Vulnerable Jobs and the Wage Effects of Import Competition

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Abstract:
Do job characteristics modulate the relationship between import competition and workers' wages? Using pooled cross-sectional, linked employee-establishment Census Bureau microdata and O*NET occupational characteristics, the paper models import competition and wages for over 1.6 million individuals, grouped by job vulnerability defined by routineness, analytic complexity, and interpersonal interaction. Results show import competition is associated with wages that are: lower in routine and less complex jobs; higher in nonroutine and complex jobs; and higher for the highest *and* lowest levels of interpersonal interaction. This demonstrates the importance of accounting for occupational characteristics in understanding how trade and wages relate.

Disclaimer:
This research uses confidential data from the US Census Bureau. Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the US Census Bureau. All results have been reviewed to ensure that no confidential information has been disclosed.

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1: Introduction

Over the past half century, dramatic improvements in transportation technologies have significantly reduced the cost of moving goods (e.g., Levinson, 2006). Advances in communication technologies have simultaneously reduced the cost of information exchange. These changes fostered a great expansion in trade of goods and services, enabling firms to better develop and control value chains distributed across the globe (Bonacich & Wilson, 2008; Coe & Yeung, 2015; Gereffi & Korzeniewicz, 1994; Kleibert, 2015). The rise in the complexity of global production networks, related-party trade, and foreign direct investment flows indicate that growing numbers of businesses are exploiting newfound capacities to fragment production across developed and developing economies alike. Unlike traditional spatial divisions of labor built around finished goods such as those described by Ricardo (1891), or on monopolistic competition between varieties of goods as analyzed by Krugman (1979), the contemporary reworking of the production and trade landscape involves a much finer-grained division of production possibilities that Baldwin (2006), Blinder (2006) and Grossman and Rossi-Hansberg (2006) tie not to industries but to production *tasks*.

Tasks represent all the incremental steps of the production process necessary to design, test, construct, assemble, sell, and deliver intermediate goods and, eventually, final products and services. More specifically, Grossman and Rossi-Hansberg define tasks as "the finest possible addition to the value added of a good or service done by a particular factor of production" (2012, p. 595), with the production of intermediate goods comprising "bundles" of tasks. The proliferation of trade in such bundles of tasks has relied on the ability to integrate and control distributed production networks, involving the efficient and cost-effective coordination of the movement of goods, services, and information across the globe. This is remapping patterns of global trade and specialization.

This article joins a growing literature exploring how these substantial shifts have affected worker welfare. It builds on prior work that discriminates between workers on the basis of the tasks they perform. This work argues that relatively routine tasks, meaning those that can be readily codified, are increasingly vulnerable to being offshored (Baldwin, 2006; Blinder, 2006; Leamer and Storper, 2001), or replaced by computers, robots, and related technological investments (e.g., Autor, Levy, and Murnane, 2003). When workers performing these tasks are *not* displaced by foreign competition or automation, they likely experience downward pressure on their wages, driven by import competition from low wage countries. In contrast, tasks that involve complex judgment-based decisions, and those requiring interpersonal interaction, are more costly to offshore and automate. For firms with workers specialized in these less routine tasks, globalization may actually increase demand and wages. We theorize that while trade today is more complicated than 'wine for cloth,' shifts in comparative advantage are simply more fine-grained, hewing closer to tasks than final goods. The distributional consequences of these patterns of trade should be visible in the relative wages earned by workers engaged in different kinds of tasks.

This paper explores whether the job characteristics of US workers influence how import competition from low-wage countries shapes their wages. We expect that workers will be more vulnerable to low-wage country import competition if the tasks they perform are (a) highly routine, (b) require little analytic complexity, and (c) involve scant interpersonal interaction. To test these hypotheses, we build standard measures of low-wage import competition using annual US Trade data, and relate these to individual and establishment characteristics derived from US

Census Bureau data. We estimate pooled cross-sectional models predicting annual wages for 1.6 million workers across the years 1990, 2000 and 2007. Each worker's occupation is the basis for their task profile, built from the US Department of Labor's O*NET database. The resulting dataset allows us to model the effect of low-wage import competition on the wages of workers with different occupational characteristics, net of the effects of education, demographics, and establishment characteristics.

In relation to important recent work in the same area, we add value in a few ways. We add to the findings of Autor *et al.* (2013a; 2014; 2016) by linking the impacts of rising import competition on worker wages to the task character of different occupations, responding to their call for "recharacterizing the sets of individuals who are likely candidates for opposing distributional consequences from economic integration" (Autor *et al.*, 2016, p. 234). We expand on the insights of Ebenstein *et al.* (2013) that note the importance of thinking less about industry and more about occupations when trying to unpack the impacts of globalization, by observing multiple trade-vulnerable task characteristics. Cumulatively, this builds the understanding of these dynamics in the US context. In doing so, we are also in conversation with similar work in Germany (Baumgarten *et al.*, 2013) and Denmark (Hummels *et al.*, 2014); this contributes to the growing evidence of the importance of occupational tasks in modulating the impacts of import competition across advanced economies.

To preview the findings, we show that task characteristics mediate the wage effects of low-wage import competition. Import competition from low-wage countries is associated with lower wages for workers with highly routine manual jobs and workers with jobs that have low analytic complexity. At the same time, workers in jobs with less routine manual tasks and greater analytic complexity earn higher wages when low-wage import competition rises. The influence of interpersonal task intensity on the trade-wage relationship is less straightforward to unpack. Workers in occupations with high levels of interpersonal interaction have higher wages when there is greater import competition from low-wage countries. Interestingly, the same is true for workers with the lowest levels of interpersonal interaction in their jobs. Only workers with medium-low levels of interpersonal interaction in their occupations suffer lower wages with increased low-wage import competition. Interaction effects show that the mediating relationship of task intensity is non-linear. These results demonstrate the importance of accounting for occupational characteristics to more fully understand the relationship between trade and wages and suggest underappreciated aspects of trade's distributional effects within countries.

The remainder of this article proceeds as follows. Section 2 provides a review of the literature on trade, tasks, and labor market effects. Section 3 outlines an empirical model to capture the importance of task characteristics in describing the relationship between trade and wages. Data sources, variable construction, and a series of empirical concerns are discussed. Section 4 presents the results from estimating a series of related statistical models. Section 5 concludes, summarizing the key findings.

2: Trade, tasks, and labor market effects: A brief review of key literature

Researchers argue that global economic integration shapes the geography of trade, production, and labor market dynamics at multiple spatial scales (Autor *et al.*, 2013b; Bernard *et al.*, 2006; Gereffi and Korzeniewicz, 1994). Significant attention has been directed at north-south linkages captured through increased levels of low-wage country (LWC) import competition within older industrialized economies (Bernard *et al.*, 2006), often with a focus on the rapid growth of China and its growing importance in global manufacturing activity (Autor *et al.*, 2016).

The surge in LWC imports from China and elsewhere is driven not only by arms-length trade, but by offshoring, the movement of jobs previously located in one country to other parts of the world (Blinder and Krueger, 2013). Jobs that are offshored may remain within the same company or they may be outsourced, moving from one firm to another. More and more trade takes place within global production networks that tie firms and countries to one another through complex webs of trade in intermediate goods and services (Gereffi & Korzeniewicz, 1994; Coe *et al.*, 2004). The United Nations Conference on Trade and Development estimates that 80% of all global trade in 2013 was undertaken by transnational corporations moving inputs and outputs along their global value chains (UNCTAD, 2013). Estimates by the US Department of Commerce suggest that approximately two-thirds of United States' imports and exports comprise "related-party" trade (Barefoot, 2012).

These shifts require renewed attention to the changing geography and structure of international trade, and substantial retheorization, especially in regards to trade's welfare impacts (see Grossman and Rossi-Hansberg, 2006, 2008; Baldwin and Robert-Nicoud, 2014). It is already clear that it makes little sense to explore the influence of trade across industries, as segments of industrial sectors are broken apart and moved between countries. At least for a while, we tended to think of education and skills as the key determinants of trade-based job vulnerability (Frobel *et al.*, 1980; Feenstra and Hanson, 2001). However, Baldwin (2006) and Blinder (2006) make clear that the "second great unbundling" of work today is based upon a separation of job tasks that is only weakly correlated with workforce skill and levels of schooling (Jensen and Kletzer, 2010; Blinder and Krueger, 2013). The fine-grained level of competition that this new trade permits makes clear that its effects will be differentially located not only within industries but also within firms and across groups of workers previously thought to share the same fate (Baldwin & Robert-Nicoud, 2006). This reality complicates modeling efforts as well as policy responses, prompting reconsideration of workforce and job characteristics that shape the contours of trade impacts.

Theoretical models

Beyond the models commonly used to understand impacts of trade on workers and firms (e.g., Bernard *et al.*, 2006; Ethier, 2005; Feenstra & Hanson, 1996, 2001), there are a number of explicit models of trade in tasks that are particularly helpful in examining the potential effects of trade on workers with different task profiles.[i] The present research draws most heavily upon Grossman and Rossi-Hansberg (2008), who argue that what is traded, or offshored, is determined by weighing the costs of monitoring and controlling workers in another country against the potential savings from lower labor costs. It is assumed that the costs of coordinating workers from a distance are lower for more routine tasks than for nonroutine tasks, that routine tasks are more likely to be performed by low-wage workers and nonroutine tasks by high-wage workers (e.g., Autor *et al.*, 2003). Reductions in trade costs, particularly communications costs, lead to increased offshoring of trade-vulnerable tasks.

