Import Competition and Skill Content in U. S. Manufacturing Industries*

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Abstract

Skill content varies enormously across industries and over time. This paper shows that import competition can explain a significant portion of the variation in various skill measures across manufacturing industries. Those industries that face more intense import competition employ more non-routine skill sets, including cognitive, interpersonal, and manual skills, and fewer cognitive routine skills. In addition, we find that the impact of import competition on skills is not driven by imports from low-wage countries or from China. A number of robustness checks also suggest that our results are unlikely to be driven by econometric problems.

Keywords: import competition, skills, labor market.

JEL classification: F16, J24, J82.

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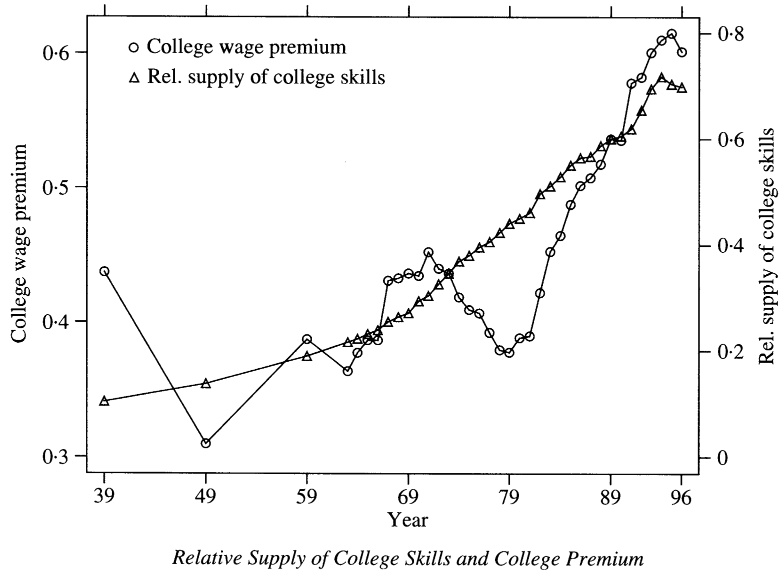

Figure 1: Reproduced from Acemoglu (2002). The log of the college wage premium and relative supply of college skills measured by the number of weeks worked by college equivalents divided by those worked by non-college equivalents.

1 Introduction

This paper assesses empirically whether import competition explains skill content in manufacturing industries. And, if so, which skill sets are employed more in the face of more intense import competition?

These questions are motivated by two important trends in the U.S. in the past few decades that have changed the structure of the manufacturing sector dramatically: (i) the shift in labor demand toward skilled workers (Berman, Bound and Griliches, 1996) and (ii) the substantial rise in imports because of globalization.

Figure 1 is taken from Acemoglu (2002). It shows that over the past several decades, the relative supply of skills (measured by college skills) in the U.S. has increased rapidly, but there has been no concomitant reduction in the college wage premium. On the contrary, there has been a sharp rise in this premium.

Figure 2 shows the import competition trend in the manufacturing sector. It can be seen that there has been an upward trend in the share of imports from both the rest of the world

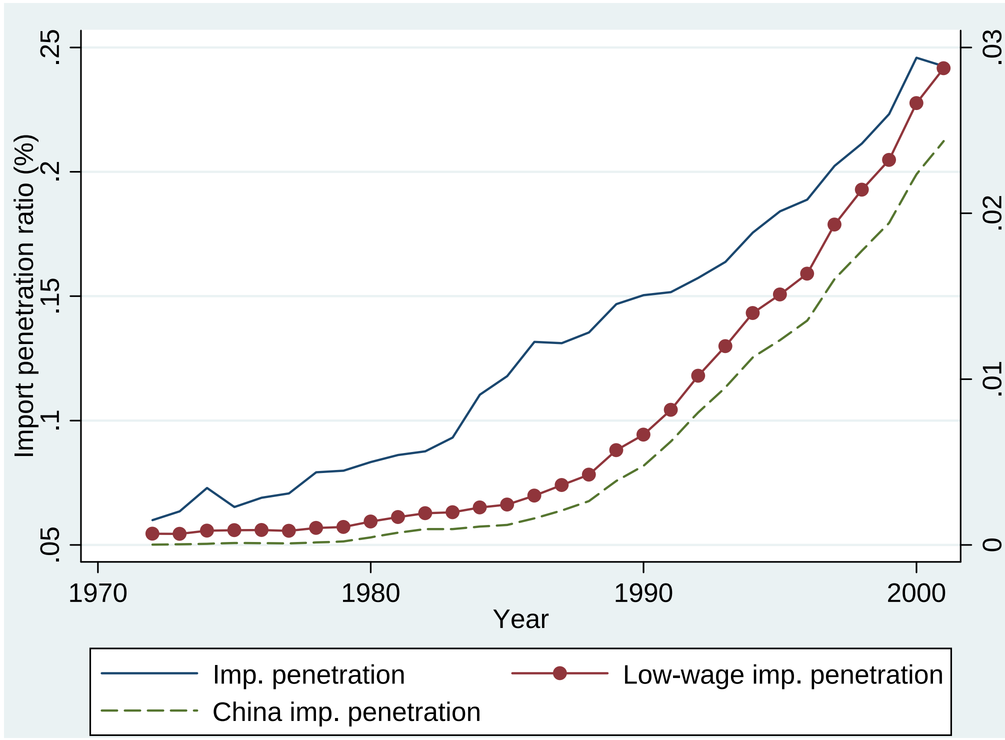

Figure 2: Import competition for the manufacturing sector. Authors' calculation from the NBER manufacturing database and the U.S. import and export data (Feenstra, 1996, 1997; Feenstra, Romalis and Schott, 2002). The import penetration ratio follows the scale on the left axis, whereas the China and low-wage countries' import penetration ratios follow the scale on the right axis. Low-wage countries are listed in Table 3.

and from low-wage countries.

We employ the Dictionary of Occupational Titles (DOT) to measure skills directly across industries over time. An advantage of using the DOT is that we do not have to infer skills from the ratios of production to non-production workers or college graduates to non-college graduates. Because both non-production workers and college graduates encompass a variety of different skills, inferring skills from these ratios would create difficulties in assessing the particular types of skills that respond to change. Following Autor, Levy, and Murnane (2003), we group the skill measures in the DOT into five types of skills: (1) cognitive non-routine (including general educational development in mathematics and reasoning and relationship to data), interactive non-routine (including general educational development in language, relation to people, and direction, control, and planning), cognitive routine (including set limits, tolerances, or standards), manual non-routine (including eye-hand-foot coordination), and manual routine (including finger dexterity).[1] To measure the intensity of import competition, we employ the import penetration ratio, as is standard practice in the literature (see, e.g., Revenge, 1992; Guadalupe, 2007; Cuñat and Guadalupe, 2009).

Section 2 of this paper discusses the economic links between import competition and different skills. To identify the impact of import competition on skill content, we pay special attention to the potential endogeneity associated with import competition in our empirical estimation. First, there is potential reverse causality: skill content may have shaped the level of imports within an industry. Second, it is impossible to exhaust all relevant variables that may explain skill content in our estimation. In particular, there is no universal measure of a diverse set of policies across industries over time. Policies that affect skill content are also likely to affect the level of import competition. Third, measures of import competition inevitably contain noise, which may substantially bias our estimates toward zero in panel estimation. We tackle these endogeneity issues by instrumental variable (IV) estimation. We employ the U.K. import penetration ratios of corresponding industries to instrument those of U.S. industries. Section 4 details our use of the IV.

Our results show that import competition explains a substantial portion of the variation in skills employed by manufacturing industries. More specifically, industries that face more intense import competition tend to employ more non-routine skill sets, including cognitive, interactive, and manual non-routine skills and are likely to require fewer routine skills.

These results are robust to the use of the import-weighted exchange rate as an alternative IV.[2] They also remain robust to additional controls, including the capital-to-labor ratio, lagged dependent variables, and other industry-year-varying variables. In addition, we find that the impact of import competition on our skill measures is not driven by imports from China or from other low-wage countries.[3]

[1] More information about these skill measures can be found in Section 3.1 and Table 1.

[2] Bertrand (2004), Cuñat and Guadalupe (2009), Guadalupe(2007), and Revenga (1992) also employ import-weighted exchange rates as instrumental variables for the degree of import competition.

[3] The list of low-wage countries is given in Table 3.

This paper is related to the literature on the impact of trade on the U.S. labor market.[4] Revenga (1992) documents import competition's significant impact on employment and the wage differential for skilled and unskilled labor in U.S. manufacturing industries. Feenstra and Hanson (1996) show that the widening wage gap between skilled and unskilled workers is associated with increasingly globalized competition. In a later study (Feenstra and Hanson, 1999), they evaluate the impact of outsourcing and computerization on the wage structure and find that both explain the increase in the relative wage of non-production workers. Bertrand (2004) shows that increased import competition affects the labor market by making wages more sensitive to unemployment rates. Guadalupe (2007) exploits two historical events, the 1992 European Single Market Program and the sharp appreciation of the British pound in 1996, to show that an increase in foreign competition raises the returns to skill in the UK. Overall, the literature suggests a strong link between import competition and the labor market.

