Training and Foreign Competition: Evidence from the US Manufacturing Sector

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Abstract
While a substantial literature exists investigating the effects of foreign trade on wage levels, wage inequality and job displacement, relatively little attention has been paid to the effect of trade on investment in human capital through job training. This paper examines the relationship between rising imports, particularly those from low-wage countries and China, and the amount of time workers in the US manufacturing sector spend in training events. Controlling for industry and individual fixed effects, the analysis indicates that rising import shares are associated with more time spent in training due to the adoption of new technology, supporting the assertion that firms respond to foreign competition by increasing their technology adoption.

JEL Codes: F16, J31

Key Words: training, imports, US manufacturing
I. Introduction

Past research has shown that training constitutes an important source of wage increases (Veum 1999). Much of the research on training provision and participation has focused on explaining why it is that firms pay for general training (see for example Acemoglu and Pische 1998 and Aghion et al 1999, amongst others), while other studies work towards understanding the determinants of enrollment in training. Relatively little attention has been paid to the possible impact of foreign competition on training provision and enrollment. While the substantial literature examining the labor market effects of trade has focused primarily on employment, wages and wage inequality, rising foreign competition might result in greater enrollment in training by inducing firms to require more training in order to remain competitive and preserve market share. It has been shown that trade can spur innovative activity and technology adoption (Bloom et al 2008, Gorodnichenko et al 2011) which in turn leads to greater training provision (Zeytinoglu et. al. 2009, Xu et al 2011).

Clearly, enrollment in training will increase if the firm makes training a required part of continued employment and advancement. Even when not compelled to do so, increased access to training might induce more participation in training events if either the financial or time cost of participating in employer sponsored training is lower than alternative training opportunities. Independent of these training provision effects, the effect of greater product market competition on participation in training depends on how it affects the expected returns to investing in human capital acquisition. Workers who believe the greater competition increases the likelihood of suffering a layoff and also believe that training will not help them retain their job or find a new one are less likely to enroll in training events. By contrast, workers who believe that training will help them keep their jobs in the face of higher layoffs or find a new one if they are in fact
laid off are more likely to participate in training. Thus, the effect of foreign trade on worker’s training decisions may not be uniform.

The present paper contributes to the literature by analyzing the effect of foreign product market competition on the intensive margins (number of training events and weeks spent in training) of enrollment in training programs by US workers in the manufacturing sector. This is the first paper to focus on the link between foreign competition and participation in training by US workers. Controlling for training provision by the firm, we find that workers spend more time in training that is associated with the adoption of new technology when faced with greater foreign competition. This effect appears to be stronger for imports from low-wage countries and for Chinese imports and for workers who are lower in the ability distribution.

There are relatively few studies examining the link between job training and product market competition. We are aware of only one paper investigating the link between foreign competition and training using U.S data. As part of his doctoral dissertation, Li (2010) examines the effect of foreign competition on the incidence of company provided training using the 1988-1996 waves of the NLSY79 data, restricting his analysis to the sample of men only. The author finds that rising imports result in a lower probability that a worker’s employer will offer company sponsored training. A handful of papers investigate the link between product market competition and training using Canadian data. Using the Workplace and Employee Survey (WES), Zeytinoglu and Cooke (2009) find that workers in firms implementing information technology and those facing competition from foreign firms are more likely to train. Xu and Lin (2011) also employ the WES data and report a positive impact between international competition and participation in employer provided training, in addition to a positive link between technological innovation and training incidence. It should be noted that the foreign competition
variables used in these studies are developed from self-reported measures of the perceived degree of foreign competition faced by the firm. Tat-kei and Ng (2011) find a positive impact on training provision from competition in general.

This paper also ties into the literature examining the effects of foreign competition on labor markets by analyzing worker level data. This is a relatively small, but growing literature as older studies in this area have generally relied on industry-level data. Worker-level data has been used to investigate the effect of globalization on wages (Kosteas 2008, Ebenstein et al 2011), offshoring on the skill-premium (Tempesti 2010), and the sensitivity of wages to the unemployment rate as foreign competition increases (Bertrand 2004) for US workers in the manufacturing sector. As with the present analysis, each of these studies merges industry-level trade data with individual-level data using either NLSY (Kosteas 2008) or CPS data (Bertrand 2004, Ebenstein et al 2011 and Tempesti 2010).

II. Theoretical Background and Estimation Strategy

While theorists have tackled the question of how competition affects firm behaviors such as innovation, the theoretical literature is relatively silent on how product market competition affects workers’ decisions about whether (and how much) to invest in their human capital via job training. However, the models dedicated to analyzing firm behavior do provide some important insights for the question at hand. Ultimately, the question is whether greater competition raises or lowers the return to training. The answer rests on the tension between two mechanisms. First, greater competition from foreign producers might increase the level of job displacement in the worker’s industry (Addison et al 2000 and Kletzer 1998), which decreases the expected return to training by lowering the expected amount of time spent working. At the same time the
probability an individual worker is laid off should decrease with training. In industries characterized by low levels of layoffs and job displacement, this benefit from training may be relatively small. However, in industries characterized by high levels of job loss, the job saving aspect (from the worker’s perspective) of training may be relatively large. Furthermore, the relative strength of these two effects is likely to vary across individuals. More productive workers may be able to keep from being laid off by investing in training while less productive workers may feel that training will do nothing to save their jobs. Conversely, more productive workers may feel more secure in their employment, feeling less pressure to participate in additional training in order to keep their jobs. Karabay and McLaren (2010) develop a model where trade leads to lower wages but less wage volatility while offshoring raises wages and increases income volatility for workers in richer countries while Krishna and Senses (2011) find evidence that trade is associated with higher income risk. This increased risk is not due solely to job loss and thus represents a broader measure of labor market uncertainty for workers in import competing industries. This increased risk can lead to decreased investment for risk averse individuals if the training has any significant cost to the individual.

