Can Import Competition Explain the Skill Content in the United States?*

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Abstract

Skill content varies enormously across industries and overtime. This paper shows that in addition to differences in capital-to-labor ratios, differences in import competition can explain an economically and statistically significant portion of the variations of various skill measures across the manufacturing industries. Specifically, industries facing more intense import competition employ more non-routine sets of skills, including cognitive, interpersonal and manual skills, and less cognitive routine skills. In addition, we find that the impact of import competition on skills is not specific to imports from low-wage countries or from Chinese imports. A number of robustness checks suggest that the results are unlikely to be driven by econometric problems.

Keywords: import competition, skills, labor market

JEL classification: F16, J24, J82.

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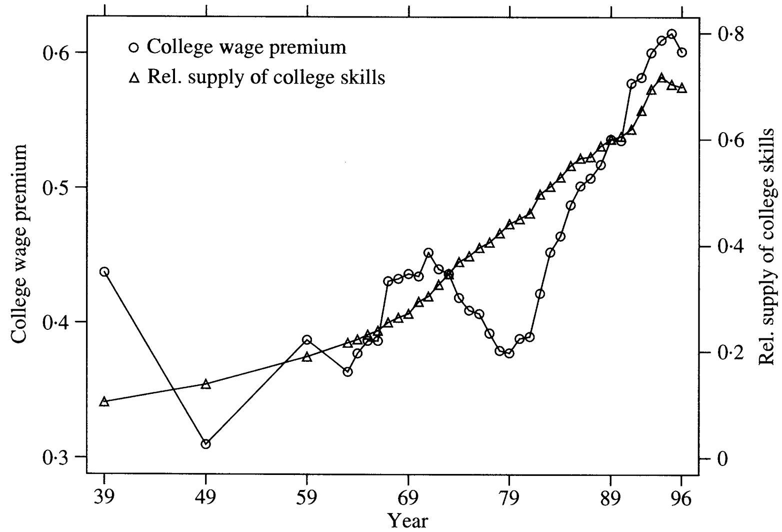

Relative Supply of College Skills and College Premium

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

1 Introduction

This paper empirically assesses whether import competition explains skill content, after controlling for the extent of capital-deepening. And if so, under more intense import competition, which sets of skills become more "demanded"?

These questions are motivated by three important trends in the US in the past few decades that have changed the structure of the manufacturing sector dramatically: (i) the shift in labor demand favoring skilled workers (Berman, Bound and Griliches, 1996), (ii) the rapid capital-deepening in terms of speedy rises in the capital-to-labor ratio, and (iii) the substantial rise in imports due to globalization.

Figure 1 duplicates Figure 1 of Acemoglu (2002). It shows that over the past several decades, the US relative supply of skills (measured by college skills) has increased rapidly. There is, however, no tendency that such a rapid rise in supply lowers the college wage premium. On the contrary, there has been a sharp rise in the college wage premium.

Panel A of Figure 2 shows the trend of import competition in the manufacturing sector.

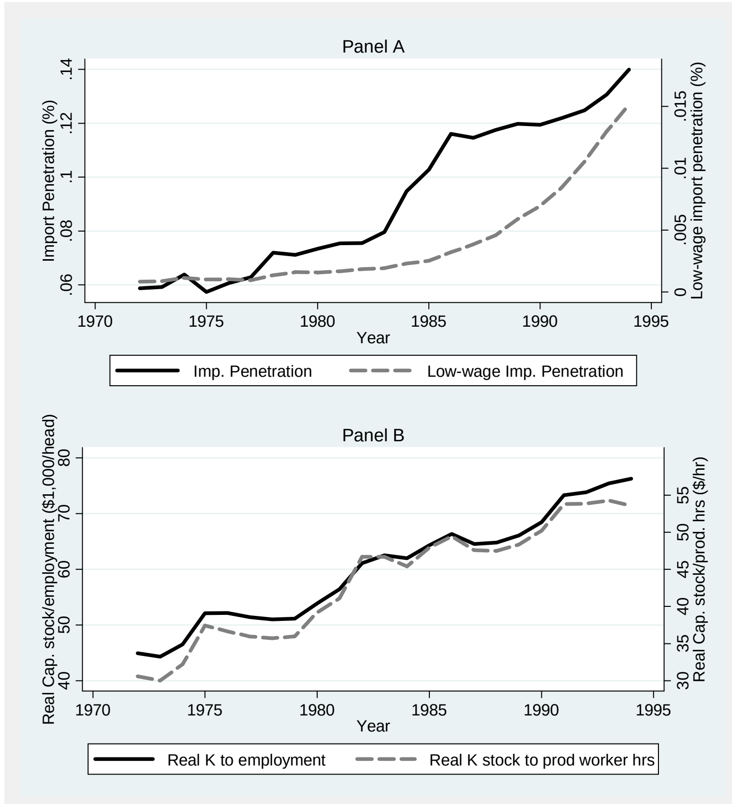

Figure 2: Import competition and capital-deepening for manufacturing sector. Authors' calculation from the NBER manufacturing database and from the US Import and Export data.

There was an upward trend for both the share of imports from the rest of the world and from low-wage countries.[1] It is thus natural to examine whether

$$\text{Imports}\uparrow \longrightarrow \text{Skills}\uparrow,$$

i.e., the rise in import competition is one of the major forces behind the trend in skill content. Panel B of Figure 2 shows the upward trend of capital-to-labor ratio (the real capital stock over the total employment and the number of production worker hours). From early 70s to mid 90s, the capital-to-labor ratio almost doubled.

The literature has documented that

[1] Table 3 lists the low-wage countries.

$$\frac{\textit{Capital}}{\textit{Labor}}\uparrow \longrightarrow \text{Skills}\uparrow,$$

i.e., capital-deepening drives skills demand. Griliches (1969) gives a fundamental argument of why capital deepening leads to the employment of relatively more skilled labor. Capital is generally complementary to both skilled and unskilled labor, but the degree of complementarity is higher for skilled than unskilled labor. Consequently, capital deepening tends to increase the relative demand for skilled labor.[2] Autor, Levy, and Murnane (2003) go deeper into examining the different degree of complementarity between various skills and computer and show that the dramatic fall in the computer cost acts as an exogenous force for capital-deepening, which in turn raises the demand for non-routine sets of skills among industries.

Since capital-deepening drives skills demand, to examine whether import competition drives skills demand, we need to control for the extent of capital-deepening. Our approach therefore becomes

$$\begin{tikzcd} \text{Imports}\uparrow \arrow[r] \arrow[rr, bend right] & \frac{\textit{Capital}}{\textit{Labor}}\uparrow \arrow[r] & \text{Skills}\uparrow, \end{tikzcd}$$

i.e., whether the dramatic rise in import competition is one of the major factors why industries have undergone rapid capital-deepening, which in turn leads to the rise in the demand for skills. And having controlled for the extent of capital-deepening, whether the dramatic rise in import competition also drives the demand for skills through other channels.

It is reasonable to expect import competition drives the rise in the demand for skilled workers through its effect on capital-deepening. As a recent New York Times article argues, one way the US manufacturing firms have found to survive competition from low-wage countries is to become more capital intensive.[3] The founder of a US motorcycle company

[2]For literature reference, please see Krusell, Ohanian, Ríos-Rull, and Violante (2000), and Autor, Levy, and Murnane (2003).

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

stated that to compete with lower-priced foreign competitors, they require "workers to help squeeze out labor costs through automation and other efficiencies." Theoretical reasons are also abundant. By a combination of plant closures, plant declines, and plant product-mix changes, import competition leads firms and industries to become more capital intensive.[4] Figure 2 in fact shows that the period in which the United States manufacturing sector hugely upgraded its capital coincides very well with the period of rising import competition.

Various reasons suggest that imports do drive the skill contents through channels other than capital-deepening. (a) Facing more intense import competition, firms upgrade the skills of their labor faster than they otherwise would;[5] (b) firms also tend to upgrade their capital faster than they otherwise would and that makes a particular set of skills relatively more valuable than others; (c) firms also tend to outsource their production processes faster than they otherwise would and those processes are more likely to be associated with more routine sets of skills; (d) firms who fail to do the above three points are less likely to survive under more intense import competition.

