How Import Competition Affects Displaced Workers in the U.S.

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Abstract – I use the Displaced Worker Survey and bilateral trade data to assess the impact of import competition, particularly from low-wage countries, on displaced workers' unemployment duration and re-employment wages. These outcomes are more sensitive to imports from low-wage countries than to overall imports. In a given industry of displacement, a 10 percent increase in imports from low-wage countries results in 4.8 percent reduction in re-employment wages and 2.7 weeks increase in unemployment duration. Higher imports raise the likelihood of industry relocation upon re-employment, leading to loss of industry-specific human capital.

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I. Introduction

As a result of the increased globalization of the U.S. economy in the last 30 years, researchers have devoted substantial effort to understanding how international trade affects domestic labor market outcomes. The industry level studies in the 1980s found little effect of import competition on industry employment (Krueger 1980; Grossman 1987). More recently, researchers have documented a negative correlation between employment growth and imports (Freeman and Katz 1991; Sachs and Shatz 1994), and a (small) negative impact of import prices on wages (Revenga 1992). While there is substantial disagreement on how much trade affects local labor market outcomes, the most popular view is perhaps best summarized by Freeman (1995), p. 30, who asserts that "… trade matters, but it is neither all that matters nor the primary cause of observed [employment and wage] changes …". Kletzer (2002) provides an excellent comprehensive review of the current state of the literature.

While a large number of studies have been devoted to examining the effect of increased foreign competition on domestic employment and wages, very few have considered the impact of import competition on *displaced* workers' labor market transition. In this study, I use data from the only large-scale and nationally representative survey of displaced workers – the biennial Displaced Workers' Supplement (DWS) to the Current Population Survey (CPS) – and data on bilateral U.S. trade to investigate the impact of import competition, particularly from labor-abundant developing, or "low-wage" countries, on displaced workers' jobless spell duration and re-employment wages.

My study is related in spirit to Addison, Fox, and Ruhm (1995), Kletzer (2001), and Kletzer (2002). Addison et al. (1995) use descriptive statistics and sample correlations from the 1988 DWS to conclude that industry trade sensitivity, defined as either import or export penetration rates, is weakly associated with re-employment earnings; but in their analysis, trade sensitivity does not affect the jobless spell duration. Kletzer (2001) uses data from nine years of the DWS (1984-2000); her industry import competition variable is an indicator which does not change over time and is based on industry import share changes during the period 1979-1994.[1] She finds that workers displaced from manufacturing industries with high import competition face lower re-employment probabilities and somewhat lower re-employment wages, but neither of the effects is statistically significant when worker characteristics are included in the regression.[2] Using the same data, Kletzer (2002) computes industry import shares, which she also splits into developed and developing country shares, and relates them to industry employment growth and job displacement rates. Her results indicate that rising import shares, overall or from developing countries, are associated with higher displacement rates, but the coefficients are small and estimated imprecisely.[3] Rising import penetration, on the other hand, is statistically significantly associated with employment decline, and the negative impact of imports from developing countries is estimated to be larger.

Unlike Addison et al. (1995), I use formal regression analysis and data from ten years of the DWS from 1984 to 2002 to relate import competition in the industry of displacement to re-employment wages and jobless spell duration. Unlike Kletzer (2001), I use *within* industry variation in import shares, overall *and* from low-wage, developing countries; and unlike Kletzer (2002), I investigate the effect of import competition on the re-employment wage and the unemployment duration. In contrast to Addison et al. (1995), Kletzer (2001), and Kletzer (2002), I find robust evidence that rising import penetration, particularly from low-wage, developing countries, affects displaced manufacturing workers' labor market outcomes.

The importance of analyzing the effects of foreign competition coming from labor-abundant, low-wage countries cannot be underscored enough. Over the last 20 years overall imports in the U.S.

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[1] Industry import share is imports as a fraction of industry consumption (industry shipments plus imports net of exports).

[2] Kletzer (2001) defines high import competing manufacturing industries as those ranking in the top 25 percent in import share changes during the period 1979-1994.

[3] The estimated association is stronger across industries than within industries.

manufacturing sector tripled in size, increasing from 8 percent of domestic manufacturing consumption in 1980 to 22 percent in the year 2000 (Table 1, column 1.1). Imports from low-wage countries, on the other hand, have increased eightfold, from 0.4 percent in 1980 to 3.2 percent of total manufacturing consumption in the year 2000 (Table 1, column 1.2). Moreover, low-wage countries are (less-skilled) labor-abundant and their exports to the U.S. are produced using (less-skilled) labor-intensive as opposed to capital- or skill-intensive manufacturing techniques. This contributes to the lower prices for such imports compared to similar goods produced in the U.S. and other developed economies (see Schott 2004). Imports from low-wage countries therefore put more competitive pressures on the domestic product markets than do imports from non-low-wage countries.

The theoretical framework in the next section considers the effects of import competition on displaced workers' jobless spell duration and re-employment wages. The theory implies that workers displaced from industries experiencing higher import competition face longer unemployment duration and lower re-employment wages. The model also implies that the lower re-employment wages are due in part to industry relocation upon re-employment, which in turn leads to loss of human capital, skills, and training that are specific to the industry of displacement.

My empirical analysis confirms the theoretical predictions. Higher import competition in the industry of displacement leads to longer jobless spell duration. Both overall import penetration and import penetration from low-wage countries in the pre-displacement industry have positive, statistically and economically significant effects on the unemployment duration. The impact of import penetration from low-wage countries is estimated to be about twice as large as the effect of overall import penetration, implying that a worker displaced from an industry with 10 percent (approximately 2 sample standard deviations, see Table 2) higher import penetration from low-wage countries faces about 2.7 weeks longer jobless spell duration. The magnitude of the estimated effect is reasonable – it is about a quarter of the size of the estimated effect of the state unemployment rate, a proxy for a comparable domestic product market demand shock.

Additionally, import penetration from low-wage countries in the pre-displacement industry has a negative and statistically significant impact on the re-employment wage. As a given manufacturing industry's imports from low-wage countries rise by 10 percentage points (approximately 2 sample standard deviations) of the industry's domestic consumption, workers displaced from that industry experience an average of 4.8 percentage points decline in their re-employment wages. The magnitude of the estimated wage effect is also reasonable – it is about one half of the size of the estimated effect of the state unemployment rate, a proxy for a comparable domestic product market demand shock. The overall import penetration in the industry of displacement, on the other hand, does not have a statistically or economically significant effect on the re-employment wage.

In the context of the broader displacement literature, Jacobson et al. (1993) and Stevens (1997) have shown that displaced workers suffer between 10 and 25 percentage points earnings loss following displacement. Further, they document that displaced manufacturing workers who leave the manufacturing sector upon re-employment suffer much larger earnings losses than workers who do not. My estimates then imply that foreign import pressures can account for at least 20 percent of the decline in earnings for manufacturing workers displaced from industries with 10 percentage points (approximately 2 sample standard deviations) higher import penetration from low-wage countries. As expected from theory, and consistent with the findings in Jacobson et al. (1993), I also show that the impact of import competition on the re-employment wage is predominantly due to sectoral relocation. I find that higher imports from low-wage countries in the pre-displacement industry significantly raise the likelihood of leaving that industry or the manufacturing sector altogether upon re-employment. This evidence is consistent with Bernard, Jensen, and Schott (2006), who document that plant employment growth is lower and the probability of plant death is higher in U.S. manufacturing industries that experience higher imports from low-wage countries. This type of competition shrinks the industry and limits displaced worker's re-employment opportunities, which consequently leads to longer jobless spell duration and industry relocation upon their re-employment. Because of the industry relocation, workers lose human capital and skills specific to the industry of displacement (see Neal 1995) or the manufacturing sector, and ultimately experience lower re-employment wages. Therefore, my findings justify the current focus of the Trade Adjustment Assistance (TAA) program on worker retraining and relocation.

The two main contributions of this study are as follows. First, it uses micro-level data on displaced workers from the DWS, spanning 23 years from 1979 to 2001, to assess the impact of trade on worker's post-displacement outcomes. Second, it analyzes the effects from not only overall import penetration but also import penetration from low-wage countries on both the jobless spell duration and the re-employment wage. The remainder of this paper is organized as follows. In the next section I provide a theoretical framework to help guide intuition. In sections III and IV, I describe the data and present simple summary statistics. Section V describes my identification strategy, which is followed by the presentation and discussion of my major findings in section VI. Section VII concludes.

II. Theoretical Framework

Although the effects of increased import competition on post-displacement wages may be analyzed by simply considering standard trade models (e.g. the sector-specific factors model or the Heckscher-Ohlin model), investigating the effects of import competition on the jobless spell duration requires a framework which explicitly models the market imperfections (uncertainty, imperfect knowledge, etc.) that lead to unemployment duration. I consider a simple continuous time version of the standard job search model (see, for example, Devine and Kiefer 1991). The optimal policy in this model is a constant reservation wage, w^r, implicitly defined by the following Bellman equation

$$w^r = b + \frac{\pi}{r}\int_{w^r}^{\infty}(w - w^r)dF(w) \qquad (1),$$

where b is time-invariant unemployment benefit, π is the job offer arrival rate, r is a constant discount rate, w is a wage offer drawn from a known wage offer distribution with a finite mean, μ, variance, σ, cumulative distribution $F(w)$, and density $f(w)$.[4]

This equilibrium condition allows me to investigate the consequences of exogenous changes in the wage offer distribution, and the offer arrival rate, π, on the expected re-employment wage, $E_w[w \mid w \geq w^r]$, and the expected jobless spell duration, $\mathrm{E}[T] = 1/\tau$, where τ is the hazard of leaving unemployment, $\tau = \pi \int_{w^r}^{\infty} f(w)dw = \pi(1 - F(w^r))$.[5]

Next, I demonstrate how increased import competition in the worker's industry of displacement effectively shifts the worker's wage offer distribution to the left. In the theoretical framework of Grossman (1983), and Hill and Mendez (1983), with labor being partially mobile due to industry-specific human capital, one can show that increased import competition in the worker's industry of employment leads to job displacement, industry relocation and lower equilibrium wage (offers) both in the worker's former industry and the rest of the economy (see the Technical Appendix for details). There are two

[4] If b declines with unemployment duration – in practice the period of unemployment insurance receipt is capped at 26 weeks – the reservation wage will also decline. If workers displaced from industries with higher import competition have longer time limits on unemployment benefit duration, their reservation wage would be declining more slowly and their jobless spell duration would be longer. Although, for simplicity, I do not model that aspect explicitly, in the empirical analysis I control for state of residence and industry of displacement to account for both the size and time limits on the unemployment benefits. I use the state of residence at the time of the survey as a proxy for the state of residence at the time of displacement because information on the latter is not available. A similar issue is search intensity. Longer or more generous unemployment insurance benefits may reduce search intensity as workers take some of the "windfall" as leisure.

[5] The model implies that the distribution of the unemployment spells is exponential. The assumption of no duration dependence is relaxed in the empirical set-up when I estimate the hazard rate using a flexible specification.

reasons for this result. First, higher import competition in an industry depresses the wage per efficiency unit of labor in that industry and less so in all other industries of the economy. Second, increased import competition causes relocation of workers to industries with lower import competition where they lose the returns to the industry of displacement specific human capital, skills, and training.

Altogether, this framework implies that higher import competition in a worker's industry of employment leads to higher likelihood of displacement and subsequent industry relocation. Increased import competition also leads to lower wage offers for the displaced worker both in the industry of displacement and the rest of the economy. Assume, for simplicity, that lower wage offers translate into a uniform leftward shift in the wage offer distribution, which only lowers its mean, μ. Higher import competition in the industry of displacement then implies a lower mean for the wage offer distribution faced by the worker.

