TRADE POLICY, HUMAN CAPITAL, AND COSTLY WORKER TRANSITIONS

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Abstract

Accumulation of human capital, through formal education and on-the-job experience, shapes workers' adjustment to job displacements after tariff reductions – whether they switch industries, become unemployed, or leave the labor force. We develop an economic model that uses individual-level longitudinal CPS data on the employment transitions of U.S. manufacturing workers to estimate prospective labor adjustments in response to hypothetical reductions in tariff rates on U.S. manufacturing imports. The simulation suggests that a worker's observable human capital characteristics are important determinants of labor market outcomes following a trade policy change.

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1 Introduction

The impact of international trade on the labor market outcomes of workers, such as employment and wages, is an important topic in the international economics literature.[1] Changes in trade policy, like tariff reductions on U.S. imports of manufactured goods, affect the domestic industry by reducing labor demand. The resulting effects on employment are distributed unevenly across groups of workers that vary in their human capital characteristics, specifically their education and age.

Riker (2023a) estimates prospective modeled-based measures of trade exposure that vary by worker demographic groups using an employment-weighted average of trade intensities.[2] Based on data on U.S. manufacturing industries in 2021 and a hypothetical ten-percent increase in trade costs, the author finds that workers' race and education have larger effects on the trade exposure measures than the workers' gender, ethnicity, or occupation. In an extension, Riker (2023b) reapplies the model with demographic groups defined by race, sex, age, and educational attainment in a retrospective analysis of rising trade costs on U.S. manufacturing imports between 2021 and 2022. Riker (2023b) also considers changes in trade costs on imported intermediate goods, in addition to changes in trade costs on imported final goods.

This paper presents an economic model to estimate labor market transitions by worker characteristics following a hypothetical trade policy change. The model is consistent with economic theory and industry data, transparent and reproducible, and detailed but practical in its data requirements. In particular, the model builds on the employment-weighted average approach from Riker (2023a) and incorporates data on recently displaced workers and the

[1] For example, Autor, Dorn and Hanson (2013) study the impact of rising import competition from China on local labor markets in the United States. Another example includes Autor, Dorn, Hanson and Song (2014), who use worker-level data from the U.S. Social Security Administration to study the impact of rising import competition from China on earnings and employment of U.S. workers.

[2] The trade exposure measure builds on the work of Ebenstein, Harrison, McMillan and Phillips (2014), who conduct retrospective analysis on potential wage impacts across occupations.

transition of displaced workers using worker-level data from the Current Population Survey (CPS). We focus on trade in manufactured goods and wages are assumed to be downward-rigid, so reductions in labor demand translate into unemployment of some U.S. workers.

The model estimates the percentage of displaced workers who are initially employed in manufacturing and become unemployed, exit the labor force, switch to another manufacturing industry, or switch to a non-manufacturing industry. These employment transitions are estimated for worker groups defined by age and education, which serve as proxies for the human capital of the workers. The model can be extended to include other worker groups. As an alternative, we group workers by age and gender rather than age and education.

We simulate a hypothetical reduction in U.S. tariffs on imported manufactured goods from 2022 rates to 2017 rates for industries that experienced an average tariff increase between 2017 and 2022.[3] The percentage of initial employed manufacturing workers who are estimated to experience a transition range between 0.005 and 0.186 percent across the worker groups of age and education. We find that workers who are 40 years or older and are not college graduates are more likely to exit the labor force, switch to another manufacturing industry, or switch out of manufacturing. Younger workers (less than 40 years old) who are not college graduates are the most likely to exit to unemployment, but only slightly more than older workers who are also not college graduates. For each of the worker groups, switching to employment outside of the manufacturing sector is the most likely transition.

The rest of the paper is organized into five parts. Section 2 derives the modeling framework. Section 3 describes the data sources, aggregations, and definitions. Section 4 reports a simulation of labor adjustments following a reduction in U.S. tariffs on manufactured imports, with U.S. tariffs reduced to 2017 tariff rates. Section 5 describes a spreadsheet version of the model that replicates the simulation and can be easily modified to consider alternative

[3]For two NAICS manufacturing industries, we set the tariff change to zero for the simulations as these industries experienced an average tariff decrease between 2017 and 2022.

policy scenarios. Section 6 discusses the estimates and provides concluding remarks.

