Import Exposure and Skill Content:
Plant-Level Evidence from the US

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May 2017

PRELIMINARY AND INCOMPLETE

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Abstract

We use detailed establishment-level data to study the effects of import exposure on the distributions of occupations, skill content, and wages at US manufacturers. Our empirical model uses instrumental variables and fixed effects to exogenously identify Chinese supply shocks in US markets between 2000 and 2013. In our preliminary analysis, we find that import penetration decreases the use of routine skill occupations and increases the use of non-routine skills. These effects occur due to both within-plant changes and the endogenous exit of plants which employ more routine occupations. Our initial analysis finds new evidence that the effects of import penetration on skill content are heterogeneous within industries and concentrated at larger establishments.

JEL: J24, F16, F66

Keywords: Skill Content, Import Competition, Trade Liberalization

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1. Introduction

The pervasive anti-trade rhetoric in the 2016 US Presidential election echoed frustrations over the rise in imports from China and other low-wage countries and the contemporaneous disappearance of manufacturing jobs. Local economies in the rustbelt and beyond have struggled as the once-booming manufacturing industries in their region have declined. Empirical evidence shows that import competition, in addition to skills-biased technical change, has contributed to wage inequality and polarization in the labor market via the loss of middle-wage, routine-skill manufacturing jobs (Lake and Millimet, 2016; Autor, Dorn, and Hanson, 2013; Ebenstein et al., 2014; Keller and Utar, 2016). Despite a large literature on the importance of firm heterogeneity[4], however, little attention has been paid to where and how these adjustments occur and the role of firms in the so-called hollowing out of the middle. [5]

In this paper, we exploit microdata on the occupational and wage distributions of plants in the US to examine how changes in the composition of employment within and across import-exposed plants contribute to job polarization. In particular, we focus on how import competition from China has affected skill content at US plants both in manufacturing and non-manufacturing. Our preliminary analysis finds results that are consistent with the existing literature; we find that import penetration decreases the use of routine skills, while increasing the use of non-routine skills. These effects result from both within-plant changes and the endogenous exit of plants which employ more routine occupations. We also find new evidence that the effects of import penetration on skill content vary with plant size within industries and are concentrated at larger plants.

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[4] Following Melitz's (2003) general equilibrium model of heterogeneous firms and free trade, empirical studies have found that trade differentially affects firm employment and survival outcomes (e.g. Uysal, Yotov, and Zylkin, 2015; Holmes and Stevens, 2014; Bernard, Jensen, and Schott, 2006).
[5] Kerr, et al. (2015), Bockerman et al. (2013), and Maliranta (2013) are exceptions that focus on non-US firms.

Several studies have already noted the significant impact of Chinese import competition on US employment, especially in manufacturing.[6] Acemoglu, et al. (2016) estimate that rising import competition between 1999 and 2011 resulted in 2.0-2.4 million job losses. Similarly, Autor, Dorn, and Hanson (2013) find that Chinese import competition explains 25% of the decline in manufacturing employment between the years 1990 and 2007. As they point out, the previous focus on wage effects misses other important aspects of labor-market adjustment to trade. While Acemoglu, et al. (2016) and Autor, Dorn, and Hanson (2013) focus on aggregate employment effects, we examine which types of occupations are affected.

Our paper is most closely related to Lu and Ng's (2015) study of the effects of import exposure on industry-level skill content. We make three contributions with respect to their study. First, we use data from 2000-2013 to better examine the China shock and find that, in contrast to their conclusions using data through 2001 only, Chinese import exposure has statistically and economically significant consequences for the skill content of US manufacturing industries. Second, we make use of establishment-level data to identify important heterogeneity in plant-level responses that are masked at the industry level. Third, we study the role of intensive and extensive margins by identifying changes in skill content that occur within plants and changes driven by plant deaths. These margins are important: we find that changes in skill composition within plants and differences across plants in an industry explain over half of the overall variation at US establishments.

Our evidence on changes in occupational mix contributes to a growing literature on plant-level responses to Chinese import exposure. Utar and Torres-Ruiz (2013) find that Chinese import competition has a negative impact on employment and plant growth in Mexican

[6] Relatedly, Pierce and Schott (2016) examine how the certainty of China's WTO entrance contributed to the decline in manufacturing employment.

maquiladoras through both the intensive and extensive margins. Mion and Zhu (2013) examine similar questions, but then take one step further and find that import competition from China results in an increase in the share of non-production workers in low-tech manufacturing Belgian firms. The definition of non-production worker can be quite broad though. We exploit the detailed occupational data in the OES, in order to examine the implications of studies such as Bloom, Draca, and Van Reenan (2016). They find that Chinese import competition increases innovation within surviving firms and reduces employment and survival probabilities in firms that are in low-tech industries.

This study also relates to recent work on the occupational and wage consequences of trade using worker-level datasets. Ebenstein, et al. (2014) find that Chinese import competition leads to lower wages through the reallocation of workers away from high-wage manufacturing jobs. Autor, Dorn, Hanson, and Song (2014) find similar results for low-wage workers. High-wage workers, on the other hand, are better able to adjust without suffering wage losses. We view this paper to be complementary to these worker-level studies. We instead examine how firm-level decisions are contributing to these shifts in employment patterns across occupations.

The rest of the paper proceeds as follows. Section 2 describes the underlying channels through which import competition may affect employment patterns. Section 3 describes the data used in our analysis. This section is followed by a description of our identification strategy in Section 4. Results of our baseline analysis are presented in section 5. In section 6, we explore to what extent the results can be attributed to the intensive or extensive margins. The analysis is expanded to include upstream and downstream plants and those results are presented in section 7. Finally section 8 concludes the paper.

2. Theory

There are several channels through which import exposure stands to affect skill content within and across affected firms. First, increased import competition could affect a firm's input mix for a given production technology. Second, it could affect a firm's output mix for a given set of inputs, requiring a different set of skills. Lastly, increased import competition could contribute to changes in a firm's production technology altogether.

More competition encourages firms to look for less costly ways to produce their output. With growing globalization and improvements in transportation and information technology, the easiest avenue for cost-savings potentially comes from outsourcing, whether it be at home or abroad. At home, a firm could decide to outsource production of its intermediate parts or services such as cleaning, for example. With more import competition then, one might see an increase in establishments specializing in outsourceable tasks.

Firms can instead choose to outsource abroad, or offshore, when trade costs are low enough. According to the theory of offshoring by Grossman and Rossi-Hansberg (2008), offshoring could lead to productivity gains that benefit everyone, including workers whose tasks are being offshored. Otherwise, offshoring could also lead to workers being displaced. If the industry is able to expand, displaced workers could find work performing different tasks.

Various studies have attempted to identify tradeable tasks (Jensen and Kletzer, 2006; Blinder, 2009; Firpo, et al., 2011). The tradeability of a task might not be related to the amount of skill required or the wage it is paid. Furthermore, the tradeability of a task is ever changing with technological advances, so researchers have found it difficult to pin down a moving target. However, these studies generally agree that tasks that are easily codified and performed with the aid of information technology are most easily traded. Therefore, more import competition might result in more non-routine tasks that require face-to-face interactions at home.

Instead of changing their input mix, intense import competition may force firms to instead differentiate their output. As in Khandewal (2010), firms may choose to differentiate themselves by switching to a higher-quality product. In his theory, the ability to switch output is limited by the extent of vertical differentiation in the industry. These higher quality products may require relatively more R&D-related tasks.

