, D. N. (1999), "High Wage Workers and High Wage Firms", *Econometrica*, 67, 251-333.

Amiti, Mary; Davis, Donald R.; 2011. "Trade, Firms, and Wages: Theory and Evidence", forthcoming, *Review of Economic Studies*.

Amiti, Mary; Konings, Jozef; 2007. "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia", *American Economic Review* 97, No. 5, pp. 1611-1638.

Autor, David H., Frank Levy and Richard J. Murname, 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration", *Quarterly Journal of Economics* 118(4).

Autor, David H., David Dorn and Gordon Hanson, 2012. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States", American Economic Revew, forthcoming.

Angrist, Joshua D. and Jorn-Steffen Pischke. 2009. Mostly Harmless Econometrics, Princeton University Press, Princeton and Oxford.

Bernard, Andrew B. and J. Bradford Jensen. 1997. "Exporters, Skill Upgrading and the Wage Gap." *Journal of International Economics* 42, 3-31.

Bernard, Andrew B. and J. Bradford Jensen. 1999. "Exceptional Exporter Performance: Cause, Effect, or Both." *Journal of International Economics* 47: 1-25.

Bertrand, M. 2004. "From the Invisible Handshake to the Invisible Hand? How Import Competition Changes the Employment Relationship". Journal of Labor Economics, vol. 22(4), 723-765.

Botero, Juan C., Simeon Djankov, Rafael La Porta, Florencio Lopez-De-Silanes and Andrei Shleifer. 2004. "The Regulation of Labor." *Quarterly Journal of Economics* 119(4), 1339-1382.

Burstein, Ariel, and Jonathan Vogel. 2011. "Globalization, Technology, and the Skill Premium: A Quantitative Analysis", NBER working paper 16459.

Bustos, Paula. 2011. "Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms", *American Economic Review* 101(1), 304-340

Caselli, Francesco and Wilbur J. Coleman, "Cross-Country Technology Diffusion: The Case of Computers," American Economic Review (May 2001), vol. 91(2), 328-335.

Christensen, B. J., R. Lentz, D. T. Mortensen, G. R. Neumann and A. Werwatz; 2005, "On-the-Job Search and the Wage Distribution", *Journal of Labor Economics* 23, pp. 31-58.

Dahl, C. M.; D. le Maire; J. R. Munch; 2012. "Wage dispersion and decentralization of wage bargaining", Journal of Labor Economics, forthcoming.

Davis, D. and J. Harrigan, 2011; Good Jobs, Bad Jobs, and Trade Liberalization, Journal of International Economics 84, pp. 26-36.

Ebenstein, Avraham, Ann Harrison, Margaret McMillan and Shannon Phillips. 2012. "Estimating the Impact of Trade and Offshoring on American Workers Using the Current Population Surveys". Review of Economics and Statistics, forthcoming.

Egger, H. and U. Kreickemeier, 2009, Firm Heterogeneity and the Labor Market Effects of Trade Liberalization, International Economic Review 50, pp. 187–216.

Feenstra, Robert C. and Gordon H. Hanson. 1996. "Foreign Investment, Outsourcing and Relative Wages", in R.C. Feenstra, G.M. Grossman and D.A. Irwin, eds., The Political Economy of Trade Policy: Papers in Honor of Jagdish Bhagwati, Cambridge, MA: MIT Press, pp. 89-227.

Feenstra, R.C. and Gordon H. Hanson. 1997. "Foreign Direct Investment and Wage Inequality: Evidence from Mexico's Maquiladoras." *Journal of International Economics*, 42, pp. 371-93.

Feenstra, R.C. and Gordon H. Hanson. 1999. "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States." *Quarterly Journal of Economics*, 114, pp. 907-40.

Feenstra, R.C. and Gordon H. Hanson. 2003. "Global Production Sharing and Rising Inequality: A Survey of Trade and Wages", in Handbook of International Trade, edited by Kwan Choi and James Harrigan, Blackwell Publishing.

Feenstra R.C. and and Bradford Jensen. 2012. "Evaluating Estimates of Materials Offshoring From U.S. Manufacturing", NBER working paper 17916.

Frias, Judith A., David S. Kaplan, and Eric A. Verhoogen, 2009. "Exports and Wage Premia: Evidence from Mexican Employer-Employee Data", mimeo, Columbia University.

Goldberg, Pinelopi K., Amit Khandelwal, Nina Pavcnik and Petia Topalova. 2010. "Imported

Intermediate Inputs and Domestic Product Growth: Evidence from India". *Quarterly Journal of Economics*, 125, 17727-1767.
Goldberg, Pinelopi K., and Nina Pavcnik. 2007. "Distributional Effects of Globalization in Developing Countries." *Journal of Economic Literature* 45(1), 39-82.
Grossman, Gene and Esteban Rossi-Hansberg, 2007. "The Rise of Offshoring: It's Not Wine for Cloth Anymore", *The New Economic Geography: Effects and Policy Implications,* Federal Reserve Bank of Kansas City, Jackson Hole Symposium.
Grossman, Gene and Esteban Rossi-Hansberg, 2008. "Trading Tasks: A Simple Theory of Offshoring", *American Economic Review*, 98, pp. 1978-1997.
Hanson, Gordon H. and Ann Harrison. 1999. "Trade and Wage Inequality in Mexico." *Industrial and Labor Relations Review* 52(2), 271-288.
Harrison, Ann, John McLaren and Margaret S. McMillan. 2011. "Recent Findings on Trade and Inequality". Annual Review of Economics 3, pp. 261-289.
Helpman, Elhanan, Oleg Itskhoki and Stephen Redding. 2010. "Inequality and Unemployment in a Global Economy". *Econometrica* 78(4), 1239-1283.
Hsieh, C.T. and Woo, K.T. 2005 "The Impact of Outsourcing to China on Hong Kong's Labor Market", *American Economic Review*, 95(5), 1673-1687.
Hummels, D. (2007), Transportation Costs and International Trade in the Second Era of Globalization, *Journal of Economic Perspectives* 21, 131-154.
Hummels, David; Ishii, Jun; Yi, Kei-Mu; 2001. "The Nature and Growth of Vertical Specialization in World Trade", *Journal of International Economics*, June 2001, v. 54, iss. 1, pp. 75-96.
Hummels, David, Rasmus Jørgensen, Jakob R. Munch, and Chong Xiang. 2011. "The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data", NBER wp. 17496.
Hummels, David, Jakob R. Munch, Lars Skipper, and Chong Xiang. 2012. "Offshoring, Transition, and Training: Evidence from Danish Matched Worker-Firm Data", American Economic Review vol. 102(3), pp. 424-428.
Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan; 1993, "Earnings losses of displaced workers", *American Economic Review* 83, pp. 685–709.
Kambourov, G. and I. Manovskii, 2009. "Occupational Specificity of Human Capital". International Economic Review vol. 50(1), 63-115.
Kasahara, Hiroyuki and Rodrigue, Joel 2008, "Does the Use of Imported Intermediates Increase Productivity? Plant-Level Evidence" *Journal of Development Economics* 87, pp. 106-118.
Krishna, P., J. P. Poole, and M. Z. Senses; 2011, "Wage Effects of Trade Reform with Endogenous Worker Mobility", NBER Working Paper 17256.
Manning, A., 2011, Imperfect Competition in the Labor Market, in O. Ashenfelter and D. Card, eds., Handbook of Labor Economics Vol. 4B, Amsterdam: North Holland.
Martins, Pedro S. and Luca D. Opromolla. 2009. "Exports, Imports and Wages: Evidence from Matched Firm-Worker-Product Panels". IZA discussion paper 4646.
Melitz, M.J.; 2003, "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity", *Econometrica*, 71, 1695-1725.
Munch, J.R. and J.R. Skaksen. 2008. "Human Capital and Wages in Exporting Firms." *Journal of International Economics* 75, 363-372.
Ottaviano, Gianmarco I.P., Giovanni Peri and Greg C. Wright. 2012. "Immigration, Offshoring and American Jobs", American Economic Review, forthcoming.
Parent, D. 2000. "Industry-Specific Capital and the Wage Profile: Evidence from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics", Journal of Labor Economics, vol. 18(2), 306-323.
Schank, Thorsten, Claus Schnabel and Joachim Wagner. 2007. "Do Exporters Really Pay Higher Wages? First Evidence from German Linked Employer-Employee Data." *Journal of International Economics* 72, 52-74.

Verhoogen, Eric. 2008. “Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector.” *Quarterly Journal of Economics*, 123(2), 489-530.

Walker, W.R. 2012. “The Transitional Costs of Sectoral Reallocation: Evidence from the Clean Air Act and the Workforce”. Mimeo, UC Berkeley.

Wooldridge, Jeffrey M. 2002. Econometric Analysis of Cross Section and Panel Data. The MIT Press, Cambridge and London.

