Gender Inequality in the Aftermath of Negative Trade Shocks: Evidence from the U.S.

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Abstract

We study the differential post-layoff responses in labor market outcomes for men vs. women when unemployment is caused by international trade. Our paper is the first to capitalize on the richness and unique design of the U.S. Trade Act Participant Report database (in combination with the Petition for Trade Adjustment Assistance dataset) to analyze gender differentials in wages and employment. The analysis identifies trade-affected workers as an overlooked and vulnerable group with very pronounced gender gaps in earnings. Three main results stand out from our estimates. First, the pre-layoff wage gap between men and women who have lost their jobs due to trade is very wide; a 30% premium for men, even after controlling for education, experience, race, and other demographic characteristics. Second, the success rate in finding employment for women who have been laid off because of trade is not significantly lower as compared to men, however we do observe significant differences across some states and some sectors. Third, the pre-layoff wage premium for men is completely eliminated upon re-employment. However, we attribute this result to wage compression. Finally, our data enable us to document a series of gender-related outcomes across demographic characteristics, retraining choices, geography, and sectors.

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"Women's participation in the labour force has increased in most regions of the world; [...] and there are signs of a narrowing of the wage gap between men and women in many countries [...] Against this background, the forces of globalization, of which international trade is one of the most important channels, may bring additional challenges and opportunities. [...] There is therefore a need to assess the impact of trade on gender equality in order to assist countries in designing appropriate strategies and policies to support the objective of gender equality in the context of an open multilateral trading system."

Rubens Ricupero, Secretary-General of UNCTAD,
Angela E.V. King, Special Adviser to the UN Secretary-General
on Gender Issues and the Advancement of Women
UNCTAD (2012)

1 Introduction

Gender differentials in the labor market have been of significant interest to academics and policy makers alike for a long time, cf. Altonji and Blank 1999, Blau and Kahn 2000, and Bertrand 2011. Traditionally, most of the focus in both the scholarly literature and in policy making has been on the inequality between men and women at the national level. However, as motivated by the opening quote, owing to strong globalization and integration forces, gender inequality has become an international phenomenon.

International organizations, such as the United Nations (UN), the World Bank, the World Trade Organization (WTO), and the Organization for Economic Cooperation and Development (OECD), have paved the way to recognizing the link between international trade and gender inequality. In an effort to promote women empowerment and the development of women in a global environment, at various points of time each of these institutions has established dedicated units and special task forces.[1] In addition, these organizations have held a series of joint events (seminars, discussions, panels, etc.) that emphasize the importance of trade openness for gender equality. Most recently, "[o]n September 28th, [2016], Special Representative to the UN and WTO, Jos Verbeek participated in a panel discussion on Women's

[1] For example, in 2003 the United Nations' Inter-Agency Network on Women and Gender Equality created a task force on gender and trade. In 2010, the OECD launched a Gender Initiative to promote gender equality and developed a Gender Data Browser with gender gap indicators in OECD countries and key non-OECD countries.

Economic Empowerment and Trade at the WTO Public Forum. The debate, which used the Secretary General's High Level Panel on Women's Economic Empowerment as background discussion, argued that *women's economic empowerment can be achieved through improved access to trade.*"[2]

The issue of gender equality has also been addressed directly and more prominently in recent trade policy negotiations, and it has been covered by special clauses and chapters in most of the modern regional trade agreements (RTAs). For example, the Comprehensive Economic and Trade Agreement (CETA) between Canada and the European Union explicitly states that "A Party breaches the obligation of fair and equitable treatment [...] if a measure or series of measures constitutes [...] targeted discrimination on manifestly wrongful grounds, *such as gender*, race or religious belief;" (Article 8.10, CETA, emphasis added by authors). Similar statements that specifically target various dimensions of possible discrimination, including gender, can be found in the provisions of other major initiatives to form regional trade agreements such as the Trans-Pacific Partnership (TPP) and the Transatlantic Trade and Investment Partnership (TTIP).

Despite such notable and intensified efforts, the question of whether and how international trade affects gender inequality is still largely unanswered and, mainly due to lack of appropriate data, most of the empirical evidence on the links between international trade and gender inequality is anecdotal. We contribute to this question by focusing on trade-induced layoffs, comprising an overlooked and vulnerable group of workers. To that end, we capitalize on the unique design and rich multi-dimensional coverage of the Trade Act Participant Report (TAPR) and the Petition for Trade Adjustment Assistance (PTAA) databases,[3] which

[2]The emphasis in this quote have been added by the authors. The original source of the quote is http://www.worldbank.org/en/events/2016/10/18/world-bank-group-on-women-economic-empowerment-and-trade.

[3]The PTAA and the TAPR database are constructed and maintained by the Employment and Training Administration of the U.S. Department of Labor (DoL). The PTAA data contain information on all petitions for Trade Adjustment Assistance (TAA) in the United States, while the TAPR dataset contains information on all participants who were certified as affected by trade by the U.S. government and who entered the TAA program. In sections 3 and 3.2 we offer a review of the TAA program as well as detailed descriptions of the PTAA and the TAPR databases.

enable us to assess a series of post-layoff labor market outcomes for men and women when those layoffs were caused by international trade during the period 1999-2005.[4] We identify pronounced gender gaps in earnings of the workers who have been laid off due to trade, thus, pointing to an additional and important dimension of income and gender inequality that has to be considered by policy makers in trade negotiations and beyond.

Three main results stand out from our analysis. First, we focus on the gender differences in earnings for those men and women who were laid off because of international trade. One of the most important findings of our analysis is that, on average, U.S. women who lost their jobs because of trade earned about 30% less than similar men, and this finding is statistically significant at the 1% level. This is a substantial gap, especially given that it is obtained after controlling for a series of demographic factors (e.g. education, race, experience, etc.) that have been used to explain gender differentials in earnings. This result is in contrast with the findings from a series of influential studies, e.g. Blau and Kahn 2006, Blau and Kahn 2007, and Goldin 2014 that demonstrate that, on average, the wage gap between men and women in the U.S. has steadily decreased in the 80s and the 90s to reach rates of about 20% in the early 2000s. While the estimates from the above-mentioned studies are obtained for the U.S. population as a whole, an important implication of our findings is that the negative impact of international trade in the U.S. has fallen on a vulnerable group of disadvantaged women, who, therefore, deserve special attention from policy makers.

Stimulated by the large average gap in earnings between men and women in our sample, we further investigate the corresponding differences across states and across 2-digit SIC manufacturing sectors. At the state level, we consistently observe significant wage premiums for men, which vary widely across states. The wage gap is most pronounced in the southern states of Alabama (52.5%), Missouri (48%), South Carolina (48%), Mississippi (46%), and in the more sparsely populated states like Arizona (48%), Nevada (45%), and South Dakota

[4] In addition to the specific features of the databases that we employ, the time period 1999-2005 is of separate importance because it immediately predates and overlaps with the "China Shock", cf. Autor, Dorn, and Hanson 2013, covers the first five years of the boom in Chinese exports to the United States, and ends before the hit of the financial crises.

(43%). On the opposite side of the spectrum, the difference in pay between men and women is the least in New York (25%), Oregon (25%), New Jersey (26%), Maryland (29%), Montana (30%), and California (30%). A possible explanation for this positive result in some of these states is that they specialize in high-tech manufacturing production. Turning to the variation of gender differentials across sectors, we (once again) find that men within U.S. manufacturing enjoy significant wage premiums, which vary across sectors. The gender wage gap is most pronounced in *Petroleum and Coal Products* (45%) and *Rubber Products* (34%), and it is the smallest in *Lumber and Wood Products* (11%), *Furniture and Fixtures* (17%), and *Fabricated Metal Products* (19%).

Our second main focus is on re-employment, and to obtain our results on that front we estimate a probit model for the likelihood that an individual who lost his/her job due to international trade is employed after his/her participation in the TAA program. Overall, we find that, on average, women with the benchmark characteristics are equally likely to be re-employed after the Trade Adjustment Assistance (TAA) program as compared to men. We do obtain positive and marginally significant effects in re-employment probability for women in most manufacturing sectors. However, without any exception, all sectoral estimates that we obtain in favor of women are very small in terms of economic magnitude, ranging from 0.36% in Chemical and Allied Products to 0.49% Petroleum and Coal Products and in Transportation Equipment. We also document a similar pattern in terms of probability of re-employment across states. In our sample, we observe significant differential effects of re-employment probability between men and women only for six states. The probability of re-employment for women is higher in Indiana (4.6%), Minnesota (8.3%), Ohio (4.1%) and Oklahoma (4.5%), while it is lower in Kentucky (-6.4%) and New York (-3.7%). Combined with the corresponding insignificant sectoral estimates, the variation in our estimates across states points to the influence (or lack) of state-specific policies.