Another closely related body of literature measures skills directly rather than inferring them from education levels or the ratio between production and non-production labor. Blum and Marigee (2010) measure U.S. employment skills directly using the DOT database and show that rising wage inequality and the male-female wage gap can be explained by changes in skill prices. Spitz-Oener (2006) employs a unique dataset from West Germany that measures skill requirements directly and shows that occupations require more complex skills today than they did in 1979. Further, she shows that changes in skill requirements are most pronounced in occupations that underwent rapid computerization.

[4] Feenstra (2001) conducts a comprehensive survey of the literature on trade and wage structure.

2 Impact of import competition on skill content: a theoretical discussion

We discuss three channels through which import competition is related to skills. Increased import competition speeds up changes in industries' (a) input mix, (b) output mix, and (c) production technology to transform inputs into outputs. In turn, it changes industries' skill content. It is important to note that these three channels are not mutually exclusive and, in fact, are likely to occur simultaneously.

(a) Input mix. Increased import competition encourages industries to switch from consuming certain domestic production processes (inputs) to those provided aboard. In his study of labor market polarization, a major phenomenon in the U.S. labor market, Autor (2010) points out that any production processes (inputs) that can be packaged as discrete activities have the potential to be off-shored in a foreign location. This potential has been increasingly realized with the rapid reduction in IT costs, thus rendering coordination among distant locations much more plausible than it was decades ago. Levy and Murnane (2004) distinguish between routine and non-routine tasks. They argue that rule-based work, which involves minimal complexities and misunderstandings, is a likely candidate for off-shoring. Leamer and Storper (2001) make a similar distinction between tasks that require "codifiable" versus "tacit" information and argue that the former is relatively easier to off-shore. If increased import competition shifts up the gear of these input mix changes, then it also raises the level of demand for non-routine and interactive skills relative to routine skills.

(b) Output mix. Suppose that the sets of inputs consumed domestically and off-shored both remain constant. To the extent that different outputs require different inputs, output mix changes alone can drive changes in the use of different skills. Output mix changes along two dimensions: vertical and horizontal.

Interestingly, Khandelwal (2010) shows that short quality-ladder industries shrink to a dis-proportionally greater degree in the face of import competition relative to their long quality-ladder counterparts, with quality-ladder referring to the extent of vertical differentiation in an industry.[5] When threatened by imports, domestic producers "escape" by switching to higher-quality products. Such escape, however, is limited by the industry's extent of vertical differentiation. Those with a short quality-ladder have less room to escape and are therefore more affected by import competition. A recent TIME magazine article accords well with Khandelwal (2010) by pointing out that Germany remains strong in manufacturing even though imports are flooding all of Europe.[6] The country's manufacturing sector survives by focusing exclusively on the manufacture of high-quality, but not necessarily fancy, products. For instance, Germany produces very high-quality chainsaws. To the extent that higher-quality products require relatively more non-routine than routine skills, because interactions with customers, innovative product development and design, and disciplined engineering are more important in higher-quality product provision, Khandelwal's (2010) finding implies that import competition drives demand for non-routine skills.

Holmes and Stevens (2010) adopt a structural trade model to explain why plant size distribution data show increased import competition to affect large-scale plants more than small-scale plants in the U.S. Large plants differ substantially from small ones: they are more associated with the mass production of standardized products, whereas small plants generally engage in the craft production of specialty products. As the provision of specialty goods, often custom-made goods, requires face-to-face interaction between traders, the foreign imports entering the U.S. are less likely to be custom-made than standardized goods. Standardized imports thus harm large plants more than small ones. To the extent that face-to-face interaction and product customization are more reliant on non-routine than routine skills, Holmes and Stevens' (2010) model predicts that import competition increases the use of non-routine skills and decreases that of routine skills.

(c) Production technology. In the face of increased import competition, industries

[5]In sharp contrast to the previous literature employing prices to proxy quality, Khandelwal (2010) adopts an innovative structural approach to back-out quality from price and quantity data. The estimated range of product qualities within an industry proxies for the extent of vertical differentiation in that industry.

[6]Schuman, Michael. 2011 (March 7). "How Germany Became the China of Europe." TIME.

tend to upgrade their capital faster than they otherwise would. They do so both through individual firm upgrading and across-firm, within-industry reallocation. A New York Times article reports greater capital-intensity to be one way that U.S. manufacturing firms survive foreign competition.[7] The founder of a U.S. motorcycle company stated that to compete with lower-priced foreign competitors, it requires "workers to help squeeze out labor costs through automation and other efficiencies."

Guadalupe (2007) points out that if competition fosters technological change, such as computerization, that is skill-biased, then competition will be positively associated with the relative demand for skilled labor. She also links product market competition to the weakening of both trade and labor union power, two of the major impediments to the replacement of unskilled labor with capital. Bloom, Draca, and Van Reenen (2009) show that Chinese imports do indeed induce technological adoption among U.S. firms. To the extent that unskilled labor is relatively more reliant on union protection than skilled labor is, competition is associated with higher relative demand for skilled labor.

Even if individual firms do not adopt technological change faster in the face of increased import competition, the accelerated across-firm, within-industry reallocation of activities will upgrade an industry's capital.[8] Bernard, Jensen, and Schott (2006) demonstrate that plant survival and employment growth are negatively associated with exposure to low-wage country imports. Within industries, imports also lead to the disproportionate reallocation of manufacturing activities to more capital-intensive plants. The more intense import competition is, the faster such within-industry reallocation takes place. Provided that capital-intensive plants are more likely to employ non-routine than routine-skills, we expect a positive association between import competition and non-routine skills.

[7]Uchitelle, Louis, 2005 (September 4). "If You Can Make It Here," New York Times, Section 3, page 1, column 2.

[8]See Helpman (1984), Melitz (2003), and Helpman et al. (2004) for more theoretical arguments.

3 Data and Variables

3.1 Skill measures

We combine data from the DOT, and the U.S. Current Population Survey (CPS). The DOT is a database that characterizes the multiple skill requirements of various occupations. Matching the DOT and CPS data allows us to characterize workers' skills at the industry level.

The U.S. Department of Labor has published the DOT since 1939. It thus provides measures of the tasks required or performed in more than 10,000 occupations and how they have changed over time. The latest editions are the fourth (1977) and the revised fourth (1991) editions. The information in the 1977 edition was collected between 1966 and 1976, and that in the 1991 revised edition was collected between 1978 and 1990. The former edition describes in great detail the skill levels required in occupations in the 1970s, whereas the latter describes those in the 1980s.

The occupational definitions in the DOT are the result of comprehensive interviews carried out by trained occupational analysts to ascertain how jobs are performed in establishments across the nation and are composites of data collected from diverse sources. The two editions contain 44 skill measures and job characteristics that fall into seven categories: work functions, required General Educational Development (GED), aptitude needed, temperament needed, interests, physical demands, and working conditions. For the sake of consistency, the variables are re-scaled such that higher values denote higher-level requirements.

Our employment data come from the March CPS from 1971 to 2001. Our sample includes all employed workers aged 18 to 65, with the number of non-missing hours worked. The DOT includes scores for more than 12,000 occupations, whereas the CPS has only 450 occupation codes. The DOT measures are therefore aggregated to a time-consistent census occupation level. All analyses are performed using full-time equivalent hours of the labor supply as weights, that is, the product of individual CPS sampling weights times the hours of work in a sample reference week. Appendix A details the data construction.

Following Autor, Levy, and Murnane (2003), we construct measures for five skills: 1) cognitive non-routine, 2) interactive non-routine, 3) cognitive routine, 4) manual non-routine, and 5) manual routine. Table 1 describes in detail the nine raw skill measures in the DOT. As in Bacolod and Blum (2010), we employ principal component analysis to form more meaningful skill measures. We combine GEDM (math), GEDR (reasoning), and DATA (data) to construct our measure of cognitive non-routine skills, and PEOPLE (people), DCP (direction, control, and planning), and GEDL (language) to construct that of interactive non-routine skills. Cognitive routine skills correspond to the raw measure of set limits, tolerances, or standards (STS). Manual non-routine skills correspond to the raw measure of eye-hand-foot coordination (APTE), and manual routine skills correspond to the raw measure of finger dexterity (APTF). A higher score means the industry requires more of that particular skill set. We z-standardize these five measures to facilitate comparison of the impact of import competition across skills.

Table 2 presents the summary statistics of these skills. The skill measures make economic sense when we examine the industries that score the highest and lowest. For cognitive non-routine skills, the industry with the highest score is electronic computing equipment, and that the lowest is footwear, except rubber and plastic. Electronic computing equipment also scores the highest on interactive non-routine skills, whereas dyeing and finishing textiles, except wool and knit goods scores the lowest. For cognitive routine skills, apparel and accessories, except knits comes out on top, whereas drugs is at the bottom. The logging industry achieves the highest score for manual non-routine skills and not specified manufacturing industries the lowest. Finally, apparel and accessories, except knits and sawmills, planning mills, and millwork score the highest and lowest, respectively, for manual routine skills.

3.2 Import competition

Following Bertrand (2004), we measure import competition using the natural log of the import penetration ratio, *imp*, i.e.,

$$imp = \ln(\text{imports}/(\text{imports} + \text{domestic shipments - exports})). \tag{1}$$

We employ U.S. import and export data of the manufacturing industries from 1970 to 2001 compiled by and discussed in Feenstra (1996, 1997) and Feenstra, Romalis, and Schott (2002). Domestic shipment data is the variable *Total value of shipments* from the NBER manufacturing productivity database. We also further break down imports into those from low-wage and non-low-wage countries using Feenstra's bilateral data for the years before 1989 and Schott's bilateral trade data from 1989. The import penetration ratios have the same level of aggregation as the skill measures.

