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Trading Away What Kind of Jobs? Globalization, Trade and Tasks in the U.S. Economy

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Trading away what kind of jobs? Globalization, trade and tasks in the U.S. economy

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Abstract

Economists and geographers are calling for a reassessment of the impact of international trade on labor markets in developed and developing countries. There is growing recognition that 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. The growing volume of intra-industry trade signals a remapping of the spatial division of labor that challenges existing industry-based accounts and calls for investigation of the impacts of trade within, rather than between, sectors of the economy. In this paper we investigate the extent to which international trade stimulates within-industry changes in the task structure of U.S. employment. We link highly detailed U.S. trade data from 1972 to 2006, to the NBER manufacturing database, to the Decennial Census, and to occupational and task data from the Dictionary of Occupational Titles. After accounting for the effect of technological change, we find that trade stimulates greater relative demand for nonroutine tasks, particularly those requiring high levels of interpersonal interaction. Unlike most previous studies, we find that the impact of trade on the nature of work is substantially larger than the impact of new technology.

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1 Introduction

Between 1970 and 2005, the value of commodity imports into the United States has grown far more rapidly than domestic output. These import flows increasingly originate in the developing world. Indeed, over approximately the last thirty years, the share of total U.S. imports from developing economies increased from 8% to nearly 40%. These developments signify an historic change, with profound implications for the nature of work and welfare (Blinder, 2006; Baldwin, 2006; Grossman and Rossi-Hansberg, 2006). It is not merely that imports from developing countries have increased in magnitude, or that they increasingly comprise manufactured goods and services rather than primary products, but that the nature of global integration is itself being transformed. Earlier waves of globalization were characterized by the intensified 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. By contrast, recent declines in trade costs, due especially to new possibilities for coordination enabled by information technology, have stimulated the 'unbundling' not simply of production and consumption, but of fine-grained tasks within industrial sectors (Jones and Kierzkowski, 1990; Baldwin, 2006). No longer does comparative advantage operate at the level of whole industries, as it did in the days of Ricardo, or even Heckscher and Ohlin. Today, instead, it functions at the level of individual tasks (Grossman and Rossi-Hansberg, 2006). Agents can now seize upon factor cost arbitrage at a new level of granularity as they are able to effectively interact and share information over greater distances, making practical the offshoring of an increasingly large range of design, production and service activities..

Scholars have generated several new models to describe this process of 'task trade' (Baldwin, 2007; Grossman and Rossi-Hansburg, 2008; Kohler, 2008; Robert-Nicoud, 2008). Though approaches differ, a common theme is that the delocalization of tasks decreases production costs, and generates gains that resemble those won by advances in production technology. Moreover, the effects of task trade, like the impact of technological change, could be biased toward a particular subset of the labor force, generating negative Stolper-Samuelson dynamics for local workers whose labor comprises those tasks that are most likely to be offshored. Task trade with developing countries could significantly reallocate labor in advanced economies toward certain kinds of tasks and away from others.

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 and Krueger, 2009; Blinder, 2007). If these scholars are correct, it remains unclear to what extent nonroutine analytical, physical and interactive tasks conform to familiar distinctions, such as white/blue collar and high/low skill, that have traditionally been used to understand the impact of international trade (Markusen, 2005; Baldwin, 2006). What we do know is that the task structure of the labor forces in many advanced, industrialized economies such as the U.S., Germany, and Britain 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 hold that skill-biased technological change, and in particular computerization, explains changes in task content. But task trade with developing economies might equally be responsible for this structural transformation of labor markets in developed economies (Autor et al., 2008).

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 U.S. economy between 1970 and 2005. To test this idea, we build a dataset that describes trade flows, industries, workers and the tasks that comprise their occupations. Specifically, we combine disaggregated U.S. import data with the NBER-CES productivity database that includes various industry-specific variables, which are then linked to sector-specific measures of the share of nonroutine tasks. 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). Linking these task structures to a vector of industry-specific characteristics and trade flows allows us to estimate the impact of sector-specific import competition. 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.

