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Trading away what kind of jobs? Globalization, trade and tasks in the US economy

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Abstract Economists and other social scientists are calling for a reassessment of the impact of international trade on labor markets in developed and developing countries. Classical models of globalization and trade, based upon the international exchange of finished goods, fail to capture the fragmentation of much commodity production and the geographical separation of individual production tasks. This fragmentation, captured in the growing volume of intra-industry trade, prompts investigation of the effects of trade within, rather than between, sectors of the economy. In this paper we examine the relationship between international trade and the task structure of US employment. We link disaggregate US trade data from 1972 to 2006, the NBER manufacturing database, the Decennial Census, and occupational and task data from the Dictionary of Occupational Titles. Within-industry shifts in task characteristics are linked to import competition and technological change. Our results suggest that trade has played a major role in the growth in relative demand for nonroutine tasks, particularly those requiring high levels of interpersonal interaction.

Keywords Offshoring · Task trade · Labor markets · Globalization

JEL Classification F16 · J21 · L23

1 Introduction

Between 1970 and 2005, the value of US merchandise imports has grown far more rapidly than domestic output. These imports increasingly originate in the developing

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world. Indeed, over the last thirty years, the share of total US imports from developing economies increased from 8% to nearly 40%.[1] These trends signify a historic change, with profound implications for the nature of work and welfare (Baldwin 2006; Blinder 2006; Grossman and Rossi-Hansberg 2006). It is not merely that imports from developing countries have increased in magnitude, nor that they increasingly comprise manufactured goods and services rather than primary products, but rather that the nature of global integration is itself being transformed.

Earlier waves of globalization were characterized by growth in the international exchange of final products, whether port for wheat, or automobiles for apparel. Reductions in trade costs, and in particular the cost of physical transportation, led to new possibilities for the spatial separation of consumers and producers. In contrast, recent declines in trade costs, largely enabled by new information technologies, have stimulated the 'unbundling' not simply of production and consumption, but of fine-grained activities within industrial sectors (Jones and Kierzkowski 1990; Baldwin 2006). No longer is comparative advantage determined at the level of final goods or whole industries, as it was in the days of Ricardo, or even Heckscher and Ohlin. Today, because agents can interact and share information effectively over great distances, comparative advantage operates at the level of individual tasks (Grossman and Rossi-Hansberg 2006). The result has been the offshoring of an increasingly large range of design, production and service activities.

A number of new models describe this process of 'task trade' (Baldwin and Robert-Nicoud 2007; Grossman and Rossi-Hansberg 2008; Kohler 2008; Robert-Nicoud 2008). Though approaches differ, a common theme is that delocalization of tasks reduces production costs and generates gains resembling those won by advances in production technology. Moreover, the effects of task trade, like the impact of technological change, may be biased toward a particular subset of the labor force, generating negative Stolper–Samuelson dynamics for local workers whose labor comprises the tasks most readily offshored to developing economies, where wages are lower.

Many scholars believe that offshoring will replace physical and intellectual tasks that can easily be routinized and rendered in blueprints (Leamer and Storper 2001; Grossman and Rossi-Hansberg 2006). For others, the key distinction between tradable and nontradable tasks is the related idea of interpersonal interaction (Blinder 2007; Blinder and Krueger 2009). Currently, we do not know the extent to which nonroutine analytical, physical and interactive task categories disturb familiar distinctions, such as white/blue collar and high/low skill, that have traditionally been employed to understand the form and the impact of international trade (Markusen 2005; Baldwin 2006). What we do know is that the task structure of work in many advanced, industrialized economies has made a pronounced shift toward nonroutine interactive and analytical activity, and away from routine cognitive and manual labor (Autor et al. 2003; Spitz-Oener 2006; Goos and Manning 2007). Labor economists describe this shift using data on occupations and their constituent tasks, and argue that skill-biased technological change, and in

[1] Authors' calculations from US import data available from the Center for International Data at UC Davis.

particular computerization, explains changes in task content. However, task trade with developing economies might equally be responsible for the structural transformation of labor markets in developed economies (Levy and Murnane 2004).