In this way, we successfully construct an industry-by-year panel dataset of skill requirements using crosswalks across different datasets. The time-consistent industry classification is roughly equal to the three-digit SIC classification. We have data for 70+ manufacturing industries from 1970 to 2001. Table 2 presents the summary statistics.[9]

4 Empirical Strategy

To investigate the impact of import competition on skill content, we estimate the following equation.

$$skill_{jt} = \alpha_j + \beta \cdot imp_{jt-1} + \delta_t + \varepsilon_{jt}, \tag{2}$$

[9] As suggested by a referee, we examine the cross-industry differences in our dataset. We find that (a) industries facing a higher import penetration are associated with less subsequent employment (consistent with the results of Revenga [1992] and Bernard et al. [2006]) and (b) industries that are more non-routine-skill-intensive, or more capital-intensive, face relatively less import penetration. These results serve as good cross-checks of our data. They are not shown here but are available upon request.

where j and t represent the three-digit industry and year, respectively; $skill_{jt}$ is the skill measure of industry j in year t; and imp_{jt-1} is the natural log of the import penetration ratio of industry j in year $t-1$. The year dummy, δ_t, captures any economy-wide technological improvements, cyclical business fluctuations, or economy-wide labor market changes that would have changed the employment of skills. The industry dummy, α_j, captures any time-invariant industry-specific characteristics, such as the nature of products and production, or time-persistent industry-specific policies, rules, and regulations that may have affected an industry's skill level.

Before proceeding to our estimation results, we discuss several potential econometric problems that may cause bias in estimating equation (2).

Omitted variables. Although the dummies capture all time-invariant industry-specific factors and economy-wide time-specific factors, we cannot entirely rule out the existence of industry-time-varying relevant but omitted factors that are systematically correlated with our regressor of interest (imp_{jt-1}). More specifically, suppose that $\varepsilon_{jt} = \gamma \cdot \omega_{jt} + \upsilon_{jt}$, where ω_{jt} is the industry-time-varying variable that correlates with imp_{jt-1}, and υ_{jt} is an identically and independently distributed error term, i.e., $E\left[\omega_{jt} \cdot imp_{jt-1}\right] \neq 0$ and $E\left[\upsilon_{jt} \cdot imp_{jt-1}\right] = 0$. Hence, the correct estimation equation is

$$skill_{jt} = \alpha_j + \beta \cdot imp_{jt-1} + \delta_t + \gamma \cdot \omega_{jt} + \upsilon_{jt}. \tag{3}$$

Failing to control for ω_{jt} in the estimation biases the estimate ($\hat{\beta}$) of imp_{jt-1}, that is,

$$\hat{\beta} = \beta + \gamma \cdot \sigma,$$

where σ is the coefficient of regression imp_{jt-1} on ω_{jt} (Angrist and Pischke, 2009).

Time-varying industrial and trade policies at the industry level constitute an obvious candidate for such bias. Changes in quota policies, and technical regulations are two examples, but the policies involved should be much more diverse than these two types. The direction of the resulting bias depends on the types of policy changes that the industries enact. One example is illustrated in Essaji (2008). He shows that a more stringent set of technical regulations on products shield an industry from import competition. To the extent that enacting technical regulations is endogenous, for instance, industries employing more non-routine skills are relatively more likely to engage in technically superior products and therefore to exert a greater lobbying effort for more stringent technical regulations, then we expect the positive impact of import penetration on non-routine skills to be biased downward ($\hat{\beta} < \beta$ because $\gamma > 0$ and $\sigma < 0$ when ω_{jt} measures how stringent technical regulations are at time t for industry j.).

To the best of our knowledge, however, there is no systematic measure of a diverse set of policies that varies over time and across industries. To address this concern, we thus adopt the IV approach with two alternative instruments. The next sections details their identification assumptions.

Reverse causality. Potential reverse causality may complicate the estimation of β. To the extent that certain skills are more complementary to dealing with foreign trade than others, an industry's skill content may also shape its contemporaneous trade flow and thus its import penetration ratio. For instance, interpersonal skills are especially important in dealing with foreign traders and thus should facilitate trade more than, say, physical strength.

Potential reverse causality may also stem from importers' self-selection. If the U.S. has a comparative advantage in industries that require non-routine skills, then importers may be deterred from such industries and self-select into industries requiring routine skills instead.[10] It is thus expected that import competition's positive impact on non-routine skills is underestimated, whereas its negative impact on routine skills is over-estimated.

To alleviate concern over potential contemporaneous feedback, we employ the lag of the import penetration ratio as the explanatory variable.[11] Our IV estimation also helps to

[10]The negative association between non-routine skills and import penetration documented in Footnote 9 is consistent with this potential.

[11]Cuñat and Guadalupe (2009) also use lagged import penetration ratios instead of contemporaneous ones as their explanatory variable to examine the impact of import competition on incentive contracts within a

address this concern.

Measurement errors. Measuring competition is fundamentally challenging because realized competition does not necessarily equal potential competition.[12] In addition to this conceptual challenge, data may also constitute a challenge. Although the trade data we use to compute import competition are comprehensive and carefully constructed data, they are subject to certain limitations that render our measure of import competition noisy. First, as pointed out by Feenstra, Romalis, and Schott (2002), the import data for 1972-1994 released by Feenstra (1996, 1997) refer to "imports for consumption," whereas the updated data for 1989-2001 in Feenstra, Romalis, and Schott (2002) also include "general imports." This inconsistent import definition over time is likely to introduce measurement errors. Second, the aggregation of import value at the 10-digit HS product level to the industry level is fundamentally tricky, as the HS codes used for import data do not always correspond to a single industry. To convert these data, Feenstra (1996, 1997) employs the 1972 version SIC codes for import data in the 1972-1992 period, whereas Feenstra, Romalis, and Schott (2002) use the 1987 version for import data from 1989 to 2001. The matching between the HS and industry codes is believed to be as consistent over time as possible, but zero measurement errors remains a stringent assumption. Third, Baranga (2009) reports that the UN Comtrade data that form the basis of Feenstra's trade data are not themselves free of measurement errors.

These measurement errors may bias the estimate toward zero. In addition, Griliches and Hausman (1986) show that panel fixed-effect estimation further exacerbates this bias. To address the measurement error problem, we employ IV estimation to identify the impact of import competition on skills.

Standard errors. As Hsiao (1986) point out, any omitted variables in panel data estimation that have an effect lasting for more than one period cause the errors to be auto-

firm. Our estimation results remain robust to using the use of contemporaneous import penetration ratios.

[12]For example, the 2005 removal of the apparel quota exerted enormous competitive pressure even before 2005 but this could not have been fully reflected by the realized penetration before the removal.

correlated. In our setting, for instance, some time-varying industrial policies that we omit may have a transitory effect that lasts more than one period.[13] We follow Revenga (1992) and compute the standard errors robust to arbitrary autocorrelation and heteroskedasticity to deal with these transitory effects (Newey and West, 1987).[14]

An alternative way to address autocorrelation is to include the lagged value of the dependent variable.[15] However, such inclusion in panel estimation introduces additional estimation bias. As noted by Nickell (1981), the lagged value of a dependent variable is automatically correlated with the error term in panel fixed-effect estimation. As a robustness check, we perform dynamic panel estimation using the dynamic panel estimation method proposed by Arellano and Bond (1991).

Bad controls. In some of the robustness checks, we include several other possible determinants of skill content, such as the capital-to-labor ratio and output levels. However, the inclusion of these additional controls may introduce the "bad controls" problem discussed by Angrist and Pischke (2009), that is, these controls themselves may be outcomes of our regressor of interest and therefore bias its estimate. To address this problem, we follow Angrist and Pischke (2009) by employing pre-determined values, that is, the two-years lags of these controls.[16]

[13]We perform a Wald test discussed by Wooldridge (2002), which rejects the null that there is no autocorrelation.

[14]Alternatively, we also experiment with the bootstrap procedure to estimate the standard error, but the results are qualitatively the same as those with the heteroskedasticity- and autocorrelation-robust standard error. They are omitted in the interests of saving space, but are available upon request.

[15]We thank an anonymous referee for pointing out this alternative way of addressing autocorrelation.

[16]Alternatively, we also experiment with instrumenting these control variables. For example, we instrument the U.S. capital-to-labor ratio with the corresponding U.K. value. However, a concern with this IV estimation is that there may exist a weak instrument problem as indicated by the small value of the weak identification statistic. Nonetheless, inference based on Anderson-Rubin (1949) statistics (which are robust to the presence of weak instruments) shows that our results are qualitatively the same as those with the inclusion of the double-lagged value. To save space, we do not report the results of this alternative method, but they are available upon request.

4.1 The U.K. Instrument

We employ IV estimation to identify the impact of import competition on skill content. Our main instrument is the import penetration ratio of corresponding industries in the U.K. in the same year, denoted as imp^{UK}_{jt-1}.[17] The data come from the OECD STAN Industrial Database (1998 edition). Appendix B details the construction of the U.K. instrument.

This instrument is potentially correlated with the import penetration ratio in the corresponding industries in the U.S. because it reflects the relative competitiveness of the foreign producers on the industry and the relevant transaction costs of the industry's trade. For example, advances in the global supply-chain management of an industry's major product affects that industry's imports for both the U.S. and the U.K.