This work relates to several strands of recent empirical analysis of fragmentation, offshoring, and task trade. Feenstra and Hanson (2001) argue that the existing consensus on the relative unimportance of trade in generating wage inequality rests upon the idea that trade should reallocate work between, rather than within sectors. When they examine intra-industry reallocation, which we would expect to result from task trade, they find that trade is strongly associated with increases in wage inequality between production and non-production workers. A second group of scholars has used occupational data, either the DOT or O*Net, its successor, to determine the labor market impact of trade in tasks. For example, Blinder (2007), and Jensen and Kletzer (2007) use occupational data to estimate the number and nature of U.S. jobs that might be tradable. Others more directly measure the current relationship between offshoring and onshore task structure. For example, Becker et al. (2008), and Ebenstein et al (2009) find that offshoring within multinational enterprises is associated with the restructuring of onshore labor demand toward nonroutine tasks. Our paper adds value to these projects in several ways. First, we measure the impact of trade on task structure after accounting for the impact of technological change. Second, because we expect that much trade in tasks consists of arms-length relationships, we look beyond the locational decisions of multinational corporations to consider the broader impact of import competition on task structure. Finally, we explicitly account for potential bias in our statistical analysis, resulting from omitted variables and/or endogeneity, in order to provide robust estimates of the exogenous contribution of trade to changes in task structure.

Our findings reveal that import competition from less developed economies is significantly 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. Unlike most previous work, we find that the magnitude of the trade effect is considerably larger than the impact of technology. Disaggregating nonroutine work reveals that trade is positively related to the growth of interpersonal and analytical tasks throughout the U.S. economy, but unrelated 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 analysis of a series of statistical models. Section 5 offers a brief conclusion that summarizes our main findings and points to future research.

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 production requires relatively little skilled labor. In aggregate, there are clear gains from this exchange. However, trade generates winners and losers in each economy, and via control of the terms of trade, often between economies as well. 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 U.S. 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 (Borjas et al., 1992; Sachs et al., 1994; Wood, 1994; Lawrence, 2008). Second, scholars sought to directly test the Stolper-Samuelson theorem by examining to what extent trade induces changes in the relative prices of commodities that are intensive in high- and low-skill labor, and ultimately in the relative wages of skilled and unskilled workers (Lawrence et al., 1993; Learner, 1996; Baldwin and Cain, 2000). Neither approach has convincingly shown that trade is a significant factor driving earnings inequality in developed economies. Instead, most scholars agree that the primary determinant of rising wage inequality is 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).

The failure of studies to reveal a strong relationship between trade and wages may not point to an absent relationship as much as to an outdated conception of the workings of the global economy (Krugman, 2008; Feenstra, 2008). All trade models implicitly assume that reductions in international trade costs, a combination of tariffs, transportation, and other costs of transacting across distance, have rendered sensible the spatial separation of producers and consumers. But what if recent declines in trade costs, due more to fiber-optics networks than cheap shipping, have now enabled the widespread separation of individual tasks within sectors of the economy? Though difficult to accurately measure, existing data suggest that trade in intermediates and tasks, variously described as task trade, fragmentation, off-shoring, outsourcing, or vertical specialization, appears to be quantitatively significant and rapidly growing (Feenstra and Hanson, 2001; Blinder, 2006; Grossman and Rossi-Hansberg, 2006; Baldwin, 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 U.S. 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 five-fold 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 tasks. If this is indeed the case, estimates of the impacts of trade on labor markets must look for changes within individual sectors, rather than at between-industry shifts.

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-Hansburg, 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 means it is 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 place-bound, while tradable tasks are those characterized by routine, codifiable work conducted through stable and predictable markets (Bardhan and Kroll, 2003; Storper and Venables, 2004; Levy and Murnane, 2004; Blinder, 2006; Leamer, 2007; Storper, 2009).