Foreign competition may also affect training incentives through its impact on wage inequality. Falvey et al (2010) develop a model showing that the increase in the skill premium that results from trade liberalization induces more workers to become skilled. An important insight from their analysis is that anticipated liberalization episodes will induce skill upgrading prior to liberalization. Thus, focusing on contemporaneous effects of rising imports will understate the effect on skill acquisition. While they model skill acquisition as formal schooling, these insights extend to post-schooling human capital investments. In another recent theoretical
model (Sly 2010), workers increase their skill in response to falling consumer prices generated as a result of lower trade costs.

While the above discussion focuses on workers’ decisions regarding voluntary training, trade might also affect enrollment in training through firms’ decisions whether to require certain training events. For example, firms responding to increased foreign competition by implementing new technology are likely to require their workers learn to operate new equipment and properly execute new processes. There is a growing theoretical and empirical literature examining the link between competition and innovation. Blundell et al (1999) and Nickel (1996) find that greater product market competition leads to greater innovation. More recent work by Aghion et al (2005) finds evidence of an inverted U-shape relationship between innovation and competition and develops a theoretical model to explain this empirical observation, while Aghion et al (2009) shows that firms closer to the technological frontier will respond to greater competition by increasing innovation efforts and raising productivity while the industry laggards will decline in productivity. Focusing specifically on competition due to foreign trade, Long et al (2011) find that trade liberalization increases aggregate R&D when trade costs are low and decreases it when they are high.

A basic model of investment in training

So far, the discussion has focused on training in general. However trade might exhibit different pressures on various types of training. This section develops a simple model to analyze how an increase in foreign competition affects the optimal level of investment in training. The analysis distinguishes between three types of training: training that is specific to the current job, training that is specific to a new job and general training which applies to both. In all cases,
foreign competition refers specifically to the degree of foreign competition in the worker’s current industry of employment. To keep the model simple, I assume that both foreign competition and investment in training affect only the probability the worker suffers a layoff from her current job and the probability that she will find a new job in the event that she does lose her current job. Let i denote the amount of time invested in training and c denote the marginal cost of training. We denote the probability the worker will lose her current job as p, which is a function of foreign competition (m). In the cases of general training and training specific to the current job, p is also a function of training. Finally, let f denote the probability of finding a new job in the event the worker has suffered a layoff. In the case where training is specific to the current job, f = φ, which is a constant. Otherwise, f is a function of foreign competition. The worker chooses the level of investment to maximize his expected payoff in a two period model.

All functions are twice differentiable. Regarding the probability of suffering a layoff, we assume that imports increase the probability of suffering a layoff at a decreasing rate (pm > 0, pmm < 0). In the cases of general training and training that is specific to the current job, we assume investment in training lowers the probability of suffering a layoff at a decreasing rate (pi < 0, pii > 0), investment in training has a mitigating effect on the relationship between foreign competition and the probability of suffering a layoff (pim < 0), while greater foreign competition decreases the effect of training on lowering the probability of a layoff (pmi > 0). In the case where training is specific to a new job, p is only a function of foreign competition, allowing us to ignore the cross-partial derivatives as well as pi and pii.
Scenario 1: Training is specific to a new job

We begin with the simplest case. In this scenario, training only affects the probability the worker will find a new job in the event she has suffered a layoff. The worker maximizes her expected payoff

\[ N = w_0 - ci + (1 - p(m))\beta w_1 + p(m)f(i)\beta \gamma w_1, \]

Where \( w_0 \) is the wage on the current job in period one, \( w_1 \) is the wage on the current job in period 2, \( \beta < 1 \) is the discount factor and \( \gamma < 1 \) reflects the wage decrease associated with the new job. Taking the derivative with respect to \( i \) yields the following optimization condition

\[ \frac{dN}{di} = -c - p(m)f(i)\beta \gamma w_1 = 0 \]

To keep the model more general, we do not assume a functional form for either \( f(i) \) or \( p(m) \). Thus, we do not have an explicit solution for \( i^* \). The goal of these models is not to find an explicit solution for \( i^* \), but to determine the effect of foreign competition on \( i^* \). Taking the derivative of the left hand side of equation (2) with respect to \( m \) while evaluated at \( i^* \) gives the impact of increasing foreign competition on the optimal level of investment in training.

Applying the implicit function theorem we obtain the following simplified expression,

\[ \frac{di^*}{dm} = -\frac{F_m}{F_i} = -\frac{p_m(m)f_i(i)}{p(m)f_{ii}(i)} > 0. \]

The numerator consists of two terms, the positive impact of rising foreign competition on the probability of suffering a layoff times investment’s positive effect on the probability of finding a new job. Taken together, these derivatives imply that increasing foreign competition raises the return to training which is specific to a new job by increasing the likelihood the worker will be in a new job in the second period.
Proposition 1: foreign competition increases the payoff to training specific to a new job by raising the likelihood the worker will be employed in a new job in the second period. Thus, workers respond to an increase in foreign competition by increasing their investment in training specific to a new job.

Scenario 2: training is specific to the current job.