We use the Dictionary of Occupational Titles (DOT) to directly measure skills across industries over time. An advantage of using the dataset is that we do not have to infer skill measures from the ratio of production to non-production workers, or from the ratio of college-graduate to non-college graduate. Inferring skills from these ratios cannot answer the question of which particular skills respond to a particular changes. As both production workers and college-graduates encompass a variety of different skills. We measure the degree of exposure to import competition of the US industries by the industry's import penetration

[4] For empirical evidence, see Bernard et al. (2006). See Helpman (1984), Melitz (2003), and Helpman et al. (2004) for more theoretical arguments.

[5] The skills of foreign countries have caught up. For instance, computer-aided design (CAD) was once an advanced skills engineers in the US have a competitive edge on. Many developing countries now, however, have their own teams of CAD engineers. One of the authors visited a factory in Guangdong region of China in early 2009 specialized in photocopying machine parts. He met the large teams of local CAD engineers in the factory with constant real-time interactions with floor production workers. Their quick interactions with floor production workers enables them to adjust complex designs in a very short period of time without reporting to the Japaneses' buyers. These CAD engineers enable Chinese factories to assume more and more responsibilities from the Japanese buyers.

ratio.[6]

We pay special attention to the endogeneity of import competition in estimation. First, there is a potential reverse causality: the skill content may have shaped the level of imports of an industry. Second, it is unlikely that we can exhaust all the relevant variables that explain skill content in our estimation. In particular, there is no universal measure of a diverse set of policies across industries over time. It is likely that these policies that affect the skill content also affect the levels of import competition. We deal with these endogeneity issue by using instrumental variable (IV). We use the United Kingdom import penetration ratios of the corresponding industries to instrument those of the United States. Section 4 explains the rationale behind this IV.

Our results show that controlling for the extent of capital-deepening, import competition explains a substantial portion of the variations of skills employed by the manufacturing industries. In particular, industries facing more intense import competition tend to employ more of the non-routine sets of skills, including cognitive, interactive and manual non-routine skills. Industries with more intense import competition is also likely to require less cognitive routine skills.[7] We also show evidence suggesting that import competition affects skills through indirectly capital-deepening.

The results are robust to using import-weighted exchange rate as an alternative IV.[8] They remain robust when we use alternative measures of capital-to-labour ratios as controls, and when we include additional industry-year-varying control variables.

In addition, we find that the impact of import competition on skills is not specific to imports from the low-wage countries, and in particular, from Chinese imports. The impact of imports from non-low-wage countries on skills exhibits strikingly similar pattern.

Our paper is closely related to the literature that studies how international trade affects the US labor market. Of particular importance is the two branches of literature on the

[6]Revenge (1992), Guadalupe(Forthcoming), and Cuñat and Guadalupe (2006) also use the same measure.
[7]The section with the main result gives the precise magnitudes of the impacts in standard deviation unit.
[8]Bertrand (2004), Cuñat and Guadalupe (2009), Guadalupe(2007), and Revenga (1992) also use import-weighted exchange rates as instrumental variables for the degree of import competitions.

impact of trade on wage inequality and skill employment.[9]

Revenga (1992) documents the significant impact of import competition on employment and wage differential for skilled and unskilled labor in the U.S. manufacturing industries. Feenstra and Hanson (1996) show that the widening of wage gap between skilled and unskilled workers is associated with more globalized competition. Feenstra and Hanson (1999) evaluate the impact of outsourcing and computerization on the wage structure and found that they both explain the increase in the relative wage of non-production workers.

Bertrand (2004) shows that import competition affects the labor market by making wages more sensitive to unemployment rates whenever competition becomes more intense. The literature overall suggests a strong linkage between foreign competition and the labor market.

Instead of using education level or the ratio of production versus non-production workers to indirectly infer skill levels, another branch of literature related closely to our paper directly measures skill levels in the workplace, and explores the underlying reasons of various skill employment trends. Blum and Marigee (2010) directly measure skills of the US employment using the DOT database and conclude that the rising wage inequality and male-female wage gap can be explained by changes in skill prices. Spitz-Oener (2006), on the other hand, uses a unique dataset from West Germany that directly measures skill requirements, and shows that occupations require more complex skills today than in 1979, and that the changes in skill requirements have been most pronounced in rapidly computerizing occupations.

Autor, Levy, and Murnane (2003) also use the DOT data and show that computerization greatly affects skills demand. Computerization, a form of skill-based technological change, happened in the mid 70s among most industries. Those industries that were more computerized have experienced more rapid skill upgrading. Specifically, skill upgrading refers to an industry employing increasingly more of non-routine skills and less of routine skills. Their findings cover both the manufacturing and non-manufacturing sectors by using more aggregated NIPA level data. To assess the impact of import competition, we use more dis-

[9] For a quick reference, see Feenstra (2001) for an introductory survey of the literature on trade and wage structure.

aggregated industry classifications which are roughly equivalent to 3-digit manufacturing standard industrial classification(SIC) industry data. Data limitation, in turn, narrows our focus to the manufacturing sector only.

2 Data and Variables

2.1 Skill measures

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

The U.S. Department of Labor publishes the DOT since 1939 which provides measures of tasks as required or performed in over 10,000 occupations and how they change over time. The latest editions are the Fourth edition (1977) and the Revised Fourth (1991) edition. Information in the 1977 edition was collected between 1966 and 1976, while the information in the 1991 revision was collected between 1978 and 1990. DOT skill measures from the 1977 Fourth Edition describe in great details the skill levels required to perform occupations in the 1970s, while the 1991 Revised Fourth Edition best describe those in the 1980s.

Occupational definitions in DOT are the results of comprehensive interviews by trained occupational analysts of how jobs are performed in establishments across the nation and are composites of data collected from diverse sources. There are in total 44 different skill measures and job characteristics for occupations in both the Fourth Edition and the Revised Fourth Edition. These fall into seven categories: work functions; required General Educational Development (GED); aptitudes needed; temperaments needed; interests; physical demands; and working conditions in the environment. For consistency, we first re-scale the variables so that higher values denote higher requirements.

Our employment data comes from the March CPS from 1971 to 2001. Our sample includes all employed workers aged 18 to 65, with non-missing hours worked. The DOT has scores for more than 12,000 occupations, whereas the CPS only has 450 census occupation codes. We therefore aggregate DOT measures to a time-consistent census occupation level. All analyses are performed using as weights full-time equivalent hours of labor supply, that is, the product of the individual CPS sampling weight times hours of work in the sample reference week. We describe our data construction more thoroughly in Appendix 7.1.

Following Autor, Levy, and Murnane (2003), we construct measures of 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 DOT. As in Bacolod and Blum (2010), we employ principal component analysis to form more meaningful skill measures. In particular, we combine GEDM (math), GEDR (reasoning), and DATA (data) together to construct the measure of cognitive non-routine skill, and we combine PEOPLE (people), DCP (direction, control, and planning), and GEDL (language) to construct the measure of interactive non-routine skill. Cognitive routine skill corresponds to the raw measure of STS (set limits, tolerances or standards). Manual non-routine skill corresponds to the raw measure of APTE (eye-hand-foot coordination). Manual routine skill corresponds to the raw measure of APTF (finger dexterity). A higher score means the industry requires more of that particular set of skills. The skill measures do make economic sense when we examine the industries that scores the highest and the lowest among these five measures.[10] Table 2 presents the summary statistics of these skills.[11]

[10]For cognitive non-routine, the highest score industry is "Electronic computing equipment," and the lowest score industry is "Footwear, except rubber and plastic." For interactive non-routine, the highest score industry is "Electronic computing equipment," and the lowest score industry is "Dyeing and finishing textiles, except wool and knit goods." For cognitive routine, the highest score industry is "Apparel and accessories, except knit," and the lowest score industry is "Drugs." For manual non-routine, the highest score industry is "Logging," and the lowest score industry is "Not specified manufacturing industries." For manual routine, the highest score industry is "Apparel and accessories, except knit," and the lowest score industry is "Sawmills, planning mills, and millwork."

[11]We will describe the economic significance of our estimation results in units of standard deviations when we present the results. This would normalize the different scale of skill measures.