Our third main result is that the earnings gap between men and women disappears after they participate in the TAA program and find new jobs. Unfortunately, while seemingly positive and encouraging, this result should be interpreted conditional on the fact that, on average, both men and women accept significant wage cuts when re-employed after being laid off due to trade. Thus, the explanation for our finding of disappearing earning differential is most probably a more pronounced downward wage compression for men rather than an upward trend in women's wages relative to men's wages. This argument is supported by the fact that the average pre-layoff quarterly earnings for men and for women who have been laid off due to trade are \$9,310 and \$5,981, respectively, while the corresponding post layoff quarterly earnings for these groups are \$6,939 and \$4,781, respectively if employed and \$6,662 and \$4,605 respectively for the entire sample. A series of sensitivity experiments, including controlling for sample selection bias, confirm the robustness of our main findings.

In addition to the three main results from our analysis, we document the following gender-related findings with respect to demographics. First, focusing on re-employment, the impact of each additional year of education for being re-employed is the same for women as it is for men. However the impact of each additional year of experience on re-employment probability is slightly higher for women as compared to men. Second, with respect to wage differentials, more experienced women earned less as compared to more experienced men, while Black women, Asian women, and women who are veterans earned more as compared to their male counterparts. Third, with respect to retraining effectiveness, provision of training, provision of trade readjustment allowance during the program were effective in increasing both the probability of re-employment and the wages for women relative to men. Conversely we also find that some TAA program characteristics like travel during training had an adverse effect on women's wages relative to men.

The rest of the paper is organized as follows. Section 2 offers a review of the related literature. Section 3 describes the design and implementation of the TAA program in the United States and the data sets that we will employ, and it sets the stage for the main analysis by pointing to the questions that we will be able to address and to possible limitations in our analysis. Section 4 motivates and presents our main econometric specifications. Section

5 offers our main findings and interprets them in relation to the existing literature. Section 6 concludes with a summary of our results and possible directions for future work.

2 Related Literature

Our paper is related to several distinct strands of the literature. First, by focusing on gender inequality for women and men laid off due to international trade, we contribute to a relatively small literature that studies the impact of trade on gender labor market differentials. Black and Brainerd 2004 use changes in import competition in differently concentrated industries to study the effect on the gender wage gap and find that initially more concentrated industries see stronger declines in the gender wage gap. Ben Yahmed 2012 develops a theoretical model where trade openness reduces the gender wage gap among unskilled workers but increases the gender wage gap among high-skilled workers. Juhn, Ujhelyi, and Villegas-Sanchez 2014 extend the heterogeneous firms model of Melitz 2003 to develop a model where the relative wage and employment of women improves in blue-collar tasks, but not in white-collar tasks. They find support for the predictions of their model in a panel of establishment level data from Mexico exploiting the tariff reductions associated with the North American Free Trade Agreement (NAFTA). Our main contribution to this literature is threefold. First, we focus on the relationship between trade and gender inequality in the United States as a representative developed economy.[5] Second, a unique advantage of our databases is that they directly identify trade-induced layoffs for both men and women. Third, on a related note, our data are at the individual level and trace the evolution of a series of labor market outcomes

[5] There are two main reasons for the focus on gender inequality in the developed world. First, the gender gap, in terms of economic outcomes, in poorer and less developed nations is much more pronounced. Second, data to study the issues of gender equality are more widely available for developing countries. We refer the reader to UNCTAD 2004 for an informative survey to topics related to the link between trade and gender inequality in the developing world. We are aware of only one paper that studies the link between trade and gender outcomes in a developed nation; Boler, Javorcik, and Ulltveit-Moe 2015 develop a model in which exporters discriminate against female employees as they are exposed to higher competition and therefore require greater commitment and flexibility from their employees. The observable outcome is a higher gender wage gap for exporters compared to non-exporters. They find evidence for their mechanism using Norwegian matched employer-employee data.

for all men and women who have been negatively affected by trade during the period of investigation. These features of our data allow us to directly address unique questions that have not been answered by previous studies.

Our analysis is also related to the extensive literature on trade and labor market outcomes. Some representative studies include Goldberg and Pavcnik 2007, Helpman, Itskhoki, and Redding 2010, Dinopoulos, Syropoulos, Xu, and Yotov 2011, Amiti and Davis 2012, Autor, Dorn, and Hanson 2013 and Helpman, Itskhoki, Muendler, and Redding 2017. The common feature across these studies is that they all investigate the effect of trade liberalization on wages, wage inequality and employment from the perspective of skills. The contribution of our analysis in relation to this strand of the literature is the specific focus on gender inequality outcomes. Thus, we complement the extensive literature that is concerned with inequality due to changes in the skill premium by focusing on the impact of trade on inequality via changes in gender premium. We believe that in combination with the structural analysis at the firm level, the rich TAPR and PTAA databases can be employed to generate a series of novel insights. This brings us to a brief discussion of the last branch of the literature to which our work is related to.

From a broader perspective, our work is related to the prominent literature on the economic aspects of gender inequality. Notable surveys that summarize the major developments and the evolution of this strand of the literature over time include Altonji and Blank 1999, Blau and Kahn 2000, Bertrand 2011 and OECD 2012. Our analysis borrows and applies the established econometric methods from the labor literature on gender inequality and we relate our findings to the results from this literature. However, our contribution on that front is that we study the specific impact of negative trade shocks on several economic outcomes related to gender inequality by employing unique and rich datasets that enable us to answer a series of questions about the links between trade and income inequality for workers laid-off due to international trade and thus offer novel insights to the broader gender inequality literature.

Within the broad literature on the economic aspects of gender inequality, our paper is related to a subset of papers that trace the evolution and study the determinants of the gender earnings inequality within the United States. Notable papers in this area include Blau and Kahn 2006, Blau and Kahn 2007, and Goldin 2014. As briefly summarized earlier, a common finding of these influential papers is that they all document a trend of earnings convergence between men and women in the U.S. during the 1980s and 1990s. Our contribution in relation to these studies is that we find that the earnings gap is quite pronounced among the men and women in U.S. manufacturing who have been laid-off due to international trade.

Finally, our paper is related to a small literature that has taken advantage of the rich PTAA and TAPR databases. Several papers use the PTAA database to study the impact of trade on labor market outcomes.[6] Park 2012 and Kosteas and Park 2017 use the PTAA and TAPR datasets to study occupational outcomes. Kondo 2013 employs the PTAA data to investigate the effects of trade on labor market outcomes across different geographic locations, while Uysal, Yotov, and Zylkin 2015 studies the determinants of trade-induced layoffs in a setting with heterogeneous firms *a la* Melitz 2003. Finally, Monarch, Park, and Sivadasan 2014 combine the PTAA dataset with firm-level U.S. data to study how offshoring affects firm-level outcomes. The novelty of our analysis in relation to these studies is that none of them have used the gender dimension of the PTAA and the TAPR databases to study the links between trade and gender inequality.

3 TAA: Program Design and Data Collection

The objective of this section is twofold. First, we describe the process and implementation of the Trade Adjustment Assistance program in the United States. In addition, we introduce

[6] Few other papers have utilized the PTAA and TAPR datasets. Magee 1997, Magee 2001, and Laincz, Matschke, and Yotov 2016 that use the PTAA database to study the determinants of TAA certification outcomes. The papers by Magee focus on economic variables, while Laincz, Matschke, and Yotov 2016 use political determinants of TAA certification. Yotov 2010; Yotov 2013 use both the PTAA and the TAPR database to construct trade-induced unemployment variables and retraining cost variables, which appear as additional determinants of trade protection patterns in a protection-for-sale framework in the spirit of Grossman and Helpman 1994.

the PTAA and the TAPR databases, which are combined here to deliver the main dataset for our analysis.