The exclusion restriction requires that imp^{UK}_{jt-1} is not correlated with ω_{jt}. In other words, the identification assumption is that the import penetration ratio in the U.K. is not correlated systematically with trade and industrial policy changes in the U.S. Imagine an Indonesian businessman who exports to both the U.S. and the U.K. If the effort he exerts to learn about changes in U.S. industrial policies does not save him the effort of learning about U.K. industrial policies, then our identification assumption holds. To the extent that the U.K. does not systematically enact policies, rules, and regulations specific to an industry as corresponding industries in the U.S. do, we do not expect the import penetration ratio in the U.K. to correlate with ω_{jt}.

As a further strategy to make the exclusion restriction more plausible, in constructing the UK import penetration ratios, we remove the U.K.'s imports from the U.S. in the numerator. Doing so minimizes the concern that U.S. trade and industrial policies affect not only U.S. imports, but also U.S. exports to other countries, including the U.K. As long as the U.K. import penetration ratio does not include U.S. imports, our IV is arguably more exogenous to U.S. policies at the industry level.

[17] Ellison, Glaeser, and Kerr (2010) also employ the corresponding data in the U.K. to instrument the potential for Marshallian spillovers between industries in the U.S.

4.2 Import-weighted exchange rate

For a robustness check, we also use the lag import-weighted exchange rate provided by Goldberg (2004) as an alternative instrument.[18] Bertrand (2004) also employs the import-weighted industry-specific exchange rate to instrument for the import penetration ratio. Revenga (1992) uses it to instrument import prices and Cuñat and Guadalupe (2009) employ the same instrument for import competition to examine its effect on firms' incentive provisions.

The IV is relevant because exchange rate fluctuations directly affect the relative prices of imports and domestic supply, and hence they affect the intensity of import competition. It satisfies the exclusion restriction because the exchange rate is determined primarily by macroeconomic variables that, conditional on year dummies, can reasonably be regarded as exogenous to the policies of a certain industry within a certain period of time.

5 Main results

5.1 Import competition explains skill content

We examine whether $\beta \neq 0$, i.e., all else being equal, whether the intensity of import competition can explain variations in skill levels to a significant extent.

Panel A of Table 4 uses the U.K. import penetration ratio as an instrument. The period of coverage is 1971 to 1997.[19] The results in Columns 1-2 and 4 suggest that industries with more intense import competition employ more non-routine skills, including cognitive, manual, and interpersonal non-routine skills. Column 3 suggests that more intense import competition is associated with fewer cognitive routine skills. Manual routine skills, however,

[18] As suggested by an anonymous referee, we also experiment with using trade cost as an alternative IV. The results (not reported here, but available upon request) show that import competition, after being instrumented by trade cost, has a significant impact on cognitive non-routine, manual non-routine, and manual routine skills. Given that trade cost is itself a type of policy and thus violates the exclusion restriction. The associated results have to be interpreted with caution.

[19] The U.K. import penetration ratio from the OECD STAN database is available only up to 1996.

do not appear to correlate with import competition (Column 5).[20] The under-identification statistics and first-stage results (reported in the top panel of Table 13) show that the IV is strongly relevant and positively and significantly correlated with our regressor of interest, the U.S. import penetration ratio.

Because the skill measures are all z-standardized, the size of the estimated coefficients gives us information on the relative strength of the effects on different skills. Import competition appears to exert stronger effects on both interactive and cognitive non-routine skills than on manual non-routine skills.

Panel B of Table 4 adopts the import-weighted exchange rate as an alternative instrument. Data on exchange rates allow us to cover a longer period, from 1971 to 2001. The import-weighted exchange rate is at the two-digit SIC level, which is more aggregated than our industry-level classification. Consistently, the weak-identification statistics show that this IV is likely to be subject to the weak instrument. Therefore, for statistical inference, we rely on Anderson-Rubin (1949) statistics, which are robust to the presence of weak instruments.[21] These statistics show that both cognitive and interpersonal skills continue to be significantly associated with the import penetration ratio. In contrast, manual routine skills are now negatively and significantly associated with this ratio. Manual non-routine skills are insignificant. The general picture, however, is that import competition does explain a substantial portion of the skill content of industries.

For comparison, we report the corresponding OLS estimates in Panel C. They are largely statistically insignificant. Consistent with our previous arguments, this striking difference between the OLS and IV results may reflect the endogeneity stemming from both omitted variable bias and potential reverse causality. The OLS estimates are much closer to zero in

[20]For manual routine skills, when we re-estimate the regression by excluding the top and bottom 5% of observations, we recover a negative, albeit marginally insignificant, coefficient. We also conduct other checks to ensure that our results are not driven by the presence of outliers, e.g., instrumental variable quantile regressions and identification of outliers using the method in Hadi (1992, 1994). The results are not reported here but are available upon request.

[21]The test's null hypotheses is that the coefficient of the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

size too. This pattern is consistent with the concern that measurement errors are exacerbated in panel fixed-effect estimation (Griliches and Hasuman, 1986), thus severely biasing the estimates down toward zero.

Overall, the results suggest that more intense import competition is associated with the employment of relatively more non-routine skills, be they cognitive, interactive, or manual. These results from the U.S. strongly support those in Guadalupe (2007), who finds the U.K.'s returns to skill (high-skill relative to low-skill group) to increase under increased product market competition due to exogenous foreign pressure.[22] Because computerization also lowers the cost of trading at a distance (Autor, 2010), our findings are also consistent with those of Autor, Levy, and Murnane (2003). Further, cognitive routine skills decline when there is more intense import competition, although there is no such significant decline for manual routine skills.

Our results may appear to differ from those in Bernard, Jensen, and Schott (2006) who, using the U.S. plant-level data, find that more skill-intensive plants are not more likely to grow within industries experiencing the same level of import penetration. One possible explanation is that the change in skill content within an industry takes place at the extensive rather than intensive margin.[23] Indeed, in Melitz (2003), the resource reallocation triggered by import competition occurs at the extensive margin (that is, the entry and exit of plants) rather than at the intensive margin (that is, the growth of incumbent plants). Meanwhile, Hummels and Klenow (2005) find that the extensive margin is the primary avenue of export growth for large economies, and Evenett and Venables (2002) find that the extensive margin plays a significant role in export growth in developing economies.

[22]Guadalupe's (2007) high-skill group includes managers and administrators and those in professional occupations that are likely to require relatively more non-routine cognitive and interactive skills than manual and routine skills. The corresponding low-skill group includes those in occupations of clerical, secretarial, personal and protective, sales services, plant and machine operatives, and in agriculture, forestry, fishing, and other elementary occupations. These are likely to require relatively more routine and manual skills.

[23]We thank an anonymous referee for suggesting this explanation.

5.2 Controlling for capital deepening

The literature has linked capital deepening to changes in skill demand. Capital is more complementary to skilled than unskilled labor. Consequently, capital deepening increases the relative demand for skilled labor. Autor, Levy, and Murnane (2003) examine the different degrees of complementarity between various skills and computerization and show that the dramatic fall in computer costs has acted as an exogenous capital-deepening force, which in turn raises the relative demand for non-routine sets of skills among industries.

Autor (2010) points out that capital deepening exerts similar, but not identical, effects on different skills to import competition. Although we focus on the role of import competition in explaining changes in skill demand, unless capital deepening in the U.S. is correlated with our IV (causing a violation of our empirical identification), our findings regarding this role are not driven by capital deepening. This section assesses whether import competition affects skill content, conditional on capital deepening.

To avoid the aforementioned "bad controls" problem when we control for capital deepening in the regression, we follow Angrist and Pischke (2009) in using a pre-determined value, that is, the 2-year lagged value of total real capital stock over total employment. Table 5 presents the estimation results. Consistent with the intuition that capital is relatively more complementary to cognitive and interactive non-routine skills than to other skills, the estimated coefficients of the capital-to-labor ratio are positive and significant for these skills. Consistent with Autor, Levy, and Murnane (2003), capital deepening does indeed appear to replace cognitive routine skills. The results for manual skills, however, are mixed. With respect to our central concern, our finding that import competition explains skill content to a significant extent remains robust to the control of capital deepening.

Panel C of Table 5 experiments with four different measures: total real capital stock over total employment, real equipment capital stock over total employment, real equipment capital stock over total production worker hours, and total real capital stock over total production worker hours. The results are reassuringly robust with a very similar magnitude, thus ruling out concerns that our particular measure of capital deepening drives our results.

Comparing the magnitude of the estimated coefficients in Table 5 with the corresponding estimates in Table 4, we find that controlling capital deepening generally shrinks this magnitude. More specifically, the magnitude of the coefficients for cognitive non-routine, interactive non-routine, and cognitive routine skills drops by roughly 15%, although that for manual non-routine skills increases slightly. These results imply that part of import penetration's impact on skills is associated with capital deepening, which is consistent with the third channel in Section 2.[24]

5.3 The results are unlikely to be driven by low-wage countries

Many politicians in Europe and the U.S. have become increasingly vocal in opposing the recent dramatic increase in trade with low-wage countries. One reason for this opposition is that the dramatic increase coincides with a period of increasing wage inequality in the U.S. The recent financial crisis has further reinforced this sentiment. In addition, Bernard, Jensen, and Schott (2006) show that plant survival and growth in the U.S. are significantly affected by import competition from low-wage countries.