In fact, labor economists have already shown that the task structure of advanced economies has shifted from an emphasis on routine to nonroutine tasks (Autor et al., 2003; Spitz-Oener, 2006; Goos and Manning, 2007). Although these authors believe that a kind of task-biased technological change lies behind these changes, trade, and in particular trade with developing countries could conceivably push in the same direction. Several researchers have recently explored this idea empirically. Ebenstein et al (2009) match occupational data with the Current Population Survey (CPS) in order to demonstrate that domestic workers performing nonroutine tasks in U.S. multinational enterprises (MNEs) find their wages less strongly affected by trade with subsidiaries in developing economies than workers that perform routine tasks. Similarly, Becker et al (2008) use micro-data on workers and trade in German MNEs to show that the ratio of nonroutine-to-routine workers in these firms increases with related-party trade with developing economies. However, neither of these papers explicitly accounts for technological change. Feenstra and Hanson (Feenstra and Hanson, 2001) do consider both trade and technological change, although they predict changes in the sector-specific wage share of nonproduction workers, a crude proxy for both skill (Forbes, 2001; Breau and Rigby, 2006), and nonroutine tasks.

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 the U.S. economy between 1970 and 2005. We assume that imports from developing countries embody routine physical and intellectual labor that displaces jobs in the U.S. 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 in time t, S measures gross output, K denotes physical 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 equation (1), we need industry-specific data on U.S. imports, technological change and other characteristics, as well as task intensities. Our merchandise trade data originate with import and export statistics collected annually by the Foreign Trade Division of the U.S. Census Bureau. This 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 annually from the National Bureau of Economic Research.

Our industry data are taken from the NBER-CES Manufacturing Industry Database that spans the period 1958 to 2005. This dataset 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. Unfortunately, these industry data have limited information regarding each sectors workforce, recording only the distribution of wages for white- and blue- collar 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 2005-07. For the year 1970, we use the one-in-100 Metro sample. We use five percent extracts for the years 1980, 1990 and 2000, and the three percent 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 Decennial manufacturing industries. Due to a lack of detailed data on service imports, we restrict our attention to the manufacturing sector. We focus on non-institutionally employed individuals between the ages of 18 and 65, who work full-time over the full year.[1]

To describe the task characteristics of labor, we use data from the 1991 Revised Fourth Edition of the Dictionary of Occupational Titles (DOT).[2] The DOT was created

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

[2]In 1998, the DOT was replaced by the Occupational Information Network, or O*Net. O*Net represents not simply an update by a change in general approach, responding to criticisms ranging from excessive e focus on tasks, measurement problems, and inadequate focus on nonmanufacturing industries. For the purpose of this particular project however, task emphasis and a manufacturing

Table 1: Selected Task Variables from the Dictionary of Occupational Titles, Rev. 4

Task Type	Name	Description
Nonroutine 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

in 1939 as a means of evaluating and placing job seekers in the newly created U.S. Employment Service. The fourth and most recent edition of the dictionary was issued by U.S. Department of Labor in 1977, and subsequently revised in 1991. To construct the DOT, occupational specialists performed over 75,000 on-site analyses of work activities. These data are supplemented by secondary research.

The DOT evaluates over 12,000 distinct occupations along objective and subjective criteria. In addition to verbal descriptions of the kinds of tasks that a particular job demands, each occupation is assigned a nine-digit code, of which six digits evaluates the job in terms of the technology used, and describes worker complexity in terms of the occupations relationship to "Data, People and Things" (U.S. Department of Labor, 1991a). DOT occupations are additionally assigned values on 44 task characteristics, which supplement the worker complexity variables present in the nine-digit identifier with various measures of Training Times, Aptitudes, Temperaments, Interests, Physical Demands, and Working Conditions.[3]

From the 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,

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).

[3]See U.S. Department of Labor (1991b) for more complete details on these subcomponents of the DOT Master File.

