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

David Hummels, Purdue University and NBER

Rasmus Jørgensen, University of Copenhagen

Jakob R. Munch, University of Copenhagen

Chong Xiang, Purdue University and NBER

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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 track the outcomes for workers after a job spell and find that those displaced from offshoring firms suffer greater earnings losses than other displaced workers, and that low-skilled workers suffer greater and more persistent earnings losses than high-skilled workers.

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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 and employment opportunities? 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,[2] 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. We also assess the wage effects of exporting; even if wages are dampened by offshoring they may still rise with trade if exports boost labor demand. Further, since we see specific workers before, during, and after their employment in specific firms we can also assess the effects of offshoring on the wages of displaced workers.

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[1] See also Amiti and Konings (2007), Kasahara and Rodrigue (2008), Goldberg et al. (2010) and Bustos (2011).
[2] This worker-firm data set has been used previously in the labor literature (e.g. Christensen et al 2005.), but has not used the link to detailed trade data from Danish customs that we employ.

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 exchange rates, transportation costs, and world-wide shocks to export supply and import demand for the relevant partner country x product. 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, 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 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, 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 −1.6% to −1.9%. Importantly, we find these results only if we instrument for offshoring. For high-skilled workers, offshoring has a wage elasticity of +3.1% to +3.6% 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 +3.7% to +4.4%, and similar estimates for high-skilled wage elasticity. These results suggest that rising exports are a rising tide that lifts all boats.

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 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) and those that expose workers to

[3] This literature typically examines the effects on the relative high-skilled wage (or relative high-skilled demand). We show the effects on the levels of both low-skilled and high-skilled wages.

potentially unsafe working conditions 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. (2009) find that wage losses from offshoring are more pronounced for the workers who perform routine tasks. Ottaviano et al. (2010) 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.

In a final exercise we examine the effect of offshoring on displaced workers, employing a framework similar to Jacobson et al. (1993). We find that (mass-layoff) displacement from a firm with rising offshoring generates larger and more persistent wage and earnings losses than those suffered by other displaced workers. One year from displacement, skilled workers displaced from offshoring firms lose 15% of their pre-displacement earnings (versus 7% for other displaced skilled workers) while unskilled workers lose 21% (versus 15% for other displaced unskilled workers). Workers displaced from offshoring firms have higher rates of unemployment and are less likely to re-attach to firms within the same industry.

Our paper is related to the literature on offshoring and wages (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. Harrison, McLaren and McMillan (2010) survey recent empirical work, most of which uses firm-level or matched worker-firm data. For example, Amiti and Davis (2011) study how imports of intermediates affect average wages at the firm level. Martins and Opromolla (2009) use Portuguese data to estimate the wage effects of both imports and exports, controlling for job-spell fixed effects. Krishna et al (2011) use Brazilian data to compare effects of trade reforms on within job-spell wages for trading and non-trading firms. In recent theoretical work, Burstein and Vogel (2011) argue that offshoring between identical countries could increase the skill premium.

Our paper is also related to the literature on exporting and skill premium. For example, 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) show that Mexican firms improve product quality in order to export, raising the demand for skilled labor and the skill premium. 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 wage changes within-job spell versus 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). Our findings are but one channel through which globalization affects income inequality.[4]

In what follows, section II describes our data and presents stylized facts about offshoring. Section III provides a simple model to guide our empirical work, 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 wage effects for the workers displaced by mass lay-offs. Section VI concludes.

[4] For example, we do not focus on how globalization affects employment or resource reallocation, the subject of a number of recent studies using matched worker-firm data (e.g. Menezes-Filho and Muendler 2011).

II. Data Description

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

II.1. The Danish Labor Market

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. 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.[5] Decentralization has increased

[5] Some wage contracts are negotiated exclusively between workers and firms. This type of contract represents 30% of the labor market in 2005, up from 5% in the late 1980s. In other cases a minimum wage is set at the industry level and supplemented by personal payments negotiated between workers and firms. This type of contract represents 54% of the labor market in 2010, down from 74% in 1995.

wage dispersion in the Danish labor market (Dahl et al. 2009), 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

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,[6] 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 (see the Data Appendix for more details).

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.[7] We classify a worker as high-skilled if he/she has a tertiary education

[6] The firm identifier is in FirmStat 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.
[7] The use of annual hours 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

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.[8]

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 earnings of displaced 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 informal sector is almost non-existent in Denmark, 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, allowing us to 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.

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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.

[8] 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.

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.[9] 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 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 be missing intra-EU trade data.

All other firms are in the sample in the years in which they both import and export. 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.[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

[9] In 2002 the thresholds were DKK 2.5 million for exports and DKK 1.5 million for imports.
[10] Firms that discretely change their trade status tend to be small with small initial year trade volumes.

the year, and roughly 20% of all private sector employment. Table 1 contains summary statistics of the data.

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 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 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 account for 21% of total Danish imports and they supply 50% of Danish exports, with non-manufacturing firms comprising the remainder. To illustrate the difference between the imports of manufacturing and non-manufacturing firms, we draw on a variable measuring the value of inputs that are purchased and then sold by the firm with no value added. We calculate the share of these purchases in total inputs and call it 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] We have also done spot checks of particular manufacturing firms, and confirmed that the import product categories make

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

sense as likely input purchases given the goods they are making.[13] 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 define "broad offshoring" to be the total value of imports by a given manufacturing firm in a given year.

A second concern is that manufacturing firms are purchasing foreign goods but these inputs do not substitute for labor within the firm. This 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 because the input is too far from the firm's area of specialization. Feenstra and Hanson (1999) define "narrow offshoring" as purchases of inputs belonging to the same industry as that of producing firms. 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. 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 follow this definition, but applied more specifically to the inputs and outputs (both domestic sales and exports) of individual firms. We present more evidence that imports, measured as narrow offshoring, are likely to substitute for firms' own labor in Table 3 and section IV.

Table 2 shows that roughly 71% of imports are within the same HS4 category as that firm's outputs, and 87% of all imports are in the same HS2 category. We define narrow offshoring to be the sum of imports in the same HS4 category as goods sold by the firm either domestically or in exports. (A narrow-offshoring measure based on matching at the HS2 level yields similar results in our regressions). Imports of raw materials are then counted in broad offshoring, but are omitted from narrow offshoring.

[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.

Imports of machinery are also 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.[15]

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.

We can now characterize the trading activities of firms in our sample. Figures 1a and 1b plot the total value and regional composition of imports (broad offshoring) and exports from 1996-2006

[15] 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…".

by firms in our sample. In this period, both imports and exports more than doubled. 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. The regional pattern of trade has been largely stable over this period. 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 exhibit substantial time series variation in trade for a given firm. To show this we calculate the deviation of log (exports) by firm *j* in year *t* from its sample period mean for firm *j*, and similarly for broad and narrow offshoring. Table 1 shows that offshoring and exports vary substantially within firms over time, with log deviations from the firm mean of .49 (broad offshoring), .82 (narrow offshoring) and .46 (exports). The extent of changes over time also varies widely across firms. In Figures 2a and 2b we display the distribution of within-firm changes in log (narrow offshoring) and log (exports). The means of the distributions are zero by construction, but show wide variation. For narrow offshoring, 55 percent of the firm-year observations are either 30 percent above or 30 percent below the firm mean. The rich variation in within-firm changes for both offshoring and exports will be key to identifying their effects on wages.

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. This approach implies that all firms within an industry employ the same mix of inputs (and at typical levels of aggregation, firms from every industry buy nearly every input, albeit in different quantities). In contrast, our data reveals very different information about the input-output structure at the firm level. We distinguish input both by exporting source and HS-6 digit product code. The firms in our sample buy many foreign inputs, 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% of imports for the median firm, and the top 5 exporter-HS6 categories account for 92% of median firm imports. The pattern is similar for exports, with the median firm reporting 19 distinct importer-HS6 export categories, with 59% of exports coming from the top 2 categories and 77% from the top 5 categories.

Further, 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 display the distribution in Figure 3a. For the median product, just 1 firm out of 2000 buys the input, while a product in the 90th percentile has 3 purchasers. Figure 3b provides the distribution of the number of firms who export the same product to the same destination country. Again, the median is 1 firm, and the 90th percentile is 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 section IV.

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 to 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

Let *j* index firms and *t* index years. The production function for firm *j* in year *t* is

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

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 σ > 0 is the substitution elasticity for unskilled labor and imported inputs.[16] Imported inputs correspond to offshoring in 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).[17] Using equation (1) we can derive the demand for unskilled labor by firm *j* in year *t*,

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

Holding fixed the level of output (and other factors), an increase in imported inputs lowers unskilled labor demand if $1/\sigma-(\alpha+\beta)<0$. The intuition is that the increase in M_{jt} has two effects: it increases the composite input, C_{jt}, at the rate $1/\sigma$, but diminishing returns to C_{jt} set in at the rate $-(\alpha+\beta)$. When unskilled labor and imported inputs are very close substitutes so that $1/\sigma \to 0$, diminishing returns dominate and unskilled labor demand decreases. When labor and imported inputs are imperfect substitutes, however, demand for unskilled labor could actually

[16] 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 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.