We perform a conceptual exercise here to determine whether our findings on the impact of import competition on skills are driven by low-wage countries. More specifically, we compute the import penetration ratio excluding imports from low-wage countries as a whole and from China alone, and then re-run the IV estimations.[25] Table 3 lists the countries that Bernard, Redding, and Schott (2006) regard as low-wage countries. The U.K. instrument is also re-constructed by excluding imports to the U.K. from China and from other low-wage countries.

[24]Bernard, Jensen, and Schott (2006) show that the impact of import penetration on plant survival is attenuated by capital intensity. To investigate such an attenuating effect, we experiment with the inclusion of an interaction term between import penetration and capital deepening in the regression. We generally find no significant attenuating effect for capital deepening (except for the estimation of manual non-routine skills). Importantly, our main findings regarding the impact of import penetration on skills remain robust to the inclusion of the interaction term. The results are not reported here, but are available upon request.

[25]More precisely, the import penetration ratio excluding imports from a set of countries (denoted J) is measured as ln((imports - imports from J)/(imports + domestic shipments - exports))

The results excluding imports from China are reported in Table 6. Panels A and B suggest that our main results regarding the impact of import competition on skills remain robust to the exclusion of these imports. There are slight increases in the magnitude of the estimated coefficients of cognitive non-routine and interactive non-routine skills, but decreases in those of cognitive routine and manual non-routine skills. Panels A and B of Table 7 exhibit similar patterns when imports from low-wage countries as a whole are excluded, except manual non-routine skills becoming marginally insignificant.

These results suggest that occupational skills in the U.S. from the 1970s to 1990s are unlikely to be driven by imports from low-wage countries. Relative to low-wage countries, non-low-wage countries tend to produce goods of a similar variety and quality to those produced in the U.S. Faced with import competition, U.S. producers may move upwards on the product-quality ladder or innovate to produce new and differentiated products (Khandelwal, 2010). Both moves require more non-routine skills. They are also likely to be associated with the development of new production technologies that further reinforce the need for workers with more non-routine skills. These results are consistent with the output and production technology channels discussed in Section 2.

A concern with Panels A and B in the Tables 6 and 7 is the omission of imports from China/low-wage countries. If they are correlated with our IVs, then our estimates may be biased. Panel C of the two tables therefore directly controls for and instruments import penetration from China/low-wage countries.[26] With respect to the central issue, non-routine interactive and cognitive skills remain significantly related to imports when low-wage countries are excluded. The weak instrument for imports from China/low-wage countries, however,

[26] The independent variables are re-defined as the natural log of one plus the import penetration ratio to avoid having an undefined natural log of zero for the import penetration ratio of China/low-wage countries. Since the re-definition shrinks the standard deviation of the variable, the estimated coefficients of the import penetration ratio from non-low-wage countries are expected to increase to preserve the order of the effects. Because imports from China/low-wage countries may be endogenous, they are also instrumented by the corresponding U.K.'s import penetration from China/low-wage countries. These instruments, however, are rather weak (as shown in their corresponding first stages in Panels B and C of Table 13). Controlling, but not instrumenting them, we find the estimated coefficient of the import penetration ratio from non-low-wage countries to be statistically significant for all skills except manual-routine skills.

enlarges the standard errors, thus rendering the other skills less significant.

6 Robustness

6.1 Reduced-form regressions

Our identification thus far requires that the instrument be relevant and uncorrelated with the error term in the second stage of IV estimation. As a robustness check, we conduct reduced-form regressions: regressing skills on our IVs directly. As noted by Angrist and Krueger (2001), the absence of any correlation between our skill variables and the IVs in these reduced-form regressions would cast doubt on whether our regressor of interest does indeed have an impact on skill content. Table 8 shows our IVs to have statistically significant effects on skills, thus ruling out their irrelevance.

6.2 Controlling for the lagged dependent variable

Because autocorrelation in a static panel estimation may bias the variance-covariance matrix and therefore the statistical inference, we check the robustness of our results using an alternative approach: including the lagged dependent variable as a control. However, as the lagged dependent variable is necessarily correlated with the error term, we employ the dynamic panel estimation method in Arellano and Bond (1991).

The results, which are reported in Table 9, show that import competition's impact on cognitive and interactive skills remain robust to this alternative estimation method. Although manual skills have the right signs, they are not statistically significant. These results imply that autocorrelation is unlikely to be the major driving force behind the static panel estimation results.[27] At the same time, as the lagged dependent variable also proxies for certain industry-time-varying variables, the dynamic panel estimation results lend further

[27]We experiment with dynamic panel estimation in all of our remaining robustness checks and obtain similar results (available upon request).

support to the validity of our instruments.

6.3 Additional industry-year-varying controls

A concern with the U.K. IV is that it may be correlated with certain other industry-year-varying characteristics that, in turn, may be correlated with both the import penetration ratio and the skill content of industries. If so, then the exclusion restriction would fail.

To address this potential concern, we further control for several other industry-year-varying control variables in the IV estimation: employment, shipment value, and shipment value-to-labor.[28] To address the potential "bad controls" problem, we follow Angrist and Pischke (2009) in using pre-determined values, that is, two-year lagged. The results, reported in Table 10, suggest that our main results regarding the impact of import competition on skills remain robust to these alternative time-varying industry controls.

6.4 Ratio of non-production to production workers

The ratio of non-production to production workers is a common proxy for skills in the literature (e.g., Berman, Bound, and Griliches, 1994). To compare our findings with those in the literature, we collect the information on total employment and the number of production workers from the NBER manufacturing productivity database and calculate the ratio of non-production workers as (Total employment - Production workers)/ Production workers.[29] Table 11 presents the unconditional pairwise correlations between the ratio of non-production workers and our skill measures. This ratio is positively correlated with cognitive non-routine and interactive non-routine skills, but negatively correlated with cognitive routine, manual non-routine, and manual routine skills.

Table 12 presents the results of our re-estimation of equation (2) using the ratio of non-production workers as the dependent variable and two alternative instruments. We

[28] These three variables are from the NBER manufacturing productivity database.

[29] Production workers are workers in manufacturing plants excluding supervisors above the line-supervisor level and clerical, sales, office, professional, and technical staffs.

again find a significantly positive relationship between this ratio and the import penetration ratio. This result suggests that import penetration increases demand for high-skilled labor in U.S. manufacturing industries, consistent with the findings in the literature. It is also consistent with our previous findings. However, with more disaggregated skill measures, we are able to further show that import penetration increases demand for some types of skills (i.e., cognitive non-routine, interactive non-routine, and manual non-routine skills), but also decreases demand for others (i.e., cognitive routine and manual routine skills).

7 Conclusion

This paper assesses empirically whether import competition explains the skill content of the U.S. manufacturing industries. Our empirical results provide supportive evidence of the proposition that import competition explains the variation in skill content across industries over time. We address endogeneity by employing an IV that is strongly relevant and unlikely to fail the exclusion restriction.

Our estimation suggests that industries that face more intense import competition employ more non-routine skill sets, including cognitive, interpersonal, and manual non-routine skills. Further, they tend to employ fewer cognitive routine skills. These results are robust to the use of the import-weighted exchange rate as an alternative IV covering a longer period of time. They are also robust to the inclusion of additional control variables and to the use of alternative measures to proxy the level of capital intensity. These effects are unlikely to be driven entirely by imports from low-wage countries.

Several possible future extensions are worthy of note. First, in this paper, we do not distinguish between the impact of intermediate imports and that of final goods imports on skills. Second, we do not distinguish between intra-firm and inter-firm imports. Theoretically, these four types of imports may possibly differ in the way in which they affect skills. Data are becoming more disaggregated, thus making it possible to conduct the required investigation in future research.

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Data Appendix

A Dictionary of Occupation Titles (DOT)

We must first acknowledge Marigee P. Bacolod and Bernardo S. Blum for their hard work in coding the DOT into time-consistent industry classifications. The following is an outline of their algorithm.

The fourth (1977) and the revised fourth (1991) editions of the DOT provide fine measures of skills.[30] The DOT was first developed in response to the need of an expanding public employment service for standardized occupational information to support job placement activities. The U.S. Employment Service recognized this need in the mid-1930s, soon after the passage of the Wagner-Peyser Act established a federal-state employment service system. DOT information is used primarily for job matching applications, employment counseling, occupational and career guidance, and labor market information services. A few economists have also used the DOT, most notably, Autor, Levy, and Murnane (2003), Wolff (2000), and Ingram and Neumann (2005).

The period that our study covers coincides with the information in the two aforementioned editions. Data in the 1977 edition were collected between 1966 and 1976, and those in the 1991 revised edition were collected between 1978 and 1990. Thus, the DOT skill measures in the former describe occupations in the 1970s, and those in the latter describe occupations in the 1980s and 1990s.

The 1991 revised fourth edition surveyed a total of 12,742 occupations, of these, 763 were newly created. Of the 12,099 occupations scored in the 1977 fourth edition, 2,453 were updated, 25 were deleted, and 51 were combined with other DOT occupations in the revised edition in 1991. Hence, 10,289 occupations in the later edition were not updated from 1977.

To derive the demand for skills across industries and occupations, the skill characteristics

[30] ICPSR Study Nos.7845 and 6100, respectively. The first edition of the DOT was published in 1939, and it was subsequently updated in 1949, 1965, 1977, and 1991.

of various occupations need to be mapped to the employment of individuals in these occupations and industries, which is available in the U.S. Census. This employment-weighted measure of skills by the U.S. Census industry is then mapped to the industry level into which trade data can be merged.