Figure 1: The Overall Effects of Offshoring

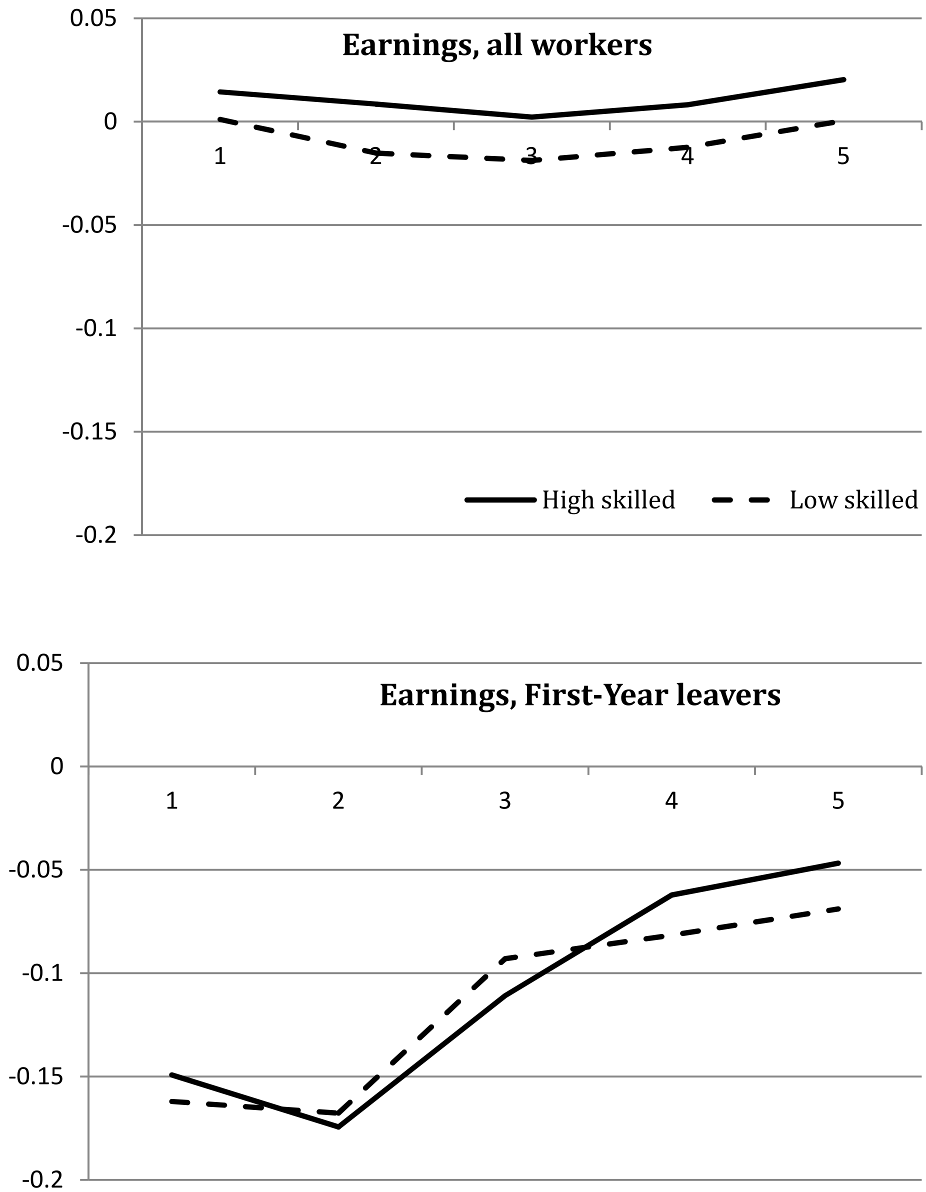

Table 1: Descriptive Statistics

	Obs	Mean	Std. dev.
Firm-level data…			
log Employment	9,820	4.94	0.89
log Gross Output	9,804	18.89	1.05
log Capital per worker	9,759	12.39	0.98
log Average wage bill per worker	9,772	12.54	0.22
log Accounting Profits	7,816	9.07	1.70
High-skill share	9,772	0.16	0.12
Low-skill share	9,772	0.84	0.12
Firm-level trade data…			
Log(broad offshoring)	9,820	16.85	1.53
Broad Offshoring/gross output	9,804	0.19	0.16
Broad Offshoring/material purchases	9,756	0.43	0.29
Broad Offshoring, log deviation from firm mean	9,820	0.49	0.57
Log(narrow offshoring)	9,249	16.00	2.26
Narrow offshoring/gross output	9,804	0.12	0.15
Narrow offshoring/material purchases	9,756	0.27	0.28
Narrow offshoring, log deviation from firm mean	9,249	0.82	0.94
Log(exports)	9,555	17.54	2.06
Exports/gross output	9,804	0.45	0.32
Exports, log deviation from firm mean	9,555	0.46	0.66
Worker-firm data…			
Hourly wage	1,950,896	192.85	70.19
Log hourly wage	1,950,896	5.19	0.31
Log gross output	1,950,896	20.50	1.69
Log employment	1,950,896	6.44	1.49
Log capital per worker	1,950,896	12.59	0.89
High-skill	1,950,896	0.19	0.14
Experience	1,950,896	17.93	9.31
Union	1,950,896	0.88	0.33
Married	1,950,896	0.59	0.49

Notes: The data used for the last panel titled "Worker-firm data …" has worker-firm-year observations, and the data used for the other panels has firm-year observations. For each variable we calculate its value for each observation and then report its mean and standard deviation across all observations.

Table 2: Some Patterns of Offshoring and Exports

	Share of import value…
Raw Materials	7.8%
Machinery and Machinery Parts	16.9%
Narrow Offshoring, Same HS2 as Sales	87.4%
Narrow Offshoring, Same HS4 as Sales	70.8%
	Share of Trade…
Top 2 Products in Imports	67.9%
Top 5 Products in Imports	92.1%
Top 2 Products in Exports	51.3%
Top 5 Products in Exports	77.0%
	Pre-sample Flows…
In-sample share of Imports	64.4%
In-sample share of Exports	77.7%

Notes: The data used for Table 2 has firm-year-product-source-country observations for import flows, and firm-year-product-destination-country observations for export flows. The panel titled "share of import value…" shows the fractions of total import value accounted for by various categories; e.g. the sum of raw-materials imports across all observations is 7.8% of the sum of import values across all observations in our sample. The "Share of Trade…" panel shows the fractions of total import/export value accounted for by the top 2/5 products of a given firm-year. The "Pre-sample Flows…" panel shows the fractions of total import/export values accounted for by the firm-product-country flows that appear in the pre-sample years.

Table 3: Firm-level Effects of Trade

	OLS	Firm FE	Firm FE, Predicted Offshoring	Firm FE Predicted Offshoring & Exports	
Dependent Variables	Offshorer dummy	log(offshoring)	log(offshoring)	log(offshoring)	log(exports)
	(1)	(2)	(3)	(4)	(5)
log employment	0.681***	0.044***	-0.106**	-0.205***	0.374***
log gross output	0.958***	0.082***	0.394***	0.143**	0.511***
log accounting profits	0.953***	0.066***	0.506***	0.00	0.908***
log (capital per worker)	0.161*	0.005	0.245***	0.119***	0.243**
log(wage bill per worker)	0.040**	0.014***	0.224***	0.131***	0.113***
log material inputs	1.162***	0.083***	0.195**	-0.140*	0.725***
log domestic material inputs	0.668	0.037***	0.355***	-0.082	0.847***
Share of high-skilled workers	-0.007	0.002*	0.091***	0.053***	0.055**
Materials/output	0.093***	0.005**	-0.049*	-0.063**	0.057*
Domestic materials/output	-0.043**	-0.011***	0.012	-0.03	0.073**

Notes: The cells are coefficient estimates of various regressions (*** p<0.01, ** p<0.05, * p<0.1), whose dependent variables are down the rows and regressors are along the columns. E.g. column (1) shows that when we regress log(employment) on the offshorer dummy (=1 if firm j has positive offshoring value in year t), we get a coefficient of 0.681 (significant). The data used for column (1) includes all firm-years, that for (2) and (3) only the firm-years that have positive offshoring values, and that for (4) and (5) only the firm-years with positive offshoring and export values (which corresponds to our main estimation sample). In column (3)-(5) we correct the standard errors for the fact that the covariates are estimated, following Wooldridge (2002).

Table 4: First-Stage FE-IV Regressions

Dependent variable:	Log(offshoring)		... *x* high skill		Log(exports)		... *x* high skill	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log WES, offshoring	0.1928***	0.3087***	-0.0428***	-0.0255***	0.0068	0.0869	-0.0232***	-0.0106
	[2.70]	[4.38]	[-5.74]	[-3.61]	[0.08]	[1.02]	[-3.28]	[-1.44]
Log transport costs, offshoring	-17.1988***	-19.7103***	0.2078	-0.3583	3.4490	1.0740	0.7999**	0.3821
	[-3.04]	[-3.41]	[0.40]	[-0.75]	[1.35]	[0.40]	[2.39]	[1.34]
Log WID, exports	-0.0839	0.0778	-0.0541***	-0.0253***	0.2346***	0.3606***	-0.0339***	-0.0125**
	[-0.66]	[0.62]	[-5.37]	[-3.03]	[3.12]	[4.67]	[-4.23]	[-2.03]
Log transport costs, exports	22.1646***	23.5056***	-2.7704***	-2.1234**	-7.8695	-5.8672	-0.6316	-0.0246
	[3.18]	[3.34]	[-2.98]	[-2.50]	[-1.33]	[-0.97]	[-0.96]	[-0.04]
Interactions with high skill dummy:								
Log WES, offshoring	-0.0564	-0.0827	0.3551***	0.3495***	0.1086*	0.0841	0.2684***	0.2646***
	[-0.83]	[-1.29]	[4.66]	[4.62]	[1.75]	[1.33]	[5.30]	[5.13]
Log transport costs, offshoring	1.0166	-0.6953	-17.6820***	-18.288***	2.6859	0.8210	1.3016	0.8182
	[0.27]	[-0.18]	[-3.09]	[-3.19]	[1.12]	[0.32]	[0.37]	[0.23]
Log WID, exports	0.0519	0.1489	0.3585***	0.3750***	-0.1898***	-0.1143**	0.3374***	0.3494***
	[0.58]	[1.61]	[4.55]	[4.74]	[-3.90]	[-2.32]	[6.35]	[6.52]
Log transport costs, exports	-2.7041	-4.4856	26.2738***	25.9308***	-3.0533	-4.3535	-5.6607*	-5.9273*
	[-0.77]	[-1.25]	[4.42]	[4.35]	[-1.03]	[-1.44]	[-1.80]	[-1.88]
Additional firm controls	Yes	No	Yes	No	Yes	No	Yes	No
Additional worker controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,928,599	1,928,599	1,928,599	1,928,599	1,950,896	1,950,896	1,950,896	1,950,896
Number of job spell fixed effects	383,035	383,035	383,035	383,035	384,257	384,257	384,257	384,257
R-squared	0.146	0.107	0.074	0.063	0.207	0.157	0.074	0.059
F-statistics for instruments	4.379	30.040	5.300	19.330	8.618	22.360	10.140	15.740