2 Modeling Framework

This section derives an equation for estimating the effect of changes in tariffs on labor demand and employment based on an industry-specific partial equilibrium model of international trade. The model uses conventional functional forms and its derivation follows Riker (2023a). The equation for domestic employment effects is abbreviated in this case, compared to Riker (2023a), because we focus on exposure to import shocks and we do not include exposure to export shocks. We extend the model to include estimates for the employment transition paths of different worker groups and estimates of the average wage effects for these worker groups.

In the model derivation, we assume there are two countries (domestic and foreign) and domestic imports from the foreign country are subject to import tariffs.[4] The value of domestic shipments of industry i has the constant elasticity of substitution (CES) form in equation (1).

$$V_i = \theta_i \; E \; (P_i)^{\sigma_i - 1} \; (p_i)^{1 - \sigma_i} \tag{1}$$

V_i is the value of shipments of domestic producers in the industry, and p_i is the producers' price. E is aggregate expenditure in the domestic market, and θ_i is the expenditure share of products in industry i. P_i is the CES industry price index in equation (2), and σ_i is the elasticity of substitution between domestic and imported varieties.

$$P_i = \left[\, n_i \; (p_i)^{1 - \sigma_i} + n_i^* \; (p_i^* \; \tau_i)^{1 - \sigma_i} \right]^{\frac{1}{1 - \sigma_i}} \tag{2}$$

[4]For the simulations, the domestic country is the United States and the foreign country is an aggregate rest of the world. It is straightforward to increase the number of countries in the model.

n_i and n_i^* are the numbers of domestic and foreign varieties in the industry, p_i^* is the price of foreign varieties, and τ_i is a tariff factor on imports that is increasing in tariff rates. τ_i is equal to one plus the tariff rates in industry i, also known as the power of the tariff.

We assume that production in industry i has a Leontief technology that combines labor and materials in fixed proportions. w is the marginal cost of labor, and c is the marginal cost of materials. a_{wi} and a_{ci} are industry-specific unit factor requirements.

In addition, we assume that there is monopolistic competition in the domestic market.[5] There is a continuum of firms, and each has monopoly power in the unique variety that it produces. Each firm perceives that the own-price elasticity of demand for its variety is a constant, so its price is a constant mark-up over its marginal cost of production, as presented in equation (3).

$$p_i = \left(\frac{\sigma_i}{\sigma_i \ - \ 1}\right) \ (a_{wi} \ w \ + \ a_{ci} \ c) \tag{3}$$

Equation (3) implies equation (4), where the second equality is obtained by multiplying the numerator and denominator by the quantity of shipments of domestic producers.

$$\sigma_i = \frac{p_i}{p_i - a_{wi} \ w - a_{ci} \ c} = \frac{V_i}{V_i - W_i - C_i} \tag{4}$$

W_i is the industry's total domestic wage payments, and C_i is the industry's total cost of materials.

Equation (5) is the percent change in industry labor demand (and equivalently employment) resulting from changes in the tariff factor in industry i.[6] It is a first-order log-linear approximation evaluated at the initial equilibrium in the domestic market.

[5]The models of monopolistic competition and trade in differentiated products in Krugman (1980), Melitz (2003), Chaney (2008), Helpman, Melitz and Rubinstein (2008), and subsequent studies also assume that consumers have CES preferences.

[6]Alternative assumptions about labor supply would break the equivalence between the percent changes in revenues and employment in the domestic industry.

$$\hat{L}_i = \left(\frac{L_i \; - \; L_i^*}{L_i} \right) \hat{V}_i \; - \; \hat{p}_i \tag{5}$$

L_i is total employment of domestic manufacturers in industry i, and L_i^* is their employment associated with exports, so $\frac{L_i^*}{L_i}$ is equal to the industry's exports as a share of its total shipments, χ_i. $\hat{L}_i$ is the proportional (or percent) change in employment in the domestic industry, $\frac{dL_i}{L_i}$, and $\hat{\tau}_i$ is the proportional change in the tariff factor. L_i and V_i are endogenous variables that change in response to changes in trade costs. p_i is an endogenous variable that does not change, because it is fixed according to equation (3).