The derivation of occupational scores from the Census occupation and industry codes makes use of a data source that includes the fourth edition DOT codes and 1970 U.S. Census occupation and industry codes. The April 1971 Current Population Survey (CPS) has been coded with both the 1970 Census occupation and industry codes and the occupational descriptions from the 1977 DOT. In addition, the dataset includes sufficient cases to produce reliable estimates for the Census occupational categories.[31]

After constructing a mapping vector between the 1977 and 1991 DOTs for DOT occupations whose titles (or codes) changed between editions, this vector is then merged with the 1977 DOT information from the April 1971 CPS and 1991 DOT. Occupations deleted between 1977 and 1991 and those newly created in 1991 are identified from the scanned pages of the ICPSR Codebook for Study No. 6100.

To attach employment weights to the DOT occupation characteristics, the DOT occupation codes are mapped to the Census classification scheme. The only information available in the 1977 DOT is the occupation and industry information in the 1970 Census classification scheme. The following crosswalks are then employed.

Census occupation codes were merged to the DOT using the crosswalk from the National Crosswalk Service Center.[32] This occupation crosswalk includes a direct mapping from the DOT 1991 occupation codes to the Census occupation codes in the 1990 Census classification scheme and from the DOT 1977 codes to the Census occupation codes in the 1980 Census occupation classification scheme.

Although the foregoing crosswalk guarantees a Census occupation code for each DOT

[31]Note that in using this data, of the 2,453 DOT occupations updated in 1991, 612 did not appear in the 1977 data. They tend to be occupations that account for a very low degree of employment in the population.

[32]http://webdata.xwalkcenter.org/ftp/download/XWALKS/

occupation, there is still a need to identify the industry in the Census classification scheme. The only information provided in the April 1971 CPS is the DOT occupation industry in the 1970 Census classification scheme ("ind1970"). To map the variable "ind1970" to the Census industry classifications in the 1980 and 1990 Census classification schemes, the crosswalk kindly provided by David Autor is used.

The occupation and industry crosswalks give the occupation and industry codes in the Census classification schemes for 1970, 1980, and 1990. The derived summary scores of DOT characteristics by Census occupation and industry are thus obtained by collapsing the data to the means of the DOT variables by Census occupation and industry in the 1990 classification scheme. In collapsing the data for analysis, the decision about which census year (1970, 1980, or 1990) to use to index the observation is largely arbitrary. The substantive issue is that by 1990, the Census had disaggregated certain occupations and/or industries (such as computer-related ones). The 1990 classification scheme made necessary the indexing of the occupation-industry unit of observation for analysis.

To attach employment weights by census occupation and industry to the DOT occupation characteristics, the decennial Censuses of 1970, 1980, and 1990 are used. The employed population in each Census data gives us the calculated full-time equivalent employment counts by occupation and industry in each year. In other words, a full-time equivalent weight for each individual is first created: his/her sampling weight multiplied by the number of his/her weekly hours worked divided by 35 hours.[33] This weight is created in such a way that an individual who works full time (at least 35 hours a week) counts more than a part-time worker. These full-time equivalent weights were then added up within each occupation and industry in each Census year. Thus, the final number represents the total number of workers in each occupation and industry in full-time equivalents.

[33]Given that the hours and weeks worked are categorized and reported as intervals in the Census, the midpoint of each interval for a continuous measure is used.

B The UK instrument

The 1998 edition of the OECD STAN Industrial Database uses 3-digit ISIC version 2 industrial classifications. To map it to our time-consistent industry classification, we employ Jon Havemen's crosswalk.[34] The database covers the 1970 to 1996 period and contains such variables as imports an exports, but no domestic shipments. It does, however, contain domestic production. Domestic production differs from domestic shipments because an industry can produce more or less than it ships. The discrepancy will be reflected by the change in the level of inventory. However, we would not expect domestic shipments to differ from domestic production consistently. We therefore compute the U.K. import penetration ratio by replacing domestic shipments with domestic production, but employ a three-year moving average to acknowledge the discrepancy between the two variables. As shown by the first-stage statistics, however, the U.K. import penetration ratio is strongly relevant.

To break down U.K. imports from low-wage and non-low-wage countries, and those from or not from China, and to exclude U.K. imports from the U.S., we use bilateral trade data to construct the ratios of U.S. to non-U.S., low-wage to non-low-wage, and Chinese to non-Chinese imports from Nicita and Olarreaga (2006) for years starting in 1978 and from the OECD International Trade by Commodity Statistics SITC Rev. 2 4-digit-level U.K. bilateral trade data for 1970 to 1977.

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Table 1: Descriptions of skill measures

	DOT Variable	DOT Definition	Description	Coding
1	GEDM	General educational development in *Mathematics*	General educational development in mathematics required to perform job.	6 “adv calc; mod algebra; stats” 5 “algebra; calculus; stats” 4 “algebra; geometry; shop math” 3 “algebra; gometry” 2 “add, subtract, multiply, divide” 1 “basic arithmetic”
2	GEDR	General educational development in *Reasoning*	General educational development in reasoning required to perform job.	6 “most abstract problems/concepts” 5 “define problems; draw valid conclusions” 4 “practical problems” 3 “understand instructions” 2 “commonsense; take detailed instructions” 1 “commonsense; 1 or 2 step instructions”
3	GEDL	General educational development in *Language*	General educational development in language required to perform job.	6 “literature, tech journals, reports” 5 “same as 6” 4 “novels, business reports” 3 “magazines, tools manuals” 2 “5-6,000 word vocab.” 1 “2,500 vocab.”
4	DATA	Relationship to *Data*	Information, knowledge, and conceptions related to data, people, or things obtained by observation, investigation, interpretation, visualization, and mental creation. Data are intangible and include numbers, words, symbols, ideas, concepts, and oral verbalization.	7 “synthesizing” 6 “coordinating” 5 “analyzing” 4 “compiling” 3 “computing” 2 “copying” 1 “comparing”
5	PEOPLE	Relationship to *People*	Human beings; also animals dealt with on an individual basis as if they were human.	9 “mentoring” 8 “negotiating” 7 “instructing” 6 “supervising” 5 “diverting” 4 “persuading” 3 “speaking” 2 “serving” 1 “take instructions”
6	DCP	Direction, control, and planning	Adaptability to accepting responsibility for direction, control, or planning of an activity.	1 “yes” 0 “no”
7	STS	Set limits, tolerances, or standards	Adaptability to situations requiring attainment of set limits, tolerances, or standards.	1 “yes” 0 “no”
8	APTF	Segment of population possessing *finger* dexterity	Ability to manipulate objects with fingers rapidly and accurately required to perform job.	5 “top 10%” 4 “highest 1/3 except top 10%” 3 “middle third” 2 “lowest third except 10%” 1 “bottom 10%”
9	APTE	Segment of population possessing *eye-hand-foot* coordination	Ability to use eyes, hands, feet in coordination in accordance with visual stimuli to perform job.	5 “top 10%” 4 “highest 1/3 except top 10%” 3 “middle third” 2 “lowest third except 10%” 1 “bottom 10%”

Table 2: Summary statistics

Variable	no. of obs	mean	s.d.	min	max
Skill measures					
Cognitive non-routine	2340	0	1	-3.440	4.772
Interactive non-routine	2340	0	1	-2.917	5.894
Cognitive routine	2340	0	1	-4.346	3.850
Manual non-routine	2340	0	1	-2.169	5.198
Manual routine	2340	0	1	-4.556	6.671
Main variable					
ln(import penetration)	2103	-2.292	1.277	-8.404	0.000
ln(import penetration) low-wage countries excluded	2101	-2.377	1.280	-8.510	-0.125
ln(import penetration) China excluded	2101	-2.348	1.280	-8.410	-0.124
Controls					
ln(real capital stock/total employment)	2103	4.141	0.812	1.615	7.023
ln(real capital stock/production worker hours)	2103	3.791	0.849	1.178	6.632
ln(real equipment stock/production worker hours)	2103	3.219	0.930	0.395	6.196
ln(real equipment stock/total employment)	2103	3.570	0.903	0.831	6.586
ln(shipment value/total employment)	2103	4.850	0.816	2.694	8.152
ln(total employment)	2103	5.109	1.224	1.705	8.130
ln(shipment value)	2103	9.959	1.370	5.853	13.950
Instrumental variables					
U.K. import penetration ratio	1872	0.255	0.124	0.000	0.861
Import-weighted exchange rate	2232	107.989	13.077	71.470	156.020

Table 3: List of low-wage countries

Afghanistan	China	India	Pakistan
Albania	Comoros	Kenya	Rwanda
Angola	Congo	Lao PDR	Samoa
Armenia	Equatorial Guinea	Lesotho	Sao Tome
Azerbaijan	Eritrea	Madagascar	Sierra Leone
Bangladesh	Ethiopia	Malawi	Somalia
Benin	Gambia	Maldives	Sri Lanka
Bhutan	Georgia	Mali	St. Vincent
Burkina Faso	Ghana	Mauritania	Sudan
Burundi	Guinea	Moldova	Togo
Cambodia	Guinea-Bissau	Mozambique	Uganda
Central African Rep	Guyana	Nepal	Vietnam
Chad	Haiti	Niger	Yemen