In Holmes and Stevens (2014), import competition affects larger plants that produce more standardized goods relative to smaller plants that make more custom goods are relatively insulated. To the extent that these custom goods require more interaction with customers, import competition could lead to an increase in the relative demand for tasks requiring face-to-face interactions.

Quality upgrading could go hand in hand with upgrading of capital. Firms may try to survive competition by reducing labor costs and increasing production with automation. According to Guadalupe (2007), such technical change due to import competition is skills biased. Indeed, Bloom, Draca, and Van Reenen (2016) find empirical evidence that import competition from China does induce technological upgrading and leads to higher relative demand for skilled labor.

It is also possible that reallocation occurs within industry toward more capital-intensive plants. Bernard, Jensen and Schott (2006) show that import competition is negatively related to plant survival and employment growth. The plants that do survive are the more capital-intensive ones, which require relatively more skilled workers. This reallocation of activity induced by import competition would then also result in a shift in occupational distribution toward more non-routine tasks that are not easily automated.

It is difficult to clearly disentangle these channels; indeed, all the literature indicates that all three are likely occurring simultaneously. Our main empirical analysis captures the net effect of all of these mechanisms on skill content.

3. Data

We use plant-level data on occupational and wage distributions from the US Bureau of Labor Statistics' Occupational Employment Survey (OES). The survey is designed to produce employment and wage estimates for over 800 detailed occupations based on the Standard Occupational Classification (SOC) system at disaggregated geographic and industry levels. About 200,000 establishments are sampled twice a year from all fifty states, as well as the District of Columbia, Puerto Rico, Guam, and the Virgin Islands.[7] Large establishments are sampled with certainty no more than once every three years. Smaller establishments are sampled with probability. Six samples are then combined on a rolling basis to produce the semi-annual estimates.[8] All part- and full-time non-farm employees covered by the unemployment insurance system are included in the survey.[9]

We also make use of plant-level data from the Quarterly Census of Employment and Wages (QCEW) for measures of annual employment and plant age, even for years where the

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[7] Puerto Rico, Guam, and the Virgin Islands are excluded from our analysis. We also focus on privately owned establishments.

[8] This twice yearly sampling strategy began in the fall of 2002. In each subsequent year, the observations for the spring and fall samples are pooled. As a result, only half the number of establishments were surveyed in 2002. Prior to 2002, samples were only drawn once yearly. As a robustness, we restrict the sample to exclude observations from before 2003, and we find consistent, albeit a bit noisier, results.

[9] Self-employed, owners and partners in unincorporated firms, household workers, and unpaid family workers are excluded.

plant is not covered by the OES sample. This allows us to use lagged values for these plant characteristics without considerably limiting the estimating sample.

We employ Autor, Levy, and Murnane's (2003), or ALM, task framework to characterize occupations by their use of five different types of skills: analytic non-routine, interactive non-routine, cognitive routine, manual routine, and manual non-routine skills. ALM use data from the fourth edition of the US Department of Labor's Dictionary of Occupational Titles (DOT) to construct a 0-10 measure of the use of each skill in an occupation. These data are based on interviews across the country conducted by occupational analysts between 1978 and 1991 and are plausibly exogenous to the shock in Chinese import exposure that we study. We crosswalk the scores for the 485 Census occupations in the DOT data to the 791 SOC occupations defined in our OES data.[10] Table 1 provides the types of tasks associated with each skill set, the DOT variable used to measure each skill, and examples of occupations that are relatively intensive in each type of skill.

For each measure, we define an establishment's skill intensity as the weighted average of the occupations it employs in a year. We then z-score each skill measure based on the 2000 distribution across plants. A unit increase in each measure therefore reflects a one-standard deviation change in the skill usage relative this distribution.

We also construct a one-dimensional index of the routineness of an occupation's required skill set by dividing the sum of the two routine skill measures by the sum of all five skill measures, as in Ebenstein et al. (2014). We similarly define the routineness of a plant's employment as the weighted average of the occupations it employs and z-score this measure as

[10] Specifically, we crosswalk the 1990 Census occupational categories to the 2000 version and then crosswalk those to 2000 SOC categories. Each of the 791 SOC occupations directly matches to one of the Census occupations. The crosswalks are both provided by the US Census at https://www.census.gov/people/io/methodology.

well for consistent interpretation. Figure 1 illustrates how these measures have changed over time in our sample. Each line represents a different skill measure. The y-axis represents the number of standard deviations away from the mean in 2000. All measures show a dip during the recession in 2007-2009, but then seem to resume their pre-crisis trajectory. Consistent with the job polarization literature findings, we see that non-routine tasks have increased over this period, while routine tasks have declined.

Figure 2 illustrates the change in the routine index, which is an aggregated measure of the ALM indexes, against the change in the import penetration measure. Again, the y-axis represents the number of standard deviations away from the mean in 2000. The figure clearly shows a negative correlation between the two variables.

Variation in skill intensity in the US during this period can be explained by changes over time, differences across industries, differences across plants within each industry, and changes within plants over time. We estimate how much each dimension contributes to the overall variation in our data by regressing the routine index on these sets of fixed effects, adapting a strategy employed in Mundlak et al. (2012) and Castro et al. (2016). The results are shown in Table 3. Less than 1% of the variation in employment-weighted routine skill intensity is explained by common changes over time, meanwhile 41% of the variation is explained by differences across industries. Over half of the variation arises within industries. We estimate that differences across plants in each industry explain 49% of the variation in skill intensity and changes within plants over time contribute the remaining 10%.[11] Changes within plants and changes in the distribution of operating plants – both masked by industry-level analysis – are potentially important margins for changes in the overall skill distribution.

[11] Our estimates of the contribution of across(within)-plant changes is likely upward(downward)-biased by the unbalanced nature of our panel. Plant fixed effects absorb all variation in plants with only one observation.

Our measure of Chinese import penetration in industry j and year t is the ratio of US imports from China to total domestic absorption in the industry:

$$IP_{jt} = \frac{Imports_{jt}^{US,China}}{DomesticShipments_{j,1998}^{US} + Imports_{j,1998}^{US,World} - Exports_{j,1998}^{US,World}}.$$

We use pre-period (1998) values such that variation in the measure over time is explained by changes in imports only. We use Census data for US imports and exports by trading partner, graciously provided by Peter Schott on his website. These data are constructed by cross-walking the Census data on HS10 product-level trade flows to the NAICS6 industries in the US that produce each good. Domestic shipments data are from the NBER-CES Manufacturing Industry Database (Becker et al., 2016), which also provides data for constructing controls for industry capital-to-labor ratios and total factor productivity. In addition, we construct an instrumental variable for import penetration that uses 1995 values for domestic absorption in the denominator and replaces the numerator with Chinese imports in other OECD countries.[12] We use Pierce and Schott's (2012) crosswalk to map HS6 product level trade data from the UN Comtrade database to NAICS6 industries. Summary statistics for both the trade and employment data are provided in Table 2. In looking at mechanisms, we use the US Bureau of Economic Analysis'1992 input-output tables to construct upstream and downstream measures of import penetration, described in more detail below.