In this scenario, training only affects the probability the worker will suffer a layoff. The worker maximizes his expected payoff

$$S = w_0 - ci + (1 - p(m, i))\beta w_1 + p(m, i)\phi \beta y w_1$$

Taking the derivative with respect to $i$ yields the following

$$\frac{ds}{di} = (\phi y - 1)p_i(m, i)\beta w_1 - c = 0$$

Taking the derivative of the left hand side of equation (5) with respect to $m$ while evaluated at $i^*$ gives the impact of increasing foreign competition on the optimal level of investment in training specific to the current job. Applying the implicit function theorem we derive the following simplified expression,

$$\frac{di^*}{dm} = \frac{F_m}{F_i} = -\frac{p_{im}(m, i)}{p_{i}(m, i)} < 0. $$

The numerator reflects how rising imports lower’s the ability to reduce the likelihood of suffering layoff by investing more in training specific to the current job.

Proposition 2: foreign competition lowers the return to investment in training specific to the current job by raising the probability of losing the current job. Thus, workers respond to an increase in foreign competition by decreasing their investment in training specific to the current job.
Scenario 3: general training

In this scenario, training lowers the probability the worker will suffer a layoff and raises the probability the worker will find a new job if she is indeed laid off. The worker maximizes her expected payoff

\[ G = w_0 - ci + (1 - p(m, i))\beta w_1 + p(m, i)f(i)\beta \gamma w_1. \]

Taking the derivative with respect to \( i \) yields the following,

\[ \frac{dg}{di} = (\gamma f(i) - 1)p_i(m, i)\beta w_1 + p(m, i)f_i(i)\beta \gamma w_1 - c = 0. \]

Taking the derivative of the left hand side of equation (5) with respect to \( m \) while evaluated at \( i^* \) gives the impact of increasing foreign competition on the optimal level of investment in training specific to the current job. Applying the implicit function theorem,

\[ \frac{di^*}{dm} = -\frac{F_m}{F_i} = -\frac{p_{im}(m, i)(\gamma f(i) - 1) + p_{m}(m, i)f_i(i)}{2p_i(m, i)f_i(i) + p_i(m, i)(\gamma f(i) - 1) + f_i(i)p(m, i)\gamma} \neq 0. \]

Since each term inside the brackets in the denominator is negative, the entire denominator is negative. The numerator shows the competing tensions of rising imports on training incentives. General training increases expected wages by both lowering the probability of losing the current job and increasing the probability of finding a new job in the event the worker suffers a layoff. Rising imports lower the returns to training by decreasing training’s negative effect on the probability of suffering a layoff. This effect is represented by the first term in the numerator which is negative since \( \gamma f(i) < 1 \). The second term is positive since both \( p_{m}(m, i) \) and \( f_{i}(i) \) are positive. Given these opposing effects, we are unable to sign the effect of imports on the optimal level of investment.
Proposition 3: Rising foreign competition has an ambiguous effect on investment in training that develops general human capital due to competing effects.

Empirical strategy

By focusing on participation in training events and controlling for whether the employer makes training opportunities available, we mitigate some of the potential endogeneity between foreign competition and training provision. The biggest remaining challenge to identifying a causal link between foreign competition in the product market and individual training decisions comes from the sorting of individuals into industries and firms with different rates of training according to unobservable worker characteristics. For example, individuals with higher levels of (unobservable) ability may also have higher returns to training. As such, they are more likely to seek out careers with greater training opportunities. If more skill-intensive industries also require more training, then high ability workers are likely to sort into these industries. Given the comparative advantage the US has in skill-intensive industries, these industries are likely to be characterized by relatively lower import penetration rates. Thus, there will be a negative correlation between foreign competition and training driven by this sorting of workers across industries. If the causal effect of greater foreign competition is to increase training, then a failure to account for the sorting will lead to a downward bias in estimates obtained via simple least squares estimation.

One simple solution to this problem is to control for industry fixed effects and rely on within industry variation in foreign competition and training to identify the model. This approach assumes worker sorting is driven by time-invariant industry characteristics. However, this assumption may be flawed as industry-level rates of training may vary for reasons unrelated
to international trade. According to product cycle theories, younger industries are characterized by higher rates of technical change. Thus, younger industries are also likely to exhibit higher rates of training as workers need to adjust to constantly evolving production methods and products.\footnote{Vernon (1966) first developed the life cycle hypothesis. A recent paper (Xiang 2005) finds evidence that new goods have substantially higher skilled-labor intensity, lending support to the notion that younger industries/products are characterized by higher rates of R&D and technical change.} As the industry matures, the rate of change in products and processes slows down, and along with it training intensity. In this case, industry fixed effects will not sufficiently address the sorting problem. As a next step, specifications for each model are estimated controlling for individual fixed effects. In this case, identification relies on within-individual and within-industry variation in the data.

There are five dependent variables, each measuring aspects of the intensive margin of training (weeks spent in training). The first two variables represent different aspects of the intensive margin of investment. The first measures the number of training events in which the individual enrolled in since the last interview, while the second captures the total number of weeks spent in training since the last interview. Each measure has its plusses and minuses. The weeks spent in training measure makes use of the full information available. This is important since not all training events are equal. A minor training event might only last a day while another might represent an ongoing program spanning the course of several weeks. On the other hand, there is likely to be more measurement error in the weeks variable. Additionally, while the individual is likely to have some say in whether or not to enroll in a specific training event, it is not likely she will have much control over the duration of the training episode. Thus, the events variable may provide a better measure of the individual’s choices over investment in human capital through training.
The remaining three variables measure the number of weeks spent in training for specific reasons. The analysis investigates training undertaken for the following reasons: promotion or advancement on the current job, the adoption of new technology, as part of a continuing program to upgrade employee skills. The first category was chosen because it has the greatest connection to training that is specific to the current job. While there may well be a degree of generality to some of the training captured in this category, it does provide the best fit to scenario 2 described in the theory section. The other two categories were chosen for two primary reasons. First, these events likely reflect the acquisition of skills with a high degree of generality, conforming to scenario 3 set forth in the theory section. Second, both of these variables reflect firms’ decisions to acquire and implement new technologies and production methods, providing a link to the existing body of research which shows that greater foreign competition may lead firms to increase their adoption/creation of new technology. While the data set does provide a category that makes a good fit with scenario 1 in the theory section, training specific to a new job, it is observed only for a very small fraction of the sample and frequently associated with individuals not employed at the time of training.