The purpose of this paper is to determine whether rising import competition from developing countries is associated with changes in the task structure of the US economy between 1970 and 2005. To examine this relationship, we build a data set that describes trade flows, industries, workers and the tasks that comprise their occupations. Specifically, we combine disaggregated US import data with the NBER-CES productivity database that includes various industry-specific variables, that are then linked to sector-specific measures of the share of nonroutine tasks. We use a measure of computer investment in manufacturing sectors to represent technological change. To describe the structure of tasks by industry, we merge selected task characteristics from the Dictionary of Occupational Titles (DOT) with workers on the basis of their industry and occupation in the Decennial Census (1970–2000) and the American Community Survey (2005–2007). Due to the limitations of both the trade and industry data, we measure the relationship between trade and tasks for manufacturing industries only, and exclude the international exchange of services.[2]

Our results show that import competition from less developed economies is associated with sector-specific increases in the demand for nonroutine tasks. The direction of the relationship between trade and task structure resembles that of technological change, in keeping with theoretical expectations. Computer investment in manufacturing, our proxy for skill-biased technological change, has no significant relationship with nonroutine task shares. When we disaggregate our indicator of nonroutine tasks into its constituent components, we find that imports from developing countries are positively and significantly related to the growth of interpersonal and analytical tasks throughout the US economy, but inversely related to changes in demand for nonroutine manual labor.

The remainder of this paper is organized in four sections. Section 2 reviews the literature on task trade, location and labor markets. Section 3 outlines our empirical strategy, including sources of data, variable construction and estimation concerns. Section 4 provides results from a series of statistical models. We conclude in Sect. 5.

2 Task trade, location and labor demand: a review of the literature

The canonical Heckscher–Ohlin model of international trade predicts that economies will specialize and trade in sectors or goods that intensively use abundant local factors of production. This results in a pattern of trade in which advanced economies specialize in the production of commodities that require high levels of skill, exchanging those goods for commodities from developing countries whose

[2] Trade in services is an area of growing importance. US service imports have nearly tripled since 1992, and they accounted for 15% of total imports in 2005 (Bureau of Economic Affairs 2010). Though their exclusion may affect overall results, data on service trade remain far too aggregate at this time for the kind of analytical approach pursued here.

production requires relatively little skilled labor. In aggregate, there are clear gains from this exchange. However, trade generates winners and losers in each economy. As a result of factor-price equalization, high-skilled workers in advanced economies gain from trade, while their low-skill colleagues lose. The reverse should be true in developing economies.

In the 1990s, many scholars considered that expansion in world trade might explain the observed rise in earnings inequality within the United States and other developed economies. They used two main empirical approaches to examine this relationship. First, factor-content studies sought to delineate the factors of production embodied in trade flows and thus the impact of substituting imports for domestic production (Borjas et al. 1992; Sachs et al. 1994; Wood 1994; Lawrence 2008). Second, direct tests of the Stolper–Samuelson theorem analyzed trade flows and changes in the relative prices of commodities produced with varying inputs of high- and low-skill labor (Lawrence et al. 1993; Leamer 1996; Baldwin and Cain 2000). Neither approach demonstrated that trade was a major determinant of the increased earnings inequality observed in developed economies. Instead, most scholars agreed that the primary determinant of rising wage inequality was skill-biased technological change. That is, the increased penetration of computers and other technologies into the economy has raised the productivity and wages of workers with high levels of human capital, while having little impact on the wages of less-skilled workers (Freeman 1995; Haskel and Slaughter 2001, 2002).

Failure to find a strong link between trade and wages may not point to the absence of a relationship as much as to an outdated conception of the workings of the global economy (Krugman 2008; Feenstra 2008). Classical trade models implicitly assume that reductions in international trade costs—a combination of tariffs, transportation, and other costs of transacting across space—rendered sensible the geographical separation of producers and consumers. The result of this process ought to be national specialization in a subset of industries, and labor market impacts that vary *between* sectors according to industry-specific requirements for workers of different skills. But what if recent declines in trade costs, due more to fiber-optics networks than to cheap shipping, have now enabled the widespread separation of tasks *within* sectors of the economy?