4. Identification

Our baseline specification regresses measures of skill at plant *i* in year *t* on lagged import penetration in its primary industry *j*:

[12] These eight countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

$$skill_{ijt} = \beta_0 + \beta_1 IP_{j,t-1} + \delta_j + \delta_t + u_{ijt}.$$

There are several threats to exogenously identifying the effects of import penetration on skill usage. First, it is likely that industries are systematically different in ways that relate to both skill content and Chinese import penetration. For example, China tends to have a greater comparative advantage in industries which employ more routine skills. We address this issue by using NAICS6 industry fixed effects to account for time invariant differences in skill intensity across the most disaggregate industry classification that may also be correlated with import penetration. Second, trends in the US labor market such as automation and skill-biased technical change explain changes in the skill content of US employment that will be spuriously correlated with the general rise in import penetration over the period. We therefore include year fixed effects to account for trends and shocks in skill content that affect skill usage across all industries. Third, the dynamics of plant-level adjustment to import competition are somewhat unclear. With regards to skill, it takes time for firms to adjust their input and/or output mixes or technology in ways that affect their skill content or for some firms to leave the market. On the extensive margin, it takes time for the marginal firms to shut down in response to import shocks. We follow the literature (e.g. Ebenstein et al., 2014) and regress skill content on import penetration in the previous year to allow for delayed responses over this period.

We focus on Chinese import penetration both because of the considerable variation over the period we study and because this variation can be largely attributed to plausibly exogenous Chinese productivity shocks stemming from its accession to the WTO in 2001 and its transition to a market-oriented economy (cites). Still, some variation in US imports from China is likely correlated with other factors such as US demand shocks which are also correlated with skill content. We address this concern using instrumental variables analysis. Following Autor et al.

(2013), Acemoglu et al. (2016), and others, we use Chinese imports in other OECD countries to instrument for Chinese imports in the US. Given the industry fixed effects, the identifying assumption is that the common within-industry variation in Chinese imports in the two markets is explained by supply shocks that are exogenous to the skill content of US establishments.

There are several threats to this assumption to consider. First, correlated demand shocks may explain some of the correlation across the US and other OECD countries so that the instrument does not exogenously identify supply shocks. In their seminal application of this instrument Autor et al. (2013) employ a gravity based approach as a robustness check to show that correlated demand shocks are not driving the wage and employment effects they find with the IV, however, and we proceed with the assumption that they do not explain our estimates for changes in skill usage either. A second concern is that the common variation in Chinese imports in the US and other OECD countries is driven by other unobserved shocks that are also related to skill content at US establishments. For example, adverse productivity shocks in the US may reduce both domestic output and exports to other OECDs which is in turn replaced by Chinese imports. The issue is in part addressed with year fixed effects which account for common shocks across US establishments. While we cannot entirely rule out unobserved industry-specific shocks of this sort, it seems reasonable to assume that the common variation is primarily explained by China's historic productivity growth of over 8% per year during this period (Brandt et al., 2012). A related concern is that there are common technology shocks in both the US and other OECD countries that are correlated with both skill content and Chinese imports. These shocks would not seem to explain the considerable variation in Chinese imports over this period, however, given that there is not a commensurate rise in imports from other low- and middle-wage countries which could similarly exploit adverse shocks to domestic producers.

Last, we note that our analysis does not capture endogenous changes in the task requirements of specific occupations as a result of import penetration. We lack time-varying data on task requirements that could be used to identify this intensive margin.[13] Notably, the disaggregated level at which we identify occupations in our data somewhat mitigates this concern. Our estimates capture transitions across detailed occupations that would be considered an intensive adjustment in the task requirement of an aggregate occupational classification. Still, to the extent import competition changes task requirements within these occupational classifications our estimates will not capture the full effects. On the other hand, to the extent these intensive changes reflect the broader changes across occupations with regards to tasks, our analysis will somewhat understate the cumulative effect of import competition on task employment.

Our theory section outlines several reasons to suspect that import competition has heterogeneous effects across establishments within an industry. Out of consideration for these potential sources of heterogeneity, we also estimate the following specification:

$$Skill_{ijt} = \beta_0 + \beta_1 IP_{j,t-1} + \beta_2 IP_{j,t-1} Size_{ij,t-1} + \beta_3 Old_{ij,t-1} + \beta_4 Size_{ij,t-1} + \delta_j + \delta_t + u_{ijt},$$

where $Size_{ij,t-1}$ is measured as the natural log of employment and $Old_{ij,t-1}$ is an indicator variable for plants that are five years or older.

We add a control for plant age in the size specification to account for the life-cycle dynamics of a plant. According to Haltiwanger, Jarmin, and Miranda (2013), there is potential for omitted variables bias when estimating the effect of plant size without controlling for firm

[13] The 1991 edition of the DOT is the last in the series. Its replacement, O*NET, characterizes occupations using different measures of skills that do not directly compare to those in the DOT used here.

age.[14] To the extent that import competition affects young/small businesses differently than old/small businesses, estimates of the role of size and estimates of the role of age may confound each other if both variables are not included in the estimation. As in Fort, et al. (2013), we only divide plants into two age categories: plants less than five years old and plants that are five years or older. While aggregating start-ups with other young plants does miss the interesting differential dynamics between the two groups, Haltiwanger, Jarmin, and Miranda (2013) show that plants exhibit average growth conditional on survival after five years.

5. Results

5.1 Baseline Results

We begin by regressing the set of skill measures at US establishments on import penetration in their primary NAICS6 industry. These benchmark results are shown in Table 4. The OLS results in Panel A show that import penetration leads to a significant decrease in the share of routine skills employed at a plant ($p<0.01$). This is driven by both significant decreases in the use of routine skills and increases in the use of non-routine skills. These results are potentially confounded by unobserved correlates of both US imports and skill content, however. To address this potential bias, we use other OECD imports from China as an instrument for US imports and present the 2SLS results in Panel B. The last column shows that import penetration significantly decreases the routine index of occupations at the average plant ($p<0.01$). Moving an industry from the 25th to 75th percentile of Chinese import penetration – an increase of 0.105 – reduces the share of routine skills employed by the average plant in the following year by about 0.03 standard deviations.

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[14] While other studies emphasize the conventional wisdom that small firms have higher net growth rates than large firms, they find that this relationship disappears after controlling for firm age.

The other columns show that the composite effect is driven by both a decline in routine skills and an increase in non-routine skill usage. Specifically, import penetration significantly decreases the use of cognitive routine skills ($p<0.01$), while the effect on manual routine skills is also negative but not statistically significant. Meanwhile, import penetration significantly increases the use of analytic non-routine ($p<0.01$) and interactive non-routine skills ($p<0.01$) and has a positive but insignificant effect on manual non-routine skills in this specification.

5.2 Employment-Weighted Results

The estimates in Table 4 are based on unweighted regressions and therefore give the effects of import penetration on skill content at the average manufacturing establishment. In this section we identify the model using weights to estimate the average effect for a representative worker and the average effect across unweighted industries. The results are provided in Table 5. In Panels A and B we weight each plant by its employment to estimate the effects of import penetration on the skills of the average US manufacturing worker. Consistent with our baseline findings, both the OLS and 2SLS estimates show that import penetration significantly decreases the average routine index of occupations employed in an industry. Increasing Chinese import penetration by the interquartile range reduces the share of routine skills employed in an industry by 0.12 standard deviations. On average, workers' use of both manual and cognitive routine skills and manual non-routine skills decreases with import penetration, while the use of analytic and interactive non-routine skills increases.

In Panels C and D we weight establishments by share of industry employment such that the results directly compare to unweighted estimates using industry-level skill data (e.g. Lu and Ng, 2013). The results are of similar sign and magnitude to our baseline, but are not statistically significant in most cases. The lack of significant estimates suggests that failing to account for industry size masks important effects at the average plant and for the average worker.

