TRADE LIBERALIZATION, DISPLACEMENT, AND UNEMPLOYMENT IN A PE FRAMEWORK

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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 1,767 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 probability of being one of the displaced workers and the length of the resulting unemployment spell of displaced workers depends on characteristics of the individual workers, 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 their historical probability of being displaced, using data from the last six Displaced Worker Supplements (DWS) of the Current Population Survey (CPS). Second, we estimate an econometric model that links the individual characteristics of workers to the length of their unemployment spells after displacement, again using data from the last six CPS DWS samples. Third, 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 models 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.[1]

Our paper contributes to the economic literature that analyzes the DWS, including several 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 models of displacement and 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 Econometric Models of Displacement and Prolonged Unemployment

The econometric models focus on the link between displacement or 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

[1] An earlier version of this paper was released as USITC Economics Working Paper 2021-07-B. The main difference between the papers is that the new paper estimates displacement probabilities while the previous paper assumed displacement was proportional to a group's frequency within the effected industry. Various smaller improvements have been made to the estimations in this paper as well as the presentation and explanation of those estimations. Finally, new robustness checks and alternate specifications have been added, including a specification using controls for broad industry category.

the reason why the workers lost their jobs.[2]

While it would be simpler to calculate the probabilities of displacement and prolonged unemployment for each worker type and industry based on observed frequencies in the DWS, data by industry is too sparse in that dataset. Instead, we pool together DWS workers from all industries and estimate econometric models of displacement and prolonged unemployment as a function of observable worker characteristics. Finally, we apply those econometric models to estimate the probabilities of displacement and prolonged unemployment to workers within each industry using the Annual Social and Economic Supplement (ASEC), which is less sparse. An important caveat is that applying the estimated probabilities for displacement and prolonged unemployment to the structural model implicitly assumes that displacements from trade are no different than displacements for other reasons. This is a necessary assumption since trade versus non-trade reasons for displacement are not distinguished in the data.

2.1 Data

We estimate the econometric models using data from the DWS and the core section of the Current Population Survey in 2010, 2012, 2014, 2016, 2018, and 2020. The public use micro-sample that we analyze is documented in Flood, King, Rodgers, Ruggles and Warren (2020). A displaced worker is defined as one who lost a job during the prior three calendar years. In this paper, we focus on two types of events in the data: displacement from a job and the length of a worker's unemployment spells after displacement.[3] Table 1 reports the share of displaced workers in recent CPS DWS samples and table 2 reports the shares of displaced workers reporting unemployment spells of various lengths.[4]

[2]Displacement could be due to changes in trade or technology, management failure, or some other reason.
[3]Technically, 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.
[4]These shares are weighted by the DWS sample weights.

Table 1: Percentage of displaced workers by CPS DWS sample year

	Not displaced	Displaced
2010	92.92	7.08
2012	94.23	5.77
2014	95.80	4.20
2016	96.81	3.19
2018	97.13	2.87
2020	97.37	2.63

Table 2: Length of unemployment after displacement

Unemployment length	Percentage of displaced workers
Some unemployment	85.25
More than 12 weeks	32.61
More than 26 weeks	17.64
More than 52 weeks	4.56

2.2 Econometric Estimates

We estimate two logit models of displacement and prolonged unemployment. The dependent variable in the first indicates whether the worker reported displacement in the three years before the survey. The dependent variable in the second indicates whether the worker reported an unemployment spell lasting 26 weeks or longer following displacement. (26 weeks is the typical length of time before standard unemployment insurance benefits are exhausted.) The explanatory variables in both models 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 survey (for displacement regression) or year of displacement (for prolonged unemployment regression).

For each of these models, each worker j is represented by a combination of characteristics indexed by c with estimated coefficient β_c. An indicator variable x_{jc} 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 displaced or unemployed for longer than a set threshold after displacement, depending on the model m.

$$p_j^m = \frac{e^{\sum_c \beta_c \; x_{jc}}}{1 \; + \; e^{\sum_c \beta_c \; x_{jc}}} \tag{1}$$

There are some things to keep in mind when interpreting the regression tables. For each model, the estimated effect of each characteristic is described as an odds ratio rather than the estimated logistic regression coefficient. Values greater than one indicate that the characteristic increases the estimated probability of the outcome variable (displacement or prolonged unemployment) while values less than one indicate that the characteristic decreases the estimated probability of the outcome variable. Estimated odds ratios very close to one are not statistically significant, which is indicated on the tables with significance stars. The pseudo R^2 is a rough measure of model fit, although it cannot be interpreted the same way as an R^2 for a linear model and will usually be much smaller than an R^2 from a linear model. In general, a higher pseudo R^2 indicates better fit. The results of a Wald test are also presented in each table, testing whether the model is significantly different from a similar model that restricts the odds ratios of the explanatory variables (excluding the fixed effects) are restricted to be one (that is, assumed to have no effect on the outcome variable).