Theoretical models that account for the growth of offshoring or task trade have proliferated in recent years. Feenstra and Hanson (1996, 2001) consider a scenario in which offshoring is motivated by international competition in industries producing heterogeneous inputs subject to differences in the relative demand for unskilled and skilled labor. Yeaple (2005) introduces a model of heterogeneous firms and workers where international competition spurs more productive firms to enter the export market, in turn raising the demand for skilled labor and thus shifting relative wages. In a similar framework, Verhoogen (2008) describes a situation whereby incentives to trade induce product-quality upgrades, increasing the demand for skilled workers and their wages. Acemoglu (2003) and Ekholm and Midelfart (2005) argue that trade liberalization may increase wage inequality through skill-biased process innovation. Grossman and Rossi-Hansberg (2008) develop an explicit model of task-trade where reductions in trade costs (mostly advances in communications) lead to increased offshoring of routine production operations. For them, foreign production reduces overall costs and affects wages through changes in the terms of trade, labor supply conditions and productivity shocks. All these models suggest the influence of trade upon wages is likely to be felt within industries as much as between them. A new round of empirical research has begun to examine these claims.

Trade in intermediates and tasks is difficult to measure accurately, but it appears to be significant and rapidly growing (Feenstra and Hanson 2001; Baldwin 2006; Blinder 2006; Grossman and Rossi-Hansberg 2006; Venables 2009). Fully 50% of the rapid growth in merchandise trade between 1962 and 1999 can be attributed to national specialization in subsets of manufacturing production (Yi 2003). Moreover, the import share of total inputs into US manufacturing more than doubled between 1972 and 2000 (Grossman and Rossi-Hansberg 2006). Imports of 'Other Private Services,' a category that includes business and professional services, have grown fivefold since 1992 (Bureau of Economic Affairs 2009). This new spatial separation between subsets of manufacturing and service activities suggests that the locus of comparative advantage is shifting from industries and finished goods to more fine-grained subsets of activity.

Many scholars believe that task trade will result in far-reaching changes in the spatial division of labor (Baldwin 2006; Blinder 2006; Grossman and Rossi-Hansberg 2008). These changes might challenge our reliance on familiar distinctions between high- and low-skill, or blue- and white-collar workers (Markusen 2005; Baldwin 2006; Ekholm and Ulltveit-Moe 2007). Baldwin (2006) posits that, while trade costs relate predictably to the size and weight of physical goods, their operational logic with respect to tasks is more uneven, which makes it harder to predict which tasks will be footloose and which will remain placebound. One central distinction has emerged in the literature as defining the tasks that can and cannot be offshored. Tasks that demand significant interpersonal interaction or complex problem solving, together referred to as nonroutine cognitive tasks, are considered to be placebound, while tradable tasks are those characterized by routine, codifiable work conducted through stable and predictable markets (Bardhan and Kroll 2003; Levy and Murnane 2004; Storper and Venables 2004; Blinder 2006; Leamer 2007; Storper 2009).

In fact, labor economists have already shown that the task structure of several advanced economies has shifted from an emphasis on routine to nonroutine tasks (Autor et al. 2003; Spitz-Oener 2006; Goos and Manning 2007). These authors believe that a kind of task-biased technological change lies behind these changes, but trade, and in particular trade with developing countries, could conceivably push in the same direction. Several researchers have recently explored this idea empirically. Blinder (2007), and Jensen and Kletzer (2007) use occupational data to estimate the number and type of US jobs that might be tradable. Others more directly measure the current relationship between offshoring and onshore task structure. Ebenstein et al. (2009) match occupational data with the Current Population Survey (CPS) to show that the wages of domestic workers performing nonroutine tasks in US multinational enterprises (MNEs) are less affected by trade with subsidiaries in developing economies than the wages of workers that perform routine tasks. Similarly, Becker et al. (2008) use microdata on workers and trade in

German MNEs to show that the ratio of nonroutine-to-routine workers increases through related-party trade with developing economies. Mion et al. (2010) explore, more generally, the impact of trade with less developed economies on skill upgrading within Belgian industries and firms. In similar fashion, Bustos (2007) shows how trade-induced technical change promotes skill upgrading in a panel of Argentinian manufacturing firms.

We extend this work by examining how increased trade with less developed economies is related to the growth in sector-specific demand for nonroutine tasks within the US economy, controlling for shifts in technology and other covariates. Unlike a number of the papers above, we look beyond the decisions of multinational corporations to consider the broader impact of import competition on task structure, because we expect that much trade in tasks consists of arms-length relationships.