In the basic specification, each model is fitted using the Tobit estimator. As a second specification I fit each model using a linear fixed effects estimator. The empirical model for the Tobit and linear regression models are as follows:

\[(10) \quad T_{ijt} = c + \beta m_{jt} + \gamma X_{it} + \delta Z_{jt} + \alpha_t + T_t + I_j + \varepsilon_{ijt}\]

for individual i in industry j at time t. T is the training outcome variable, m is a measure of foreign competition, X is a vector of individual and workplace characteristics, Z is a vector of industry characteristics, T are year fixed effects, I are industry fixed effects, \(\alpha\) are the individual fixed effects and \(\varepsilon\) is an iid error term.
An extended model is employed to capture some of the heterogeneity in training enrollment responses to increased foreign competition. Since we do not have a direct measure of productivity, we need to use proxies in order to capture these differences.

III. Data Description

The paper uses the 1991-2004 waves of the National Longitudinal Surveys of Youth 1979 cohort (NLSY79). The survey was conducted annually beginning in 1979 through 1994 and in even numbered years thereafter. The original sample contains 12,686 individuals who were fourteen to twenty-two years old in 1979. This full sample includes oversamples of minorities and the poor in addition to a supplemental sample representative of individuals enrolled in the four branches of the military. The military sample was dropped after the 1984 survey while the oversampling of poor whites was dropped in 1991. The present study uses data only for individuals in the nationally representative cross-section, which originally contained 6,111 individuals. Actual sample sizes are smaller due to attrition and missing information for the key variables employed in the analysis. Furthermore, the study focuses on individuals employed in the manufacturing sector, for which we have import values to construct our measures of foreign competition.

The international trade data come from Peter K. Schott’s website. They were developed for use in the study by Bernard, Jensen and Schott (2006) and are described in detail in Schott (2010). The data are aggregated up from the product level to the 4-digit standard industry classification (SIC) level and cover the period from 1972-2005. However, there was a significant change in the way the value of trade was measured beginning in 1989, creating a significant discontinuity in the data. The sample period is further restricted due to the fact that
one of the key training variables is only available for the 1991-2004 survey years. For all years, contemporaneous trade measures are merged with the individual-level data. The trade dataset contains information in the value of imports, exports and domestic production for each industry. Additionally, the dataset provides separate information on the value of imports coming from China and the value of imports from low-wage countries. This information is available for roughly 400 4-digit industries in each year. These industries represent over ninety percent of all manufacturing output.

Until the 2000 survey, the NLSY coded the industry of occupation according to the 1980 census classification. Beginning with the 2002 survey, the NLSY switched to the 2000 Census industry classifications. In order to provide a consistent industry classification across all years of data analyzed in this study, it was necessary to create a bridge between the two Census classification systems. While it was relatively straightforward to incorporate most of the Census 2000 industry categories into the 1980 classification, some industries did not combine into a single 1980 category. In order not to lose these observations, five industry pairs (using the 1980 classification) were merged, leaving us with seventy-four industries. Merging the industry trade data into the NLSY required the use of a bridge between the SIC classification system and the industry classifications used in the NLSY. The documentation for the industry and occupation classifications used in the NLSY provides a bridge between 3-digit SIC industries and the 1980 Census industry classification. Accordingly, all industry-level data was aggregated into the seventy-four final industry classes.

The NLSY contains information on up to four training events and also asks individuals who report on four training episodes whether they participated in additional training beyond the

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2 A country is categorized as being low wage if its per-capita GDP was less than five percent of the US’s per capita GDP in the year 2000. Hence, the set of countries considered low-wage does not change over the sample period.
four events detailed. In these cases, the number of training events variable is given a value of five. Thus, the number of training episodes variable takes values from zero to five. This top-coding of the training events variable does not raise any significant issues for the estimation since there are only two observations where the respondent reported attending more than four training events in our estimation sample. In fact, only three percent of the sample reports more than one training event, mostly representing cases where the individual participated in two training events. These three training variables are constructed from follow up questions inquiring into the nature of the training events attended. We create the total number of weeks spent in training variable by adding up the number of weeks spent in all reported training events for the individual-year observation.

The three variables measuring weeks spent in training for specific reasons make use of a follow up question which asks respondents to list the reason for each training event. Survey participants were asked to select from the following list of responses: 1) training was associated with promotion or job advancement opportunity, 2) new methods or processes introduced – additional training required to continue same job, 3) the training was part of a regular program to maintain and upgrade employee skills, 4) the training was necessary when I began a job, 5) the training was necessary for a license or a certificate, 6) the training was associated with looking for a new job, 7) other. The categories are mutually exclusive. Analogous to the total weeks of training variable, each of the three reason specific training variables is constructed by adding the total weeks spent in training for that specific reason. The information for categories (4) and (5) is excluded from the analysis since these training episodes generally reflect a new job and we do not want to pick up training effects associated job turnover and foreign competition. While category (6) would appear to provide a nice fit with scenario 1 in the theory section, it is only
observed for a small fraction of training episodes and frequently associated with unemployed workers looking to move into a new occupation. With the exception of the new technology and upgrade skills variables, these training events are not restricted to employer sponsored or on-the-job training (as should be clear from reason for training option six). This distinction is important since this paper focuses on the individual’s training participation activity, not the firm’s decision of whether to offer training to its employees. Since the total weeks spent in training variable includes all of these categories, it captures a fairly comprehensive measure of training, regardless of whether the training events were company sponsored. Focusing on this more inclusive measure of training enrollment is important since individuals employed in an industry facing substantial foreign competition may enroll in training events to prepare for employment in another industry or occupation in the event of a job displacement. These pressures would not be captured by variable focusing exclusively on on-the-job or company sponsored training.

