Part of the Ewing Marion Kauffman Foundation’s Entrepreneurship Scholars initiative, the Kauffman Dissertation Fellowship recognizes exceptional doctoral students and their universities. The annual program awards Dissertation Fellowship grants to Ph.D., D.B.A., or other doctoral students at accredited U.S. universities to support dissertations in the area of entrepreneurship.

Since its establishment in 2003, this program has helped to launch world-class scholars into the exciting and emerging field of entrepreneurship research, thus laying a foundation for future scientific advancement. The findings generated by this effort will be translated into knowledge with immediate application for policymakers, educators, service providers, and entrepreneurs as well as high-quality academic research.
THE MAIN CHAPTER OF THIS DISSERTATION (CHAPTER I) ANALYZES HOW THE US’S LARGEST POLICY FOR RETRAINING TRADE-DISPLACED WORKERS—TRADE ADJUSTMENT ASSISTANCE (TAA)—AFFECTS EARNINGS AND EMPLOYMENT OUTCOMES FOR DISTRESSED WORKERS, AND THE EXTENT TO WHICH TAA IS AN EFFECTIVE TOOL FOR REEQUIPPING THESE WORKERS FOR THE INNOVATION ECONOMY.

Prior research has been limited by two challenges precluding credible empirical estimates of these effects: a lack of quality data to track worker movements across employers, and selection bias from certain types of workers electing to retrain, making it difficult to disentangle whether retraining outcomes are linked to TAA itself, or instead predetermined characteristics of workers who choose to opt into training. To tease these apart, I leverage an institutional feature of TAA that assigns two otherwise equal TAA applicants to investigators of varying approval leniencies. Merged with Census Bureau microdata on 300,000 displaced workers from TAA winning and losing petitions, this allows me to estimate worker salary returns to TAA retraining from 1990 to 2011.

Using this strategy, I find TAA-trained workers have $50,000 higher cumulative earnings after ten years. Returns are further concentrated in the most disrupted regions, where workers switch industries and move to labor markets with better opportunities in response to training. This is consistent with a theory of optimal job transitions being constrained by adjustment frictions. The results imply that current policy efforts are much more effective than previously thought at retraining displaced workers for the global economy.
CHAPTER 1 : Can Displaced Labor Be Retrained? Evidence from Quasi-Random Assignment to Trade Adjustment Assistance

1.1. Executive Summary

Between 2000 and 2016 the US shed approximately 6 million manufacturing jobs, resulting in the lowest level of manufacturing employment since the onset of World War II (BLS, 2017).\(^1\) Strikingly, this decline contrasted with record revenue growth in both manufacturing and non-manufacturing industries over the same period (see Figure 1.1). In light of increasing pressure from trade and automation, are today’s workers able to adjust to labor market disruptions as they have in the past?

While economists have generally considered worker adjustment to shocks such as trade to be relatively frictionless, the unusual speed of these recent structural changes has prompted a fresh look at whether growing industries can absorb and offset declining earnings among displaced workers. Standard Ricardian trade theories predict that relatively higher- and lower-skilled economies stand to “gain from trade” if skill-intensive labor markets specialize in high value-added activities (like computer software) and trade for lower value-added goods and services (such as textiles). However, these models also conventionally assume that workers facing short-run job displacement from trade either adjust instantaneously to newly expanding sectors (i.e. labor is perfectly mobile), or are compensated by redistributive government transfers that preserve trade’s Pareto-improving qualities.\(^2\)

Though many studies have shown that removing trade barriers can increase growth and

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\(^1\) Pierce and Schott (2016) highlight that the recent manufacturing decline contrasts with a stable employment trend which had varied around 18 million jobs from 1965 until the accession of China to the World Trade Organization (WTO) in 2001.