[17] 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.

increase. In contrast, it is straightforward to see from equation (1) that an increase in imported inputs raises the marginal product of and demand for skilled labor. In our empirical work we allow for the possibility that labor of different types could be substitutes or complements for foreign materials.

Equation (2) illustrates an important endogeneity issue in estimating the effect of offshoring on labor demand. Suppose $1/\sigma < (\alpha + \beta)$ so that for a given level of output a rise in offshoring reduces demand for unskilled labor. An increase in either firm productivity A_{jt} or output demand ψ_{jt} will raise the demand for unskilled labor, 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}.

A related problem emphasized in the trade literature is that offshoring may have a secondary effect on labor demand. Suppose that offshoring raises productivity or lowers production costs. The firm will respond by increasing output and inputs of all types, including unskilled labor. Depending on the magnitudes of response, the productivity effect may partially offset or even reverse the negative effect of offshoring on unskilled labor demand. 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 will distinguish these effects in our empirics by holding output and capital fixed to isolate the direct effect, while allowing output and capital to change in response to offshoring to capture the additional productivity effect.[18]

[18] We are grateful to Gene Grossman for pointing out this distinction.

Our empirical work focuses on wages. We assume that the firm faces an unskilled labor supply curve with elasticity γ_{Ls} and similarly for skilled labor, γ_{Hs}. If labor supply is perfectly elastic, $\gamma_{Ls} \to \infty$, then shocks to labor demand will result in employment changes but not wage responses. If labor supply curves slope upward,[19] then the wage response to an offshoring or exporting shock will have the same sign as the labor demand response. For example, the response of unskilled wages to offshoring (holding output constant) is

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

where $c_0 \in (0,1)$ is a constant and $\gamma_{L,D} < 0$ is the elasticity of labor demand. $b_{L,M} < 0$ if $1/\sigma < (\alpha + \beta)$ which is the same condition under which offshoring lowers labor demand. A similar demonstration shows that offshoring raises skilled labor wages and exporting raises wages for both skilled and unskilled workers.

III.2. Specification

Our wage data are specific to each worker-firm-year. To translate the homogeneous input framework used above to our data, we 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 $w_{L,ijt} = w_{L,it} h_{ijt}$. Similar expressions govern high skill labor wages. Using equation (2) and assuming finite labor supply elasticities we have

[19] The Journal of Labor Economics devoted the April 2010 issue to upward-sloping firm-level labor supply curves.

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

In equation (3), S_i is a dummy variable that equals 1 if worker i is high-skilled. $b_{L,M}$ 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. 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, industry, and region fixed effects (φ_t, φ_{IND}, and φ_R) and a price index that is specific to j's industry, $P_{IND,t}$, to control for those respective components of A_{jt} and ψ_{jt}. We use job-spell fixed effects to absorb η_{ij}, the unobserved ability specific to the worker-firm match (Abowd et al. 1999). 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) to control for effects on labor demand net of the productivity effect. These modifications yield the following estimating equation

$$\text{(4)} \qquad \begin{aligned} \ln w_{ijt} &= b_{L,M} \ln M_{jt} + b_{M1} S_{it} \ln M_{jt} + b_{L,X} \ln X_{jt} + b_{X1} S_{it} \ln X_{jt} \\ &\quad + x_{it}\beta_1 + z_{jt}\beta_2 + \beta_3 P_{IND,t} + \alpha_{ij} + \varphi_t + \varphi_{IND} + \varphi_R + \varepsilon_{ijt}. \end{aligned}$$

Because it incorporates a vector of firm controls, the estimation of equation (4) corresponds to the direct effect of offshoring on wages. However, if offshoring raises productivity or lowers production costs, including firm controls will eliminate an important channel through which offshoring might boost labor demand and wages. We show in the theory appendix that the wage response inclusive of the productivity effect can be estimated by simply eliminating the firm controls

(5)
$$\ln w_{ijt} = b^*_{L,M} \ln M_{jt} + b^*_{M1} S_{it} \ln M_{jt} + b^*_{L,X} \ln X_{jt} + b^*_{X1} S_{it} \ln X_{jt} + x_{it}\beta_1 + \beta_3 P_{IND,t} + \alpha_{ij} + \varphi_t + \varphi_{IND} + \varphi_R + \varepsilon_{ijt}.$$

By comparing the coefficient estimates of regressions (4) and (5) we can determine whether the productivity effect boosts labor demand and wages.[20] 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.

III.3. 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, exchange rates, and

[20] The estimates of equation (5) are consistent under the assumption that our instruments reflect trade shocks exogenous to individual firms and are thus uncorrelated with the firm control variables z_{jt} .

transport costs. The exports instruments are world import demand, exchange rates and transport costs.[21]

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, whether arising from changes in production price, product quality, or variety.[22] 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*.

The exchange rate and transport costs capture shocks to the delivered price of particular inputs purchased by Denmark. The exchange rate E_{ct} is the annual average rate, denoted in foreign currency *c* per DKK so that an increase in E_{ct} is an appreciation of the DKK. Since we are aggregating over source countries, we normalize E_{ct} by its over-time mean value to remove unit differences.

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 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 captured in an 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

[21] Other studies of offshoring exploit variation in tariff or changes in tariff due to a liberalization episode. We experimented with using tariffs with little change in the results. 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.

[22] Using a similar strategy, Autor, Dorn and Hanson (2011) instrument U.S. imports from China by Chinese exports to other high-income, non-U.S. countries.

2005. 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 exchange rate instruments have country-time variation and all the other instruments have country-product-time variation. To get a single value for each firm-year we aggregate as follows. Let I_{ckt} represent instrument $I \in (tc, E, WES)$ 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).[23] 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 and exchange rates may become more favourable, or country *c* may experience changes in its production costs, production 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*

[23] 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.

intensively uses input *k* from country *c* more than other firms it disproportionately benefits from these changes. Recall from Figure 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*.

The use of pre-sample shares, s_{jck}, implies that our sample consists of firm-year observations with positive import and export values. We handle entry into offshoring by using the entry year as the pre-sample and exploiting subsequent variation in offshoring. That is, our estimates do not reflect wage changes resulting from a discrete change from no offshoring to the start of offshoring. This is not problematic in our sample because these discrete changes generally affect small firms with small trade volumes.

To summarize, we instrument for offshoring (exporting) using the weighted averages of world export supply (world import demand), transport costs, and exchange rates. The weights are pre-sample import (export) shares, and these 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 exchange rates or 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 industry, region, and time fixed effects, and will include a time varying industry price index. These controls should absorb shocks to demand via oil prices. 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. This would be especially the case in our narrow offshoring measures (where inputs and final sales are in the same industry), but less so with broad offshoring. However, by incorporating the industry price index, we control for time varying shocks to demand for particular industries within Denmark, and by incorporating firm exports, we control for time-varying demand shocks outside of Denmark.[24] In addition, 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. (2011).

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.

[24] 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.

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. (All variables in Table 3 are significant at the 1% level so we omit standard errors.)

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 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 instrumenting for our trade variables and so correcting for simultaneity. (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 imports (instrumented). 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 instrumented imports and 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 sharp 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. The "strongest" instruments, in terms of the variation they explain, are the world export supply (for imports), world import demand (for exports) and transportation costs. This is likely because these variables exhibit much more time-series variation across inputs and source countries, while exchange rates exhibit no variation across products and no variation across the countries within the Euro zone.

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 6-10 times larger in magnitude. Offshoring lowers an unskilled worker's wage (elasticity 1.6 to 1.9%), so that being in a firm that doubles its offshoring has an effect similar in magnitude to losing one year's experience on the job. In contrast, offshoring raises a skilled workers wage by 3.1 to 3.6%. These results suggest that offshoring tends to raise the skill premium. In the theory section we noted the difference between running these regression with firm controls and without. The former is equivalent to a move along an isoquant while the latter 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. Wage losses for unskilled workers are greater (and wage gains for skilled workers 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 .037 to .044, 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 while exporting increases input use across the board.

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 saw in Figure 1, 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.

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 in which we place 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 5.28 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 4.9 percent relative to the previous year. Overall, the median of the distribution is close to 0, with half of low skill workers experiencing wage gains and half experiencing wage losses. The standard deviation is 2.84%; 12% of low skilled workers have predicted wage changes above 1.5%, while 10% have wage changes below –1.5%.

Panel B of Table 6 reports predicted wage changes for high-skilled workers. The majority (65%) of high skilled workers have positive predicted wage changes, as both offshoring and exporting tend to increase high skilled wage. The distribution has a median of 0.29% and is highly variable, with a standard deviation of wage changes of 4.58%. 26% of skilled workers have predicted wage changes above 1.5% and 13% have wage changes below –1.5%.

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 very close 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.