The decline in μ brought about by higher import competition affects both the expected re-employment wage, $E_w[w \mid w \geq w^r]$, and the expected jobless spell duration, $E[T]$. Burdett and Ondrich (1985) show that

$$\frac{dE_w[w \mid w \geq w^r]}{d\mu} > 0 \quad (2), \qquad \text{and} \qquad \frac{dE[T]}{d\mu} < 0 \quad (3),$$

where (2) holds with the added condition that the truncated mean function of the wage offer distribution has a slope less than one, i.e. the offer density is log-concave (such as exponential, uniform, or normal). Therefore, higher import competition in the industry of displacement would lead to lower expected re-employment wage and higher expected unemployment duration.

To the extent that higher import competition in the industry of displacement lowers demand for domestic production in that industry, it may also lower the offer arrival rate, π, or at least the offer arrival rate for jobs from the industry of displacement. Burdett and Ondrich (1985) further show that

$$\frac{dE_w[w \mid w \geq w^r]}{d\pi} > 0, \qquad \text{and} \qquad \frac{dE[T]}{d\pi} < 0,$$

where the second inequality holds with the added condition outlined above. Therefore, the effects of import competition on the expected re-employment wage and unemployment duration through its potential impact on the job offer arrival rate only reinforce the effects of import competition through its impact on the mean of the wage offer distribution.[6]

III. Empirical Trade Measures

As a proxy for import competition in the empirical analysis I use the ratio of total industry imports to total industry consumption (domestic production plus imports net of exports) (see Freeman and Katz 1991, and Kletzer 2002):

$$IndImp_j = \frac{M_j}{Q_j - X_j + M_j} \qquad (4),$$

where M_j represents the total industry value of imports into industry *j*, Q_j is the value of industry *j*

[6] Additionally, if *z* is the parameter of riskiness of *F*(*w,z*) (see Burdett and Ondrich 1985) and $\partial F(w,z)/\partial z \geq 0$, then $dE_W[w \mid w \geq w^r]/\mathrm{dz} \geq 0$ and $dE[T]/\mathrm{dz} \geq 0$. The parameter *z* is a measure of risk similar to the variance of the wage offer distribution, *σ*. Therefore, the conditions above imply that as the risk of the wage offer distribution, i.e. as the dispersion of wage offers, declines due to higher import competition both the re-employment wage and jobless spell duration decline. The re-employment wage result re-enforces the previous conclusions, while the effect of lower wage dispersion on the jobless spell duration opposes the effects of μ and π on E[T]. It is unlikely that the wage offer dispersion effect dominates the effects of μ and π previously discussed – replacing a low wage offer with no wage offer would most likely increase the unemployment duration, and not shorten it.

domestic output (industry shipments), and X_j is the value of industry *j* exports.[7]

Recent evidence from Schott (2004) shows that import unit-values (a proxy for import prices) for highly disaggregated product categories differ widely across U.S. trading partners and are related to partner's income level, as captured by per capita GDP, and partner's factor endowments. Schott (2004) documents that products imported from labor-abundant, low-wage, i.e. low per capita GDP, countries are manufactured using (less-skilled) labor-intensive techniques, and have lower unit-values, i.e. lower import prices, than similar goods imported from non-low-wage countries. Imports from low-wage countries then would exert more competitive pressures on the domestic product markets than would imports from non-low-wage countries. Evidence consistent with this hypothesis is found in Bernard et al. (2006) who show that controlling for industry imports from non-low-wage countries, plant employment growth is lower and the probability of plant death is higher in industries facing higher imports from low-wage countries. Hence, if an industry's overall imports do not change but imports from low-wage countries rise, given that the latter have lower prices than the former, using imports from low-wage countries in a measure of import penetration would capture the extent of competitive import pressures more accurately than using overall imports. To this end, I construct a second measure of import competition, import penetration from low-wage (LW) countries as a share of industry domestic consumption:

$$IndImp_j^{LW} = \frac{M_j^{LW}}{Q_j - X_j + M_j} \qquad (5).$$

[7] Another candidate for an import price pressure measure is an import price index. Such an index is calculated by the International Price Program (IPP) at the Bureau of Labor Statistics (BLS). Unfortunately, it does not cover all product groups, it is calculated in an industry classification fundamentally different from the industry classification of the DWS, and it is not available for the entire period, 1979-2001, that the DWS data covers.

Following Bernard et al. (2006), I define a country as "low-wage" if its per capita GDP is 5 percent or less of the U.S. per capita GDP. For details and the list of low-wage countries refer to the Technical Appendix.[8] The largest importers in the group are China, India, Indonesia and the Philippines, with China being by far the largest in the late 1990s.

IV. Data

To investigate the effects of import competition on displaced workers' post-displacement outcomes, I use data from the only large-scale and nationally representative data source – the Displaced Workers' Supplement, a biennial supplement to the January or February Current Population Survey (CPS). The first DWS was instituted in January of 1984, and I use all the surveys through year 2002, which supplies data on displaced workers from 1979 to 2001. The industry classification used in DWS was altered significantly after 2002 (see the Technical Appendix for details). Because the trade measures I employ are constructed by industry and there is no consistent industry assignment before and after 2002, I cannot use the 2004 and 2006 surveys. DWS is intended for all workers who have been displaced from their jobs in the 3 (or 5) years prior to the survey. In addition to personal characteristics found in the regular monthly CPS, DWS collects information on both old and new employment for displaced workers – previous and current wages, hours, current industry, industry of displacement, reason for displacement, occupation, and duration of unemployment, among other things. I also use data on the annual state unemployment rate matched to the displaced worker's state of residence and year of displacement. In the main analysis, I use data on workers who were between the ages of 21 and 65 when they were displaced from a full-time job in manufacturing and who were still in the labor force at the date of the survey. I

[8] In particular, I calculate the average real per capita GDP for every country for the period 1985-1990 and then compare that to 5 percent of the average for that period of the U.S. real per capita GDP. If the former is smaller from the latter, the country is classified as "low-wage" and used in calculating the numerator in (5) for all years from 1979 to 2001.

focus on workers displaced from manufacturing because trade data for non-manufacturing industries are not available.

Industry information in the DWS is based on the Census of Population Industry Classification (CIC), which in turn was based on the Standard Industry Classification (SIC) until 2002. CIC contains about 78 manufacturing industries, which correspond to 3-digit or groups of 4-digit manufacturing SIC industries. To construct the measures of industry import competition, I use data on bilateral U.S. trade from Feenstra (1996) and Feenstra, Romalis, and Schott (2002). The data are only available for manufacturing industries and they are disaggregated 4-digit SIC industry level time series of bilateral U.S. manufacturing trade from 1979 to 2001. I supplement the trade data with 4-digit SIC industry shipments data, which enables me to construct the two import penetration measures (4) and (5).

Columns 1.1 and 1.2 in Panel A of Table 1 show overall manufacturing import penetration, $IndImp_{jt}$, and overall manufacturing import penetration from low-wage countries, $IndImp_{jt}^{LW}$. Both measures of import competition have increased over time. While overall imports as a fraction of manufacturing consumption have tripled in size in the twenty years from 1980 to 2000, imports from low-wage countries have soared to nearly 10 times their original levels. Column 1.3 shows the measure of import penetration from low-wage countries calculated without China – this measure of import penetration grows at a similar rate as the overall import penetration measure in column 1.1. It is therefore the rise in imports from China that accounts for most of the extraordinary growth of imports from low-wage countries.

Panel B of Table 1 shows the industry import competition measures I have computed for selected CIC industries. Generally, both measures – the overall import penetration and import penetration from low-wage countries – are increasing over time for the majority of industries, although there is heterogeneity across industries. For example, in computers and related equipment (CIC industry 322), both measures have increased substantially over time; in sugar and confectionary products (CIC industry

112), both measures have decreased over time; in miscellaneous textile mill products (CIC industry 150), overall imports have increased, but those from developing countries have declined.

In addition to calculating import measures (4) and (5), I also construct two more industry trade measures which I later use in robustness checks. The first one is a simple ratio of industry export volume to industry shipments,

$$IndExp_j = \frac{X_j}{Q_j} \qquad (6),$$

and it captures the industry's export orientation. The second one is a statewide average of industry import penetration from low-wage countries across all manufacturing industries within a state, where I use each manufacturing industry shipments as fraction of the state's total manufacturing sales as industry weights:

$$StateImp_s^{LW} = \sum_{j=1}^{J}\left(\frac{Q_{sj}}{\sum_{j=1}^{J} Q_{sj}}\right) IndImp_j^{LW} \qquad (7).$$

The second measure captures the average import competition pressures in all of manufacturing in a given state, which I assume is the displaced worker's local labor market area.

Finally, I match the industry import penetration measures and the industry export measures, which are appropriately calculated by CIC industry and year, to the displaced workers' CIC industry of displacement and year of displacement for each year between 1979 and 2001 in all ten years of the DWS (1984-2002). The state import competition measure, constructed by state of residence and year of displacement, I match by worker's state of residence and year of displacement.

Descriptive statistics for workers displaced from manufacturing in the DWS are reported in Table 2. Note that not everyone is re-employed at the date of the survey, in part because some have been displaced just a few weeks before the interview. About 60 percent of the observations come from the first four surveys 1984-1990 (not shown in the table) as manufacturing employment was higher in the 1980's than in the 1990's.

Table 2 also contrasts the descriptive statistics for workers displaced from industries with low (below the median) and high (above the median) import penetration from low-wage countries. Industries with high $IndImp_{jt}^{LW}$ tend to employ higher fractions of female, black and non-metropolitan workers, as well as higher fractions of workers without high school education. To account for these differences when identifying the effects of import competition from low-wage countries, I employ two strategies. First, I control for a host of personal, lost job, and current job characteristics. Second, as I discuss in the next section, I use industry of displacement dummies in the regression equations, which amounts to using only *within* industry changes over time in $IndImp_{jt}^{LW}$ for identification in the re-employment wage regressions.

Table 3 documents the correlations among the various trade measures calculated across workers in the DWS data. In addition to the trade measures defined thus far, I also construct state overall import penetration, $StateImp_{st}$, state export ratio, $StateExp_{st}$, and industry import penetration from low-wage countries without China, $IndImp_{jt}^{LW\ without\ China}$.[9] The correlation between import competition in the pre-displacement industry, $IndImp_{jt}$, and import competition from low-wage countries in the pre-displacement industry, $IndImp_{jt}^{LW}$, is relatively high at 0.67. Also, the correlation between $IndImp_{jt}^{LW}$ and $IndImp_{jt}^{LW\ without\ China}$ is even higher at 0.83.

V. Econometric Strategy

I present the analysis of the unemployment duration first, as it is observed first, and it is also the outcome which allows observation of a re-employment wage.

[9] The state export measure is calculated as the state import measure in (7) but averaging over industry export ratios.

V.1 Unemployment Duration

The jobless spell durations in the DWS are recorded in weeks. Following McCall (1996), I group the durations into two-week intervals, for two reasons. First, in a specification with a flexible baseline hazard (see Meyer 1990), the grouping lowers the number of baseline hazard parameters that need to be estimated. Second, grouping reduces the possible bias from piling the reported unemployment durations at even weeks as evident from inspection of the weekly empirical hazard function. Since the unemployment duration data are discrete, following McCall (1996), I take a grouped data approach (see Meyer, 1990; Lancaster, 1990; and Wooldridge, 2002).