\(^2\) Economists have relied on the notion of “Kaldor-Hicks Efficiency” (Kaldor, 1939; Hicks, 1939) to relax strong Pareto assumptions which preclude “losers” from trade. Instead, an allocation is Kaldor-Hicks efficient if losing factors of production can hypothetically be compensated by winning factors. Building on the work of Dixit and Norman (1986), Feenstra and Lewis (1994) show that redistributive compensation from levying taxes on winning factors are more likely to result in a Pareto-improving allocation if combined with mobility subsidies to overcome adjustment frictions.
consumer welfare through specialization, lower goods prices, and higher variety; less attention has been given to adverse labor outcomes because imports from low-wage countries had been relatively inconsequential until the 1990s (Autor et al., 2016). More recently however, influential papers in empirical trade and labor economics have documented that displaced workers may remain persistently underemployed and underpaid (with respect to prior earnings) years beyond their initial job separation (Bartik A., 2017; Lachowksa et al., 2017; Pierce and Schott, 2016; Flaaen et al., 2016; Autor et al., 2014, 2013; Autor and Dorn, 2013; Harrison and McMillan, 2011). As jobs and tasks become increasingly outsourcable and automated, there is also growing concern about how future generations of US workers will sustain wage growth in a rapidly transforming innovation economy. For example, 1.3 million truck drivers will likely compete with the emergence of self-driving vehicle technology by 2026 (CEA, 2016). Such issues were especially salient during the 2016 US Presidential election, which featured protectionist backlash against trade on both sides of the political aisle.

Yet in spite of widespread concern and a growing literature on adjustment frictions, surprisingly little is known about whether the US’s largest and longest standing incentive program for retraining displaced workers—the Department of Labor’s 1974 Trade Adjustment Assistance (TAA) program—is a necessary, effective, or efficient means to accelerate adjustment. The main contribution of this paper is to provide large-sample empirical estimates of the causal effects of retraining trade-impacted workers on labor market outcomes. Credible parameter estimates of these effects have historically been complicated by two factors: (1) A lack of detailed worker-level data to track TAA participants before and after displacement events across employers; (2) Confounding

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3Recent work by Fajgelbaum and Khandelwal (2016) further suggests low-income workers have the most to gain from trade, as they bear a disproportionate incidence of lower consumer prices due to a higher propensity to consume tradable goods.

4Feenstra et al. (2017) and Feenstra and Sasahara (2017) find that manufacturing job losses are offset by service job growth, however these papers do not address distributional consequences which can persist despite aggregate gains.

5Autor et al. (2016) study the effects of rising trade exposure on political polarization, and find that exposure to trade with China decreased the number of moderate congressional representatives in office.
factors correlated with qualifying for TAA, particularly pre-determined skills and
trends associated with tradable-good production and training take-up—selection biases
which preclude reliable estimates of the program’s effects. In this paper, I employ a
quasi-experimental research design that builds on the rapidly maturing examiner (judge
randomization) methodological literature to circumvent these endogeneity concerns.
Applying this strategy in a “big data” setting, I estimate the causal effects of TAA benefits
on displaced worker earnings, employment, education, and mobility outcomes from 1990
to 2011.⁶

I first assemble a new dataset combining restricted-use administrative data from the US
Census Bureau’s Longitudinal Employer-Household Dynamics (LEHD) dataset with the
universe of TAA winning and losing petitions (applications) attained through Freedom
of Information Act requests at the US Department of Labor (DOL). This unique merger
allows me to track a sample of approximately 300,000 displaced workers as they move in
and out of unemployment status and across employers of diverse industries and regions,
both before and after their initial job separation. Critically, DOL petition data contain the
unique names of investigators responsible for determining whether workers qualify for
TAA. These investigators are tasked with subjectively determining whether applicants
were laid off by companies whose decline in production (sales) was due to increased
imports or offshoring—an adjudication of the firm’s trade exposure or “tradability” status.

I show that this institutional feature of TAA effectively assigns two otherwise identical
worker cohorts (displaced from the same industry), different TAA approval probabilities
based on whether their case is directed to a more lenient versus strict investigator.
If assigned quasi-randomly to more lenient investigators, displaced workers have a
higher likelihood of receiving TAA benefits. These include up to $10,000/year for two

⁶Recent examples of such examiner designs include Dobbie and Song (2015), who use the random
assignment of bankruptcy judges to establish the causal effects of consumer bankruptcy insurance on
debtor outcomes; Autor et al. (2015), who study the welfare impact of disability benefits in Norway;
and Mueller-Smith (2015), who studies the impacts of incarceration. The original idea to exploit judge
randomization as a causal design can be attributed to Kling (2006).
years of training and on average $15,000/year of extended unemployment insurance (UI) while training. I leverage this assignment as an exogenous source of variation in training take-up to identify the causal effects of TAA in a two stage least squares (2SLS) setting—mapping out differential and dynamic earnings responses using investigator leniency as an instrumental variable.\footnote{While this design is well-equipped to estimate an important adjustment parameter with respect to training, the TAA treatment effect (estimated here using an intent-to-treat framework) should be thought of as just one input into a richer trade model characterizing the full efficiency and distributional consequences of trade liberalization.}

