

**DISPLACED WORKERS AND
PROLONGED UNEMPLOYMENT:
ESTIMATES FOR USE IN TRADE POLICY ANALYSIS**

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Abstract

We develop a method for estimating the number of workers displaced and then unemployed for six months or longer as a result of a reduction in the tariff rate in a specific industry. We combine an econometric model based on data from the Displaced Worker Supplement of the Current Population Survey, data on the education, location, and demographics of workers in the liberalizing industry from the Annual Social and Economic Supplement, and a trade model that simulates the reduction in labor demand. We apply the method to recent data from the U.S. electrical equipment, appliances, and component manufacturing industry. The estimates indicate that eliminating the current 2.92% average tariff rate in the industry could result in unemployment lasting for 26 weeks or longer for 1,737 workers in the industry.

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1 Introduction

Reductions in tariffs can reduce labor demand in import-competing U.S. industries, potentially displacing U.S. workers and leading to prolonged unemployment spells. Unemployment can result in lost income, interrupted skill accumulation, and significant stress. Worker displacement is generally recognized as a short-run cost of trade liberalization, but it is not clear how large this cost is.

To quantify this potential labor loss, we develop a method for estimating the length of unemployment spells after an industry-specific tariff reduction. The number of workers displaced by a tariff reduction depends on labor demand factors in the industry like the import penetration rate and the magnitude of the tariff reduction. On the other hand, the length of the resulting the unemployment spell of displaced workers depends on characteristics of the individual workers that affect their likelihood of finding new jobs quickly, including the workers' educational attainment and demographic attributes.

We combine these two parts in order to estimate the number of workers displaced and then unemployed for six months or longer as a result of the tariff reduction. First, we estimate an econometric model that links the individual characteristics of workers to the length of their unemployment spells after displacement, using data from the last five Displaced Worker Supplements (DWS) of the Current Population Survey. Second, we use a trade model that simulates the reduction in labor demand resulting from a hypothetical elimination of a tariff on U.S. imports, specifically the recent 2.92% average tariff rate in the U.S. electrical equipment, appliances, and component manufacturing industry. Finally, we combine the econometric model of displaced workers with data on the distribution of worker characteristics in the industry's workforce to estimate the number of displaced workers that remain unemployed for half a year or more.

Our paper contributes to the economic literature that analyzes the DWS, including sev-

eral studies that link these labor transitions to international trade. Kletzer (1998) provides a general introduction to displaced worker data. Clark, Herzog and Schlottmann (1998), Kletzer (2001) and Kletzer (2004) find workers displaced by trade are likely to report longer unemployment spells after displacement if they are female, less educated, non-white, and older. Ferrantino (2002) and USITC (2002) uses DWS data to model unemployment spells and other aspects of labor transitions from the U.S. textile and apparel sector after a hypothetical removal of import restraints, and reach similar conclusions.

The rest of the paper is organized into three parts. Section 2 presents the econometric model of prolonged unemployment following displacement. We discuss the data used in this analysis, the econometric estimates, and a series of sensitivity analyses. Section 3 provides an illustrative application of the model to recent data for the U.S. electrical machinery, appliances, and component manufacturing industry. Section 4 concludes with a summary of findings and suggestions for further research.

2 Model of Prolonged Unemployment

The econometric model focuses on the link between prolonged unemployment spells of displaced workers and their educational attainment and demographic characteristics. The model pools together displaced workers from all U.S. industries and without regard to the reason why the workers lost their jobs.¹

2.1 Data

We estimate the econometric model using data from the DWS and the core section of the Current Population Survey in 2012, 2014, 2016, 2018, and 2020. The public use micro-sample that we analyze is documented in Flood, King, Rodgers, Ruggles and Warren (2020).

¹Displacement could be due to changes in trade or technology, management failure, or some other reason.

A displaced worker is defined as one who lost a job during the prior three calendar years. In this paper, we focus on the length of a worker’s unemployment spells, specifically the number weeks without a job after displacement.² Table 1 reports the shares of displaced workers reporting unemployment spells of various lengths.³

Table 1: Length of Unemployment after Displacement

| Weeks Unemployed | Share of Displaced Workers |
|--------------------|----------------------------|
| Some Unemployment | 85.16% |
| 12 Weeks or Longer | 32.50% |
| 26 Weeks or Longer | 17.66% |

2.2 Econometric Estimates

We estimate a logit model of prolonged unemployment. The dependent variable indicates whether the worker reported an unemployment spell lasting 26 weeks or longer. (26 weeks is the typical length of time before standard unemployment insurance benefits are exhausted.) The explanatory variables in the model include controls for the educational attainment, race, gender, and age of the worker, as well as fixed effects for the worker’s location and year of displacement.