2.2 Import competition and other control variables

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

$$imp = \ln(\text{import}/(\text{import} + \text{domestic shipment - export})). \tag{1}$$

Our international trade data is from the US Import and Export Data for the manufacturing industries from 1970 to 2001 Robert Feenstra and is discussed in detail in Feenstra (1996, 1997) and Feenstra, Romalis and Schott (2002).[12] The domestic shipment data is the variable *Total value of shipments* from the NBER manufacturing productivity database. Bartelsman and Gray (1996) discuss the database in detail.[13]

We control for the extent of capital-deepening of industries by including the natural log of the capital-to-labor ratio in our estimation. The ratio is from the NBER manufacturing productivity database as well.

With all the crosswalks across years and different datasets, we successfully construct an industry-by-year panel dataset of skill requirements. The time-consistent industry classification is roughly equal to 3-digit Standard Industrial Classification(SIC). We have data for 70+ manufacturing industries from 1971 to 2001. Table 2 presents the summary statistics.

3 Empirical Strategy

To investigate the impact of import competition on the skill content of the manufacturing industries, we use the following specification:

$$\text{skill}_{jt} = \alpha_j + \beta imp_{jt-1} + \gamma(K/L)_{jt} + \delta_t + \text{error}_{jt}, \tag{2}$$

[12]Unfortunately, we do not find any comparable international trade data for non-manufacturing industries.
[13]We use the 2009 updated version of the NBER database.

where skill_{jt} is the skill measure of industry j at year t, imp_{jt-1} is the natural log of the import penetration ratio of industry j in year $t-1$. The year dummies, δ_t, capture any sector-wide technological improvements, business cyclical fluctuations, and sector-wide labour market changes that would have changed the employment of skills. The industry dummies, α_j, capture any time-invariant industry-specific characteristics, such as the products and production nature, the time-persistent industry-specific policies, rules, and regulations that may have affected an industry's levels of skills.

In particular, we include the capital-to-labor ratio, $(K/L)_{jt}$, to control for the extent of capital-deepening that would have made a particular set of skills relatively more productive. For instance, Autor, Levy, and Murnane (2003) give a model that formally illustrates how computer increases the relative productivity of non-routine skills as compared to routine skills. To deal with the possible heteroskedasticity and autocorrelation problem, standard errors are heteroskedasticity- and autocorrelation-robust.

We acknowledge that there are other omitted factors that may determine the skill content of industries. In particular, we have in mind over time changes in the industrial policies and the trade policies at the industry-level. We therefore expect $\text{error}_{jt} = \omega_{jt} + \epsilon_{jt}$, where ϵ_{jt} is an identically and independently distributed error term, and ω_{jt} denotes those policies that we failed to control for. Our estimated coefficient β is biased if ω_{jt} is correlated with imp_{jt-1}. To cite some examples, a change in quota policies for a specific type of products would affect both the industry's import penetration ratio and the skill content. A more stringent set of technical regulations on products may shield the industry from import competition and therefore also change the skill content of the industries.[14]

Potential reverse causality also complicates the estimation of β.[15] To the extent that

[14] Essaji (2008) documents that technical regulations substantially impinge on poor countries' exports to the United States.

[15] One way to deal with this issue is to use the lag level of import penetration ratio, i.e., imp_{jt-1}, instead. Cuñat and Guadalupe (2006) also use the lagged import penetration ratio instead of the current one as their explanatory variable to examine the impact of import competition on incentive contracts within a firm. The estimation results are, in fact, very similar when we use the contemporaneous import penetration ratio. The results are available upon request.

some specific skills are more complementary to dealing with foreign trade relative to others, an industry's skill content may have also shaped its levels of trade, and therefore its import penetration ratios. For instance, interpersonal skills are especially important in dealing with suppliers and therefore should facilitate trade more than, say, physical strength. Using the lag of the import penetration ratio, as we do here, only partially alleviates our concern for the potential reverse causality.

To the best of our knowledge, however, we are not aware of any systematic measure of a diverse set of policies that varies over time and across industries. We therefore rely on instrumental variables for unbiased estimates.

3.1 The UK Instrument

We deal with the endogeneity by using the import penetration ratios of the corresponding industries in the United Kingdom in the same year, denoted as imp^{UK}_{jt-1}, as instrument for the import penetration ratio.[16] We use the data from OECD STAN Industrial Database 1998 edition to construct this instrument.[17]

This instrument is potentially correlated with the import penetration ratio in the corresponding industries in the United States because it reflects the relative competitiveness of foreign producers in this industry and the relevant transaction cost of trading within this industry. For example, an advancement in the global supply-chain management of a major product of an industry is likely to lead to an increase in the imports of the industry both in the US and in the UK.

The exclusion restriction requires that imp^{UK}_{jt-1} does not correlate with ω_{jt}. In words, the identification assumption is that the degree of import penetration ratio in the UK does not systematically correlates with the trade and industrial policy changes in the US. Imagine an Indonesian businessman who exports to both the US and the UK expands effort to update

[16] Ellison, Glaeser, and Kerr (Forthcoming) also use the corresponding data in United Kingdom to instrument the potential for Marshallian spillovers between industries in the United States.

[17] A detailed description of the variable construction is in the Data Appendix.

himself on the changes of the US industrial policies. It is quite unlikely that such an effort would also help him update the changes of the UK industrial policies. In principle, to the extent that the United Kingdom does not systematically enact policies, rules, and regulations specific to an industry as it does in the corresponding industries in the United States, we do not expect import penetration ratio in the UK to correlate with ω_{jt}.

A potential concern is whether international agreements on the trading of a particular set of products would affect the import penetration ratios in both countries. This is possible, but our specification is likely to have taken care of this concern. International agreements tend to persist substantially longer in time relative to domestic industrial policies.[18] They are therefore more likely to be captured by the industry dummies. Import penetration ratios, on the other hand, tend to capture year-by-year changes.

3.2 Import-weighted exchange rate

As a robustness check, we also use the import-weighted exchange rate provided by Goldberg (2004) as an alternative instrument for imp_{jt-1}. In an insightful paper, Bertrand (2004) also uses the import-weighted industry-specific exchange rate to instrument for import penetration ratio. Revenga (1992) uses it to instrument import price. Cuñat and Guadalupe (2006) also use the same instrument for import competition and examine the effect of import competition on incentive provisions within firms.

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

[18] For instance, the recent GATT and WTO trade rounds are: Tokyo 1973, Uruguary 1986, and Doha 2001.

4 Main results

4.1 Import competition explains skill content

We examine whether $\beta \neq 0$, i.e., everything else equal, the level of intensity of import competition significantly explains the variations in the skill levels.

The top panel of Table 4 uses the United Kingdom import penetration ratios as an instrument. The period of coverage is from 1971 to 1997.[19] The results, however, suggest a rather different story. In particular, the results in column 1-4 and 7-8 suggest an industry with more intense import competition employs more non-routine skills, including both cognitive, manual, and interpersonal non-routine skills. This is true whether or not we control for the capital-to-labor ratio. Column 5-6 suggests that more intense import competition is associated with less cognitive-routine skills. Manual-routine skills, however, does not seem to correlate with import competition. Meanwhile, the first-stage statistics suggest the instrumental variable is strongly relevant to the endogenous variable.[20]

To gauge the economic significance, we calculate the magnitude of the change in skill measures when there is a one standard deviation increase in the import penetration ratio. The bottom row of the top panel in Table 4 shows this significance. Specifically, controlling for the extent of capital-deepening and all the dummies, a one standard deviation increase in the import penetration ratio leads to 1.02 standard deviation increase in cognitive non-routine skills. The corresponding figures for interactive non-routine, cognitive routine, and manual non-routine are 1.2, -0.58, and 0.65, respectively.

The middle panel of Table 4 uses the import-weighted exchange rate as an alternative instrument. Data on exchange rate allows us to cover a longer period, from 1971 to 2001. A concern is that the import-weighted exchange rate is at the 2-digit SIC level, which is more aggregated than our industry-level classification. Consistent to this concern, the weak identification statistics shows that this IV is likely to be subject to the problem of weak instrument.

[19]The UK import penetration ratio from the OECD Stan database is available only up to 1996.

[20]For brevity, we did not report the first-stage regression results. But they are available upon request.