The Grossman-Rossi-Hansberg (2008) framework suggests that offshoring reduces costs and affects wages in the high-wage (onshore) country in three ways: through terms of trade effects (reducing the price of the imported goods since they are likely made by workers with lower wages); labor supply effects (with demand decreasing for workers with the task trade vulnerable characteristics), and; productivity effects (where the onshore workers refocus on higher-productivity tasks). The aggregate effect of these three wage effects is not clear from the model itself. The second effect suggests that average wages for workers in the home country will fall, but the first and third effects suggest that average wages could rise. Note that Rojas-Romagoas (2010) runs numerical simulations of the Grossman and Rossi-Hansberg model and finds that with nearly all combinations of endowments, robust to a wide a range of parameters, the model leads to increased inequality in the onshore, high-wage country.

However, beyond aggregate effects, this model highlights how the effects of trade and offshoring will impact workers differentially. Even if trade-vulnerable workers benefit from terms of trade and general productivity effects, demand for their labor falls. This can translate directly into job loss (Kemeny *et al.*, 2015), but it may also erode their bargaining power, and inhibit wage growth. Thus, as trade with low-wage countries increases, wage patterns should track differential task profiles among workers.

Which tasks will be vulnerable to import competition?

While the basic routine-nonroutine continuum underlies the Grossman and Rossi-Hansberg (2008) model, an evolving body of work seeks to identify which tasks are most vulnerable to offshoring (e.g., Jensen and Kletzer, 2010; Blinder and Krueger, 2013). Building from extant theoretical and empirical contributions we focus here on three key characteristics: manual routineness, analytical complexity, and interpersonal interaction.

Autor *et al.* (2003) define routine tasks as those requiring “a limited and well-defined set of cognitive and manual activities, those that can be accomplished by following explicit rules” (p. 1280). In decline in high-wage economies like the US, the UK and Germany (Autor *et al.*, 2003; Goos and Manning, 2007; Spiz-Oener, 2006), routine tasks are susceptible to investments in labor-replacing technology as well as (as formalized by Grossman & Rossi-

Hansberg, 2006 and Baldwin & Robert-Nicoud, 2014) offshoring within global production networks (Oldenski, 2012).[ii]

For Leamer and Storper (2001), while routineness allows tasks to be performed far from the firm's headquarters or management, it is not the characteristics of individual tasks that matter, but rather the coordination between them. Newly fractured production processes may *technically* be performed in any number of places, but at sufficiently high levels of coordination costs, it will be more efficient to keep fragments co-located. Blinder (2006) identifies a related distinction between services in which personal contact is key and those "that can be delivered electronically over long distances with little or no degradation in quality" (p. 114).

While coordination costs and distance-sensitivity are not easily observed directly, one might discern both by measuring task requirements for interpersonal interaction (Becker et al, 2013; Baumgarten *et al.*, 2013).

Closely related empirical work

There has been a recent proliferation of empirical research on the impacts of trade amid the ongoing global remapping of production networks. This work has largely focused on the impacts of trade on labor markets and in some cases worker compensation.

In a series of important papers, Autor *et al.* (2013a, 2014, 2016) explore the influence of China's rapid growth and global economic engagement on workers across the United States. Using labor market variation in low-wage country import exposure (driven largely by imports from China) and assumed low levels of worker geographical mobility, they show that the local labor market effects of import competition drive increases in unemployment, reduce levels of labor force participation, and increase reliance on transfer payments (Autor *et al.*, 2013a).

Beyond area effects, individual workers are also directly affected. Autor *et al.* (2014) show that workers in sectors experiencing the largest import shocks face significantly lower cumulative earnings, fewer hours of work and more sectoral job volatility. These impacts are greater for low-wage workers, those who face the most direct competition from low-wage country imports. While this research controls for demographic characteristics of workers it does not examine the heterogeneity of trade impacts by education, skill, or most importantly, task status.

The importance of occupation on the relative fortunes of workers is demonstrated by Ebenstein *et al.* (2013), who show that occupational exposure to trade and offshoring has a larger impact than industrial exposure. Their measure of occupation exposure, along a continuum of routine to nonroutine tasks, links to other import task-oriented studies. For example, Oldenski (2012) focuses on the decisions by MNCs to move tasks offshore to foreign affiliates or to outsource them domestically. She finds US MNCs were more likely to offshore routine tasks to foreign affiliates and more likely to keep complex and nonroutine tasks in the US. Kemeny and Rigby (2012) develop a similar approach to Oldenski, but they ask a broader question exploring the effects of all trade from low-wage countries (and not just related party MNC trade) on the demand for occupations with different task characteristics. They find that import competition from low-wage countries increases sector-specific demand for nonroutine tasks, both in the form of interpersonal interaction and nonroutine analytical tasks, and lowers demand for routine tasks. Ottaviano *et al.* (2013) relate shifts in MNC offshoring activities to the reallocation of employment, considering domestic effects on both natives and immigrants. They find evidence of a link between offshoring and greater demand for natives performing communication-intensive tasks.

Related work on industrialized countries outside the United States reveals similar patterns (e.g., Becker *et al.*, 2013; Mion & Zhu, 2013; see Autor *et al.*, 2016 for more). Of particular relevance for the research presented in this article, Baumgarten *et al.* (2013) examine the offshoring impacts on individual male workers' wages in Germany. They find substantial negative wage effects from offshoring, particularly when, conceptually similar to Ebenstein *et al.* (2013), they allow for cross-industry offshoring effects, essentially assuming that workers can find work in their chosen occupation in a number of industries. Their analysis shows that that highly non-routine or interactive occupations, built from the tools used in occupations (Becker *et al.*, 2013), mitigate the negative wage effects of offshoring. Using Danish matched employer-employee data, Hummels *et al.* (2014) find that routine occupations (within skill groups determined by education level) are associated with wage losses from offshoring by their own firm. Interestingly, beyond the more commonly used routine or interactive task divisions, they also examine area of study associated with occupations. Here they find that math skills key within non-routine occupations, which are protective against pressures from offshoring, and other areas such as the social sciences also support wage premia. In both Baumgarten *et al.* (2013) and Hummels *et al.* (2014), the rich longitudinal micro data support a strong analytical approach and compelling findings.

This paper makes several contributions to enrich this area of study. First, closely complementing Baumgarten *et al.* (2013) and Hummels *et al.* (2014), this study provides evidence of the task-inflected wage impacts of international competition, but for the United States. Since our data are structured somewhat differently than theirs, the rich set of individual and industry-location variables we include explicitly measure some of what is absorbed by their fixed effects, providing additional information. Examining these relationships across different national contexts lends support to these findings as likely to be more broadly generalizable across advanced economies. This is also strengthened by the relatively long timeframe in this paper, which may better capture a longer-run process of trade induced labor market impacts. Second, specific to prior studies based on US data, this study complements and expands the knowledge in several ways. It expands on the research showing certain tasks are more likely to be offshored (Oldenski, 2012; Kemeny and Rigby, 2012; Ottaviano *et al.*, 2013) to observes the wage effects of these pressures on jobs remaining onshore. And in observing wage patterns (Autor *et al.*, 2013a, 2014; Ebenstein *et al.*, 2013), our use of matched employer-employee data attend to task characteristics and provide additional important controls on plant level characteristics. Thus, we gain more purchase on whether the tasks performed by US workers exert a significant effect on individual level wage adjustments prompted by import competition after worker and establishment characteristics are accounted for.

3: Empirical strategy

Our analysis rests on a wage model that relates the wages of individual manufacturing workers to low-wage import competition, and includes a set of standard control variables. To estimate how task characteristics shape the influence of import competition on wages, we estimate the wages of workers grouped by their occupational task characteristics. Before describing the wage model, we describe the data used.

3.1 Data

3.1.1 Matched employer-employee data

In the U.S., there is a jobs frame matched employee-employer dataset based on administrative data (see McKinney and Vilhuber, 2011). However at the time of this research, these data lacked workers' occupation codes, essential to the current study. Thus, the analytical sample in this study is derived from a matched employer-employee database that we built using confidential versions of the US Census Bureau's Decennial Census (1990 and 2000), American Community Survey (ACS 3-year 2005-2007 file), and Census of Manufactures (CMF 1992, 2002, 2007 files). Using variables for place of work and industry of work for individuals employed in the manufacturing sector in the Decennial and ACS, we made a probabilistic match to establishments in the CMF based on industry codes and detailed plant location. The locations used in the matching process start with census tracts; to maintain consistent areal boundaries across all years of the data, some census tracts are grouped together creating slightly larger geographical units. We differentiate between approximately 70 industry classes and approximately 60,000 census tracts and tract-groups to build our linked employer-employee data.