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 decisionsnegotiating with individuals and groups" (U.S. Department of Labor, 1991b, 10-1). Air traffic controllers as well as litigators score highly on this metric. 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. Professional athletes, firefighters and airline pilots score highest on this indicator. STS measures routine cognitive tasks, and involves "complying with precise instruments and specifications for materials, methods, procedures and techniques to attain specified standards" (U.S. Department of Labor, 1991b, 10-4). Machinists, bookbinders and mechanical engineering technicians all achieve high scores on this metric. Secretaries, dental assistants, and textile sewing machine operators score highly on FINGDEX, our indicator of routine manual work.

These measures correspond to the task characteristics used by Autor et al. (2003) in their study of the task structure of U.S. 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 receives 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 as compared with another occupation scoring a 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. In terms of the five selected task characteristics, lawyers in 1970 and 2005, for example, are assumed to operate under identical working conditions.

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 as many as 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 tasks and nr is a subset of r that identifies 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 cognitive tasks (DCP and GED-MATH), nonroutine interactive tasks (DCP), and nonroutine analytic tasks (GED-MATH). These measures represent dependent variables in various models, permitting us to estimate the impact of trade on the sector-specific share of various types of nonroutine task inputs.

We utilize a simple measure of trade competition within each industry, taking the ratio 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 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 U.S. production and employment.

3.3 Descriptive Results

Figure 1 shows changes in the general task structure of the U.S. 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 reveals that demand for nonroutine tasks has increased steadily since 1970, while demand for routine tasks, cognitive and manual, has declined over this same period. These results broadly conform to those presented in Autor et al. (2003).

Figure 2 describes changes in import competition and total factor productivity across all manufacturing industries since the early 1970s. The ratio of overall manufactured imports to U.S. manufacturing output nearly doubled over this period, increasing from 11% in 1972 to 19% by 2005. While the rate of total factor productivity growth was similar to that of import competition through the 1970s, it has lagged substantially behind since 1980. Between 1972 and 2005, the annual average compound growth rate of import competition was 11%. Annual average compound growth in total factor productivity was only 0.5% over the same period, more than an order of magnitude lower than import competition.