We therefore rely on two statistics that are robust to the presence of weak instruments: the Anderson-Rubin (1949) statistic and the Stock-Wright (2000) S statistic.[21] These statistics show that both cognitive and interpersonal skills continue to be significantly associated with the import penetration ratio, with or without controlling for the capital-to-labor ratios. In contrast, the measure of manual-routine skills is now negatively and significantly associated with import penetration. The manual non-routine skills is no longer significant. The general picture, however, is that controlling for the extent of capital-deepening, import competition does explain a substantial portion of the skill content of industries.

The IV results also suggest a channel through which import penetration may potentially change the skill content. In all ten sets of IV estimates, with the exception of the manual skills, the magnitude of the effect of import penetration universally drops after we control for the capital-to-labor ratio. This suggests the inter-play between import competition and capital-to-labor ratio: capital-deepening is an important channel through which import competition affects skill content. Again, this is consistent with our intuition that more intense import competition drives firms to upgrade their capital to remain competitive; more than they otherwise would have been had their import competition been less intense. In addition to such an indirect channel through more rapid capital-deepening that affects skills, however, import competition still continues to affect skill content through some other channels.

As in Revenga (1992) and Bertrand (2004), the OLS results (bottom panel) are at odds with the IV results. We conduct test to examine whether the import penetration ratio can indeed be treated as exogenous. In all the skills regressions, the null hypothesis that the import penetration ratio is indeed exogenous is rejected at the 5% significance level for skills except manual routine, for which the IV results are insignificant.[22]

[21]The null hypothesis of the two tests are that the coefficient of the endogenous regressor in the structural equation is equal to zero and that the over-identifying restrictions are also valid. Both tests are robust to the presence of weak instruments.

[22]We instrument the capital-to-labor ratio with the corresponding ones in U.K. and perform the same endogeneity test. The null hypothesis that capital-to-labour ratio is indeed exogenous cannot be rejected at 15% significance level. Baum, Schaffer, and Stillman (2007) give more detailed explanation of the endogeneity test.

All in all, the results suggest that more intense import penetration is associated with the employment of relatively more non-routine skills, be it cognitive, interactive, or manual. Provided that computerization lowers the overall cost of trading with the rest of the world, this is consistent with the results in Autor, Levy, and Murnane (2003). It is also the case that cognitive routine skills drop when there is more intense import competition. For manual routine skills, however, there is no significant drop.

In addition, consistent with the intuition that capital is relatively more complementary to cognitive non-routine skills than other skills do, the estimated coefficients of capital-to-labor ratio are positive and significant for cognitive and interactive non-routine skills. For routine skills, consistent with Autor, Levy, and Murnane (2003), capital appears to significantly replace the need for employing cognitive routine skills. The results for manual skills, however, are mixed.

4.2 The results are unlikely to be specific to low-wage countries

Bloom, Draca, and Van Reenen (2009) study how Chinese imports induce technological change in the United States. They acknowledge the fact that many politicians in Europe and the US have been increasingly vocal in opposing the dramatic increase in Chinese trade. One reason is that the dramatic trade increase with China coincides very well with the period of increasing wage inequality in the United States. The recent financial tsunami further reinforces the sentiment that opposes imports from low-wage countries.

We perform a conceptual exercise here: we ask whether the way how imports affect skill content in the US is specific to low-wage countries? Is it generally the case for the imports from the non-low-wage countries too?

We compute the import penetration ratio without the imports from low-wage countries and from China. For comparison, we re-estimate the same set of regressions as we did in Table 4.

Table 5 reports the estimation results without the imports from China.[23] The top panel shows that, except the cognitive non-routine skills with capital-to-labor ratio as control, the signs and statistical significance of the effects of import penetration on skills exhibit strikingly similar pattern as those in Table 4. This suggests that even without China, the way how import competition shapes skill content would have been very much similar across different sources of imports.

Table 6 reports the estimation results when we take away the imports from low-wage countries.[24] Table 3 lists all the countries for which we regard as low-wage countries. The list roughly corresponds to the list of countries that had around 5% or lower of per-capita income of that of the United States.[25] Looking at the top panel, again, almost all of the estimated coefficients maintain their signs and statistical significance, suggesting that the results from Table 4 cannot be specific to low-wage countries only.

A potential concern is that we are using the same instrument, i.e., imp_{jt-1}^{UK} in the top panels of Table 5 and Table 6, as we did in Table 4. Can we use the import penetration ratio from all countries in the United Kingdom to instrument those in the United States, while taking away imports from the low-wage countries and China? The last row of the top panel gives the weak identification statistics. Relative to those in Table 4, the statistics in Table 5 and Table 6 are smaller, suggesting that the instrument is weaker. However, the magnitude is still substantially above the critical value of 10 suggested by Staiger and Stock (1997), thus relieving this concern.

The results suggest that the dramatic increase in imports from China and the low-wage countries may indeed be one of the shifters of skill content in the United States. But the way how imports affect skills is unlikely to be driven entirely by these imports.

[23] Precisely, the import penetration ratio without imports from China is measured as ln((import - import from China)/(import + domestic production - export)).

[24] Precisely, the import penetration ratio without imports from low-wage countries is measured as ln((import - import from low-wage countries)/(import + domestic production - export)).

[25] The 5% cut-off is also the definition of low-wage countries employed by Bernard, Redding, and Schott (2006).

5 Robustness

5.1 Further checks on the exclusion restrictions

This section provides two sets of tests to alleviate the concern that the United Kingdom import penetration ratio, as an instrument, may fail the exclusion restriction.

5.1.1 Additional industry-year-varying controls

One may concern about whether the UK import penetration ratio, as an instrument, may have correlated with some other industry-year-varying characteristics that in turn are correlated with the skill content of the industries. If it is so, then the exclusion restriction would fail.

We alleviate this concern by adding additional industry-year-varying control variable. First, we add the one period lag of the skill measure. The rationale is that the global industry may have responded to the US skill sets by changing its import competition pattern, such as exporting more to the US rather than to the UK. The skill content also reflects contemporaneously features in the international trade market. As such, this is a channel through which the exclusion restriction may have failed to hold.

Table 7 shows the results, controlling for the one period lag. The results continue to be robust.

We also control for the employment size of the industry (using log of the total employment), the size of the industry as measured by its shipment value (using log of the shipment value), and the productivity of the industry (using log of the shipment value over the total employment). Again, the rationale is that an industry in the US may have been productive enough, or big enough to have altered the international trade pattern of that industry. If so, failing to control whether it is big enough or productive enough would render our exclusion restriction fails. Table 8 shows that the results continue to be robust.

5.1.2 Are the US imports driving the world pattern?

Since the US is likely to be one of the biggest player in most of the manufacturing industries, being big may be enough to drive the import pattern across the world. If the US importers' behaviors are influenced by the US policies, and in turn their behaviors drive the import pattern across the world, including UK, our IV would be correlated with the US policies.

We address this concern by indirectly testing if this channel is viable. The idea is to exploit the fact that if the US policies is going to affect the imports of other countries, it is natural to expect that the imports from Canada and Mexico, due to their proximity and the NAFTA, is more likely to be affected relative to the imports from other countries.

If the US policies ever correlate with the UK import penetration ratio (i.e., our exclusion restriction fails), then including and excluding Canada and Mexico imports from the endogenous variables would theoretically make a significant difference to our estimation results. As suggested in Table 8, however, when we have excluded Canada and Mexico imports, we do not find hugely different estimation results: instrumented by the UK import penetration ratio, the US import penetration ratio continues to drive non-routine skills significantly. This gives some confidence that the concern that the US policies affecting the UK importing behavior through its size effect is not plausible.

5.2 Alternative measures of the extent of capital-deepening

Autor, Levy, and Murnane (2003) show that industrial computerization is one major driving force for skill content in the US in both the manufacturing and the non-manufacturing industries. We complement their empirical findings by asking whether the intensity of import competition also drives the skill content, controlling for the technical change of industries and capital-deepening by including time dummies and capital-to-labor ratio.

One concern is that we may not be controlling for computerization as precisely as the literature did. We only control for the general trend of capital-deepening. For one, the real capital stock used in Table 4 captures both structures, and equipment.[26] In addition, Feenstra and Hanson (1999) point out that the evaluation of the relative impact of trade and computerization measures is sensitive to the particular measures of computerization.