Table 2 reports the benchmark version of the logit model. The table reports the estimated coefficients with robust standard errors in parentheses. All of the estimated coefficients are significantly different from zero at the 5% level except for a few of the many fixed effects coefficients (not reported individually). The estimates in Table 2 have the expected signs: a college graduate is less likely to have a prolonged unemployment spell, while non-white, female, and older workers are more likely to experience prolonged unemployment.⁴

²Technically, this is the length of *joblessness* and not necessarily unemployment, since the worker can leave the labor force, but we will use the term *unemployment* in our descriptions.

³These shares are weighted by the DWS sample weights.

⁴This is consistent with the findings in Kletzer (2001), Ferrantino (2002), and Kletzer (2004).

Table 2: Benchmark Logit Model

| Dependent Variable: | Indicator for Unemployed 26 Weeks or Longer |
|--|---|
| Worker Attributes: | |
| College Graduate | -0.1488 (0.0685) |
| Non-White Worker | 0.2500 (0.0852) |
| Female Worker | 0.1382 (0.0642) |
| Age 40 or Older | 0.4681 (0.0649) |
| Fixed Effects for Year of Displacement | Included |
| Fixed Effects for State | Included |
| Number of Observations | 9,464 |
| Wald Test χ^2 (64 degrees of freedom) | 506.23 |
| Wald Test p value | 0.000 |

Next, we calculate the probability that an individual displaced worker is unemployed for 26 weeks or longer. Each worker j is a combination of characteristics indexed by c with estimated coefficient β_c . x_{jc} is an indicator variable that is equal to one if worker j has characteristic c and is equal to zero otherwise. Given the assumptions of the logit model, equation (1) is the probability that displaced worker j will be unemployed for 26 weeks or longer.

$$p_j = \frac{e^{\sum_c \beta_c x_{jc}}}{1 + e^{\sum_c \beta_c x_{jc}}} \quad (1)$$

Table 3 provides an illustrative example with two different workers. The example uses the coefficient estimates from the benchmark model in Table 2. Worker 1 is a non-white female worker over the age of 40 who is not a college graduate, lives in Michigan, and was displaced in 2018. She would have a probability of prolonged unemployment after displacement equal to approximately 21%. On the other hand, worker 2 is a white male college graduate over the age of 40 who also lives in Michigan and was displaced in 2018. He would have a probability of prolonged unemployment equal to approximately 13%.

2.3 Sensitivity Analysis

As a first sensitivity analysis, we redefine the dependent variable in the logit model as an indicator of whether the worker is unemployed for 12 weeks or longer after displacement. The coefficients reported in Table 4 have the same signs as the coefficients in the benchmark model in Table 2, except for college education. The coefficient estimates are no longer statistically significant for college graduate and female worker.

Table 5 reports additional alternatives to the benchmark model. In the first additional model, we add a control for whether the worker is a high school graduate. This variable does not have a significant effect on the length of the unemployment spell after controlling for being a college graduate. There are only slight changes in the other estimated coefficients.

Table 3: Example with Two Types of Workers

| Worker Characteristics: | Worker 1 | Worker 2 |
|---------------------------------------|----------|----------|
| Constant | -0.9340 | -0.9340 |
| Year = 2018 | -1.3160 | -1.3160 |
| State = Michigan | 0.0523 | 0.0523 |
| College Graduate | | -0.1488 |
| Non-White Worker | 0.2500 | |
| Female Worker | 0.1382 | |
| Age 40 or Older | 0.4681 | 0.4681 |
| Sum of Coefficients | -1.3414 | -1.8784 |
| Probability of Prolonged Unemployment | 20.73% | 13.26% |

Table 4: Model for Alternative Length of Unemployment

| Dependent Variable: | Indicator for Unemployed 12 Weeks or Longer |
|--|---|
| Worker Attributes: | |
| College Graduate | 0.0697 (0.0555) |
| Non-White Worker | 0.1580 (0.0709) |
| Female Worker | 0.0725 (0.0527) |
| Age 40 or Older | 0.4720 (0.0526) |
| Fixed Effects for Year of Displacement | Included |
| Fixed Effects for State | Included |
| Number of Observations | 9,469 |
| Wald Test χ^2 | 527.71 |
| Wald Test p value | 0.000 |