3.1 Program Design and Implementation

Trade Adjustment Assistance (TAA) is a program for dislocated workers that was created by the Trade Act of 1974, and it is administered by the Department of Labor (DOL). In a nutshell, the TAA program is intended to help workers find re-employment who have lost their jobs due to various trade related reasons.[7] In order to ease the exposition in this section, Figure 1 offers a timeline of the steps associated with the TAA program for a representative participant from the time of layoff to the time of re-employment. The top panel of Figure 1 highlights the program design and implementation while the bottom panel describes the data that we obtain from the TAA and TAPR databases at different points in time.

When layoffs take place, workers themselves or any representing entity (company, union or state) may file a petition for that plant on the condition that three or more workers were subject to this layoff. The petition filing process is straightforward, and it requires the petitioner to fill out a two-page form with basic information about the employer including name and address, reason of layoff and the separation dates of the three or more workers listed on the form. The TAA petition may be faxed/mailed at practically no cost within a year from the separation date.

It is reasonable to believe that all firms and workers who have been affected by trade would apply for TAA, because the filing process is easy and the petitions are "practically free". However, it is also likely that the costless nature of filing the petition would encourage workers who were laid off due to non-trade reasons to also apply for TAA benefits. In order to ensure that TAA is granted only to those affected by trade, upon filing each petition is assigned an investigator from the United States DOL to conduct interviews at the petitioning plant and identify the actual reason of layoff. A "trade-related layoff" certification is granted

[7] Starting in 2002, the TAA program started classifying petitions into three groups: i) offshoring events, ii) import-competition events and iii) denied petitions.

if the investigators conclude that the reason behind the job loss is either replacement of in-house tasks with imported tasks, increase in imports of the plant's product at the aggregate level, or loss of business as an upstream supplier or downstream producer for the firm(s) that is (are) TAA certified.

Once certified, all workers who were laid off from that plant between the initial layoffs and two years from the impact date are eligible for various benefits mentioned under the TAA program. The most important benefits provided by the TAA program are training and income support. If the career counseling services determine that a TAA participant does not possess the necessary skills for re-employment, he/she may enroll in occupational skills training for a maximum period of 104 weeks. While enrolled in training, TAA participants are entitled to different types of income support including subsistence allowance, (basic and additional) Trade Readjustment Allowances (TRAs), job search allowance, and relocation allowance. Training is however voluntary. Participants may obtain a training waiver under which they are entitled to basic TRA for 26 weeks. A waiver is issued if the participant does not need training due to inherent possession of marketable skills or due to health related reasons.

3.2 PTAA and TAPR: Description and Key Variables

Both of the datasets that we employ are constructed and maintained by the U.S. Department of Labor. The main dataset for our analysis is TAPR. We use the 2002 through 2006 waves of the TAPR data, which contain information on every certified TAA participant starting from 1999 to 2005. The TAPR data are acquired through a Freedom of Information Act primarily and consist of three sections. Using the section on *Individual Information*, we construct demographic and human capital characteristics of individuals including potential experience (in years since leaving full-time schooling),[8] education (in years)[9] gender (whether the person

[8] We keep individuals who are born after 1910 and before 1987.

[9] To create a continuous measure of education, we use the information on the schooling grade provided in the TAPR data. Specifically, if the reported grade is less than 17, we assign the educational level to be equal

is female), and whether the person is Spanish. Having information about an individual's age and education, we calculate an individual's potential experience as time (in years) after leaving full-time schooling (i.e., age − education − 6). Further, we construct a set of racial indicators for whether the person is black, Native American, or Hawaiian (keeping white individuals as an excluded base category).[10] We also construct indicators for whether the person is a veteran and if he/she has limited proficiency in English language.

Next, using the TAPR section on *Services and Activities*, we create a set of individuals' characteristics that describe their participation in the TAA program. Specifically, we create indicators for whether the person received any training, whether training was completed, whether the person received a waiver from training, and whether he/she traveled while in training. We also construct indicators for whether the person received a subsistence allowance while in training, any TRA, and a jobs search allowance. In addition, we create variables that contain information on training duration (in days) and program duration (in days) for each individual. Using data on individual information and worker activities prior to and during the TAA program allows us to construct a set of potential controls for use in our econometric analysis.

Finally, we use the *Outcomes* section of the TAPR dataset to construct an indicator for whether the person is fully employed during the entire length of the third quarter after his/her participation in the TAA program. We also create a variable containing his/her (pre- and post-TAA participation) total quarterly earnings. Specifically, we create an individual's total quarterly earnings in the third full quarter before his/her job loss and the third full quarter after exiting the TAA program which differentiated by gender is one of our main variables of interest representing the post-trade effect of gender wage gap. We keep observations with

to the number of school grades completed. If grade is recorded as 87, 88 or 89, we assign the education level to 12 years, implying completion of 12 years of schooling, which is consistent with the variable definitions provided in the TAPR documentation. Similarly, if the recorded grade is 90 or 91, we assign the educational level to be 13 and 14 years, respectively.

[10]To have clear definitions of all the racial and ethnic groups and not to make potentially erroneous decisions on how to classify multiracial/multiethnic people, we exclude 550 individuals who are multiracial/multiethnic from our sample. Keeping multiracial/multiracial people in the sample as a separate group does not affect the estimation results qualitatively (the estimation results are available upon request).

earnings more than $1 but less than $300,000. Table 1 contains the names, types and brief definitions of all the variable that we construct using the TAPR data and then employ in our analysis.

The TAPR data set alone does not provide any information on the location or industry of the workers. It only provides individual data of those workers who were certified to be laid off because of a trade shock. This prevents us from knowing the detailed industry and location of the workers which might be crucial as some states and industries were hit more by import competition from China, for example, and hence experienced higher job losses. However, information on the industry and location of the firms who had to lay off workers because of trade is available in the PTAA database. In particular, the PTAA data provides a firm identifier and name, detailed 4-digit Standard Industrial Classification (SIC) code for the firm's main product industry, geographical information including state and zip code, the exact date when the petition was filed, the dates on which investigation was started and also when the DOL reached a determination on the case. Finally, it provides a government certified firm level measure of estimated workers threatened with total or partial separation due to trade.

In order to take advantage of the additional information contained in the PTAA database, we merge these data with the individual-level data from TAPR database using a unique TAA firm petition number, which is common across the two datasets. The result is a combined database that includes information on the type of workers according to their gender, ethnicity, earnings and distribution of firms according to their industry classification and geographical location affected due to trade-related reasons. Using the PTAA part of our merged database, we construct indicators for the states, where individuals are located in, as well as indicators for the industries, where individuals worked before they lost their jobs due to international trade.

In our final sample, we exclude the state of Hawaii as there is only one observation in this state in our sample.[11] We also exclude observations with missing industrial classification, which would prevent us from controlling for sector fixed effects later in the analysis. Our analysis is conducted using the SIC industrial classification by focusing mainly on manufacturing industries. In the SIC classification, the starting digit of a manufacturing industry is either "2" or "3".[12] Summary statistics for the key variables that we employ in our analysis are presented in Table 2 for both the pre-trade induced unemployment period (Before, columns (1)-(4)) and the post-TAA period (After, columns (5)-(12)).

Note that that the number of individuals we observe before they lose their jobs due to international trade is larger than that after they exit the TAA program, as Table 2 suggests. This is so for three reasons. First, some of the individuals do not report their earnings after they exit the TAA program. Second, some of the individuals who do report their earnings after their exit from the TAA program do not report their employment status in the third full quarter after the TAA program.[13] Third, some of the individuals who claim to have positive earnings during the third full quarter after their exit from the TAA program report that they are unemployed during the same period. For the purposes of our analysis, we focus only on two types of individuals. First, we focus and thus include in our sample those individuals who report being unemployed during the third full quarter after the TAA program and report zero earnings during that period. Second, we also include in our sample those individuals who report being employed during the third full quarter after their exit from the TAA program and report having positive earnings between $1 and $300,000 during that period.[14] Because the number of individuals observed in our sample decreases between

[11] Note, however, that we do not exclude the Hawaiians that live in states other than Hawaii.

[12] In the data, many industries were classified as 3-digit (not 4-digit) industries. Identifying those industries as agricultural sectors from product definitions, we added a leading zero to make them four-digit. However, about 700 of them were actually manufacturing industries and we re-classified them as appropriate manufacturing sectors depending on their product description.