We use alternative measures of capital-to-labor ratio to tackle this concern. The benchmark measure used in Table 4 is the total real capital stock over the total employment. We use three alternative measures of the capital-to-labor ratio in Table 9. In panel A, we use the real equipment capital stock over the total employment. In panel B, we use the real equipment capital stock over the total production worker hours. In panel C, we use the total real capital stock over the total production worker hours. We use the United Kingdom import penetration ratios as the instrument.

The results show that the effect of import competition on skills are unlikely to be driven by the specific measures of capital-to-labor ratio.

5.3 Durable goods industries

Do the results simply reflect the differences between durable and non-durable industries? After all, we know that durable goods industries like professional equipments faced much higher import competition relative to non-durable goods like food manufacturing. As well, the skill content of the two sectors systematically differ.

We deal with this concern by looking only at the durable industries. Table 10 shows the estimation results. For brevity, we do not report the OLS regressions. The signs and the significance are broadly consistent with those in Table 3, suggesting that it is unlikely that the results simply document the differences between durable and non-durable industries.

[26] Krusell, Ohanian, Ríos-Rull, and Violante (2000) also made explicit distinction between structures and equipment in their structural model.

6 Conclusion

This paper empirically assesses whether import competition can explain the skill content of the US manufacturing industries. Our empirical results support the idea that both import competition and capital-deepening have played a role in explaining the variations of the skill content across industries over time. The rise in import competition has likely speeded up capital-deepening among manufacturing industries, which in turn affects their skill content. But import competition does appear to have affected the skill content of the US through channels other than capital-deepening.

We tackle the endogenity concern by using instrumental variable. We provide support to the claim that our instrument is strongly relevant and satisfies the exclusion restriction. The estimation suggests that industries facing more intense import competition employs more of non-routine sets of skills, including cognitive, interpersonal, and manual non-routine skills. It also tends to employ less of cognitive routine skills. These results are robust to using import-weighted exchange rate as an alternative IV that covers a longer period of time. The results are also robust to the inclusion of additional control variables, to using alternative measures to proxy the extent of capital-deepening, and they are also valid for a sub-sample of durable goods industries only.

Our results also show that the impact of import competition on the skill content in the US is not driven only by the dramatic increase in imports from the low-wage countries, and in particular, from China.

A few possible future extensions are noteworthy. First, we do not distinguish between the impact of intermediate imports and final goods imports on skills. Second, we do not distinguish intra-firm and inter-firm imports. Theoretically speaking, it is possible that these four types of imports differ in the way how they affect skills. Data is becoming more disaggregated and it is becoming more plausible that one may disentangle these four different types of imports in future research.

7 Appendix

7.1 Data

7.1.1 Dictionary of Occupation Titles (DOT)

We would first like to acknowledge Marigee P. Bacolod and Bernardo S. Blum for sharing of their hard work on coding the DOT into the time-consistent industry-classification. The following is the outline of their algorithm.

The Fourth Edition (1977) and Revised Fourth Edition (1991) of the Dictionary of Occupation Titles (DOT) provide fine measures of skills.[27] The DOT was first developed in response to the demand of an expanding public employment service for standardized occupational information to support job placement activities. The US 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. The use of DOT information mainly has been for job matching applications, employment counseling, occupational and career guidance, and labor market information services. A few economists also have used the information in DOT, most notably, Autor, Levy, and Murnane (2003), Wolff (2000, 2003), and Ingram and Neumann (2005).

The period our study covers coincides well with information from the 1977 Fourth Edition and the 1991 Revised Fourth Edition. Data in the 1977 Fourth Edition was collected between 1966 and 1976, while data in the 1991 revision were collected between 1978 and 1990. Thus, DOT skill measures from the 1977 Fourth Edition describe occupations in the 1970s, while occupations in the 1980s and 1990s are best described by the 1991 revised Fourth Edition.

The 1991 revised Fourth Edition surveyed a total of 12,742 occupations. Of these, 763 occupations were newly created in the 1991 revised Fourth Edition. Of 12,099 occupations scored in the 1977 Fourth Edition, 2,453 occupations were updated, 25 occupations were

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

deleted, and 51 were combined with other DOT occupations in the 1991 revised Fourth Edition. This produced a total of 10,289 occupations in the 1991 revised Fourth Edition that were not updated from 1977.

In order to derive the demand for skills across industries and occupations, the skill characteristics of occupations need to be mapped to the employment of individuals in these occupations and industries, as available in the US Census. This employment-weighted measures of skills by Census industry will then be ultimately mapped to industry-level in which trade data can be merged.

Deriving occupational scores by Census occupation and industry codes makes use of a data source that includes the fourth edition DOT codes and the 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 as well as the occupational descriptions from the 1977 DOT. In addition, the data has enough cases to produce reliable estimates for Census occupational categories.[28]

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

In order to attach employment weights to DOT occupation characteristics, DOT occupation codes were mapped into the Census classification scheme. The only information available in the 1977 DOT described is occupation and industry in 1970 Census classification scheme. It then became necessary to employ the following crosswalks.

Census occupation codes were merged to the DOT using the crosswalk from the National

[28]Note that in using this data, of the 2,453 DOT occupations updated in 1991, 612 DOT occupations end up were not in the 1977 data for. These tend to be occupations with very low employment in the population.

Crosswalk Service Center.[29] This occupation crosswalk has a direct mapping from DOT 1991 occupation codes to Census occupation codes in the 1990 Census classification scheme. There is also a direct mapping from the DOT 1977 codes to Census occupation codes in the 1980 Census occupation classification scheme.

While the above crosswalk guarantees a Census occupation code for each of the DOT occupations, there is still a need to identify industry in Census classification scheme. The only information provided in the April 1971 CPS was the DOT occupation's industry in 1970 Census classification scheme ("ind1970"). To map the variable "ind1970" into Census industry classifications in 1980 and 1990 Census classification scheme, the crosswalk kindly provided by David Autor is used.

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

7.1.2 Employment Weights from the Decennial Censuses of 1970, 1980, 1990

To attach employment weights by census occupation and industry to DOT occupation characteristics, the decennial Censuses of 1970, 1980, and 1990 are used. The employed population in each Census data gives the calculated full-time equivalent employment counts by occupation and industry in each year. That is, a full-time equivalent weight for each person is first created; this is his/her sampling weight multiplied by his/her weekly hours worked

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

divided by 35 hours.[30] This weight is created so that a person who works full time (at least 35 hours a week) would count more than part-time workers. These full-time equivalent weights were then added up within each occupation and industry in that Census year. Thus, this number represents the total number of workers in each occupation and industry in full-time equivalents.

7.1.3 The construction of the UK IV

The OECD Stan Industrial Database 1998 edition uses the 3-digit ISIC version 2 industrial classification. To map it to our time-consistent industry classification, we employ the crosswalk from Jon Havemen.[31] The database covers 1970 to 1996 for various countries, including the United Kingdom. It contains variables such as imports, exports, but not domestic shipment. It does, however, contains domestic production. Domestic production is different from domestic shipment because an industry can produce more or less than it ships; the discrepancies would be reflected by the change in the level of inventory. However, we would not expect domestic shipment to always differ in a unilateral direction from domestic production. We therefore compute the United Kingdom import penetration ratio by replacing domestic shipment with domestic production, but we use a three year moving average to acknowledge the discrepancy between the two variables. As shown by the first-stage statistics, however, the UK import penetration ratio is strongly relevant.

In addition, in a footnote, we also mention that we did instrument the capital-to-labor ratios using the United Kingdom capital-to-labor ratios of the corresponding industries. We gather the data from the EU KLEMS Growth and Productivity Accounts: March 2008 Release.[32]. But we fail to reject the null hypothesis that the capital-to-labor ratio is exogenous. Therefore, we did not instrument the capital-to-labor ratio in our main estimation.