Equation (6) is the percent change in the total value of domestic shipments resulting from changes in the tariff factor in industry i.

$$\hat{V}_i = (\sigma_i \; - \; 1) \; \left(\hat{P}_i \; - \; \hat{p}_i \right) = (\sigma_i \; - \; 1) \, \mu_i \; \hat{\tau}_i \tag{6}$$

μ_i is the industry's import penetration rate, $\frac{M_i}{V_i - E_i + M_i}$. M_i is the value of imports in industry i. To simplify these expressions for percent changes, we have held E, w, c, a_{wi}, a_{ci}, θ_i, σ_i, and p_i^* constant. The delivered price in the domestic market $(\tau_i \; p_i^*)$ is not constant when τ_i changes. We assume that n_i and n_i^* remain fixed in the short run.

Equation (7) is the reduced-form expression for the percent change in domestic industry employment in response to a change in tariff rates. It is derived by substituting equation (6) into equation (5).

$$\hat{L}_i = (1 \; - \chi_i) \, (\sigma_i \; - \; 1) \, \mu_i \; \hat{\tau}_i \tag{7}$$

This is the labor demand and employment effect of changes in the tariff factor on industry imports.

Equation (8) is the percentage of workers in group g that were initially employed in manufacturing industry i who are displaced and experience transition k (switch within the manufacturing sector, switch to another sector, become unemployed, or leave the labor force) due to changes in tariff rates.

$$\phi_{gi}^{k} = \beta_{gi}^{k}\ \gamma_{gi}\ (-\hat{L}_i) \tag{8}$$

γ_{gi} is the share of workers displaced from industry i that are in group g. β_{gi}^{k} is the share of workers in group g transitioning from industry i who experience transition k.

To aggregate across the manufacturing industries indexed by i, equation (9) takes an employment-weighted average of equation (8). Equation (9) is the percentage of workers in group g that were initially employed in manufacturing who are displaced and experience transition k due to changes in tariff rates.

$$\phi_{g}^{k} = \sum_{i} \lambda_{gi}\ \phi_{gi}^{k} \tag{9}$$

The share of group g workers who are employed in industry i, λ_{gi}, is equal to $\frac{L_{gi}}{L_g}$. $L_g = \sum_i L_{gi}$ is total domestic employment of workers in group g across all manufacturing industries indexed by i, and L_{gi} is domestic employment of group g workers in industry i.

According to equations (8) and (9), the labor adjustments of each group of workers in response to a change in tariff rates depends on the industry's import penetration rate (μ_i), the industry's export share (χ_i), the extent of substitution between its domestic and imported varieties (σ_i), the change in the tariff rate ($\hat{\tau}_i$), the group's work transition rates (β_{gi}^{k}), the share of workers displaced from industry i who are in group g (γ_{gi}), and the group's labor share of each industry (λ_{gi}).

Each industry employs experienced incumbent workers and can also hire additional inexperienced and less productive new workers. We assume that the supply of inexperienced labor is perfectly elastic at exogenous wage w. Workers are paid the value marginal product of their labor. Experienced incumbent workers in an industry receive a wage premium $\omega \geq w$

reflecting their higher productivity in the specific industry. If displaced from the industry, they lose some or all of their wage premium. We assume that the wages of incumbent workers are downward-rigid, and they cannot avoid displacements by making wage concessions.

Equation (10) is the average change in the wage of workers in group g that were initially employed in the manufacturing industry and were displaced due to changes in tariff rates, $\Delta\ \omega_g$.

$$\Delta\ \omega_g = \sum_k \sum_i\ \lambda_{gi}\ \phi^k_{gi}\ \Delta\ \omega^k_{gi} \tag{10}$$

$\Delta\ \omega_g$ is an average over all worker in group g. It is the ex-ante expected value for workers in group g before displacement. It is substantially smaller than $\Delta\ \omega^k_{gi}$, which is the change in wage income of workers who are displaced and are making costly transition k.