The universe of respondents differs in the two models. The universe for the models of length of unemployment only includes workers that have been displaced. The universe for the model of displacement is slightly more complicated. Two alternatives are shown for the logit model of displacement. The first universe includes all respondents to the CPS DWS. However, that universe would include people who did not work within three years leading up to the sample. That group would never be displaced since they would have no job within the reference period from which to be displaced. The model using that universe would potentially confuse characteristics that imply working and not displaced with characteristics that imply not formally working. The other universe, which is used for the benchmark results in this paper, attempts to address this issue. The universe in the benchmark displacement model only considers respondents who were displaced and respondents who were not displaced but were either working, unemployed (looking for a job) and not a brand new worker, or not in the labor force due to retirement. This universe was chosen under the rationale that workers currently attached to the labor force (or retired) would be more likely to have been attached to the labor force within the preceding three years. However, this is still an imperfect distinction since it 1) does not include people who left the labor force for other reasons than retirement and 2) does include people who may be recent entrants (direct to employment) or re-entrants (employed or unemployed but not brand new workers).

Table 3 reports the results of the logit model of displacement. The table reports the estimated odds ratios with robust standard errors in parentheses. All of the estimated odds ratios (not including some of the many fixed effects odds ratios, not reported individually) are significantly different from one at the 5% level. Being female, age 40 or older, or a college graduate all reduce the probability of being a displaced worker while being nonwhite increases that probability. The specification with only workers is used for the benchmark results.

Table 4 reports the results of the logit model of various lengths of prolonged unemployment for displaced workers. The table reports the estimated odds ratios with robust standard errors in parentheses. All of the estimated odds ratios except for the odds ratio on female workers (not including some of the many fixed effects odds ratios, not reported individually) are significantly different from one at the 5% level. For each of the models, the statistically significant estimated odds ratios in table 4 have the expected results: a college graduate is less likely to have a prolonged unemployment spell, while non-white and older workers are more likely to experience prolonged unemployment.[5] The specification for prolonged unemployment more than 26 weeks is used for the benchmark results.

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

One important fact to note is that the effect of some characteristics are reversed between the two stages. In particular, being female and being aged 40 or older both decrease the probability of being displaced but increase the probability of being unemployed for more than 26 weeks given that displacement occurs. On the other hand, being non-white increases the probability of of both events while being a college graduate decreases the probability of both events. As a whole, these interactions have important implications about who is affected by job displacement and the severity of the results.

Consider an illustrative example with two different workers that uses the estimates in tables 3 and 4. 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. The historical frequency of displacement for workers with her characteristics would be 4.80% and her probability of prolonged unemployment of more than 26 weeks after displacement would be 21.82%. 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. The historical frequency of displacement for workers with his characteristics would be 3.77% and his probability of prolonged unemployment of more than 26 weeks after displacement would be 14.49%. Later in this paper, the historical probability of displacement will not be used directly (the number of displaced workers in the industry overall will be estimated by the structural partial equilibrium model); instead, it will matter that 4.80% is 27% greater than 3.77%, meaning that worker 1 will be about 27% more likely than worker 2 to be affected by the displacement.

Table 3: Logit model of worker displacement

	(1) Displaced	(2) Displaced
Non-white	1.094***	1.121***
	(0.0238)	(0.0247)
Female	0.656***	0.805***
	(0.0107)	(0.0133)
Age 40 or older	0.657***	0.905***
	(0.0108)	(0.0149)
College graduate	0.879***	0.701***
	(0.0158)	(0.0127)
State dummies	Yes	Yes
Year dummies	Yes	Yes
Observations	503,919	328,691
Pseudo R2	0.0306	0.0261
Wald test degrees of freedom	4	4
Wald test χ^2	1,383.53	622.69
Wald test p value	0.00	0.00

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Specification (1) includes all respondents to the Displaced Worker Supplement, and would therefore include respondents who did not have a job to be displaced from during the period. The universe of Specification (2) consists of respondents to the Displaced Worker Supplement who either responded yes to having been displaced or who responded no to being displaced but were either employed or unemployed but not a new worker at the time of the survey.
The Wald test estimates the probability that all of the worker characteristic odds ratios can be held as one without changing the outcome of the model. The p value indicates that the worker characteristics are indeed statistically important.