3 Empirical strategy

We seek to measure the extent to which rising import competition from developing economies is associated with changes in the task structure of industries in the US manufacturing sector between 1970 and 2006. We assume that commodity imports from developing countries embody routine physical and intellectual labor that displaces jobs in the US that exhibit the same task characteristics. To model this relationship, we adapt a specification that has been frequently employed in the literature, notably by Berman et al. (1994) and Feenstra and Hanson (1996). Where those papers analyze changes in the sector-specific share of white-collar wages in the total industry wage bill, we predict the share of nonroutine tasks in an industry's overall task structure as follows:

$$\theta_{it}^{NR} = f(S_{it}, K_{it}, X_{it}, C_{it}) \tag{1}$$

where θ_{it}^{NR} represents the share of nonroutine tasks in the total tasks of industry i at time t, S measures gross output, K denotes capital intensity, X represents the state of technology, and C provides a measure of import competition.

3.1 Data

In order to explore the relationship set out in Eq. 1, we need industry-specific data on US imports, technological change and other characteristics. We also require a sector-specific measure of the structure of tasks. Our merchandise trade data originate with import and export statistics collected annually by the Foreign Trade Division of the US Census Bureau. These highly disaggregated, product-level data have been compiled and matched with various industrial classification systems (including the Standard Industrial Classification [SIC], and North American Industry Classification System [NAICS]) by Feenstra et al. (2002), and are available from the National Bureau of Economic Research.

Our primary industry data are taken from the NBER-CES Manufacturing Industry Database that spans from 1958 to 2005. This data set contains annual information at the level of 459 4-digit (SIC) manufacturing sectors on a host of variables, including shipments, capital stocks and total factor productivity. To measure technological change, we complement our main industry data set with an indicator of spending on "computers and peripheral data processing equipment", taken from Census of Manufactures. To account for differences in industry size, we divide computer equipment spending by total capital investments for each 4-digit (SIC) industry. As a check on the robustness of our findings, we use total factor productivity as an alternative measure of technology in some specifications.

Unfortunately, the NBER-CES data offer limited information regarding each sector's workforce, providing only employment and wage data for production and non-production workers. We therefore match industry and trade data to individual worker characteristics using Census Integrated Public Use Microdata Series extracts of the Decennial Household Census (Decennial) for the years 1970, 1980, 1990 and 2000, and the American Community Survey (ACS) for 2005–2007 (Ruggles et al. 2010). For the year 1970, we use the one-in-100 Metro sample. We use 5% extracts for the years 1980, 1990 and 2000, and the 3% sample of the ACS. This linkage reduces the number of time periods available for analysis to five, while also diminishing the granularity of our industries to approximately 82 Census manufacturing sectors. We focus on non-institutionally employed individuals between the ages of 18 and 65, who work full-time over the entire year.[3]

To describe the task characteristics of labor, we use data from the 1991 Revised Fourth Edition of the Dictionary of Occupational Titles (DOT).[4] The DOT evaluates over 12,000 distinct occupations along objective and subjective criteria. From a total of 44 occupational characteristics, we select those that reveal the intensity with which a specific job demands nonroutine interpersonal interactivity, nonroutine analytics, nonroutine manual activity, routine manual, or routine cognitive tasks. DCP, our chosen measure for nonroutine interactive tasks, refers to activities in which a "worker is in a position to negotiate, organize, direct, supervise, formulate practices, or make final decisions...negotiating with individuals and groups" (US Department of Labor 1991, 10-1). GED-MATH, describing nonroutine analytic tasks, measures general educational development in mathematics, and ranges from basic addition and subtraction to the application of advanced calculus. EHF, our measure for nonroutine manual tasks, indicates physical coordination. STS measures routine cognitive tasks, and involves "complying with precise instruments and specifications for materials, methods, procedures and techniques to attain specified standards" (US Department of Labor, 1991, 10-4). FINGDEX indicates routine manual work.

[3] Fulltime work is defined as at least 35 hours each week on average. We define full year employment to mean at least 48 weeks each year.

[4] In 1998, the DOT was replaced by the Occupational Information Network, or O*Net. O*Net represents not simply an update but a change in general approach, responding to criticisms ranging from excessive focus on tasks, measurement problems, and inadequate focus on nonmanufacturing industries. For the purpose of this particular project however, task emphasis and a manufacturing focus are less problematic. Moreover, O*Net is not appropriate to the kind of time series analysis performed in this investigation. For a fuller discussion of the strengths and weaknesses of DOT, see Cain and Treiman (1981) and Peterson et al. (2001).