Notes: Table 4 presents the first stage regressions for log offshoring, log exports and their skill interactions, using world export supply (WES), world import demand (WID) and transport costs as excluded instruments. Only these excluded instruments are reported. All specifications include job spell, industry-year and regional fixed effects. Additional firm controls are log output, log employment, log capital-labor ratio and the share of high-skilled workers. Additional worker controls include experience, experience squared and dummies for union membership and marriage. Robust T-statistics in brackets. Standard errors clustered at firm-year levels. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Worker-Level Wage Regressions

Dependent variable:	Log hourly wage				Log labor income	
	FE		FE-IV		FE-IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Log offshoring	-0.0025**	-0.0014	-0.0222**	-0.0228***	-0.0148**	-0.0100*
	[-2.43]	[-1.41]	[-2.56]	[-3.70]	[-2.06]	[-1.94]
Log offshoring x high skilled	0.0060***	0.0061***	0.0510***	0.0523***	0.0220***	0.0239***
	[5.59]	[5.57]	[7.71]	[7.78]	[3.59]	[3.84]
Log exports	0.0044**	0.0060***	0.0493***	0.0531***	0.0391***	0.0538***
	[2.02]	[2.82]	[4.48]	[7.63]	[3.44]	[6.47]
Log exports x high skilled	-0.0005	0.0000	0.0008	0.0019	0.0364***	0.0398***
	[-0.25]	[0.02]	[0.08]	[0.18]	[3.62]	[3.83]
Log output	0.0141***		0.0064		0.0071	
	[4.56]		[0.88]		[0.87]	
Log employment	0.0158***		-0.0043		0.0251**	
	[4.62]		[-0.39]		[2.51]	
Log capital-labor ratio	0.0039***		0.0051***		0.0009	
	[3.16]		[4.15]		[0.73]	
Share, high-skilled workers	0.0879***		0.1436***		0.1361***	
	[5.07]		[6.66]		[5.14]	
Experience	0.0171***	0.0181***	0.0156***	0.0157***	0.2186***	0.2188***
	[13.27]	[14.00]	[11.58]	[11.42]	[34.43]	[34.33]
Experience^2 x 100	-0.05***	-0.05***	-0.05***	-0.05***	-0.11***	-0.11***
	[-84.53]	[-84.77]	[-80.68]	[-77.89]	[-95.33]	[-94.18]
Union	0.0142***	0.0141***	0.0156***	0.0153***	0.0301***	0.0301***
	[13.38]	[13.29]	[14.29]	[14.49]	[21.34]	[21.59]
Married x 100	0.34***	0.35***	0.29***	0.29***	-0.80***	-0.81***
	[6.42]	[6.59]	[5.43]	[5.39]	[-8.92]	[-8.96]
Observations	1,928,599	1,928,599	1,928,599	1,928,599	1,928,428	1,928,428
#. job spell fixed effects	383,035	383,035	383,035	383,035	383,033	383,033
R-squared	0.155	0.153	0.155	0.153	0.103	0.101

Notes: Table 5 presents the results from worker-level Mincer regressions, using either log hourly wage or log annual labor income as dependent variables. All specifications include job spell, industry-year and regional fixed effects. Log offshoring, log exports and their skill interactions are instrumented using world export supply (WES), world import demand (WID) and transport cost in the FE-IV columns. Robust T-statistics in brackets. Standard errors clustered at firm-year levels. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. We report 100 times the coefficient estimates for experience^2 and marital status.

Table 6: Net Effect of Trade on Wages

			Annual %-change in exports			
			Min	-30%	0%	30%
			-30%	0%	30%	Max
Panel A: Low-skilled workers						
Annual %-change in offshoring	Min	-30%	3.1%	6.7%	5.6%	2.2%
			-0.92%	**0.73%**	**2.06%**	**6.60%**
	-30%	0%	1.9%	13.7%	9.7%	1.4%
			-2.12%	**-0.17%**	**0.74%**	**2.94%**
	0%	30%	1.6%	9.8%	15.2%	2.8%
			-2.90%	**-0.78%**	**0.25%**	**2.14%**
	30%	Max	1.5%	5.3%	13.3%	6.3%
			-6.15%	**-1.96%**	**-0.72%**	**1.44%**
Panel B: High-skilled workers						
Annual %-change in offshoring	Min	-30%	3.2%	6.3%	4.5%	1.4%
			-7.08%	**-2.38%**	**-1.00%**	**0.56%**
	-30%	0%	1.6%	15.1%	10.9%	1.4%
			-3.10%	**-0.66%**	**0.17%**	**1.93%**
	0%	30%	1.8%	11.3%	16.4%	2.8%
			-2.16%	**-0.05%**	**0.95%**	**2.91%**
	30%	Max	1.3%	5.0%	12.4%	4.6%
			-1.28%	**1.11%**	**2.20%**	**5.68%**

Notes: Table 6 presents the net effect of trade, including both offshoring and exports, on worker-level hourly wages. For Panel A we group the firm-year observations into 16 bins according to the annual changes in offshoring and export values, and these bins correspond to the 16 cells. For each cell we report two numbers. The bold-faced number is the predicted median hourly wage change for low-skilled workers (calculated using the wage-elasticity estimates from table 5), and the normal-fonted figure is the fraction of low-skilled workers in this cell. E.g. for the firm-year observations for which offshoring decreases by more than 30% (1st row) and exports increase by more than 30% (last column), the median predicted hourly wage for low-skilled workers rises by 6.60%, and these low-skilled workers account for 2.2% of the low-skilled workforce in our sample. Panel B is similarly structured for high-skilled workers.

Table 7: Robustness Exercises

Dependent variable:	Log Hourly Wage		Log Hourly Wage		Log Hourly Wage		Log Hourly Wage	
Robustness check:	I. 7+ year job spells		II. High income countries		III. 3-year MAs (WID/WES)		IV. Drop computers and building supplies	
	FE-IV		FE-IV		FE-IV		FE-IV	
Log(offshoring)	-0.0105	-0.0155***	-0.0168**	-0.0190***	-0.0177**	-0.0181***	-0.0354***	-0.0317***
	[-1.64]	[-2.83]	[-2.53]	[-3.67]	[-2.14]	[-3.01]	[-3.44]	[-4.53]
Log(offshoring) x high-skilled	0.0510***	0.0536***	0.0271***	0.0269***	0.0519***	0.0530***	0.0833***	0.0892***
	[7.06]	[7.24]	[4.94]	[4.88]	[7.49]	[7.47]	[9.57]	[9.92]
Log(exports)	0.0665***	0.0621***	0.0464***	0.0492***	0.0478***	0.0503***	0.0488**	0.0656***
	[6.21]	[7.46]	[4.52]	[7.14]	[4.77]	[6.87]	[2.50]	[7.18]
Log(exports) x high-skilled	0.0055	0.0026	0.0344***	0.0370***	0.0057	0.0060	-0.0436***	-0.0461***
	[0.48]	[0.22]	[3.87]	[4.28]	[0.54]	[0.57]	[-3.20]	[-3.25]
First stage IV *F*-statistics:								
log offshoring	7.21	13.42	6.25	11.62	4.46	9.13	4.76	8.33
... *x* high skill	28.49	24.10	22.41	17.53	22.56	21.05	26.21	18.97
log exports	5.79	14.92	5.35	10.43	4.977	10.30	3.80	7.92
... *x* high skill	17.54	16.11	18.45	15.36	16.60	16.52	18.90	14.70
Other firm-level controls	Yes	No	Yes	No	Yes	No	Yes	No
Obs	967,053	967,053	1,917,625	1,917,625	1,928,599	1,928,599	1,692,736	1,692,736
No. job spells	103,989	103,989	380,781	380,781	383,035	383,035	338,922	338,922
R2	0.186	0.183	0.1550	0.1533	0.1551	0.1533	0.1564	0.1546

Notes: Table 7 presents the results from worker-level Mincer regressions, using log hourly wage as the dependent variable. All specifications include job spell, industry-year and regional fixed effects. Log offshoring, log exports and their skill interactions are instrumented using world export supply (WES), world import demand (WID) and transport costs. "MAs" stand for moving-averages. Robust T-statistics in brackets. Standard errors clustered at firm-year levels. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Wage Effects by Task Characteristics and Industry Experience

Interaction term (*Z*):	Routine	Non-Routine	Non-Routine (Other than Math)	Social Sciences	Natural Sciences	Communica-tion	Industry-specific experience
Log(offshoring)	0.0075	-0.0034	-0.0055	-0.0049	-0.0155*	0.0030	-0.0248***
	[0.83]	[-0.40]	[-0.66]	[-0.54]	[-1.70]	[0.34]	[-2.85]
Log(offshoring) x high-skilled	-0.0081	-0.0264***	-0.0227***	0.0151**	0.0465***	-0.0081	0.0512***
	[-1.20]	[-3.89]	[-3.37]	[2.40]	[6.88]	[-1.28]	[8.53]
Log(offshoring) x *Z*	-0.0422***	0.0497***	-0.0443***	0.0377***	-0.0008	0.0446***	-0.0002
	[-17.36]	[14.10]	[-13.56]	[16.09]	[-0.44]	[17.23]	[-1.12]
Log(exports)	0.0588***	0.0238**	0.0147	0.0557***	0.0467***	0.0424***	0.0374***
	[5.25]	[2.04]	[1.25]	[4.96]	[4.21]	[3.78]	[3.37]
Log(exports) x high-skilled	-0.0002	0.0140	0.0201**	0.0003	0.0079	0.0071	-0.0028
	[-0.02]	[1.41]	[2.04]	[0.03]	[0.78]	[0.73]	[-0.30]
Other firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1,570,088	1.570.088	1.570.088	1.570.088	1.570.088	1.570.088	1,906,704
No. job spells	376,590	376.590	376.590	376.590	376.590	376.590	378,474
R2	0,142	0,143	0,143	0,142	0,141	0,143	0,155

Notes: *** p<0.01, ** p<0.05, * p<0.1. T-statistics in brackets. Standard errors clustered at firm-year levels. Industry-time, regional and job spell fixed effects included in all specifications. Industry experience measured as the number of years in the 2-digit NACE industry between 1988 and the beginning of the job spell, and this value remains unchanged during the job spell. Task characteristics measured as the number of standard deviations from the mean. Coefficient estimates of the other variables not reported to save space.