I find evidence of large initial returns to TAA. Workers inferred to take up benefits forego roughly $10,000 in income while training, yet ten years later have approximately $50,000 higher cumulative earnings relative to all-else-equal workers that do not retrain. I estimate that 40\% of these returns are driven by higher wages—a sizable share which suggests that TAA-trained workers are not only compensated through greater labor force participation or higher priority in job queues. Rather, TAA workers also appear to be paid a premium for their newly acquired human capital. But these large relative gains also decay over time. In fact, annual incomes among TAA and non-TAA workers fully converge after ten years. In conjunction with two additional pieces of evidence—that TAA has no effect on formal education, and diminishing returns are restricted to states with low training durations—I attribute this depreciation to short-run demanded skills becoming obsolete (consistent with rapid skill-biased technological change or an overall declining labor share).\footnote{For a discussion of the potential determinants of the declining labor share in the United States, see Autor \textit{et al.} (2017).} Indeed, 62\% of TAA training programs confer vocational degrees with shorter program lengths than typical community college or 4-year college degrees which have been shown to have durable earnings returns \textit{(Card (2001); Kane and Rouse (1995))}. While these results provide strong evidence that overall earnings returns to TAA are largely positive, government intervention in the adjustment process is only warranted economically in the presence of market failures or if redistribution is socially desirable.\footnote{There are arguably other less distorting ways to achieve the latter redistributive goal. See for example recent work by Lyon and Waugh (2017), who consider optimal progressive taxation schemes to redistribute...}
While human capital theory suggests that wage differentials across occupations should provide ample incentives for workers and firms to privately undertake skill upgrading (Becker, 1964), laid off machine operators in Detroit’s automobile sector may face a variety of frictions that prevent them from acquiring productive employment in expanding sectors such as robotics occupations in Pittsburgh’s burgeoning 3D-printing industry. Among several possible barriers to adjustment, these frictions may be spatial or industrial—high mobility costs across labor markets and industries stagnate worker wages in trade-afflicted labor markets (Bartik A., 2017; Yagan, 2014; Kline and Moretti, 2013; Blanchard and Katz, 1992); informational—search costs result in job mismatch after displacement (Moretensen and Pissarides, 1994); financial—liquidity constraints preclude the necessary investments in retraining and education required for work in the modern economy (Lochner and Monge-Naranjo, 2011); or behavioral—workers may be “present-biased” or make forecasting errors about the future viability of their local industries (Augenblick et al., 2015).

To unpack which frictions underlie the main effects (if any), I conduct a variety of empirical tests exploiting the rich heterogeneity of the administrative data to identify potential mechanisms. I find strongest support for spatial and industrial adjustment frictions. Merging county-level Bureau of Labor Statistics (BLS) unemployment rate data to the LEHD panel, I define “high” and “low” shock severity regions based on whether the county in which a TAA-qualified worker was displaced was above or below median unemployment in their quarter of separation. I find that workers in highly disrupted regions are more likely to switch both industries and commuting zones (a now widely used geographic measure of local labor markets) in response to training. Workers are approximately 30 percentage points more likely to move commuting zones and 50 percentage points more likely to switch industries (at the 2-digit North American Industrial Classification System (NAICS) level), with respect to the location and industry of their pre-layoff employer. While not as well identified due to potential selection

the gains from trade.
concerns (but nonetheless supported by common pre-trends), I also present suggestive evidence that positive earnings returns among “movers” drive the overall effects relative to “stayers”.\textsuperscript{10} Lastly, I find no evidence that TAA subsidies lead to deferred job search, which suggests that effects are more likely due to the training itself rather than relieving liquidity or search constraints.