Where there is only a single establishment in an industry-location cell, workers with that same industry-location combination can be unambiguously matched to that establishment. These uniquely matched individuals slightly over-represent men and uniquely matched plants are larger than average, but less likely to be in urban areas. When there is more than one establishment in an industry-location cell, a unique match between plant and worker is impossible. In these cases, we link the workers in that industry-location to a synthetic establishment, which has the average of the characteristics of the individual plants in that industry and location. The main tradeoff involved in this averaging is between some loss of establishment heterogeneity and keeping a larger set of manufacturing workers, notably many of those who work in urban areas and dense manufacturing areas.

This matching process, which links workers from the Decennial and ACS to plants observed in the CMF, results in over a million and a half workers across all our cross sections. The set of matched workers appears to be broadly similar to the entire manufacturing workforce (see top of Table 1). However, the sample of matched plants clearly includes plants with much larger output, which is related to greater exports (also visible in this comparison see the bottom of Table 1). While this may limit the applicability of our sample to the smallest manufacturers, the large number of workers employed by larger establishments (see Appendix Figure A1) suggest that our sample still has importance for understanding the wage dynamics for a large segment of the manufacturing workforce.

[Table 1 about here]

The characteristics of individual workers and manufacturing plants included in the Decennial, ACS, and CMF provide the main dependent variable used – wage and salary earnings – as well as a set of key control variables. For individual workers, these include age, sex, nativity, race-ethnicity, and education level. For plants, these include establishment output (measured as total value of shipments), capital-labor ratio, the value of exports, and computer share of investment. The Decennial and ACS data also provide the inputs to calculate the percent of immigrant workers with less than a high school diploma in the labor market of each industry and state.

3.1.2. Constructing measures of import competition and task characteristics

Similar to Bernard *et al.* (2006), we measure low-wage country import competition using the ratio of low-wage imports within industry *i* in year *t* to the value of output in industry *i* and year *t* that is available for domestic consumption:

$$LWICOMP_{it} = \frac{IMPORTS_{it}^{LWC}}{IMPORTS_{it}+SHIPMENTS_{it}-EXPORTS_{it}} \tag{1}$$

where $IMPORTS_{it}^{LWC}$ is the industry- and year-specific value of imports to the US originating in low-wage countries and $IMPORTS_{it}$ is the value of imports from all countries; $SHIPMENTS_{it}$ is the total US domestic production (shipments) and $EXPORTS_{it}$ represents US exports. Yearly information on imports and exports are derived from the individual level transactions compiled by the Foreign Trade Division of the US Census Bureau. Shipments are from the CMF, aggregated from the establishment level to industry-year measures.[iii] Low-wage countries are defined by the World Bank country classification. We use countries classified in the low-income group for 1992 throughout our analysis. These countries had Gross National Income (GNI) per capita less than or equal to US$545 in 1992.[iv] This set of 51 countries (notably including China) remains consistent in our LWICOMP calculations, even though some countries move out of the World Bank low income class by 2007.[v] Once constructed, LWICOMP measures are linked to the analytical sample based on the reported industry of each worker, as recorded in the Decennial or ACS data.

The other key variables characterize the occupational tasks or job attributes of each worker, based on definitions from O*NET (Occupational Information Network). O*NET is a publicly available dataset supported by the US Department of Labor that identifies different characteristics of occupations, based on surveys of workers in each occupation.[vi] Within O*NET, 'work activities' correspond most closely to the conceptions of tasks developed in the theoretical literature and follow previous empirical work by Oldenski (2012) using O*NET.[vii] To generate measures of task-intensity for each occupation, we use principal components analysis with varimax rotation to reduce several work activities down to individual task measures. The input variables and the constructed primary components are summarized in Table 2. We create a single measure of routine manual labor using the first principal component derived from the job categories performing general physical activities, handling and moving objects, and controlling machines and processes ("routine manual"). We depart from Oldenski's nonroutineness measure that incorporates both creativity and communication, opting instead for two separate measures. The first captures analytical and decision making tasks ("complex analytic") built from a combination of analyzing, decision making and problem solving, creative thinking, and objectives and strategies development. The second is a measure of interpersonal interaction intensity ("complex interpersonal"), based on communications, relationship management, conflict resolution, and consulting and advising others. As Table 2 indicates, for each task type, we retain only the first principal component that explains at least 70 percent of the underlying variation in all cases.

[Table 2 about here]

To help ground this discussion, Table 3 shows the task intensities for several occupations. In Panel A, below each task intensity measure (routine manual, complex analytic, and complex interpersonal) are the component dimensions. The component dimensions are scaled from 0 to 1. The task intensity measures are transformed so that the entire range is always a positive number. Note that the scales for each task intensity measure are not directly comparable. Panel B shows the range of variation in the values in terms of standard deviations, with the industrial production manager as the reference category (Column 1). The other occupations involve far more routine manual tasks – ranging from just over a half a standard deviation below the industrial production manager on the routine scale (sewing machine operators – Column 5) to over one and a half standard deviations above the production manager occupation (cutting, punching, pressing machine operators – Column 4). Industrial production managers have higher levels of complex analytical and interpersonal task measures than the other occupations. Here, the levels of these tasks are two to three standard deviations lower among these occupations compared to the production manager. This table shows not only the substantial variation in these measures across particular occupations, but also reveals reassuringly intuitive comparisons across the occupations. Once constructed, we linked the three occupation-specific task intensity scores to individual workers in the analytical sample based on each person's occupation as reported in the Decennial and ACS.

[Table 3 about here]

The resulting dataset is a pooled cross-section (1990, 2000, and 2007) that includes over 1.6 million unique individuals. For the entire analytical sample, Table 4 shows the means, standard deviations, and the correlations among the wages, low-wage import competition, task intensity measures, and other variables. The measure of routine manual tasks is negatively correlated with both complex analytic and interpersonal task intensity. It is also negatively correlated with wages, whereas complex analytic and interpersonal task measures are positively correlated with wages.

[Table 4 about here]

3.2 Estimation

The aim of the analysis is to explore how different job or task characteristics mediate the relationship between low-wage country import competition and the wages of US manufacturing workers. We estimate a series of regression models for this purpose. The dependent variable in these models is annual wages (year dummies control for inflation) and observations correspond to individual workers over the years examined. Workers are placed into quartiles according to their occupation along an index of intensity for a given task type – routine manual, complex analytic and complex interpersonal. Equation (2) outlines the base specification that is run separately across our three task types

$$W_{jist} = a \quad + \boldsymbol{\beta}'_u \boldsymbol{P}_{ujist} + \boldsymbol{\beta}'_v \boldsymbol{E}_{vkist} + \beta_m M_{ist} + \beta_l LWICOMP_{it} + \delta_t + \delta_i + \delta_s + \varepsilon_{jist} \tag{2}$$

where W_{jist} is the wage of worker *j* in industry *i*, state *s* at time *t* ; $\boldsymbol{P}_{jist}$ is a *u*-element vector of worker characteristics for worker *j* , including age, sex, nativity, race-ethnicity, and education level; $\boldsymbol{E}_{kist}$ denotes a *v*-element vector of features of establishment *k*, including establishment output (total value of shipments), capital-labor ratio, the value of exports, and an establishment-specific measure of the computer share of investment that proxies for skill-biased technological change; M_{ist} measures the prevalence of low-education immigrant workers with less than a high school diploma in the industry and state of the worker; $LWICOMP_{it}$ is the measure of import competition from low-wage countries, specific to each industry and year. This specification also includes three fixed effects terms: δ_t is a year dummy that accounts for business cycle dynamics and other time-specific shocks; δ_i is an industry fixed effect that captures sector-specific wage shocks; δ_s absorbs state-specific shocks. Finally, ε is an error term that is assumed to satisfy classical regression assumptions.

We estimate these equations as pooled cross-sections using ordinary least squares with heteroscedasticity-robust standard errors. We recognize the potential for unobserved heterogeneity in this specification, which in related contexts the authors have addressed using panel data and fixed effects approaches (i.e. Rigby *et al.*, 2017). However, the present data offers much richer and more comprehensive information about both workers and establishments than can be found in longitudinal matched employer-employee data for the US. While we may not be able to measure all possible sources of heterogeneity in our data, we are able to capture a wide range of relevant control variables, which should raise confidence that we can produce efficient estimates of the relationship of interest.

An additional source of potential bias in our specification may result from the correlation of low-wage import competition and sector-specific demand or productivity changes in the US not captured elsewhere in the model. To account for this potential endogeneity bias, we follow Autor *et al.* (2013a) and instrument for low-wage import competition using a measure of year- and industry-specific imports into the EU-15 European nations from the same low-wage countries used in our measure of US-based import competition. This instrument is constructed from United Nations COMTRADE data. The logic of this instrument assumes that European countries face similar exposure to low-wage import competition when imports reflect factors inherent in low-wage countries, or in the dynamic of trade between low-wage and high-wage countries, but that other factors influencing domestic wages should be relatively uncorrelated between the United States and the EU. In specifications employing two stage least squares, this instrument should help to identify the independent effect of low-wage import competition on US manufacturing wages.