[13] We attempt to test whether the individuals who choose to report their employment status in our sample are statistically different from individuals who choose not to report their employment status using a double selection test, where the first selection is a selection into finding a job after the TAA program and the second selection is a selection into reporting their employment status. However, all the reasonable model specifications we consider do not converge. Therefore, we abandon this attempt and focus on testing for a single selection into finding a job after the TAA program.

[14] In Section 5.3 we provide some robustness checks for the potential sensitivity of our findings to our

the two time periods we employ in our analysis, we report the summary statistics for the variables that are time-invariant in nature (e.g. ethnicity, race, etc.) for both time periods.

Columns (1)-(4) of Table 2 provide the mean and standard deviation of worker characteristics by gender, three quarters prior to facing unemployment due to trade. We observe that on average individuals getting laid off are similar in age (in years), education levels (in years of schooling) and, thus, potential experience (in years since leaving full-time schooling) across genders. Individuals' ethnicities do display a small degree of heterogeneity as Spanish and Black women are more likely to get laid off than their male counterparts. However, with respect to workers facing unemployment because of trade-related reasons, there seems to be a significant difference in wage gap across genders. Before facing unemployment, men on average earn almost \$3,330 more than women, with a significantly higher dispersion in their earnings as measured by the standard deviation. The wide wage gap between men and women that is captured in Table 2 already suggests that gender inequality is particularly pronounced across the workers who were laid-off due to trade. As demonstrated in the econometric analysis below, this gap remains wide even after we control for a series of characteristics that have been used in the related literature in order to explain the wage differences across men and women.

In columns (5) through (12) of Table 2, we observe worker-level outcomes post their participation in the TAA program. A small drawback of the data is that we do not observe the industry or geographical location of re-employment and hence cannot identify if workers relocated to a different state or county to find a job. However the low take-up rates of relocation allowance (0.6% and 0.2% for men and women respectively) suggests that they did not relocate to a far off location relative to where they were laid off due to trade. In the *After* panel, we particularly focus on the TAA program characteristics and worker outcomes in terms of employment and earnings by gender both for all men (women) and separately for those men (women) who found employment by the third full quarter since exiting the

sample choice.

program. We observe that, on average, earnings of both men and women decline significantly, with men experiencing a larger fall in their average earnings thereby leading to a decline in gender wage gap as compared to pre-trade induced unemployment. Additionally, men are slightly less likely than women to get employed. However, men are somewhat more likely than women to undertake and complete training, to travel during training and to also receive a waiver to skip training while in the program. Men are also noticeably more likely than women to receive a subsistence allowance while in training. Women, on the other hand, undertake training for longer periods, are more likely to receive any TRA and attend the program for a longer duration than men, on average.

4 Identifying Gender Gaps: Econometric Specifications

Drawing on the analysis and discussion from the previous section, this section defines the main questions of interest in our study and presents the econometric specifications that will be used to identify gender differentials in employment and earnings and their evolution for the trade affected U.S. workers in our sample. We study two main (and related) aspects of the gender gap: (i) differences in employment and (ii) difference in earnings between men and women who were laid off due to international trade. In addition to controlling for standard determinants of the employment and earnings gender differentials, e.g. (potential) experience, education, etc., we also capitalize on some specific features of the PTAA and TAA datasets, e.g. various forms of training, geography and sectoral dimension in order to offer additional insights about the determinants of the differences in employment and wages between men and women. Given the difference in the nature of the two dependent variables in our analysis and the natural chronological link between them, we proceed in three steps. First, in Section 4.1, we describe our econometric approach to explain employment. Then, in Section 4.2 we focus on the wage gap. Finally, in Section 4.3 we also present the Heckman 1979 two-step selection correction procedure that will enable us to control for possible sample selection bias in our earnings specifications.

4.1 Estimating Gender Differentials in Employment

In order to study the gender differences in employment, we estimate the following binary outcome model for the likelihood that an individual i who lost his/her job due to international trade is employed in the third full quarter after his/her participation in the TAA program:

$$\begin{aligned} Employed_i = 1[&\alpha_1 Female_i + \mathbf{X}_i\alpha_{2m} + Female_i * \mathbf{X}_i\alpha_{2f} + \\ &+ \mathbf{P}_i\alpha_{3m} + Female_i * \mathbf{P}_i\alpha_{3f} + \alpha_{4m}Z_i + \alpha_{4f}Female_i * Z_i + \mathbf{S}_i\alpha_5 + \varepsilon_i \geq 0], \end{aligned} \tag{1}$$

where $1[\cdot]$ is an indicator function. Here, *Employed* is a binary indicator for whether the individual is employed in the third full quarter after the TAA program. An individual's employment status is determined by whether the individual is female, $Female$, a vector of additional individual human capital and demographic characteristics that are not related to the individual's participation in the TAA program per se, $\mathbf{X}$, and a vector of individual characteristics that are related to the TAA program, $\mathbf{P}$, and an idiosyncratic shock, ε.[15]

Given the focus of our study, we allow the effects of all the individual characteristics to be gender-specific, i.e. we interact vectors $\mathbf{X}$ and $\mathbf{P}$ with the female indicator. Further, we are concerned that an individual's employment status may depend on the state the individual lives in and the industrial sector s/he works for. Therefore, we introduce a set of state and industrial sector controls, $\mathbf{S}$, which may be interacted with the female dummy in some model specifications. Finally, we include an indicator for whether a person received subsistence allowance while in training (denoted by Z) that is later used as an exclusion restriction to test for sample selection bias when estimating the gender wage gap.[16] We allow the latter characteristic to be gender-specific.[17]

[15] We refer the reader to Section 3.2 for a detailed description of the specific variables that are included in each vector of covariates.

[16] We provide a detailed discussion of our choice of the exclusion restriction for the sample selection test in Section 4.3.

[17] In order to understand potential mechanisms driving gender gaps in employment and earnings, it would

4.2 Estimating the Gender Earnings Gap

We follow much of the previous literature, which extends on the classic work of Mincer 1974, and employ the following model to estimate the gender differences in earnings for those who were affected by international trade and chose to participate in the TAA program:

$$\begin{aligned} ln(earnings_{it}) = \beta_1 Q_t + \beta_2 Female_i + \beta_3 Female_i * Q_t + \mathbf{X}_{it}\beta_{4m} + Female_i * \mathbf{X}_{it}\beta_{4f} + \\ + Q_t * \mathbf{P}_i\beta_{5m} + Female_i * Q_t * \mathbf{P}_i\beta_{5f} + \mathbf{S}_i\beta_6 + u_{it}, \end{aligned} \tag{2}$$

where $ln(earnings_{it})$ represents a person i's natural log of earnings at time t, and u_{it} is an idiosyncratic shock. Here, we exploit two time periods—three full quarters before a person lost a job and then participated in the TAA program and three full quarters after a person participated in the TAA program. For simplicity, in what follows, we will refer to these periods as the periods before and after a person participated in the TAA program.[18]

To capture aggregate changes in earnings between the two periods, we include an indicator for whether t is a time period for the third full quarter after the TAA program, Q_t. An individual's earnings depend on whether the individual is female or not, and the gender effect on earnings may be different before and after the TAA program, i.e. we include $Female_i$ and $Female_i{*}Q_t$. Similar to our analysis of employment, we maintain that the individual's human capital and demographic characteristics, $\mathbf{X}$, may explain the individual's earnings. Most of the latter characteristics are acquired before the person's participation in the TAA program and are time-invariant except for the person's potential experience (in quadratics). Moreover, the individual's characteristics related to his/her TAA program participation (observable in the second period), $\mathbf{P}$, may also affect the individual's earnings. Again, we allow all the individual characteristics to be gender-specific, and, thus, include their interactions with the gender indicator. Finally, we include a set of state and industrial sector controls, $\mathbf{S}$, which, in some model specifications, we interact with the female dummy.

be interesting to control for changes in occupations. Unfortunately, we only have information about post-layoff occupations of the individuals, which prevents us to control for changes in occupations.

[18]See Section 3 for a description of the TAA program participation time line.

4.3 Accounting for Sample Selection Bias

A possible concern that may arise with our analysis of the earnings gap is due to the fact that in the second period we observe total quarterly earnings only for those individuals from the first period who found jobs and were employed in the third full quarter after the TAA program. Since equation (2) does not account for the potential non-randomness of our sample in the second period, we are concerned about potential sample selection bias in the estimates of equation (2). To address this concern, we test for the presence of the sample selection problem in our earnings model using the Heckman 1979 two-step selection correction approach, which we adjust to fit our setting.

