ESTIMATING THE DISTRIBUTIONAL EFFECTS OF TRADE POLICY CHANGES ON LABOR

Samantha Schreiber

ECONOMICS WORKING PAPER SERIES
Working Paper 2021–05–E

U.S. INTERNATIONAL TRADE COMMISSION
500 E Street SW
Washington, DC 20436

May 2021

Office of Economics working papers are the result of ongoing professional research of USITC Staff and are solely meant to represent the opinions and professional research of individual authors. These papers are not meant to represent in any way the views of the U.S. International Trade Commission or any of its individual Commissioners. Working papers are circulated to promote the active exchange of ideas between USITC Staff and recognized experts outside the USITC and to promote professional development of Office Staff by encouraging outside professional critique of staff research. Please address correspondence to samantha.schreiber@usitc.gov. Thanks to David Riker for helpful comments on this paper.

Estimating the Distributional Effects of Trade Policy Changes on Labor
Samantha Schreiber
Office of Economics Working Paper 2021–05–E
May 2021

Abstract

This paper extends the partial equilibrium model presented in Riker (2021) by introducing multiple worker types. Firms operate under monopolistic competition and employ multiple worker types as imperfect substitutes in the production of their product variety. Workers belong to a broader labor supply pool and are mobile across the industries inside the pool. In the short run, changes in tariff rates have heterogeneous impacts on wages and employment for different worker types. We explore how the model works with a series of illustrative simulations on the medical equipment (NAICS 3391) manufacturing sector.

Samantha Schreiber
Research Division, Office of Economics
samantha.schreiber@usitc.gov

1 Introduction

Trade policy changes have heterogeneous impacts on the work force. Production workers may be more exposed to a trade policy change on a heavy manufacturing product. Women may be more impacted by trade policy changes on services sectors like healthcare or education. In this paper, we expand the partial equilibrium employment model presented in Riker (2021) to simulate the effects of trade policy changes on different worker demographics. Firms operate under monopolistic competition and employ multiple worker types as imperfect substitutes in the production of their product variety. The industry is part of a broader labor pool, reflecting perfect labor mobility across industries included in the pool. Changes in tariff rates have differential impacts on wages and employment by worker type in the short run, when the number of firms is fixed and only variable labor inputs can adjust to changes in the wage.

We present the model theory in Section 2, describing how to augment the model equations from the standard model to include different labor types. In Section 3, we detail a source of data and method to calculate labor shares for the specific industry analyzed. In Section 4, we present two sets of simulations to illustrate how the model works using the NAICS 3391 medical equipment manufacturing sector as an example. The first set of simulations have four labor types, by sex and education level, and the second set of simulations add in race as an additional dimension. Finally, we conclude in Section 5.

2 Model Theory

The theory in this section closely follows the approach first described in Riker (2021). Industry i is characterized by monopolistic competition with a large number of symmetrically differentiated domestic firms.[1] Domestic and imported product groups are differentiated by source country and firm and are imperfect substitutes with constant elasticity of substitution (CES) demands. Each domestic firm employs multiple labor types to produce their variety, with a CES production function and elasticity of substitution γ_i. To derive the demand equation for variable labor of each worker type, we start with the production function in equation (1):

$$q_i = \left(\sum_t (a_{it} \ L_{vit})^{\frac{\gamma_i - 1}{\gamma_i}} \right)^{\frac{\gamma_i}{\gamma_i - 1}} \tag{1}$$

where q_i is the quantity of output for industry i, L_{vit} is the variable labor input of type t (v subscript for variable, which will be important later), and a_{it} is a technology parameter specific to the type. The elasticity γ_i must be positive. A γ_i value of zero would indicate no substitution across labor types (Leontief), a value between zero and one implies gross complements, a value of one is Cobb-Douglas, and a value greater than one implies that the labor types are substitutes. Then the marginal product of labor of type t is:

$$MPL_{it} = \left(\sum_k (a_{ik} \ L_{vik})^{\frac{\gamma_i - 1}{\gamma_i}} \right)^{\frac{\gamma_i}{\gamma_i - 1} - 1} a_{it}^{\frac{\gamma_i - 1}{\gamma_i}} L_{vit}^{\frac{-1}{\gamma_i}} \tag{2}$$