Table 4: Logit model of prolonged unemployment for displaced workers

	(1) More than 12 weeks	(2) More than 26 weeks	(3) More than 52 weeks
Non-white	1.198**	1.280***	1.309*
	(0.0727)	(0.0929)	(0.168)
Female	1.068	1.107	1.028
	(0.0480)	(0.0607)	(0.101)
Age 40 or older	1.515***	1.602***	1.899***
	(0.0677)	(0.0889)	(0.193)
College graduate	1.029	0.861*	0.874
	(0.0494)	(0.0509)	(0.0914)
State dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	12,646	12,646	10,204
Pseudo R2	0.0349	0.0474	0.0762
Wald test degrees of freedom	4	4	4
Wald test χ^2	96.90	90.01	44.17
Wald test p value	0.00	0.00	0.00

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The Wald test estimates the probability that all of the worker characteristic odds ratios can be held as one without changing the outcome of the model. The p value indicates that the worker characteristics are indeed statistically important.

2.3 Sensitivity Analysis

We perform several sensitivity analyses to demonstrate the robustness of this approach. First, we re-run the econometric models using alternate specifications for worker characteristics related to education or age. Second, we re-run the econometric models with fixed effects for aggregated industry categories.

2.3.1 Alternate worker characteristics

Tables 5 and 6 report additional alternatives to the benchmark model. In the first alternative specification, we add a control for whether the worker is a high school graduate. In the second alternative specification, we change the age categories.

The benchmark model for displacement restricts the sample to the people who most likely had a job from which to be displaced. Controlling for being a high school graduate does have a big impact on the estimated odds ratios of the other controls, although it should be noted that college graduates would also be high school graduates, meaning the effects of those two controls compound. Controlling for age using different age categories does not have big impacts on the regression results.

The benchmark model for prolonged unemployment of displaced workers estimates the probability of being unemployed for more than 26 weeks. Controlling for high school graduation causes the odds ratio estimates on being female and being a high school graduate to not be significant at the 5% level. The other estimated odds ratios do not see big changes. Controlling for age using different age categories does not have big impacts on the regression results.

We also consider an interaction term between race and sex. Table 7 displays alternatives to the benchmark models that include an indicator for being both nonwhite and female. This specification accounts for the possibility that the empirical effect of being a nonwhite woman

Table 5: Alternate worker characteristics in a logit model of displacement

	(1) Displaced	(2) Displaced
Non-white	1.122***	1.124***
	(0.0247)	(0.0248)
Female	0.808***	0.804***
	(0.0134)	(0.0133)
High school graduate	0.874***	
	(0.0253)	
College graduate	0.713***	0.702***
	(0.0132)	(0.0127)
Age 40 or older	0.905***	
	(0.0149)	
Age 30 or older		0.954*
		(0.0200)
Age 60 or older		0.932**
		(0.0235)
State dummies	Yes	Yes
Year dummies	Yes	Yes
Observations	328,691	328,691
Pseudo R2	0.0263	0.0260
Wald test degrees of freedom	5	5
Wald test χ^2	646.06	609.73
Wald test p value	0.00	0.00

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: In both of these specifications, the universe consists of respondents to the Displaced Worker Supplement who either responded yes to having been displaced or who responded no to being displaced but were either employed or unemployed but not a new worker at the time of the survey. The Wald test estimates the probability that all of the worker characteristic odds ratios can be held as one without changing the outcome of the model. The p value indicates that the worker characteristics are indeed statistically important.

is not just a combination of the effects of being nonwhite and being a woman. Expressed differently, this specification checks whether the difference between white and nowhite men is different than the difference between white and nonwhite women. In both the displacement and prolonged unemployment models, the new term is not statistically significant at the 5% level.[6] Additionally, the models use a Wald test to determine whether restricting the odds ratio of that term to one has a significant impact on the model results overall–in both cases, the answer is no. This indicates that within this data set, it is sufficient to include separate sex and race terms without including an interaction term.

[6]Similar alternative models with a different interaction term–either white female or nonwhite male–also have insigificant results (unreported). Multiple interaction terms cannot be included in a single model due to multicollinearity.