Finally, rather than estimating quantile regressions over the full range of workers, we opt for estimates for particular subsets of workers grouped by task intensity, since the former proved too computationally intensive, even given the considerable computing resources in the Federal Statistical Research Data Centers. To compare coefficients across task subsamples we calculate *z*-scores as described in Clogg *et al.* (1995):

$$z = {(\hat{\beta}_{m1} - \hat{\beta}_{m2})} \Big/ {s^2_{m1}(\hat{\beta}_{m1}) - s^2_{m2}(\hat{\beta}_{m2})} \qquad (3)$$

where s is the standard error for a given estimated coefficient $\hat{\beta}$ and mn indicates the specific regression models being compared. The null hypothesis tested is that there are no differences between the coefficients in the pair of models, against an alternative that one coefficient is larger than another, indicating a one-tailed test. We tested each pair of import competition coefficients within each table – for example, low versus high routineness – and for each pair we reject the null hypothesis: the differences between the task-quartile subsamples are statistically different from each other.

4: Results

Based on equation (2), we estimate worker wages using OLS and two-stage least-squares for individuals in occupations characterized by low, medium-low, medium-high, and high task intensity measures. We are most interested in highlighting the contrasting extremes of the task intensities, which should give the clearest signal on the role of tasks in shaping the relationship between import competition and wages. Furthermore, because quartiles are somewhat arbitrary cut points and we have no clear guidance on where exactly the theorized boundaries should be along the task intensity index, the main results we present are from the highest and lowest quartiles of each measure. Results for all quartiles are available in the appendix. Every model includes state, industry, and year fixed effects. The exact sample sizes and coefficients are rounded simply as a precaution to protect the confidentiality of data respondents. The first results reported are for workers grouped by the level of routine manual tasks in their occupations.

Table 5 reports estimates of the relationship between low-wage import competition and wages for workers grouped by the level of routine manual tasks in their occupations. The first column reports the results for workers who are engaged in highly routine manual tasks; their occupations score high on moving and handling objects, general physical activities, and controlling machines. For these workers, increases in low-wage country import competition lowers wages, fitting with expectations. A one unit increase in import competition, a very large gain (see Table 4), is associated with an decrease in routine manual wages of roughly $9,000, a bit larger than the gender pay gap for these workers.

The control variables (in this model, and subsequent ones) operate much as expected. Being older, white and non-Hispanic, having higher levels of formal education, and working in a metro area are all associated with higher wages. In this column, bring born in the US is also associated with higher wages. In states and industries with higher concentrations of foreign born workers with low educational attainment, wages are lower. Working in larger plants, with higher capital to labor ratios and more exports pays more; but where investments in computers are higher, wages are lower.

[Table 5 about here]

For workers in occupations involving little routine manual tasks (Column 2), low-wage import competition exerts a significant, positive influence on wages. A one unit increase in low-wage import competition increases wages by an average of close to $29,000, again slightly larger than the gender pay gap for these group of workers. The control variables operate largely, though not completely, as expected. Here, it is surprising that being born in the US is associated with lower earnings. Though neither is statistically significant, the computer share of investment and the value of export shipments are both negatively related to wages for this group of workers.

Columns 3 and 4 in Table 5 presents results estimated using two-stage least-squares fixed effects estimators, using EU imports as an instrument for LWICOMP. In all models the first stage diagnostics reported at the bottom of the table indicate the suitability of the instrument. The

Kleibergen-Paap K-P rk LM Chi-squared/p-value statistics indicate that the instrumented model passes this underidentification test. The Kleibergen-Paap (K-P) F-statistic reports on the instrument relevance, here with a value well above the critical Stock-Yogo threshold. We conclude that the instrument is relevant and not weak.

The results in these columns are broadly similar to the OLS estimations in that the direction of the relationships stays the same. However, the coefficient for import competition for the most routine jobs (Column 3) is no longer statistically significant, and the same coefficient is roughly double the magnitude for low routine jobs (Column 4).

It is difficult to assess which set of regression coefficients provides the best estimates of the influence of import competition between the two sets of models in Table 5. The OLS results might be compromised with endogeneity issues. However, use of instrumental variables also generates biased coefficients. In addition, the relatively large standard errors in the 2SLS models – they are roughly double the size of the LWICOMP standard errors in the OLS models – also suggests loss of precision in estimation. Note that the inflation of coefficients and their standard errors for measures of import competition is commonly observed in the literature (Bernard *et al.*, 2006). We emphasize, however, the consistent contrast between the two sets of workers, those doing nonroutine versus highly routine tasks in their occupations.

Table 6 presents results for workers grouped by the intensity with which their jobs involve complex analytic tasks. Recall that this task characteristic includes elements of creative thinking, analysis, problem-solving, decision-making, and developing objectives and strategies. The results shown include those for workers with the least engagement in complex analytic tasks (Columns 1 and 3) and the highest intensity of complex analytic tasks (Columns 2 and 4). Throughout, the covariates operate in much as we might expect.

[Table 6 about here]

In Table 6, Column 1, which reports the OLS estimates for workers with the lowest-complex analytic jobs, low-wage import competition is negatively and significantly associated with wages. A one percentage point increase in low-wage country import competition reduces the annual wage of workers in the lowest quartile of complex analytic jobs by approximately $12,715. As the complex analytic tasks required in occupations increases beyond this lowest quartile, the relationship with import competition is reversed. This suggests that analytic complexity insulates workers from import competition and that such insulation rises rapidly in occupations that demand levels of complexity and analytical skills greater than those found in the lowest quartile. Column 2 shows that for workers with the greatest intensity of complex analytic tasks in their jobs, those in the top quartile of complex analytic tasks, the relationship between low-wage import competition and wages is positive and significant. We interpret this to be a reflection of the reorientation of US comparative advantage, with fine-grained intra-industry adjustment towards high-skill kinds of manufactures resulting in rising wages for workers performing in-demand tasks.

In the two-stage least-squares models shown in Table 6, Columns 3 and 4, the results are consistent with the OLS results. The first-stage test statistics lead us to conclude that the model is not underidentified and that the instrument is not weak. The notable difference between the two sets of results is that the coefficient on LWICOMP for the 2SLS models are roughly double what they are in the OLS results. The standard errors for LWICOMP in the 2SLS models are also roughly double what they are in the OLS models.

Table 7 presents results for workers grouped based on the extent to which their jobs involve complex interpersonal tasks. Column 1 reports results for workers with low complex interpersonal task intensity in their occupations. Contrary to expectations, low-wage import competition has a positive and significant association with wages for this group. For these workers, the low levels of interpersonal interaction (communicating with people outside the organization, establishing and maintaining personal relationships, resolving conflicts, and providing consultations and advice) would seem to fit with the idea that imports from low-wage countries should be competitive rather than complementary, but this is not what the results show. For the other groups of workers, however, the results support the idea that interpersonal interaction intensive jobs should be less vulnerable to offshoring, and therefore also more likely to benefit from low-wage imports. In Column 2, the medium-low intensity group displays a negative and significant relationship between LWICOMP and wages. In Column 3, the group with highest intensity of complex interpersonal tasks in their occupations, low-wage import competition is positively and significantly related to wages. The other covariates operate as expected.

[Table 7 about here]

The instrumented 2SLS results (Table 7, Column 3 and 4) have the same pattern as the OLS results, and again the first-stage test statistics lead us to conclude that the model is not underidentified and the instrument is not weak. As in previous tables, the 2SLS results have much larger coefficients on low-wage import competition than the OLS results.

The unexpected sign on the LWICOMP coefficient for the workers with the least interpersonal interaction is not easy to explain. It is possible that the variables used to construct the measure of interpersonal interaction are missing a crucial aspect of vulnerability to offshoring; they give a good sense of the necessity of face-to-face communication, but they do not capture the necessity of physical presence that might not require communication. Janitors might be a good example. They do not necessarily need to talk much to do their jobs effectively and so would score low on the interpersonal interaction measure, but they also cannot email or ship their work in from another country. So it is possible that this constructed measure of interpersonal interaction is not capturing everything intended. Alternatively, it is possible the findings are valid as is. They are consistent with some of the literature looking at the polarization in the workforce in countries like the US and UK, where employment and wages are gaining at the very top and very bottom of the wage spectrum, but 'hollowing out' in the middle (e.g., Goos & Manning, 2007).

Interacting LWC import competition and task characteristics

In addition, we estimated equation on all the workers pooled together and included a variable interacting LWICOMP and each task intensity measure separately (results not shown here for brevity, available upon request). The results reveal that the effect of LWICOMP is statistically significantly greater as task intensity increases. Thus, net of the effect of LWICOMP and routineness by themselves, LWICOMP has a larger negative effect on wages as routineness increases. Complexity and interpersonal interaction show the same pattern, but with the sign reversed to reflect their positive association with wages. The interacted term shows that as the complexity or level of interpersonal interaction increase, the positive effect on wages from LWICOMP also increases.

5: Conclusion

An important feature of the changes in international trade over the past few decades is increasing fragmentation of production processes across countries linked by trade. One of the key implications of this fine-grained fragmentation is that it changes what can conceivably be ‘unbundled’ and produced elsewhere. This specialization of production in different countries linked by trade is now occurring at the level of tasks and no longer at the level of sectors. Education and production/ nonproduction status among workers tells us less about how workers are affected by trade and are no longer the only way to conceptualize and measure vulnerability to trade competition. It is helpful to think about other ways the effects of trade might be ‘visible.’