The empirical analysis makes use of three separate measures for foreign competition. The primary measure is the import penetration share. This variable is constructed by taking the value of all imports in the industry and dividing by the value of domestic shipments plus the value of imports minus the value of exports. For industry j in year t:

$$\text{import share}_{jt} = \frac{\text{imports}_{jt}}{\text{shipments}_{jt} + \text{imports}_{jt} - \text{exports}_{jt}}.$$  

By construction, the import share variable takes values between zero and one. The denominator is interpreted as the total value of all goods placed into the domestic market (which is why we must subtract the value of exports). Thus, the import share is the share of goods in the domestic market coming from foreign producers. Likewise, I construct market penetration measures for imports from low-wage countries and for Chinese imports.

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3 Since this category is included in the overall training variables, a robustness check is performed excluding workers who have six months of tenure or less with the current employer.
The remaining explanatory variables are a combination of individual characteristics, employer information and industry-level characteristics. Both the individual characteristics and employer information come from the NLSY while the industry characteristics come from the National Bureau of Economics Research’s productivity database. The individual characteristics included in the empirical models are: highest grade completed, the armed forces qualify test (AFQT) score percentile, age, log of tenure with the current employer, the number of children in the household and indicator variables for whether the individual is married, in a white-collar occupation, female, black or Hispanic.\textsuperscript{4} The employer characteristics are the log number of employees at the respondent’s location of employment and an indicator variable for whether the individual’s employment is covered by a union contract. The industry-level characteristics are the log of total factor productivity (TFP), the non-production worker wage share (referred to as skill intensity) and the log of capital per worker (referred to as capital intensity) where capital is measured in dollar value. Each specification also includes a vector of indicator variables for year and industry.

Before turning to the empirical results, a quick look at the annual statistics for each of the trade measures helps to put the findings into context. Figure 1 shows the upward trend in the aggregate import share for the US manufacturing sector over the sample period. The import share nearly doubles between 1989 and 2005, increasing from 13.37 to 25.81 percent. Figure 2 shows even sharper increases for low-wage and Chinese import shares. The low-wage import

\textsuperscript{4} White collar occupations include the following broad categories: executive, administrative and managerial, professional specialty occupations, technicians and related support and sales occupations. These occupations correspond to codes 1-299 in the 1980 occupation classification.
share rises from 0.75 to 6.83 percent while the Chinese import share increases from 0.41 to 5.75 percent. Additionally, both series show an increase in the growth of both the low-wage and Chinese import shares beginning around the 2000s. We will use these changes in the import shares to calculate the estimated impact of rising foreign competition on training enrollment.

Table 1 presents summary statistics for the training variables, imports and industry characteristics variables as well as the individual and employment characteristics included in the empirical models. Workers averaged 0.178 training events per observation period. They spent a total of 0.628 weeks in training on average, with 0.129 weeks enrolled in training due towards a promotion/career advancement, 0.111 weeks due to the implementation of new technologies or production processes, and 0.155 weeks as part of an ongoing company program to maintain or upgrade their skills. In nearly sixty-one percent of observations workers report that the firm makes company sponsored training available to its employees. The average import share over the sample period is 17.76 percent, while the low-wage and Chinese import penetrations are 2.05 and 1.56 percent, respectively. Roughly thirty-one percent of worker-year observations are for white-collar workers. The average educational attainment is just over thirteen years of schooling and the average AFQT score percentile is 49.36. Consistent with previous reports, the sample shows that manufacturing is a male-dominated sector. There are also relatively few minorities employed in the manufacturing sector, with less than nine percent of the sample being black and less than five percent Hispanic.

IV. Results and Discussion

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5 The average educational attainment and AFQT score percentile are comparable to those for the full sample including individuals employed in all sectors.
Table 2 presents the results of the basic empirical models for each of the dependent variables fitted with the Tobit estimator. Standard errors are reported in parentheses for all models; all models control for industry and year effects. Rising imports do not show a significant correlation with either the number of training events attended or the total number of weeks spent in training. None of the three industry characteristics show a statistically significant correlation with the number of training events and only a weak correlation between productivity growth and total weeks spent in training. The lack of a significant relationship between industry characteristics and overall training is likely due to the inclusion of the industry fixed effects.\(^6\) Individuals working for a firm that offers training attend 0.86 more training events and spend nearly 5.7 more weeks in training; a significant relationship given the sample averages of 0.178 training events and 0.628 weeks of training. Given the limitations of the data, we are unable to determine how much of this correlation is due to an increase in voluntary enrollment in training due to greater access to training opportunities and how much of it is due to the fact that firms offering training often also make that training a required part of the job. More educated and more able (as measured by the AFQT score percentile) individuals participate in more training, as do those working for larger firms. The remaining variables fail to show a statistically significant correlation with the probability an individual will attend training.