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

[31] http://www.macalester.edu/research/economics/page/haveman/Trade.Resources/tradeconcordances.html

[32] http://www.euklems.net/eukdata.shtml

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Table 1: Descriptions of the skill measures

	DOT Variables	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 standard	1 ”yes” 0 ”no”
8	APTF	Segment of population possessing *finger* dexterity	The requirement of the ability to manipulate objects with fingers rapidly and accurately	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	The requirement of the ability to use eye-hand-foot coordination	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	2264	0.009	1.716	-5.890	8.171
interactive non-routine	2264	0.018	1.633	-4.742	9.581
cognitive routine	2264	0.558	0.114	0.065	1.000
manual non-routine	2264	1.388	0.180	1.000	2.324
manual routine	2264	2.496	0.152	1.805	3.512
					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
					Ivs
import penetration for UK	1872	0.289	0.147	0.000	1.078
industry-specific exchange rate	2232	107.989	13.077	71.470	156.020

Table 3: The list of low-wage countries

Afghanistan	Congo	Lao	Sierra Leone
Albania	Equatorial Guinea	Madagascar	Somalia
Angola	Ethiopia	Malawi	Sri Lanka
Benin	Guinea-Bissau	Mali	Saint Kitts and Nevis
Bangladesh	Gambia	Mauritania	Sudan
Burkina Faso	Ghana	Mozambique	Togo
Burundi	Guinea	Nepal	Uganda
Central African Republic	Guyana	Niger	USSR
Cambodia	Haiti	Pakistan	Vietnam
Chad	India	Rwanda	Yemen (North)
China	Kenya	Samoa	Yemen (South)

Table 4: The effects of import competition on skills

	1	2	3	4	5	6	7	8	9	10
Dep. variables:	Cognitive-non		Interactive-non		Cognitive-rou		Manual-non		Manual-rou	
Panel A. IV: UK import penetration ratio (period: 1971-1997)										
Lag Import penetration	1.355**	1.207*	1.438**	1.321**	-0.055*	-0.049*	0.083***	0.090***	0.016	0.018
	[0.626]	[0.660]	[0.611]	[0.639]	[0.029]	[0.029]	[0.031]	[0.032]	[0.028]	[0.029]
Capital-to-labor		0.524***		0.465***		-0.022***		-0.024**		-0.009
		[0.160]		[0.168]		[0.008]		[0.012]		[0.009]
Obs	1803	1802	1803	1802	1803	1802	1803	1802	1803	1802
2nd-stage F-statistics	60.02	63.53	40.84	40.46	54.4	55.93	92.17	92.13	154.3	147.3
Under id test statistic	27.86	27.01	27.86	27.01	27.86	27.01	27.86	27.01	27.86	27.01
Under id test p-value	0	0	0	0	0	0	0	0	0	0
Weak id test statistic	22.66	21.47	22.66	21.47	22.66	21.47	22.66	21.47	22.66	21.47
Impact of imp	1.143	1.019	1.304	1.199	-0.656	-0.584	0.599	0.650	0.146	0.165
Panel B. IV: import-weighted exchange rate (period: 1971-2001)										
Lag Import penetration	1.725**	1.118	2.570**	2.022**	-0.224**	-0.196**	-0.098	-0.076	-0.253**	-0.247**
	[0.870]	[0.693]	[1.169]	[1.002]	[0.096]	[0.088]	[0.074]	[0.070]	[0.116]	[0.116]
Capital-to-labor		0.558***		0.494***		-0.022		-0.027**		-0.006
		[0.139]		[0.186]		[0.015]		[0.010]		[0.018]
Obs	2174	2171	2174	2171	2174	2171	2174	2171	2174	2171
2nd-stage F-statistics	52.41	73.2	28.93	33.75	14.66	17.26	77.9	92.62	20.18	20.56
Under id test statistic	6.861	6.371	6.861	6.371	6.861	6.371	6.861	6.371	6.861	6.371
Under id test p-value	0.009	0.012	0.009	0.012	0.009	0.012	0.009	0.012	0.009	0.012
Weak id test statistic	6.441	6.002	6.441	6.002	6.441	6.002	6.441	6.002	6.441	6.002
Anderson-Rubin statistics	10.93***	4.95**	20.72***	13.55***	27.69***	22.02***	3.39*	1.92	24.75***	23.79***
Stock-Wright S statistic	10.77***	4.97**	20.06***	13.47***	25.91***	21.33***	3.29*	1.89	21.33***	20.92***
Impact of imp	1.416	0.913	2.264	1.775	-2.672	-2.327	-0.720	-0.556	-2.316	-2.251
Panel C. OLS (period: 1971-2001)										
Lag Import penetration	0.000	-0.007	0.024	0.021	-0.005*	-0.005*	0.002	0.003	-0.002	-0.003
	[0.039]	[0.040]	[0.042]	[0.043]	[0.003]	[0.003]	[0.004]	[0.004]	[0.003]	[0.003]
Capital-to-labor		0.596***		0.561***		-0.028***		-0.029***		-0.015*
		[0.099]		[0.107]		[0.007]		[0.008]		[0.008]
Obs	2174	2171	2174	2171	2174	2171	2174	2171	2174	2171
R-squared	0.797	0.802	0.693	0.699	0.739	0.743	0.845	0.847	0.777	0.778

Note: Robust standard errors, corrected for heteroskedasticity and autocorrelation are reported in the brackets. All regressions include a constant, year and industry dummies. The under-id test employs the Kleibergen-Paap rk LM statistic, whereas the weak id test uses the Kleibergen-Paap rk Wald F statistic. Both the Anderson-Rubin statistics and the Stock-Wright S statistic are robust to the weak IV; they jointly test whether the endogenous regressor is statistically significant and that the overidentifying restrictions are also valid. **Impact of imp** refers to the change of the dependent variable (in standard deviation unit) when *Lag import penetration* increases by one standard deviation. $*$, $**$ and $***$ represent statistical significance at the 10% 5% and 1% level.

Table 5: The effects of import competition on skills (excluding imports from China)

	1	2	3	4	5	6	7	8	9	10
Dep. variables:	Cognitive-non		Interactive-non		Cognitive-rou		Manual-non		Manual-rou	
Panel A. IV: UK import penetration ratio (period: 1971-1997)										
Lag Import penetration	1.499**	1.328*	1.587**	1.439**	-0.053*	-0.046	0.067**	0.073**	0.019	0.022
	[0.689]	[0.715]	[0.669]	[0.689]	[0.031]	[0.030]	[0.031]	[0.031]	[0.030]	[0.030]
Capital-to-labor		0.609***		0.572***		-0.028***		-0.021*		-0.01
		[0.160]		[0.170]		[0.009]		[0.012]		[0.009]
Obs	1731	1730	1731	1730	1731	1730	1731	1730	1731	1730
2nd-stage F-statistics	55.07	58.88	36.24	36.7	54.76	56.74	101	101.7	141.7	135.2
Under id test statistic	25.27	24.93	25.27	24.93	25.27	24.93	25.27	24.93	25.27	24.93
Under id test p-value	0	0	0	0	0	0	0	0	0	0
Weak id test statistic	18.79	17.84	18.79	17.84	18.79	17.84	18.79	17.84	18.79	17.84
Panel B. IV: import-weighted exchange rate (period: 1971-2001)										
Lag Import penetration	2.012**	1.303*	3.067**	2.315**	-0.251**	-0.204**	-0.07	-0.041	-0.252**	-0.221**
	[0.989]	[0.730]	[1.345]	[1.038]	[0.104]	[0.083]	[0.072]	[0.062]	[0.113]	[0.097]
Capital-to-labor		0.648***		0.670***		-0.039**		-0.032***		-0.027
		[0.156]		[0.211]		[0.016]		[0.010]		[0.018]
Obs	2032	2029	2032	2029	2032	2029	2032	2029	2032	2029
2nd-stage F-statistics	47.55	66.64	23.25	29.34	12.23	16.05	91.96	117.5	22.99	26.66
Under id test statistic	7.123	7.604	7.123	7.604	7.123	7.604	7.123	7.604	7.123	7.604
Under id test p-value	0.008	0.006	0.008	0.006	0.008	0.006	0.008	0.006	0.008	0.006
Weak id test statistic	6.609	7.105	6.609	7.105	6.609	7.105	6.609	7.105	6.609	7.105
Anderson-Rubin statistics	11.73***	6.10**	23.79***	16.61***	30.18***	23.78***	1.34	0.52	20.58***	18.92***
Stock-Wright S statistic	11.44***	6.07**	22.27***	15.97***	26.90***	21.70***	1.33	0.52	18.18***	17.10***
Panel C. OLS (period: 1971-2001)										
Lag Import penetration	-0.018	-0.016	0.012	0.017	-0.003	-0.004	0.002	0.002	-0.004	-0.004
	[0.035]	[0.035]	[0.038]	[0.038]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Capital-to-labor		0.594***		0.575***		-0.030***		-0.031***		-0.018**
		[0.103]		[0.112]		[0.007]		[0.009]		[0.008]
Obs	2032	2029	2032	2029	2032	2029	2032	2029	2032	2029
R-squared	0.799	0.805	0.692	0.698	0.732	0.735	0.846	0.848	0.777	0.777