Responding to these issues, this paper examines the effects of trade on workers based on the intensity of key task characteristics in occupations. We explore how occupation-specific variation in several task characteristics mediates the relationship between low-wage import competition and wages of US manufacturing workers. While our sample over-represents workers employed in large plants with more output and exports than average, this is representative of a large proportion of the manufacturing labor force. It is important to note though that our results may not be as applicable to workers in small plants. That said, controlling for a variety of establishment and person characteristics, including educational attainment, we find that low-wage import competition is associated with lower wages for workers with highly routine manual jobs and workers with low complex analytic intensity jobs. Additionally, workers in jobs with low routine manual tasks and high complex analytic tasks earn higher wages when there is greater import competition. Looking at interpersonal interaction, this paper provides a slightly less straightforward finding. Workers with the lowest and highest levels of complex interpersonal tasks in their occupations receive higher wages in the face of higher import competition, but workers with medium-low intensity of this characteristic have lower wages with greater import competition. Interactions show that the magnitude of the effect is not linear, but grows as the task intensity grows.

In general, these results suggest that workers who perform tasks that are theoretically more vulnerable to offshoring and task trade face negative wage effects associated with low-wage import competition. The map of global trade continues to shift as the imperatives of capitalism respond to changes in transportation, communication, and production technologies. As it does, workers face new challenges and opportunities. This study shows that in the US, as in several European nations (Baumgarten *et al.*, 2013; Hummels *et al.*, 2014), in response to increasing competition from low-wage country imports, these challenges and opportunities appear to be mediated by the characteristics of their occupations.

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Figures and Tables:

Table 1: Summary statistics for pooled cross-section of full time, full year workers and manufacturing plants, comparing the matched analytical sample to the broader sample of all worker and all plants

Worker Characteristics	All manufacturing workers (Decennial/ACS)	Analytical sample of matched workers
Average Annual Nominal Wages	31, 872	40,797
Average Education Category	1.8 (HS/Some college)	1.7 (HS/Some college)
Average Age	40	41
Percent Male	63%	72%
Percent US Born	91%	88%
Percent White, Non-Hispanic	83%	83%
Percent Working in a Metro Area	76%	81%
Ave. % Foreign Born < GED (year-state-ind)	3.69%	5.36%
Business Characteristics	All manufacturing plants (CMF)	Analytical sample of matched plants
Total Value of Shipments	20,061	254,679
Capital-Labor Ratio	91	107
Value of Export Shipments	1,689	30,285
Computer Share of Investments	0.07	0.09

Authors' calculations from the FSRDC versions of 1) the Decennial Census Long Form Sample in 1990, and 2000, 2) the American Community Survey 2005-2007 3-year estimates, and the Economic Censuses from 1992, 2002, and 2007. Right-hand column shows the pooled analytical sample, which is constructed by matching workers and plants via industry and location, and which is used in the models. Left-hand column provides a comparison to all full time manufacturing workers and all manufacturing plants.

Table 2: Variable Construction - Principal Component Analysis Variables

Concept of Interest	O*NET Component Variables	Proportion of variance explained in retained eigenvector
Routine Manual	Performing General Physical Activities Handling and Moving Objects Controlling Machines and Processes	86.9% (2.61)
Complex Analytic	Analyzing Data or Information Making Decisions and Solving Problems Thinking Creatively Developing Objectives and Strategies	70.8% (2.83)
Complex Interpersonal	Communicating with Persons Outside Organization Establishing and Maintaining Interpersonal Relationships Resolving Conflicts and Negotiating with Others Provide Consultation and Advice to Others	76.1% (2.28)

Authors' calculations using O*NET data. Eigenvalues in parentheses. Each factor analyzed using principal components with (orthogonal) varimax rotation. In each case only the first principal component is retained after rotation. Eigenvector loadings associated with this components are used to generate our summary measures of occupational characteristics. Analogous procedures using maximum likelihood and iterated principal factor approaches generated variables that are strongly correlated with the PCA results that form the basis of the analysis.

Table 3: Task Intensities of Illustrative Occupations

	(1) Industrial Production Managers	(2) Electrical, Electronics, and Electromechanical Assemblers	(3) Butchers and Other Meat, Poultry, and Fish Processing Workers	(4) Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	(5) Sewing Machine Operators
Panel A - Task-Intensity Measures and Their Component Dimensions					
Routine Manual	**9.685**	**10.956**	**10.883**	**11.25**	**10.296**
Performing General Physical Activities	0.4	0.639	0.68	0.643	0.475
Handling and Moving Objects	0.41	0.754	0.788	0.773	0.555
Controlling Machines and Processes	0.403	0.646	0.51	0.83	0.588
Complex Analytic	**10.774**	**9.025**	**8.381**	**8.662**	**8.346**
Analyzing Data or Information	0.54	0.355	0.293	0.3	0.275
Making Decisions and Solving Problems	0.828	0.613	0.488	0.538	0.483
Thinking Creatively	0.635	0.44	0.268	0.315	0.298
Developing Objectives and Strategies	0.595	0.268	0.278	0.318	0.255
Complex Interpersonal	**11.261**	**8.933**	**8.643**	**7.935**	**8.108**
Communicating with Persons Outside Organization	0.603	0.23	0.25	0.165	0.158
Establishing and Maintaining Interpersonal Relationships	0.79	0.589	0.423	0.358	0.43
Resolving Conflicts and Negotiating with Others	0.788	0.345	0.364	0.223	0.2
Provide Consultation and Advice to Others	0.54	0.276	0.297	0.205	0.238
Panel B - Differences in terms of Standard Deviations (Reference category is managers)					
Routine Manual	0	1.23	1.16	1.52	0.59
Complex Analytic	0	-1.89	-2.59	-2.29	-2.63
Complex Interpersonal	0	-2.14	-2.41	-3.06	-2.90

Authors' calculations using O*NET data. Task intensity measures from first principal components, transformed such that every possible value is a positive number. Component dimensions are scaled from 0 to 1. Example occupations provide intuitive illustrations of the task intensity measures.

Table 4: Means, Standard Deviations, and Correlations for Occupational Characteristic Sample

	Mean	S.D.	Wage	Sex	Nativity	Ethnicity-Race	Age	Metro	Percent Foreign Born	TVS	K-L
Wage	40797	39703	1								
Sex (proportion male)	0.72	0.45	0.185	1							
Nativity (proportion US-born)	0.88	0.33	0.015	0.032	1						
Ethnicity-Race (proportion white)	0.83	0.38	0.073	0.067	0.520	1					
Age	41	11	0.185	0.013	0.017	0.061	1				
Work in a Metro Area (proportion)	0.81	0.39	0.125	0.040	-0.137	-0.115	0.044	1			
Percent Foreign Born with < High school Degree (by year, state, industry)	5.4	8.3	-0.021	-0.064	-0.381	-0.301	-0.008	0.138	1		
Total Value of Shipments	254,679	851,770	0.098	0.037	0.028	-0.006	0.036	0.068	-0.091	1	
Capital-Labor Ratio	107	325	0.077	0.027	0.023	0.008	0.031	0.023	-0.063	0.171	1
Exports	30,285	196,467	0.061	0.019	0.008	-0.002	0.011	0.046	-0.050	0.529	0.098
Computer Share of Investments	0.09	0.32	0.020	-0.011	-0.017	-0.006	0.001	0.030	0.000	-0.005	-0.026
Education Category	1.7[a]	1.1	0.351	0.086	0.050	0.103	-0.030	0.126	-0.093	0.072	0.061
LWICOMP (Import Competition)	0.036	0.067	0.029	-0.129	-0.134	-0.101	0.030	-0.005	0.246	-0.060	-0.045
Complex	9.93	0.92	0.345	0.155	0.030	0.096	0.054	0.115	-0.051	0.028	0.036
Routine	10.07	1.03	-0.282	0.136	-0.024	-0.091	-0.052	-0.127	-0.023	0.007	-0.009
Interpersonal Interaction	9.76	1.09	0.330	0.024	0.064	0.114	0.081	0.106	-0.009	0.008	0.027

[a] The education category average corresponds to between having a high school diploma and some college.