Regarding the specific reasons for training, only training due to the adoption of new technology shows a statistically significant correlation with rising imports. A ten percentage point increase in the import share is associated with an additional two weeks spent in training for this purpose. Workers spend more time in training to further their careers but less time in upgrading skills in industries with faster productivity growth, while the reverse is true in

\(^6\) Fitting the model without industry indicators yields positive and highly statistically significant coefficients for both the non-production worker’s wage share and the capital-labor ratio.
industries with a higher skill and capital intensity. Workers spend more time in each type of training when the firm provides opportunity. Interestingly, higher ability individuals spend less time in training to chase career advancement (perhaps reflecting the Peter Principle or a belief by less able individuals that they need the additional training to advance their careers while more able ones do not) but more time in training to upgrade their skills and due to the adoption of new technology. Workers in larger firms spend more time in all three types of training, while women, blacks, and Hispanics are less likely to chase career advancement through training. Having more children is also associated with less time spent in training for career advancement.

For the linear fixed effects estimates (table 3), I will focus on the training due to technology adoption model since it is the only one to show a significant link between imports and training. A worker experiencing a ten percentage point increase in his industry’s import share spends an additional 0.1 weeks in training, on average. This difference is roughly equivalent to the average amount of time spent in training for this purpose. As before, workers spend more time to adjust to new technology in larger firms and those which provide training opportunities. Education no longer shows a statistically significant correlation with training, a result that is likely due to the fact that there is relatively little within-person variation in educational attainment in the sample. Generally, the results do not show a strong link between training and the overall level of imports.

Low-wage and Chinese imports

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7 These results are consistent with discrimination in the process of identifying and selecting candidates for these training opportunities. They are also consistent with the observation that women are less aggressive in seeking advancement and the possibility that all three groups are less likely to take up these opportunities.

8 The respondents in the sample range from twenty-four to forty-nine years of age with nearly three-quarters of the observations being for individuals thirty years of age and older.
Additional results test whether the results presented in table 3 are being driven by low-wage or Chinese imports. These models contain the same set of explanatory variables as the extended model, replacing the import share with the low-wage import share (columns 1-5) and the Chinese import share (columns 6-10). All models are fitted using linear fixed effects estimation. The results using the low-wage import share show a positive correlation between rising imports and total weeks spent in training, however the coefficient is only statistically significant at the ten percent level. A ten point increase in the import share results in three additional weeks spent in training. Low-wage imports show an even stronger impact than overall imports on the amount of time spent training due to new technology. A ten point increase in the low-wage import share is associated with an additional 0.13 weeks spent in training. Imports from non low-wage countries do not show a statistically significant correlation with any of the five training variables. The results for Chinese imports mirror those for the models including low-wage imports. A ten percentage point increase in the Chinese import share results in nearly an additional 3.5 weeks spent in training and an additional 1.5 weeks spent in training due to the implementation of new technology. In general, the results presented in table 4 show that imports from lower-wage countries, and in particular China, have a strong correlation with decisions to attend training due to the adoption of new technology. Taken together with the results presented in table 3, these findings support theoretical models which postulate increasing competitive pressure due to international trade leads to more technology upgrading by firms, which in turn leads to additional worker training.

Robustness check: excluding workers with less than six months tenure
To mitigate the prospect our results are being driven by workers who are in the early phases of new jobs (a time when workers are more likely to spend significant time in training, regardless of competitive pressures), we restrict the sample to individuals reporting more than six months (twenty-six weeks) tenure with the current employer. This leads to a loss of 503 observations, or roughly 9.6 percent of the primary sample. Only the models for number of training events, total weeks training and weeks training due to new technology are presented as the other models have not show any significant relationship between training and imports in our previous analyses. The results for this sample of tenured workers are presented in table 5. None of our three import share measures shows a significant correlation with total weeks of training. However, the estimates for the new technology model reinforce those presented in tables 3 and 4. All three import variables show a positive and statistically significant correlation with weeks spent in training due to the adoption of new technology. While the coefficient on the import share variable (column 3) is only statistically significant at the ten percent level, it is greater in magnitude than the estimate obtained using the full sample (table 3, column 4). The coefficients on low-wage (column 4) and Chinese imports (column 9) are also larger in magnitude than the estimates presented in table 4; they also continue to be highly statistically significant.

* Differential effects by ability *

Up to this point our investigation has restricted the effect of imports on training to be constant across all workers in the same industry. Here we relax this assumption by including an interaction term between the import share variables and the AFQT score percentile. This specification of the model reflects the differential impact foreign competition has on workers depending on the types of tasks they perform. We could have distinguished between types of
workers based on some broad measures, such as whether the individual is in a white-collar occupation; however this type of distinction would fail to capture the complexity of the production process while allowing for less flexibility than our chosen specification. Furthermore, workers in the same broad occupational or job category might still feel differential job pressure from rising imports. Since higher ability workers sort into more complex jobs, both across and within occupations, the current specification provides the best chance of capturing the differential impact of foreign competition felt by different types of workers. This interaction was also employed by Kosteas (2008), finding a differential impact of low-wage imports on manufacturing wages by level of ability for the 1989-1996 period. Results for the number of training events and total weeks spent in training models are presented in table 6. The results indicate that workers at the lower end of the ability spectrum respond to rising imports with a sizable increase in the number of training events, with a smaller response for workers higher up the ability distribution. This effect is larger or low-wage and Chinese imports relative to overall imports. There also appears to be variation in the effect of imports on total weeks spent in training. However, the coefficients on the interaction terms are only significant at the ten percent level for low-wage and Chinese imports and not significant at conventional levels for the overall imports specification. In general, the results support the hypothesis that foreign competition affects workers’ training decisions differentially by ability.