3 Data Sources, Aggregations, and Definitions

The model uses individual-level micro-data on U.S. workers initially employed in a manufacturing industry. The data on the industry of the workers, as well as their age and educational attainment, are from public use micro-data files of the Annual Social and Economic (ASEC) supplement of the CPS.[7]

This CPS longitudinal data link an individual's survey response in March of one year to the individual's response in March of the next year. The dataset reports the worker's industry, employment status, wages, household income, and demographic characteristics in both years. We categorize each worker as either not transitioning during the one-year period and staying in the same industry or transitioning by switching to another industry within the manufacturing sector, switching to another industry outside of the manufacturing sector, becoming unemployed, or leaving the labor force.

[7]These data are publicly available at `https://cps.ipums.org/cps/`.

When calculating the share of workers who experience transition k, β_{gi}^k, we focus on workers who are initially employed in a U.S. manufacturing industry and experienced a decline in wages over the one-year period, since these workers are most likely to have experienced involuntary displacement due to negative labor demand shocks. The estimates of β_{gi}^k also do not include workers who left the labor force and are 60 years or older, since they are likely retirements rather than involuntary displacements.

In addition to this worker-level information, the model uses industry-level data on shipments, payrolls, and costs of materials by NAICS three-digit U.S. manufacturing industry in 2021 from the U.S. Census Bureau's Annual Survey of Manufactures (ASM).[8] The model also uses data on the 2021 and 2022 free alongside value of domestic exports and the landed duty-paid value and customs value of imports for consumption by NAICS three-digit industry from the U.S. International Trade Commission's Trade Dataweb.[9]

Finally, the model calibrates the elasticity of substitution parameter for each manufacturing industry using the approach in Ahmad and Riker (2019). Their formula for calibrating σ_i is presented in equation (4). It uses data on the value of shipments, wage payments, and costs of materials of domestic producers in the industry in the 2021 ASM.

Table 1 provides a summary of industry-level inputs of the model. The elasticity of substitution values range from 1.81 for the beverage and tobacco products industry to 4.86 for the petroleum and coal products industry. The industries' import penetration rates range from 8.1 percent for the printing and related products industry to 95.3 percent for the leather and allied products industry. The industries' export share range from 4.9 percent for the beverage and tobacco products industry to 51.3 percent for the leather and allied products industry.

Industry average tariff rates rose in all manufacturing industries from 2017 to 2021 (and

[8]These data are publicly available at `https://www.census.gov/programs-surveys/asm/data/tables.html`.

[9]These data are publicly available at `https://dataweb.usitc.gov/`.

would *decline* if tariffs were returned to 2017 rates) except in the beverages and tobacco products and petroleum and coal products industries. These industries experienced a 0.02 percent and 0.05 percent decrease, respectively, between 2017 and 2022. For the simulations, the change in the tariff rate is set to zero for these two industries (i.e., $\hat{\tau}_i = 0$ if i is NAICS code 312 or 324).

Table 1: Industry-Level Model Inputs

Manufacturing Industry Name and NAICS Code	Elasticity of Substitution	Import Penetration (%)	Export Share (%)	Tariff in 2017 (%)	Tariff in 2022 (%)
Food manufacturing (311)	3.33	10.1	8.4	1.34	2.21
Beverage and tobacco products (312)	1.81	16.9	4.9	0.41	0.40
Textile mills (313)	3.54	37.3	29.5	4.48	6.75
Textile product mills (314)	3.24	62.8	11.7	6.21	8.71
Apparel (315)	3.19	94.2	31.9	13.41	14.92
Leather and allied products (316)	3.44	95.3	51.3	10.80	12.60
Wood products (321)	2.74	20.0	5.0	0.98	2.25
Paper manufacturing (322)	2.96	12.4	12.1	0.24	2.38
Printing and related products (323)	2.91	8.1	6.0	0.01	2.40
Petroleum and coal products (324)	4.86	12.6	15.0	0.21	0.16
Chemical manufacturing (325)	2.08	35.0	28.1	0.79	1.45
Plastic and rubber products (326)	2.88	25.7	11.8	2.51	5.78
Nonmetallic mineral products (327)	2.56	19.8	7.7	3.11	6.03
Primary metal products (331)	2.90	39.0	21.2	0.37	2.43
Fabricated metal products (332)	2.97	21.7	10.1	2.14	6.77
Machinery manufacturing (333)	3.19	44.9	31.6	0.71	3.16
Computers and electronics (334)	2.88	69.5	35.9	0.18	1.17
Electrical equipment et al. (335)	2.92	62.8	30.4	1.65	5.37
Transportation equipment (336)	4.54	36.0	22.7	0.96	2.02
Furniture (337)	3.10	46.9	5.6	0.20	6.52
Miscellaneous manufacturing (339)	2.39	60.3	27.4	1.00	1.56