While the paper’s identification strategy provides robust evidence of positive earnings returns and higher mobility associated with TAA, this does not inform us about the cost-effectiveness of the program. Toward this second end, I compare the ten year stream of estimated TAA differential earnings returns as benefits, with average TAA expenditures on training, extended UI, and foregone earnings while training, as costs. I estimate an internal rate of return (IRR) to TAA of between 0.0% and 9.1%, which I interpret as a lower bound for two reasons. First, earnings returns are calculated from an intent-to-treat (ITT) estimator which likely understates benefits due to imperfect compliance with the treatment (i.e. partial take-up of TAA attenuates earnings estimates toward zero and understate the treatment-on-treated (TOT) effect of interest). Second, TAA may induce worker substitution away from other costly social insurance programs such as disability insurance (DI), which would further understate program costs.\textsuperscript{11}

One important caveat however, is that positive earnings returns are estimated from a local average treatment effect (LATE) that does not capture the fact that firms may be incentivized to lay off additional workers after learning of their TAA eligibility status. Nevertheless, back-of-the-envelope calculations show that these are unlikely to outweigh potentially much larger downward pressures.

Overall, this paper provides new quasi-experimental evidence that earnings returns from trade-adjustment targeting via retraining may be larger and more effective than previously

\textsuperscript{10} As is discussed further below, whether a worker switches or stays in their initial commuting zone or industry is defined by their ex-post mobility decisions, which may reflect a self-selected sample that differs along a number of unobservables.

\textsuperscript{11} Autor et al. (2014) find that DI is in fact the predominant margin through which workers adjust to trade shocks.
thought. More work is needed however, to fully understand the extent to which such targeting alleviates aggregate worker adjustment barriers. Despite some noteworthy inefficiencies, TAA may serve as an important tag for redistributing the growth from trade. However, whether these results can be extrapolated to future types of trade and automation pressures remains an open question.

1.2. Expanded Results

The main results of the paper rely on the notion that workers randomly assigned to more lenient investigators receive greater earnings in the long run because they are more likely to be eligible for TAA. This is illustrated in the bottom panel of Figure 1.3.

Using this strategy, the main results of the paper consider the effects of TAA on worker earnings 10 years before being laid off, to 10 years after (including 8 years after retraining for two years). As is seen clearly in Figure 1.4 (with corresponding results in Table 1.3), workers inferred to take up benefits forego roughly $10,000 in income while training for two years, but receive substantial gains after training with respect to all-else-equal workers. Perhaps unexpectedly however, large initial returns decay over time. Annual incomes among TAA and non-TAA workers in fact, fully converge after ten years. Further tests reveal that this pattern is driven by the intensity of human capital, and the speed at which newly demanded skills become obsolete.

The bottom panel of Figure 1.4 implements the same estimation but calculating the dependent variable as within-worker cumulative earnings from $\tau = -10$ to the event year on the x-axis. The results from these cumulative earnings regressions suggest that indeed, effects are being driven by both earnings as well as labor force participation. Furthermore, cumulative earnings have an appealing interpretation. Ten years out, workers have approximately $50,000 higher cumulative earnings relative to all-else equal workers that do not retrain. This pattern is fully stable to using the larger “full” sample which does not only restrict attention to workers that were more highly attached to the labor force.
Figure 1.5 further shows that workers displaced in slacker labor markets (higher unemployment counties) have returns that are almost double those of low unemployment rate counties. Foregone earnings are higher for workers in high-shock regions, which suggests they train for longer. However, the vast majority of workers are located in high-shock counties, which is also evidenced by the summary statistics. I thus interpret the main effects as being driven by high-shock regions, and subsequently examine high and low shocks separately when analyzing mobility effects.

Toward this end, I find that workers in highly disrupted regions are more likely to switch both industries and commuting zones in response to training. Workers are approximately 30 percentage points more likely to move commuting zones and 50 percentage points more likely to switch industries (at the 2-digit North American Industrial Classification System (NAICS) level), with respect to the location and industry of their pre-layoff employer. These are large effects, when compared with baseline mobility rates of 0.26 and 0.23 for commuting zones and 2-digit industries respectively.