Table 4: Effects of import competition on skills

	1	2	3	4	5
Dependent variable	Cognitive-non	Interactive-non	Cognitive-rou	Manual-non	Manual-rou
Panel A: IV: U.K. import penetration ratio (period: 1971 - 1997)					
Import penetration	0.715**	0.827**	-0.541**	0.400**	0.078
(1-yr lag)	[0.323]	[0.340]	[0.261]	[0.172]	[0.178]
Observations	1803	1803	1803	1803	1803
2nd-stage F-statistic	65.54	43.27	51.44	99.48	159.8
Under id test statistic	29.25***	29.25***	29.25***	29.25***	29.25***
Weak id test statistic	24.8	24.8	24.8	24.8	24.8
Panel B: IV: Import-weighted exchange rate (period: 1971 - 2001)					
Import penetration	1.0077**	1.5809**	-1.9589**	-0.5461	-1.6638**
(1-yr lag)	[0.508]	[0.719]	[0.840]	[0.410]	[0.760]
Observations	2174	2174	2174	2174	2174
2nd-stage F-statistic	52.41	28.93	14.66	77.9	20.18
Under id test statistic	6.861***	6.861***	6.861***	6.861***	6.861***
Weak id test statistic	6.441	6.441	6.441	6.441	6.441
Anderson-Rubin statistic	10.93***	20.72***	27.69***	3.39	24.75***
Panel C: OLS (period: 1971 - 2001)					
Import penetration	0	0.015	-0.042*	0.009	-0.013
(1-yr lag)	[0.023]	[0.026]	[0.025]	[0.022]	[0.021]
Observations	2174	2174	2174	2174	2174
R-squared	0.797	0.693	0.739	0.845	0.777

Note: Robust standard errors, adjusted for arbitrary heteroskedasticity and autocorrelation, are reported in brackets. All regressions include constant, year, and industry dummies. The under-id statistic is the Kleibergen-Paap rk LM statistic; the weak id statistic is the Kleibergen-Paap rk Wald F statistic. The Anderson-Rubin statistic is robust to weak IVs; it jointly tests whether the endogenous regressor is statistically significant and whether the over-identifying restrictions are also valid. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% levels, respectively. The corresponding first-stage results are presented in Panel A of Table 13.

Table 5: Controlling for capital deepening

	1	2	3	4	5
Dependent variable	Cognitive-non	Interactive-non	Cognitive-rou	Manual-non	Manual-rou
Panel A: IV: U.K. import penetration ratio (period: 1971 - 1997)					
Import penetration	0.603*	0.714**	-0.456*	0.433**	0.106
(1-yr lag)	[0.320]	[0.336]	[0.250]	[0.171]	[0.177]
Real capital stock over total employment	0.353***	0.362***	-0.278***	-0.097	-0.091
(2-yrs lag)	[0.086]	[0.100]	[0.079]	[0.070]	[0.066]
Observations	1801	1801	1801	1801	1801
2nd-stage F-statistics	72.06	44.69	55.11	95.35	150.2
Under id test statistic	28.77***	28.77***	28.77***	28.77***	28.77***
Weak id test statistic	24.1	24.1	24.1	24.1	24.1
Panel B: IV: Import-weighted exchange rate (period: 1971 - 2001)					
Import penetration	0.521	1.045**	-1.496**	-0.363	-1.431**
(1-yr lag)	[0.338]	[0.502]	[0.626]	[0.345]	[0.632]
Capital-to-labor	0.370***	0.401***	-0.337***	-0.140**	-0.164
(2-yrs lag)	[0.074]	[0.105]	[0.126]	[0.057]	[0.118]
Observations	2172	2172	2172	2172	2172
2nd-stage F-statistics	85.69	40.7	20.66	99.71	24.66
Under id test statistic	7.512***	7.512***	7.512***	7.512***	7.512***
Weak id test statistic	7.092	7.092	7.092	7.092	7.092
Anderson-Rubin statistic	3.822*	11.93***	21.57***	1.636	23.15***
Panel C: Estimates of import penetration with alternative capital-to-labor measures					
Real equipment stock over total employment	0.621**	0.732**	-0.479*	0.422**	0.104
(2-yrs lag)	[0.316]	[0.332]	[0.251]	[0.171]	[0.176]
Real capital stock over total production worker hours	0.596*	0.705**	-0.456*	0.418**	0.109
(2-yrs lag)	[0.316]	[0.331]	[0.249]	[0.169]	[0.176]
Real equipment stock over total production worker hours	0.617**	0.727**	-0.478*	0.412**	0.105
(2-yrs lag)	[0.314]	[0.329]	[0.249]	[0.169]	[0.176]

Note: Robust standard errors, adjusted for arbitrary heteroskedasticity and autocorrelation, are reported in brackets. All regressions include constant, year, and industry dummies. The under-id statistic is the Kleibergen-Paap rk LM statistic; the weak id statistic is the Kleibergen-Paap rk Wald F statistic. The Anderson-Rubin statistic is robust to weak IVs; it jointly tests whether the endogenous regressor is statistically significant and whether the over-identifying restrictions are also valid. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% levels, respectively. The corresponding first-stage results are presented in Panel A of Table 13.

Table 6: Effects of import competition on skills (excluding imports from China)

	1	2	3	4	5
Dependent variable	Cognitive-non	Interactive-non	Cognitive-rou	Manual-non	Manual-rou
Panel A. IV: U.K. import penetration ratio					
Import penetration	0.790**	0.900**	-0.512*	0.288*	0.064
(1-yr lag, excluding China)	[0.348]	[0.363]	[0.263]	[0.165]	[0.184]
Observations	1731	1731	1731	1731	1731
2nd-stage F-statistic	60.35	38.98	52.53	111.1	153.4
Under id test statistic	27.3***	27.3***	27.3***	27.3***	27.3***
Weak id test statistic	21.23	21.23	21.23	21.23	21.23
Panel B. IV: Import-weighted exchange rate					
Import penetration	1.1753**	1.8867**	-2.1986**	-0.3871	-1.6572**
(1-yr lag, excluding China)	[0.578]	[0.827]	[0.914]	[0.399]	[0.745]
Observations	2032	2032	2032	2032	2032
2nd-stage F-statistic	47.55	23.25	12.23	91.96	22.99
Under id test statistic	7.123***	7.123***	7.123***	7.123***	7.123***
Weak id test statistic	6.609	6.609	6.609	6.609	6.609
Anderson-Rubin statistic	11.73***	23.79***	30.18***	1.345	20.58***
Panel C. IV: U.K. Chinese and non-Chinese import penetration ratios					
Import penetration (ln(1+))	9.713**	8.774*	-2.827	-1.578	-6.701
(1-yr lag, excluding China)	[4.734]	[5.314]	[3.978]	[4.819]	[7.898]
Import penetration (ln(1+))	-35.573	-21.722	-5.351	28.952	58.443
(1-yr lag, from China)	[32.414]	[38.138]	[31.412]	[34.839]	[59.583]
Observations	1731	1731	1731	1731	1731
2nd-stage F-statistic	45.65	33.22	62.4	68.99	26.11
Under id test statistic	1.645	1.645	1.645	1.645	1.645
Weak id test statistic	0.548	0.548	0.548	0.548	0.548

Note: Robust standard errors, adjusted for arbitrary heteroskedasticity and autocorrelation, are reported in brackets. All regressions include constant, year, and industry dummies. The under-id statistic is the Kleibergen-Paap rk LM statistic; the weak id statistic is the Kleibergen-Paap rk Wald F statistic. The Anderson-Rubin statistic is robust to weak IVs; it jointly tests whether the endogenous regressor is statistically significant and whether the over-identifying restrictions are also valid. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% levels, respectively. The corresponding first-stage results are presented in Panel B of Table 13.

Table 7: Effects of import competition on skills (excluding imports from low-wage countries)

	1	2	3	4	5
Dependent variable	Cognitive-non	Interactive-non	Cognitive-rou	Manual-non	Manual-rou
Panel A. IV: U.K. import penetration ratio					
Import penetration	0.796**	0.917**	-0.527**	0.261	0.042
(1-yr lag, excluding low-wage)	[0.349]	[0.365]	[0.264]	[0.166]	[0.184]
Observations	1731	1731	1731	1731	1731
2nd-stage F-statistic	61.14	38.81	51.88	114.3	156.6
Under id test statistic	27.78***	27.78***	27.78***	27.78***	27.78***
Weak id test statistic	21.18	21.18	21.18	21.18	21.18
Panel B. IV: Import-weighted exchange rate					
Import penetration	1.1715**	1.8807**	-2.1916**	-0.3859	-1.6520**
(1-yr lag, excluding low-wage)	[0.565]	[0.807]	[0.893]	[0.395]	[0.729]
Observations	2032	2032	2032	2032	2032
2nd-stage F-statistic	48.82	23.68	12.34	92.38	23.39
Under id test statistic	7.532***	7.532***	7.532***	7.532***	7.532***
Weak id test statistic	7.008	7.008	7.008	7.008	7.008
Anderson-Rubin statistic	11.73***	23.79***	30.18***	1.345	20.58***
Panel C. IV: U.K. low-wage and non-low-wage import penetration ratios					
Import penetration (ln(1+))	7.296**	8.516**	-4.656*	-2.348	-4.551
(1-yr lag, excluding low-wage)	[3.135]	[3.423]	[2.771]	[4.189]	[4.690]
Import penetration (ln(1+))	-15.503	-18.751	8.822	33.883	39.764
(1-yr lag, from low-wage)	[16.397]	[20.360]	[19.130]	[28.020]	[34.067]
Observations	1731	1731	1731	1731	1731
2nd-stage F-statistic	71.86	38.12	52.12	58.12	41.26
Under id test statistic	2.369	2.369	2.369	2.369	2.369
Weak id test statistic	0.951	0.951	0.951	0.951	0.951

Note: Robust standard errors, adjusted for arbitrary heteroskedasticity and autocorrelation, are reported in brackets. All regressions include constant, year, and industry dummies. The under-id statistic is the Kleibergen-Paap rk LM statistic; the weak id statistic is the Kleibergen-Paap rk Wald F statistic. The Anderson-Rubin statistic is robust to weak IVs; it jointly tests whether the endogenous regressor is statistically significant and whether the over-identifying restrictions are also valid. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% levels, respectively. The corresponding first-stage results are presented in Panel C of Table 13.