Table 6: Alternate worker characteristics in a logit model of prolonged unemployment for displaced workers

	(1) More than 26 weeks	(2) More than 26 weeks
Non-white	1.280***	1.263**
	(0.0929)	(0.0918)
Female	1.104	1.113
	(0.0605)	(0.0611)
High school graduate	1.099	
	(0.116)	
College graduate	0.851**	0.849**
	(0.0513)	(0.0501)
Age 40 or older	1.602***	
	(0.0889)	
Age 30 or older		1.629***
		(0.120)
Age 60 or older		1.498***
		(0.136)
State dummies	Yes	Yes
Year dummies	Yes	Yes
Observations	12,646	12,646
Pseudo R2	0.0475	0.0480
Wald test degrees of freedom	5	5
Wald test χ^2	90.33	94.72
Wald test p value	0.00	0.00

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The Wald test estimates the probability that all of the worker characteristic odds ratios can be held as one without changing the outcome of the model. The p value indicates that the worker characteristics are indeed statistically important.

Table 7: Alternate specifications of benchmark logit model of displacement with race and sex interaction terms

	(1) Displaced	(2) More than 26 weeks
Non-white	1.150***	1.250*
	(0.0340)	(0.123)
Female	0.815***	1.094
	(0.0148)	(0.0657)
Nonwhite female	0.944	1.055
	(0.0404)	(0.151)
Nonwhite male	1	1
	(.)	(.)
White female	1	1
	(.)	(.)
Age 40 or older	0.905***	1.602***
	(0.0149)	(0.0889)
College graduate	0.701***	0.861*
	(0.0127)	(0.0509)
State dummies	Yes	Yes
Year dummies	Yes	Yes
Observations	328,691	12,646
Pseudo R2	0.0261	0.0474
Wald test degrees of freedom	5	5
Wald test χ^2	1.81	0.14
Wald test p value	0.18	0.71

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: In the model of displacement, the universe consists of respondents to the Displaced Worker Supplement who either responded yes to having been displaced or who responded no to being displaced but were either employed or unemployed but not a new worker at the time of the survey. In the model of prolonged unemployment, the universe isworkers who had been displaced. The Wald test in both of these models tests whether the nonwhite female indicator can be removed from the model (odds ratio set to one) without significantly impacting the model.

2.3.2 Controlling for industry categories

The benchmark models estimate how worker characteristics are expected to impact the probability of displacement or prolonged unemployment, using only year and state as controls. However, it could be that all of those effects are actually stemming from the nature of each worker's industry. If there is a strong correlation between certain worker characteristics and working in a specific industry, the previous regressions would not distinguish what was driving worker displacement or prolonged unemployment. Table 8 shows one example of this, displaying the prevalence of male and female workers in several aggregated industry categories.

Table 8: Percentage of displaced workers by industry category

	Displaced	More than 26 weeks
Agricultural, forestry, and fisheries	4.15	9.98
Mining	8.75	17.33
Construction	8.73	13.22
Manufacturing - Non-durable	6.15	15.06
Manufacturing - Durable	7.01	20.92
Transportation, communication, and public utilities	5.89	17.48
Wholesale trade	6.12	13.34
Retail trade	6.12	17.55
Finance, insurance, and real estate	5.52	20.45
Business and repair services	7.82	18.11
Personal services	5.06	17.38
Entertainment and recreational services	6.24	13.62
Professional and related services	3.84	16.98
Public administration	2.42	16.29
Armed forces	7.78	.

As indicated earlier in this paper, it is not possible to control for workers' specific industry due to the scarcity of data on displaced workers. Table 9 shows the results of incorporating controls for aggregated industry categories instead of specific industries.

Table 9: Logit models of worker displacement and prolonged unemployment including industry controls

	(1) Displaced	(2) More than 26 weeks
Non-white	1.145***	1.281***
	(0.0273)	(0.0950)
Female	0.876***	1.102
	(0.0172)	(0.0666)
Age 40 or older	0.861***	1.571***
	(0.0154)	(0.0893)
College graduate	0.835***	0.835**
	(0.0170)	(0.0526)
State dummies	Yes	Yes
Year dummies	Yes	Yes
Industry dummies	Yes	Yes
Observations	325,801	12,298
Pseudo R2	0.0347	0.0517
Wald test degrees of freedom	4	4
Wald test χ^2	212.15	81.82
Wald test p value	0.00	0.00

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: In the model of displacement, the universe consists of respondents to the Displaced Worker Supplement who either responded yes to having been displaced or who responded no to being displaced but were either employed or unemployed but not a new worker at the time of the survey. In the model of prolonged unemployment, the universe is workers who had been displaced.
The Wald test estimates the probability that all of the worker characteristic odds ratios can be held as one without changing the outcome of the model. The p value indicates that the worker characteristics are indeed statistically important.