5.3 Plant-Level Heterogeneity

We next consider that import exposure differentially affects plants in an industry. Table 6 shows the results allowing for heterogeneity related to plant size. Consistent with our baseline estimates, we find that Chinese import penetration in an industry tends to decrease the use of routine skills and increase the use of non-routine skills. These results reveal important heterogeneity in the effects across plants in an industry, however. The effects for both sets of skills are heterogeneous and increasing in plant size, such that the marginal effects at plants with 500 employees are 2-3 times greater than those at plants with 50 employees. Shifting an industry from the 25th to 75th percentile of import penetration decreases the share of routine skills employed in the industry by 0.05 standard deviations among plants with 50 employees and by 0.09 standard deviations among plants with 500 employees.

These results show that the average effects are largely driven by changes in skill distribution at larger establishments, which decrease use of routine-skill occupations and increasing use of non-routine-skill occupations in response to import competition.

6. Intensive and Extensive Margins

These changes in skill distributions within import-competing industries are potentially due to both within-plant changes in skill usage and changes in the distribution of plants that relate to skill. In this section we study the role of these intensive and extensive adjustment margins.

We first consider within-plant changes in relative skill by including plant fixed effects in our specification. There is little understanding of how much the shift in occupational distribution occurs within plants due to the lack of data at the plant level on employment patterns. We exploit the details in our data and include plant-level fixed effects by estimating the following:

$$Skill_{ijt} = \beta_0 + \beta_1 IP_{j,t-1} + \beta_2 IP_{j,t-1} Size_{ij,t-1} + \beta_3 Old_{ij,t-1} + \beta_4 Size_{ij,t-1} + \delta_i + \delta_t + u_{ijt}.$$

These within-plant effects of import penetration are provided in Table 7. Consistent with the other estimates, import penetration tends to increase non-routine skills and decrease routine skills at all but the smallest plants. These results substantiate the importance of the internal margin: surviving plants in import-competing industries increase the use of non-routine skills and decrease the use of routine skills.

The within-plant estimates are somewhat smaller than our baseline results, suggesting that some but not all of the changes in occupational mix occur along this intensive margin. Thus, we next examine how plant exit due to import competition affects skill content. Bernard, Jensen, and Schott (2006) finds that import competition differentially affects firm shutdown rates, with less-capital-intensive firms being more likely to exit as a result. One might expect these less capital-intensive firms to be ones with more routine workers, who have not yet been replaced by automation.

We identify this margin by regressing a dummy for plant exit over a five-year period on import penetration with an interaction term to allow for heterogeneous effects across plants using the following linear probability model:

$$Exit_{ij}^{t:t+5} = \beta_0 + \beta_1 IP_{j,t-1} + \beta_2 IP_{j,t-1} X_{ijt} + \beta_3 X_{ijt} + \beta_4 Old_{j,t} + \delta_j + \delta_t + u_{ijt}.$$

where X_{ijt} includes the following plant characteristics: routine index, employment size, share of low wage jobs, and share of high-wage jobs. Low-wage jobs are defined as those occupations that pay median wages in the bottom 25th percentile of the wage distribution. High-wage jobs are defined as those occupations that pay median wages in the top 25th percentile of the wage distribution. These results are provided in Table 9.

We find that import penetration is less likely to shut down larger establishments, consistent with the existing literature. In addition, we find new evidence that the effects depend also on the occupational distribution of plant employment. Plants which employ more routine occupations are more likely to exit following an import shock, as are plants that tend to employ relatively low-wage occupations. Our results support the hypothesis that differential plant exit due to import competition drives changes in the occupation and wage distributions. Heterogeneous plant responses along both intensive and extensive margins explain the related industry-level findings in the literature.

7. Mechanisms

Theory and existing evidence suggests several potential channels through which import competition stands to affect skill usage. These can be broadly categorized as changes in the plants input mix, changes in its output mix, and changes in its production technology. In this section we use our data to shed some light on these mechanisms.

7.1 Input Mix and Input-Output Linkages

We begin by studying whether import competition causes firms to change their input mix in ways that are related to skill usage. One reason for this adjustment is access to cheaper intermediate goods. To test for these effects, we regress firm skills use on import penetration in its supplying industries.

Following the literature (e.g. Acemoglu et al., 2016; Pierce and Schott, 2016) upstream import penetration in an industry j is defined as the weighted average of import penetration in all supplying industries k:

$$IP_{jt}^{Up} = \sum_k w_{jk}^{Up} IP_{kt}.$$

The upstream weights w_{jk}^{Up} are defined as the share of industry j's inputs that are sourced from industry k.[15] As in Pierce and Schott (2016) we construct these weights using the BEA's 1992 input-output total requirements table. The value requirement coefficients measures the value of production in industry k required both directly and indirectly to produce a dollar of output in industry j. We analogously construct a measure for downstream import penetration using the value requirement coefficients for j's output in each downstream industry k as weights.[16] For both upstream and downstream measures we set the weights equal to zero for industries within the same NAICS3 family in recognition that establishments sometimes produce output corresponding to multiple NAICS6 industries within the same NAICS3. As with our direct measure, we construct instruments for both upstream and downstream import penetration using Chinese imports in other OECD countries, using the same weights for industry linkages.

We estimate the following specification to account for sectoral linkages[17]:

$$Skill_{ijt} = \beta_0 + \beta_1 IP_{j,t-1}^{Direct} + \beta_2 IP_{j,t-1}^{Down} + \beta_3 IP_{j,t-1}^{Up} + \delta_i + \delta_t + u_{ijt}.$$

[15] As we defined it, the estimated coefficients on this term capture the effects of import penetration upstream of a plant (i.e. with its suppliers). In the later versions of their paper, Acemoglu et al. (2016) use the reverse labels such that their downstream measure captures the downstream effects of IP and therefore corresponds to our upstream measure, and vice versa.
[16] These estimates capture first-order input-output linkages such that an industry j is affected by direct import exposure in a supplying or demanding industry k but not by indirect upstream or downstream exposure in k.
[17] We do not interact each import measure with plant size in this specification. There is not a theoretical explanation for potential heterogeneity related to size among non-manufacturers.

These regressions again are limited to the manufacturing firms in our data. We include establishment fixed effects in these regressions to allow for unobserved heterogeneity in skill usage across this diverse set of establishments.

The results are provided in Table 10. We find that import penetration in supplying industries increases establishments' use of manual routine ($p<0.01$) and manual non-routine ($p<0.01$) skills, ceteris paribus. The results suggest that access to foreign inputs increases the use of manual skills at US establishments.

Establishments tend to decrease the use of routine skills and increase the use of non-routine skills in response to direct import penetration. Exposing an industry's buyers to import competition ceteris paribus has similar effects, although only the decreases in manual routine ($p<0.05$) and manual non-routine skills ($p<0.01$) are statistically significant. Comparing the estimated effects of direct and downstream import penetration highlights distinctions that are not captured by studies on employment, which find that import exposure in both dimensions similarly decreases industry employment (Acemoglu et al., 2016; Pierce and Schott, 2016).