In sum, in the first step we run a probit model provided in equation (1) that is based on all the observations we have for the second period, i.e. not only those individuals who found jobs after the TAA program but also those who did not find jobs after the TAA program and thus are not used when estimating equation (2). Then, using the estimation results from the probit model, we construct the Inverse Mills Ratio (IMR) for those individuals who found jobs. In the second step, we include the IMR interacted with the second period dummy as an additional regressor in equation (2), and use observations for the two periods using only those individuals who did find jobs after their participation in the TAA program. Note that we interact the IMR with the second period dummy in order to account for the fact that the sample selection problem in our case might arise only in the second period. This is the case since we observe all individuals in the first period and only a subset of those who have jobs in the second period.

Formally, we take the following steps to amend and implement a version of the Heckman 1979 two-step procedure to account for sample selection bias in our specific setting:

1. Using observations on the individuals after the TAA program (i.e. for the third full quarter after the TAA program), both who found and did not find jobs, obtain the

probit estimate $\hat{\delta}$ from the model

$$P(Employed_i = 1) = \Phi(\mathbf{W}_i \delta), \tag{3}$$

where $\mathbf{W}_i = (\mathbf{X}_i, Female_i * \mathbf{X}_i, \mathbf{P}_i, Female_i * \mathbf{P}_i, Z_i, Female_i * Z_i, \mathbf{S}_i)$, and $\delta = (\alpha_1, \alpha_{2m}^{'}, \alpha_{2f}^{'}, \alpha_{3m}^{'}, \alpha_{3f}^{'}, \alpha_{4m}, \alpha_{4f}, \alpha_5^{'})^{'}$. Then obtain the estimated inverse Mills ratios

$$\widehat{\lambda}_i \equiv \frac{\phi(\mathbf{W}_i \hat{\delta})}{\Phi(\mathbf{W}_i \hat{\delta})} \tag{4}$$

for those individuals who found jobs after the TAA program.

2. Using observations on all the individuals before the TAA program (i.e. for the third full quarter before the job loss) and the individuals after the TAA program (i.e. for the third full quarter after the TAA program) who found jobs, obtain $\hat{\gamma} = (\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_{4m}^{'}, \hat{\beta}_{4f}^{'}, \hat{\beta}_{5m}^{'}, \hat{\beta}_{5f}^{'}, \hat{\beta}_6^{'}, \hat{\pi})^{'}$, where $\hat{\pi}$ is the coefficient estimate on $Q_t * \hat{\lambda}_i$, from the Pooled Ordinary Least Squares (POLS) regression

$$\begin{gathered} ln(earnings_{it}) \text{ on } Q_t,\ Female_i,\ Female_i * Q_t,\ \mathbf{X}_{it},\ Female_i * \mathbf{X}_{it}, \\ Q_t * \mathbf{P}_i,\ Female_i * Q_t * \mathbf{P}_i,\ \mathbf{S}_i,\ Q_t * \hat{\lambda}_i. \end{gathered} \tag{5}$$

The proposed procedure is essentially the selection correction procedure due to attrition that is provided in Section 19.9.3 of Wooldridge 2010. The first stage of our method is identical to that of the procedure correcting for attrition in Wooldridge 2010. However, the second step of the procedure in Wooldridge 2010 uses first differenced equation (2) in contrast to the second step of our procedure, which does not first difference equation (2). We use the standard t-test on the coefficient estimate for the $Q_t * \hat{\lambda}_i$ in the second step as a test of the null hypothesis of no selection bias. If the null hypothesis of no sample selection is rejected, we correct the standard errors in the second step for the presence of the generated regressor – $Q_t * \hat{\lambda}_i$ – using bootstrapping.

To construct the IMR, we need to impose an exclusion restriction on the set of individual characteristics. The excluded characteristic we choose should have a direct impact on employment but no direct impact on earnings, and will be contained in Z of equation (1). We speculate that demographic and human capital characteristics acquired before job loss are less likely to determine the likelihood of re-employment after the TAA program than the program characteristics that individuals acquire while participating in the TAA program. At least in part, this is so since individuals' demographic and human capital characteristics are obtained prior to their participation in the TAA program and are time-invariant in our setting. We use an indicator for whether the individual received a subsistence allowance while in training as our exclusion restriction in the earnings equation (2).[19]

In essence, we maintain that receiving a subsistence allowance while in training creates an effective environment for the TAA beneficiaries to seek re-employment since having financial security while in training allows individuals to focus on improving their skills and becoming more attractive to potential employers instead of worrying about financially supporting themselves and their families while out of work. Furthermore, we speculate that while having a subsistence allowance provides incentives for finding a job, receiving a subsistence allowance plays no role in explaining his/her earnings once re-employed. We establish some (indirect) empirical support for our choice of the exclusion restriction by estimating equation (2) using our exclusion restriction as part of the individual characteristics vector, $\mathbf{P}$. As columns (2) and (4) of Table 6 suggest we find that receiving a subsistence allowance while in training plays no statistically significant role when present in the earnings equation as an additional regressor.

[19]Since 1988, all workers are required to participate in training in order to receive TAA benefits. Some workers may be eligible for a waiver of the training requirement, however.

5 Empirical Findings and Policy Implications

Following the exposition in the previous section, Subsection 5.1 focuses on the gender differences in re-employment after the job loss and participation in the TAA program. Then, in Subsection 5.2, we study the gender earnings gap before and after the job loss due to trade.

5.1 Gender Differences in Employment

Our main findings regarding gender differences in employment are presented in Table 3, which reports the coefficient estimates for the probit model provided in (1) and is based on the manufacturing sectors only.[20] The results in column (1) of Table 3 represent the probit estimates when full sets of state and industry dummies are included in the equation. Column (2) contains probit estimates when, in addition to the full sets of state and industry dummies, we also introduce interactions between each of the state fixed effects and the female indicator variable. The idea behind this specification is that it will enable us to identify gender differences in re-employment across the U.S. states. Finally, column (3) reports estimates when the full sets of state and industry dummies are augmented by interactions between the female dummy and the full set of sector dummies. The motivation for this specification is that it will enable us to study the heterogeneity in female re-employment across sectors. For brevity and clarity of exposition, the estimates of the interactions between the female dummies and the state and industry fixed effects are reported in separate tables, Table 4 and Table 5, respectively. All standard errors reported in Table 3 are heteroskedasticity-robust.

The benchmark coefficient estimates for men are reported in Panel A of column (1) in Table 3. As expected, we find that experience plays a very important role for the probability of being employed for men. In particular, we find that each additional year of experience improves men's chances of being employed (1% level of significance) up to some point af-

[20] We focus on manufacturing in our main analysis for two related reasons. First, U.S. manufacturing has traditionally been the sector that has suffered the most from import competition. Second, this is clearly reflected in the TAA databases where the overwhelming majority of observations (more than 98% of TAA petitions) belong to the manufacturing sector.

ter which the direction of the experience's influence on the probability of being employed becomes the opposite. Our estimates suggest that better educated men are less likely to be employed (5% level of significance). This is an interesting result that is in contrast to estimates from the existing literature and points to effects that are specific to those men who were negatively affected by trade. We also observe that men who are veterans are less likely to be employed after the TAA program than non-veteran men (significant at the 1% level), Asian men are more likely to be employed after the TAA program than white men (significant at the 5% level). Finally, we note that these findings are robust across the alternative specifications in Table 3.

Next, and most important for the purposes of this study, we turn to the coefficient estimate on $Female_i$, which allows us to gauge the importance of gender in the probability that a person is employed after a negative international trade shock and his/her participation in the TAA program. To preserve a meaningful interpretation of the coefficient estimate on the female indicator, we demean an individual's experience before interacting it with $Female_i$.[21] Thus, the coefficient estimate on the female dummy will capture the importance of gender for re-employment after the TAA program for individuals with the following benchmark characteristics: (1) average potential experience, (2) zero years of education,[22] (3) white, (4) non-Spanish, (5) non-veteran, and (6) full English language proficiency. For simplicity, when discussing the estimation results below, we will refer to individuals of either gender with such characteristics as individuals with benchmark characteristics. Importantly, the estimate on $Female_i$ from column (1) in Panel B of Table 3 reveals that, on average, there is no evidence to suggest that there is a gender difference in re-employment after the TAA program. In fact, the only statistically significant (at 5%) difference in the probability of being employed between men and women that we observe in Panel B is the difference in the effect of an additional year of experience. However, while statistically significant, this difference is quite small from the economic standpoint.