1.3. Concluding Remarks

One of the most prominent challenges facing low-income workers in a modern, global labor market, is how labor will adjust to a rapidly changing and increasingly automated economy. Trade-impacted workers have received a large share of this attention, which became particularly visible as a policy issue during the 2016 Presidential Election. While low-income households have benefited tremendously from trade in terms of lower costs of goods, higher variety, and quality of life improvements associated with technological advancement, recent evidence suggests that they have also been persistently negatively affected in terms of earnings and employment outcomes. Despite growing evidence that trade’s disperse benefits also come with concentrated costs, little is known about policy efforts that deliberately target the adjustment process for those most affected by regionally and industrially shocked labor markets. Credible empirical estimates are made difficult by both a lack of detailed worker-level data and confounding factors correlated with
qualifying for adjustment programs—selection biases which generally preclude reliable estimates.

This paper estimates the causal effects of Trade Adjustment Assistance (TAA)—the United States’ largest and longest standing public incentive program for retraining—on worker outcomes, by leveraging quasi-random assignment of TAA cases to investigators of varying approval leniencies. Using employer-employee matched Census data on 300,000 displaced workers, the paper provides evidence of large initial returns to TAA. Workers inferred to take up benefits forego roughly $10,000 in income while training, yet ten years later have approximately $50,000 higher cumulative earnings relative to all-else-equal workers that do not retrain. I estimate that 40% of these returns are driven by higher wages—a sizable share which suggests that TAA-trained workers are not only compensated through greater labor force participation or higher priority in job queues. Rather, TAA workers also appear to be paid a premium for their newly acquired human capital.

But these large relative gains also decay over time. In fact, annual incomes among TAA and non-TAA workers fully converge after ten years. In conjunction with two additional pieces of evidence—that TAA has no effect on formal education, and diminishing returns are restricted to states with low training durations—I attribute this depreciation to short-run demanded skills becoming obsolete (consistent with rapid skill-biased technological change or an overall declining labor share). Indeed, 62% of TAA training programs confer vocational degrees with shorter program lengths than typical community college or 4-year college degrees which have been shown to have durable earnings returns.

I provide suggestive evidence that TAA-trained workers were previously bound by adjustment frictions. However, one limitation to the study is that I do not identify whether TAA is effectively expanding a feasible job match radius for its participants, or instead alleviating other frictions, which may include worker present-bias, household liquidity constraints, and other hypotheses. If in fact these workers are facing trade shocks which
are spatially correlated (and industrially concentrated if sufficiently agglomerated in those regions), this might also explain why earnings returns are especially strong among movers.

Lastly, a cost-benefit analysis produces a conservative internal rate of return (IRR) on TAA between 0.0% and 9.1%. Despite this being a relatively low IRR, policymakers may still consider the efficiency costs associated with TAA investments a worthwhile trade-off as a redistributive policy toward this sub-population. This would be especially true if there were either other externalities associated with TAA training, or current social insurance programs were shown to be insufficient for these workers.

One outstanding and related puzzle is if labor markets signal high private returns to human capital investments such as TAA training, and this study confirms those high returns, then why are take-up rates so persistently low? Future work will need to explain this puzzle, and further examine whether the results from this paper are relevant to other types of labor market pressures such as automation.
Figure 1.1: Manufacturing Employment and Real Output

NOTES—This figure shows seasonally adjusted data from the Bureau of Labor Statistics (BLS), retrieved from FRED, Federal Reserve Bank of St. Louis. The solid line plots monthly US workers employed in manufacturing industries (BLS Current Employment Statistics, CES3000000001). The dashed line shows a quarterly index of nonfarm business sector real output (BLS Labor productivity and Costs) where 2009q1=100. In a similar figure, Pierce and Schott (2016) show the upward pattern in output persists for manufacturing sector value added, which suggests falling labor intensity drives the decline rather than secular stagnation. Source: BLS (2017)
NOTES—These maps show the cumulative number of TAA filers by 1990 commuting zone (geographies taken from Dorn (2009)). The top sample reflects the universe of TAA filers from 1974 to 2016. The bottom sample displays all filers in 24 LEHD-approved states from 1990 to 2011, forming the basis of the matched analysis sample. Both maps display cumulative numbers by quintile. See Appendix 1.B.6 for a population-weighted version of the same maps. Source: DOL (OTAA) petition database attained via FOIA request
Figure 1.3: Displaced Worker Earnings, naive Difference-in-Differences (Top) versus Leniency IV “Reduced Form” (Bottom)