By optimally setting the price times MPL_{it} equal to the wage, the variable labor demand for type t in industry i is then:

$$L_{vit} = \frac{q_i}{a_{it}} \left(\frac{(w_{it}/a_{it})^{1-\gamma_i}}{\sum_k (w_{ik}/a_{ik})^{1-\gamma_i}} \right)^{\frac{-\gamma_i}{1-\gamma_i}} \tag{3}$$

where w_{it} are type-specific wages. The model user can define labor types depending on their research question, and could include demographic attributes such as sex, educational

[1] The monopolistic competition model originally comes from the seminal Krugman (1980) paper. Ahmad (2019) presents an extension to the standard monopolistic competition model to conduct profitability analysis and employment effects.

attainment, skill level, or race. Different choices of types will be explored in the illustrative simulation section of this paper. Demand for the domestically produced product q_i has a CES functional form:

$$q_i = A_i \; P_i^{\sigma_i - 1} \; p_i^{-\sigma_i} \tag{4}$$

P_i is the price index and is defined in equation 5, p_i is the output price of the domestic variety, σ_i is the elasticity of substitution between varieties, and A_i is total expenditures of the products in industry i. In the price index, p_i^* is the producer price of the imported variety, τ_i is the tariff factor equal to one plus the tariff rate, and b_i is a demand asymmetry parameter.[2] N_i are the number of symmetrically differentiated domestic firms. In the short run, the number of firms is fixed, as firms have already paid the fixed costs to operate. In the long run, the number of firms is determined by entry and exit and a zero profit condition.

$$P_i = \left(N_i \; (p_i)^{1-\sigma_i} + b_i \; (p_i^* \; \tau_i)^{1-\sigma_i}\right)^{\frac{1}{1-\sigma_i}} \tag{5}$$

The price of the domestic variety is a constant markup over marginal costs. In this version of the model, firms employ several types of workers, so marginal costs are a function of multiple wages. W_i is the wage index and θ_i is the unit labor requirement.

$$p_i = \left(\frac{\sigma_i}{\sigma_i - 1}\right) \; \theta_i \; W_i \tag{6}$$

$$W_i = \left(\sum_k (w_{ik}/a_{ik})^{1-\gamma_i}\right)^{\frac{1}{1-\gamma_i}} \tag{7}$$

Profits for each of the N_i symmetrically differentiated firms in industry i are:

[2]The import price p_i^* is exogenous in this version of the model.

$$\pi_i = p_i \ q_i - \sum_t w_{it} \ L_{vit} \ - \sum_t w_{it} \ L_{fit} \tag{8}$$

where L_{vit} is employment of labor inputs that are considered variable in the short run, and L_{fit} is employment of labor inputs that are fixed in the short run. Therefore, total domestic employment for worker type t in industry i is the summation of variable and fixed employment:

$$L_{it} = N_i \ L_{vit} + N_i \ L_{fit} \tag{9}$$

The market clearing condition for each worker type t, representing total employment across the labor pool, is:

$$L_t = L_{it} + \sum_{k \neq i} L_{kt} \tag{10}$$

In the short run, the number of firms is fixed ($\hat{N}_i = 0$) and profits may be positive or negative ($\pi_{it} \neq 0$). Fixed costs are already incurred and irreversible in the short run. By totally differentiating and log-linearizing model equations (3) through (10), the short-run equilibrium can be characterized by the following equations:

$$\hat{L}_{vit} = (\sigma_i - 1) \ \hat{P}_i - \sigma_i \ \hat{p}_i \ - \ \gamma_i \ (\hat{w_{it}} - \sum_k (v_{it} \ \hat{w_{ik}})) \tag{11}$$

$$\hat{P}_i = (1 - m_i) \ \hat{p}_i + m_i \ \hat{\tau}_i \tag{12}$$

$$\hat{p}_i = \sum_t v_{it} \ \hat{w_{it}} \tag{13}$$

$$s_{it} \ \hat{L_{vit}} + \sum_{k \neq i} s_{kt} \ \hat{L_{vkt}} = 0 \tag{14}$$

$$\hat{L_i} = \left(\frac{L_{vi}}{L_i}\right) \hat{L_{vi}} \tag{15}$$

where m_i is the initial import penetration rate in i, v_{it} is the cost share associated with each type, and s_{it} is the share of the total labor pool that is initially employed in industry i. Hat variables represent percent changes ($\hat{x} = \frac{dx}{x}$).