[21]In Table 3 (as well as later in Table 6) we denote the sample mean of potential experience by μ.

[22]In our estimating sample, about 3% of all the individuals have zero years of education.

Next, we describe the results concerning the program characteristics. Our estimates for men appear in Panel C of Table 3, and the estimates of the differential effects for women are in Panel D of Table 3. The estimates from Panel C reveal that completion of training, training waiver and subsistence allowance all have a highly positive effect on re-employment for men. However, Trade Readjustment Allowance (TRA) has a significant negative impact on re-employment probability for men. The estimates from Panel D provide information about the impact of program characteristics related to the gender gap. Our estimates reveal that provision of training, TRA, and subsistence allowance have statistically significant positive differential effects for getting re-employed after the TAA program for women relative to men, while the estimate of the effect of the length of the program ('program duration') is negative.

The results in column (2) of Table 3 are obtained after adding interactions between the state dummies with the female dummy (in addition to the state and industry dummies). The idea behind this specification is to test for and to identify gender differences in re-employment across the U.S. states. Concerning the individual characteristics and the program characteristics, as well as the gender difference, results from column (2) are very similar to those in column (1). Hence, our main findings are robust to the inclusion of interactions between the state dummies with the female dummy. However, we do obtain some significant evidence for gender difference in re-employment across states.

For brevity and expositional simplicity, Table 4 reports only the statistically significant average partial effects that we obtain of being female on re-employment across the U.S. states. While, our estimates from Panel B of Table 3 suggest no evidence of differences in re-employment across men and women *on average* in the U.S., the estimates from Table 4 reveal that the probability of re-employment for women is higher in some states (e.g. Indiana, Minnesota, Ohio and Oklahoma) and lower in a couple of states (e.g. New York and Kentucky). We are not aware of the existence of systematic evidence and studies on re-employment opportunities for men and women across states, however, our finding in the case of New York is consistent with the BLS report[23] that New York appears to be the state where the probability of employment for women is lowest compared to men, and this state had the lowest proportion of women who worked for pay.

Finally, the results in column (3) of Table 3 are obtained after adding interactions between the female dummy and the industry dummies in order to identify possible heterogeneity in female re-employment across sectors.[24] First, we note that the results from column (3) regarding individual and program characteristics, as well as the gender difference, are very similar to those from column (1). Hence, our main findings are also robust to the inclusion of interactions between the industry dummies and the female dummy. Once again, for expositional clarity, we do not report the sector-specific $Female_i$ estimates in Table 3. Instead, we present them separately in Table 5. Two main results stand out. First, all, except one, of the estimates in Table 5 are positive and marginally significant, suggesting an advantage for re-employment of women relative to men. However, second, we also note that, without any exception, all estimates in Table 5 are very small in terms of economic magnitude, suggesting that in practice men and women, who have been laid off due to trade, are treated equally in terms of re-employment opportunities across sectors.

5.2 Gender Earnings Differentials

This section presents and discusses our estimates on earning differentials, which are based on specification (2) and appear in Table 6. Columns (1) and (2) are based on a sample of individuals with earnings more than \$1 but less than \$300,000 regardless of their self-reported employment status in the third full quarter after the TAA program. The remainder of Table 6, i.e. specifications (3)-(8), are based on a sample of individuals who in addition to reporting their earnings between \$1 and \$300,000, also report being employed during the third quarter after their participation in the TAA program and hence the latter individuals are a subset

[23]Source: https://www.bls.gov/opub/ted/1999/aug/wk3/art05.htm.

[24]We caution the reader that in order for this interpretation to be valid, we have to assume that people were re-employed in the same 2-digit manufacturing industry.

of the sample used in columns (1) and (2). Columns (1) and (3) in Table 6 contain the same sets of controls as column (1) in Table 3. To investigate the issue of (single) sample selection bias due to finding a job after the TAA program, in columns (2) and (4) of Table 6, we use subsistence allowance on its own and interacted with the female dummy to establish empirical support for our choice of exclusion restriction. In column (5), we formally test for sample selection following the procedure provided in Section 4.3. Standard errors for specifications (1)-(5) are robust to heteroskedasticity and serial correlation. Since the interaction of the IMR and the second period dummy in column (5) is statistically significant at the 1% level, we account for the sample selection problem and report bootstrapped standard errors in columns (6)-(8). Finally, columns (6)-(8) of Table 6 contain the same sets of controls (except for the IMR and second period dummy interaction term) as columns (1)-(3) in Table 3, respectively.

We begin with a discussion of the findings from our tests for sample selection bias. In order to implement the modified Heckman selection method described in Section 4.3, we investigate cash benefits – income support (TRA), job search allowance, and subsistence allowance – as potential candidates for the exclusion restrictions in the earnings equation. The structure of the TAA program cash benefits as well as how these benefits might affect TAA participants' incentives to seek re-employment and high wages are carefully discussed in Baicker and Rehavi 2004. Building on their analysis and applying it to our context, we use an indicator for whether the individual received subsistence allowance while in training as our exclusion restriction in the earnings equation (2). In column (1) of Table 3, we show that the availability of subsistence allowance positively affects employment probability and in columns (2) and (4) of Table 6, we establish that receiving a subsistence allowance while in training plays no statistically significant role when present in the earnings equation as an additional regressor. Based on this empirical support for our choice of exclusion restriction and the significant estimate of the interaction between the inverse Mills ratio and the second period dummy in column (5) of Table 6, we are unable to reject the possibility of sample selection bias in our model. Therefore, columns (6)-(8) of Table 6 report bootstrapped standard errors in order to correct for the presence of the generated regressor – the interaction term between the estimated IMR and the second period dummy – in the second step of their estimation procedures. In what follows we focus on the estimation results that account for the sample selection problem and that are provided on columns (6)-(8) of Table 6.

For completeness and consistency with the presentation from the previous section, we start with a brief discussion of the benchmark estimates for men, which appear in Panels A, C, and E of Table 6. Column (6) resents our baseline results. The estimates in Panel A reflect the impact of individual characteristics of men before entering the program. Experience and education both have significant positive effects on earnings: on average an additional year of both experience and education lead to 2.8% higher wages on average for men (ignoring the square term, which is negligibly small). For veteran men, the wage on average is 10.8% $((\exp(0.103) - 1) \times 100))$ higher. On the other hand, we find that Spanish and Black men, as well as men with limited English skills earn 8.2%, 10.8%, and 15.0% less on average, respectively. Turning to the impact of individual characteristics for men after the program, which are presented in Panel C, we find that experience, education and being a veteran negatively affect earnings for men post TAA participation, while men with limited English skills earn almost 15% more on average. These results can be explained with skilled, less paying jobs for TAA participants where more experienced men suffer wage cuts and men with limited English skills (and presumably belonging to the lower end of the skill distribution) earn more on average. Finally, in terms of the program characteristics, the estimates from column (6) of Panel E reveal that travel while in training had a positive impact on men's earnings, while training duration impacted them negatively.

Next, we turn to the estimates on the gender wage differential that are of main interest to us, and which are presented in Panels B, D, and F of Table 6. As before, we demean an individual's experience before interacting it with $Female_i$ to preserve a meaningful interpretation of the coefficient estimate on the female indicator before the TAA program. Most importantly, the estimate on $Female_i$ from our main specification in column (6) of Panel B suggests that, on average, the difference between women and men who have been laid off due to trade is about 30% $((\exp(-0.362) - 1) \times 100))$, and this finding is statistically significant at the 1% level.[25]

The wage gap differential estimate that we obtain is in contrast with findings from some recent and influential papers, e.g. Blau and Kahn 2006, Blau and Kahn 2007, and Goldin 2014 that demonstrate that, on average, the wage gap between men and women in the U.S. has steadily decreased in the 80s and the 90s to reach about 20% in the early 2000s. We view our results as complementary to the estimates from the above-mentioned studies, which focus on the wage differential in the US population. Instead, an important contribution of our work is that we identify the men and women who have been laid off due to trade as a group where women are particularly vulnerable and the gender gap is very pronounced. We think that this result has important implications for gender and income inequality that should be considered seriously by policy makers. For most of the individual characteristics presented in Panel B of Table 6, we find no significant differential impact on pre-layoff earnings for women. Asian women and women veterans earn 13% and 6% more, respectively, than their male counterparts, while more experienced women earn slightly less.