First, I convert the unit of analysis from a displaced worker to a jobless spell interval (two-week period) at risk of leaving the unemployment pool. I divide the time line into 79 intervals, [0,2), [2, 4), …, [156, ∞) as there are no observed durations greater than 156 weeks. Following Wooldridge (2002), for a displaced worker i, I define $c_{i,m}$ to be a binary censoring indicator equal to unity if the duration is right-censored in the interval m, m = 1, 2, …, 79, and zero otherwise. Note that $c_{i,m}=1$ implies that $c_{i,m+1}=1$. There are two sources of right-censoring in the data. First, durations in the 1992 DWS and earlier years were top-coded at 99 weeks, and second, some workers were still unemployed at the date of the survey.[10] I define $y_{i,m}$ to be a binary indicator equal to unity if displaced worker's i unemployment duration ends in the m^{th} interval and zero otherwise. Hence, $y_{i,m}=1$ implies that $y_{i,m+1}=1$. If duration is censored in the m^{th} interval ($c_{i,m}=1$), I set $y_{i,m}\equiv 1$. Thus, I obtain a balanced panel, where for each displaced worker i, I observe ($y_{i,m}$, $c_{i,m}$).

Given a hazard function $\phi(t; \boldsymbol{Z}_i, \boldsymbol{\eta})$, where $\boldsymbol{\eta}$ is the vector of parameters to be estimated, and $\boldsymbol{Z}_i$ is the matrix of personal and industry characteristics, one can now calculate all the probabilities that $y_{i,m}$

[10] Unemployment durations were top-coded at 168 weeks after 1992, but this is not binding for the sample of manufacturing workers I use as the longest reported duration is 156 weeks.

takes on a value of zero or one given ($y_{i,m-1}$, …, $y_{i,1}$), ($c_{i,m}$, …, $c_{i,1}$), and $\boldsymbol{Z}_i$.[11] The only two such probabilities that are not identically zero or one are $\mathrm{P}(y_{i,m}=1 \mid y_{i,m-1}=0, \boldsymbol{Z}_i, c_{i,m}=0) = 1-\alpha_m(\boldsymbol{Z}_i, \boldsymbol{\eta})$, and $\mathrm{P}(y_{i,m}=0 \mid y_{i,m-1}=0, \boldsymbol{Z}_i, c_{i,m}=0) = \alpha_m(\boldsymbol{Z}_i, \boldsymbol{\eta})$, for m = 1, 2, …, 79, where

$$\alpha_m(\boldsymbol{Z}, \boldsymbol{\eta}) \equiv exp\left[-\int_{m-1}^{m} \phi(t; \boldsymbol{Z}, \boldsymbol{\eta})ds\right].$$

I specify the log-likelihood function to be maximized as

$$log\, L_1 = \sum_{i=1}^{\mathrm{N}} \sum_{h=1}^{m(i)-1} log[\alpha_h(\boldsymbol{Z_i}, \boldsymbol{\eta})] + d_i\, log[1 - \alpha_{m(i)}(\boldsymbol{Z_i}, \boldsymbol{\eta})] \qquad (8),$$

where d_i is a censoring indicator equal to unity if the duration of displaced worker i is uncensored, and N is the number of displaced workers included in the analysis.

Before I can implement conditional MLE, I need to specify the hazard function, $\phi(t; \boldsymbol{Z}_i, \boldsymbol{\eta})$. A popular choice due to its flexibility is a piecewise-constant proportional hazard

$$\phi(t; \boldsymbol{Z}_i, \boldsymbol{\eta}) = exp(\boldsymbol{Z}_i \boldsymbol{\eta})\phi_m \qquad (9),$$

for m =1, 2, …, 79, and $m\text{-}1 \le t < m$. For identification, I estimate interval-specific baseline hazard rate, ϕ_m, for all intervals in which there is at least one exit from the unemployment pool, and I suppress the constant in $\boldsymbol{Z}_i$. With the hazard rate assumptions in place,

$$\alpha_m(\boldsymbol{Z}_i, \boldsymbol{\eta}) \equiv exp[-exp(\boldsymbol{Z}_i \boldsymbol{\eta})\phi_m],$$

for m =1, 2, …, 79, and I use conditional maximum likelihood to estimate (9), where $\boldsymbol{\eta}$, and ϕ_m are the parameters to be estimated.

The matrix of personal and industry characteristics, $\boldsymbol{Z}_i$, can be written as

$$\boldsymbol{Z_i} = [\boldsymbol{X}_{ikjst} \mid IndImp_{jt}^{LW} \mid U_{st}^{RATE} \mid \delta_k \mid \lambda_j \mid \sigma_s \mid \tau_t],$$

[11] Note that by definition, these probabilities only depend on $y_{i,m-1}$, $c_{i,m}$, and $\boldsymbol{Z}_i$.

which includes $\boldsymbol{X}_{ikjst}$ – a vector of personal characteristics for individual *i*, surveyed in year *k*, displaced from industry *j* in year *t*, and residing in state *s*. Personal characteristics included are education, current age, current age squared, tenure and occupation on the lost job, the natural logarithm of the lost job weekly wage rate, and dummies for race, sex, marital status, and metropolitan area residence status.[12] I use six education categories – no high school, high-school dropout, high-school graduate, some college, college graduate, and advanced degree. The omitted category in the regression is high-school graduate. Because I pool observations for both male and female displaced workers, I include a full set of interactions of the female indicator with the rest of the individual-level covariates in $\boldsymbol{X}_{ikjst}$. The state unemployment rate at the time of displacement, U_{st}^{RATE}, is included as a proxy for the local labor market condition, which affects the likelihood of re-employment. To control for time-invariant industry of displacement or state of residence characteristics, such as Trade Adjustment Assistance (TAA) availability or unemployment benefits generosity, $\boldsymbol{Z}_i$ includes industry of displacement and state of residence dummies – λ_j, σ_s. Year of displacement and year of the survey dummies, τ_t and δ_k, are added to absorb annual economy-wide shocks in the year of displacement and year of the survey. Finally, $\boldsymbol{Z}_i$ also includes the explanatory variable of interest, the industry of displacement import penetration from low-wage countries, $IndImp_{jt}^{LW}$, which varies by industry and year.

An alternative hazard function specification to (9) is the Weibull hazard

$$\phi(t;\boldsymbol{Z}_i,\boldsymbol{\eta}) = exp\,(\boldsymbol{Z}_i\boldsymbol{\eta})\varphi t^{\varphi-1} \qquad (10)\ .$$

It captures a monotonically increasing or monotonically decreasing hazard – if φ > 1, the hazard exhibits positive duration dependence, and if φ < 1, it exhibits negative duration dependence. It turns out that the estimated vector of parameters, $\hat{\boldsymbol{\eta}}$, using the Weibull specification is almost identical to the estimated vector of parameters if one uses the more flexible specification (9). Also, for further computational

[12] I use 46 occupation indicators corresponding to the CPS detailed occupation groups-recode.

simplicity, one can assume that the grouped data is continuous instead of discrete and estimate the Weibull model maximizing the following log-likelihood function

$$log\, L_2 = \sum_{i=1}^{N} \{d_i\, log[f(t_i \mid \boldsymbol{Z}_i, \boldsymbol{\eta})] + (1-d_i)\, log[1 - F(t_i \mid \boldsymbol{Z}_i, \boldsymbol{\eta})]\} \qquad (11),$$

where the Weibull distribution with covariates has the following conditional density

$$f(t_i \mid \boldsymbol{Z}_i; \boldsymbol{\eta}) = exp\,(\boldsymbol{Z}_i\boldsymbol{\eta})\varphi t^{\varphi-1}\, exp\,[-exp\,(\boldsymbol{Z}_i\boldsymbol{\eta})t^{\varphi}]\,.$$

The estimated vector of parameters, $\hat{\boldsymbol{\eta}}$, using the Weibull hazard specification and treating the data as continuous, is again almost identical to the estimated vector of parameters using the flexible hazard specification (9) and treating the data as discrete.

There are two features that make the continuous Weibull model appealing for implementation and presentation given that the estimated vector of parameters does not change from specification (9). First, the continuous (Weibull) model is computationally much less demanding. Second, the Weibull model has an accelerated failure time (AFT) representation, allowing the interpretation of the estimated coefficients in the AFT representation as semi-elasticities of the expected unemployment duration with respect to a given covariate. This is useful as I am primarily interested in how the observed covariates, in particular the import penetration in the industry of displacement, $IndImp_{jt}^{\mathrm{LW}}$, affect the mean jobless spell duration.[13]

For this reason, further adding unobserved heterogeneity to my hazard specification is not necessary – it will not change the mean effects but only the error distribution (see Wooldridge 2002). I do, however, for a robustness check, add unobserved Gamma heterogeneity to the Weibull specification (10), resulting in a hazard of the following form

$$\phi(t; \boldsymbol{Z}_i, \boldsymbol{\eta}) = \nu_i\, exp(\boldsymbol{Z}_i\boldsymbol{\eta})\varphi\, t^{\varphi-1} \qquad (12),$$

[13] In the next section I report results from specifications (8), (11) and the AFT representation of specification (11).

where v_i ~ Gamma (θ, θ), with E(v_i)=1 and Var((v_i)=1/θ. For inference, I calculate robust standard errors clustered by industry of displacement.

Unlike the re-employment wage, the jobless spell duration is observed for all displaced workers both re-employed and those still looking for a job at the date of the interview. For the latter group, I only observe interrupted (right-censored) spells, which were accommodated in the likelihood function. Hence, problems associated with selection based on worker's re-employment status do not arise in the analysis of unemployment duration. Recall bias, on the other hand, may potentially bias the estimates both in the jobless spell duration regressions as well as in the re-employment wage regressions. However, the variable of interest, $IndImp_{jt}^{LW}$, is a variable whose value I assign myself and workers only need to recall their industry and year of displacement. Also, if erroneous recall is assumed to behave as a classical measurement error, in the context of the linear re-employment wage regressions in the next section, the effects of such a bias would be toward zero, which implies that the magnitudes of the estimated coefficients may be biased downward and the true effects are even more pronounced.

V.2 Re-employment Wage

Regression equation (13) below relates the second outcome of interest, the logarithm of the weekly re-employment wage for an individual *i* surveyed in year *k*, displaced from an industry *j* in year *t*, and residing in state *s*, to the import penetration from low-wage countries in the industry and year of displacement, $IndImp_{jt}^{LW}$.

$$ln(w_{ikjst}^{re-employment}) = \beta_0 + \boldsymbol{X}_{ikjst}\boldsymbol{\beta}_1' + \beta_2 IndImp_{jt}^{LW} + \beta_3 U_{\mathrm{st}}^{RATE} + \delta_k + \lambda_j + \sigma_s + \tau_t + \varepsilon_{ikjst} \qquad (13),$$

where, as before, $\boldsymbol{X}_{ihkjst}$ is a vector of personal characteristics that includes the same set of covariates used in the unemployment duration analysis. Similarly, equation (13) includes industry of displacement, λ_j, and state of residence, σ_s, fixed effects. Additionally, in a number of specifications, to check for robustness I include industry-specific as well as a state-specific time trends. Year of displacement and year of the survey dummies, τ_t and δ_k, absorb annual economy-wide shocks in the year of displacement and year of the survey. Note that as I include both year of displacement and year of the survey dummies, I effectively control for the time since displacement. Because equation (13) is a linear specification, the identification of the effects of import penetration from low-wage countries in the pre-displacement industry, $IndImp_{jt}^{LW}$, only exploits annual variation in this measure *within* the industry of displacement.