Table 4: Means, Standard Deviations, and Correlations for Occupational Characteristic Sample (continued)

	Comp. Investments	Educ.	Import Comp.	Complex	Routine	Interpersonal Interaction
Wage						
Sex (proportion male)						
Nativity (proportion US-born)						
Ethnicity-Race (proportion white)						
Age						
Work in a Metro Area (proportion)						
Percent Foreign Born with < High school Degree (by year, state, industry)						
Total Value of Shipments						
Capital-Labor Ratio						
Exports						
Computer Share of Investments	1					
Education Category	0.035	1				
LWICOMP (Import Competition)	0.043	-0.001	1			
Complex	0.028	0.441	-0.032	1		
Routine	-0.043	-0.497	-0.067	-0.532	1	
Interpersonal Interaction	0.024	0.425	0.001	0.757	-0.709	1

Table 5: Routine Manual Tasks and LDC Import Competition - Relationship to Wages: OLS and 2SLS Models

	(1)	**(2)**	**(3)**	**(4)**
	High Routine Manual	Low Routine Manual	High Routine Manual	Low Routine Manual
	OLS	OLS	2SLS	2SLS
Import Competition	-8860	28819	-3476	67197
	(1,639)***	(3,119)***	(4269)	(6,338)***
Sex, 1=Male	7716	23154	7702	23133
	(115)***	(207)***	(115)***	(207)***
Nativity, 1=US Born	2488	-2066	2490	-1956
	(181)***	(479)***	(181)***	(480)***
Ethnicity-Race Dummy	3275	10664	3279	10726.9
(White & Not Hispanic=1)	(158)***	(369)***	(158)***	(369.45)***
Age	310	901	310	901
	(4)***	(11)***	(4)***	(11)***
Education Categories	2914	12440	2914	12449
	(55)***	(123)***	(55)***	(123)***
Work in a Metro Area (1=yes)	3067	5583	3059	5507
	(94)***	(311)***	(94)***	(311)***
% Foreign Born with <GED	-98	-235	-97	-212
	(12)***	(27)***	(12)***	(28)***
Total Value of Shipments	0.0027	0.0009	0.0027	0.0009
	(0.0002)***	(0.0002)***	(0.0002)***	(0.0002)***
Capital/Labor Ratio	4.47	0.77	4.49	0.8
	(0.42)***	(0.25)***	(0.42)***	(0.25)***
Value of Export Shipments	0.0002	-0.0002	0.0002	-0.0002
	(0.0006)	(0.0005)	(0.0006)	(0.0005)
Computer Share of Investments	-1361	-401	-1395	-414
	(263)***	(447)	(264)***	(448)
Observations (rounded)	360000	403000	360000	403000
R-squared	0.26	0.23	-	-
Kleibergen-Paap rk LM (underid)			1390	1.10E+04
Chi-sq(1) P-val			0	0
Cragg-Donald Wald F (weak id)			7.20E+04	1.50E+05
Kleibergen-Paap rk Wald F			3931	3.70E+04
Instrument			EU Imports	EU Imports

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

NB: Industry, State, and Year fixed effected included in all models; Observations rounded to protect confidentiality.

Table 6: Complex Analytic Tasks and LDC Import Competition - Relationship to Wages: OLS and 2SLS Models

	(1) Low Complex Analytic OLS	(2) High Complex Analytic OLS	(3) Low Complex Analytic 2SLS	(4) High Complex Analytic 2SLS
Import Competition	-12716	23095	-20429	46070
	(1,258)***	(3,065)***	(1,921)***	(6,133)***
Sex, 1=Male	7764	17506	7769	17451
	(86)***	(202)***	(86)***	(203)***
Nativity, 1=US Born	3151	-1536	3127	-1476
	(168)***	(427)***	(169)***	(427)***
Ethnicity-Race Dummy	2801	12504	2786	12533
	(137)***	(339)***	(137)***	(339)***
Age	270	1066	270	1066
	(4)***	(11)***	(4)***	(11)***
Education Categories	3181	13523	3183	13512
	(53)***	(104)***	(53)***	(104)***
Work in a Metro Area	2853	5826	2876	5781
	(98)***	(275)***	(99)***	(275)***
% Foreign Born with <GED	-34	-195	-36	-180
	(8)***	(24)***	(8)***	(24)***
Total Value of Shipments	0.0021	0.001	0.0021	0.001
	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***
Capital/Labor Ratio	0.95	0.97	0.93	0.99
	(0.30)***	(0.24)***	(0.30)***	(0.24)***
Value of Export Shipments	0.0009	0.0001	0.0009	0.0001
	(0.0005)*	(0.0004)	(0.0005)*	(0.0004)
Computer Share of Investments	-1178	-70	-1129	-74
	(200)***	(85)	(197)***	(85)
Observations (rounded)	408000	474000	408000	474000
R-squared	0.2	0.2	-	-
Kleibergen-Paap rk LM (underid)			2796	9347
Chi-sq(1) P-val			0	0
Cragg-Donald Wald F (weak id)			2.10E+05	1.80E+05
Kleibergen-Paap rk Wald F			1.50E+04	3.50E+04
Instrument			EU Imports	EU Imports

*Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%*

NB: Industry, State, and Year fixed effected included in all models; Observations rounded to protect confidentiality.

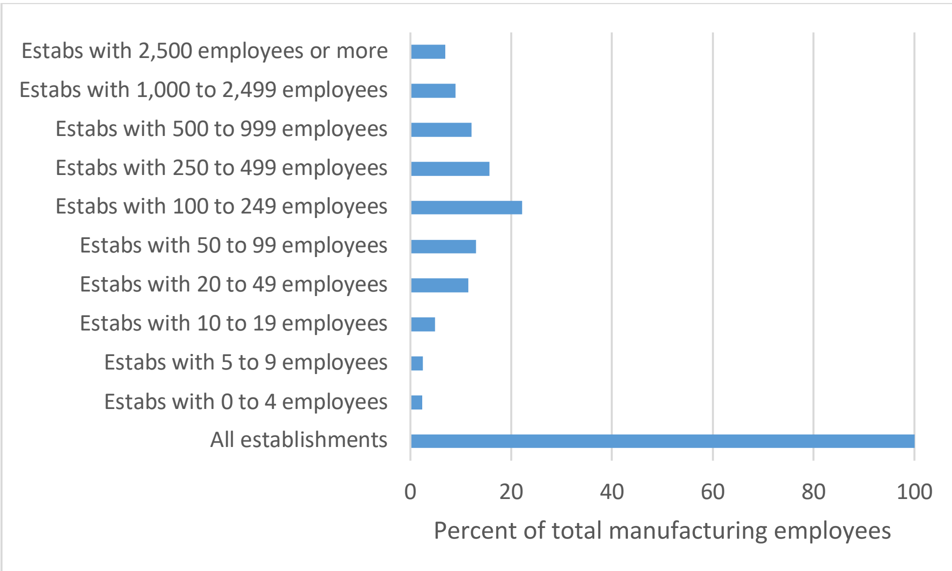
Table 7: Complex Interpersonal Tasks and LDC Import Competition - Relationship to Wages: OLS and 2SLS

	(1)	(2)	(3)	(4)	(5)
	Low Complex Interpersonal	Med-low Complex Interpersonal	High Complex Interpersonal	Low Complex Interpersonal	High Complex Interpersonal
	OLS	OLS	OLS	2SLS	2SLS
Import Competition	9058	-6745	20726	29970	55400
	(1,521)***	(1,845)***	(4,361)***	(2,630)***	(8,444)***
Sex, 1=Male	8870	8883	22785	8771	22731
	(103)***	(91)***	(279)***	(103)***	(280)***
Nativity, 1=US Born	730	2620	-5162	765	-5093
	(182)***	(164)***	(678)***	(182)***	(679)***
Ethnicity-Race Dummy	3695	2981	14167	3710	14236
	(151)***	(133)***	(520)***	(151)***	(520)***
Age	296	325	1172	295	1172
	(4)***	(4)***	(15)***	(4)***	(15)***
Education Categories	5155	3992	14510	5125	14511
	(63)***	(53)***	(151)***	(63)***	(151)***
Work in a Metro Area	3041	3241	6617	2984	6569
	(101)***	(100)***	(402)***	(101)***	(402)***
% Foreign Born with <GED	-219	-123	-216	-216	-193
	(10)***	(11)***	(35)***	(10)***	(35)***
Total Value of Shipments	0.0028	0.0019	0.0008	0.0028	0.0008
	(0.0002)***	(0.0001)***	(0.0002)***	(0.0002)***	(0.0002)***
Capital/Labor Ratio	3.15	3.61	0.94	3.22	0.97
	(1.25)**	(0.75)***	(0.33)***	(1.28)**	(0.33)***
Value of Export Shipments	0.0028	0.0015	0.0008	0.0027	0.0008
	(0.0008)***	(0.0004)***	(0.0007)	(0.0008)***	(0.0007)
Computer Share of Investments	-1264	-1322	-126	-1395	-130
	(286)***	(245)***	(89)	(292)***	(90)
Observations (rounded)	409000	396000	316000	409000	316000
R-squared	0.29	0.25	0.18	-	-
F	684.9	466.07	252.8	653.03	252.81
Prob > F	0	0	0	0	0
K-P LM (underid)				2619	6985
Chi-sq(1) P-val				0	0
Cragg-Donald Wald F (weak)				2.40E+05	1.20E+05
Kleibergen-Paap rk Wald F				1.60E+04	2.60E+04
Instrument				EU Imports	EU Imports

*Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%*
NB: Industry, State, and Year fixed effected included in all models; Observations rounded to protect confidentiality.

Appendix A

Figure A1: Establishment size and percent of total employment in the manufacturing sector



Source: Authors calculation from US Census Bureau's 2007 Economic Census of the United States, Summary Series (Table EC0731SG3, Industry codes 31-33).