NOTES—These plots show locally smoothed polynomial regressions of annual earnings before and after worker separation (with 10% confidence intervals for exposition). Unconditional means are estimated for the main analysis sample: working-age individuals (22-65) with 2 years of positive earnings above the annual minimum wage equivalent prior to filing ($7.25 * 2,082 average working hours in 2010 ≈ $15,000), earning less than $50,000 annually in the pre-period. Monetary variables are deflated to 2010 US dollars, seasonally adjusted, and winsorized at 1% to limit outliers. Leniency quartiles (bottom panel) are calculated across 250 investigators. 25th and 75th percentiles correspond to approval rates of 0.56 and 0.79 respectively. Source: LEHD; DOL
Figure 1.4: Dynamic Effects of TAA on Worker Earnings

NOTES—These plots show the main 2SLS coefficient estimates of the effects of TAA on annual earnings (top) and within-worker cumulative earnings (bottom), dynamically across event years relative to the TAA petition decision ($\tau = 0$). Each point estimate is from a separate cross-sectional regression by event year. Cumulative earnings are summed from $\tau = -10$ to the event year on the x-axis. Vertical lines partition the support into pre-TAA, during-TAA, and post-TAA periods. Sample restrictions and variable definitions are identical to those described in Table 1.5, column 6 (the paper’s preferred earnings specification). Dotted lines represent 90% confidence intervals with standard errors clustered at the investigator level. Source: LEHD; DOL

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NOTES—This figure shows two series of 2SLS estimates, corresponding to each $\beta_1$ and $\beta_2$ of equation (5) of the draft. Coefficients reflect workers displaced in high (top) and low (bottom) initial unemployment rate regions. Each point estimate is from a separate regression by event year, showing the effects of TAA on worker earnings by high and low training duration in the state and year in which the worker was laid off. “High” and “Low” are defined relative to median training duration, which is calculated for each quarter across states using TAA performance data from 2001 to 2016 (training duration data are not available prior to 2001). Vertical lines partition the pre-TAA, during-TAA, and post-TAA periods. Besides the data constraint from limited performance data, sample restrictions and variable definitions are identical to those described in Table 1.5, column 6. Dotted lines represent 90% confidence intervals with standard errors clustered at the investigator level. Source: LEHD; BLS Local Area Unemployment Statistics (LAUS)
Table 1.1: Location of Top 10 “Trade Displaced” TAA Zip Codes

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Flint, MI</td>
<td>Seattle, WA</td>
<td>Los Angeles, CA</td>
<td>Fremont, CA</td>
</tr>
<tr>
<td>2.</td>
<td>Detroit, MI (a)</td>
<td>Fort Worth, TX</td>
<td>Seattle, WA</td>
<td>Detroit, MI</td>
</tr>
<tr>
<td>3.</td>
<td>Detroit, MI (b)</td>
<td>Houston, TX</td>
<td>East Chicago, IN</td>
<td>Nashville, TN</td>
</tr>
<tr>
<td>4.</td>
<td>Detroit, MI (c)</td>
<td>Linden, NJ</td>
<td>Long Beach, CA</td>
<td>St. Louis, MI</td>
</tr>
<tr>
<td>5.</td>
<td>Detroit, MI (d)</td>
<td>Flint, MI</td>
<td>San Jose, CA</td>
<td>Wichita, KS</td>
</tr>
<tr>
<td>6.</td>
<td>Detroit, MI (e)</td>
<td>Los Angeles, CA</td>
<td>Scranton, PA</td>
<td>Dayton, OH</td>
</tr>
<tr>
<td>7.</td>
<td>Saginaw, MI</td>
<td>Houston, TX</td>
<td>Washington, NC</td>
<td>Warren, OH</td>
</tr>
<tr>
<td>8.</td>
<td>Dayton, OH</td>
<td>Milwaukee, WI</td>
<td>New York, NY</td>
<td>Wilmington, OH</td>
</tr>
<tr>
<td>9.</td>
<td>Kokomo, IN</td>
<td>Toledo, OH</td>
<td>Dallas, TX</td>
<td>Los Angeles, CA</td>
</tr>
<tr>
<td>10.</td>
<td>Ann Arbor, MI</td>
<td>Framingham, MA</td>
<td>Seattle, WA</td>
<td>Detroit, MI</td>
</tr>
</tbody>
</table>

**Affected Industries (Mode)**
- Motor Vehicles, Parts, Accessories
- Oil & Gas Extract., Exploration, Aircraft, Textiles
- Electronics, Aircraft, Computers
- Pharmaceuticals