Note: Robust standard errors, corrected for heteroskedasticity and autocorrelation are reported in the brackets. All regressions include a constant, year and industry dummies. The under-id test employs the Kleibergen-Paap rk LM statistic, whereas the weak id test uses the Kleibergen-Paap rk Wald F statistic. Both the Anderson-Rubin statistics and the Stock-Wright S statistic are robust to the weak IV; they jointly test whether the endogenous regressor is statistically significant and that the overidentifying restrictions are also valid. **Impact of imp** refers to the change of the dependent variable (in standard deviation unit) when *Lag import penetration* increases by one standard deviation. $*$, $**$ and $***$ represent statistical significance at the 10% 5% and 1% level.

Table 6: The effects of import competition on skills (excluding imports from low-wage countries)

	1	2	3	4	5	6	7	8	9	10
Dep. variables	Cognitive-non		Interactive-non		Cognitive-rou		Manual-non		Manual-rou	
Panel A. IV: UK import penetration ratio (period: 1971-1997)										
Lag Import penetration	1.519**	1.343*	1.608**	1.455**	-0.054*	-0.047	0.068**	0.074**	0.019	0.022
	[0.698]	[0.723]	[0.679]	[0.697]	[0.031]	[0.030]	[0.031]	[0.031]	[0.031]	[0.030]
Capital-to-labor		0.618***		0.582***		-0.028***		-0.020*		-0.01
		[0.160]		[0.171]		[0.009]		[0.012]		[0.009]
Obs	1731	1730	1731	1730	1731	1730	1731	1730	1731	1730
2nd-stage F-statistics	47.04	51.15	31.45	31.95	52.84	55.38	95.34	97.31	152.5	142.1
Under id test statistic	18.77	18.55	18.77	18.55	18.77	18.55	18.77	18.55	18.77	18.55
Under id test p-value	0	0	0	0	0	0	0	0	0	0
Weak id test statistic	14.72	14.11	14.72	14.11	14.72	14.11	14.72	14.11	14.72	14.11
Panel B. IV: import-weighted exchange rate (period: 1971-2001)										
Lag Import penetration	2.006**	1.294*	3.057**	2.299**	-0.250**	-0.202**	-0.069	-0.041	-0.251**	-0.220**
	[0.968]	[0.713]	[1.313]	[1.006]	[0.102]	[0.080]	[0.071]	[0.062]	[0.111]	[0.094]
Capital-to-labor		0.653***		0.679***		-0.040**		-0.033***		-0.028
		[0.156]		[0.210]		[0.016]		[0.010]		[0.018]
Obs	2032	2029	2032	2029	2032	2029	2032	2029	2032	2029
2nd-stage F-statistics	40.41	57.83	19.89	25.46	10.51	13.88	91.77	116.3	19.02	22.21
Under id test statistic	5.64	6.141	5.64	6.141	5.64	6.141	5.64	6.141	5.64	6.141
Under id test p-value	0.018	0.013	0.018	0.013	0.018	0.013	0.018	0.013	0.018	0.013
Weak id test statistic	5.245	5.759	5.245	5.759	5.245	5.759	5.245	5.759	5.245	5.759
Anderson-Rubin statistics	11.73***	6.10**	23.79***	16.61***	30.18***	23.78***	1.34	0.52	20.58***	18.92***
Stock-Wright S statistic	11.44***	6.07**	22.27***	15.97***	26.90***	21.70***	1.33	0.52	18.18***	17.10***
Panel C. OLS (period: 1971-2001)										
Lag Import penetration	-0.01139	-0.00885	0.01525	0.02103	-0.00257	-0.0034	0.00171	0.00252	-0.00294	-0.0037
	[0.03524]	[0.03508]	[0.03821]	[0.03816]	[0.00256]	[0.00253]	[0.00346]	[0.00340]	[0.00279]	[0.00278]
Capital-to-labor		0.59379***		0.57540***		-0.03047***		-0.03069***		-0.01780**
		[0.10281]		[0.11171]		[0.00701]		[0.00861]		[0.00800]
Obs	2032	2029	2032	2029	2032	2029	2032	2029	2032	2029
R-squared	0.799	0.805	0.692	0.698	0.732	0.735	0.846	0.848	0.777	0.777

Note: Robust standard errors, corrected for heteroskedasticity and autocorrelation are reported in the brackets. All regressions include a constant, year and industry dummies. The under-id test employs the Kleibergen-Paap rk LM statistic, whereas the weak id test uses the Kleibergen-Paap rk Wald F statistic. Both the Anderson-Rubin statistics and the Stock-Wright S statistic are robust to the weak IV; they jointly test whether the endogenous regressor is statistically significant and that the overidentifying restrictions are also valid. **Impact of imp** refers to the change of the dependent variable (in standard deviation unit) when *Lag import penetration* increases by one standard deviation. $*$, $**$ and $***$ represent statistical significance at the 10% 5% and 1% level.

Table 7: The effects of import competition on skills with additional controls

	1	2	3	4	5	6	7	8	9	10
Dep. variables	Cognitive-non		Interactive-non		Cognitive-rou		Manual-non		Manual-rou	
Panel A										
Lag import penetration	0.991*	1.065*	1.145**	1.228**	-0.054*	-0.057*	0.070**	0.073**	0.004	0.003
	[0.561]	[0.572]	[0.572]	[0.577]	[0.031]	[0.032]	[0.027]	[0.029]	[0.028]	[0.029]
Lag of dep. variable	0.264***	0.251***	0.364**	0.680***	-0.018**	-0.029***	-0.020*	-0.007	-0.008	-0.009
	[0.045]	[0.043]	[0.149]	[0.165]	[0.008]	[0.010]	[0.011]	[0.012]	[0.008]	[0.009]
Capital-to-labor	0.392***	0.667***	0.234***	0.220***	0.198***	0.197***	0.245***	0.245***	0.228***	0.228***
	[0.143]	[0.145]	[0.036]	[0.036]	[0.046]	[0.046]	[0.036]	[0.037]	[0.037]	[0.037]
ln(employmen)		0.511**		0.588***		-0.020*		0.025**		-0.003
		[0.208]		[0.214]		[0.011]		[0.011]		[0.010]
Observations	1802	1802	1802	1802	1802	1802	1802	1802	1802	1802
2nd-stage F-statistics	88.58	89.93	51.93	54.53	62.25	62.4	125.8	123.6	187.1	185.6
Under id test statistic	27.82	28.64	27.54	28.38	26.96	28.02	26.87	27.83	26.99	28.33
Under id test p-value	0	0	0	0	0	0	0	0	0	0
Weak id test statistic	22.75	23.69	22.03	23.06	22.2	23.62	21.33	22.63	22.1	23.8
Panel B										
Lag import penetration	1.108*	1.055*	1.262**	1.200**	-0.058*	-0.056*	0.075**	0.073**	0.004	0.004
	[0.579]	[0.569]	[0.585]	[0.581]	[0.032]	[0.032]	[0.031]	[0.030]	[0.029]	[0.029]
Lag of dep. variable	0.244***	0.253***	0.443**	0.068	-0.022**	-0.009	-0.023*	-0.038***	-0.013	-0.011
	[0.043]	[0.044]	[0.176]	[0.226]	[0.010]	[0.011]	[0.013]	[0.013]	[0.009]	[0.011]
Capital-to-labor	0.398**	0.079	0.218***	0.229***	0.197***	0.198***	0.244***	0.244***	0.227***	0.228***
	[0.161]	[0.226]	[0.037]	[0.0367]	[0.046]	[0.046]	[0.037]	[0.037]	[0.037]	[0.036]
ln(employmen)	-0.244		-0.068		-0.002		-0.017		-0.0127	
	[0.273]		[0.284]		[0.015]		[0.0218]		[0.015]	
ln(shipment)	0.709**		0.614*		-0.017		0.040*		0.010	
	[0.361]		[0.360]		[0.019]		[0.023]		[0.018]	
ln(shipment/employment)		0.907**		0.849**		-0.026		0.050*		0.008
		[0.429]		[0.432]		[0.022]		[0.025]		[0.020]
Observations	1802	1802	1802	1802	1802	1802	1802	1802	1802	1802
2nd-stage F-statistics	84.21	83.55	48.91	45.69	61.1	60.61	121.3	123.5	181.1	183
Under id test statistic	26.29	25.93	26.17	25.83	25.84	25.27	25.74	25.28	26.19	25.42
Under id test p-value	0	0	0	0	0	0	0	0	0	0
Weak id test statistic	22.78	22.31	22.35	21.85	22.84	21.99	22.01	21.28	22.99	21.91