Figure 1: Changes in the Composition of Tasks in the U.S. Economy, 1970-2005

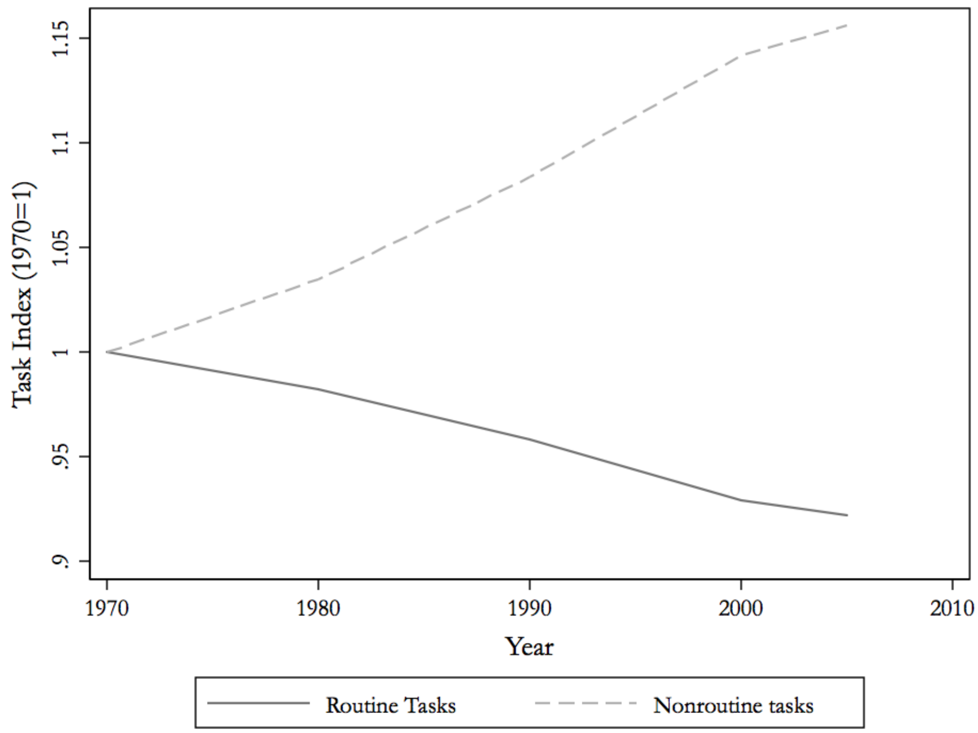
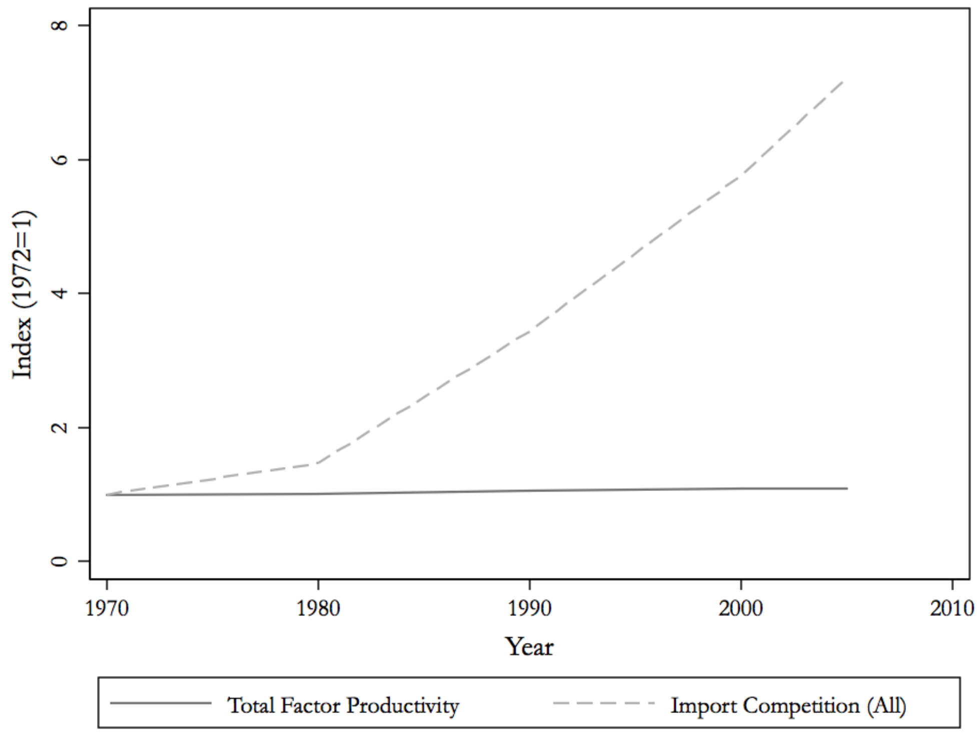


Figure 3 illustrates the rapid growth of imports into the U.S. from less developed countries (LDCs). Between 1972 and 2005, the annual average compound growth rate of imports from less developed economies was 16%, significantly higher than the annual growth rate of imports from developed economies at 9.5%.

3.4 Estimation

To adequately estimate equation (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 of more of our independent variables. These unobserved factors are captured in the composite disturbance term ε_{it} shown in