Table 5: Additional Alternative Logit Models

| Dependent Variable: | Indicator for Unemployed 26 Weeks or Longer | Indicator for Unemployed 26 Weeks or Longer |
|--|---|---|
| Worker Attributes: | | |
| High School Graduate | 0.1007 (0.1277) | |
| College Graduate | -0.1609 (0.0698) | -0.1673 (0.0684) |
| Non-White Worker | 0.2508 (0.0852) | 0.2482 (0.0854) |
| Female Worker | 0.1357 (0.0641) | 0.1455 (0.0643) |
| Age 40 or Older | 0.4693 (0.0650) | |
| Age 30 or Older | | 0.5110 (0.0868) |
| Age 60 or Older | | 0.4707 (0.1035) |
| Fixed Effects for Year of Displacement | Included | Included |
| Fixed Effects for State | Included | Included |
| Number of Observations | 9,464 | 9,464 |
| Wald Test χ^2 | 506.59 | 530.64 |
| Wald Test p value | 0.000 | 0.000 |

In the second additional model, we replace the control for age 40 or older with two alternative measures: an indicator of whether the worker is 30 or older and another indicator of whether the worker is 60 or older. Both are statistically significant. Again, there are only slight changes in the other estimated coefficients.

3 Industry Application

Next, we estimate the impact of a hypothetical tariff reduction on the number of displaced workers who are unemployed for 26 weeks or longer using recent data for the U.S. electrical equipment, appliances and components manufacturing industry (NAICS code 335).

3.1 Industry Data

We calculate the industry’s import penetration rate, average tariff rate, and elasticity of substitution between imports and domestic products using 2018 data from the Annual Survey of Manufactures (ASM) and the USITC’s Trade Dataweb.⁵ Table 6 reports key economic statistics for the industry.

Table 6: Key Economic Statistics

| Industry-Specific Measures | 2018 Value |
|---------------------------------|------------|
| Import Penetration Rate | 60.16% |
| Average Tariff Rate | 2.92% |
| U.S. Employment in the Industry | 347,561 |

Table 7 reports the share of workers with different characteristics, based on the 2018 Annual Social and Economic Supplement (ASEC) of the Current Population Survey, which

⁵The ASM is available online at census.gov/programs-surveys/asm/data/tables.html. The Trade Dataweb is available online at dataweb.usitc.gov. The import penetration rate is calculated as the ratio of the landed duty paid value of imports to apparent consumption, defined as the total value of shipments minus the value of exports plus the landed duty paid value of imports.

is not limited to displaced workers. The public use micro-sample that we analyze is also documented in Flood et al. (2020).

Table 7: Worker Characteristics within the Industry

| Attributes: | Weighted Share of Workers |
|-------------------|---------------------------|
| College Graduates | 0.4891 |
| Non-White Workers | 0.2982 |
| Female Workers | 0.3021 |
| Age 40 or Older | 0.6284 |

The states with the largest shares of industry employment in 2018 were California (21.7%), Texas (9.2%), Illinois (4.6%), New York (4.4%), and Pennsylvania (4.4%).

3.2 Simulated Length of Unemployment

Equation (2) is the simulated change in labor demand (ΔL) as a function of the import penetration ratio in the industry (μ), its initial employment level (L_0), the percent change in the tariff factor on industry imports ($\hat{\tau}$), and the elasticity of substitution between imports and domestic products in the industry (σ).

$$\Delta L = L_0 (\sigma - 1) \mu \hat{\tau} \quad (2)$$

From Table 6, $\mu = 0.6016$, $\hat{\tau} = -0.0283$ (complete tariff elimination), and $L_0 = 347,561$. The elasticity of substitution is set at $\sigma = 3.0$, based on the industry-specific estimate in Ahmad and Riker (2020). Therefore, the change in labor demand in the domestic industry is $\Delta L = -11,835$, a 3.4% decline. This translates into 11,835 displaced workers.