Firms can also offshore tasks to cut costs. This will differentially affect occupations which tend to complete tasks that are more easily offshored. Autor and Dorn (2013) and Firpo et al. (2011) measure the offshoring potential of jobs based on the average of two tasks from O*NET: face-to-face contact and on-site job. A lower score indicates that an occupation depends less on proximity to work location and/or interpersonal interactions and is therefore more susceptible to offshoring. Going forward, we plan to test whether firms tend to shed jobs that are more easily offshored in response to Chinese import penetration and how those contribute to changes in the skill distribution.

7.2 Output Mix

We next consider that establishments could change their output mix in response to import competition in ways that relate to skill use. One means for this is quality upgrading. Khandelwal (2010) finds that the employment and output effects of low-wage country import competition are less in industries with greater scope for quality differentiation. To relate this to skill, we identify the differential effects of import penetration on skills in industries with above- and below-average quality ladders using Khandelwal's data. The results are shown in Table 11. We find that the effects of import penetration on skills are concentrated in industries with shorter quality ladders, consistent with them being hit harder by more competitive foreign imports. The linear combination of the first two coefficients shows that adjustments are negligible in industries with greater scope for quality differentiation, however, such that we fail to find suggestive evidence of quality upgrading driving our results for skills.

While we do not observe product-level output, OES contains the six-digit NAICS industry code corresponding to the majority of a plant's economic activities each year. Going forward, we plan to test whether plants change their primary industry of activity in response to import competition, as in Bernard et al. (2006). Comparing skill intensity in plant's old and new industries will shed light on how these major shifts in output mix affect the skill distribution.

7.3 Technology

We lastly consider that endogenous changes in production technology contribute to the consequences of import penetration on skills. We test whether the effects are concentrated in industries which are increasing in capital intensity during this period. We use NBER data on capital investment per worker to split the sample into industries with above- and below-average growth in capital investment between 2000 and 2011, the last year for which data is available.

We interact this measure with import penetration to identify the differential effects on skill content across the two groups of industries. Table 12 presents the results. We fail to find significant evidence of heterogeneity related to capital deepening, with the exception of manual non-routine skills ($p<0.10$).

Going forward, we plan to use the detailed classifications in our data to study endogenous changes in technology-related occupations, following related work in Harrigan, Reshef, and Toubal (2016). We will then relate these indicators of technology upgrading to changes in the skill and wage distribution.

8. Conclusion

This paper examines the job polarization phenomenon in the US at the establishment level. In particular, we study how Chinese import competition in the US has affected the occupational mix at manufacturing and non-manufacturing establishments. According to our preliminary analysis the "hollowing-out" of the routine, middle wage jobs is a result of both within-plant changes and the endogenous exit of plants that employ more routine occupations. We also find that the effects of import penetration on skill content are heterogeneous across plants within an industry. In particular, both decreases in routine-skill occupations and increases in non-routine-skill occupations are concentrated at larger plants.

Our analysis thus far is still preliminary. The ALM task framework is just one lens through which we can characterize occupations to examine the effects of import competition on the US labor market. We can characterize occupations along other dimensions related to tradeability or technology and R&D, for example. This will be useful in continuing to explore the underlying mechanisms. Furthermore, we would like to push the analysis toward understanding the consequences of the resulting job reallocation for the wage distribution.

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Table 1: Skill Measures and Examples

Skill Set	Types of Tasks	DOT Measure	Examples of Skill-Intensive Occupations
Analytic Non-routine	Forming Hypotheses, Medical Diagnosis	GED Math	Engineers, Scientists, Architects
Interactive Non-routine	Managing Others, Persuading/Selling	Direction, Control, and Planning	Managers, Administrators, Teachers
Cognitive Routine	Record-Keeping, Calculations, Repetitive Interactions with Customers	Set Limits, Tolerances, or Standards	Mechanics, Machine Operators, Electricians
Manual Routine	Picking, Sorting, Repetitive Assembly	Finger Dexterity	Assemblers, Machinists, Painters
Manual Non-routine	Janitorial Services, Driving	Eye-Hand-Foot Coordination	Industrial Equip. Operators, Truck Drivers

Table 2: Summary Statistics for US Manufacturers			
	N	Mean	Std Dev
Annual Industry-Level Data for Manufacturing			
US Imports from China (100 million)	537,340	1.41	4.05
Other OECD Imports from China (100 million)	537,340	1.05	2.65
Chinese Import Penetration	537,340	0.04	0.09
Chinese Import Penetration IV	537,340	0.03	0.07
Establishment Level Data			
Employment*			
Establishment Age	4,716,419	13.39	16.01
Dummy: Old*			
Analytic Non-routine Skills (Raw)	4,711,832	3.56	1.34
Interactive Non-routine Skills (Raw)	4,711,832	2.09	1.63
Cognitive Routine Skills (Raw)	4,711,832	4.16	1.97
Manual Routine Skills (Raw)	4,711,832	3.79	0.70
Manual Non-routine Skills (Raw)	4,711,832	1.08	0.82
Routine Index	4,711,832	0.54	0.11
Dummy: Exit in a Year*			

Notes: Starred variables have not yet been cleared for public consumption. Industry sample includes those covered by the NBER-CES Manufacturing Industry Database (NAICS 31xxxx-33xxxx). Industry data are from 1999 through 2012 and correspond to their lagged values in the regressions on establishment data from 2000 to 2013. Import penetration measures may exceed unity because domestic absorption is defined by its 1998 value. Industries are weighted by total employment. Establishments are weighted by employment except in the case of employment. Data sources are described in the paper.

Table 3: Variation in Routine Index	
Source of Variation (Fixed Effects)	Percentage Variation
Across Years (t)	0.2
Across Industries (j, t)	43.7
Across Establishments (i, j, t)	46.8
Within Establishments	9.3

Notes: Each components contribution to variation is measured as the marginal decline in the residual sum of squares. Within-establishment variation is measured as that which remains after establishment fixed effects are added.

Table 4: Benchmark Results

	Analytic Non-routine *(GED-Math)*	Interactive Non-routine *(Direction, Control, & Planning)*	Cognitive Routine *(Set Limits, Tolerances, or Standards)*	Manual Routine *(Finger Dexterity)*	Manual Non-routine *(Eye-hand-foot Coordination)*	Routine Index
Panel A: OLS						
$IP_{j,t-1}^{Direct}$	0.067**	0.189***	-0.066***	-0.049*	0.041**	-0.151***
	(0.033)	(0.029)	(0.025)	(0.026)	(0.016)	(0.029)
FEs	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year
N	537200	537200	537200	537200	537200	537200
Years	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013
R^2	0.360	0.187	0.251	0.345	0.446	0.203
Panel B: 2SLS						
$IP_{j,t-1}^{Direct}$	0.264***	0.381***	-0.116***	-0.048	0.019	-0.308***
	(0.057)	(0.051)	(0.043)	(0.044)	(0.031)	(0.051)
FEs	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year
N	537200	537200	537200	537200	537200	537200
Years	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013

Notes: Robust standard errors are clustered by establishment and reported in parentheses. The first stage regressions are identical for all columns and have an adjusted R-squared on 0.907 and pass a weak instruments test with a robust F-statistic of 5505.3.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 5: Weighted Average Effects