Figure 2: Growth of Total Factor Productivity and Import Competition, 1972-2005

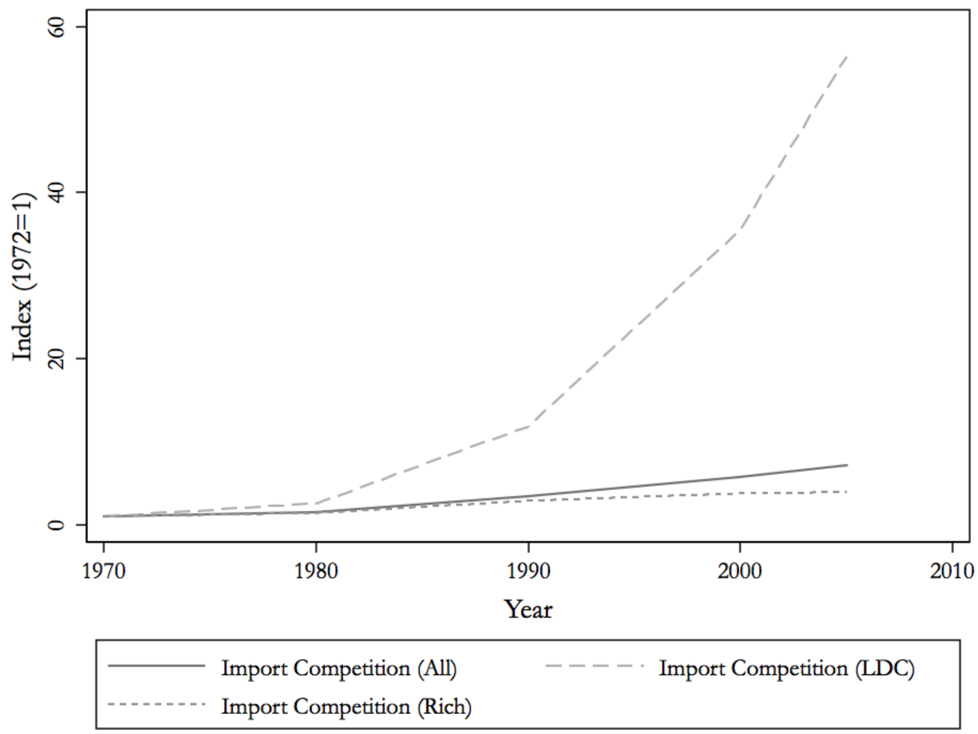


equation (2):

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

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

Figure 3: Growth of Import Competition (All, LDC, Rich), 1972-2005



A second issue that we must confront in terms of estimation is potential endogeneity in our model as a result of reverse causality. It is likely that industry output, capital investment and technological change might be influenced by the changing structure of employment within an industry, and that shifts in the nature of jobs might induce changes in offshoring strategies. Instrumental variables techniques provide the standard method to address endogeneity. Unfortunately, we do not have a readily available set of exogenous variables with the desired properties that might serve as instruments. We thus employ lagged values of the independent variables in equation (2) to serve as instruments.

Concern with the strength of these instruments leads us to make use of the system-generalized method of moments (GMM) estimator introduced by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998) for use with dynamic panel models. We do not incorporate a lagged value of the dependent variable on the right-hand side of our model and in this respect we are estimating a fixed effects model where we use GMM-style instrumental variables to represent our original independent variables. Of course, we require that these instruments be exogenous. System-GMM estimates equation (2) in first-difference and level form. In first-difference form, the GMM estimator employs lags of the endogenous independent variables as instruments. In levels form, once-lagged first-differences of the endogenous independent variables are used as instruments.

4 Results

Table 2 shows the results of estimating equation (2) using a variety of different estimation techniques. All regressions incorporate time dummies to control for common period-specific shocks. We start with the results from an ordinary least squares specification in column I of Table 2. Huber-White heteroscedasticity-corrected standard errors are reported in parentheses for the OLS and fixed effects results. Industry shipments, capital intensity and total factor productivity are all positively related to the growth of the nonroutine share of tasks in U.S. manufacturing, and all are statistically significant at the 0.01 level. The coefficient on import competition is negative, running counter to theoretical expectations, though it is insignificant.

The estimates from OLS do not account for unobserved effects or endogenous regressors. We deal with 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 estimation are shown in column II of Table 2. Diagnostics from the FE model reveal that most of the variation in the dependent variable is related to industry differences in nonroutine tasks shares. Indeed, an F-test indicates that