Table 8: Reduced-form relationship between instruments and skills

	1	2	3	4	5
Dependent variable	Cognitive-non	Interactive-non	Cognitive-rou	Manual-non	Manual-rou
Panel A: U.K. import penetration ratio (period: 1971 - 1997)					
UK Import penetration	1.294***	1.496***	-0.979**	0.723**	0.141
(1-yr lag, UK)	[0.473]	[0.481]	[0.419]	[0.301]	[0.332]
Observations	1803	1803	1803	1803	1803
R-squared	0.81	0.709	0.762	0.858	0.796
Panel B: Import-weighted exchange rate (period: 1971 - 2001)					
Import-weighted exchange rate	-0.006***	-0.009***	0.011***	0.003*	0.010***
(1-yr lag)	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Observations	2174	2174	2174	2174	2174
R-squared	0.798	0.697	0.745	0.845	0.781

Note: Robust standard errors, adjusted for arbitrary heteroskedasticity and autocorrelation, are reported in brackets. All regressions include constant, year, and industry dummies. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Effects of import competition on skills in dynamic panel estimation

	1	2	3	4	5
	Cognitive-non	Interactive-non	Cognitive-rou	Manual-non	Manual-rou
Panel A: IV: U.K. import penetration					
Import penetration	0.387**	0.551**	-0.678**	0.168	-0.123
(1-yr lag)	[0.172]	[0.260]	[0.309]	[0.173]	[0.219]
1-yr lagged skill measure	0.072*	0.064	0.037	0.129***	0.128**
	[0.043]	[0.051]	[0.093]	[0.047]	[0.062]
Observations	1731	1731	1731	1731	1731
Panel B: IV: Import-weighted exchange rate					
Import penetration	0.348**	0.438*	-0.671**	0.164	-0.104
(1-yr lag)	[0.168]	[0.242]	[0.283]	[0.165]	[0.206]
1-yr lagged skill measure	0.105***	0.138***	0.067	0.176***	0.148***
	[0.034]	[0.052]	[0.080]	[0.047]	[0.053]
Observations	2032	2032	2032	2032	2032

Note: The Arrellano-Bond (1991) GMM dynamic panel estimators are reported where 2- to 5-year lagged skill measures are used as internal instruments. Year dummies are included. The corresponding Arellano-Bond tests for AR(1) are statistically significant at the 1% level, whereas those for AR(2) are not statistically significant at the 10% level for any of the estimations. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10: Effects of import competition on skills with additional controls

	1	2	3	4	5
Dependent variable	Cognitive-non	Interactive-non	Cognitive-rou	Manual-non	Manual-rou
Panel A: Controlling for employment size					
Import penetration	0.766**	0.890**	-0.565**	0.434**	0.083
(1-yr lag)	[0.334]	[0.350]	[0.274]	[0.185]	[0.188]
Employment size	0.253**	0.302**	-0.114	0.141**	0.021
(2-yrs lag)	[0.113]	[0.120]	[0.088]	[0.062]	[0.055]
Observations	1801	1801	1801	1801	1801
2nd-stage F-statistic	67.43	44.4	50.54	95.28	157.2
Under id test statistic	28.39***	28.39***	28.39***	28.39***	28.39***
Weak id test statistic	24.79	24.79	24.79	24.79	24.79
Panel B: Controlling for industry output					
Import penetration	0.786**	0.907***	-0.577**	0.434**	0.083
(1-yr lag)	[0.335]	[0.352]	[0.276]	[0.190]	[0.191]
Industry output	0.307***	0.342***	-0.148*	0.129**	0.021
(2-yrs lag)	[0.116]	[0.123]	[0.090]	[0.064]	[0.058]
Observations	1801	1801	1801	1801	1801
2nd-stage F-statistic	67.41	45.05	50.11	94.81	156.8
Under id test statistic	26.92***	26.92***	26.92***	26.92***	26.92***
Weak id test statistic	24.22	24.22	24.22	24.22	24.22
Panel C: Controlling for output-per-worker					
Import penetration	0.726**	0.839**	-0.549**	0.405**	0.079
(1-yr lag)	[0.324]	[0.342]	[0.263]	[0.176]	[0.181]
Output-per-worker	0.563***	0.538**	-0.309*	0.08	0.022
(2-yrs lag)	[0.210]	[0.219]	[0.159]	[0.123]	[0.111]
Observations	1801	1801	1801	1801	1801
2nd-stage F-statistic	65.54	40.52	49.94	95.8	157.6
Under id test statistic	27.71***	27.71***	27.71***	27.71***	27.71***
Weak id test statistic	24.23	24.23	24.23	24.23	24.23

Note: The IV is U.K. import penetration for all panels. Robust standard errors, adjusted for arbitrary heteroskedasticity and autocorrelation, are reported in brackets. All regressions include constant, year, and industry dummies. The under-id statistic is the Kleibergen-Paap rk LM statistic; the weak id statistic is the Kleibergen-Paap rk Wald F statistic. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11: Pairwise correlation between the ratio of non-production workers to production workers and different skill sets

	Non-prod/prod	Cognitive-non	Interactive-non	Cognitive-rou	Manual-non	Manual-rou
Non-prod/prod	1					
Cognitive-non	0.6578	1				
Interactive-non	0.6677	0.9027	1			
Cognitive-rou	-0.2794	-0.0952	-0.3923	1		
Manual-non	-0.3786	-0.5143	-0.4354	-0.0654	1	
Manual-rou	-0.0575	0.1228	-0.1396	0.7259	-0.1337	1

Note: The pairwise correlations are all statistically significant at the 1% level.

Table 12: Effects of import competition on the ratio of non-production workers to production workers

	1	2
Dependent variable	Non-production to production workers	
IV	UK IV	Ex rate
Import penetration	0.080*	0.529**
(1-yr lag)	[0.044]	[0.222]
Observations	1802	2171
2nd-stage F-test	153.4	29.36
Under id test statistic	29.22***	6.663***
Weak id test statistic	24.77	6.257

Note: Robust standard errors, adjusted for arbitrary heteroskedasticity and autocorrelation, are reported in brackets. All regressions include constant, year, and industry dummies. The under-id statistic is the Kleibergen-Paap rk LM statistic; the weak id statistic is the Kleibergen-Paap rk Wald F statistic. $*$, $**$, and $***$ represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 13: First-stage regressions

	1	2	3	4
Panel A: Tables 4 and 5				
The corresponding 2nd stage	Table 4 panel A	Table 4 panel B	Table 5 panel A	Table 5 panel B
Dependent variable	Import penetration (1-yr lag)			
U.K. import penetration	1.809***		1.866***	
(1-yr lag)	[0.363]		[0.380]	
Import-weighted exchange rate		-0.006**		-0.006***
		[0.002]		[0.002]
Real capital stock over total employment			-0.109	-0.074
(2-yrs lag)			[0.088]	[0.074]
Observations	1803	2174	1801	2172
R-squared	0.897	0.887	0.897	0.887
Panel B: Table 6				
The corresponding 2nd stage	Table 6 panel A	Table 6 panel B	Table 6 panel C	Table 6 panel C
Dependent variable	Import penetration (1-yr lag, excluding China)		Import penetration (1-yr lag, excluding China, ln(1+))	Import penetration (1-yr lag, from China, ln(1+))
U.K. import penetration (exclude China)	1.923***		0.275***	0.029
(1-yr lag)	[0.417]		[0.060]	[0.018]
Import-weighted exchange rate		-0.006**		
		[0.002]		
U.K. import penetration (from China)			0.588	0.434
(1-yr lag)			[0.863]	[0.385]
Observations	1731	2032	1731	1731
R-squared	0.878	0.868	0.822	0.438
Panel C: Table 7				
The corresponding 2nd stage	Table 6 panel A	Table 6 panel B	Table 6 panel C	Table 6 panel C
Dependent variable	Import penetration (1-yr lag, excluding low-wage)		Import penetration (1-yr lag, excluding low-wage, ln(1+))	Import penetration (1-yr lag, from low-wage, ln(1+))
U.K. import penetration (exclude low-wage)	1.959***		0.286***	0.025
(1-yr lag)	[0.426]		[0.062]	[0.020]
Import-weighted exchange rate		-0.006***		
		[0.002]		
U.K. import penetration (from low-wage)			0.09	0.357
(1-yr lag)			[0.644]	[0.285]
Observations	1731	2032	1731	1731
R-squared	0.88	0.87	0.83	0.47

Note: Robust standard errors, adjusted for arbitrary heteroskedasticity and autocorrelation, are reported in brackets. All regressions include a constant, year, and industry dummies. $**$ and $***$ represent statistical significance at the 5% and 1% levels, respectively.