	Analytic Non-routine *(GED-Math)*	Interactive Non-routine *(Direction, Control, & Planning)*	Cognitive Routine *(Set Limits, Tolerances, or Standards)*	Manual Routine *(Finger Dexterity)*	Manual Non-routine *(Eye-hand-foot Coordination)*	Routine Index
Panel A: Average Worker Effect, OLS						
$IP_{j,t-1}^{Direct}$	0.358*	0.755***	-0.253	-0.519***	-0.092	-0.517**
	(0.213)	(0.235)	(0.176)	(0.164)	(0.066)	(0.210)
FEs	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year
N	330329	330329	330329	330329	330329	330329
Years	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013
Panel B: Average Worker Effect, 2SLS						
$IP_{j,t-1}^{Direct}$	0.867***	1.420***	-0.699***	-0.987***	-0.273**	-1.176***
	(0.334)	(0.352)	(0.270)	(0.260)	(0.131)	(0.210)
FEs	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year
N	330329	330329	330329	330329	330329	330329
Years	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013
Panel C: Unweighted Average Industry Effect, OLS						
$IP_{j,t-1}^{Direct}$	0.015	0.275*	-0.054	-0.064	-0.105	-0.061
	(0.137)	(0.155)	(0.115)	(0.121)	(0.064)	(0.146)
FEs	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year
N	330329	330329	330329	330329	330329	330329
Years	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013
Panel D: Unweighted Average Industry Effect, 2SLS						
$IP_{j,t-1}^{Direct}$	0.127	0.539*	-0.110	-0.001	-0.091	-0.259
	(0.220)	(0.238)	(0.199)	(0.202)	(0.135)	(0.233)
FEs	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year
N	330329	330329	330329	330329	330329	330329
Years	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013

Notes: Panels A and B weight plants by employment in previous year. Panels C and D weight plants by share of industry employment in the previous year. Robust standard errors are clustered by establishment and reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 6: Heterogeneous Responses by Size

	Analytic Non-routine *(GED-Math)*	Interactive Non-routine *(Direction, Control, & Planning)*	Cognitive Routine *(Set Limits, Tolerances, or Standards)*	Manual Routine *(Finger Dexterity)*	Manual Non-routine *(Eye-hand-foot Coordination)*	Routine Index
$IP_{j,t-1}^{Direct}$	-0.419***	-0.132**	0.137**	0.220***	0.453***	0.237***
	(0.076)	(0.064)	(0.058)	(0.060)	(0.044)	(0.068)
$IP_{j,t-1}^{Direct} \times Size_{ij,t-1}$	0.217***	0.167***	-0.081***	-0.094***	-0.138***	-0.176***
	(0.014)	(0.012)	(0.011)	(0.012)	(0.009)	(0.001)
$Size_{ij,t-1}$	-0.048***	0.025***	0.015***	-0.092***	0.034***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Old_{ij,t}$	0.004	-0.003	0.001	0.034***	-0.014***	0.008**
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Marginal Effects of Import Penetration by Plant Size						
Emp = 50	0.430***	0.520***	-0.179***	-0.149***	-0.086***	-0.452***
	(0.057)	(0.051)	(0.042)	(0.044)	(0.032)	(0.051)
Emp = 100	0.580***	0.636***	-0.235***	-0.215***	-0.181***	-0.574***
	(0.059)	(0.052)	(0.044)	(0.045)	(0.033)	(0.052)
Emp = 250	0.779***	0.788***	-0.309***	-0.301***	-0.307***	-0.732***
	(0.064)	(0.056)	(0.047)	(0.049)	(0.036)	(0.057)
Emp = 500	0.930***	0.904***	-0.365***	-0.367***	-0.402***	-0.857***
	(0.069)	(0.061)	(0.051)	(0.053)	(0.040)	(0.061)
FEs	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year
N	536282	536282	536282	536282	536282	536282
Years	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013

Notes: Size is measured as the natural log of plant employment. Old is a dummy for a plant being at least 5 years old. Robust standard errors are clustered by establishment and reported in parentheses.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 7: Within-Plant Responses by Size						
	Analytic Non-routine *(GED-Math)*	Interactive Non-routine *(Direction, Control, & Planning)*	Cognitive Routine *(Set Limits, Tolerances, or Standards)*	Manual Routine *(Finger Dexterity)*	Manual Non-routine *(Eye-hand-foot Coordination)*	Routine Index
$IP_{j,t-1}^{Direct}$	-0.552***	-0.382***	0.219**	0.209**	0.071	0.550***
	(0.108)	(0.093)	(0.090)	(0.097)	(0.073)	(0.099)
$IP_{j,t-1}^{Direct} \times Size_{ij,t-1}$	0.151***	0.158***	-0.083***	-0.079***	-0.029*	-0.179***
	(0.027)	(0.023)	(0.021)	(0.022)	(0.016)	(0.024)
$Size_{ij,t-1}$	-0.089***	-0.043***	0.040***	-0.033***	0.036***	0.065***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
$Old_{ij,t}$	-0.002	0.010*	-0.007	-0.019***	-0.004	-0.009*
	(0.006)	(0.005)	(0.005)	(0.006)	(0.004)	(0.006)
Marginal Effects of Import Penetration by Plant Size						
Emp = 50	0.039	0.235***	-0.107***	-0.099***	-0.041	-0.152***
	(0.048)	(0.040)	(0.033)	(0.035)	(0.029)	(0.040)
Emp = 100	0.144***	0.345***	-0.164***	-0.154***	-0.061**	-0.277***
	(0.054)	(0.046)	(0.035)	(0.037)	(0.030)	(0.044)
Emp = 250	0.283***	0.489***	-0.241***	-0.226***	-0.088**	-0.441***
	(0.070)	(0.060)	(0.045)	(0.048)	(0.037)	(0.057)
Emp = 500	0.387***	0.599***	-0.298***	-0.281***	-0.108**	-0.566***
	(0.084)	(0.073)	(0.056)	(0.060)	(0.046)	(0.070)
FEs	Plant, Year	Plant, Year	Plant, Year	Plant, Year	Plant, Year	Plant, Year
N	536302	536302	536302	536302	536302	536302
Years	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013

Notes: Size is measured as the natural log of plant employment. Old is a dummy for a plant being at least 5 years old. Robust standard errors are clustered by establishment and reported in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 8. Plant Employment		
	Routine Index, R_{ijt}	Employment Share by Wage Group
$IP^{Direct}_{j,t-1}$	1.776***	-1.193***
	(0.212)	(0.108)
$IP^{Direct}_{j,t-1} \times Size_{ijt}$		
$IP^{Direct}_{j,t-1} \times R_{ijt}$	-3.649***	
	(0.322)	
$IP^{Direct}_{j,t-1} \times ShareMed_{ijt}$		1.508***
		(0.139)
$IP^{Direct}_{j,t-1} \times ShareHigh_{ijt}$		0.851***
		(0.206)
R_{ijt}	-0.450***	
	(0.036)	
$ShareMed_{ijt}$		-0.308***
		(0.013)
$ShareHigh_{ijt}$		0.430***
		(0.027)
Old_{ijt}	1.031***	1.032***
	(0.006)	(0.006)
FEs	NAICS, Year	NAICS, Year
N	531846	531846
Years	2000-2010	2000-2010

Notes: The dependent variable is log employment at each plant. Old is a dummy for a plant being at least 5 years old. Robust standard errors are clustered by establishment and reported in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