As not every displaced worker is re-employed by the date of the survey, I do not have information on the re-employment wage for those who are still unemployed at that date. As a result, I estimate the re-employment equation (13) for those who are employed at the time of the interview, but I show that the censoring (potential selection) problem does not affect the results much, and it may lead to a downward (in magnitude) bias in the impact of $IndImp_{jt}^{LW}$. First, note that I include both year of the survey and year of displacement dummies in the re-employment wage equation (13). Because they control for the length of time between the date of the survey and the date of displacement, which is intrinsically associated with the re-employment censoring (selection) mechanism, these dummies alleviate selection concerns.[14] Second, while about 24 percent of all those surveyed were still unemployed at the date of the interview (see Table 2), less than 10 percent of those who were displaced 3 years prior to the survey were still unemployed. To this end, I re-estimate the re-employment wage equation (13) using only those workers who were displaced at least 3 years prior to the interview. I find that the effect of $IndImp_{jt}^{LW}$ becomes even more pronounced, suggesting that the impact of import competition from low-wage countries is even larger for workers who experience longer unemployment duration. Finally, to avoid potential selection issues, instead of estimating equation (13) by OLS, I employ a two-step Heckman correction procedure (see Heckman 1979) which delivers consistent estimates in the presence of selection.

[14] The difference between the year of the survey and the year of displacement is the length of the period (in years) since displacement, which is associated with the censoring mechanism as those who were more recently displaced would have had less time to locate a job by the time of the DWS interview.

Given the difficulty of finding a good exclusion restriction, these estimates, which are presented and discussed in the Technical Appendix, should be interpreted with caution. Nonetheless, the results from this correction procedure are consistent with the estimates from the equation (13) using displaced workers who are employed at the date of the survey.

VI. Results

VI.1 Unemployment Duration

I present the results for the hazard rate of leaving unemployment and the jobless spell duration in Table 4. Estimates from the hazard rate specifications are in Panel A, and results for the unemployment duration are in Panel B. Columns 4.1-4.3, are from specification (8) with hazard rate (9) and take the grouped data approach treating unemployment duration as discrete. In 4.1, I proxy for import competition using overall import penetration in the industry of displacement, $IndImp_{jt}$, while in 4.2 I use import penetration from low-wage countries, $IndImp_{jt}^{LW}$. Both proxies are statistically and economically significant in reducing the hazard of leaving unemployment, but the effect of imports from low-wage countries is estimated to be about twice as large. When both $IndImp_{jt}$ and $IndImp_{jt}^{LW}$ are used in a single regression, as reported in column 4.3, their estimated coefficients diminish in magnitude and their standard errors increase compared to the specifications where they enter the regression alone. These are typical signs of a multicollinearity problem driven by the high (0.67) sample correlation between $IndImp_{jt}$ and $IndImp_{jt}^{LW}$ (see Table 3). To conserve space, the coefficients for the rest of the covariates are reported in the Technical Appendix; all of these estimates have the expected signs.

As I previously discussed, the estimates using (8), flexible hazard specification (9), and treating the data as discrete are nearly identical to the estimates using (11) with the Weibull hazard specification (12) and treating the data as continuous – results from the Weibull specification (12) are in columns 4.4-4.6. Note that the Weibull duration dependence parameter, $\hat{\varphi}$, is estimated at 0.95 and statistically significantly smaller than 1, which implies negative duration dependence.

In the first three columns of Panel B, I present the results from the AFT representation of the Weibull model (11) and (12), which allows interpretation of the estimated coefficients as semi-elasticities of the expected unemployment duration with respect to a given covariate.[15] From 4.7, one can conclude that a worker displaced from an industry with 10 percent higher overall import penetration suffers a 5.9 percent, or 1.4 weeks at the mean, longer jobless spell duration.[16] Alternatively, if one uses $IndImp_{jt}^{LW}$ to proxy for import pressures, a worker displaced from an industry with 10 percent higher import penetration from low-wage countries suffers about 11.4 percent, or about 2.7 weeks at the mean, longer jobless spell duration. The unemployment duration is estimated to be about twice as sensitive to imports from low-wage countries as to overall imports. Additionally, the estimated magnitudes are quite reasonable – based on the results in 4.8, the impact of one standard deviation increase in $IndImp_{jt}^{LW}$ is about a quarter of the size of the impact of one standard deviation increase in a similar domestic product market demand shock captured by the state unemployment rate, U_{st}^{RATE} .

I further perform a number of robustness checks in columns 4.10-4.14. I only report robustness checks using $IndImp_{jt}^{LW}$, similar results hold if I use $IndImp_{jt}$ instead. Because higher demand for U.S.- produced goods abroad can be correlated with higher import pressures and may stimulate local labor markets thereby reducing unemployment duration, I further control for exports, as well. The estimated coefficient of $IndImp_{jt}^{LW}$ in 4.8 is robust to inclusion of industry of displacement exports ($IndExp_{jt}$) in 4.10, state manufacturing imports from low-wage countries ($StateImp_{st}^{LW}$) in 4.11, or state manufacturing exports ($StateExp_{st}$) in 4.12. While, as expected, higher exports in the industry of

[15] To convert the coefficients in 4.4-4.6 to their AFT representation in 4.7-4.9, I have multiplied by -1, divided by the estimate of the Weibull duration dependence parameter, $\hat{\varphi}$, and adjusted the standard errors accordingly.

[16] The mean unemployment duration is 11.87 two-week periods, see Table 2.

displacement decrease the unemployment duration in 4.10, state exports in manufacturing, $StateExp_{st}$, do not have the expected sign in 4.12 – higher state exports are associated with higher jobless spell duration, not lower. Neither of the effects, however, is statistically significantly different from zero.

To the extent that higher $StateImp_{st}^{LW}$ proxies for higher import competition in all of manufacturing in the local labor market, the coefficient estimated in 4.11 has the expected sign but it is not statistically significant. Its magnitude is about 4 times larger than the magnitude of the coefficient on $IndImp_{jt}^{LW}$. However, the sample standard deviation of $StateImp_{st}^{LW}$ is about 4 times smaller than the sample standard deviation of $IndImp_{jt}^{LW}$ (see Table 2) indicating that the impact of one standard deviation increase in either import measure is the same. This is consistent with the fact that the two variables proxy for the same product demand shock.

As previously discussed, the extraordinary growth of manufacturing imports from low-wage countries is primarily due to the increase in imports from China. To check if the effects of the pre-displacement industry imports from low-wage countries on the jobless spell duration are entirely due to imports from China, I use another measure, $IndImp_{jt}^{LW\ without\ China}$, which is similar to $IndImp_{jt}^{LW}$ but it excludes China from the list of low-wage countries. In 4.13, I use $IndImp_{jt}^{LW\ without\ China}$ in place of $IndImp_{jt}^{LW}$. The results are not too different – the estimated coefficient is still statistically significant, about twice as large but not statistically significantly different from the estimated coefficient on $IndImp_{jt}^{LW}$ in the baseline specification 4.8.

Finally, as I discussed in the section on identification, I augment the Weibull specification by adding unobserved Gamma heterogeneity as in hazard specification (12). The estimates, presented in the last column of Panel B, 4.14, do not change much, and remain statistically and economically significant. Note that the variance of the Gamma heterogeneity, $1/\theta$, is statistically significant, and the estimate of the Weibull duration parameter, $\hat{\varphi}$, is now statistically significantly larger than one.

I have also estimated specification (11) including interactions between the schooling dummies and $IndImp_{jt}^{LW}$. The results, presented in the Technical Appendix, do not reveal much – most of the coefficients on the interactions are not estimated precisely, indicating that the effects of imports from low-wage countries on the jobless spell duration may be fairly similar across education groups.

VI.2 Re-employment Wage

Results from the re-employment wage regression, equation (13), are presented in Table 5. In column 5.1, I use the overall import penetration in the pre-displacement industry, $IndImp_{jt}$, as a measure of import competition; in 5.2, I use the imports from low-wage countries alone, $IndImp_{jt}^{LW}$; and in 5.3, I control for both overall imports and imports from low-wage countries. With both measures in the same regression, the overall imports measure, $IndImp_{jt}$, controls for imports from non- low-wage countries.

When the two import competition measures enter regression (13) separately, both have the expected negative sign, but only the estimated effect of $IndImp_{jt}^{LW}$ is economically and statistically significant. When entered jointly in column 5.3, $IndImp_{jt}^{LW}$ is still the only one that matters statistically. The estimated coefficient on $IndImp_{jt}^{LW}$ slightly decreases moving from column 5.2 to column 5.3, but the two estimates are not significantly different from each other. I conclude that displaced worker's re-employment wage is sensitive to the import penetration from low-wage countries into the worker's industry of displacement, $IndImp_{jt}^{LW}$, and not overall imports, $IndImp_{jt}$. The estimated coefficient on $IndImp_{jt}^{LW}$ in the baseline specification 5.2 implies that as a given manufacturing industry's imports from low-wage countries rise by 10 percent of the industry's domestic consumption, workers displaced from that industry experience an average of 4.8 percent decline in their re-employment wages. Alternatively, one standard deviation increase in $IndImp_{jt}^{LW}$, or 0.041 (see Table 2), would lead to a 2.0 percent decrease in the worker's re-employment wage. The estimated magnitudes are quite reasonable – based on the results in 5.2, the impact of one standard deviation increase in $IndImp_{jt}^{LW}$ is about one half of the size of the impact of one standard deviation increase in a similar domestic product market demand shock captured by the state unemployment rate, U_{st}^{RATE}. To conserve space, the coefficients for rest of the covariates are reported in the Technical Appendix; all of these estimates have the expected signs.

In columns 5.4-5.13, I perform a number of robustness checks. In 5.4, I add a control for industry of displacement exports, $IndExp_{jt}$. The estimated coefficient on $IndImp_{jt}^{LW}$ does not change much and remains statistically significant. In the two specifications 5.5 and 5.6, I control for a trade measures based on the state of residence – $StateImp_{st}^{LW}$ and $StateExp_{st}$. The coefficient of $IndImp_{jt}^{LW}$ is stable and remains statistically significant. As was the case with the unemployment duration, the estimate of the state import penetration from low-wage countries, $StateImp_{st}^{LW}$, is of the expected sign; but it is not precisely estimated. Interestingly, the effect of $StateExp_{st}$ is negative, contrary to expectations that larger exports from the local labor market would increase labor demand and contribute to higher wages.

To test if the effects of the industry of displacement imports from low-wage countries on the re-employment wage are entirely due to imports from China, I use $IndImp_{jt}^{LW\ without\ China}$ in place of $IndImp_{jt}^{LW}$ in 5.7. The results are not very different from previous estimates – the coefficient is about 1.5 times larger but not statistically significantly different from the coefficient on $IndImp_{jt}^{LW}$ in the baseline specification 5.2. To check if the decrease in the weekly wage due to import penetration is perhaps a result of a decline in hours, in 5.8, I explicitly control for weekly hours on the new job.[17] The estimated coefficient on $IndImp_{jt}^{LW}$ in 5.8 is very similar to the benchmark estimate in 5.2, suggesting the decline in weekly earnings that results from import penetration from low-wage countries is not due to lower hours.

[17] The results are similar if I instead include a dummy for full time employment.