3 Calculating Labor Shares

The model requires an estimate of the number (or share) of both variable and fixed domestic workers by labor type. Data is needed for both the industry and the broader labor pool. The shares should be specific to the industry being modeled, and not aggregate labor shares for the domestic economy. One useful source of labor data by industry is the Current Population Survey (CPS) Annual Social and Economic Supplements (ASEC). The CPS ASEC survey is a representative sample of U.S. households and contains detailed questions covering social and economic characteristics of each person who is a household member on the interview date. There are industry codes associated with each survey response that are easily concorded to NAICS codes, so labor shares can be calculated based on the demographic data of respondents that work in the industry being analyzed. The labor shares can be used in combination with an industry-level and pool-level total employment estimate to understand the number of workers of each defined type.

In the 2017 survey used in the illustrative simulations below, there are 95,006 households and 185,914 people surveyed, covering 278 selected core-based statistical areas (CBSA), 217 counties, and 76 central cities. The survey includes data on sex, education level, race, marriage status, occupation, industry, and several measures of income.[3] Table 1 shows

[3]The CPS ASEC dataset can be downloaded through the Integrated Public Use Microdata Series (IPUMS), a tool that provides census and survey data in readable formats for statistical software (Flood, King, Rodgers, Ruggles and Warren, 2020).

survey-level summary statistics.

Survey occupation codes can be mapped to variable and fixed employment categories. In the illustrative simulations in Section 4, we group natural resources, construction, maintenance, production, transportation, and material moving occupations into the "variable" category. Management, business, science, services, and sales occupations are grouped into the "fixed" category. The grouping of variable and fixed should depend on the industry analyzed; for example, it may make sense to include services and sales in the variable labor group. Mapping occupation codes to variable and fixed categories allows for heterogeneous labor shares across employment types, instead of applying the same shares to each group.

Table 1: 2017 CPS ASEC Summary Statistics

Sex:	
Male	52.07%
Female	47.93%
Education:	
High school diploma or less	35.96%
Above high school diploma	64.04%
Race:	
White	78.46%
Black	11.24%
Asian	6.48%
Other Race or Multiracial	3.81%

The steps below outline how to calculate labor shares with the CPS ASEC survey:

1. Determine NAICS or CPS industry code that matches focus industry; determine NAICS or CPS industry codes that comprise the defined labor pool.

2. Identify the demographic details of interest and define labor types (e.g. gender, race). Ensure there are enough observations in the survey by industry code and demographic for your labor type definitions.

3. Categorize CPS occupation codes into variable and fixed for your industry.

4. Collapse data by labor type and employment type (fixed/variable) to calculate shares (the number of workers in the industry for that type divided by the total number of workers in the industry).

There are a few limitations to using this survey data for labor shares. For a modeling analysis on an agricultural product, the agriculture industry codes provided in the CPS ASEC survey are detailed enough to delineate between crops and livestock, but do not provide enough detail to map to individual agricultural products. For example, census industry code 0170, crop production, maps to NAICS code 111. Census industry code 0180, animal production, maps to NAICS code 112. But it is not possible to tell what crop was produced. Additional research and data sources are needed to calculate heterogeneous shares for individual agricultural sectors.

The U.S. Bureau of Labor Statistics (BLS) Occupational Employment Statistics (OES) is another source of information that can be used to calculate labor shares. This dataset is at the firm level though, not the household level, and may not have the demographic information needed for a more disaggregated analysis. The CPS ASEC works well for micro-level analysis because it contains rich employment and wage information for each observation. However, if one wanted to further disaggregate the survey by region, it may be difficult to perform state-level analyses with the CPS ASEC survey because of lower participation rates for some states.

4 Illustrative Simulations

We include a series of simulations to illustrate how the model works. The focus industry is NAICS 3391, manufacturing of medical equipment. This NAICS code includes medical equipment, surgical and medical instruments, dental equipment, opthalmic goods, and dental laboratories. The workers in this industry are part of a broader labor pool, NAICS

339, miscellaneous manufacturing. NAICS 339 includes manufacturing of musical instruments, sporting and athletic goods, toy and game manufacturing, office supplies, and sign manufacturing.