Table 9: Differential Plant Exit

	Size	Routine Index, R_{ijt}	Employment Share by Wage Group
$IP^{Direct}_{j,t-1}$	0.128***	-0.066	0.069***
	(0.028)	(0.050)	(0.026)
$IP^{Direct}_{j,t-1} \times Size_{ijt}$	-0.027***		
	(0.005)		
$IP^{Direct}_{j,t-1} \times R_{ijt}$		0.177**	
		(0.072)	
$IP^{Direct}_{j,t-1} \times ShareMed_{ijt}$			-0.026
			(0.036)
$IP^{Direct}_{j,t-1} \times ShareHigh_{ijt}$			-0.084**
			(0.041)
R_{ijt}		-0.041***	
		(0.007)	
$ShareMed_{ijt}$			0.005
			(0.003)
$ShareHigh_{ijt}$			0.019***
			(0.005)
$Size_{ij,t-1}$	0.023***	0.022***	0.022***
	(0.001)	(0.001)	(0.001)
Old_{ijt}	0.005***	0.005***	0.005***
	(0.002)	(0.002)	(0.002)
FEs	NAICS, Year	NAICS, Year	NAICS, Year
N	430199	430076	430076
Years	2000-2010	2000-2010	2000-2010

Notes: Size is measured as the natural log of plant employment. Old is a dummy for a plant being at least 5 years old. Robust standard errors are clustered by establishment and reported in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

Table 10: Accounting for Input-Output Linkages

	Analytic Non-routine *(GED-Math)*	Interactive Non-routine *(Direction, Control, & Planning)*	Cognitive Routine *(Set Limits, Tolerances, or Standards)*	Manual Routine *(Finger Dexterity)*	Manual Non-routine *(Eye-hand-foot Coordination)*	Routine Index
$IP^{Direct}_{j,t-1}$	-0.061	0.127**	-0.129***	-0.085*	0.006	-0.100*
	(0.061)	(0.051)	(0.045)	(0.048)	(0.036)	(0.053)
$IP^{Down}_{j,t-1}$	0.268	-0.106	-0.104	-0.359**	-0.439***	-0.104
	(0.172)	(0.142)	(0.135)	(0.153)	(0.110)	(0.148)
$IP^{Up}_{j,t-1}$	-0.310	0.324	0.358	0.720***	0.629***	0.243
	(0.296)	(0.245)	(0.227)	(0.262)	(0.174)	(0.249)
FEs	Plant, Year	Plant, Year	Plant, Year	Plant, Year	Plant, Year	Plant, Year
N	537025	537025	537025	537025	537025	537025
Years	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013

Notes: Robust standard errors are clustered by establishment and reported in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

Table 11: Accounting for Quality Ladders

	Analytic Non-routine *(GED-Math)*	Interactive Non-routine *(Direction, Control, & Planning)*	Cognitive Routine *(Set Limits, Tolerances, or Standards)*	Manual Routine *(Finger Dexterity)*	Manual Non-routine *(Eye-hand-foot Coordination)*	Routine Index
$IP_{j,t-1}^{Direct}$	0.788***	0.600***	-0.173**	-0.087	-0.196***	-0.540***
	(0.93)	(0.083)	(0.074)	(0.077)	(0.055)	(0.087)
$IP_{j,t-1}^{Direct}$ $\times Long\ Ladder$	-0.491***	-0.286***	0.182**	0.041	0.211***	0.325***
	(0.100)	(0.090)	(0.077)	(0.081)	(0.056)	(0.092)
$Long\ Ladder$	0.233***	0.046	-0.070*	0.045	-0.129***	-0.106**
	(0.047)	(0.041)	(0.038)	(0.041)	(0.029)	(0.047)
FEs	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year
N	417608	417608	417608	417608	417608	417608
Years	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013

Notes: Robust standard errors are clustered by establishment and reported in parentheses. Long ladder is an indicator of the scope for quality differentiation in the industry. Here, it is defined as an indicator variable for an industry having an above-average ladder.
* p<0.10, ** p<0.05, *** p<0.01

Table 12: Accounting for Capital Intensity

	Analytic Non-routine *(GED-Math)*	Interactive Non-routine *(Direction, Control, & Planning)*	Cognitive Routine *(Set Limits, Tolerances, or Standards)*	Manual Routine *(Finger Dexterity)*	Manual Non-routine *(Eye-hand-foot Coordination)*	Routine Index
$IP_{j,t-1}^{Direct}$	0.597***	0.389***	-0.088	-0.012	-0.192*	-0.317**
	(0.151)	(0.135)	(0.132)	(0.135)	(0.110)	(0.136)
$IP_{j,t-1}^{Direct} * Capital\ Intensity$	-0.192	-0.086	-0.141	-0.170	0.173*	-0.156
	(0.147)	(0.131)	(0.126)	(0.131)	(0.104)	(0.132)
$More\ Capital\ Intensity$	0.210***	-0.063*	0.229***	0.498***	-0.378***	0.267
	(0.040)	(0.026)	(0.034)	(0.033)	(0.034)	(0.042)
FEs	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year	NAICS, Year
N	531846	531846	531846	531846	531846	531846
Years	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013	2000-2013

Notes: Robust standard errors are clustered by establishment and reported in parentheses. More Capital Intensity is an indicator that capital intensity exceeds the mean capital intensity.
* p<0.10, ** p<0.05, *** p<0.01