Table 9 Worker Mobility in Response to Rise in Offshoring

	High skilled		Low skilled	
Variables:	All	Leavers	All	Leavers
Hourly wage rate	244.03	235.19	173.49	167.27
Experience	15.17	12.51	18.00	15.34
Tenure	4.78	3.17	6.23	4.53
Union Status	0.70	0.70	0.91	0.90
Age	39.21	36.69	40.20	37.65
Female	0.32	0.32	0.34	0.35
Married	0.63	0.56	0.58	0.51
Number of obs.	75964	9045	358399	39429

Notes: Table 9 compares the pre-shock characteristics of the workers who separate from their employers ("leavers") after a positive offshoring shock with those of the full set of workers ("All"), including the leavers and those who stay. To be specific, an offshoring shock is an increase in predicted offshoring of more than 10% annually, where the predicted values are obtained as in section V. For each firm with a positive offshoring shock we consider the workers employed by this same firm two years prior to the shock.

Table 10 The Overall Effects of Offshoring

	All workers						First-Year Leavers	
	Wages		Earnings		Gross earnings		Earnings	
	High skilled	Low skilled	High skilled	Low skilled	High skilled	Low skilled	High skilled	Low skilled
Offs. shock year 1	-0.0097*	-0.0274***	0.0144***	0.0011	0.0118**	-0.0029	-0.1492***	-0.1621***
	[-1.76]	[-3.61]	[2.89]	[0.29]	[2.51]	[-0.80]	[-6.29]	[-6.16]
Offs. shock year 2	-0.0126**	-0.0394***	0.0085	-0.0152***	0.0082	-0.0133***	-0.1744***	-0.1677***
	[-2.22]	[-5.95]	[1.56]	[-3.72]	[1.59]	[-3.48]	[-6.96]	[-6.85]
Offs. shock year 3	-0.0047	-0.0253***	0.0022	-0.0188***	0.0026	-0.0152***	-0.1109***	-0.0930***
	[-0.74]	[-4.85]	[0.41]	[-5.46]	[0.52]	[-5.20]	[-4.68]	[-4.24]
Offs. shock year 4	-0.0012	-0.0197***	0.0082	-0.0124***	0.0082	-0.0109***	-0.0622**	-0.0816***
	[-0.19]	[-3.49]	[1.42]	[-3.61]	[1.51]	[-3.56]	[-2.56]	[-3.91]
Offs. shock year 5	0.0150**	-0.0109*	0.0203***	0.0005	0.0191***	-0.0011	-0.0468*	-0.0689***
	[2.07]	[-1.86]	[3.06]	[0.11]	[3.04]	[-0.32]	[-1.76]	[-3.09]
Five year PDV	-0.0144	-0.1155***	0.0492**	-0.0415**	0.0457**	-0.0404***	-0.5147***	-0.5408***
	[0.64]	[4.89]	[2.26]	[2.96]	[2.22]	[3.13]	[5.34]	[5.81]
Observations	920291	4280135	920303	4280135	920303	4280135	96366	419415

Notes: Table 10 reports the overall effects of offshoring, including both wages and displacement, on workers' present and future income streams using regression (6). All regressions include cohort fixed effects, year fixed effects and the change in log predicted exports and the change in average experience as control variables. First-year leaves are workers who are no longer employed by the firm in the year after the base year. The five-year PDV is the discounted sum of coefficients using a 4% discount rate. The regressions are weighted by the base year cohort size and these weights are reflected in the reported observation numbers. T-statistics in square brackets. Standard errors clustered at firm-year levels. The reported standard errors for the five year PDVs are calculated using the delta method. *** p<0.01, ** p<0.05, * p<0.1.

Data Appendix

1. More details about Data Sources and Construction

For the firm data, the firm identifier in FirmStat is derived from the register "Old Firm Statistics" for the period 1995-1999 and from "General Firm Statistics" for the period 1999-2006. These two registers in combination allow us to track the same firm during the entire period 1995-2006 despite the structural break in 1999. For our firm-characteristics variables, the number of employees is from FirmStat and is calculated as the number of full-time equivalent workers in a year. Capital stock, measured as the value of land, buildings, machines, equipment and inventory is from the Accounting Statistics register. Gross output (net of taxes) is from the VAT register. Firm-level skill-intensities are computed using the educational attainment records of individual workers in IDA which are then aggregated to the firm-level using the matched worker-firm link (FIDA).

For the worker data, we use annual hours which is common in the literature (e.g. Christensen et al. 2005). A concern is that annual hours do not capture overtime work. For a portion of our sample in 2006 we have data for overtime work. A wage rate including overtime is correlated 0.86 with our main wage-rate variable, and overtime hours are uncorrelated with offshoring (0.015 for the full sample and -0.017 for the subsample of high-skilled workers). This suggests that our results are unlikely to be driven by the issue of overtime work. We measure labor market experience as actual time in employment since 1964. Other worker-level information regarding union membership and marriage are also derived from the IDA database. We experimented with breaking low-skilled workers into two subgroups, medium-skilled (those with a vocational education, defined as the final stage of secondary education that prepares students for entry into the labor market) and very-low-skilled (those with the equivalent of high school education or less). We obtained very similar results.

Our trade data, the Foreign Trade Statistics Register, consists of two sub-systems, Extrastat (trade with non-EU countries) and Intrastat (trade with EU countries). Extrastat has close-to-complete coverage as all extra-EU trade flows are recorded by customs authorities. Intrastat does not have complete coverage because firms are only obliged to report intra-EU trade if the annual trade value exceeds a threshold. In 2002 the thresholds were DKK 2.5 million for exports and DKK 1.5 million for imports.

After merging data on manufacturing workers, firms, and trade flows, we have 2.8 million worker-firm-year observations. We then trim our sample as follows. Since we have annual data we cannot investigate the changes in wage or employment status at weekly, monthly or quarterly frequencies. Thus we drop all the worker-firm-year observations of which the employment relationship, or job spell, lasts for a single year (about 200,000 observations). We also drop all the workers whose skill level changes in our sample period (about 35,000 observations), in order to get a clean identification of how the effects of offshoring vary across skill groups. We next drop the firms with fewer than 50 employees and less than 0.6 million DKK in imports, which corresponds to average annual wages for two manufacturing workers. This eliminates another 600,000 observations. This de minimis restriction eliminates from our sample very small firms who in some cases have imputed balance sheet variables and are more likely to fall below the reporting thresholds for intra-EU trade data.

For data on occupational characteristics, The occupation variable in IDA is based on a Danish version of the International Standard Classification of Occupations (ISCO-88) developed by the International Labour Office (ILO). We map the O*NET data into the ISCO-88 classification system using the crosswalk at the National Crosswalk center ftp://ftp.xwalkcenter.org/DOWNLOAD/xwalks/. For non-routine tasks we use the principal component of mathematical reasoning (O*NET task id 1.A.1.c.1), response orientation (1.A.2.b.3), gross body coordination (1.A.3.c.3), mathematics (2.A.1.e), thinking creatively (4.A.2.b.2), and organizing, planning, and prioritizing work (4.A.2.b.6). For routine tasks we use manual dexterity (1.A.2.a.2), finger dexterity (1.A.2.a.3), multilimb coordination (1.A.2.b.2), processing information (4.A.2.a.2), and evaluating information to determine compliance with standards (4.A.2.a.3). For social sciences we use the principal component of 2.C.1 (2.C.1.a, 2.C.1.b, etc.), 2.C.6, 2.C.7, 2.C.8, 2.C.9, 2.C.4.e, and 2.C.4.f. For natural sciences we use 2.C.2, 2.C.3, 2.C.5, 2.C.4.b, 2.C.4.c, 2.C.4.d, 2.C.4.g, 2.C.10, and 2.A.1.f. For communication and language we use 4.A.4.a, 2.B.1, 1.A.1.a, 4.C.1.a.4, 4.C.1.b.1, 2.A.1.a, 2.A.1.b, 2.A.1.c, and 2.A.1.d. For on-the-job hazards we use 4.C.2.c, 4.C.2.b.1, and 4.C.2.e.1.

2. Construction of the transport-cost instruments

The Danish trade data do not contain information on transportation costs paid by firms. To construct transportation costs we proceed in two steps. First, we use data on ad-valorem shipping costs taken from US sources to estimate costs as a function of transportation mode, product weight/value, fuel prices, and distances shipped. Second, we construct fitted cost measures using these same variables that are specific to Danish firms.

During our pre-sample years, 42% of Danish imports by value arrive by sea, 20% by air, 37% by truck, and 1% by rail. For sea and air transport we employ data on transportation costs taken from US Imports of Merchandise data for the 1995-2006 sample period. For sea transport we estimate

$$f_{ckt} / v_{ckt} = -4.16 + 0.393 \ln \frac{w_{ckt}}{v_{ckt}} + 0.351 \ln oil_t + 0.027 DIST_c + .0063 \ln oil_t * DIST_c$$

where c indexes exporters, k indexes HS6 products, t = year, f = transportation charge, v = value of shipment, and w = weight in kg, DIST = distance in 1000km measured to the nearest US coast. For air transport we estimate

$$f_{ckt} / v_{ckt} = -3.80 + 0.435 \ln \frac{w_{ckt}}{v_{ckt}} + 0.209 \ln JETFUEL_t + 0.033 DIST_c + .018 \ln JETFUEL_t * DIST_c$$

Note that this generates air shipping costs that are higher in levels, more sensitive to fuel prices, and more sensitive to the interaction between fuel prices and distance. Also, jet fuel prices, while correlated with crude oil prices, can vary from year to year as a function of differences in refining capacity and availability of high grade crude suitable for distilling light fuels.