In the first set of simulations below, we include a division of the labor force by sex, educational attainment, and occupation type. The model simulates tariff liberalization for medical equipment manufacturing and the outputs include which worker types are most affected by the tariff removal. In the second set of simulations, we add race as an additional dimension to understand tariff liberalization effects by sex, race, educational attainment, and occupation type. Both sets of simulations use the industry data presented in Table 2.

The model requires the total value of shipments in the industry (NAICS 3391) and pool (NAICS 339) and the free alongside ship (FAS) value of exports to isolate the value of shipments destined for the domestic market. The landed duty-paid value (LDPV) value of imports for both industry and pool is also required, as is the total number of employees in both the industry and the pool. Both the domestic shipments data and domestic employment data were obtained from the Annual Survey of Manufactures (ASM) as of 2019. Imports data were obtained from USITC's DataWeb. The tariff rate in table 2 is one of the lower rates for this NAICS group. These simulations are meant to be illustrative to show how the model works with different labor type specifications. If a researcher wants an estimate of the actual effects of tariff liberalization, more work is needed to understand the average tariff rate.

4.1 Simulation 1: Four Labor Types

In this first version of the model, labor is disaggregated by sex and education level. There are two sexes: male and female. The two education types are high school and college, where college indicates the decision to attend regardless of graduation status, and high school includes survey respondents who did not graduate. In total, there are four worker types: high-

Table 2: Industry Data for Illustrative Simulations

	Industry NAICS 3391	**Pool** NAICS 339
Domestic shipments	91,887,978,000	155,001,660,000
Domestic exports	27,997,641,262	46,499,660,806
Imports	45,181,048,223	135,374,195,416
Total number of employees	272,817	531,085
Initial Tariff Rate	35%	

Note: Domestic shipments and employment data was obtained from the Annual Survey of Manufactures 2019 dataset. Imports and exports data are also as of 2019 and obtained from DataWeb.

school educated males, college-educated males, high-school educated females, and college-educated females. Each of these groups have workers categorized as either variable or fixed labor inputs in the model. Variable workers are an aggregate of production, transportation, natural resources, construction, and materials moving occupations. Fixed workers are an aggregate of management, business, science, services, sales, and office occupations.

Using the CPS ASEC 2017 survey and the methodology described above, labor shares are calculated for each group in Table 3. Table 4 reports the number of employees in both industry NAICS 3391 and pool NAICS 339, calculated using the labor shares from Table 3. In these simulations, we assume a γ_i value of 3. The calibrated elasticity of substitution for the industry is 1.85 and the pool is 1.91.[4]

Table 3: Industry and Pool Labor Shares

	Industry: Variable NAICS 3391	**Industry: Fixed** NAICS 3391	**Pool: Variable** NAICS 339	**Pool: Fixed** NAICS 339
High-school educated females	16.21	6.73	12.36	5.54
College educated females	3.67	17.43	5.68	16.76
High-school educated males	16.21	6.73	15.06	5.82
College educated males	9.79	23.24	13.64	25.14

Note: This table presents labor shares for the focus industry (NAICS 3391) and broader labor pool (NAICS 339). Labor shares were calculated with the CPS ASEC 2017 survey, and are specific to the industries listed. There are 327 observations concorded to NAICS 3391, and 704 observations for NAICS 339.

[4]The methodology used to calibrate the elasticity of substitution across domestic and import varieties is described in Riker (2021).

Table 4: Industry and Pool Number of Workers

	Industry: Variable NAICS 3391	**Industry: Fixed** NAICS 3391	**Pool: Variable** NAICS 339	**Pool: Fixed** NAICS 339
High-school educated females	44,224	18,361	65,642	29,422
College educated females	10,012	47,525	30,166	89,010
High-school educated males	44,224	18,361	79,981	30,909
College educated males	26,709	63,403	72,440	133,515

Note: This table presents the number of variable and fixed workers for each labor type, for both the industry and pool. The total number of workers for NAICS 3391 and NAICS 339 were obtained from the Annual Survey of Manufactures.

The structural model and industry data can be used to calculate implied labor supply elasticities (LSEs) for each labor type in the simulation (Table 5).[5] The short-run LSEs assume the number of firms is fixed in the short run and only variable workers can adjust to changes in the wage (fixed labor inputs are fixed in the short run). The LSE can be interpreted as the percent change in the variable labor inputs after a one percent change in the wages. The long-run LSEs assume the number of firms can vary and the zero profit condition is binding. As expected, the LSEs are larger in the long run, as fixed labor inputs become variable and firms can enter or exit.