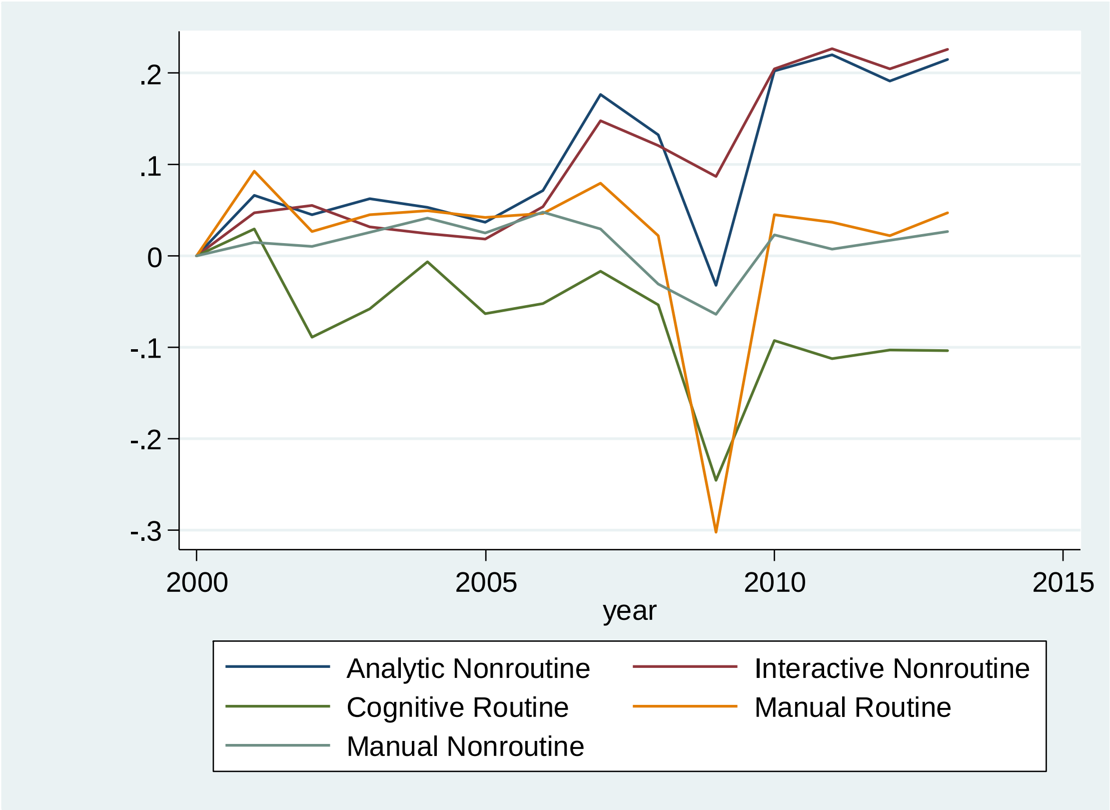

Figure 1. Change in skill content from 2000-2013

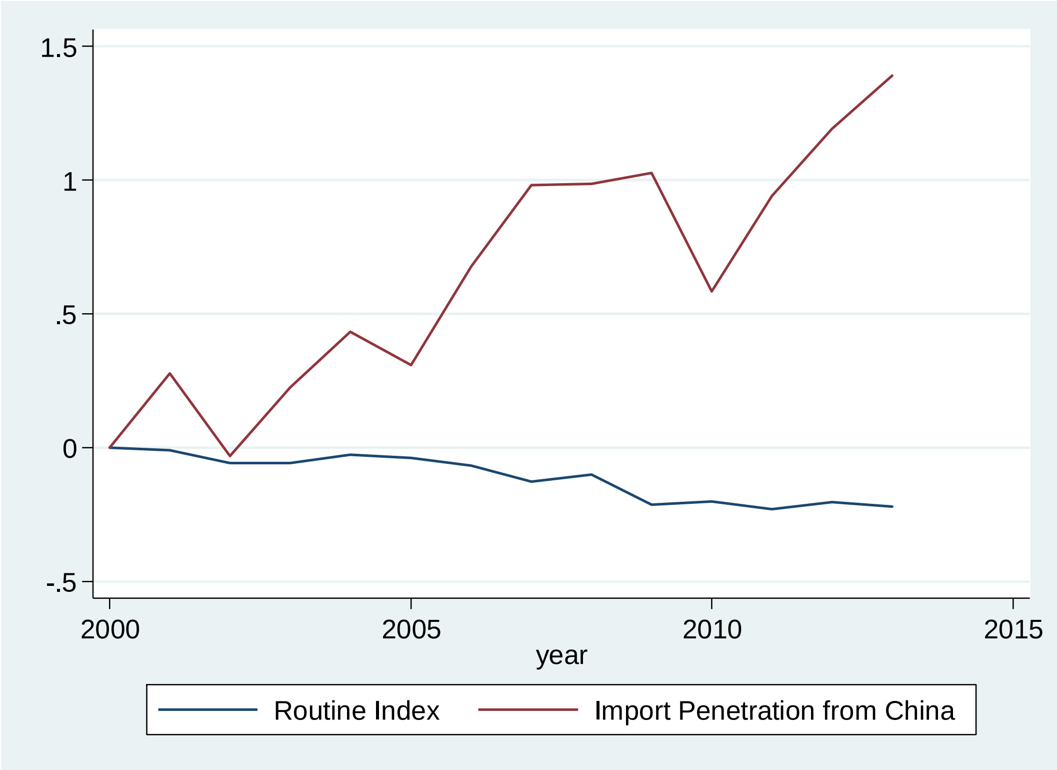

Figure 2. Change in the routine index and import penetration from China, 2000-2013

A. Online Data Appendix

Occupational Employment Survey

As with any survey, there are a number of non-respondents for which the data are imputed. About 30% of the surveyed establishments do not respond on average each year. For each non-respondent, the occupational distribution of the establishment is imputed using nearest-neighbor “hot-deck" imputation method. A responding establishments are linked to a non-respondent based on geographic area, industry, and employment size with the current panel of any of the previous five panels. A donor from the most recent panel is then used to prorate the non-respondent's occupational distribution.

In order to further bring the sample to be more representative of the population of privately-owned establishments, we post-stratify our sample based on size (using the same size classes as those in OES sampling: 1-19, 20-49, 50-249, 250+), six-digit NAICS industry, and metropolitan statistical area (MSA). Since MSA boundaries change over time, we construct MSA’s using county data to reflect MSA designations in 2015. We use the Quarterly Census of Employment and Wages to derive the population counts at each stratification level.

Occupational Task Data

We use data from the Dictionary of Occupational Titles graciously made available by David Autor on his website. For each of the five skill measures used in the paper, the dataset provides a 0-10 score on the importance of the skill at each occupation, with 10 being the greatest importance. We concord this data from Census 1990 to Census 2000 occupation categories and then to Standard Occupational Clasification (SOC) equivalents using crosswalks provided by the US Census.[1]

Trade Data

Our data on US bilateral trade comes from the US Census Bureau via Peter Schott (2008) and is made publicly available on his website. This data is already mapped from ten-digit Harmonized System (HS) product categories to the corresponding six-digit NAICS industries that manufacture each product using the crosswalk in Pierce and Schott (2012a). We follow Acemoglu et al. (2016) and Autor et al. (2014) in using the annual Personal Consumption Expenditures deflator to inflate imports and other nominal values to constant 2012 US dollars.

Data on Chinese imports in the other OECD countries in our instruments is taken from the UN Comtrade Database. These data are at the six-digit HS product level. The majority (90%) of HS6 product families map to only one NAICS industry in the Pierce and Schott crosswalk. For those that do not, we follow Autor et al. (2013) and use US imports to construct weights for the crosswalk. Specifically, we map HS6 imports to each industry based on the share of its imports that map to that industry at the HS10 level. We use US imports in the year 2000 for the mapping. As a check, we use this process to construct estimates of US imports based on Comtrade data; the correlation coefficient between these values and those constructed using HS10-level data from the Census is 0.97.

One issue that we must contend with is that observations in both the establishment and trade data are recorded by the prevailing industry codes at the time. While our sample begins

[1] These are available at https://www.census.gov/people/io/methodology/.

after the introduction of the first edition of NAICS in 1997, it spans three changes in the codes, 2002, 2007, and 2012. In each change, some industries are split into multiple new codes and some are consolidated. Failing to account for these changes will lead to measurement error by introducing spurious changes in imports over time as industries are realigned. This will bias our estimates if the changes in codes are endogenous to import competition, which seems plausible. To account for this we generate time consistent NAICS codes such that the same industry identifier covers all NAICS which are linked together either directly (i.e. part of a split or consolidation at any point in time) or indirectly (share a common direct or indirect link). The process for generating these time consistent NAICS codes is adapted from Pierce and Schott's (2012b) work on creating time consistent HS product codes and follows similarly. This process consolidates the 1378 six-digit NAICS codes that appear in any of the four editions to 914 time consistent industries; it consolidates 536 manufacturing industries into 350.

We use the Total Requirements Input-Output Table from the Bureau of Economic Analysis to construct our measures of upstream and downstream import penetration. While each of the 471 IO industry codes distinctly identifies a NAICS6 industry, this is not true of our time consistent industry classifications. We therefore slightly aggregate these to 388 codes such that each of the time consistent NAICS industries maps to only one of the aggregated IO industry codes. We aggregate the input-output table accordingly.

To generate upstream and downstream import penetration measures we first crosswalk the NAICS-level import data to the aggregated IO industry codes. We then construct the upstream and downstream measures of import penetration as described in the text. Lastly, we assign each NAICS the import penetration measures of its IO industry. Where IO industries are comprised of multiple NAICS codes each is effectively assigned weighted average measures of import penetration for its family.