Conclusion

This paper estimates the impact of rising imports on worker training. It is the first paper to focus on foreign competition’s impact on worker enrollment in training events (as opposed to firms’ decisions about whether to provide training to its workers) for US workers in the
manufacturing sector. The results find a robust, positive relationship between rising imports and training related to the adoption of new technology. This effect is particularly strong for low-wage and Chinese imports and is larger for workers who are lower on the ability distribution.

These findings have important implications for the literature estimating the labor market effects of globalization. Failure to account for post-schooling training may lead to an underestimation of the downward wage pressures faced by more educated workers employed in the manufacturing sector. The evidence presented here adds another piece to the puzzle in our understanding of the links between international trade and labor market outcomes for US workers.
References


Sly, Nicholas (2010). “Skill acquisition, incentive contracts and jobs: labor market adjustment to trade.” Mimeo


Table 1: Summary statistics for key variables

<table>
<thead>
<tr>
<th>Description</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
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<tbody>
<tr>
<td>Total weeks spent in training</td>
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<td>4.114677</td>
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<tr>
<td>Weeks spent in training towards a promotion/advancement</td>
<td>.1283228</td>
<td>1.583731</td>
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<tr>
<td>Weeks spent in training due to new technology</td>
<td>.1111111</td>
<td>.9001875</td>
</tr>
<tr>
<td>Weeks spent in training as part of program to upgrade employee skills</td>
<td>.1549053</td>
<td>1.398335</td>
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<td>Number of training events</td>
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<tr>
<td>import share</td>
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<tr>
<td>low-wage import share</td>
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<td>Hispanic</td>
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N 5229

Table provides summary statistics for the key variables.
<table>
<thead>
<tr>
<th></th>
<th>Number of Events</th>
<th>Total Weeks</th>
<th>Promotion</th>
<th>New Technology</th>
<th>Upgrade Skills</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>import share</strong></td>
<td>0.171</td>
<td>49.17</td>
<td>-3.412</td>
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<td>-9.565</td>
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<tr>
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<td>(11.62)</td>
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<td><strong>productivity growth</strong></td>
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<td>(0.189)</td>
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<td><strong>skill intensity</strong></td>
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<td>(1.424)</td>
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<td>(5.376)</td>
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<td>0.0879</td>
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<td>5% Level</td>
<td>10% Level</td>
<td>1% Level</td>
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<td>----------</td>
<td>-----------</td>
<td>----------</td>
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<td>female</td>
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<td>(1.710)</td>
<td>(0.498)</td>
<td>(1.302)</td>
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</table>

Observations 5229 5229 5229 5229 5229

The table presents the coefficient estimates for Tobit estimation with standard errors in parentheses. 

+, *, ** denote significance at the 10%, 5% and 1% levels, respectively.

All models contain industry and year indicators.
### Table 3: Fixed effects estimates of foreign competition on training

<table>
<thead>
<tr>
<th>Variable</th>
<th>Number of Events</th>
<th>Total Weeks Training</th>
<th>Promotion</th>
<th>New Technology</th>
<th>Upgrade Skills</th>
</tr>
</thead>
<tbody>
<tr>
<td>import share</td>
<td>0.291 (0.270)</td>
<td>9.042 (5.752)</td>
<td>-1.097</td>
<td>1.055*</td>
<td>0.00148</td>
</tr>
<tr>
<td>productivity growth</td>
<td>-0.00125 (0.00699)</td>
<td>0.137+ (0.0745)</td>
<td>0.0345</td>
<td>-0.00519</td>
<td>-0.0508*</td>
</tr>
<tr>
<td>skill intensity</td>
<td>0.140 (0.0969)</td>
<td>1.143 (0.863)</td>
<td>-0.131</td>
<td>-0.0740</td>
<td>0.568*</td>
</tr>
<tr>
<td>log capital to labor ratio</td>
<td>0.0147 (0.0175)</td>
<td>0.151 (0.145)</td>
<td>-0.130+</td>
<td>0.0119</td>
<td>0.105*</td>
</tr>
<tr>
<td>firm offers training</td>
<td>0.0574** (0.0201)</td>
<td>-0.0657 (0.190)</td>
<td>-0.131</td>
<td>0.118*</td>
<td>-0.133+</td>
</tr>
<tr>
<td>white collar occupation</td>
<td>0.0486+ (0.0280)</td>
<td>0.198 (0.215)</td>
<td>-0.00956</td>
<td>0.0761</td>
<td>0.0135</td>
</tr>
<tr>
<td>education</td>
<td>0.0145 (0.0268)</td>
<td>0.276 (0.236)</td>
<td>0.191</td>
<td>0.0433</td>
<td>-0.0796</td>
</tr>
<tr>
<td>log of tenure in years</td>
<td>0.0130+ (0.00769)</td>
<td>-0.0997 (0.0910)</td>
<td>-0.00554</td>
<td>0.00627</td>
<td>0.0337+</td>
</tr>
<tr>
<td>log number of employees</td>
<td>0.0100 (0.00647)</td>
<td>0.0286 (0.0766)</td>
<td>-0.0126</td>
<td>0.0370**</td>
<td>0.0697*</td>
</tr>
<tr>
<td>age</td>
<td>-0.00276 (0.0275)</td>
<td>0.425+ (0.217)</td>
<td>0.134</td>
<td>0.0651</td>
<td>-0.0833</td>
</tr>
<tr>
<td>married</td>
<td>0.0197 (0.0286)</td>
<td>0.0895 (0.236)</td>
<td>0.183</td>
<td>-0.0561</td>
<td>0.0634</td>
</tr>
<tr>
<td>number of children</td>
<td>-0.0235+ (0.0139)</td>
<td>-0.0860 (0.0930)</td>
<td>-0.0733*</td>
<td>-0.00412</td>
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<tr>
<td>Observations</td>
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<td>5229</td>
<td>5229</td>
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<tr>
<td>R-squared</td>
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Results from models estimated via fixed effects.