Table 5: Short-run and long Run Labor Supply Elasticities Implied by the Model

	Short-Run LSE	**Long-Run LSE**
High-school educated males	1.24189	3.75267
College educated males	2.06841	6.25018
High-school educated females	0.835018	2.52321
College educated females	1.72365	5.20841

Table 6 report the effects of tariff liberalization on workers in the medical manufacturing industry in the short run ($\hat{N}_i = 0$). Tariff liberalization leads to higher volumes of imports as the price of imports becomes relatively cheaper. This shifts demand away from the domestic variety, so domestic prices and wages decline. Wage rates decline between two and three percent (median = -3.23%) for each of the four labor types, with largest wage declines for

[5] The short-run LSE is $LSE_{SR} = \sum_{k \neq i} \frac{s_k}{s_i}(\sigma_k - (1-m_k)(\sigma_k - 1))$, so the LSE approaches infinity when the industry is a small part of the labor supply pool. The long-run LSE is $LSE_{LR} = \sum_{k \neq i} \frac{s_k}{s_i}(\frac{\sigma_k}{1-m_k} - (\sigma_k - 1))$.

high-school-educated females. Variable employment declines between three and six percent (median = -4.97%). The largest change in variable employment is for college-educated males and females.

Next, we vary the elasticity of substitution between worker types to understand the responsiveness of model outcomes to this parameter value. In the first column of Table 7, we use a low elasticity value of 2. The low elasticity simulations show wage changes that are the most heterogeneous across workers. One interpretation of the low elasticity is that worker types provide a diverse set of contributions to the firm that are not perfectly substitutable. In the second set of simulations, we use a medium elasticity value of 5. The last column shows an elasticity of substitution value of 10, implying that worker types are nearly perfect substitutes of one another. This means that workers are undifferentiated, and firms easily switch to the relatively lower cost worker type in the event of a wage increase. In this high elasticity scenario, changes in wages roughly equalize across worker types. Note that the range of wage results presented in Table 7 are small.

Table 6: Short-Run Results, Wages and Variable Employment

			Variable Employment	
	Wage	**Pre-simulation**	**Change**	**Post-simulation**
	% Change	# of Workers	% Change	# of Workers
High-school educated females	-3.7004	44,224	-3.56354	42,648
College educated females	-3.0901	10,012	-5.39444	9,472
High-school educated males	-3.37375	44,224	-4.54351	42,214
College educated males	-2.93274	26,709	-5.86653	25,142

Note: This table reports employment outcomes after a tariff liberalization in the medical equipment and supplies manufacturing industry. A γ_i value of 3 was used in the model to generate these results.

Table 7: Sensitivity of Wage Results to the Elasticity of Substitution across Labor Types

	Low Substitutability ($\gamma_i = 2$)	**Medium Substitutability** ($\gamma_i = 5$)	**High Substitutability** ($\gamma_i = 10$)
High-school educated females	-3.86442	-3.56919	-3.47078
College educated females	-2.94897	-3.20301	-3.28769
High-school educated males	-3.37444	-3.37319	-3.37278
College educated males	-2.71293	-3.10859	-3.28769

4.2 Simulation 2: 16 Labor Types

In this second set of simulations, we add race as an additional dimension to the defined labor types in the model. Race is grouped into four categories: Black, White, Asian, and other or multiracial. The number of race categories could be increased to capture more detailed labor changes, but the number of types was limited by the number of observations available in the CPS ASEC survey. For NAICS 3391, four race categories was the highest number that still ensured there were enough observations for each type.[6]

The number of workers in both industry and pool were computed using the calculated labor shares and an estimate of the total number of workers from the ASM, reported in table 8. There are some types with no observations; it is expected that some industries may not have representation from all labor types as the number of types grows.

Model results are reported in table 9. Wage effects are heterogeneous by worker type, with a median wage change of -3.15 percent. Variable employment declines for all worker types (median = -5.20 percent), with the highest declines for Black college-educated females, Black high-school educated males, and college-educated males in the other or multiracial category.