To assess the potential effects of selection due to fact that not all displaced workers are re-employed by the date of the survey, in 5.9 and 5.10, I restrict the sample to those who were displaced at least 2 years prior (5.9) and those who were displaced at least 3 years prior to the survey (5.10). Note that while about 24 percent of all surveyed were still unemployed at the date of the survey interview (see Table 2), less than 15 percent of those who were displaced 2 years ago were still unemployed, and less than 10 percent of those who were displaced 3 years ago were still jobless at the data of the interview. The estimated effects of $IndImp_{jt}^{LW}$ in 5.9 and 5.10 are even larger (in magnitude) than the benchmark estimate in 5.2, though they are not statistically significantly different from it. This evidence suggests that the impact of import competition from low-wage countries is even larger for workers who experience longer unemployment durations and that the censoring (potential selection) problem does not affect the results much, perhaps leading to a downward (in magnitude) bias in the impact of $IndImp_{jt}^{LW}$.[18]

Finally, in 5.11 and 5.12, I include industry of displacement specific time trends and state specific time trends. The estimated impact of $IndImp_{jt}^{LW}$ rises in magnitude to - 0.83 (0.45), but it is not statistically significantly different from the benchmark estimate of - 0.48 (0.10) in specification 5.2.

I next identify the channel through which import competition affects the re-employment wage. From theory, when import competition in an industry intensifies, demand for domestically produced goods in that industry declines, and some workers employed in the industry are displaced. Upon re-employment, these workers are reallocated to a different industry which experiences less foreign competition. Therefore, a worker displaced from a manufacturing industry with high import competition would have a higher probability of industry relocation and greater likelihood of leaving the manufacturing sector. Neal (1995) provides evidence that some part of human capital is industry or sector specific, and therefore not transferable. One would expect then that workers displaced from industries with higher

[18] Additionally, a Heckman correction specification presented in the Technical Appendix, produces an estimate of - 0.40 (0.20), which is very similar to the benchmark estimate of - 0.48 (0.10) in 5.2.

import competition would face higher likelihood of an industry or sector relocation upon re-employment and that they would consequently experience lower re-employment wages.

To investigate this scenario, I first estimate a linear probability regression for the likelihood of leaving the industry of displacement and for the likelihood of leaving the manufacturing sector upon re-employment for displaced manufacturing workers. The results are presented in columns 6.1 and 6.2 in Panel A of Table 6.[19] About 81 percent of all displaced manufacturing workers change industries when re-employed and about 54 percent leave manufacturing altogether (see Table 2). The estimates in 6.1 and 6.2 indicate that $IndImp_{jt}^{LW}$ increases the likelihood of both leaving the pre-displacement industry and leaving the manufacturing sector altogether. In particular, if import penetration from low-wage countries rises by 10 percent of industry domestic consumption, workers displaced from that industry experience an average of 1.2 percent increase in the likelihood of industry relocation when re-employed and an average of 3.4 percent increase in the likelihood of leaving the manufacturing sector. These results are consistent with Bernard et al. (2006) who find that plant employment growth is lower and the probability of plant death is higher in industries exposed to higher imports from low-wage countries.[20]

To further investigate the role of the industry change, I estimate the re-employment equation (13) on the sample of displaced manufacturing workers who did not change industries and compare the estimates with the results obtained from the sample of workers who did leave their industry of displacement. Similarly, I split the sample between those who left manufacturing and those who did not.

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[19] This specification is analogous to equation (13).

[20] The three main reasons for job displacement (90 percent of the sample) are plant closing, slack/insufficient work, and position abolished. All of these reasons may imply a decrease in product demand brought about by import competition. Dummies for these three reasons are weakly correlated with $IndImp_{jt}^{\mathrm{LW}}$ – the dummy for plant closing is weakly positively correlated with $IndImp_{jt}^{\mathrm{LW}}$, while the dummy for slack/insufficient work is weakly negatively correlated with $IndImp_{jt}^{\mathrm{LW}}$.

The results are presented in Panel B of Table 6. The estimates in 6.3 and 6.4 show that $IndImp_{jt}^{LW}$ has almost no effect on workers re-employed in their pre-displacement industry, whereas the effect is large and statistically significant for workers who were reallocated to a different industry. Columns 6.5 and 6.6 indicate that $IndImp_{jt}^{LW}$ has almost no negative effect on workers re-employed back in manufacturing, while it had a large and statistically significant effect on those who are re-employed outside the manufacturing sector. These results are consistent with the estimates in Panel A of Table 6 pointing to the conclusion that higher import competition leads to a higher likelihood of industry and sector relocation and loss of the returns to industry or sector specific human capital upon re-employment.

Finally, I also estimate equation (13) including interactions between the education dummies and $IndImp_{jt}^{LW}$. Just as in the case of the unemployment duration, the results, which are reported in the Technical Appendix, do not reveal much – most of the coefficients on the interactions are not estimated precisely and some are economically small, indicating that the decline in the re-employment wage due to imports from low-wage countries may be fairly similar across education groups.

VII. Conclusion

This study uses data from the only large-scale and nationally representative survey of displaced workers, the DWS, to assess the impacts of foreign competition, particularly from low-wage countries, on displaced U.S. manufacturing workers' jobless spell duration and re-employment wages. Imports from low-wage, labor-abundant countries are manufactured using (low-skilled) labor-intensive techniques and their prices are lower compared to similar goods produced in the U.S. or other capital- and skill-abundant countries (see Schott 2004). Imports from low-wage countries then put more competitive pressures on the product markets in the U.S. and further affect labor market outcomes of displaced workers. Two broad conclusions emerge from my analysis.

First, higher import competition in the industry of displacement leads to longer jobless spell duration. In this case, both overall import penetration and import penetration from low-wage countries in the industry of displacement have positive, statistically and economically significant effects on unemployment duration. The impact of import penetration from low-wage countries, however, is estimated to be about twice as large as the effect of overall import penetration, implying that a worker displaced from an industry with 10 percentage points (approximately 2 sample standard deviations) higher import penetration from low-wage countries faces about 2.7 weeks longer jobless spell duration. The magnitude of the estimated effect is quite reasonable – it is about a quarter of the size of the estimated effect of the state unemployment rate, which can be considered as a proxy for a comparable product demand shock.

Second, as predicted by theory, import penetration from low-wage countries in the industry of displacement has a negative impact on the re-employment wage. The estimates imply that as a given manufacturing industry's imports from low-wage countries rise by 10 percentage points (approximately 2 sample standard deviations) of the industry's domestic consumption, workers displaced from that industry experience an average of 4.8 percentage points decline in their re-employment wages. This result is both statistically and economically significant. The overall import penetration in the industry of displacement, on the other hand, does not have a statistically or economically significant effect on the re-employment wage. Given the magnitudes of earnings losses following displacement found by Jacobson et al. (1993) and Stevens (1997), my estimates then imply that foreign import pressures can account for at least 20 percent of the decline in earnings for manufacturing workers displaced from industries with 10 percentage points (approximately 2 sample standard deviations) higher import penetration from low-wage countries.

As expected from theory, and consistent with Bernard et al. (2006), the impact of import competition on the re-employment wage is predominantly due to workers' industry relocation. Higher imports from low-wage countries in the pre-displacement industry significantly raise the likelihood of leaving manufacturing upon re-employment, which, consistent with Neal (1995), leads to loss of manufacturing specific human capital, skills, and training, and ultimately to a lower re-employment wage in the non-manufacturing sector. The findings here therefore justify the current focus of the Trade Adjustment Assistance (TAA) program on worker retraining and relocation.

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TABLES

Table 1

Manufacturing import penetration as a fraction of total manufacturing consumption over time

Panel A: All manufacturing

Year	1.1 Overall import penetration ($IndImp_{jt}$)	1.2 Import penetration from low-wage countries ($IndImp_{jt}^{LW}$)	1.3 Import penetration from low-wage countries excluding China ($IndImp_{jt}^{LW\ without\ China}$)
1980	0.082	0.004	0.003
1985	0.117	0.004	0.003
1990	0.139	0.009	0.005
1995	0.172	0.020	0.008
2000	0.220	0.032	0.011

Source. – Authors' calculations with data from Feenstra (1996), Feenstra et al. (2002), and the BEA.

Panel B: Selected manufacturing industries

DWS Industry (DWS industry number)	Overall import penetration ($IndImp_{jt}$)			Import penetration from low-wage countries ($IndImp_{jt}^{LW}$)		
	1980	1990	2000	1980	1990	2000
Meat products (100)	0.040	0.036	0.037	0.003	0.001	0.001
Sugar and confectionery products (112)	0.151	0.103	0.100	0.048	0.031	0.025
Carpets and rugs (141)	0.051	0.059	0.106	0.023	0.029	0.053
Yarn, thread, and fabric mills (142)	0.046	0.106	0.173	0.005	0.017	0.041
Miscellaneous textile mill products (150)	0.119	0.125	0.150	0.046	0.011	0.015
Apparel and accessories, except knit (151)	0.130	0.354	0.582	0.019	0.115	0.269
Miscellaneous fabricated textile products (152)	0.043	0.118	0.183	0.010	0.033	0.087
Leather tanning and finishing (220)	0.123	0.296	0.317	0.015	0.023	0.009
Footwear, except rubber and plastic (221)	0.299	0.633	0.814	0.010	0.091	0.511
Leather products, except footwear (222)	0.268	0.496	0.697	0.017	0.183	0.462
Furniture and fixtures (242)	0.043	0.114	0.212	0.002	0.007	0.062
Fabricated structural metal products (282)	0.009	0.014	0.034	0.000	0.000	0.002
Computers and related equipment (322)	0.083	0.380	0.577	0.001	0.002	0.088
Household appliances (340)	0.069	0.180	0.276	0.000	0.024	0.093
Toys, amusement, and sporting goods (390)	0.225	0.463	0.579	0.009	0.122	0.379

Source. – Author's calculations with data from Feenstra (1996), Feenstra et al. (2002), and the BEA.

Table 2
Descriptive statistics for workers displaced from manufacturing

Variable	Displaced and Re-employed			$IndImp_{jt}^{LW}$ below median	$IndImp_{jt}^{LW}$ above median	Displaced		
	Mean	Std. Dev.	N	Mean	Mean	Mean	Std. Dev.	N
Fraction re-employed at date of survey	1.00	-	10,013	1.00	1.00	0.76	-	13,262
Current weekly wage (constant 2003 dollars)	571.52	370.64	8,883	593.78	504.56	-	-	-
Current weekly hours	39.65	13.19	9,798	39.95	38.74	-	-	-
Lost weekly wage (constant 2003 dollars)	685.64	413.89	8,902	721.27	575.25	666.30	404.28	11,820
Unemployment duration (weeks)	19.58	24.88	8,955	19.45	19.95	22.02	26.64	12,075
Unemployment duration (two-week intervals)	10.66	12.41	8,955	10.60	10.84	11.87	13.28	12,075
Female	0.32	-	10,013	0.27	0.48	0.33	-	13,262
Black	0.09	-	10,013	0.08	0.10	0.11	-	13,262
Married	0.68	-	10,013	0.68	0.65	0.65	-	13,262
Metropolitan area	0.67	-	9,949	0.69	0.62	0.67	-	13,184
No high school	0.05	-	10,013	0.04	0.09	0.06	-	13,262
High school dropout	0.11	-	10,013	0.10	0.14	0.13	-	13,262
High school graduate	0.42	-	10,013	0.42	0.42	0.42	-	13,262
Some college	0.25	-	10,013	0.26	0.21	0.24	-	13,262
College graduates	0.12	-	10,013	0.12	0.10	0.10	-	13,262
Advanced degree	0.06	-	10,013	0.06	0.04	0.05	-	13,262
Age (years)	38.76	10.44	10,013	38.69	38.98	38.89	10.65	13,262
Lost job tenure (years)	6.14	7.15	9,919	6.24	5.83	6.14	7.24	13,118
Changed industry from lost to current job	0.81	-	10,013	0.82	0.79	-	-	-
Left manufacturing after job loss	0.54	-	10,013	0.55	0.51	-	-	-
U_{st}^{RATE}	0.07	0.02	10,013	0.07	0.07	0.07	0.02	13,262
$IndImp_{jt}$	0.144	0.132	9,960	-	-	0.148	0.135	13,190
$IndImp_{jt}^{LW}$	0.015	0.041	9,960	-	-	0.016	0.043	13,190
$IndImp_{jt}^{LW\ without\ China}$	0.007	0.020	9,960	-	-	0.008	0.021	13,190
$StateImp_{st}$	0.129	0.044	10,013	-	-	0.130	0.044	13,262
$StateImp_{st}^{LW}$	0.010	0.011	10,013	-	-	0.010	0.011	13,262

Source. – Author's calculations with data from DWS 1984-2002, Feenstra (1996), Feenstra et al. (2002), and the BEA.