Our second robustness check is motivated by the finding in Table 2 that firms concentrate their import purchases and export sales in just a few categories. We are concerned that our measures for offshoring and exporting aggregate over both the main categories of trade flows as well as very small and inconsequential trade flows. We thus employ only the top 5 categories of pre-sample import and export flows (in terms of values). Again, we find similar patterns as in Table 5.

Thus far 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, but less precisely estimated, effects of offshoring on wages. The low skill wage elasticity is 2 to 3 times larger in magnitude than Table 5, and there is a more pronounced difference between low and high skill wages. 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.

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.[25] 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, albeit with slightly smaller elasticities. The estimated wage elasticities with respect to exports are now quite different, with high skill workers 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.

Finally, 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. (2011) we drop the industries that include computers, steel, flat glass and cement. We see in the final columns of Table 7 that this produces similar wage elasticity estimates.

Table 7 suggests that our basic findings in Table 5 are robust to alternative specifications.[26] Below, we apply our estimation framework to explore particular occupations or task characteristics, and then investigate the effect of offshoring on the earnings of displaced workers.

[25] In recent work 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 differing in productivity for specific 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.

[26] We have also experimented with the following alternatives, and obtained similar results. (1) break low-skilled workers into medium-skilled and very low-skilled. They have similar wage elasticity estimates (see also note 8~~7~~);

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.[27] We then 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 (OCC = 0) are not much affected by offshoring (the coefficients of offshoring and offshoring x high-skill are both insignificant).[28] Workers with above-the-average routineness (OCC > 0) suffer larger wage

(2) use the top 2 categories of pre-sample trade flows; (3) employ only the job spells longer than 5 years; and (4) define narrow offshoring as imports within the same HS2 categories as sales.

[27] 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.

[28] These results do not contradict Table 5 because educational attainment is negatively correlated (-0.54) with routine-ness.

losses (the coefficient of offshoring x OCC is negative and significant). In contrast, non-routine tasks interact positively with offshoring.

We next examine the individual task characteristics in the non-routine category. We start with math.[29] As shown in Table 8, the results for math are different from non-routineness. Among the workers with average math requirements (OCC = 0), the high-skilled see a wage elasticity of about 2.5 percent while the low-skilled see a wage elasticity close to 0 with respect to offshoring. The high-skilled workers with math requirements 1 standard deviation above the mean (OCC = 1) see an additional wage elasticity of 2.7 percent, for a total of 5.2 percent. This "math premium" implies that in response to increases in offshoring, college-educated workers with strong math skills have larger wage increases than other college-educated workers. In contrast, non-routine skills other than math negatively interact with offshoring.

Our results for math motivate us to examine the other main categories of college education: communication and language, social sciences and natural sciences.[30] We report the results in the lower panel of Table 8. The "social science premium" is 3.7 percent and the "communication premium" is 4.4 percent. For interpretation, these results imply that, for example, for a college educated (high skill = 1) director or chief executive (communication = 2, or 2 standard deviations above average), the wage elasticity is 2x4.4% = 8.8% with respect to offshoring. Natural sciences, however, have a weak and negative interaction with offshoring. Finally, to better understand why low skill workers suffer from offshoring we examined the interaction between offshoring and hazardous working conditions. Hazardous working conditions have an effect similar to doing routine tasks.[31]

[29] It is the principal component of mathematical reasoning and mathematics.
[30] Examples of social sciences are economics and accounting, of natural sciences, engineering and technology, and of communication, persuasion and negotiation. The full lists are in the Data Appendix.
[31] Examples of hazardous conditions are exposure to contaminants, and exposure to minor burns and cuts.

VII. Earnings losses after layoffs

So far we have examined the wage effects of offshoring and exports for the workers who remain employed. We now examine how trade affects the earnings of displaced workers, drawing on the framework of Jacobson et al. (1993). The specifics of the estimation strategy and sample selection are described in the Data Appendix. Briefly, we follow a sample of workers who are in the data continuously from 1995-2006. We control for observable characteristics of workers (including worker fixed effects) and compare the earnings-profile of non-displaced workers to workers who separate from the firm as part of a mass layoff event. We take this further by distinguishing whether workers were displaced immediately after their former employers substantially increased offshoring (labeled: offshorers) and all other displaced workers (labeled: non-offshorers). We also examine whether this comparison depends on worker skill levels.

We start with a data sample of all Danish manufacturing workers, and then cut down this sample to match the requirements imposed in section II.2. Further, following Jacobson et al. (1993) we focus on high-tenure workers because they are the ones most likely to have accumulated firm-specific human capital in the predisplacement firm (see the Data Appendix for more details of the sample construction). We define displaced workers as those separating from firms where at least 30% of the particular workers in the initial year are no longer employed by the firm the following year.[32] We classify worker *i* as an offshorer if he/she is displaced in a mass layoff event from firms that were increasing their predicted offshoring at least 10% (taken from the first stage regression in Table 3) between the predisplacement year and the displacement year.[33,34] Approximately 9% of

[32] Our definition uses gross flows, since our data has the full population of workers and firms. The literature (e.g. Jacobson et al. 1993) typically defines mass-layoff events using net flows. Net flows could miss displacement events if a firm substantially changes the composition of its employment, which, as shown in Table 3, happens with offshoring. We also experimented with using net flows and obtained similar results.

[33] Predicted offshoring is measured at the worker level, but predicted offshoring is only observed for displaced workers in the predisplacement year. Therefore we measure predicted offshoring in the displacement year for the predisplacement firm as an average over all remaining workers in the firm. The change in predicted offshoring measured this way is valid, if the within-firm dispersion across workers in predicted offshoring is low. This is indeed the case – the median firm-level coefficient of variation of predicted offshoring is 0.004 with a maximum of 0.056.

the resulting sample (6,208 workers in total) are displaced at least once over the years 1998-2006. The low proportion of displaced-workers is typical of the displacement literature, because mass-layoff events are uncommon. Almost half of the displaced workers do not have an observed change in predicted offshoring in the pre-displacement firm, due to missing instruments for some firms and to the fact that some of the pre-displacement firms closed down. Of the remaining 3,301 displaced workers, roughly 20 percent are classified as offshorers.

We summarize our results in Figure 4. The top three panels show the profile of log hourly wage rate, annual labor earnings and annual gross earnings for high skill workers. The bottom panels show the same profiles for low skill workers. Changes in earnings and gross earnings are measured in levels of DKK rather than in percentage terms so as to include those workers who exhibit zero labor income. Each panel displays results for offshorers (light grey) and non-offshorers (black) separately. The comparison group in each case are non-displaced workers.

The top left panel shows that high-skill non-offshorers do not experience a reduction in hourly wage rate (relative to non-displaced workers), while high-skill offshorers suffer small but persistent wage losses of 4 percent. The top middle panel shows that for high-skilled non-offshorers there are pronounced drops in annual labor earnings, peaking in the year after displacement at 30,000 DKK. For high-skilled offshorers the drop in earnings is even steeper, peaking at 64,000 DKK.

To put the numbers in perspective, the average high skill wage in the sample is 419,000 DKK so the peak loss of 30,000 DKK for non-offshorers represents 7% of pre-displacement earnings and the peak loss of 64,000 DKK for offshorers represents 15% of pre-displacement earnings. Combined with the small changes in hourly wages after displacement, we can conclude that losses in annual labor earnings are driven primarily by reductions in hours worked. Finally, the top right

[34] We use the 10% cutoff because we want to focus on displaced workers that have been hit by a pronounced offshoring shock. Larger cutoffs become problematic because they cut down on the number of displaced workers from which to estimate the wage profile.

panel shows that even after accounting for income transfers during unemployment the earnings losses from displacement are still substantial. Offshorers in particular lose DKK 52,000 the year after displacement, or 12% of predisplacement earnings.

Looking at the bottom left panel, we see that for low-skilled workers, offshorers suffer a larger wage loss (8%) than non-offshorers (5%), and a larger loss in labor earnings (60,000 DKK) than non-offshorers (44,000 DKK). The gap between these groups persists five years after displacement.

These losses in earnings are similar to those of displaced high-skill workers in absolute terms, but since displaced low-skilled workers have lower earnings (285,000 DKK on average), their losses are higher in percentage terms. Non-offshorers lose 15% of pre-displacement earnings and offshorers lose 21%. Finally, income transfers are not close to fully compensating for earnings losses. The bottom right panel shows that one year after displacement, annual gross earnings drop by 30,000 DKK (or 12%) for non-offshorers and 50,000 DKK (or 17%) for offshorers.

To summarize, Figure 4 shows that all displaced workers suffer substantial earnings losses. Offshorers, in particular, suffer greater earnings losses than non-offshorers of the same skill type. One explanation for this finding is that offshorers have obsolete skills or have specialized in doing tasks that are now imported from abroad, and so they tend to have worse reemployment opportunities in the Danish labor market. To explore this further we track the labor market status in the year after displacement for offshorers and non-offshorers. We find that a higher proportion of offshorers remain unemployed (19%) or out of the labor force (10%) than non-offshorers (11% and 5% respectively). Among the workers who are reemployed, a higher proportion of offshorers switch four-digit industries (92%) than non-offshorers (56%), although the proportion of reemployed workers who switch four-digit occupations is similar for offshorers (44%) and non-offshorers (43%).