Table 2: Estimates of Sector-Specific Share of Nonroutine Tasks

	(I) OLS	(II) FE	(III) 2SLS	(IV) GMM
ln(Shipments)	0.0119***	0.0100*	0.0412**	0.0395***
	(0.0025)	(0.0048)	(0.0142)	(0.0083)
Capital	0.0262**	0.0101	-0.0007	0.0395
	(0.0084)	(0.0057)	(0.0204)	(0.0382)
TFP	0.0237***	0.00422	0.0340	0.0342***
	(0.0059)	(0.0034)	(0.0197)	(0.0074)
Imports	-0.00113	0.0157***	0.0247***	0.0181**
	(0.0061)	(0.0023)	(0.0061)	(0.0056)
Year Dummies	Yes	Yes	Yes	Yes
Adjusted R^2	0.174	n/a	0.367	n/a
AR(1)				z=0.23
				ρ=0.82
AR(2)				z=1.25
				ρ=0.21
Hansen				x^2=37.14
				ρ=0.24
Hansen Difference				x^2=17.83
				ρ=0.12
Observations	374	374	291	374
Industries	81	81		81
Instruments	0	0	4	41

Robust standard errors in parentheses.
Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
OLS and FE models: Huber-White heteroscedasticity-robust standard errors.
2SLS FE model: standard errors are robust to heteroscedasticity
and AR(1) serial autocorellation

there are significant industry-level fixed effects, and thus that pooled-OLS likely yields inconsistent estimates. From the fixed effects model results, all continuous independent variables are positive in sign, but our measure of technological change, proxied by TFP, is insignificant. The influence of import competition from less developed economies on the nonroutine task share is now consistent with our theoretical expectations, and is significant at the 0.01 level.

We use a two-stage least squares estimator (2SLS) of a fixed effects panel model in order to extend our analysis to deal with endogeneity. The results are shown in Column III of Table 2. We instrument for our independent variables using one period lags of those same variables, so we have an equation that is exactly identified. All diagnostics report that our instruments are valid. Note that our standard errors are robust to heteroscedasticity and first-order serial correlation. Our final coefficient estimates appear quite different from those reported in column II, though a Hansen test of the difference in point estimates between the models in columns II and III, suggests that our concern with endogeneity is barely supported. Our 2SLS fixed effects model indicates that industry output, technological change and import competition have positive signs and that the partial regression coefficients for these variables are significantly different from zero.

Finally, we report estimates from a "dynamic" panel model in column IV of Table 2, though we reiterate that we do not incorporate a lagged value of the dependent variable in this specification. Dynamic panel models exploit more of the available information in a sample than 2SLS estimation, for instance, by allowing more lagged values of independent variables to serve as instruments for later observations in panel data. Concern with the strength of our instruments prompts use of GMM estimators that in a system-GMM context include lagged levels of independent variables as instruments as well as lagged differences. When errors are not independent and identically distributed, generalized method of moment techniques are also more efficient than 2SLS approaches. Our system-GMM estimates are, on the whole, quite close to those from the 2SLS results. Industry output (shipments), total factor productivity and import competition from less developed economies all have the anticipated positive sign and all are significant at the 0.01 level. Hansen tests of overidentifying restrictions reveal that our instruments are exogenous. The difference-Hansen tests reveal that the additional levels instruments in the model are also valid. Diagnostics indicate that we do not have a problem with serial correlation.

The results from the system-GMM estimates of Table 2 confirm the importance of both technological change and import competition on the nonroutine task share. Note that the partial regression coefficient for technological change is approximately twice that for import competition. However, the growth rate of the latter variable is more than an order of magnitude larger than that of the former and thus we can be confident in reporting that trade has a more important influence on the growth of nonroutine tasks in U.S. manufacturing than does technology change.

Table 3 provides a check of the robustness of these results using an alternative measure of technological change. In it, we present an abbreviated set of results for equation (2) estimated with fixed effects panel techniques and using system-GMM estimators, using a measure of the share of investment on computer equipment in total capital investment as an alternative to total factor productivity. This variable, built from Census of Manufactures data that gauges sector-specific spending on various forms of capital investment, including 'computers and peripheral data processing equipment', is widely used as a proxy for skill-biased technological change. The results in Table 3 lend further support to the claim that import competition is a more important driver of changes in manufacturing tasks than technological change. In both FE panel estimation and system-GMM models, the computer share of overall investment was not significantly related to nonroutine task shares, while trade remained positively and significantly related to nonroutine task shares, while trade continues to be positively and significantly related to the sector-specific share of nonroutine tasks.