These are the same variables used by Autor et al. (2003) in their study of the task structure of US employment. Using data provided by the authors, we link DOT data to Census workers, in order to describe changing task requirements. Workers in our selected Decennial extracts receive task means for each of the five task categories listed in Table 1, on the basis of their occupational classification. These task means vary continuously on a scale of 0 to 10, with 10 indicating that a given occupation makes comparatively intensive use of a given task characteristic. Hence, an occupation scoring a 10 on the DCP metric would involve significantly more nonroutine interpersonal tasks than another occupation scoring 3 on the same scale. Because we cannot directly observe individual Census respondents at their workplaces, we assume that workers in the same occupation have the same distribution of task intensities. Moreover, because we use the Fourth Revised Edition of the DOT, we do not exploit intertemporal change within occupations. Lawyers practicing in 1970 and 2006, for example, are presumed to engage in the selected task types with an intensity that does not vary over time.

3.2 Variable construction

To construct θ_{it}^{NR}, our time- and sector-specific measure of the share of nonroutine tasks in total tasks, we assign survey-weighted manufacturing workers in each Decennial extract, as well as their individual task values, to a maximum of 82 Census industries. For each industry, we construct task shares as follows:

$$\theta_{it}^{NR} = \frac{\sum task_{it}^{nr}}{(\sum task_{it}^{r})}$$

where r is the set of all routine and nonroutine tasks and nr is a subset of r that identifies specifically nonroutine tasks. We build several variations of θ_{it}^{NR} that account for a few key combinations of nonroutine task types: nonroutine tasks overall (DCP, GED-MATH and EHF), nonroutine interactive tasks (DCP), and nonroutine analytic tasks (GED-MATH). These measures represent dependent variables in different models, permitting us to estimate the impact of trade on the sector-specific share of various types of nonroutine tasks.

We use a simple measure of trade competition within each industry, taking the ratio of the value of imports from developing countries to the value of shipments. We focus on developing economies because it is these countries that are thought to provide the most likely substitutes for routine tradable tasks. Less-developed

Table 1 Selected task variables from the dictionary of occupational titles, Rev. 4

Task type	Name	Description
Interactive	DCP	Direction, control, and planning
Nonroutine analytic	GED-MATH	General educational development in mathematics
Nonroutine manual	EHF	Eye-hand-foot coordination
Routine cognitive	STS	Sets limits, tolerances or standards
Routine manual	FINGDEX	Manual dexterity

countries are defined in our analysis as those that the World Bank categorizes as belonging to 'Lower' and 'Lower-Middle' income groups in 1987, the midpoint in our analysis. Import competition is measured as:

$$C_{it} = \frac{LDCimports_{it}}{shipments_{it}}$$

We prefer this measure over an indicator of import penetration of the domestic market, such as $\frac{imports}{shipments + exports - imports}$ because it is more clearly related to the substitution of foreign production and employment for US production and employment. Note, however, that our results are broadly consistent across both measures.

3.3 Descriptive results

Figure 1 shows changes in the general task structure of the US manufacturing sector between 1970 and 2005. Industry-specific values of nonroutine and routine task shares are weighted by industry employment to yield aggregate statistics for the manufacturing sector as a whole. The figure illustrates that demand for nonroutine tasks has increased steadily since 1970, while demand for routine manual and cognitive tasks has declined over this same period. These results broadly conform to those presented in Autor et al. (2003).

Figure 2 describes changes in our key variables across all manufacturing industries since the early 1970s. The ratio of overall manufactured imports to US manufacturing output nearly doubled over this period, increasing from 11% in 1972 to 19% by 2005. The most visible trend on the figure is the expansion of imports from developing countries. Between 1972 and 2005, the annual average compound growth rate of imports from less developed economies was 16%, significantly higher than the annual growth rate of imports from developed economies at 9.5%.