Note. – Workers displaced from a full-time manufacturing job between 1979 and 2001, ages 21 to 65 at displacement. All figures are fractions unless otherwise specified.

Table 3
Correlations among trade measures

Trade Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $IndImp_{jt}$	1.00						
(2) $IndImp_{jt}^{LW}$	0.67	1.00					
(3) $IndImp_{jt}^{LW\ \ without\ \ China}$	0.57	0.83	1.00				
(4) $IndExp_{jt}$	0.54	0.22	0.16	1.00			
(5) $StateImp_{st}$	0.36	0.29	0.21	0.29	1.00		
(6) $StateImp_{st}^{LW}$	0.33	0.36	0.27	0.31	0.83	1.00	
(7) $StateExp_{st}$	0.29	0.29	0.20	0.35	0.81	0.80	1.00

Source. – Author's calculations with data from Feenstra (1996), Feenstra et al. (2002), the BEA, and DWS 1984-2002.

Note. – Correlations are across workers in the DWS data based on industry trade data matched to worker's industry of displacement or state of residence.

Table 4

Hazard rate of leaving unemployment and unemployment duration specifications

Panel A: Hazard rate of leaving unemployment.

Variable	4.1	4.2	4.3	4.4	4.5	4.6
$IndImp_{jt}$	- 0.55*** (0.21)	-	- 0.29 (0.27)	- 0.56** (0.23)	-	- 0.26 (0.30)
$IndImp_{jt}^{LW}$	-	- 1.03*** (0.28)	- 0.71* (0.40)	-	- 1.09*** (0.32)	- 0.79* (0.44)
U_{st}^{RATE}	- 8.69*** (1.03)	- 8.73*** (1.05)	- 8.69*** (1.03)	- 9.02*** (1.06)	- 9.06*** (1.08)	- 9.02*** (1.07)
Weibull duration dependence parameter - $\hat{\varphi}$	-	-	-	0.95*** (0.01)	0.95*** (0.01)	0.95*** (0.01)
Log Likelihood	- 29,282	- 29,282	- 29,281	- 16,351	- 16,350	- 16,349
N	10,736	10,736	10,736	10,736	10,736	10,736

Note. – Columns 4.1-4.3 are MLE estimates of equation (8) with flexible hazard specification (9); 4.4-4.6 are MLE estimates of the Weibull model (11).

Panel B: Unemployment duration.

Variable	4.7	4.8	4.9	4.10	4.11	4.12	4.13	4.14
$IndImp_{jt}$	0.59** (0.24)	-	0.28 (0.31)	-	-	-	-	-
$IndImp_{jt}^{LW}$	-	1.14*** (0.33)	0.83 (0.46)	1.25*** (0.37)	1.12*** (0.34)	1.13*** (0.34)	-	1.00*** (0.33)
$IndExp_{jt}$	-	-	-	- 0.17 (0.25)	-	-	-	-
$StateImp_{st}^{LW}$	-	-	-	-	3.57 (3.75)	-	-	-
$StateExp_{st}$	-	-	-	-	-	1.92 (1.33)	-	-
$IndImp_{jt}^{LW\ \ without\ \ China}$	-	-	-	-	-	-	2.16*** (0.61)	-
U_{st}^{RATE}	9.46*** (1.09)	9.50*** (1.11)	9.45*** (1.09)	9.52*** (1.11)	9.20*** (1.05)	9.18*** (1.11)	9.53*** (1.11)	10.75*** (1.22)
Weibull duration dependence parameter, $\hat{\varphi}$	0.95*** (0.01)	0.95*** (0.01)	0.95*** (0.01)	0.95*** (0.01)	0.95*** (0.01)	0.95*** (0.01)	0.95*** (0.01)	1.30*** (0.03)
Variance of Gamma Heterogeneity, $\widehat{1/\theta}$	-	-	-	-	-	-	-	0.75*** (0.06)
Log Likelihood	- 16,351	- 16,350	- 16,349	- 16,350	- 16,349	- 16,349	- 16,351	- 16,155
N	10,736	10,736	10,736	10,736	10,736	10,736	10,736	10,736

Note. – All estimates in Panel B are AFT representations from MLE Weibull model (11). Both coefficients and their corresponding standard errors in all specifications are already transformed to reflect semi-elasticities.

Note. – Workers displaced from a full-time manufacturing job between the ages of 21 and 65 at displacement. All specifications include industry of displacement, lost job occupation, state, year of the survey, and year of displacement dummies. Additionally, all specifications include controls for education, age, age squared, lost job tenure, lost job weekly wage, sex, race, marital status, metropolitan area residency, as well as interaction terms between the female indicator and the indicators for race and marital status. Robust standard errors clustered by industry of displacement are reported. *** Indicates significance at 1 percent, ** at 5 percent, and * at 10 percent.

Table 5

Re-employment wage regressions

Variable	5.1	5.2	5.3	5.4	5.5	5.6	5.7	5.8	5.9	5.10	5.11	5.12
	$ln(w^{re\text{-}employment})$											
$IndImp_{jt}$	- 0.21**	-	- 0.07	-	-	-	-	-	-	-	-	-
	(0.09)		(0.12)									
$IndImp_{jt}^{LW}$	-	- 0.48***	- 0.40***	- 0.43***	- 0.48***	- 0.48***	-	- 0.40***	- 0.61***	- 0.72***	- 0.83*	- 0.83*
		(0.10)	(0.15)	(0.11)	(0.10)	(0.10)		(0.08)	(0.23)	(0.18)	(0.45)	(0.47)
$IndExp_{jt}$	-	-	-	- 0.09	-	-	-	-	-	-	-	-
				(0.12)								
$StateImp_{st}^{LW}$	-	-	-	-	- 0.47	-	-	-	-	-	-	-
					(1.63)							
$StateExp_{st}$	-	-	-	-	-	- 0.35	-	-	-	-	-	-
						(0.61)						
$IndImp_{jt}^{LW\ without\ China}$	-	-	-	-	-	-	- 0.77***	-	-	-	-	-
							(0.29)					
Current Hours	-	-	-	-	-	-	-	0.02***	-	-	-	-
								(0.00)				
U_{st}^{RATE}	- 2.29***	- 2.28***	- 2.28***	- 2.27***	- 2.24***	- 2.22***	- 2.30***	- 1.96***	- 2.65***	- 2.18***	- 2.16***	- 2.02***
	(0.52)	(0.52)	(0.52)	(0.52)	(0.53)	(0.53)	(0.52)	(0.47)	(0.49)	(0.57)	(0.52)	(0.58)
Industry Trends	-	-	-	-	-	-	-	-	-	-	Yes	Yes
State Trends	-	-	-	-	-	-	-	-	-	-	-	Yes
R^2 (Log Likelihood)	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.57	0.45	0.48	0.46	0.46
N	7,781	7,781	7,781	7,781	7,781	7,781	7,781	7,463	5,867	3,925	7,781	7,781

Note. – Estimates of the re-employment wage equation (13), the dependent variable is Log Current Weekly Wage – $ln(w^{re\text{-}employment})$. Workers displaced from a full-time manufacturing job between the ages of 21 and 65 at displacement. All specifications include industry of displacement, lost job occupation, state, year of the survey and year of displacement dummies. All specifications include controls for education, age, age squared, lost job tenure, lost job weekly wage, sex, race, marital status, and metropolitan area residency, as well as interaction terms between the female indicator and the indicators for race and marital status. Robust standard errors clustered by industry of displacement are reported. Specification 5.9 includes only workers who were displaced at least 2 years prior to the survey; and 5.10 includes only workers who were displaced at least 3 years prior to the survey. *** Indicates significance at 1 percent, ** at 5 percent, and * at 10 percent.

Table 6
Industry and sector relocation upon re-employment

Panel A: Linear probability model for leaving industry of displacement and for leaving manufacturing.

Variable	6.1	6.2
	Leave pre-displacement industry	Leave manufacturing
$IndImp_{jt}^{LW}$	0.12	0.34**
	(0.19)	(0.17)
U_{st}^{RATE}	- 1.03***	- 0.44
	(0.30)	(0.39)
R^2	0.14	0.11
N	12,412	12,412

Note. − Workers displaced from a full-time manufacturing job between the ages of 21 and 65 at displacement. All regressions include industry of displacement, lost job occupation, state, year of the survey and year of displacement dummies. Additionally all specifications include controls for education, age, age squared, lost job tenure, lost job weekly wage, sex, race, marital status, metropolitan area residency, as well as interaction terms between the female indicator and the indicators for race and marital status. Robust standard errors clustered by industry of displacement are reported. ***Indicates significance at 1 percent, ** at 5 percent, and * at 10 percent.

Panel B: Re-employment wage regressions for leavers and stayers.

Variable	6.3	6.4	6.5	6.6
	$ln(w^{\text{re-employment}})$			
	Stayed in pre-displacement industry	Left pre-displacement industry	Stayed in manufacturing	Left manufacturing
$IndImp_{jt}^{LW}$	- 0.18	- 0.55***	- 0.09	- 0.59***
	(0.22)	(0.15)	(0.14)	(0.15)
U_{st}^{RATE}	0.34	- 2.81***	- 0.54***	- 3.21***
	(0.91)	(0.54)	(0.52)	(0.74)
R^2	0.70	0.43	0.61	0.41
N	1,523	6,258	3,732	4,049

Note. − Workers displaced from a full-time manufacturing job between the ages of 21 and 65 at displacement. All regressions include industry of displacement, lost job occupation, state, year of the survey and year of displacement dummies. Additionally, all regressions include controls for education, age, age squared, lost job tenure, lost job weekly wage, sex, race, marital status, metropolitan area residency, as well as interaction terms between the female indicator and the indicators for race and marital status. Robust standard errors clustered by industry of displacement are reported. ***Indicates significance at 1 percent, ** at 5 percent, and * at 10 percent.

TECHNICAL APPENDIX

A. Data

The DWS (1984-2002) data used in this study is available from the Inter-University Consortium for Political and Social Research (ICPSR) on-line at http://www.icpsr.umich.edu. As suggested by Angrist and Krueger (1999), I "winsorized" displaced workers' wages at the tails, replacing values in the lower or upper 1 percent tails with values at the 1st and 99th percentiles, respectively. It is not possible to incorporate DWS's after 2002 in the present analysis because starting with the 2004 DWS, the industry classification used changed fundamentally from a classification reflecting 1987 SIC to a classification reflecting the 2002 North American Industry Classification System (NAICS). Thus, it is no longer possible to use within industry identification, i.e. control for industry of displacement, since there is no consistent assignment of displaced workers to industries after 2002. Before 2002, the DWS industry classification, which is the same as the Census of Population Industry Classification (CIC), changed once, but the change was trivial – it reflected the change from 1972 SIC to 1987 SIC.