The other index of central interest to us is the estimate of coefficient on $Female_i * Q_t$, which appears in the top row of Panel D of Table 6 and captures the earnings gap after the TAA program between men and women with benchmark characteristics. In other words, when looking only at those individuals who chose to participate in the TAA program, β_2 represents the gender earnings gap for those individuals who were affected by international trade before the actual changes in trade took place, and β_3 reveals the gender earnings gap for those who were affected by international trade after the changes in trade took full effect.

Importantly, we do not find any statistically significant difference in earnings of men and women with the benchmark characteristics after they participated in the TAA program.

[25] We remind the reader that this estimate is obtained after accounting for selection and controlling for most of the characteristics that have been used in the literature to explain the earnings differential gap between men and women. For a list of the determinants of the wage gap in the U.S. and their relative importance, we refer the reader to Table 1 of Blau and Kahn 2007.

While seemingly encouraging, this result has to be interpreted conditional on the fact that, on average, both men and women accept significant wage cuts when re-employed after being laid off due to trade. The only significant estimate that we obtain in column (6) of Panel D is on the positive effect on experience, however, it is very small in magnitude. Finally, in terms of the program characteristics, the estimates in column (6) of Panel F suggest that 'travel while in training' is the only factor that had a significant (at the 10% level) impact on the post-TAA earnings for women.

The estimates in column (7) of Table 6 are obtained by adding interactions between the state dummies and the female dummy (in addition to the state and industry dummies). The idea behind this specification is that it will enable us to identify differences in female earnings across the U.S. states before job loss. Our results are presented in Table 7 and we also offer a visualization in 'heat map' of the United States in Figure 2, where darker shades imply lower earnings for women compared to men (and hence higher gender earnings gap) for those individuals who were laid off due to trade. The absolute value of the APEs are used in the map. Unlike what we found with respect to re-employment probability distribution across states, Figure 2 and Table 7 highlight the fact that gender difference in earnings are very pronounced and vary across states. We obtain significant differential (negative) effect on women earnings relative to men for all states in the sample. Earnings gender inequality is strongest in the southern states of Alabama (52.5%), Missouri (48%), South Carolina (48%), Mississippi (46%), and in the more sparsely populated states like Arizona(48%), Nevada (45%), and South Dakota (43%). The gender wage gap is smaller, but still very wide, in New York (25%), Oregon (25%), New Jersey (26%), Maryland (29%), Montana (30%), and California (30%).

The results in column (8) of Table 6 are obtained by adding interactions between the female dummy and the industry dummies, while still controlling for state and industry effects. The rationale behind this specification is that it will enable us to study the heterogeneity in female earnings across sectors before job loss. The estimates of the interactions between the female dummy and the industry dummies appear in Table 8. Two main results stand out. First, we find that, without any exception, the wage gap between men and women who have been affected by trade is statistically significant and very pronounced in each and every U.S. manufacturing sector. Second, we observe wide heterogeneity in the estimates in Table 8. The gender earnings gap is most pronounced in *Petroleum and Coal Products* (45%) and *Rubber Products* (34%). Thus, our results identify industries where women earn about half as much as men, thereby pointing to these sectors as possible areas of policy interventions.

5.3 Robustness Checks

We conclude our discussion of the empirical results with some robustness checks to test sensitivity of our empirical findings to our sample choice. The main sample used in our analysis contains individuals who in addition to reporting their earnings between $1 and $300,000, also report being employed during the third quarter after their participation in the TAA program. There are two reasons to justify our sample choice. First, to construct our sample we choose only those individuals who report both their employment status and earnings to ensure that we can test (and if needed correct) for (single) sample selection bias. Second, we choose only those individuals who report being employed during the third full quarter after their participation in the TAA program while having positive earnings during the same period to ensure that we analyze only those individuals who are likely to be employed full-time during the entire third quarter after the TAA program. It seems plausible that individuals who report being unemployed while having positive earnings during some period work either part-time during that period or full-time for only a fraction of that period. Since the latter individuals are likely to be low-income individuals, low-income individuals are (at least in part) underrepresented in our sample (assuming our interpretation of the survey's discrepancy between individuals' employment statuses and their positive earnings is correct).

To conduct robustness checks for whether the gender differences in earnings after the

TAA program are driven by low-income individuals we split our initial (full) sample used in columns (1) and (2) of Table 6 according to the percentiles of the earnings distribution in the third full quarter after the TAA program. Specifically, we construct two subsamples of the initial sample by removing the lowest 10% and 20% of earners after their re-employment ignoring their self-reported (if at all) employment status. We estimate specification (2) using the subsamples we obtain. The estimation results for the female dummy and the interaction between the female dummy and the third quarter indicator are reported in Table 9.[26]

Column (1) of Table 9 reproduces (the shortened version of) column (1) from Table 6 while columns (2) and (3) report the estimation results for the same specification using the subsamples defined by dropping the lowest 10% and 20% of earners (after re-employment), respectively. Note that our main sample contains 136,844 individuals as columns (3)-(8) of Table 6 suggest. The latter sample size approximately corresponds to the number of individuals we obtain when dropping between the 10% and 20% of the lowest earners. While we do not know for sure that our main sample does not contain the lowest earners only, the sample size of our main sample does not contradict our interpretation that it is low-earning individuals that are omitted from our main sample due to the discrepancy between their reported employment statuses and earnings after the TAA program.

Comparisons of column (1) with columns (2) and (3) in Table 9 show that, similar to the full sample, we do not find any statistically significant gender differentials in earnings in the post TAA period for the top 90% and 80% of earners, respectively. Note that comparing the coefficient estimate for the female dummy variable might be less interesting since the alternative samples in columns (2) and (3) are obtained by dropping the lowest earners after they are laid off, while the coefficient estimate for the female dummy represents the gender wage gap before the lay-offs take place. Nevertheless, we continue finding a statistically significant gender gap in pre-layoff earnings among those individuals who are top 90% and 80% earners after they get re-employed, although these gender differentials are slightly lower

[26]The estimation results for the entire specification (2) using the constructed subsamples are available upon request.

in absolute value when compared to the corresponding gender gap based on the full sample. The above findings based on the alternative samples suggest that our sample choice does not affect our empirical findings for the gender differentials in earnings among those individuals who get re-employed after the lay-offs. Furthermore, our sample choice does not affect our findings for the gender gaps in pre-layoff earnings among the top 90% and 80% earners after their re-employment.[27]

Finally, we conduct robustness checks of our empirical findings for the gender differences in re-employment after the job loss and participation in TAA program. We re-estimate probit specification (1) using the two alternative samples defined above. The probit coefficient estimates for the female dummy using alternative samples are reported in Table 10.[28] Column (1) of Table 10 reproduces (the shortened version of) column (1) from Table 3 while columns (2) and (3) report the probit estimation results for the same specification using the subsamples defined by dropping the lowest 10% and 20% of earners (after re-employment), respectively.

Our findings based on the two alternative samples suggest that there exists no significant differences among men and women in terms of their re-employment probabilities after their TAA program participation. This conclusion is in compliance with our findings for the gender differences in re-employment based on the sample used for our main analysis as suggested by comparing the female dummy coefficient estimate in column (1) of Table 10 or Table 3 to those in columns (2) and (3) of Table 10.

[27]It would be interesting to control for occupation changes in order to investigate one potential important mechanism explaining the obtained results. While there is information in our data on the post-layoff occupations for a very limited number of individuals, there is no such information pre-layoffs. Hence, data limitations restrict us in digging deeper into this mechanism.

[28]The probit estimation results for the entire specification (1) using the alternative samples are available upon request.