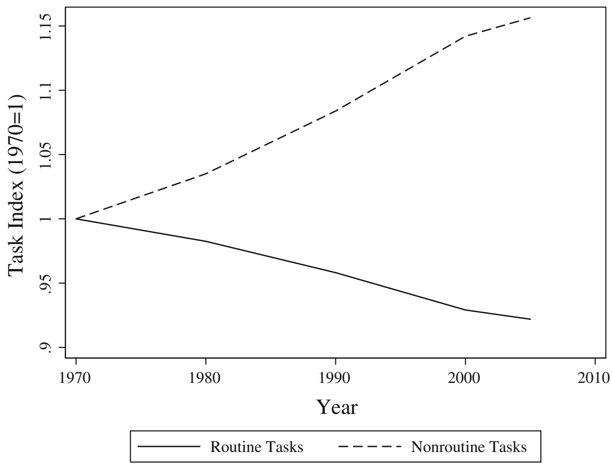

Fig. 1 Changes in the composition of tasks in the US economy, 1970–2005

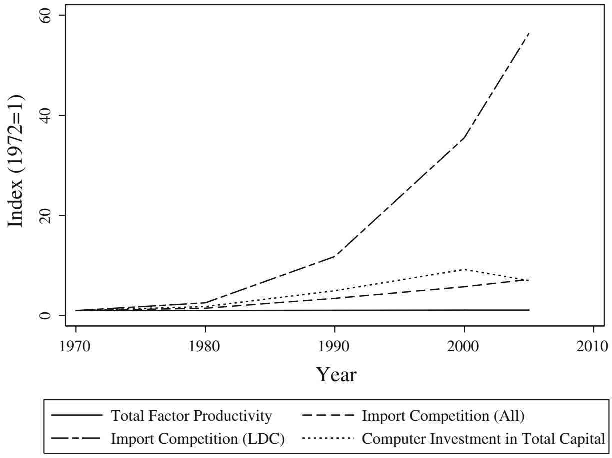

Fig. 2 Growth of computer investment, TFP, and import competition, 1972–2005

Computer investment as a share of total capital investment increased at an annual average compound growth rate of 9% from 1977 to 2000, declining slightly thereafter. Growth in total factor productivity has been quite modest as compared with the changes in import competition and spending on computer and data processing equipment.

3.4 Estimation

To estimate Eq. 1, we address a series of issues. First, we must be concerned with potential unobserved factors that might influence the nonroutine task share and that might be correlated with one or more of our independent variables. These unobserved factors are captured in the composite disturbance term ε_{it} shown in Eq. 2:

$$\theta_{it}^{NR} = S_{it} + K_{it} + X_{it} + C_{it} + \varepsilon_{it} \tag{2}$$

where $\varepsilon_{it} = \mu_i + \eta_t + v_{it}$, such that μ_i represents an industry fixed effect, η_t represents unobserved time-specific shocks that exert uniform impacts across all sectors, and v_{it} is a disturbance term that is assumed to possess the usual properties. Ordinary least squares (OLS) parameter estimates of Eq. 2 are biased and inconsistent in the presence of unobserved variables that are correlated with the observed independent variables. Unobserved industry-specific effects that are stationary over time can be removed from Eq. 2 in a panel model by using the within-groups or fixed effects estimator. We can additionally address common period-specific shocks by adding time fixed effects in the form of dummy variables.

We must also consider the possibility that there is endogeneity in our model as a result of reverse causality. Industry output, capital intensity and technological change might be influenced by the changing structure of employment within an industry, and shifts in the nature of jobs might induce changes in offshoring strategies. To address this concern, we employ instrumental variables techniques. Unfortunately, we do not have a readily available set of instruments with the desired characteristics, so we use one-period lags of our independent variables in Eq. 2 as instruments.

4 Results

Table 2 shows the results of estimating Eq. 2 using different techniques. Note that all continuously valued variables in our analysis are logged, including the dependent variable. In column 1 of Table 2, we present results from a cross-sectional model where the data are pooled across industries and years. Huber–White heteroscedasticity-corrected standard errors are reported in parentheses for the pooled cross-section and fixed effects results. Industry shipments and capital intensity are positively related to the nonroutine share of tasks in US manufacturing, and the coefficients on these variables are statistically significant at the 0.01 level. The coefficient on import competition is negative and significant, running counter to theoretical expectations. There is no significant relationship between computer investment and the relative demand for nonroutine tasks in this model.