Data on bilateral U.S. trade in manufacturing comes from Feenstra (1996) and Feenstra et al. (2002) available on-line at the NBER – http://www.nber.org/data. Data on state unemployment rates (1979-2001) were obtained from BLS on-line at http://www.bls.gov/data/home.htm. Data on industry shipments (1979-2001) were obtained from the Bureau of Economic Analysis (BEA) on-line at http://www.bea.gov/bea/dn2/gdpbyind_data.htm. Data on state industry shipments were obtained from BEA on-line at http://www.bea.gov/bea/regional/gsp. After 1998, the data on national and state industry shipments are only available in NAICS industry classification, and I use the official Census Bureau's correspondence to reclassify the industry shipments data for 1998-2001 from 1997 NAICS to 1987 SIC industry. The concordance is available on the Census Bureau's webpage at http://www.census.gov/epcd/www/naicstab.htm. Note also that state industry shipments are only available at 2-digit SIC industry level and hence I need to aggregate the industry import penetration measure to that level before I calculate the average state import penetration measure in (7).

To compute the measure for import penetration from developing countries, I follow Bernard et. al. (2006). I define a country as "low-wage" if its per capita GDP is 5 percent or less of the U.S. per capita GDP. In particular, I calculate the average real per capita GDP for every country for the period 1985-1990 and then compare that to 5 percent of the average for that period of the U.S. real per capita GDP. If the former is smaller from the latter, the country is classified as "low-wage" and used in calculating the numerator in (5) for all years from 1979 to 2001. Real per capita GDP data come from the United Nations at http://unstats.un.org/unsd/databases.htm. The following is the list of all "low-wage" countries (in alphabetical order): Afghanistan, Albania, Angola, Bangladesh, Benin, Bolivia, Burkina, Burundi, Cambodia, Cape Verde, Central African Republic, Chad, China (Mainland), Comoros, Congo, Djibouti, Dominican Republic, El Salvador, Equatorial Guinea, Gambia, Ghana, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, India, Indonesia, Ivory Coast, Kenya, Kiribati, Laos, Liberia, Madagascar, Malawi, Maldive Islands, Mali, Mauritania, Morocco, Mozambique, Nepal, Nicaragua, Niger, Nigeria, Pakistan, Papua New Guinea, Philippines, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Solomon Islands, Somalia, Sri Lanka, Sudan, Tanzania, Togo, Tuvalu Island, Uganda, Vanuatu, Vietnam, Yemen Arab Republic, Zambia, Zimbabwe.

I calculate all the trade measures by CIC industry and year using an exact CIC-SIC correspondence table on-line at BLS – http://ferret.bls.census.gov/items/value/valu_59185.htm.

B. Theory

I assume job offers arrive to a searching unemployed worker at random intervals according to a Poisson process with offer arrival rate π. Workers are assumed to maximize the expected present value of income over an infinite time horizon at a known and constant discount rate r. The net income flow (unemployment benefit) for an unemployed worker is denoted b and is time-invariant throughout any given spell of unemployment.[21] The optimal policy in this model is a constant reservation wage.

[21] See footnote 5 in the paper.

A job offer is summarized by a wage rate w; when a job is accepted it lasts forever. Successive job offers are independent realizations from a known wage offer distribution with a finite mean, μ, variance, σ, cumulative distribution $F(w)$, and density $f(w)$. There is no recall allowed.[22] Therefore, the value function for an unemployed worker, V^U, is constant over the duration of a spell, and it is implicitly defined by Bellman equation (1) below

$$V^U = \frac{1}{1+rh} bh + \frac{\pi h}{1+rh} E_w[max\{V^E(w), V^U\}] + (1-\pi h)\frac{1}{1+rh} V^U \qquad (1),$$

where h is a short time interval. The first term on the right hand side is the discounted present value of the unemployment benefit. The second term is the product of the probability of receiving an offer in the interval h and the discounted expected value of following the optimal policy if an offer w is received, where $V^E(w)$ denotes the present value of accepting the offer. The third term is the probability of no offer in the interval h times the discounted value of optimal search thereafter.[23]

The expected present value of $V^E(w)$ is the present value of expected lifetime earnings

$$V^E(w) = \frac{w}{r} \qquad (2).$$

The reservation wage w^r is the minimum acceptable wage offer defined implicitly by

$$V^E(w^r) = \frac{w^r}{r} = V^U \qquad (3).$$

Substituting (2) and (3) into (1) and taking the limit as $h\downarrow 0$ produces the Bellman equation which defines the optimal policy, a reservation wage w^r

$$w^r = b + \frac{\pi}{r}\int_{w^r}^{\infty}(w - w^r)dF(w) \qquad (4).$$

[22] With a constant reservation wage, a recall option will not be exercised if available.

[23] There is also a fourth term that involves the probability of more than 1 offer arriving during the interval h and the optimal policy thereafter, but this term vanishes as $h\downarrow 0$.

This equilibrium condition allows me to investigate the consequences of exogenous changes in the wage offer distribution, and the offer arrival rate, π, on the expected re- employment wage, $E_w[w \mid w \geq w^r]$, and the expected jobless spell duration, $E[T] = 1/\tau$, where

$\tau = \pi \int_{w^r}^{\infty} f(w)dw = \pi(1 - F(w^r))$.[24]

Next, I demonstrate how increased import competition in the worker's industry of displacement effectively shifts the worker's wage offer distribution to the left. In the framework below, I show that increased import competition in the worker's industry of employment leads to the displacement of the worker, industry relocation and lower equilibrium wage (offers) both in the worker's former industry and the rest of the economy. There are two reasons for this result. First, higher import competition in an industry depresses the wage per efficiency unit of labor in that industry and less so in all other industries of the economy. Second, increased import competition causes the relocation of workers to other industries where they lose the returns to the industry of displacement specific human capital, skills, and training.

As workers may be perfectly but not costlessly transferable across industries in an economy, I employ a model from Grossman (1983), with extensions by Hill and Mendez (1983), which treats labor as a partially mobile factor of production. The model features two sectors – M, labor-intensive manufacturing, and T, capital-intensive technology sector, with production functions *R* and *G* that are homogeneous of degree one, differentiable and strictly quasiconcave. There are two factors – capital and labor with endowments $\overline{K}$ and $\overline{L}$. Capital is costlessly transferable between the two sectors (industries) while workers differ in their efficiency in each of the two industries. There is a continuum of workers, indexed by i, $i \in [0, 1]$, such that their comparative efficiency in sector M relative to sector T is non-increasing in i. Let

[24] The model implies that the distribution of the unemployment spells is exponential. The assumption of no duration dependence is later relaxed in the empirical set-up when I estimate the hazard rate using a flexible specification.

$\alpha_T(i)$ be worker i's productive efficiency in T, $\alpha^T(i) \geq 0$, and assume for simplicity that all workers are equally productive, worth one efficiency unit, in M, then $1/\alpha^T(i)$ is their relative efficiency, so $\alpha^T(i)' \geq 0$. One can think of the worker's relative productivity, $1/\alpha^T(i)$, as dependent on the worker's industry-specific human capital, skills, and training. High values of $1/\alpha^T(i)$, i.e. low values of $\alpha^T(i)$, would be associated with high levels of industry M specific human capital.[25]

In equilibrium, there is a cut-off i^* such that all workers i, $i \in [0, i^*]$, are employed in industry M, and the rest in industry T. Therefore, there are $E_T = \overline{L}\int_{i^*}^{1} \alpha^T(i)di$ efficiency units of labor in T. The rental rate of capital, q, in equilibrium is determined by the value of the marginal product of capital

$$P^M R_K(K_M, E_M) = G_K(K_T, E_T) = q\,,$$

where the good produced in sector T is the numeraire. The wage rate per efficiency unit of labor will differ between the two sectors as workers are not costlessly transferable. Let $w^M = \mathrm{P}^{\mathrm{M}} R_E(K_M, E_M)$ be the wage rate per efficiency unit of labor in sector M. Then, a worker i employed in industry M earns w^M. It is the cut-off low-skill worker i^* that earns the same in both industries

$$\mathrm{P}^{\mathrm{M}} R_E(K_M, E_M) = \alpha_T(i^*) G_E(K_T, E_T)\,.$$

Therefore, an efficiency unit of labor employed in T earns $w^T = G_E(K_T, E_T) = w^M / \alpha^T(i^*)$.

Grossman (1983) shows that as import competition into industry M intensifies, i.e. as the P_M falls, given that relocation costs of labor are not too large, the efficiency unit wages in both M and T decline while the rental rate of capital increases

$$\hat{q} \geq 0 \geq \hat{\mathrm{P}}^{\mathrm{M}} \geq \hat{w}^{\mathrm{T}} \geq \hat{w}^M\,.[26]$$

[25] This is similar to the trade-off along a production possibilities frontier, for example.

[26] Caret (^) denotes a percentage change. This result is reminiscent of the Stolper-Samuelson theorem in the standard Heckscher-Ohlin framework.

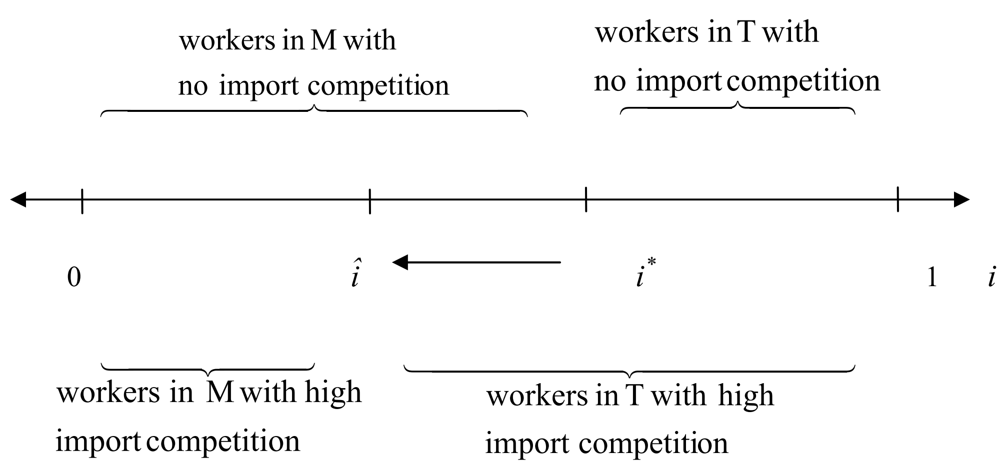
Hill and Mendez (1983) generalize the result to the case of two partially mobile factors, capital and labor, with no mobility differential between the two

$$\hat{q}^T \geq \hat{q}^M \geq 0 \geq \hat{\mathrm{P}}^{\mathrm{M}} \geq \hat{w}^T \geq \hat{w}^M \quad (5),$$

where $\hat{q}^T$ and $\hat{q}^M$ are the rental rates of capital in T and M respectively. In particular, note that more intense import competition, i.e. larger decrease in P_M, leads to a larger decline in both w^M and w^T.

As import competition in the labor-intensive sector M rises, labor is released from M and absorbed by T. The cut-off value i^* for workers employed in M moves closer to 0 at $\hat{i}$, as depicted in Figure 1 below.