For rail and truck transport we draw on transportation costs taken from the US Transborder Surface Freight data, which reports US state to Canadian province flows at the HS2 level monthly from 1994-2006. For truck transport we estimate

$$f_{spkt} / v_{spkt} = -8.18 + 0.234 \ln \frac{w_{spkt}}{v_{spkt}} + 0.862 \ln oil_t + 1.21 \ln DIST_{sp} - 0.373 \ln oil_t * \ln DIST_{sp}$$

Here, sp refers to a state-province pair. Note that we use log distance rather than levels as it provides a better fit to the land-based data. For rail transport we estimate

$$f_{spkt} / v_{spkt} = -4.37 + 0.54 \ln \frac{w_{spkt}}{v_{spkt}} + 0.079 \ln oil_t - 0.90 \ln DIST_{sp} - 0.224 \ln oil_t * \ln DIST_{sp}$$

With the exception of the rail cost function (which represents only 1 percent of our sample), these estimates are broadly consistent with estimates in the literature.

We then take the coefficients from this regression to construct the costs that would face a Danish firm with similar shipment characteristics. This is specific to each input purchased. Oil prices and distance are the same for all firms. We use data on transport mode used and weight/value ratio for all firms purchasing a particular c-k input; however to avoid introducing endogeneity we use pre-sample information in both variables. We construct transport costs for each input from the fitted equation as $\tau_{ckt} = \exp(f_{ckt} / v_{ckt})$ and aggregate over inputs using the share of each input in pre-sample trade for each firm.

To understand the source of variation generated by this approach, note that inputs travel different distances, have different bulk (product weight/value), and use different transport modes. Over time there are shocks to the level cost of each transport mode as a function of technological change and input prices. Further, oil prices fluctuate substantially in our sample, falling for 4 years and then rising sharply, as we show in Figure A1. Shocks to oil prices differentially affect costs depending on which mode is used and how far goods travel.

3. Measures of offshoring: details

3.1 Input-Output Tables

An alternative approach to identify imported inputs, commonly used in the literature, employs input-output (IO) tables. Under the "proportionality assumption" (see Feenstra and Jensen 2010 for limitations) that all firms in an industry use the same inputs and in the same ratios and that imports and domestic supplies have the same market share, one can use IO table input coefficients interacted with shocks to trade costs to generate industry-time variation in the desirability of offshoring. We do not employ this method for three reasons. One, we employ industry-time fixed effects in the estimation in order to control for demand shocks, and this eliminates all variation that can be exploited using an IO table. Two, unlike the literature we see the actual inputs purchased by firms and the data strongly reject the assumption of common input usage within an industry. Three, because the data indicate significant within-industry variation across firms in both inputs and source countries, we can use exporter-product-time variation in our instruments to better explain changes in offshoring.

Nevertheless, the IO tables provide a useful additional check on the firm level data. The most disaggregated Danish IO table is at the industry-level, covering 57 manufacturing industries, and does not distinguish inputs by source. This is in contrast to our country-product disaggregation, where we have over 13,500 distinct inputs. We make use of the import matrix of the Danish IO table for two cross-checks. First, are there instances where our trade data says that product k is an imported input for firm j, but the IO table disagrees (i.e. the industry of k is not an imported input for the industry of j)? This occurs for only 2 percent of cases.

As another cross-check on our firm-level data, we construct a hypothetical import matrix of the IO table using our trade data and compare it with the import matrix of the official Danish IO table. They are not identical, because the official IO table employ the proportionality assumption . Nevertheless, there is a broad correspondence between the inputs used by our firms and what we seem in the IO table. The input shares of our constructed import matrix have a 0.73 correlation with the official IO table.

3.2 Machinery Imports

Imports of machinery are potentially problematic in terms of interpretation. Access to foreign technology embodied in machinery imports may affect labor demand and wages (e.g. Hanson and Harrison 1999) but through a different channel than offshoring of material inputs that could have been produced by the firm. While we do not take a strong stand that we can completely separate the effects of offshoring material inputs versus technological change embodied in machinery imports, we do want to distinguish where such effects are likely to appear in our analysis.

The HS system classifies most types of machinery in HS84, "Nuclear reactors, boilers, machinery etc…", and HS85, "Electric machinery etc; sound equipment; TV equipment …". Our broad offshoring measures include imports of HS 84 and HS 85 for all firms, and this represents 16.9% of imports. Our narrow offshoring measure excludes machinery imports for all firms except for those who also produce machinery for sale. For firms that produce machinery for sale, narrow offshoring could potentially include machinery imports. The question for these firms is whether imports within HS 84, 85 represent machinery itself or parts for machinery. As an example, consider the five largest firms selling in HS 8413, "Pumps for liquids…". The top three import categories are HS 8413 itself, which could be machinery, and HS 8483, "Transmission shafts, bearings, gears…", and HS 8481, "Taps, cocks, valves…" which are clearly parts. We found similar results for the top five firms in HS 8481 and HS 8482, "Ball or roller bearings…".

At more disaggregated levels of data it is possible to distinguish machinery from parts of machinery. Looking over all firms and imports we ranked the value share for each six digit product within HS 84. Table A1 lists the top 20 products, comprising 59% of the imports of HS 84. All are parts, and not machinery itself. The largest HS6 import that is clearly a machine and not parts of a machine is HS 842240, "Packing or wrapping machinery…" It ranks 34th on the list and its share in imports is 0.007%. The results are similar for HS85. Therefore, even in those HS categories where machinery imports are concentrated, actual machinery accounts for a small share of total imports.

4. Robustness of Results to Sample Selection

To gauge the effects of our sample selection criteria, Table A2 compares the summary statistics of our estimation sample with the full sample. The full sample is the collection of workers and firms in the manufacturing sector we have before we implement our sample-selection criteria. The numbers under the heading "Estimation Sample" are identical to those in Table 1. As compared with the full sample our estimation sample has slightly larger firms that employ slightly more experienced workers with slightly higher wages, but the differences are very limited.

A related concern is that we include only the firms in the years in which they both import and export. If a large fraction of firms import/offshore but do not export, then our estimation sample may not be representative of the Danish manufacturing sector. Table A3 breaks down the trading firms (i.e. the firms that import/offshore, or export, or both) in the full sample (as defined for Table A2 above) by employment and trade categories, and shows the shares in employment (upper panel), output (middle panel) and import value (lower panel). Table A3 shows that offshoring-only firms account for 2% of employment, 1.6% of output and 0.7% of import value among all trading firms; in comparison, the firms that both offshore and export account for 86.6% of employment, 90% of output and 99% of import value. These results suggest that the offshoring-only firms are a small fraction of our Danish data.

In Table A4, we present the results of within-job-spell wage regressions with the offshoring-only firms added into the sample (columns 1-4). The number of observations (1.98 million) is very similar to our estimation sample (1.93 million, as in Table 5), consistent with the results of Table A2. Since the offshoring-only firms have export values of 0 we replace the two instrumented export variables in our main estimation with the un-instrumented variables of log(export value + 1) (columns 1 and 3), and export values as a share of output (columns 2 and 4). The coefficient estimates for offshoring and its interaction with high-skill dummy are similar to Table 5.

In Table A4 we also present the results of within-job-spell wage regressions for a balanced panel of firms that are in the sample in all years (columns 5-8). The balanced-panel sample has 40%, or roughly 800,000, fewer observations than in our estimation sample. Despite this reduction in sample size, the coefficient estimates for offshoring and its interaction with high-skill dummy are again similar to Table 5. However, the coefficient estimates for log exports are about twice their size than in Table 5, and there is a larger difference between the effects of exports on high- and low-skill wages, and a smaller difference for high and low-skill earnings. These are likely because we are unable to fit the log-export regression as well in the first-stage IV. To be specific, the WID instrument for export has a smaller coefficient estimate than in Table 4 and is not statistically significant when firm controls are included. When firm controls are not included, the WID instrument has a similar coefficient estimate to Table 4 but the WES instrument has a larger coefficient estimate. In addition, the F-statistics for the instruments are also smaller than in Table 4 (2.59 and 10.39, respectively, vs. 8.62 and 22.36 in Table 4). These are likely due to the reduction in sample size. The other first-stage IV regressions are similar to Table 4 (the first-stage IV results are available upon request).

5. Additional Robustness Exercises

To save space, we show the following two robustness exercises in Table A5. The other robustness exercises mentioned in note 34 of the text are available upon request.

In the text, we have emphasized narrow offshoring (imports purchased in same industry categories as the firm's sales) because these are more likely to be inputs the firm could have produced itself. In our next robustness check we use broad offshoring (all import purchases by the firm) instead. We find much larger effects of offshoring on wages, and more pronounced differences across skill types. A possible explanation is that broad offshoring includes inputs of all types and is therefore more likely to capture the effect of technological change operating through imports of machinery. Further, the estimation with firm controls yields a much larger wage drop than the estimation without firm controls. This is consistent with the view that the productivity effect, as distinct from the labor substitution effect, can be seen more clearly when imported inputs are different from those made by the firm.

Next, one may be concerned that firm level shocks originating within Denmark may have general equilibrium consequences for product prices in exporting and importing partners if Denmark is responsible for a large share of trade. We experiment with dropping trade flows where Denmark is responsible for more than 1% of trade with that partner and product. Results are very similar.

Online Appendix, Not for Publication

Theory Appendix

Generalizing the Production Function

To generalize our production function, equation (1), we have $Y_{jt} = A_{jt}K_{jt}^{\alpha}\prod_{f=1}^{F} C_{fjt}^{\alpha_f}$, where f = 1,2,…,F index types of labor, $C_{fjt} = \left(L_{fjt}^{\theta_f} + M_{jt}^{\theta_f}\right)^{1/\theta_f}$, $\theta_f = \dfrac{\sigma_f - 1}{\sigma_f}$, and $\sum_{f=1}^{F}\alpha_f = 1-\alpha$

In words, the production function is Cobb-Douglas in capital (whose share is α) and composite inputs C_f (whose share is α_f). Each composite input C_f is produced with imported inputs M and type-f labor L_f using CES technology with the substitution elasticity $\sigma_f > 1$. σ_f may vary across labor types. Each labor type can be a skill group or an occupation, and different labor types enter into the production function symmetrically. We first show that

(A1) $\ln C_{jft} \approx c_{of} \ln M_{jt} + (1-c_{of})\ln L_{jt} + c_{1f}$

where c_{0f}, c_{1f} are constants and $0 < c_{0f} < 1$.