Table 2 Import competition, technology and nonroutine tasks

	Pooled cross-section (1)	FE (2)	FE-IV (GMM2S) (3)
Shipments	0.0218*** (0.0070)	0.0141 (0.0154)	0.0345** (0.0137)
Capital	0.0532*** (0.0185)	0.0837*** (0.0225)	0.0967*** (0.0214)
Computer investment	−0.0150 (0.0097)	−0.0034 (0.0063)	0.0051 (0.0052)
Imports	−0.0162*** (0.0038)	0.0050 (0.0049)	0.0199*** (0.0074)
Year dummies	Yes	Yes	Yes
Industry dummies	Yes		
K-P underidentification			16.399 (0.0025)
K-P weak identification			12.42
Hansen J			1.109 (0.7749)
Adjusted R^2	0.2093		
No. of observations	358	358	271
No. of industries	81	81	76

All variables are logged. The dependent variable in each model is the sector-specific share of nonroutine tasks. **, *** indicate significance at the 5 and 1% level respectively. Robust standard errors are shown in parentheses. For the pooled cross-section and fixed effect (FE) models, those are the Huber–White heteroscedasticity robust standard errors. For the GMM2S model, coefficients are estimated using two-stage generalized methods of moments techniques with the Bartlett kernel function employed to yield a consistent covariance matrix. Standard errors are thus robust to heteroscedasticity and autocorrelation. K-P (Kleibergen–Paap) is the LM statistic testing for underidentification, with the associated *p*-value in parentheses. The Kleibergen–Paap *F*-statistic for weak identification is also shown. Hansen J is the overidentification test for all instruments with its associated *p*-value in parentheses. A Hausman test indicates that our measure of import competition is endogenous. The full set of instruments comprises one-period lagged values of all independent variables. We remove instruments that appear weak in first-stage regressions, those that have no significant relationship with the endogenous variable

The estimates in column 1 of Table 2 do not account for unobserved effects or endogenous regressors. We address the first of these problems by taking advantage of the panel structure of our data and estimating a fixed effects (within-group) model. The results from the fixed effects (FE) estimation are shown in column 2. Diagnostics from the FE model reveal that most of the variation in the dependent variable is related to between-industry differences in the relative demand for nonroutine tasks. Indeed, an *F*-test indicates that there are significant industry-level fixed effects, and thus that pooled-OLS likely yields inconsistent estimates. The results in column 2 show that capital intensity is positive and significantly related to nonroutineness. All other independent variables have partial regression coefficients (elasticities) that are not significantly different from zero.

Column 3 of Table 2 reports results from using instrumental variables techniques. We employ a generalized methods of moments (GMM) estimator along with the Bartlett kernel function that has the added benefit of making our standard errors robust to autocorrelation as well as heteroscedasticity. The GMM estimates are more efficient than those produced by the standard instrumental variables estimator (Baum et al. 2007). Our instruments comprise lagged values of the independent variables. A Hausman test indicates that only our measure of import competition is endogenous. Additional diagnostics indicate that we do not suffer from underidentification problems and that our instruments are not weak: they yield an *F*-value greater than 10 in first-stage regressions. Finally, the Hansen statistic for overidentification does not reject the hypothesis that our instruments are exogenous. The results from column 3 show that the nonroutine share of tasks in US manufacturing is positively and significantly related to import competition from less developed economies, to shipments and to capital intensity. There is no significant relationship between computer use and the nonroutine task share.

In Table 3 we turn to the individual components of the nonroutine task share, examining how trade with low wage countries is related to the relative demand for nonroutine interactive, analytical, and manual tasks. In all models we use the same set of lagged variables as instruments for import competition from less developed economies. The standard diagnostic tests indicate that these instruments perform relatively well. Import competition from low wage developing economies is significantly and positively associated with greater relative demand for nonroutine interactive and analytic tasks. Note that the elasticity on the model for the interactive task share is almost five times larger than that for the nonroutine analytical share. We take this to suggest that workers that intensively engage in activities rich in interpersonal interaction and supervision occupy jobs that are considerably more placebound than those whose jobs are focused on analytical tasks. The sign on import competition is negative for nonroutine manual tasks. This type of nonroutine employment appears susceptible to offshoring to developing economies. The results in Table 3 indicate that computer adoption in manufacturing has the anticipated positive sign with nonroutine task shares, but it is insignificant. Interactive and analytical task shares are positive and significantly related to capital intensity. This likely captures the substitution of capital for routine work in many sectors of the economy. Finally, the share of routine manual tasks is negatively related to industry output.