Using Figure 4 and Table 5, we compare the wage and earnings loss for the workers who are displaced from offshoring firms with those for their colleagues who remain employed. For low-skilled workers, the displaced suffer a wage loss of 8% and an earnings loss of 21%, while the non-displaced have a wage loss of 1.6% (inclusive of the productivity effect) if their employers double offshoring within a year and do not enjoy an increase in exports. The comparison is starker for high skilled workers. The displaced suffer a wage loss of 4% and an earnings loss of 15%, while the non-displaced enjoy a wage *gain* of 3.6% (inclusive of the productivity effect) if their employer doubles offshoring in a single year.

The magnitude of these losses, and the differences across displacement types, provides a useful comparison with existing studies. Jacobson et al. (1993) used data on mass layoffs for workers in the US, and found losses of around 25 percent of pre-displacement earnings. Studies based on European data have also found long-term negative effects of displacement but most studies find more modest effects. For example, Albæk, van Audenrode and Browning (2002) find that Danish workers earn around 6 percent less than nondisplaced workers three years after displacement. We find similarly modest displacement numbers in the non-offshorer group, and effects comparable to Jacobson et al. (1993) for the offshorer group.

VI. 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, exogenous offshoring shocks have considerably different wage effects across educational groups, raising skilled labor wages 3.6 percent and lowering wages by 1.6 percent for unskilled workers. In contrast, exporting is a rising tide that lifts all boats. 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 +1.5% per year while 13% (10%) of high skilled (low-skilled) workers have annual changes below –1.5%.

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 and those occupations that expose workers to unsafe working conditions 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 track workers before, during and after job-spells and find that displacement from a firm with rising offshoring generates large and persistent wage and earnings losses. Low skill workers displaced from offshoring firms lose 21 percent of their pre-displacement earnings, an effect roughly 13 times greater than wage losses suffered by colleagues who remain employed in offshoring firms. The losses suffered by workers displaced from offshoring firms are larger than those suffered by other displaced workers. The difference is explained by a higher propensity to remain unemployed, and a much lower likelihood of reattaching to the workforce within the same industry. This is consistent with a view that offshoring is not only replacing employment opportunities within the firm but also obsolescing similar jobs throughout the economy.

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Data Appendix

1. More details about Data Sources

For the firm data, 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 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.

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 report transportation modes employed but do not contain information on transportation costs paid by firms. To construct transportation costs we proceed in two steps.

We employ data on transportation costs taken from US Imports of Merchandise data for the 1995-2006 sample period and fit ad-valorem cost function of the following form.

$$f_{ckt} / v_{ckt} = m_{ckt} + a_k + \beta_1^m \ln \frac{w_{ckt}}{v_{ckt}} + \beta_2^m \ln oil_t + \beta_3^m DIST_c + \beta_4^m \ln oil_t * DIST_c$$

where c indexes exporters, k indexes HS6 products, t = year, f = transportation charge, v = value of shipment, m = indicator for transport mode (air, ocean, truck, train), and w = weight in kg, DIST = distance. This allows shipping costs to depend on product characteristics (a product specific intercept and the weight/value ratio), exporter characteristics (distance to market), time characteristics (oil prices) and interactions of these variables. Note that the coefficients (including the intercept) are all mode-specific so that the level of shipping costs are much higher for planes than boats, and the dependence of costs on oil prices or distance is also mode specific.

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, realize 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 (See Hummels 2007). These are revealed in the fixed effects in part 1. Further, oil prices fluctuate substantially in our sample, falling for 4 years and then rising sharply. Shocks to oil prices differentially affect costs depending on which mode is used and how far goods travel – they have a minimal effect on trains from Germany but a very large effect on airplanes from Japan.

3. Displacement Regressions

Following Jacobson et al. (1993) we restrict our sample in the following ways. We focus on manufacturing workers who, in at least one of the years 1997-2000, have at least six years of tenure. We require that the worker does not die, emigrate or turn 61 during the sample window 1995-2006. Finally, we require that the worker be employed by a firm that imports at least DKK 600,000 and has at least 50 employees to be consistent with our estimation of within-job spell wage changes in previous sections, and to eliminate very small firms and those with minimal global engagement from the analysis.

For a sample of workers (displaced and non-displaced) we estimate

$$\log y_{it} = \alpha_i + \alpha_t + x_{it}\beta + \sum_{k \geq -m} D_{it}^k \delta_k + F_{it}^1 c_i \varphi_1 + F_{it}^2 c_i \varphi_2 + F_{it}^3 c_i \varphi_3 + \varepsilon_{it}, \qquad \text{(A1)}$$

$$\text{where } c_i = (S_i, OFF_i, S_i * OFF_i).$$

y_{it} represents the earnings of worker *i* in year *t*. We employ three measures: the hourly wage rate (the variable used in sections V and VI), annual labor earnings and annual gross earnings. Annual labor earnings capture the effects on both hourly wage rate and hours worked, and annual gross earnings are the sum of annual labor earnings, unemployment insurance benefits and social assistance. The vector c_i consists of the dummy for high-skilled worker, S_i, an offshorer dummy OFF_i, and their product. α_i and α_t represent worker and year fixed effects, and x_{it} is a vector of time-varying worker characteristics (e.g. union, marriage and education status) as controls. Conditional on the control variables α_i, α_t, and x_{it} equation (A1) estimates the profile of y_{it} for the nine years surrounding the event of displacement: three pre-displacement years (*k* =-3,-2,-1), the displacement year (*k* = 0), and five post-displacement years (*k* = 1,…,5). This assumes that earnings are the same for k < -3 given the controls α_i, α_t, and x_{it}. The dummy variables, D_{it}^k jointly represent the event of displacement, with δ_k measuring the effect of displacement on a workers earnings k years following its occurrence. Equation (A1) imposes two types of restrictions on the evolution of y_{it}. First, it allows y_{it} to differ in level over time, as captured by D_{it}^{k}, assuming that the level difference is the same across workers for given k. Second, the regression also imposes three restrictions on the rate of change for y_{it} in order to distinguish between different types of displaced workers as captured by the vector c_i. (i) y_{it} grows or declines linearly from three years before displacement until the displacement year. (ii) y_{it} is constant from the displacement year to three years after displacement. And (iii) y_{it} grows or declines linearly from its value three years after displacement until the end of the sample period. The restrictions (i)-(iii) are captured, respectively, by the linear variables $F_{it}^{1}, F_{it}^{2}, F_{it}^{3}$, where $F_{it}^{1} = t-(s-4)$, if worker *i* is displaced at time s and $s-3 \le t \le s$, and $F_{it}^{1} = 0$ otherwise, $F_{it}^{2} = 1$, if worker *i* is displaced at time *s* and $t \ge s+1$, and $F_{it}^{2} = 0$ otherwise, and $F_{it}^{3} = t-(s+2)$, if worker *i* is displaced at time *s* and $t \ge s+3$, and $F_{it}^{3} = 0$ otherwise.

The baseline values for y_{it} are those of non-displaced workers (given controls α_i, α_t, and x_{it}), and the estimates of δ_k and φ show the differences in earnings of displaced workers relative to the baseline values. In addition, the coefficient vector φ shows differences in the rate of change for y_{it} across unskilled and skilled workers, and across offshorers and non-offshorers. Our results in Figure 4 are based on OLS estimates of (A1). The OLS estimates might be biased if firms selectively lay off workers whose performance is unusually poor in the years around separation. Couch and Placzek (2010) address this issue using propensity score matching (PSM), and show that the PSM estimates are similar to OLS estimates.

Theory Appendix

<u>Generalizing the Production Function</u>

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

$$\ln C_{f,jt} \approx c_{0f} \ln M_{jt} + (1 - c_{0f}) \ln L_{jt} + c_{1f} \qquad \text{(A2)}$$

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 $g(y) = \frac{\sigma}{\sigma-1}\ln(e^{y\frac{\sigma-1}{\sigma}}+1)$. 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 $g'(y_0) = \frac{e^{y_0\frac{\sigma-1}{\sigma}}}{e^{y_0\frac{\sigma-1}{\sigma}}+1}$ 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 (A2). **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 (A2) 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 $\ln M_{jt}$ in the expression for $\ln MPL_1$ 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).

We can carry out the rest of the analyses in the same way as we did in section III.1. and the results are analogous. Let $\gamma_{f,S} > 0$ be the labor supply elasticity for type-f labor. Then the wage elasticity for type-f labor, net of the productivity effect, 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 (A2). This expression is analogous to the expression for $b_{L,M}$ in section III.1.

<u>The Productivity Effect</u>

We now use the setting in section III.1. to 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 specified in the expression for $b_{L,M}$ in section III.1. 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 the expression for $b_{L,M}$ in section III.1. we show that $b_{L,M} < b_{L,M}^{*}$; i.e. the productivity effect tends to increase the wage for unskilled labor.