Proof Drop the subscripts j, f, and t, and let $y = \ln(L/M)$. Then $C = M(e^{y\frac{\sigma-1}{\sigma}}+1)^{\frac{\sigma}{\sigma-1}}$ and $\ln C = \ln M + g(y)$, where $g(y) = \dfrac{\sigma}{\sigma-1}\ln(e^{y\frac{\sigma-1}{\sigma}}+1)$. The first-order Taylor approximation for $g(y)$ is $g(y) = g(y_0) + g'(y_0)(y - y_0)$, where y_0 is a constant, and $g'(y_0) = \dfrac{e^{y_0\frac{\sigma-1}{\sigma}}}{e^{y_0\frac{\sigma-1}{\sigma}}+1}$ lies between 0 and 1 for all values of y_0. Let $c_0 = g'(y_0)$ and $c_1 = g(y_0) - y_0 g'(y_0)$ and we have equation (A1). **QED**.

Similar to equation (2) in our paper, the marginal product of type-1 labor is $MPL_1 = (1-\alpha)A_{jt}K_{jt}^{\alpha}L_{1jt}^{-\frac{1}{\sigma_1}}C_{1jt}^{\frac{1}{\sigma_1}+\alpha_1-1}\prod_{f=2}^{F}C_{fjt}^{\alpha_f}$. Taking the log of MPL_1 and using equation (A1) we obtain

$$\ln MPL_1 = \ln[(1-\alpha)A_{jt}K_{jt}^{\alpha}L_{1jt}^{-\frac{1}{\sigma}}] + \sum_{f=2}^{F}\alpha_f c_{0f}\ln L_{fjt} + +(\frac{1}{\sigma_1}+\alpha_1-1)c_{01}\ln L_{1jt}$$
$$+[(\frac{1}{\sigma_1}+\alpha_1-1)(1-c_{01}) + \sum_{f=2}^{F}\alpha_f(1-c_{0f})]\ln M_{jt}.$$

If $c_{01} = c_{0f}$ for all f = 2,..,F, the coefficient for lnM_{jt} in the expression for lnMPL_1 simplifies to $[\frac{1}{\sigma_1}+\alpha_1-1+\sum_{f=2}^{F}\alpha_f](1-c_{01})=(\frac{1}{\sigma_1}-\alpha)(1-c_{01})$, where the equality uses $\sum_{f=1}^{F}\alpha_f=1-\alpha$. Therefore, an increase in M_{jt} increases the demand for type-1 (type-f) labor if $1/\sigma_1 - \alpha < 0$ ($1/\sigma_f - \alpha < 0$). This condition is analogous to what we have in section III.1. Since σ_f differs across labor types, this condition also suggests that an increase in M_{jt} may increase the wage for some labor types (those with small σ_f) but decrease the wage for the other types (those with large σ_f).

Derivation of Equation (3)

Assume that firm j faces the following supply curve for unskilled labor

(A2) $$w_{L,jt}=c(L_{jt})^{\gamma_{L,S}},$$

where $w_{L,jt}$ is the unskilled-labor wage for firm j in year t and γ_{Ls} is the elasticity of supply for unskilled labor. Equations (2) (in the text) and (A2) imply that the response of unskilled wages to offshoring (holding output constant) is

(A3) $$b_{L,M}=\frac{\partial\ln w_{L,jt}}{\partial\ln M_{jt}}|_{K\text{ constant}}=\frac{(1/\sigma-\alpha-\beta)c_0\gamma_{L,S}}{\gamma_{L,S}-\gamma_{L,D}},$$

where $c_0\in(0,1)$ is a constant and $\gamma_{L,D}<0$ is the elasticity of labor demand implied by equation (2). Equation (A3) says that $b_{L,M}<0$ if $1/\sigma<(\alpha+\beta)$, which is the same condition under which offshoring lowers labor demand. If labor supply is perfectly elastic, $\gamma_{Ls}\to\infty$, then shocks to labor demand will result in employment changes but not wage responses. A similar demonstration shows that offshoring raises skilled labor wages and exporting raises wages for both skilled and unskilled workers.

To derive equation (3), assume that each unskilled worker i has productivity h_{ijt} in year t and $h_{ijt}=\exp(\beta_1 x_{it}+\eta_{ij})$, where x_{it} represents observable worker characteristics (e.g. experience), β_1 is a vector of coefficients, and η_{ij} represents unobservable ability that is specific to the worker-firm match. Unskilled workers are the same up to the productivity term, so that worker i receives wage

(A4) $$w_{L,ijt}=w_{L,it}h_{ijt}.$$

A similar expression governs high skill labor wages. Then it is straightforward to derive equation (3) by solving for $\log w_{L,ijt}$ using equations (A2), (A4) and equation (2) in the text.

When the production function has multiple types of labor we can carry out the analyses in the same way. In particular, to derive the counterpart of (A3), let $\gamma_{f,S} > 0$ be the labor supply elasticity for type-f labor. Then the wage elasticity for type-f labor is $\frac{\partial \ln w_{f,jt}}{\partial \ln M_{jt}}|_{K \text{ and } L_f \text{ constant}} = \frac{(\sigma_1^{-1}-\alpha)c_{0f}\gamma_{f,S}}{\gamma_{f,S}-\gamma_{f,D}}$, where $\gamma_{f,D} = -[\frac{1}{\sigma_f}+(1-c_{0f})(1-\alpha_f-\frac{1}{\sigma_1})] < 0$ is the demand elasticity for type-f labor and c_{0f} is as defined in equation (A1). This expression is analogous to (A3).

<u>The Productivity Effect</u>

Finally, we use Figure A2 to illustrate the effects of offshoring on unskilled wage, with and without the productivity effect. LS is the supply curve for unskilled labor. Suppose that unskilled labor and imported inputs are highly substitutable; i.e. $\sigma > 1/(\alpha+\beta)$. An increase in offshoring shifts the unskilled labor demand curve from LD_0 to LD_1, holding constant physical capital, K_{jt}. This is the direct wage effect of offshoring. As the increase in foreign inputs makes the firm more profitable and the firm increases the use of all inputs in response, there is a secondary shift of the unskilled labor demand curve, rising from LD_1 to LD_2. This is the productivity effect of offshoring and it tends to increase unskilled wage. If the direct effect dominates the productivity effect, LD_2 lies between LD_1 and LD_0.

We now calculate the wage elasticity of unskilled labor inclusive of the productivity effect. We assume that firm j takes the rental rate for capital, r_t, as given, and that firm j increases capital input, K_{jt}, until its marginal revenue product equals the rental rate r_t, or that $r_t = \alpha\psi_{jt}A_{jt}K_{jt}^{\alpha-1}H_{jt}^{\beta}C_{jt}^{1-\alpha-\beta}$, which implies that $\frac{\partial \ln K_{jt}}{\partial \ln M_{jt}} = \frac{\partial \ln C_{jt}}{\partial \ln M_{jt}}\frac{1-\alpha-\beta}{1-\alpha} = c_0\frac{1-\alpha-\beta}{1-\alpha} > 0$, where $0 < c_0 < 1$ is the same as defined in (A3). Using this expression and equation (2) we can show that $b_{L,M}^{*} = \frac{\partial \ln w_{jt}}{\partial \ln M_{jt}} = \frac{c_0\gamma_{L,S}}{\sigma(\gamma_{L,S}-\gamma_{L,D}^{*})}$, where $\gamma_{L,D}^{*} = -\frac{c_0}{\sigma} < 0$ is the elasticity of unskilled labor demand inclusive of the productivity effect. Comparing this expression with (A3) we show that $b_{L,M} < b_{L,M}^{*}$; i.e. the productivity effect tends to increase the wage for unskilled labor.

<u>Instrumental Variables Strategy</u>

Index Danish firms by j, years by t, exporting countries by c, products (measured at the HS-6 level) by k, and destination countries other than Denmark by d. For ease of exposition, assume that firm j only imports a single product k from a single destination country c (the case of multiple product x country is similar). Firm j's production function is given by equation (1) in the text, but we re-write firm j's imported inputs as.

(A5) $$M_{jt}^{\theta} = \lambda_{ck} (b_{ck}^{j})^{\frac{1}{\sigma-1}} \left(q_{ck}\right)^{\theta}, \theta = \left(\sigma - 1\right) / \sigma,$$

In equation (A5), λ_{ck} is a preference shifter for a given exporter-product that is common across importers. This can be thought of as quality, or in cases where there are multiple firms providing product k in exporter c, this can be interpreted as variety. In addition, there are preference weights, b_{ck}^{j}, that are idiosyncratic to each firm j. As we note in Section III, a feature of the Danish data is that for a given firm j, b_{ck}^{j} is positive for a small number of inputs, and the modally occurring case is that for a given c,k, b_{ck}^{j} is positive for only one Danish firm**.**

By the production function (1) and equation (A5), the value of firm j's imported inputs equals

(A6) $$p_{ckt} q_{ckt} = m_{ckt}^{j} = \underbrace{(1-\alpha-\beta)}_{\text{Constant}} \underbrace{(p_{ckt}^{1-\sigma} \lambda_{ckt}^{\sigma-1})}_{\substack{\text{c-k Supply} \\ \text{char.}}} \underbrace{\tau_{ckt}^{-\sigma}}_{\substack{\text{Denmark} \\ \text{Trans. Cost}}} \underbrace{\left(\frac{b_{ck}^{j} E_t^{j}}{P_t^{j}}\right)}_{\substack{\text{Firm-j Demand} \\ \text{char.}}}, P_t^{j} = b_{ck}^{j} p_{ckt}^{1-\sigma} \lambda_{ckt}^{\sigma-1} + w_{L,jt}^{1-\sigma}$$

In equation (A6) E_t^{j} is the output value of firm j, which reflects demand for j's outputs, and P_t^{j} represents the CES price index for j's imported inputs and low-skilled wage. Equation (A6) says that imports of a particular input ck can rise because there is a shock to supply characteristics (price, quality, variety), shocks to transport costs, or because overall demand for inputs rises. We want to isolate the component of the firm's changing import demand that arises from shocks to supply characteristics or to transport costs. We will measure transportation costs directly. We next discuss how we identify shocks to supply characteristics.