NOTES—This table reports the locations of the top ten “trade-displaced” zip codes as calculated from Department of Labor estimates of the total number of workers eligible for TAA, as associated with filed TAA petitions at the plant level. The reported industry reflects the qualitative description associated with the top three to five modal industries in the same decade using standard industrial classification (SIC) codes ascribed to petitions by case investigators. Source: DOL (OTAA) petition database attained via FOIA request
### Table 1.2: Descriptive Statistics for TAA Approved and Denied Workers

<table>
<thead>
<tr>
<th></th>
<th>High Labor Force Attachment</th>
<th>High &amp; Low Labor Force Attachment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TAA Approved</td>
<td>TAA Denied</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>A. Worker Demographics (LEHD)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (time of filing)</td>
<td>43.91 (10.93)</td>
<td>43.08 (11.09)</td>
</tr>
<tr>
<td>Female</td>
<td>0.54 (0.50)</td>
<td>0.53 (0.50)</td>
</tr>
<tr>
<td>Black</td>
<td>0.11 (0.32)</td>
<td>0.13 (0.33)</td>
</tr>
<tr>
<td>White</td>
<td>0.80 (0.40)</td>
<td>0.80 (0.40)</td>
</tr>
<tr>
<td>High School Degree</td>
<td>0.39 (0.49)</td>
<td>0.37 (0.48)</td>
</tr>
<tr>
<td>Some College</td>
<td>0.29 (0.45)</td>
<td>0.31 (0.46)</td>
</tr>
<tr>
<td>College Degree and Above</td>
<td>0.11 (0.31)</td>
<td>0.14 (0.35)</td>
</tr>
<tr>
<td>B. Worker Economic Variables (LEHD)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quarters Employed</td>
<td>3.21 (1.28)</td>
<td>3.14 (1.33)</td>
</tr>
<tr>
<td>Quarters Employed (full-time equivalence)</td>
<td>2.77 (1.54)</td>
<td>2.71 (1.57)</td>
</tr>
<tr>
<td>Employed</td>
<td>0.79 (0.40)</td>
<td>0.76 (0.43)</td>
</tr>
<tr>
<td># of Jobs / Year</td>
<td>4.90 (3.71)</td>
<td>3.87 (3.24)</td>
</tr>
<tr>
<td>Tenure (years at separation)</td>
<td>23.197 (5.628)</td>
<td>23.216 (5.596)</td>
</tr>
<tr>
<td>Prob(Employed at Petitioner Firm)</td>
<td>0.66 (0.47)</td>
<td>0.66 (0.47)</td>
</tr>
<tr>
<td>Prob(Employed at Petitioner 2-Digit NAICS)</td>
<td>0.7 (0.46)</td>
<td>0.71 (0.45)</td>
</tr>
<tr>
<td>Prob(Employed in Petitioner Commuting Zone)</td>
<td>0.69 (0.46)</td>
<td>0.72 (0.45)</td>
</tr>
<tr>
<td>C. Petitioner Characteristics (DOL)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Company Filer</td>
<td>0.40 (0.49)</td>
<td>0.10 (0.3)</td>
</tr>
<tr>
<td>Union Filer</td>
<td>0.14 (0.34)</td>
<td>0.19 (0.39)</td>
</tr>
<tr>
<td>Worker-Group Filer</td>
<td>0.37 (0.48)</td>
<td>0.63 (0.48)</td>
</tr>
<tr>
<td>Investigator Caseload (no. of petitions)</td>
<td>22.83 (18.25)</td>
<td>22.27 (16.21)</td>
</tr>
<tr>
<td>Investigator Tenure (decades)</td>
<td>0.979 (0.942)</td>
<td>1.02 (0.95)</td>
</tr>
<tr>
<td>Prob(Tradable) (Mian &amp; Sufi, 2011)</td>
<td>0.64 (0.48)</td>
<td>0.51 (0.50)</td>
</tr>
<tr>
<td>Offshorability Z-Score (Blinder, 2007)</td>
<td>0.29 (0.84)</td>
<td>0.09 (1.23)</td>
</tr>
<tr>
<td>Offshorability Z-Score (Autor &amp; Dorn, 2013)</td>
<td>0.23 (0.86)</td>
<td>0.27 (0.79)</td>
</tr>
<tr>
<td>Number of Petitioners</td>
<td>~3,100</td>
<td>~1,300</td>
</tr>
<tr>
<td>Number of Displaced Workers</td>
<td>~123,000</td>
<td>~54,000</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>~1,811,000</td>
<td>~810,000</td>
</tr>
</tbody>
</table>