Finally, we use Figure A1 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. σ > 1/(α+β). The effect of increased offshoring is to shift 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 and it tends to decrease unskilled wage given that σ > 1/(α+β). 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.

Figure A1. The Effects of Offshoring on Unskilled Wage

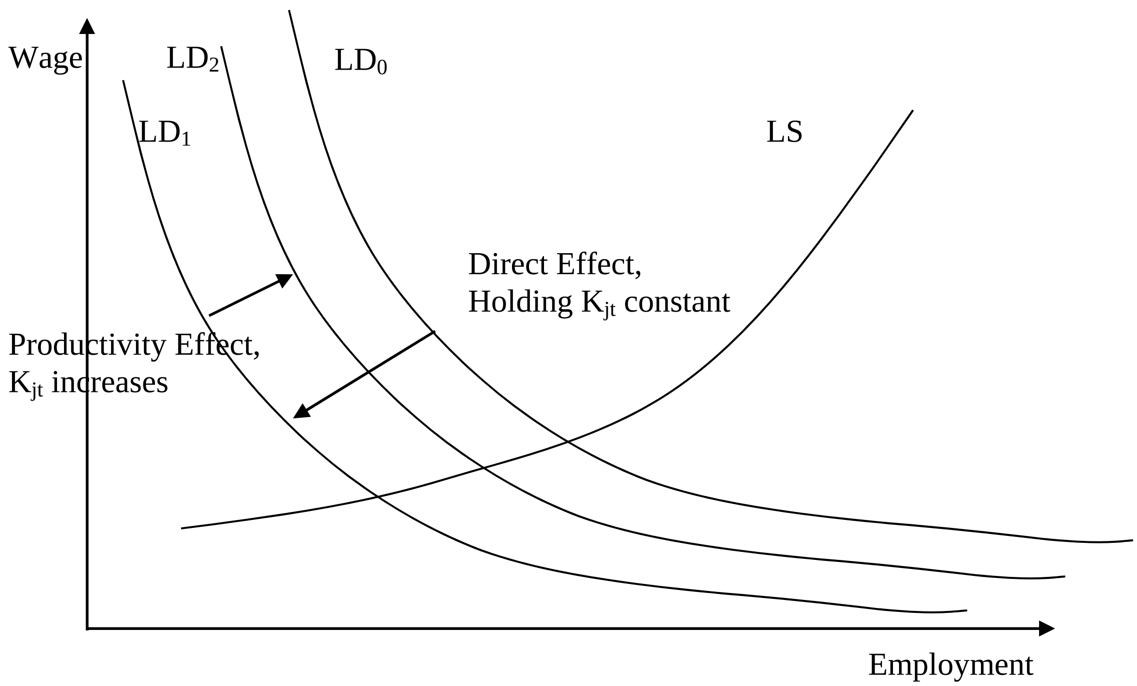

Figure 1a: Offshoring Over Time

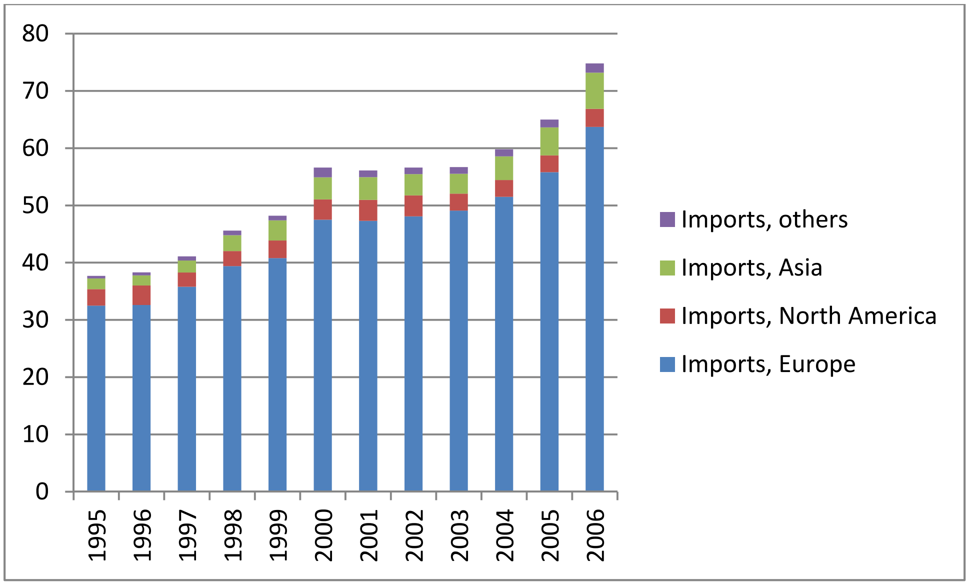

Figure 1b: Exports Over Time

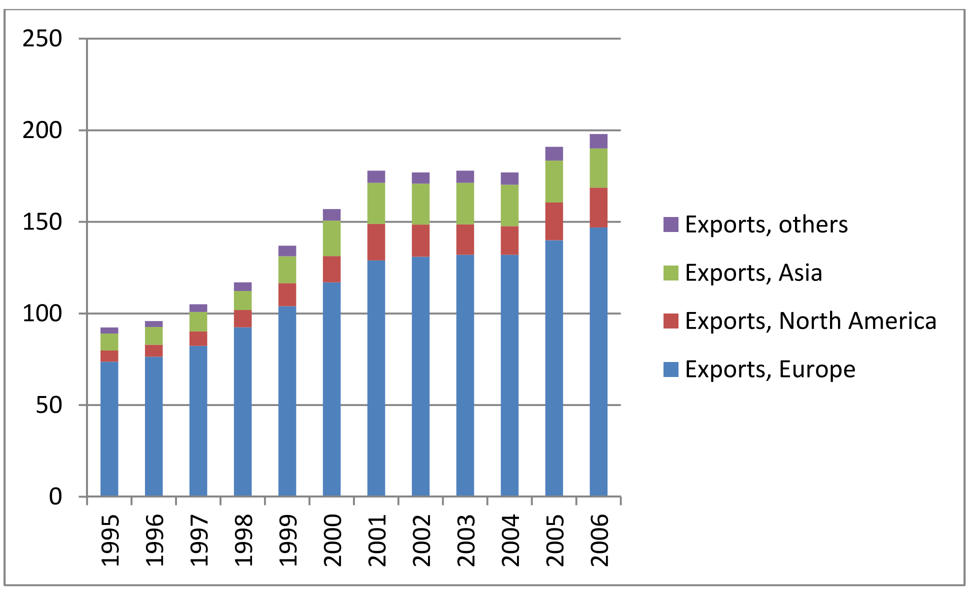

Figure 2a: Within-firm Changes in Offshoring

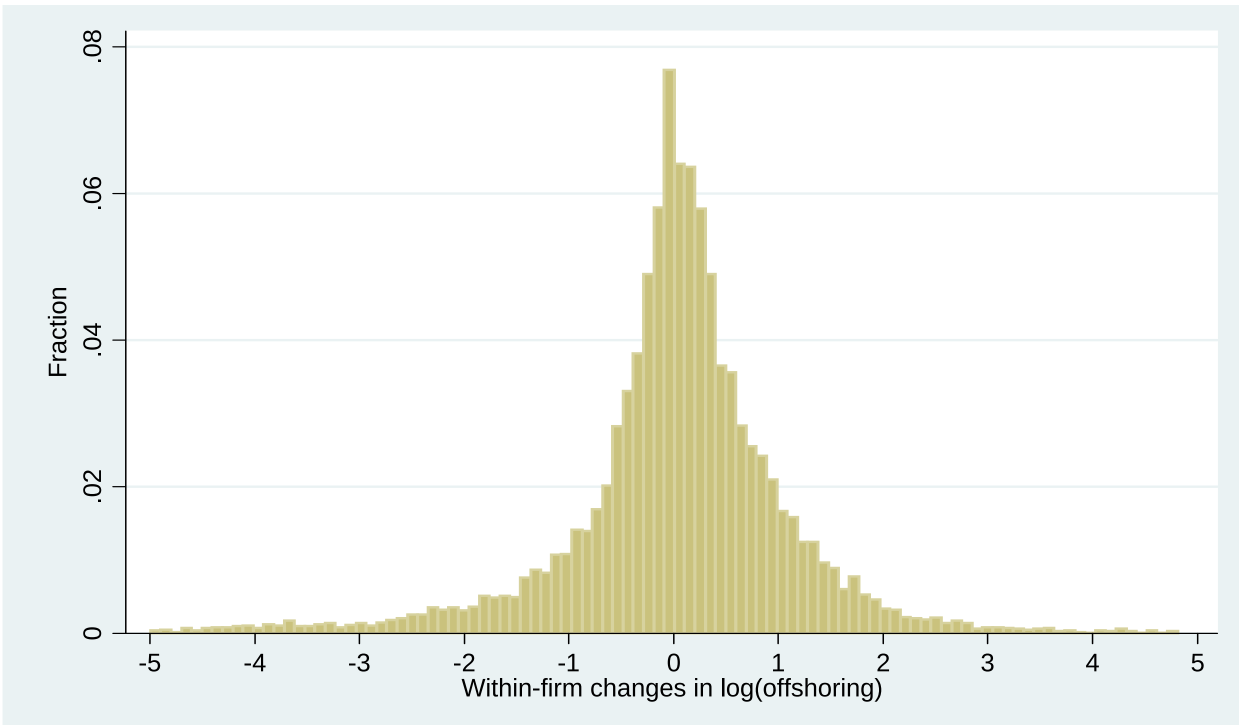

Figure 2b. Within-firm Changes in Exports

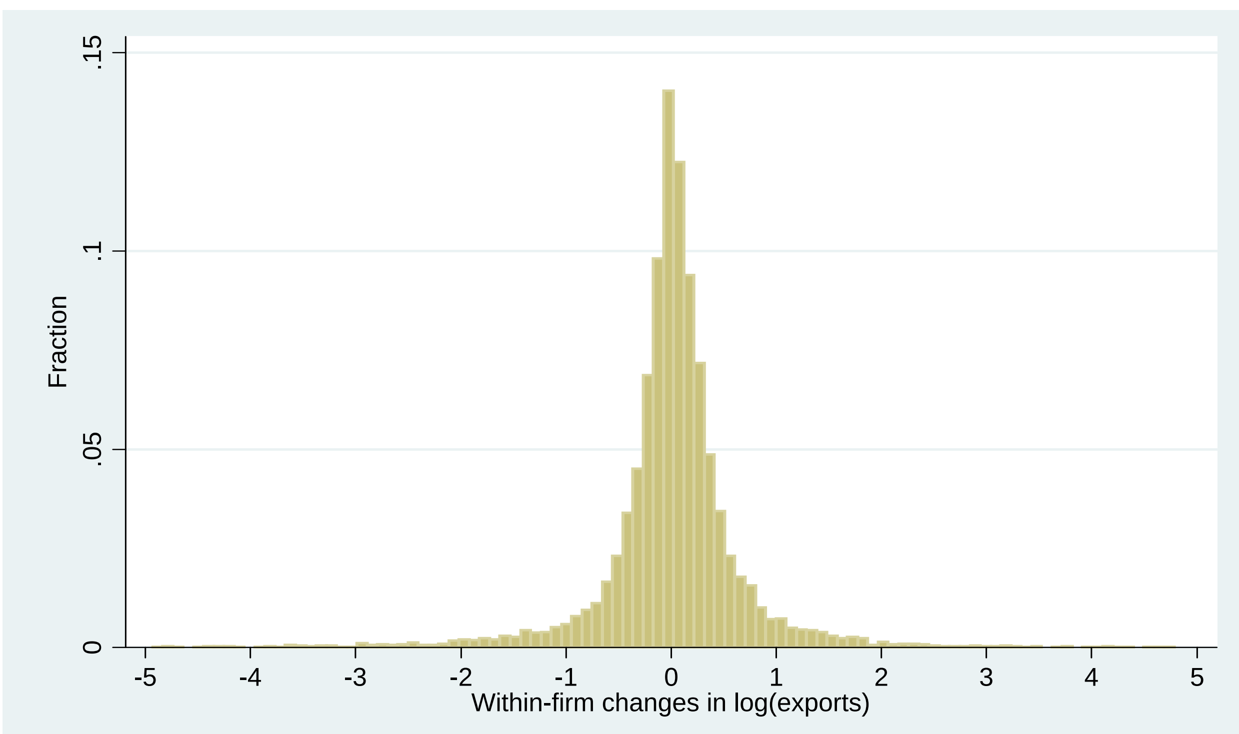

Figure 3a. The Number of Firms Who Purchase the Same Input

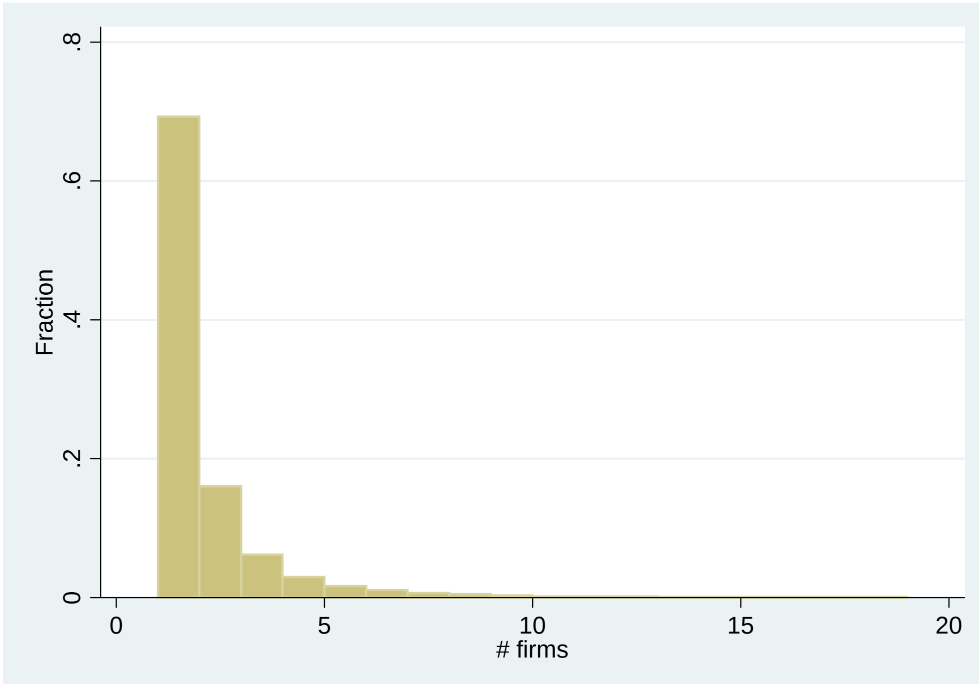

Figure 3b: The Number of Firms who Sell the Same Product

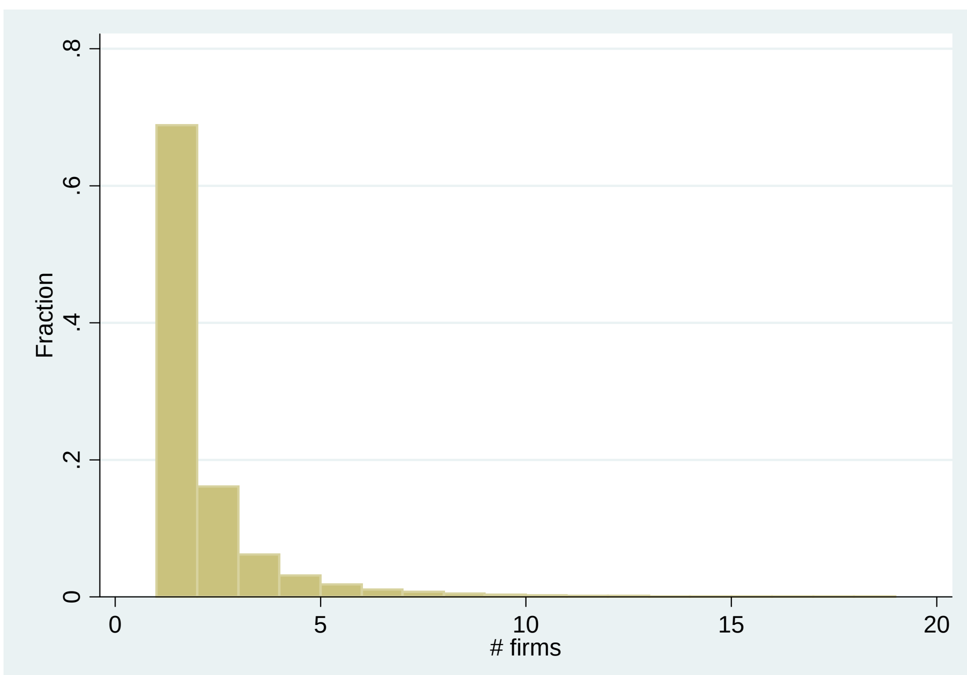

Figure 4: Wages and Earnings for Displaced Workers

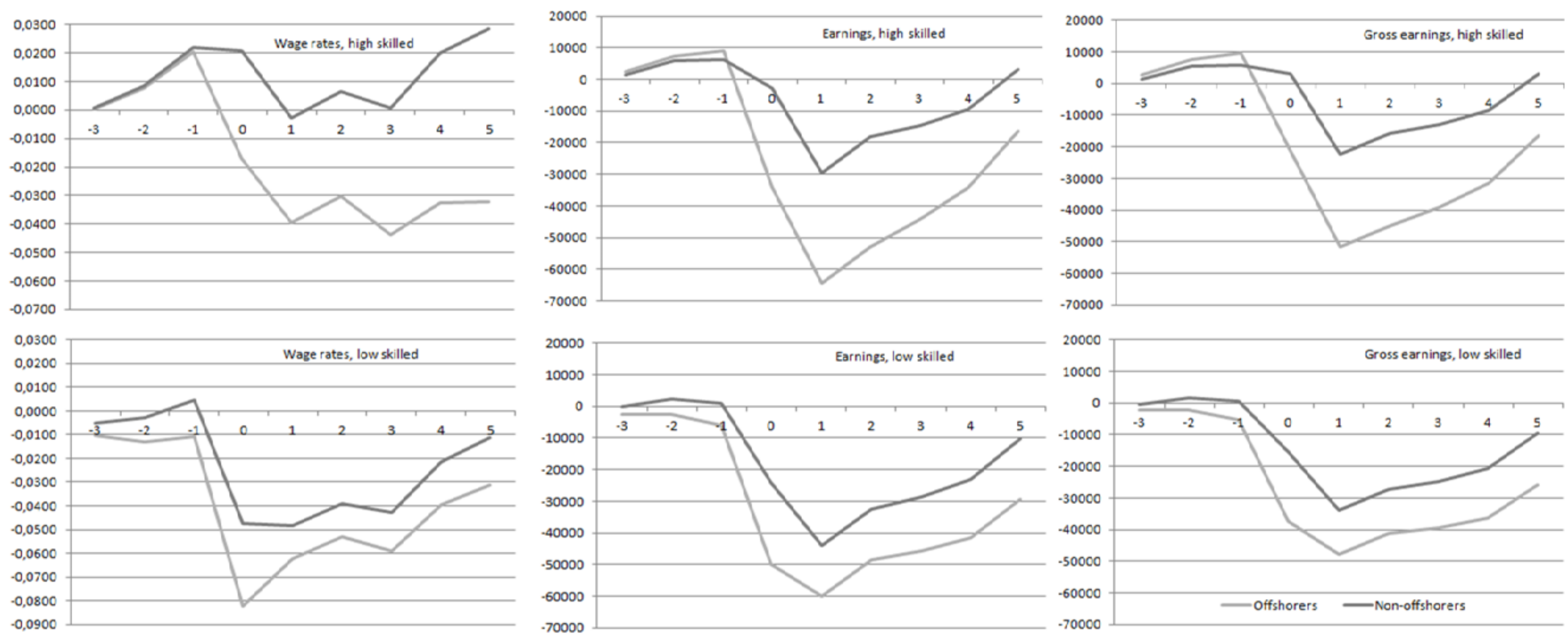

Table 1: Descriptive Statistics

	Obs	Mean	Std. dev.
In logs…			
Employment	9,820	4.94	0.89
Gross Output	9,804	18.89	1.05
Capital per worker	9,759	12.39	0.98
Average wage bill per worker	9,772	12.54	0.22
Accounting Profits	7,816	9.07	1.70
Skill shares…			
High-skill	9,772	0.16	0.12
Low-skill	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
In 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

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 offshoring	64.4
In-sample share of Exports	77.7

Table 3: Firm-level Effects of Trade

	OLS	Firm FE	Firm FE-IV	Firm FE-IV, offshoring & exports in regression	