+, *, *** denote significance at the 10%, 5% and 1% levels, respectively.

All models contain the full set of covariates, including industry and year effects.
Table 4: Effects of low-wage and Chinese imports on training

<table>
<thead>
<tr>
<th></th>
<th>Number of Events</th>
<th>Total Weeks</th>
<th>Promotion</th>
<th>New Technology</th>
<th>Upgrade Skills</th>
<th>Number of Events</th>
<th>Total Weeks</th>
<th>Promotion</th>
<th>New Technology</th>
<th>Upgrade Skills</th>
</tr>
</thead>
<tbody>
<tr>
<td>low-wage import share</td>
<td>0.606</td>
<td>31.09+</td>
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<td>1.867</td>
<td>(0.387)</td>
<td>(17.33)</td>
<td>(0.869)</td>
<td>(0.576)</td>
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</tr>
<tr>
<td>non low-wage import share</td>
<td>0.0373</td>
<td>-8.726</td>
<td>-1.730</td>
<td>0.825</td>
<td>-1.502</td>
<td>(0.368)</td>
<td>(5.644)</td>
<td>(1.453)</td>
<td>(0.854)</td>
<td>(1.188)</td>
</tr>
<tr>
<td>Chinese import share</td>
<td>0.627</td>
<td>34.99+</td>
<td>0.176</td>
<td>1.483*</td>
<td>1.972</td>
<td>(0.411)</td>
<td>(19.59)</td>
<td>(0.755)</td>
<td>(0.616)</td>
<td>(1.520)</td>
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<tr>
<td>Observations</td>
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<tr>
<td>R-squared</td>
<td>0.0403</td>
<td>0.2540</td>
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<td>0.0280</td>
<td>0.0345</td>
<td>0.0375</td>
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</table>

Results from models estimated via fixed effects.

+, *, *** denote significance at the 10%, 5% and 1% levels, respectively.

All models contain the full set of covariates, including industry and year effects.
### Table 5: Effects of imports on training for tenured workers

<table>
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<tr>
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<th>Number of Events</th>
<th>Total Weeks Training</th>
<th>New Technology</th>
<th>Number of Events</th>
<th>Total Weeks Training</th>
<th>New Technology</th>
<th>Number of Events</th>
<th>Total Weeks Training</th>
<th>New Technology</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>import share</strong></td>
<td>0.116</td>
<td>0.780</td>
<td>1.010+</td>
<td>(0.278)</td>
<td>(1.667)</td>
<td>(0.569)</td>
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<tr>
<td><strong>low-wage import share</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.232</td>
<td>2.976</td>
<td>1.496*</td>
<td>(0.381)</td>
<td>(2.333)</td>
<td>(0.675)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Chinese import share</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>0.182</td>
<td>3.053</td>
<td>1.674*</td>
<td>(0.403)</td>
<td>(2.288)</td>
<td>(0.729)</td>
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<tr>
<td><strong>Observations</strong></td>
<td>4726</td>
<td>4726</td>
<td>4726</td>
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<td>4726</td>
<td>4726</td>
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<td>4726</td>
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<tr>
<td><strong>R-squared</strong></td>
<td>0.0435</td>
<td>0.0349</td>
<td>0.0413</td>
<td>0.0435</td>
<td>0.0351</td>
<td>0.0413</td>
<td>0.0435</td>
<td>0.0351</td>
<td>0.0413</td>
</tr>
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</table>

Results from models estimated via fixed effects.

+, *, *** denote significance at the 10%, 5% and 1% levels, respectively.

All models contain the full set of covariates, including industry and year effects.
Table 6: Effects of imports on training by ability

<table>
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<tr>
<th></th>
<th>Number of Events</th>
<th>Total Weeks Training</th>
<th>Number of Events</th>
<th>Total Weeks Training</th>
<th>Number of Events</th>
<th>Total Weeks Training</th>
</tr>
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<tbody>
<tr>
<td>import share</td>
<td>0.759*</td>
<td>17.82+</td>
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<tr>
<td></td>
<td>(0.331)</td>
<td>(10.45)</td>
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<tr>
<td>import share*afqt</td>
<td>-0.00905**</td>
<td>-0.170</td>
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<tr>
<td></td>
<td>(0.00335)</td>
<td>(0.110)</td>
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<tr>
<td>low-wage import share</td>
<td></td>
<td></td>
<td>1.528*</td>
<td>73.84+</td>
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<td>(0.596)</td>
<td>(37.84)</td>
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<tr>
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<td>-0.0182*</td>
<td>-0.847+</td>
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</tr>
<tr>
<td></td>
<td>(0.00789)</td>
<td>(0.464)</td>
<td></td>
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</tr>
<tr>
<td>Chinese import share</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.646*</td>
<td>86.12*</td>
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<td>(0.666)</td>
<td>(43.50)</td>
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<tr>
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<td>-0.0203*</td>
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<td>(0.553)</td>
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<tr>
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<td>5229</td>
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<tr>
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<td>0.2474</td>
<td>0.0414</td>
<td>0.2816</td>
<td>0.0413</td>
<td>0.2876</td>
</tr>
</tbody>
</table>

Results from models estimated via fixed effects.

+, *, *** denote significance at the 10%, 5% and 1% levels, respectively.

All models contain the full set of covariates, including industry and year effects.
Figure 1 shows the aggregate import share for the sample period from 1989-2005.
Figure 2 shows the aggregate low-wage and Chinese import shares for the sample period from 1989-2005.