Next, we estimate how many of these displaced workers would experience prolonged

unemployment. Equation (3) is the total number of workers displaced and unemployed for at least 26 weeks or longer, N .

$$N = \sum_j \theta_j p_j (-\Delta L) \quad (3)$$

p_j and ΔL are defined in equations (1) and (2), and θ_j is individual worker j 's weight in the population, either nationwide or within a specific state or specific demographic group of workers. This calculation assumes a random, proportional incidence of displacement, like a lottery. It also assumes that the number of displaced workers is proportional to the reduction in labor demand in the domestic industry. This will be the case if there is downward wage rigidity in the short run. Rodríguez-Clare, Ulate and Vásquez (2020) is an interesting recent example of a model of trade and labor adjustment that features short-run downward wage rigidity.⁶

Our simulation of tariff elimination estimates that 1,737 of the 11,835 workers displaced from the the U.S. electrical equipment, appliances, and component manufacturing industry in 2018 would remain unemployed for 26 weeks or longer. Table 8 reports the national numbers, for all workers and then for several different groups of workers defined by their gender, educational attainment, age, or race. The table also reports the number as a percentage of the sub-population in the industry in 2018.

It is straightforward to calculate these numbers for different intersectionalities of the worker characteristics. For example, for female workers without a college degree and who are 40 or older, the national estimate is 249 workers, which is 0.63% of that sub-population within the industry's workforce in 2018.

⁶On the other hand, if wages in the industry decline immediately in response to the reduction in labor demand, then worker displacement will be less than proportional, and equation (3) will overstate the change in industry employment.

Table 8: National Estimates of Prolonged Unemployment

| | Number of Workers | Percentage of the Sub-Population |
|-----------------------|----------------------|-------------------------------------|
| All Workers | 1,737 | 0.50 |
| Male Workers | 1,164 | 0.48 |
| Female Workers | 573 | 0.55 |
| College Graduates | 819 | 0.48 |
| Not College Graduates | 918 | 0.52 |
| Age 40 or Older | 1,223 | 0.56 |
| Younger than 40 | 514 | 0.40 |
| White Workers | 1,145 | 0.47 |
| Non-White Workers | 592 | 0.57 |

Finally, Table 9 reports the estimated number for workers displaced and then unemployed for 26 weeks or longer in each of the top 20 states.

Table 9: Estimates for Top 20 States

| | Number of Workers | Percentage of State Employment | | Number of Workers | Percentage of State Employment |
|---------------|-------------------------|--------------------------------------|----------------|-------------------------|--------------------------------------|
| California | 429 | 0.57 | Washington | 48 | 0.43 |
| Texas | 151 | 0.47 | New Jersey | 48 | 0.53 |
| Illinois | 96 | 0.60 | Arizona | 47 | 0.42 |
| Wisconsin | 85 | 0.66 | North Carolina | 43 | 0.51 |
| Oregon | 82 | 0.64 | Michigan | 30 | 0.46 |
| Pennsylvania | 79 | 0.52 | Indiana | 29 | 0.37 |
| Massachusetts | 72 | 0.61 | Georgia | 27 | 0.56 |
| New York | 71 | 0.47 | Minnesota | 26 | 0.43 |
| Florida | 65 | 0.53 | Colorado | 19 | 0.40 |
| Ohio | 52 | 0.44 | Missouri | 17 | 0.42 |

4 Conclusions

Our method for estimating unemployment spells as a result of a industry-specific tariff reduction is relatively simple and has practical data requirements. It does not require observing a large number of job displacements in the specific industry in the DWS, as long as observed displacements across all industries can be linked to worker characteristics and the distribution of the characteristics in the industry’s workforce are observable in the larger ASEC sample.

We illustrated the steps in the analysis in an application to recent data for the U.S. electrical equipment, appliances, and component manufacturing industry. First, we estimated an economic model that linked the length of unemployment spells to worker characteristics. Unemployment is more likely to be prolonged for displaced workers who are female, non-white, older, and not college graduates. Second, we simulated the reduction in labor demand in the U.S. industry as a result of hypothetical tariff elimination. Assuming short-run downward wage rigidity, we estimated that 11,835 workers would be displaced, and that 1,737 of the displaced workers would remain jobless for 26 weeks or longer. This is our measure of labor losses.

There are several possibilities for further research. First, the method could be applied to other industries and to other labor market outcomes that are also tracked by the DWS, including changes in wages after displacement or worker relocations to find a new job. Second, the modeling assumption that displacements are assigned proportionally across the industry’s workforce can be improved by analyzing whether some worker types are more likely to be displaced when an industry downsizes. Finally, the structure of the labor market in the liberalizing industry will determine whether the reduction in labor demand will lead to wage reductions rather than employment reductions. We have assumed that labor adjustment will be strictly changes in employment, with no changes in wages, but other possibilities can be

considered.

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