Table 2 reports the substantial average changes in the wage and salary income of displaced workers experiencing each of the four types of transitions after displacement.[10] Exiting the labor force resulted in the greatest wage loss for all four groups, ranging from 73.4 to 89.2 percent reductions. Switching to another industry within the manufacturing sector resulted in the smallest wage loss for all four groups, ranging from 32.1 to 44.3 percent reductions.

Table 2: Loss in Annual Wage and Salary Income Associated with the Transitions

Age and Education	Exits to Unemployment $ (%)	Exits the Labor Force $ (%)	Switches within Sector $ (%)	Switches Out of Sector $ (%)
Younger than 40				
Not a College Graduate	15,119	20,292	21,612	19,324
	(49.3)	(82.9)	(44.3)	(46.3)
College Graduate	39,644	61,938	28,476	45,363
	(60.9)	(89.2)	(32.1)	(44.4)
40 or Older				
Not a College Graduate	23,177	37,758	23,206	34,708
	(52.8)	(77.3)	(35.9)	(50.4)
College Graduate	48,385	65,784	58,149	74,482
	(49.9)	(73.4)	(39.8)	(49.8)

Table 3 reports the average change in the total personal income of displaced workers experiencing each of the four types of transitions after displacement. These are smaller in percentage terms, since there are parts of income that are unaffected and in some cases income replacement.

[10] As a reminder, we focus on workers who are initially employed in a U.S. manufacturing industry and experienced a decline in wages over the one-year period, since these workers are most likely to have experienced involuntary displacement due to negative labor demand shocks.

Table 3: Loss in Annual Total Personal Income Associated with the Transitions

Age and Education	Exits to Unemployment $ (%)	Exits the Labor Force $ (%)	Switches within Sector $ (%)	Switches Out of Sector $ (%)
Younger than 40				
Not a College Graduate	13,767	18,408	22,348	17,266
	(42.4)	(71.9)	(44.0)	(39.8)
College Graduate	40,092	53,515	27,813	41,882
	(56.7)	(75.1)	(30.3)	(40.1)
40 or Older				
Not a College Graduate	18,495	28,076	22,369	33,859
	(37.3)	(50.3)	(32.4)	(44.7)
College Graduate	48,655	44,700	59,139	73,411
	(44.5)	(42.9)	(36.6)	(44.9)

There are limitations to the CPS longitudinal public use micro sample. First, workers might have been displaced and switched to another company but within the same initial manufacturing industry, and this shows up as no transition (staying). Second, the data only provide information on each worker at two time periods in consecutive years. This yields limited information on the length or severity of unemployment spells: for example, we cannot tell whether a worker lost a job in February and was unemployed one month in March, lost a job in April and was unemployed eleven months or more, or switched industries but was unemployed for a while between March and March. Third, the number of worker-level observations for calculating employment and transition shares can get limited when including more detailed worker demographic groups.

4 Estimated Effects on U.S. Manufacturing Workers

We simulate a hypothetical reduction in tariff rates on U.S. imports of manufactures from 2022 tariff rates to 2017 tariff rates. Table 4 covers four different groups of workers defined by their age and educational attainment. The table reports the estimated percentage of initial group g employment in manufacturing experiencing labor adjustment k, denoted as ϕ_g^k in equation (9).

The percentage of workers initially employed in manufacturing and that are estimated to experience a transition ranges between 0.005 and 0.186 percent across the groups of age and education. Exiting to unemployment is much more likely for workers who are not college graduates. Age does not appear to make much difference. Exiting the labor force is sensitive to age, and is especially high for workers who did not graduate from college. Switching to another manufacturing industry or to a non-manufacturing industry is most likely for older workers who are not college graduates. For each of the worker groups, switching to employment outside of the manufacturing sector is the most likely transition. Figure 1 provides a graphical illustration of these group-specific effects.