Note: The instrumental variable is the UK import penetration ratio. Robust standard errors, corrected for heteroskedasticity and autocorrelation are reported in the brackets. All regressions include a constant, year and industry dummies. The under-id test employs the Kleibergen-Paap rk LM statistic, whereas the weak id test uses the Kleibergen-Paap rk Wald F statistic. $*$, $**$ and $***$ represent statistical significance at the 10% 5% and 1% level.

Table 8: The effects of import competition on skills (excluding imports from Canada and Mexico)

	1	2	3	4	5	6	7	8	9	10
Dep. variables	Cognitive-non		Interactive-non		Cognitive-rou		Manual-non		Manual-rou	
Lag import penetration	1.232**	1.095*	1.304**	1.187**	-0.044*	-0.038	0.055**	0.060**	0.015	0.018
	[0.572]	[0.597]	[0.555]	[0.575]	[0.025]	[0.025]	[0.025]	[0.025]	[0.025]	[0.025]
Capital-to-labor		0.591***		0.553***		-0.027***		-0.022*		-0.011
		[0.167]		[0.177]		[0.009]		[0.012]		[0.009]
Obs	1731	1730	1731	1730	1731	1730	1731	1730	1731	1730
2nd-stage F-statistics	60.08	63.38	38.48	38.77	64.21	66.77	91.96	90.43	136.6	128.4
Under id test statistic	29.18	28.2	29.18	28.2	29.18	28.2	29.18	28.2	29.18	28.2
Under id test p-value	0	0	0	0	0	0	0	0	0	0
Weak id test statistic	19.97	18.63	19.97	18.63	19.97	18.63	19.97	18.63	19.97	18.63

Note: The instrumental variable is the UK import penetration ratio. Robust standard errors, corrected for heteroskedasticity and autocorrelation are reported in the brackets. All regressions include a constant, year and industry dummies. The under-id test employs the Kleibergen-Paap rk LM statistic, whereas the weak id test uses the Kleibergen-Paap rk Wald F statistic. $*$, $**$ and $***$ represent statistical significance at the 10% 5% and 1% level.

Table 9: The effects of import competition on skills with alternative measures of capital-deepening

	1	2	3	4	5
	Panel A. Equipment stock/total employment				
Dep. variables	Cognitive-non	Interactive-non	Cognitive-rou	Manual-non	Manual-rou
Lag import penetration	1.247*	1.356**	-0.052*	0.088***	0.018
	[0.652]	[0.631]	[0.029]	[0.032]	[0.029]
Capital-to-labor	0.524***	0.463***	-0.018**	-0.020*	-0.01
	[0.135]	[0.148]	[0.008]	[0.011]	[0.008]
Observations	1802	1802	1802	1802	1802
2nd-stage F-statistics	62.61	39.75	54.95	93.87	147.4
Under id test statistic	27.38	27.38	27.38	27.38	27.38
Under id test p-value	0	0	0	0	0
Weak id test statistic	21.86	21.86	21.86	21.86	21.86
	Panel B. Capital stock/production worker hours				
Lag import penetration	1.199*	1.313**	-0.049*	0.088***	0.019
	[0.654]	[0.633]	[0.029]	[0.032]	[0.029]
Capital-to-labor	0.511***	0.456***	-0.021***	-0.016	-0.010
	[0.138]	[0.150]	[0.008]	[0.011]	[0.008]
Observations	1802	1802	1802	1802	1802
2nd-stage F-statistics	64.41	41.37	56.21	91.38	147
Under id test statistic	27.65	27.65	27.65	27.65	27.65
Under id test p-value	0	0	0	0	0
Weak id test statistic	21.85	21.85	21.85	21.85	21.85
	Panel C. Equipment stock/production worker hours				
Lag import penetration	1.239*	1.349**	-0.052*	0.086***	0.018
	[0.648]	[0.628]	[0.029]	[0.032]	[0.029]
Capital-to-labor	0.505***	0.448***	-0.018**	-0.014	-0.010
	[0.120]	[0.134]	[0.007]	[0.010]	[0.007]
Observations	1802	1802	1802	1802	1802
2nd-stage F-statistics	63.37	40.63	55.27	92.63	147.4
Under id test statistic	27.76	27.76	27.76	27.76	27.76
Under id test p-value	0	0	0	0	0
Weak id test statistic	22.08	22.08	22.08	22.08	22.08

Note: The instrumental variable is the UK import penetration ratio. Robust standard errors, corrected for heteroskedasticity and autocorrelation are reported in the brackets. All regressions include a constant, year and industry dummies. The under-id test employs the Kleibergen-Paap rk LM statistic, whereas the weak id test uses the Kleibergen-Paap rk Wald F statistic. $*$, $**$ and $***$ represent statistical significance at the 10% 5% and 1% level.

Table 10: The effects of import competition on skills in durable goods industries

	1	2	3	4	5
	Panel A. IV: UK import penetration ratio				
Dep. variables	Cognitive-non	Interactive-non	Cognitive-rou	Manual-non	Manual-rou
Lag import penetration	3.063*	2.868*	-0.041	0.087**	0.032
	[1.629]	[1.475]	[0.040]	[0.042]	[0.057]
Capital-to-labor	0.243	0.234	-0.007	-0.010	-0.002
	[0.354]	[0.332]	[0.008]	[0.013]	[0.010]
Observations	958	958	958	958	958
2nd-stage F-statistics	18.47	19.31	55.46	99.35	118
Under id test statistic	22.17	22.17	22.17	22.17	22.17
Under id test p-value	0	0	0	0	0
Weak id test statistic	10.32	10.32	10.32	10.32	10.32
	Panel B. IV: import-weighted exchange rate				
Dep. variables	Cognitive-non	Interactive-non	Cognitive-rou	Manual-non	Manual-rou
Lag import penetration	1.350*	1.853*	-0.166**	0.028	-0.188**
	[0.771]	[0.974]	[0.073]	[0.045]	[0.090]
Capital-to-labor	0.451***	0.442**	-0.009	-0.009	-0.005
	[0.166]	[0.197]	[0.014]	[0.010]	[0.016]
Observations	1154	1154	1154	1154	1154
2nd-stage F-statistics	48.47	32.03	17.95	172.9	23.86
Under id test statistic	5.445	5.445	5.445	5.445	5.445
Under id test p-value	0.020	0.020	0.020	0.020	0.020
Weak id test statistic	5.547	5.547	5.547	5.547	5.547
Anderson-Rubin chi-squared test	5.537	8.217	13.82	0.388	14.04
p-value of A-R chi-squared test	0.019	0.004	0.000	0.533	0.000

Note: Robust standard errors, corrected for heteroskedasticity and autocorrelation are reported in the brackets. All regressions include a constant, year and industry dummies. The under-id test employs the Kleibergen-Paap rk LM statistic, whereas the weak id test uses the Kleibergen-Paap rk Wald F statistic. The Anderson-Rubin chi-squared test gives a valid test the significance of endogenous regressors when using weak instruments. $*$, $**$ and $***$ represent statistical significance at the 10% 5% and 1% level.