	Offshoring dummy	log(offshoring)	log(offshoring)	log(offshoring)	log(exports)
…in logs…					
employment	0.681	0.044	-0.103	-0.196	0.346
gross output	0.958	0.082	0.393	0.151	0.486
accounting profits	0.953	0.066	0.487	0.012	0.831
capital per worker	0.161	0.005	0.227	0.099	0.282
wage bill per worker	0.040	0.014	0.217	0.127	0.119
material inputs	1.162	0.083	0.216	-0.105	0.653
domestic material inputs	0.668	0.037	0.371	-0.048	0.777
…shares…					
Share of high-skilled workers	-0.007	0.002	0.087	0.048	0.066
Materials/output	0.093	0.005	-0.039	-0.050	0.032
Domestic materials/output	-0.043	-0.011	0.016	-0.020	0.061

Notes:

Columns 1,2,3 are from regressions of each firm outcome variable on a single (offshoring) variable

Columns 4, 5 include both offshoring and exports in regression

Table 4: First-Stage FE-IV Regressions

Dependent variable:	Log(offshoring)		... *x* high skill		Log(exports)		... *x* high skill	
Log WES, offshoring	0.2071**	0.3351***	-0.0396***	-0.0185***	0.0046	0.0933	-0.0150***	0.0005
	[2.46]	[4.01]	[-5.86]	[-3.18]	[0.04]	[0.80]	[-3.00]	[0.11]
Log exchange rates, offshoring	-0.2802	-0.2644	-0.0382*	-0.0280*	0.2136	0.2442	0.0046	0.0095
	[-0.91]	[-0.87]	[-1.81]	[-1.84]	[0.88]	[0.99]	[0.30]	[0.98]
Log transport costs, offshoring	-17.7718***	-21.5515***	0.2429	-0.5668	1.8464	-1.4397	0.8585***	0.2662
	[-2.94]	[-3.53]	[0.50]	[-1.39]	[0.69]	[-0.51]	[2.71]	[1.08]
Log WID, exports	-0.0778	0.1080	-0.0490***	-0.0162**	0.2689***	0.4054***	-0.0294***	-0.0061
	[-0.58]	[0.83]	[-5.15]	[-2.05]	[2.86]	[4.25]	[-3.77]	[-1.02]
Log exchange rates, exports	-0.5336	-0.7235	-0.0328	-0.0711**	0.6753	0.5215	0.0460**	0.0134