Table A1: Low-Wage Countries used in the Import Competition Measures

Afghanistan	Comoros	Haiti	Maldives	Sao Tome
Bangladesh	Congo	Honduras	Mali	Sierra Leone
Bhutan	Eqypt	India	Mauritania	Solomon Isl.
Benin	Eq. Guinea	Indonesia	Mozambique	Somalia
Burkina Faso	Ethiopia	Kenya	Myanmar	Sri Lanka
Burundi	Gambia	Laos	Nepal	Sudan
Cambodia	Ghana	Lesotho	Niger	Tanzania
Ctr. African Rep.	Guinea	Liberia	Nigeria	Togo
Chad	Guinea-Bissau	Madagascar	Pakistan	Uganda
China	Guyana	Malawi	Rwanda	Vietnam
				Zambia

NB: Classified according to the World Bank, using year 1992.

Table A2: Routineness and LDC Import Competition - Relationship to Wages, OLS Models All Quartiles

	(1)	(2)	(3)	(4)
	Low Routine-ness	Med-low Routine-ness	Med-high Routine-ness	High Routine-ness
	28818.64	695.51	-16012.11	-8859.59
Import Competition	(3,119.38)***	(2440.20)	(1,052.21)***	(1,639.24)***
	23154.21	15773.54	8714.12	7716.48
Sex, 1=Male	(206.92)***	(144.52)***	(87.00)***	(114.55)***
	-2066.17	-566.52	2636.56	2487.88
Nativity, 1=US Born	(478.70)***	(330.16)*	(151.71)***	(181.37)***
Ethnicity-Race (White & Not	10664.19	8506.32	3216.50	3274.87
Hispanic=1)	(369.07)***	(241.44)***	(120.53)***	(157.85)***
	900.76	674.93	309.96	310.08
Age	(10.90)***	(7.15)***	(3.63)***	(3.73)***
	5583.12	4464.77	3240.95	3067.08
Work in a Metro Area (1=yes)	(310.53)***	(176.44)***	(98.53)***	(93.86)***
	-234.91	-108.23	-74.32	-98.49
% Foreign Born with <GED	(27.37)***	(17.62)***	(7.58)***	(12.12)***
	0.0009	0.0014	0.0019	0.0027
Total Value of Shipments	(0.0002)***	(0.0001)***	(0.0001)***	(0.0002)***
	0.77	0.97	2.91	4.47
Capital/Labor Ratio	(0.25)***	(0.30)***	(0.63)***	(0.42)***
	-0.0002	0.0012	0.0017	0.0002
Value of Export Shipments	(0.0005)	(0.0005)**	(0.0004)***	(0.0006)
	-401.32	-230.17	-1791.78	-1360.69
Computer Share of Investments	(447.05)	(184.47)	(259.56)***	(262.65)***
	12440.55	10332.21	3466.41	2914.36
Education Categories	(122.69)***	(78.48)***	(50.56)***	(54.50)***
Observations (rounded to 1000s)	403000	417000	460000	360000
R-squared	0.23	0.23	0.27	0.26
F	487.64	473.68	756.53	546.99
Prob > F	0	0	0	0

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

NB: Industry, State, and Year fixed effected included in all models; Observations rounded to protect confidentiality.

These results correspond to Table 5.

Table A3: Routineness and LDC Import Competition - Relationship to Wages, 2SLS Models All Quartiles

	(1)	(2)	(3)	(4)
	Low Routineness	Med-low Routineness	Med-high Routineness	High Routineness
	67197.35	5726.83	-20913.85	-3475.70
Import Competition	(6,338.14)***	(4325.10)	(2,064.93)***	(4269.15)
	23132.86	15766.06	8726.90	7702.23
Sex, 1=Male	(207.14)***	(144.98)***	(86.95)***	(114.86)***
	-1956.20	-553.76	2625.75	2489.79
Nativity, 1=US Born	(479.73)***	(330.86)*	(151.88)***	(181.34)***
Ethnicity-Race (White & Not	10726.90	8515.31	3208.99	3279.31
Hispanic=1)	(369.45)***	(240.99)***	(120.58)***	(157.73)***
	900.93	674.81	310.10	309.96
Age	(10.91)***	(7.15)***	(3.64)***	(3.73)***
	5506.98	4455.85	3254.77	3058.78
Work in a Metro Area (1=yes)	(311.07)***	(176.33)***	(98.87)***	(93.75)***
	-211.52	-105.90	-75.24	-97.45
% Foreign Born with <GED	(27.50)***	(17.62)***	(7.61)***	(12.09)***
	0.0009	0.0014	0.0019	0.0027
Total Value of Shipments	(0.0002)***	(0.0001)***	(0.0001)***	(0.0002)***
	0.80	0.97	2.90	4.49
Capital/Labor Ratio	(0.25)***	(0.30)***	(0.63)***	(0.42)***
	-0.0002	0.0012	0.0017	0.0002
Value of Export Shipments	(0.0005)	(0.0005)**	(0.0004)***	(0.0006)
	-414.40	-232.63	-1761.20	-1394.97
Computer Share of Investments	(447.93)	(186.19)	(259.06)***	(264.45)***
	12448.60	10330.55	3468.15	2913.86
Education Categories	(122.83)***	(78.54)***	(50.59)***	(54.48)***
Observations (rounded to 1000s)	403000	417000	460000	360000
R-squared	-	-	-	-
F	487.59	473.53	722.91	518.24
Prob > F	0	0	0	0
Kleibergen-Paap rk LM statistic (underidentification)	1.10E+004	5431.962	2961.645	1390.401
Chi-sq(1) P-val	0	0	0	0
Cragg-Donald Wald F statistic (weak identification)	1.50E+005	1.70E+005	1.70E+005	7.20E+004
Kleibergen-Paap rk Wald F statistic	3.70E+004	2.30E+004	1.20E+004	3931.098
Instrument	EU Imports	EU Imports	EU Imports	EU Imports

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

NB: Industry, State, and Year fixed effected included in all models; Observations rounded to protect confidentiality.

These results correspond to Table 5.

Table A4: Complexity and LDC Import Competition - Relationship to Wages, OLS Models All Quartiles

	(1)	(2)	(3)	(4)
	Low Complexity	Med-low Complexity	Med-high Complexity	High Complexity
Import Competition	-12715.78	12665.44	36730.67	23095.10
	(1,258.13)***	(1,824.91)***	(3,252.53)***	(3,064.85)***
Sex, 1=Male	7763.71	10035.91	11017.04	17505.75
	(86.05)***	(94.75)***	(159.37)***	(202.19)***
Nativity, 1=US Born	3151.31	1355.02	1627.42	-1536.08
	(168.17)***	(189.73)***	(265.22)***	(426.53)***
Ethnicity-Race (White & Not Hispanic=1)	2800.82	3886.84	6143.78	12503.96
	(136.89)***	(150.08)***	(193.81)***	(338.99)***
Age	269.82	331.13	477.59	1066.09
	(3.56)***	(4.11)***	(5.75)***	(10.65)***
Work in a Metro Area (1=yes)	2852.99	3402.39	4710.11	5826.49
	(98.45)***	(100.22)***	(139.76)***	(274.60)***
% Foreign Born with <GED	-34.07	-197.45	-151.79	-195.21
	(7.76)***	(12.82)***	(18.03)***	(23.99)***
Total Value of Shipments	0.0021	0.0018	0.0016	0.0010
	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***
Capital/Labor Ratio	0.95	3.68	1.02	0.97
	(0.30)***	(0.70)***	(0.28)***	(0.24)***
Value of Export Shipments	0.0009	0.0021	-0.0002	0.0001
	(0.0005)*	(0.0005)***	(0.0004)	(0.0004)
Computer Share of Investments	-1177.54	-1662.36	-803.36	-70.09
	(199.65)***	(312.59)***	(372.10)**	(84.89)
Education Categories	3181.03	5489.11	7501.54	13522.97
	(53.28)***	(61.12)***	(67.23)***	(103.53)***
Observations (rounded to 1000s)	408000	402000	355000	474000
R-squared	0.2	0.27	0.28	0.2
F	457.1	532.3	463.7	411.45
Prob > F	0	0	0	0

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

NB: Industry, State, and Year fixed effected included in all models; Observations rounded to protect confidentiality.

These results correspond to Table 6.