Table 4: Transitions of Displaced U.S. Manufacturing Workers

Age and Education	Exits to Unemployment (%)	Exits the Labor Force (%)	Switches within Sector (%)	Switches Out of Sector (%)
Younger than 40				
Not a College Graduate	0.028	0.052	0.084	0.104
College Graduate	0.005	0.006	0.023	0.041
40 or Older				
Not a College Graduate	0.027	0.130	0.177	0.186
College Graduate	0.007	0.040	0.058	0.096

Figure 1: Graph of Worker Transitions from Table 4

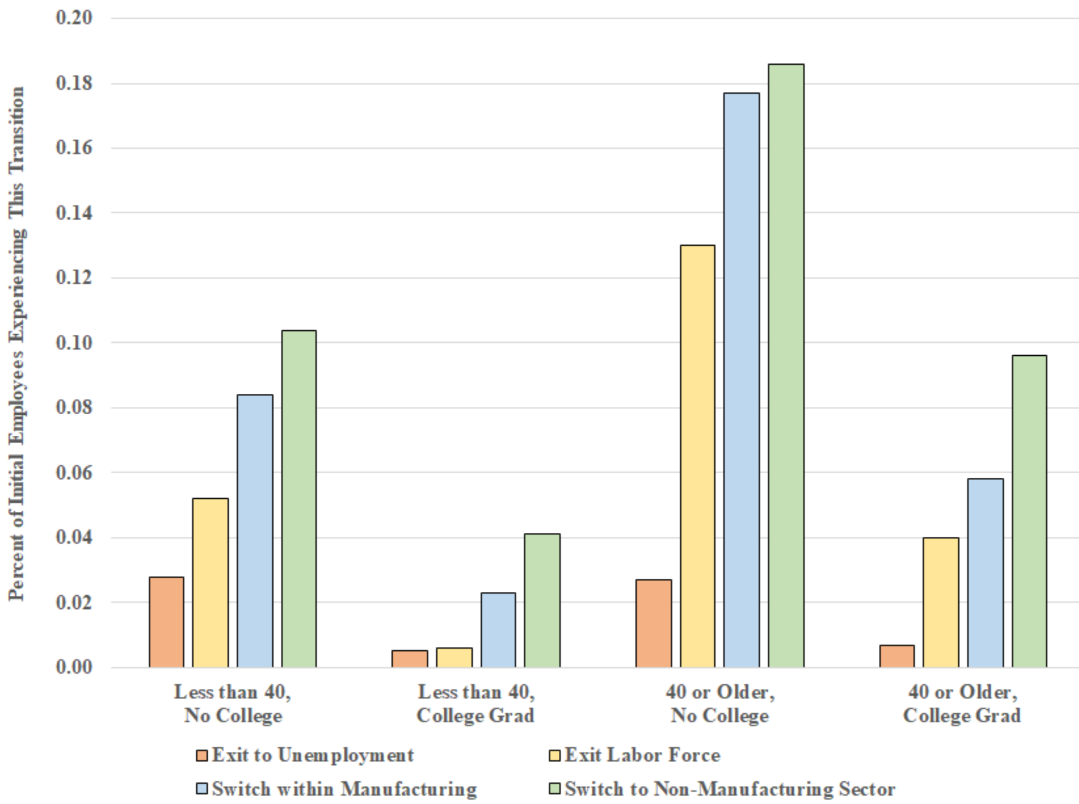

Table 5 reports the estimated average reduction in income of workers in the four groups. The largest average reductions in wage and total income are for workers who are 40 or older and not college graduates. The smallest average reductions in wage and total income are for workers who are younger than 40 and college graduates.

Table 5: Reduction in Income of Displaced Workers

Age and Education	Reduction in Wage Income Annual $ (%)	Reduction in Total Income Annual $ (%)
Younger than 40		
Not a College Graduate	53 (0.12)	50 (0.11)
College Graduate	31 (0.03)	29 (0.03)
40 or Older		
Not a College Graduate	161 (0.26)	144 (0.21)
College Graduate	135 (0.10)	126 (0.09)

Next, to highlight the flexibility of this approach for estimating transitions for different groups of workers, we extend the model to categorize workers into two gender groups rather than two education groups. Table 6 report the estimated transitions for the four new groups of workers. Older and male workers are much more likely to be displaced.