	[-1.11]	[-1.51]	[-0.91]	[-2.46]	[1.36]	[1.03]	[2.01]	[0.72]
Log transport costs, exports	22.4817***	23.1068***	-2.2394***	-1.6001**	-6.1858	-4.1498	-0.4224	0.1893
	[2.98]	[3.05]	[-3.22]	[-2.49]	[-0.94]	[-0.63]	[-1.08]	[0.53]
Interactions with high skill dummy:								
Log WES, offshoring	-0.0528	-0.0851	0.3317***	0.3232***	0.0830	0.0521	0.2686***	0.2633***
	[-0.68]	[-1.17]	[4.19]	[4.11]	[1.06]	[0.65]	[5.17]	[4.97]
Log exchange rates, offshoring	-0.6115***	-0.4617**	-0.5600**	-0.5304**	-0.1040	0.0255	0.0998	0.1182
	[-3.09]	[-2.32]	[-2.15]	[-2.02]	[-0.65]	[0.16]	[0.72]	[0.85]
Log transport costs, offshoring	1.2829	-1.1068	-17.3882***	-18.1440***	1.2450	-1.2536	0.4712	-0.1018
	[0.28]	[-0.25]	[-3.01]	[-3.14]	[0.40]	[-0.39]	[0.13]	[-0.03]
Log WID, exports	0.0318	0.1236	0.3478***	0.3658***	-0.2571***	-0.1834***	0.3271***	0.3390***
	[0.31]	[1.18]	[4.27]	[4.48]	[-4.18]	[-2.95]	[6.38]	[6.56]
Log exchange rates, exports	0.6076	0.6535*	0.5114*	0.4946*	-0.5439	-0.5630	-0.2087	-0.2264
	[1.62]	[1.71]	[1.79]	[1.67]	[-1.62]	[-1.63]	[-1.06]	[-1.13]
Log transport costs, exports	-3.2023	-4.4399	25.8055***	25.5637***	-2.7719	-3.7232	-5.1812	-5.3792*
	[-0.71]	[-0.97]	[4.29]	[4.24]	[-0.69]	[-0.91]	[-1.63]	[-1.68]
Additional Firm Controls	Yes	No	Yes	No	Yes	No	Yes	No
F-statistics for instruments	3.60	6.48	20.46	15.30	5.55	11.71	14.40	11.39
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 firms	383,035	383,035	383,035	383,035	384,257	384,257	384,257	384,257
R-squared	0.1021	0.0591	0.0655	0.0541	0.1240	0.0716	0.0636	0.0473

Notes:

Excluded instruments only reported. *** 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