One possible approach is to use highly disaggregated gravity equations to separately identify shocks to supply and demand characteristics. This is similar in spirit to Redding and Venables (2004), except that they use aggregate bilateral trade in a single cross section and extract aggregate supply characteristics by exporter country. To see how this approach works, suppose that input demand in the rest of the world is of a similar form to demand in Denmark, though we write preference weights as idiosyncratic to a destination d. Imports into destination d are then

(A7) $$m_{ckt}^{d} = \underbrace{(1-\alpha-\beta)}_{\text{Constant}} \underbrace{(p_{ckt}^{1-\sigma}\lambda_{ckt}^{\sigma-1})}_{\text{c-k Supply char.}} \underbrace{(\tau_{ckt}^{d})^{-\sigma}}_{\text{country-d Trans. Cost}} \underbrace{\sum_{l} \frac{b_{ck}^{d,l} E_t^{d,l}}{P_t^{d,l}}}_{\text{country-d Demand char.}},$$

where the summation is over the firms l in destination country d. Assume that there is no idiosyncratic component to demand (i.e. if $b_{kt}^{d} = b_{ckt}^{d,l}, \forall c$), then equation (A7) can be rewritten as

(A8) $$\ln m_{ckt}^{d} = \alpha_{ckt} + \alpha_{kt}^{d} - \sigma \ln\left(\tau_{ckt}^{d}\right), \text{ where } \alpha_{ckt} = \left(1-\sigma\right)\ln\left(p_{ckt}\lambda_{ckt}^{-1}\right) \text{ and } \alpha_{kt}^{d} = b_{kt}^{d} \sum_{l} \frac{E_t^{d,l}}{P_t^{d,l}}.$$

In principal, one could estimate (A8) for every product and time period, using vectors of origin and destination fixed effects to capture the supply characteristics α_{ckt} and demand characteristics α_{kt}^{d}. After netting off the demand and trade cost components, one collects a vector of fixed effects α_{ckt} and expressing over time changes for a given country x product, we have shocks to exporter supply.

We do not pursue this approach for two reasons. One, this decomposition requires that demand and supply shocks be linearly separable, which is not the case if destination d has unusually strong preferences for the output of origin c, i.e. if b_{ckt}^{d} varies over exporters c. Our data for Denmark show that the idiosyncratic component to demand is a salient feature of the data. That is, two Danish firms within the same industry purchase very different input bundles. Adding the additional dimensions of variation across importing country and including differences in cross industry composition likely make this idiosyncratic component to demand even more important. Two, while Redding and Venables (2004) employs aggregate bilateral trade in a single cross section, we need the supply characteristics for each exporting country by HS6 product (over 5000 in total) in each year. The typical exporter ships an HS6 product to a small and changing number of destinations each year (i.e. the large majority of bilateral trade flows are zero for a given HS6 product). This means that the average conditional value of bilateral trade, α_{ckt}, is extremely sensitive to variation in the number of destinations, itself endogenous to the time varying supply and demand characteristics of interest. Tackling these two issues is beyond the scope of our paper and so we employ a different approach.

As we discussed in the text, our approach is based on the variable WES (world export supply). Using (A8) we can derive the expression for WES by summing import demands over all destinations worldwide other than Denmark, (A9) $$WES_{ckt} = \sum_{d \neq Denmark} m_{ckt}^{d} = \underbrace{(1-\alpha-\beta)}_{\text{Constant}} \underbrace{(p_{ckt}^{1-\sigma}\lambda_{ckt}^{\sigma-1})}_{\text{c-k Supply char.}} \underbrace{\sum_{d \neq Denmark} (\tau_{ckt}^{d})^{-\sigma} \sum_{l} \frac{b_{ck}^{d,l} E_t^{d,l}}{P_t^{d,l}}}_{\text{Rest of World Trans. Cost and Demand Char.}},$$

WES can change over time because of changes in supply, trade costs, or demand. (A9) and (A6) imply that:

(A10) $$\log m_{ckt}^{j} = \log WES_{ckt} - \sigma \ln \tau_{ckt} + \underbrace{\ln(\frac{b_{ck}^{j} E_t^{j}}{P_t^{j}})}_{\text{Firm-j specific variables.}} - \underbrace{\ln\{\sum_{d \neq Denmark} (\tau_{ckt}^{d})^{-\sigma} \sum_{l} \frac{b_{ck}^{d,l} E_t^{d,l}}{P_t^{d,l}}\}}_{\textit{unobserved}}.$$

Equation (A10) motivates the specification of our first-stage IV regression. Using firm-j characteristics as controls we regress firm j's imports of inputs on WES and transportation costs, hoping to capture movements in supply characteristics, $p_{ckt}^{1-\sigma}\lambda_{ckt}^{\sigma-1}$, that are invariant to destinations and give rise to changes in exports for exporter c and product k over time, and movements in τ_{ckt}. (When focusing on instruments for exporting at the firm level, we follow a similar strategy. That is, we sum imports over all sources for a given destination to capture movements in demand that are invariant to sources and give rise to changes in imports for a given importer c and product k over time.)

We can now use the explicit form of the imports expression to describe threats to identification. The main concern for our instruments is that a worldwide shock to demand for product k will simultaneously affect world export supply and input demand for Danish firm j; i.e. in equation (A10), the unobserved variable is correlated with WES_{ckt} and the firm-j specific variables. Further, if there is overlap between the inputs that firm j uses and the products that it sells, this demand shock also affects the desirability of firm j's products and therefore labor demand, and the wage. For example, rising demand for consumer electronics affects both cell phone manufacturers and producers of memory chips, and potentially the wages of workers employed by cell phone makers. We have addressed these concerns in the text. To recap:

1. We experiment with omitting industries with obvious shocks to demand occurring in this period (housing, electronics) and obtain similar results.
2. We incorporate an industry-time fixed effect in all the wage specifications. Any time varying shock to demand at the industry level (e.g. electronics) is absorbed by the fixed effect, leaving only shocks that are idiosyncratic to firms.
3. We incorporate firm level exports, instrumented by world import demand in the wage regressions. This variable is used specifically to address the possibility that there might be idiosyncratic shocks to product demand affecting the wage equation. World import demand, constructed in a manner

symmetric to world export supply, captures movements in demand in the destination country that are invariant to sources. If there is a common shock to demand, it will affect WID, and exports. This control for shocks to demand is significant in the Danish context, where the average firm exports 45% of its output.

4. We experiment with excluding from our estimates any exporter-products where Denmark represents a large share of worldwide demand for the product. Because Denmark is small, we obtain similar results.