5 Conclusion

The model presented in this paper can be used to simulate the effects of a tariff change on domestic employment and wages for different worker types. Effects on employment and wages are heterogeneous in the short run, when the number of firms is fixed and only variable labor inputs can adjust to changes in wages. This paper provides a theory to model effects by worker demographic, details possible data sources for labor shares, and presents simulations

[6] There were 327 observations in the CPS ASEC survey that concorded to NAICS 3391, and 704 observations concorded to NAICS 339. As shown in table 8, disaggregating the model by sixteen labor categories left some worker types with zero observations. This may be reflective of the industry, or it may just be the case that the survey did not reach every group. If using survey data for labor shares, it may be best to use more aggregated groups for this reason.

Table 8: Industry and Pool Number of Workers

	Industry: Variable NAICS 3391	**Industry: Fixed** NAICS 3391	**Pool: Variable** NAICS 339	**Pool: Fixed** NAICS 339
Male, Black, high-school	4,174	0.	9,028	6,054
Male, Black, college	818	2,537	4,514	4,514
Female, Black, high-school	3,328	873	4,514	1,487
Female, Black, college	818	873	3,770	3,771
Male, White, high-school	35,875	16,724	64,899	21,881
Male, White, college	20,871	51,726	58,844	113,174
Female, White, high-school	32,547	15,851	49,816	24,164
Female, White, college	6,684	41,714	21,137	76,954
Male, Asian, high-school	4,174	1,691	4,514	3,027
Male, Asian, college	4,174	9,167	7,541	14,339
Female, Asian, high-school	8,321	846	9,028	3,027
Female, Asian, college	2,510	3,328	5,258	5,258
Male, other, high-school	0.	0.	1,540	0.
Male, other, college	818	0.	1,487	1,487
Female, other, high-school	0.	709	2,283	744
Female, other, college	0.	1,664	0.	3,027

Note: This table presents the number of variable and fixed workers for each labor type, for both the industry and pool. The total number of workers for NAICS 3391 and NAICS 339 were obtained from the Annual Survey of Manufactures.

Table 9: Short-Run Results, Wages and Variable Employment

			Variable Employment	
	Wage % Change	**Pre-simulation** # of Workers	**Change** % Change	**Post-simulation** # of Workers
Male, Black, high-school	-2.26276	4,174	-7.86725	3,846
Male, Black, college	-2.60696	818	-6.83464	763
Female, Black, high-school	-3.79772	3,328	-3.26236	3,220
Female, Black, college	-2.07257	818	-8.43783	749
Male, White, high-school	-3.45705	35,875	-4.2844	34,338
Male, White, college	-2.78954	20,871	-6.28693	19,558
Female, White, high-school	-3.63135	32,547	-3.76147	31,323
Female, White, college	-3.0483	6,684	-5.51063	6,316
Male, Asian, high-school	-4.07945	4,174	-2.4172	4,073
Male, Asian, college	-3.47002	4,174	-4.24547	3,997
Female, Asian, high-school	-4.01629	8,321	-2.60667	8,104
Female, Asian, college	-3.27243	2,510	-4.83825	2,388
Male, other, college	-2.25714	818	-7.88411	754

Note: This table reports employment outcomes after a tariff liberalization in the medical equipment and supplies manufacturing industry.

using the NAICS 3391 medical equipment manufacturing industry as an example.

There are a few limitations to this approach. First, the model does not capture movement between worker types. We cannot measure, for example, a worker change from the high-school group to the college group in response to an increase in the wage for college-educated workers. In the case of tariff liberalization, as in the illustrative simulations, all labor types experienced declines in variable employment as workers left the industry. Second, the model focuses on labor only and does not include any other factors of production. This is a common characteristic of monopolistic competition models. Finally, it may be difficult to find data for the labor shares calculation for narrowly defined industries.

References

Ahmad, S. (2019). Conducting Profitability Analysis in Partial Equilibrium Models with Monopolistic Competition, *U.S. International Trade Commission, Economics Working Paper* **2019–07–B**.

Flood, S., King, M., Rodgers, R., Ruggles, S. and Warren, J. R. (2020). Integrated Public Use Microdata Series, Current Population Survey: Version 7.0 [dataset], *IPUMS* .
URL: *https://doi.org/10.18128/D030.V7.0*

Krugman, P. (1980). Scale Economies, Product Differentiation, and the Pattern of Trade, *American Economic Review* **70**(5): 950–959.

Riker, D. (2021). Estimating the Direct Employment Effects of Industry-Specific Trade Policy, *US International Trade Commission Economics Working Paper Series* **2021–4–A**.