Table 5: Worker-Level Wage Regressions

Dependent variable:	Log hourly wage			
	FE		FE-IV	
Log(offshoring)	-0.0030**	-0.0019	-0.0191**	-0.0167**
	[-2.19]	[-1.43]	[-2.07]	[-2.07]
Log(offshoring) x high-skilled	0.0065***	0.0066***	0.0505***	0.0538***
	[4.82]	[4.88]	[7.19]	[7.68]
Log(exports)	0.0051*	0.0066**	0.0369***	0.0444***
	[1.78]	[2.36]	[3.98]	[6.65]
Log(exports) x high-skilled	-0.0006	0.0002	0.0063	0.0060
	[-0.24]	[0.07]	[0.55]	[0.56]
Log(output)	0.0148***		0.0085	
	[4.22]		[1.19]	
Log(empl)	0.0130***		-0.0008	
	[3.45]		[-0.10]	
Log(capital-labor ratio)	0.0032**		0.0042***	
	[2.25]		[2.95]	
Share, high-skilled workers	0.0782***		0.1348***	
	[4.34]		[5.23]	
Industry price index	-0.0001	-0.0004	0.0002	0.0000
	[-0.64]	[-1.62]	[0.99]	[0.13]
Experience	0.0169***	0.0179***	0.0162***	0.0164***
	[13.07]	[13.85]	[12.28]	[11.78]
Experience2	-0.0005***	-0.0005***	-0.0005***	-0.0005***
	[-84.04]	[-84.74]	[-77.01]	[-73.92]
Union	0.0137***	0.0136***	0.0147***	0.0144***
	[12.62]	[12.64]	[14.01]	[14.06]
Married	0.0035***	0.0036***	0.0031***	0.0030***
	[6.55]	[6.67]	[5.79]	[5.68]
Other firm-level controls	Yes	No	Yes	No
Obs	1,928,599	1,928,599	1,928,599	1,928,599
No. job spells	383,035	383,035	383,035	383,035
R2	0.1514	0.1496	0.1517	0.1500

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

Table 6: Net Effect of Trade on Wages

			Annual %-change in exports, by bins			
			Min -30%	-30% 0%	0% 30%	30% Max
Panel A: Low-skilled workers						
Annual %-change in imports by bins	Min	-30%	3.1	6.7	5.6	2.2
			-0.90	**0.50**	**1.58**	**5.28**
	-30%	0%	1.9	13.7	9.7	1.4
			-1.82	**-0.17**	**0.58**	**2.41**
	0%	30%	1.6	9.8	15.2	2.8
			-2.42	**-0.61**	**0.23**	**1.80**
	30%	Max	1.5	5.3	13.3	6.3
			-4.91	**-1.51**	**-0.49**	**1.40**
Panel B: High-skilled workers						
Annual %-change in imports by bins	Min	-30%	3.2	6.3	4.5	1.4
			-7.51	**-2.71**	**-1.29**	**-0.12**
	-30%	0%	1.6	15.1	10.9	1.4
			-3.09	**-0.71**	**0.09**	**1.63**
	0%	30%	1.8	11.3	16.4	2.8
			-1.80	**0.07**	**1.02**	**2.80**
	30%	Max	1.3	5.0	12.4	4.6
			-0.49	**1.55**	**2.52**	**6.16**

Notes:

Bold figures: Median 100*(log) wage change

Normal figures: Cell frequencies relative to total

Table 7: Alternative Specifications

Dependent variable:										
Robustness check:	I. 7+ year job spells		II. Top-5 pre-sample flows		III. Broad offshoring		IV. High income narrow offshoring		V.Drop computers and building supplies	
	FE-IV		FE-IV		FE-IV		FE-IV		FE-IV	
Log(offshoring)	-0.0138**	-0.0153***	-0.0230**	-0.0174*	-0.0549*	-0.0355	-0.0152**	-0.0143**	-0.0371***	-0.0287***
	[-2.39]	[-2.96]	[-2.00]	[-1.69]	[-1.88]	[-1.32]	[-2.07]	[-2.11]	[-3.27]	[-2.88]
Log(offshoring) x high-skilled	0.0543***	0.0587***	0.0559***	0.0566***	0.1277***	0.1280***	0.0292***	0.0290***	0.0727***	0.0855***
	[7.50]	[7.81]	[7.06]	[7.47]	[7.40]	[8.17]	[4.29]	[4.32]	[8.45]	[9.81]
Log(exports)	0.0447***	0.0496***	0.0345***	0.0393***	0.0534***	0.0570***	0.0269***	0.0348***	0.0339**	0.0627***
	[4.93]	[6.87]	[4.51]	[5.54]	[4.37]	[3.89]	[2.73]	[5.05]	[2.21]	[6.90]
Log(exports) x high-skilled	0.0014	-0.0018	-0.0011	0.0029	-0.0565***	-0.0521***	0.0363***	0.0416***	-0.0219	-0.0295**
	[0.12]	[-0.15]	[-0.09]	[0.26]	[-3.04]	[-3.48]	[3.45]	[4.32]	[-1.58]	[-2.24]
Other firm-level controls	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Obs	967,053	967,053	1,925,909	1,925,909	1,950,896	1,950,896	1,917,625	1,917,625	1,692,736	1,692,736
No. job spells	103,989	103,989	382,142	382,142	384,257	384,257	380,781	380,781	338,922	338,922
R2	0.1815	0.1788	0.1518	0.1500	0.1509	0.1492	0.1515	0.1498	0.1529	0.1512

First stage IV F-statistics:										
log offshoring	5.2	10.5	3.4	5.5	4.3	10.4	4.9	8.4	4.6	6.4
… x high skill	19.9	16.2	20.0	15.0	23.5	22.4	18.3	12.1	17.9	13.1
log exports	6.0	14.1	5.0	10.2	5.7	10.9	5.4	11.1	3.9	8.4
… x high skill	13.1	11.8	12.8	10.6	11.4	10.0	14.8	11.4	14.4	11.1

Note:

*** 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. Coefficient estimates of the other variables not reported to save space.

Table 8: Occupation-Specific Wage Effects

Occupational characteristics (OCC):	Routine		Non-Routine		Non-Routine (Other than Math)		Non-Routine (Math)	
Log(offshoring)	-0.0023	0.0028	-0.0057	0.0067	-0.0081	0.0053	-0.0120	-0.0061
	[-0.26]	[0.34]	[-0.71]	[0.91]	[-1.01]	[0.73]	[-1.37]	[-0.74]
Log(offshoring) x high-skilled	-0.0081	-0.0077	-0.0300***	-0.0242***	-0.0249***	-0.0189***	0.0216***	0.0250***
	[-1.18]	[-1.09]	[-4.51]	[-3.49]	[-3.77]	[-2.70]	[3.21]	[3.63]
Log(offshoring) x OCC	-0.0393***	-0.0410***	0.0494***	0.0477***	-0.0432***	-0.0413***	0.0282***	0.0271***
	[-14.17]	[-15.24]	[11.40]	[11.18]	[-10.63]	[-10.29]	[9.78]	[9.65]
Log(exports)	0.0349***	0.0434***	0.0072	0.0281***	0.0028	0.0250***	0.0283***	0.0398***
	[3.71]	[6.11]	[0.82]	[4.07]	[0.32]	[3.66]	[3.22]	[5.65]
Log(exports) x high-skilled	0.0062	0.0053	0.0167	0.0212*	0.0242**	0.0284***	0.0064	0.0090
	[0.53]	[0.45]	[1.46]	[1.91]	[2.21]	[2.65]	[0.53]	[0.77]
Other firm-level controls	Yes	No	Yes	No	Yes	No	Yes	No
Obs	1,570,088	1,570,088	1,570,088	1,570,088	1,570,088	1,570,088	1,570,088	1,570,088
No. job spells	376,590	376,590	376,590	376,590	376,590	376,590	376,590	376,590
R2	0.138	0.136	0.139	0.137	0.138	0.136	0.137	0.135

Occupational characteristics (OCC):	Social Sciences		Natural Sciences		Harzardous		Communication	
Log(offshoring)	-0.0109	-0.0057	-0.0141	-0.0112	-0.0078	-0.0072	-0.0038	0.0042
	[-1.24]	[-0.69]	[-1.55]	[-1.32]	[-0.81]	[-0.84]	[-0.45]	[0.54]
Log(offshoring) x high-skilled	0.0131**	0.0160**	0.0471***	0.0495***	0.0251***	0.0261***	-0.0100	-0.0075
	[2.02]	[2.42]	[6.32]	[6.58]	[3.20]	[3.37]	[-1.62]	[-1.18]
Log(offshoring) x OCC	0.0363***	0.0365***	-0.0048**	-0.0057***	-0.0222***	-0.0234***	0.0435***	0.0439***
	[14.53]	[14.57]	[-2.54]	[-3.03]	[-7.51]	[-8.50]	[14.58]	[14.83]
Log(exports)	0.0358***	0.0457***	0.0340***	0.0405***	0.0415***	0.0443***	0.0233***	0.0364***
	[3.92]	[6.36]	[3.84]	[5.81]	[4.47]	[6.35]	[2.61]	[5.23]
Log(exports) x high-skilled	0.0077	0.0081	0.0142	0.0145	0.0106	0.0086	0.0111	0.0126
	[0.67]	[0.73]	[1.22]	[1.30]	[0.91]	[0.76]	[0.97]	[1.14]
Other firm-level controls	Yes	No	Yes	No	Yes	No	Yes	No
Obs	1,570,088	1,570,088	1,570,088	1,570,088	1,570,088	1,570,088	1,570,088	1,570,088
No. job spells	376,590	376,590	376,590	376,590	376,590	376,590	376,590	376,590
R2	0.138	0.136	0.136	0.135	0.137	0.135	0.138	0.137

Note:

*** 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. Coefficient estimates of the other variables not reported to save space.

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%