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.[7] Table 10 reports key economic statistics for the industry.

Table 10: 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 11 reports the share of workers with different characteristics, based on the 2018 Annual Social and Economic Supplement (ASEC) of the Current Population Survey, which is not limited to displaced workers. The public use micro-sample that we analyze is also documented in Flood et al. (2020). 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%).

[7] The 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.

Table 11: Worker characteristics within the industry

Worker characteristic	Percentage of workers in industry
Non-white	29.82
Female	30.21
College graduate	48.91
Age 40 or older	62.84

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).

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

From Table 10, $\mu = 0.6016$, $\hat{\tau} = -0.0283$ (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.

$$N = \sum_j \; \hat{\theta}_j^d \; p_j^u \; (-\,\Delta L) \tag{3}$$

The effective weight $\hat{\theta}_j^d$ is worker j's ASEC sample weight in the population (θ_j) multiplied by the estimated historical probability of displacement for worker j (p_j^d), normalized so that the sum of these effective weights sum to one in the population of interest, which can be nationwide or defined within a specific state or demographic group of workers.[8] The variable p_j^u is the estimated probability of prolonged unemployment for worker j, given displacement. The variables p_j^u, p_j^d, and ΔL are defined in equations (1) and (2). If p_j^d is the same for all worker types then there is a proportional incidence of displacement, like a lottery. When p_j^d is different for various worker types, displacement will disproportionally impact some groups more than others. The equation 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.[9]

Our simulation of tariff elimination estimates that 1,767 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 12 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 combinations of the worker characteristics from the data and estimates. For example, the model estimates that 215 non-white female workers would be unemployed for more than 26 weeks, which is 0.60 percent of that subpopulation.

Finally, table 13 reports the estimated number for workers displaced and then unemployed for 26 weeks or longer in each of the top 10 states.

[8] The population used in this equation should match whatever population is being used in equation 2. For example, a state-specific population shouldn't be used in equation 3 if the nationwide population is used to calculate the change in labor demand in equation 2

[9] On 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 12: National estimates of prolonged unemployment by worker characteristic

Worker characteristics	Number of workers	Percentage of subpopulation
All	1,767	0.51
Nonwhite	624	0.60
White	1,143	0.47
Female	513	0.49
Male	1,255	0.52
College graduate	719	0.42
Not college graduate	1,049	0.59
Age 40 or older	1,208	0.55
Age under 40	559	0.43

Table 13: Estimates of prolonged unemployment in the 10 states with the highest numbers of prolonged unemployment

State	Number of workers	Percentage of subpopulation
California	433	0.58
Texas	141	0.44
Illinois	97	0.61
Oregon	91	0.72
Wisconsin	81	0.63
Pennsylvania	81	0.53
Massachusetts	79	0.66
Ohio	64	0.54
New York	62	0.41
Florida	59	0.48

Note: The percentage of the population is the estimated number of displaced workers who would experience prolonged unemployment as a percentage of the total employment in the industry within that state.

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 likelihood of displacement to worker characteristics. Second, we estimated an economic model that linked the length of unemployment spells after displacement to worker characteristics. Unemployment is more likely to be prolonged for displaced workers who are female, non-white, older, and not college graduates. Third, 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. One avenue of work would be applying similar models to other outcomes tracked by the DWS, including changes in wages after displacement or worker relocations to find a new job. A different avenue for new work would involve revisions to the structural model of the liberalizing industry, as the structure of the labor market determines whether the reduction in labor demand will lead to wage reductions rather than employment reductions. The model in this paper assumed that labor adjustment would strictly result in changes in employment, with no changes in wages, but other possibilities can be considered. A final avenue of future work would involve improving the predictive power for estimating the likelihood of displacement and prolonged unemployment. This would mean improving the measurement of the predictive power (as the pseudo R^2 presented in this paper is used as a comparison of the different models rather than an intuitive and informative statistic on predictive power) and applying alternative predictive methods, including machine learning algorithms.

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