Table 3 Import competition, technological change and nonroutine task types

	DCP share (nonroutine interactive) (1)	MATH share (nonroutine analytic) (2)	EHF share (nonroutine manual) (3)
Shipments	0.0409 (0.0401)	0.0108 (0.0154)	−0.0946** (0.0406)
Capital	0.1325** (0.0585)	0.0798*** (0.0208)	−0.1007 (0.0649)
Computer investment	0.0122 (0.0156)	0.0071 (0.0056)	0.0090 (0.0120)
Imports	0.0740*** (0.0243)	0.0152* (0.0085)	−0.0235*** (0.0088)
Year dummies	Yes	Yes	Yes
K-P underidentification	16.380 (0.0009)	14.799 (0.0006)	25.667 (0.0000)
K-P weak identification	16.669	21.903	23.566
Hansen J	3.472 (0.1763)	0.366 (0.5452)	3.261 (0.3502)
No. of observations	271	271	271
No. of industries	76	76	76

Each column title indicates the dependent variable used in each model. All models are estimated using GMM2S. *, **, *** indicate significance at the 10, 5 and 1% level respectively. See the notes to Table 2 for more details

In Table 4 we provide a check on the robustness of our results. As an alternative proxy for technology, we replace our measure of computer investment with total factor productivity, and re-estimate our model predicting the relative importance of nonroutine tasks (similar to column 3 of Table 2). Table 4 confirms the importance of the relationship between import competition from low wage countries and the task structure of work in the US economy. Imports from developing countries remain positively and significantly associated with the sector-specific share of nonroutine tasks. Total factor productivity is not significantly related to nonroutine tasks shares within manufacturing sectors.

As a further robustness check, we also employed a different set of instruments in place of our lagged independent variables. For each industry measures of exports, inventories, energy consumption and total investment provided an alternative set of instruments. We do not report these findings here, as these alternative instruments do not materially change the shape of the main relationships reported above.

Table 4 Import competition, total factor productivity and nonroutine tasks

	FE-IV (GMM2S)
Shipments	0.0278** (0.0169)
Capital	0.0866*** (0.0233)
Total factor productivity	−0.0267 (0.0481)
Imports	0.0211** (0.0092)
Year dummies	Yes
K-P underidentification	15.002 (0.0006)
K-P weak identification	12.623
Hansen J	1.006 (0.3158)
No. of observations	291
No. of industries	79

The dependent variable is the sector-specific share of nonroutine tasks. This model is estimated using GMM2S. *, **, *** indicate significance at the 10, 5 and 1% level respectively. See the notes to Table 2 for more details

5 Conclusion

New communication technologies are enabling a new global spatial division of labor. International trade was once dominated by flows of final commodities largely conceived and produced in a single nation, but trade today is increasingly characterized by the breakup of the production process across many countries. The increased fragmentation of production and its coordination over space and time open new possibilities for the separation of different production tasks. Precisely where various tasks will be concentrated in the global economy, and how the geography of task trade will shape demand for labor of different quality, and for other factors of production, remain open questions. These same possibilities raise questions about the winners and losers from this growing trade in tasks.

In this paper we explore the connection between the growth of nonroutine tasks in the US manufacturing sector and the rapid rise of imports from low-wage developing economies. Using fixed effect panel methods and instrumental variables to control for unobserved heterogeneity and potential endogeneity, we find that import competition from less developed economies exerts a positive and significant influence upon the relative demand for nonroutine activities. Growth in US imports is associated with a shift in workforce composition toward jobs that require nonroutine tasks, and away from those that are oriented toward routine activities. We find that import competition has a particularly strong positive effect on the demand for workers whose jobs require complex interpersonal interaction.

The impact of import competition remains strong after controlling for a series of covariates, including different measures of technological change. Total factor productivity and computer use in manufacturing do not exert a significant influence on within-industry growth in nonroutine tasks in models that include import competition from low-wage countries. There is little question that the influence of technology and trade on the nature of manufacturing work in advanced economies, are not strictly independent. However, the results presented here suggest that trade plays a critical role in that relationship. These results cast further doubt on claims that globalization and trade have only a minor impact on labor markets in the developed world.

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