NOTES—This table reports means and standard deviations for approved and denied TAA petitioners, pooled across all periods (pre, during, and post-TAA). Both samples are restricted to working-age individuals (22-65) making less than $50,000 annually in the pre-period, and restricted to first-time filers. The “High Attachment” sample requires 2 years of positive earnings above the annual minimum wage equivalent prior to filing ($7.25 * 2,082 average working hours in 2010 ≈ $15,000). Monetary variables are deflated to 2010 US dollars, seasonally adjusted, and winsorized at the 1% level to limit the influence of outliers. Both samples contain 250 unique case investigators (rounded for confidentiality). See text for variable descriptions. Source: LEHD, DOL
Table 1.3: Pooled Effects of TAA on Annual Earnings ($)

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>2SLS</th>
<th>2SLS</th>
<th>2SLS</th>
<th>2SLS</th>
<th>2SLS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td><strong>A. Post-Training</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1(TAA Approved)</td>
<td>-963.8***</td>
<td>14,474.4*</td>
<td>14,335.4*</td>
<td>14,812.3*</td>
<td>13,112.8**</td>
<td>10,255.9**</td>
</tr>
<tr>
<td></td>
<td>(250.2)</td>
<td>(8211.1)</td>
<td>(8449.8)</td>
<td>(8383)</td>
<td>(6432.3)</td>
<td>(5086.7)</td>
</tr>
<tr>
<td><strong>B. Pre-Training [Placebo]</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1(TAA Approved)</td>
<td>-150.9</td>
<td>405.4</td>
<td>313.1</td>
<td>169.2</td>
<td>266.9</td>
<td>333.8</td>
</tr>
<tr>
<td></td>
<td>(246.7)</td>
<td>(480.1)</td>
<td>(499.8)</td>
<td>(514.2)</td>
<td>(677.8)</td>
<td>(660.1)</td>
</tr>
</tbody>
</table>

Identification Controls:
- Filer Industry FEs (4-digit SIC) yes yes yes yes yes yes
- Investigator Concentration Controls yes yes yes yes yes yes

Precision Controls:
- Calendar Year & Filer Quarter FEs yes yes yes yes yes yes
- Baseline Controls yes yes yes yes yes yes
- Filer Type & NAFTA-TAA FEs yes yes yes yes yes yes
- Filer State FEs yes yes yes
- Demographic Controls yes

Number of Petitioners ~4,300 ~4,300 ~4,300 ~4,300 ~4,300 ~4,300
Number of Workers ~177,000 ~177,000 ~177,000 ~177,000 ~177,000 ~177,000
Number of Observations (All Periods) ~2,623,000 ~2,623,000 ~2,623,000 ~2,623,000 ~2,623,000 ~2,623,000

NOTES—This table reports the main effects of TAA on annual earnings, pooled in the “post” and “pre” periods separately such that each column presents two regression coefficients. Each specification corresponds to equation (2) of the paper for the “High Attachment” sample, which includes working-age individuals (22-65) making under $50,000 annually in the pre-period, with 2 years above the annual minimum wage equivalent prior to filing ($7.25 * 2,082 average working hours in 2010 ≈ $15,000). Baseline Controls include means over 5 to 40 quarters prior to the TAA petition decision for the following variables: worker earnings, quarters employed, worker tenure, and initial employer and state earnings. Demographic Controls include: race and gender fixed effects, a cubic in age fully interacted with baseline earnings and gender indicators. Filer-type fixed effects indicate whether a petition was filed by a company, union, worker-group, or career center (omitted). NAFTA-TAA is a dummy variable for whether a petition applied as part of the NAFTA-TAA program (see text). Monetary variables are deflated to 2010 US dollars, seasonally adjusted, and winsorized at the 1% level to limit the influence of outliers. Standard errors (in parentheses) are clustered at the investigator level. ***p<0.01, **p<0.05, *p<0.10. Source: LEHD, DOL.


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