Figure 1. Worker industry relocation due to higher import competition.



Worker i displaced from M and employed in T, $i \in (\hat{i}, i^*)$, earns $\alpha_T(i) w_{T,imports}$ when re-employed, where $w_{T,imports}$ is the wage per efficiency unit in T after import competition in M has increased, and $w_{T,no\ imports}$ is the wage before, $w_{T,imports} < w_{T,no\ imports}$ by (5). Note that the more intensive the import competition, the larger the number of workers reallocated to T and the further to the left (closer to 0) $\hat{i}$ moves. This means that higher import competition increases the number of displaced workers with higher relative productivity $1/\alpha_T(i)$ (workers closer to 0 with lower $\alpha_T(i)$ and thus higher industry M specific human capital), reallocated to T, and so it lowers the average re-employment wage for the displaced.

Altogether, this framework implies that higher import competition in a worker's industry of employment leads to higher likelihood of displacement and subsequent industry relocation. Increased import competition also leads to lower wage offers for the displaced worker both in the industry of displacement and the rest of the economy.

C. Table with covariates, interactions, and the Heckman's Section Correction Procedure

The first column of Table C.1 below presents the coefficients of the covariates in the unemployment duration specification 4.8 (Table 4) in the manuscript. The second column expands specification 4.8 to add interactions between $IndImp_{jt}^{LW}$ and the education dummies. Similarly, the third column of Table C.1 documents the coefficients of the of the covariates in the re-employment wage specification 5.2 (Table 5) in the manuscript; the fourth column expands that specification to add interactions between $IndImp_{jt}^{LW}$ and the education dummies. Finally the last two columns of Table C.1 present the estimates of a Heckman correction procedure that I now detail.

As not every displaced worker is re-employed by the date of the survey, I do not have information on the re-employment wage for those who are still unemployed at the date of the interview. To avoid potential selection issues, instead of estimating equation (13) in the manuscript by OLS, I employ a two-step Heckman correction procedure (see Heckman 1979) which delivers consistent estimates in the presence of selection. To this end, I first estimate equation (14) below, which is the reduced form re-employment equation, and then calculate the inverse Mills ratio (IMR), which I use as an added regressor in the re-employment wage regression (15).

$$\text{Prob}[\text{Re-employed}_{ikjst}] = \Phi([\pi_0 + \boldsymbol{X}_{ikjst}\boldsymbol{\pi}_1' + T_{jst}\boldsymbol{\pi}_2' + \pi_3 U_{st}^{RATE} + R_{ikjst} + \delta_k + \lambda_j + \sigma_s + \tau_t]) \qquad (14),$$

$$ln(w_{ikjst}^{re-employment}) = \beta_0 + \boldsymbol{X}_{ikjst}\boldsymbol{\beta}_1' + \beta_2 IndImp_{jt}^{LW} + \delta_k + \lambda_j + \sigma_s + IMR_{ikjst} + \varepsilon_{ikjst} \qquad (15),$$

Because they are intrinsically associated with the re-employment censoring mechanism, following Addison and Portugal (1989), the year of displacement dummies, τ_t, are excluded from the wage equation (15) and only enter the re-employment (selection) probit equation.[27] Additionally, (14) includes reason for displacement dummies, R_{ikjst}.[28] The state unemployment rate at the time of displacement, U_{st}^{RATE}, is included only in the re-employment equation as it is a proxy for the local labor market condition, which affects the likelihood of re-employment. Finally, because import pressures, or export opportunities in the industry of displacement or state of residence affect labor demand, all trade variables associated with the pre-displacement industry or state of residence are included in the trade matrix T_{jts} as determinants of the likelihood of re-employment:

$$T_{jst} = [IndImp_{jt} \mid IndImp_{jt}^{LW} \mid IndExp_{jt} \mid StateImp_{st} \mid StateImp_{st}^{LW} \mid StateExp_{st}].$$

Finally, I use bootstrap to calculate the standard errors so as to account for the generated regressor, IMR_{ikjst} on the right hand side of (15). I block-bootstrap the sample (200 replications, estimating (14) and (15) with each draw), drawing all workers in the same industry of displacement together so as to preserve the correlation structure.

In the last column, C.1.6, of Table C.1 below, I report the results from the selection (into re-employment) probit equation (14). As expected from theory, and previously documented empirically in

[27] The difference between the year of the survey and the year of displacement is the length of the period (in years) since displacement, which is associated with the censoring mechanism as those who were more recently displaced would have had less time to locate a job by the time of the DWS interview.

[28] Workers may cite the following 6 reasons for displacement: plant closing, slack/insufficient work, position abolished, seasonal job completed, self-operated business failed, and other reasons. Close to 90 percent of sample was displaced for the 3 main reasons - plant closing, slack work, or position abolished.

Kletzer (2001), higher import competition, both overall and from low-wage countries lowers the likelihood of re-employment at the date of survey. Neither of the effects, however, is statistically significant. One of the most robust predictors of re-employment is the state unemployment rate in the year of displacement, U_{st}^{RATE}. As expected, the higher the unemployment rate in the local labor market (state of residence) during the year of displacement, the lower the probability that the individual is re-employed by the time of the survey. Note, however, that using the Heckman correction still delivers the same estimate of the impact $IndImp_{jt}^{LW}$ – the estimated coefficient in C.1.5, - 0.40 (0.20), is still statistically significantly different from 0, and very similar in magnitude to the benchmark estimate in 5.2 (Table 5), - 0.48 (0.10), in the manuscript.

Table C.1
Covariates, interactions, and Heckman correction estimates

Variable	C.1.1	C.1.2	C.1.3	C.1.4	C.1.5	C.1.6
					Heckman's Selection Correction	
	Unemployment Duration		$ln(w^{\text{re-employment}})$		$ln(w^{\text{re-employment}})$	Re-employed
$IndImp_{jt}^{LW}$	1.14***	0.38	- 0.48***	- 0.28**	- 0.40**	- 0.31
	(0.33)	(0.48)	(0.10)	(0.24)	(0.20)	(0.66)
U_{st}^{RATE}	9.50***	9.69***	- 2.28***	- 2.31***	-	- 7.31***
	(1.11)	(1.09)	(0.52)	(0.52)		(1.36)
No High School	0.18***	0.21***	- 0.15***	- 0.15***	- 0.13***	- 0.28***
	(0.06)	(0.05)	(0.03)	(0.03)	(0.03)	(0.06)
High-school Drop-out	0.15***	0.14***	- 0.07***	- 0.07***	- 0.05**	- 0.27***
	(0.03)	(0.04)	(0.02)	(0.02)	(0.02)	(0.04)
Some College	- 0.10***	- 0.13***	0.03*	0.04**	0.03*	0.07*
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.04)
College Graduate	- 0.10**	- 0.11***	0.13***	0.13***	0.11***	0.24***
	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.06)
Advanced Degree	- 0.16*	- 0.14*	0.18***	0.19***	0.17***	0.24***
	(0.08)	(0.08)	(0.03)	(0.03)	(0.03)	(0.09)
Age	0.010	0.011	0.037***	0.037***	0.036***	0.006
	(0.009)	(0.009)	(0.004)	(0.004)	(0.004)	(0.010)
Age Squared / 100	0.01	0.01	- 0.05***	- 0.05***	- 0.05***	- 0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lost Job Tenure	0.008***	0.008***	- 0.006***	- 0.006***	- 0.006***	- 0.001
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Log Lost Job Weekly Wage	0.03	0.03	0.46***	0.46***	0.46***	0.01
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.04)
Female	- 0.05	- 0.05	- 0.14***	- 0.14***	- 0.16***	0.14**
	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.05)
Black	0.33***	0.33***	- 0.08***	- 0.08***	- 0.05**	- 0.39***
	(0.05)	(0.05)	(0.02)	(0.02)	(0.03)	(0.06)
Married	- 0.20***	- 0.20***	0.10***	0.010***	0.08***	0.28***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)
Metropolitan Area	0.01	0.01	0.06***	0.06***	0.05***	0.07*
	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.04)
Female × Black	- 0.00	0.00	- 0.03	- 0.03	- 0.03	0.04
	(0.07)	(0.07)	(0.04)	(0.04)	(0.04)	(0.09)
Female × Married	0.33***	0.32***	- 0.14***	- 0.14***	- 0.11***	- 0.30***
	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.06)
$IndImp_{jt}^{LW}$ × No High School	-	- 1.01	-	- 0.25	-	-
		(0.94)		(0.34)		
$IndImp_{jt}^{LW}$ × High-school Drop-out	-	0.54	-	0.04	-	-
		(1.37)		(0.30)		
$IndImp_{jt}^{LW}$ × Some College	-	2.68***	-	- 0.75	-	-
		(0.49)		(0.33)		
$IndImp_{jt}^{LW}$ × College Graduate	-	0.72	-	0.11	-	-
		(0.80)		(0.22)		
$IndImp_{jt}^{LW}$ × Advanced Degree	-	- 2.05	-	- 0.50	-	-
		(1.59)		(0.65)		

$IndImp_{jt}$	-	-	-	-	-	- 0.58 (0.47)
$IndExp_{jt}$	-	-	-	-	-	- 0.25 (0.46)
$StateImp_{st}$	-	-	-	-	-	- 1.11 (2.19)
$StateImp_{st}^{LW}$	-	-	-	-	-	1.31 (5.46)
$StateExp_{st}$	-	-	-	-	-	1.84 (2.86)
IMR_{ikjts}	-	-	-	-	- 0.18*** (0.03)	-
Weibull duration dependence parameter, $\hat{\varphi}$	0.95*** (0.01)	0.95*** (0.01)	-	-	-	-
R^2 (Log Likelihood)	(- 16,350)	(- 16,340)	0.45	0.45	0.45	(- 4,991)
N	10,736	10,736	7,781	7,781	7,781	10,638

Note. – Specifications C.1.1 and C.1.2 are AFT representations from MLE Weibull model (11) in the manuscript. Both coefficients and their corresponding standard errors are transformed to reflect semi-elasticities. Workers displaced from a full-time manufacturing job between the ages of 21 and 65 at displacement. Both C.1.1 and C.1.2 include industry of displacement, lost job occupation, state, and year of the survey and year of displacement dummies. Robust standard errors clustered by industry of displacement are reported.

Note. – Columns C.1.3 and C.1.4 present estimates of the re-employment wage equation (13) in the manuscript, the dependent variable is Log Current Weekly Wage – $ln(w^{\text{re-employment}})$. Specification C.1.5-C.1.6 is the Heckman correction model. C.1.6 is the probit selection (into re-employment) equation (14) in this Technical Appendix, the dependent variable is a dummy indicating re-employment. Workers displaced from a full-time manufacturing job between the ages of 21 and 65 at displacement. Specifications C.1.3, C.1.4, and C.1.5 use only workers who are re-employed at the date of the survey, while specification C.1.6 uses all displaced workers. Both C.1.3 and C.1.4 include industry of displacement, lost job occupation, state, and year of the survey and year of displacement dummies. Specification C.1.5 includes industry of displacement, lost job occupation, state, and year of the survey dummies Specification C.1.6 includes industry of displacement, lost job occupation, state, year of displacement, year of the survey, and reason for displacement dummies. Robust standard errors clustered by industry of displacement are reported for C.1.3 and C.1.4. Block-bootstrapped (pre-displacement industry) standard errors are reported for C.1.5 and C.1.6.

*** Indicates significance at 1 percent, ** at 5 percent, and * at 10 percent.