Figure A1 Fuel prices over time

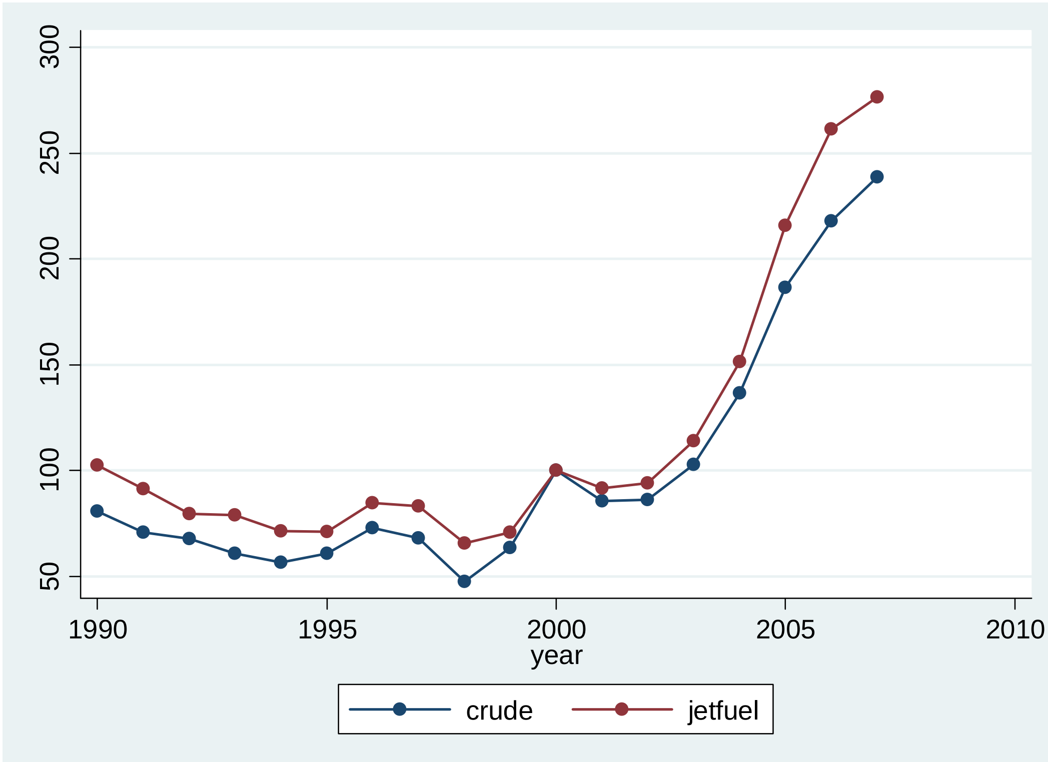

Figure A2. The Effects of Offshoring on Unskilled Wage

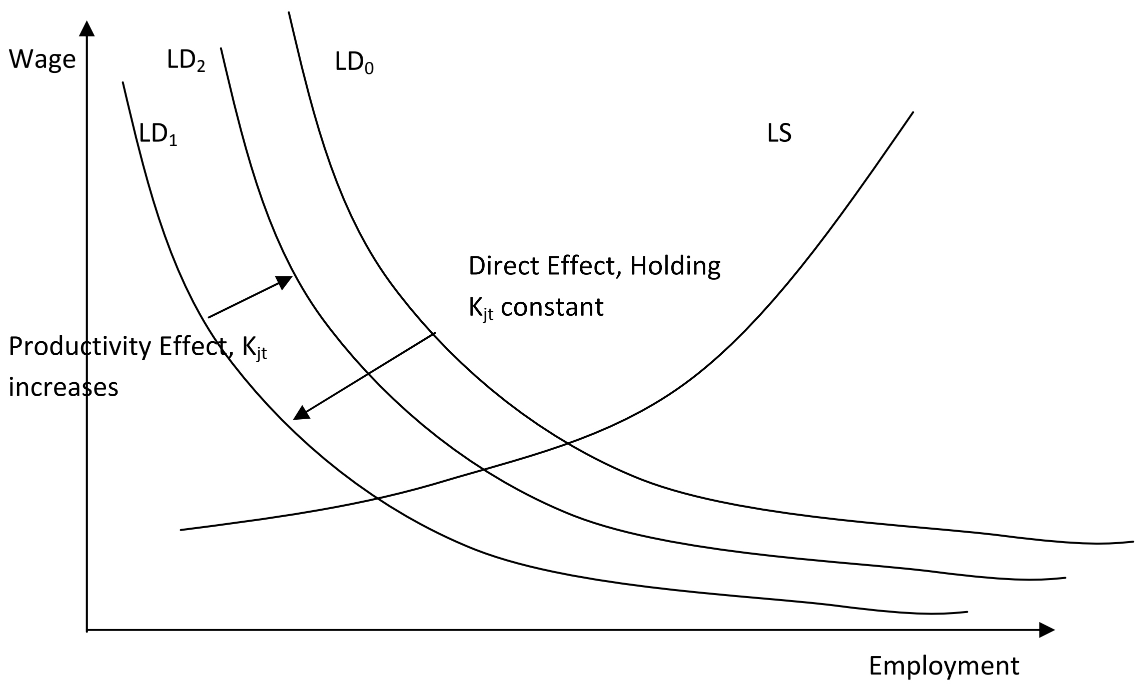

Table A1 The Top 20 HS6 Products in HS 84 (Machinery)

HS6	Description	Product Share	Cumul Share
848340	GEARS; BALL OR ROLLER SCREWS; GEAR BOXES, ETC	9.8%	9.8%
841391	PARTS OF PUMPS FOR LIQUIDS	8.8%	18.6%
848180	TAPS COCKS ETC F PIPE VAT INC THERMO CONTROL NESOI	6.3%	24.8%
840999	SPARK-IGNITION RECIPROCATING INT COM PISTN ENG PTS	5.3%	30.1%
848190	PTS F TAPS ETC F PIPE VAT INC PRESS & THERMO CNTRL	4.3%	34.4%
841290	ENGINE AND MOTOR PARTS, NESOI	3.2%	37.6%
840810	MARINE COMPRESS-IGNIN COMBUSTION PISTON ENGINE ETC	2.2%	39.8%
841370	CENTRIFUGAL PUMPS, NESOI	2.2%	41.9%
841899	REFRIGERATOR FREEZER AND HEAT PUMP PARTS NESOI	1.8%	43.7%
848210	BALL BEARINGS	1.8%	45.5%
848120	VALVES F OLEOHYDRAULIC OR PNEUMATIC TRANSMISSIONS	1.5%	47.0%
843390	PARTS FOR HARVESTER, GRASS MOWERS, SORTING EGG ETC	1.5%	48.5%
847990	PTS OF MACH/MECHNCL APPL W INDVDUL FUNCTION NESOI	1.4%	49.9%
843890	PARTS OF MACH OF CH 84, NESOI,IND PREP FOOD,DRINK	1.4%	51.3%
844900	MACH F MANUF OR FINISH NONWOVENS;HAT BLOCKS; PARTS	1.4%	52.7%
843149	PARTS AND ATTACHMENTS NESOI FOR DERRICKS ETC.	1.3%	54.0%
847330	PARTS & ACCESSORIES FOR ADP MACHINES & UNITS	1.2%	55.3%
847989	MACH & MECHANICAL APPL W INDIVIDUAL FUNCTION NESOI	1.2%	56.5%
841430	COMPRESSORS USED IN REFRIGERATING EQUIPMENT	1.2%	57.6%
848590	MACHINE PARTS WITH NO ELECTRIC FEATURES NESOI	1.1%	58.8%

Table A2 Summary Statistics for the Full Sample and the Estimation Sample

	Full sample			*Estimation sample*		
	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.
Hourly wage	2,800,537	189.36	123.50	1,950,896	192.85	70.19
Log hourly wage	2,797,956	5.14	0.41	1,950,896	5.19	0.31
Log gross output	2,797,414	20.10	1.88	1,950,896	20.50	1.69
Log employment	2,800,537	6.06	1.69	1,950,896	6.44	1.49
Log capital per worker	2,779,424	12.53	0.94	1,950,896	12.59	0.89
High-skill	2,800,530	0.18	0.14	1,950,896	0.19	0.14
Experience	2,739,597	17.02	9.96	1,950,896	17.93	9.31
Union	2,791,622	0.83	0.37	1,950,896	0.88	0.33
Married	2,739,597	0.56	0.50	1,950,896	0.59	0.49

Notes: The full sample is the collection of workers and firms in manufacturing we have before we implement our sample-selection criteria. The estimation sample is the one we use in our paper, and the summary statistics for the estimations sample are identical to those reported in Table 1. All variables are calculated over the distribution of worker-year observations, which means firm characteristics such as output are repeated as many times as there are worker-years for that firm.

Table A3 Employment, Output and Import-Value Shares by Trade and Employment Categories

	Trade categories			
Number of Employees	Offshoring and exporting	Exporting only	Offshoring only	
	% in employment			
0-50	9.9%	6.7%	0.6%	
50+	76.7%	4.7%	1.4%	100%
	% of output			
0-50	9.5%	4.7%	0.4%	
50+	80.5%	3.6%	1.2%	100%
	% of imports			
0-50	12.6%	0	0.3%	
50+	86.7%	0	0.4%	100%

Notes: The sample consists of all the trading firms in the full sample. Trading firms either import/offshore, export, or both. The full sample is the same as in Table A1; i.e. the collection of firms we have before we implement our sample-selection criteria.

Table A4 Wage Regressions with Offshoring-Only Firms and for the Balanced-Panel Sample

	Offshoring-Only Firms				Balanced Panel			
Dependent Variable:	log hourly wage		log hourly wage		log hourly wage		log labor income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log offshoring	-0.0138**	-0.0135**	-0.0355***	-0.0362***	-0.0179**	-0.0237***	-0.0354***	-0.0340***
	[-2.36]	[-2.32]	[-5.71]	[-5.69]	[-2.27]	[-3.32]	[-4.72]	[-4.98]
Log offshoring x high skilled	0.0526***	0.0530***	0.0462***	0.0462***	0.0732***	0.0734***	0.0494***	0.0552***
	[11.70]	[11.91]	[10.49]	[10.62]	[6.99]	[7.07]	[5.09]	[5.55]
Log exports					0.1019***	0.0812***	0.0875***	0.0991***
					[5.11]	[6.85]	[4.22]	[7.90]
Log exports x high skilled					-0.0337**	-0.0351**	0.0094	0.0049
					[-2.07]	[-2.11]	[0.62]	[0.30]
Log (exports + 1)	0.0010		0.0005					
	[1.57]		[0.80]					
Log (exports + 1) x high skilled	0.0008		0.0006					
	[1.55]		[1.07]					
Share, exports/output		-0.0001**		0.0005***				
		[-2.57]		[5.57]				
Firm Controls	No	No	Yes	Yes	Yes	No	Yes	No
Observations	1,976,883	1,976,883	1,976,883	1,976,883	1,124,449	1,124,449	1,124,443	1,124,443
Number of job spell fixed effects	388,575	388,575	388,575	388,575	191,653	191,653	191,653	191,653
R-squared	0.151	0.1509	0.153	0.153	0.1689	0.1669	0.1052	0.1036

Notes: Clustered (firm-year) t-statistics in brackets. *** p<0.01, ** p<0.05, * p<0.1. In columns (1)-(4) the sample is our main estimation sample plus the offshoring-only firms. The variables log (exports + 1), log(exports + 1) x high-skilled, and exports/output are not instrumented. Columns (5)-(8) are the same specification as Table 5, but the sample is a balanced panel of firms that are in the sample for the entire period.

Table A5 Additional Robustness Exercises

Dependent variable:	Log Hourly Wage		Log Hourly Wage	
Robustness check:	I. Broad offshoring		II. DK-dominant flows removed (1%)	
	FE-IV		FE-IV	
Log(offshoring)	-0.1064***	-0.0608**	-0.0179	-0.0187
	[-2.58]	[-2.31]	[-2.59]	[-3.50]
Log(offshoring) x high-skilled	0.1311***	0.1322***	0.0452***	0.0462***
	[8.93]	[9.32]	[7.32]	[7.35]
Log(exports)	0.0720***	0.0742***	0.0405***	0.0437***
	[6.32]	[5.11]	[2.88]	[4.47]
Log(exports) x high-skilled	-0.0597***	-0.0567***	0.0103	0.0123
	[-4.05]	[-3.81]	[1.03]	[1.17]
First stage IV *F*-statistics:				
log offshoring	2.55	9.03	5.20	9.70
... *x* high skill	33.79	31.93	28.10	21.80
log exports	6.08	10.97	3.95	7.75
... *x* high skill	16.29	15.26	17.26	14.38
Other firm-level controls	Yes	No	Yes	No
Obs	1,950,896	1,950,896	1,928,599	1,928,599
No. job spells	384,257	384,257	383,035	383,035
R2	0.1543	0.1525	0.155	0.1533

Notes: Table A5 presents the results from worker-level Mincer regressions, using log hourly wage as the dependent variable. All specifications include job spell, industry-year and regional fixed effects. Log offshoring, log exports and their skill interactions are instrumented using world export supply (WES), world import demand (WID) and transport costs. Robust T-statistics in brackets. Standard errors clustered at firm-year levels. *** p<0.01, ** p<0.05, * p<0.1.