Table A5: Complexity and LDC Import Competition - Relationship to Wages, 2SLS Models All Quartiles

	(1)	(2)	(3)	(4)
	Low Complexity	Med-low Complexity	Med-high Complexity	High Complexity
Import Competition	-20428.76	50098.47	76368.20	46070.37
	(1,920.76)***	(3,999.21)***	(6,263.46)***	(6,133.06)***
Sex, 1=Male	7769.43	9949.12	11044.06	17451.04
	(86.06)***	(95.05)***	(160.34)***	(202.86)***
Nativity, 1=US Born	3126.81	1405.39	1615.98	-1476.43
	(168.91)***	(189.96)***	(265.91)***	(427.26)***
Ethnicity-Race (White & Not Hispanic=1)	2785.91	3896.12	6169.76	12532.74
	(136.64)***	(150.38)***	(194.81)***	(338.88)***
Age	270.00	329.86	476.57	1065.78
	(3.56)***	(4.13)***	(5.78)***	(10.65)***
Work in a Metro Area (1=yes)	2875.70	3360.82	4642.97	5781.10
	(98.61)***	(100.66)***	(140.73)***	(274.72)***
% Foreign Born with <GED	-36.07	-184.94	-138.72	-180.26
	(7.74)***	(13.03)***	(18.31)***	(24.04)***
Total Value of Shipments	0.0021	0.0018	0.0016	0.0010
	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***
Capital/Labor Ratio	0.93	3.80	1.08	0.99
	(0.30)***	(0.71)***	(0.29)***	(0.24)***
Value of Export Shipments	0.0009	0.0021	-0.0003	0.0001
	(0.0005)*	(0.0005)***	(0.0004)	(0.0004)
Computer Share of Investments	-1128.77	-1808.35	-940.39	-74.42
	(196.78)***	(314.54)***	(376.61)**	(84.99)
Education Categories	3182.96	5457.41	7497.72	13511.51
	(53.35)***	(60.85)***	(67.44)***	(103.58)***
Observations (rounded to 1000s)	408000	402000	355000	474000
R-squared	-	-	-	-
F	450.1	519.94	467.65	411.72
Prob > F	0	0	0	0
Kleibergen-Paap rk LM statistic (underidentification)	2795.646	4792.75	3751.609	9347.055
Chi-sq(1) P-val	0	0	0	0
Cragg-Donald Wald F statistic (weak identification)	2.10E+005	1.10E+005	1.00E+005	1.80E+005
Kleibergen-Paap rk Wald F statistic	1.50E+004	1.40E+004	1.00E+004	3.50E+004
Instrument	EU Imports	EU Imports	EU Imports	EU Imports

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

NB: Industry, State, and Year fixed effected included in all models; Observations rounded to protect confidentiality.

These results correspond to Table 6.

Table A6: Interpersonal Interaction and LDC Import Competition - Relationship to Wages, OLS Models All Quartiles

	(1)	(2)	(3)	(4)
	Low Interpersonal Interaction	Med-low Interpersonal Interaction	Med-high Interpersonal Interaction	High Interpersonal Interaction
Import Competition	9057.63	-6744.67	18589.65	20726.19
	(1,520.58)***	(1,844.88)***	(1,869.80)***	(4,361.07)***
Sex, 1=Male	8869.93	8882.59	14404.56	22785.20
	(102.70)***	(90.81)***	(99.31)***	(278.99)***
Nativity, 1=US Born	729.83	2619.68	-1103.08	-5162.38
	(182.30)***	(163.74)***	(211.76)***	(677.92)***
Ethnicity-Race (White & Not Hispanic=1)	3694.50	2980.97	4969.62	14167.17
	(150.75)***	(133.14)***	(160.74)***	(519.82)***
Age	295.71	325.09	469.44	1171.57
	(3.76)***	(3.86)***	(4.74)***	(14.81)***
Work in a Metro Area (1=yes)	3040.50	3241.46	3699.37	6616.88
	(100.86)***	(100.05)***	(115.99)***	(401.57)***
% Foreign Born with <GED	-219.17	-123.16	-227.15	-216.14
	(9.86)***	(10.68)***	(11.92)***	(34.87)***
Total Value of Shipments	0.0028	0.0019	0.0016	0.0008
	(0.0002)***	(0.0001)***	(0.0001)***	(0.0002)***
Capital/Labor Ratio	3.15	3.61	0.88	0.94
	(1.25)**	(0.75)***	(0.19)***	(0.33)***
Value of Export Shipments	0.0028	0.0015	0.0002	0.0008
	(0.0008)***	(0.0004)***	(0.0003)	(0.0007)
Computer Share of Investments	-1264.26	-1321.54	-1118.79	-126.20
	(286.43)***	(244.76)***	(253.91)***	(89.23)
Education Categories	5155.49	3991.50	7440.69	14509.85
	(63.14)***	(52.64)***	(52.09)***	(151.09)***
Observations (rounded to 1000s)	409000	396000	518000	316000
R-squared	0.29	0.25	0.32	0.18
F	684.9	466.07	789.51	252.8
Prob > F	0	0	0	0

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

NB: Industry, State, and Year fixed effected included in all models; Observations rounded to protect confidentiality.

These results correspond to Table 7.

Table A7: Interpersonal Interaction and LDC Import Competition - Relationship to Wages, 2SLS Models All Quartiles

	(1)	(2)	(3)	(4)
	Low Interpersonal Interaction	Med-low Interpersonal Interaction	Med-high Interpersonal Interaction	High Interpersonal Interaction
	29970.42	-29556.98	37775.46	55400.47
Import Competition	(2,630.45)***	(3,551.59)***	(3,508.38)***	(8,443.96)***
	8771.12	8882.77	14367.10	22730.88
Sex, 1=Male	(102.79)***	(90.91)***	(99.69)***	(279.59)***
	765.47	2568.49	-1057.09	-5093.23
Nativity, 1=US Born	(182.48)***	(164.40)***	(211.95)***	(678.78)***
Ethnicity-Race (White & Not	3709.54	2953.43	5004.48	14235.86
Hispanic=1)	(150.64)***	(133.40)***	(160.92)***	(519.60)***
	294.96	325.75	468.81	1171.93
Age	(3.77)***	(3.86)***	(4.75)***	(14.82)***
	2984.29	3278.10	3663.45	6569.49
Work in a Metro Area (1=yes)	(100.74)***	(100.58)***	(116.15)***	(401.89)***
	-216.25	-131.19	-217.64	-192.86
% Foreign Born with <GED	(9.87)***	(10.81)***	(12.06)***	(34.87)***
	0.0028	0.0019	0.0016	0.0008
Total Value of Shipments	(0.0002)***	(0.0001)***	(0.0001)***	(0.0002)***
	3.22	3.54	0.90	0.97
Capital/Labor Ratio	(1.28)**	(0.73)***	(0.19)***	(0.33)***
	0.0027	0.0015	0.0002	0.0008
Value of Export Shipments	(0.0008)***	(0.0004)***	(0.0003)	(0.0007)
	-1395.32	-1230.72	-1175.09	-129.79
Computer Share of Investments	(292.29)***	(245.83)***	(255.79)***	(89.53)
	5125.45	3967.26	7432.46	14510.75
Education Categories	(63.01)***	(52.98)***	(52.15)***	(151.13)***
Observations (rounded to 1000s)	409000	396000	518000	316000
R-squared	-	-	-	-
F	653.03	470.85	788.36	252.81
Prob > F	0	0	0	0
Kleibergen-Paap rk LM statistic (underidentification)	2618.625	4237.162	6427.929	6984.596
Chi-sq(1) P-val	0	0	0	0
Cragg-Donald Wald F statistic (weak identification)	2.40E+005	5.70E+004	1.90E+005	1.20E+005
Kleibergen-Paap rk Wald F statistic	1.60E+004	7952.675	2.50E+004	2.60E+004
Instrument	EU Imports	EU Imports	EU Imports	EU Imports

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

NB: Industry, State, and Year fixed effected included in all models; Observations rounded to protect confidentiality.

These results correspond to Table 7.

Endnotes:

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[i] Other models of task trade effects on labor markets include: an extension of the Grossman and Rossi-Hansberg model that investigates the job destruction and creation effects of offshoring by relaxing full-employment conditions (Kohler & Wrona, 2011) and finds that jobs are destroyed as offshoring occurs, but the productivity effect can compensate for the job destruction effect in the long term under certain conditions; an update of the basic Heckscher-Ohlin framework that conceptualizes offshoring as 'shadow migration' of endowments, finding that Stolper-Samuelson predictions hold for the home country, implying that in countries like the US, inequality in the wages paid to skilled- and unskilled labor should rise with increased offshoring; and offshoring within a monopolistic competition framework (e.g., Robert-Nicoud, 2008; Grossman and Rossi-Hansberg 2012).

[ii] The model Grossman and Rossi-Hansberg (2006) develop is agnostic as to what actually makes a task vulnerable to offshoring or not (e.g., p. 13), but their discussion of tasks tends towards the routine/nonroutine division. (e.g., p. 10-11).

[iii] To construct the imports and exports, we use a crosswalk developed by Pierce and Schott (2012) to translate the product level information (10-digit Harmonized System (HS) codes) into the manufacturing industries that produce those products. The Pierce and Schott crosswalk translates HS product codes to North American Industry Classification System (NAICS) industry codes. To enable matching with the Decennial and ACS data, we further aggregate the NAICS industries (over 450 codes in the manufacturing sector) into Census Bureau industry codes (roughly 72 codes in manufacturing), which are the industry codes assigned to people with work experience in the demographic Censuses and Surveys collected by the US Census Bureau. CMF shipments data are similarly constructed and aggregated.

[iv] See the World Bank's Atlas methodology documentation for more details on how this was calculated: http://data.worldbank.org/indicator/NY.GNP.PCAP.CD.

[v] See Appendix A for the list of low-wage countries.

[vi] O*NET Resource Center: http://www.onetcenter.org/; O*NET Revision 14

[vii] In an interesting alternative approach, Becker et al. (2013) (and following them, Baumgarten et al. 2013) base their measures of the intensity of the tasks "non-routine" and "interactive" using the *tools* commonly deployed in each occupation.