Table 6: Transitions of Displaced U.S. Manufacturing Workers

Age and Gender	Exits to Unemployment (%)	Exits the Labor Force (%)	Switches within Sector (%)	Switches Out of Sector (%)
Younger than 40				
Female	0.005	0.023	0.016	0.035
Male	0.021	0.030	0.080	0.102
40 or Older				
Female	0.008	0.054	0.054	0.069
Male	0.023	0.107	0.179	0.205

Table 7 reports the estimated average reduction in income of workers in four groups. Older and male workers also experience the largest average reductions in wage and total income.

Table 7: Reduction in Income of Displaced Workers

Age and Gender	Reduction in Wage Income Annual $ (%)	Reduction in Total Income Annual $ (%)
Younger than 40		
Female	13 (0.03)	13 (0.03)
Male	66 (0.07)	62 (0.07)
40 or Older		
Female	54 (0.09)	52 (0.08)
Male	242 (0.18)	218 (0.15)

5 Analysis of Alternative Policy Scenarios

As a supplement to this paper, we built an easy-to-use Excel spreadsheet version of the simulation model. Using the inputs for each manufacturing industry from Table 1, the spreadsheet replicates the model estimates reported in Table 4. The spreadsheet can also be used to estimate the effects of different tariff changes, simply by altering the values of $\hat{\tau}_i$ in Column C in the Industry Inputs tab of the Excel file.[11]

Table 8 reports estimated effects when tariffs on manufacturing imports are eliminated, using the version of the model with two age groups and two education groups in section 4, *except* there is no change in tariff rates for NAICS 331 (primary metals) and 332 (fabricated metals). They are maintained at 2021 rates in this alternative simulation. Specifically, we change the values in cells C18 and C19 in the Industry Inputs tab to zero, and the simulated effects update in the Estimated Impact by Group tab.

[11]The effects of the trade policy changes could also be re-estimated for different assumptions about the value of the elasticity of substitution in each industry, by altering the values of σ_i in Column D in the Industry Inputs tab of the spreadsheet file.

Table 8: Transitions with Alternative Policy Scenario

Age and Education	Exits to Unemployment (%)	Exits the Labor Force (%)	Switches within Sector (%)	Switches Out of Sector (%)
Younger than 40				
Not a College Graduate	0.025	0.046	0.069	0.085
College Graduate	0.005	0.006	0.022	0.040
40 or Older				
Not a College Graduate	0.021	0.102	0.128	0.146
College Graduate	0.006	0.038	0.048	0.091

To facilitate comparison of the two simulations, Table 9 reports the magnitude of the effects in Table 8 (without tariff reductions in NAICS 331 and 332) relative to the magnitude of the effects in Table 4 (with tariff reductions in all manufacturing industries). The ratios are less than one for all four transitions for all groups, except for younger workers who are not college graduates exiting to unemployment or exiting the labor force.

Table 9: Ratio of the Estimated Effects, Table 8 to Table 4

Age and Education	Exits to Unemployment	Exits the Labor Force	Switches within Sector	Switches Out of Sector
Younger than 40				
Not a College Graduate	0.89	0.88	0.82	0.82
College Graduate	1.00	1.00	0.96	0.98
40 or Older				
Not a College Graduate	0.78	0.78	0.72	0.78
College Graduate	0.86	0.95	0.83	0.94

6 Discussion and Conclusions

We have developed and applied a model of employment and wage effects due to changes in trade policy with heterogeneity by worker characteristics. The model has practical data requirements and can be used in retrospective analysis, as well as the hypothetical prospective simulation in this paper. The simulation suggests that a worker's observable human capital characteristics are important determinants of labor market outcomes following a trade policy change.

The model has several limitations and these suggest potential extensions to the analysis. First, it may be possible to improve the estimated transition rates, β_{gi}^{k} and γ_{gi}, using more detailed longitudinal micro data. Second, the data can be used to calculate a full distribution of the reduction in wage income within each group, rather than average reductions. Third, the analysis could include greater disaggregation of worker types, both within age and education and to include other worker characteristics, like in Riker (2023a). Finally, it could include indirect inter-industry effects through input-output links, like in Riker (2023b).

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