Table 3: Nonroutine Tasks and Computer Investment

	(1) FE	(2) GMM
ln(Shipments)	0.0084	0.0248**
	(0.0044)	(0.0094)
Capital	0.0082	0.0512
	(0.0059)	(0.0352)
Computer Inv.	0.009	−0.0491
	(0.0136)	(0.0544)
Imports	0.0149***	0.0115*
	(0.002)	(0.0057)
Observations	374	374

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 4, we report how the individual components of the overall nonroutine task share are influenced by trade and technological change. The general relationship between trade, technology and nonroutineness holds for both interactive (DCP) and analytical (MATH) nonroutine task inputs. All else equal, technological change and import competition are each significantly associated with growth in sector-specific shares of nonroutine interactive and analytical tasks. The partial regression coefficient for technological change is about twice as high as that for import competition in the estimate predicting nonroutine interactive (DCP) task shares. For nonroutine analytical work it is almost three times as high. Increases in industry output are also positively and significantly related to the growth of nonroutine task shares. The results differ strongly when we turn to nonroutine manual work (EHF). TFP is negative and significantly related to the nonroutine manual task share, and trade exhibits no significant effect. Increases in capital intensity exert a significant positive effect on the nonroutine manual task share, and improvements in total factor productivity are significantly negatively related to the nonroutine manual task share. In the former cases this relationship likely captures the fact that greater capital inputs substitute for manual labor in many industries.

Table 4: Estimates of Sector-Specific Share of Nonroutine Task Components

	(V) Interactive	(VI) Analytic	(VII) Manual
ln(Shipments)	0.0223***	0.0226***	-0.00545
	(0.0050)	(0.0054)	(0.0054)
Capital	-0.0217	0.00953	0.0517**
	(0.0186)	(0.0203)	(0.0193)
TFP	0.0255***	0.0203***	-0.0116***
	(0.0050)	(0.0042)	(0.0027)
Imports	0.0136***	0.00648	-0.00197
	(0.0031)	(0.0038)	(0.0038)
Year Dummies	Yes	Yes	Yes
AR(1)	z=-0.91	z=0.04	z=1.48
	ρ=0.37	ρ=9.71	ρ=0.14
AR(2)	z=0.28	z=0.56	z=1.17
	ρ=0.78	ρ=0.57	ρ=0.24
Hansen	x^2=38.97	x^2=39.71	x^2=36.03
	ρ=0.19	ρ=0.16	ρ=0.29
Hansen Difference	x^2=15.26	x^2=17.79	x^2=14.50
	ρ=0.23	ρ=0.12	ρ=0.27
Observations	374	374	374
Industries	81	81	81
Instruments	41	41	41

Robust standard errors in parentheses.
Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
OLS and FE models: Huber-White heteroscedasticity-robust standard errors.
2SLS FE model: standard errors are robust to heteroscedasticity
and AR(1) serial autocorellation

5 Conclusion

In a global economy in which international exchanges are increasingly composed of goods embodying multitudinous tasks performed in various far-flung locales, imports into the U.S. from developing countries profoundly shapes the domestic structure of work. Even after accounting for the effect of skill-biased technological change, trade, in the form of import competition from less developed economies, exerts a significant, positive and sizable impact on the growth of nonroutine tasks across the U.S. manufacturing sector. Because of imports from these economies, there has been an increase in the relative demand for workers performing nonroutine tasks within manufacturing industries.

Over the study period, the overall impact of trade on the nonroutine task share is approximately an order of magnitude larger than the technology effect. Trade plays a particularly important role in shaping sector-specific task structure after the early 1980s, when total factor productivity growth slows. There is little question that the influence of technology and trade on shifts in the structure of manufacturing work in the U.S., and in other advanced industrialized economies, are not strictly independent of one another, yet the results presented here suggest that trade is the dominant partner 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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