6 Conclusion

We combine and employ two rich but underutilized databases that directly identify trade-induced layoffs in the United States in order to study differentials in employment and earnings for men vs. women when unemployment is caused by international trade. The three main results from our analysis are as follows: (i) Most importantly, women who have been laid off due to trade earned about 30% less than similar men prior to the trade shock; (ii) Second, we do not find significant evidence that women who have been laid off due to trade are less likely to be employed after the TAA program than men. However, we do obtain heterogeneous re-employment results across some states and some industries; and (iii) Finally, our results suggest that the earnings gap between men and women disappears after they participate in the TAA program and find new jobs. However this is a result of more pronounced wage compression for men rather than a faster increase in women's wages. In combination, our results identify those men, and especially women, who have been affected by trade as a special and vulnerable group with pronounced gender inequality that calls for policy intervention.[29] We also document a series of additional gender-related findings with respect to demographics, retraining effectiveness, geography, and sectoral differences.

Our data and analysis lend themselves to several extensions. First, we believe that the PTAA and TAPR datasets that we employ here can be combined with individual-level data from the Current Population Survey or restricted data from the Longitudinal Employment Household Dynamics (LEHD) database, which can be used as a reference group in order to study whether trade affects gender inequality. Second, some of our findings point to significant wage and employment differentials across race groups. We expect that a more rigorous analysis of the relationship between trade and race will generate interesting results with important policy implications. Third, the PTAA dataset provides information on the

[29] It may very well be that this wage compression is the result of occupation switches associated with destruction of human capital and wage declines in the short run. In that case, we would expect the effects to disappear in a few years, once human capital gets accumulated in the new occupation. Given the limited time span of our data, this wage compression therefore may be a short-run effect.

specific channels of trade, i.e. import competition, offshoring or upstream supply linkages that may have caused the firms to lay off workers. The possible heterogeneity in these channels in affecting gender/race related labor market outcomes could be another interesting area of future research. Fourth, the PTAA and TAPR datasets can be combined with U.S. firm-level data that can be used to answer a series of new questions that link trade to gender, race, and labor discrimination in general. In addition, linking these datasets to firm-level U.S. data can highlight if older/larger firms systematically discriminate more/less and how the effect might be different for multi-establishment firms as opposed to single-establishment ones. Finally, in reference to the local labor market literature, it will be interesting to see if there exists systematic differences in gender earnings and employment across local labor markets in response to their exposure to trade shocks. Thus, we believe that such data can be used to test Gary Becker 1971's classic theory of discrimination with the expectation that it will be feasible to test whether increased competition due to trade leads to reduced discrimination in the labor market and whether the pro-competitive trade forces drive discriminating employers out of the market.

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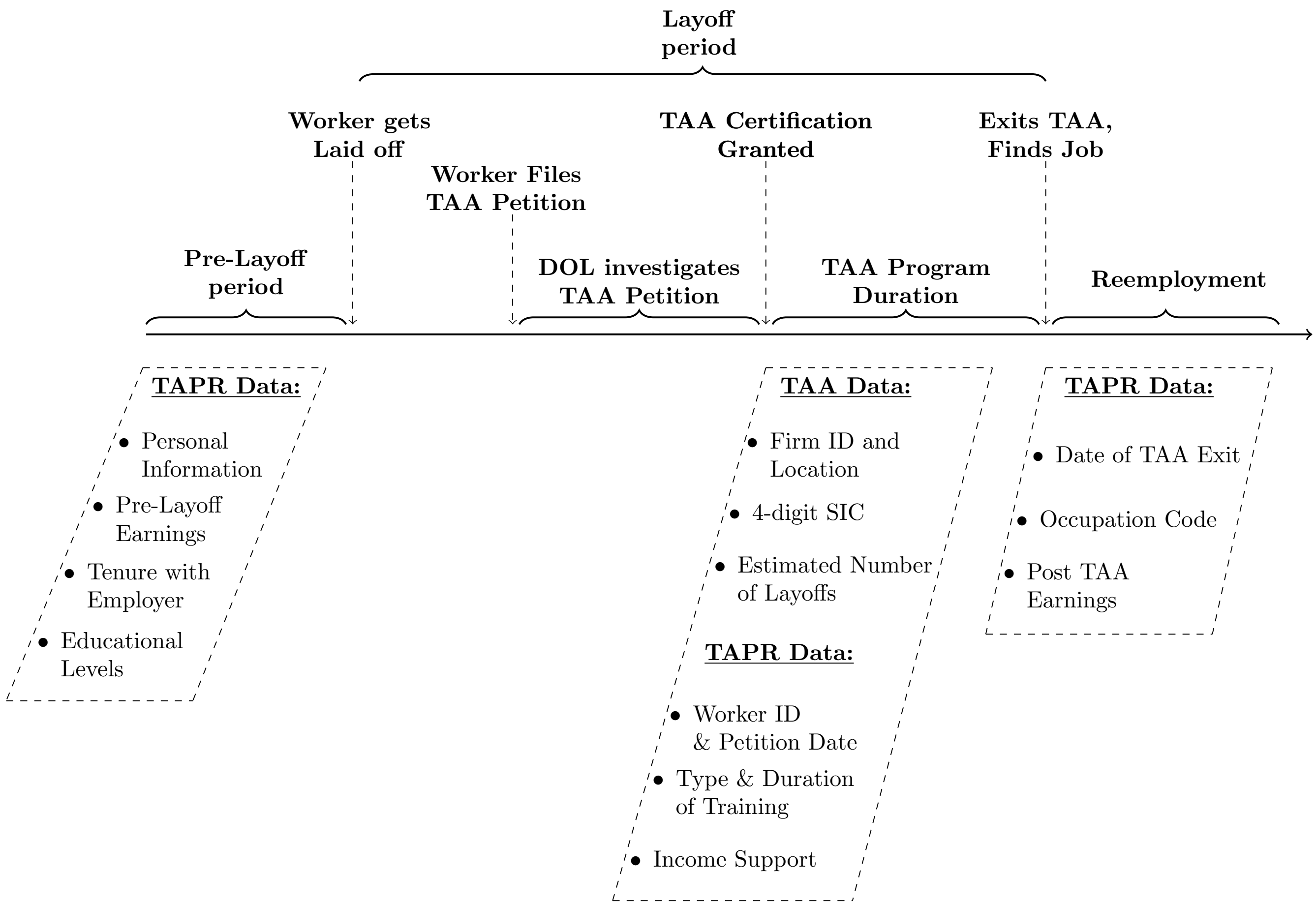
Figure 1: **Timeline of a Representative TAA Participant**



Notes: This figure traces the timeline for a representative TAA participant. The upper panel describes the different stages from pre-layoff to TAA participation and finally re-employment. The lower panel describes the data we obtain by combining the TAA and the TAPR databases at different points in time. See text for further details.

Table 1: **Variables' Types & Definitions**

Variable	Type	Definition
Age	Continuous	Age of an individual (in years)
Education	Continuous	Years of schooling
Experience	Continuous	Years of potential experience
Female	Categorical	If an individual is a female
Spanish	Categorical	If an individual is Spanish
Black	Categorical	If an individual is black
Asian	Categorical	If an individual is Asian
Native American	Categorical	If an individual is Native American
Hawaiian	Categorical	If an individual is Hawaiian
Veteran	Categorical	If an individual is a veteran
Limited English	Categorical	If an individual has limited English language proficiency
Earnings	Continuous	Individual's earnings (in U.S. $)
Log (Earnings)	Continuous	The natural log of earnings
Employment	Categorical	If an individual is employed
Received Training	Categorical	If an individual received any training in the TAA program
Training Duration	Continuous	Duration of training (in days)
Completed Training	Categorical	If an individual completed training in the TAA program
Travel While in Training	Categorical	If an individual traveled while in training
Training Waiver	Categorical	If an individual received a waiver from training
TRA	Categorical	If an individual received any Trade Readjustment Allowance during the TAA program
Job Search Allowance	Categorical	If an individual received job search allowance during the TAA program
Program Duration	Continuous	The total number of days an individual attended the TAA program
Subsistence Allowance	Categorical	If an individual received subsistence allowance during the TAA program

Notes: This table lists and describes the main variables that are employed in our analysis. Descriptive statistics for the manufacturing sectors are provided in Table 2. Please refer to the main text for further details.

Table 2: **Summary Statistics: Before & After**

	Before				After							
					All				Employed			
	Men		Women		Men		Women		Men		Women	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Demographic Characteristics												
Age (in years)	41.564	10.23	41.203	10.11	43.811	9.81	43.633	9.65	43.740	9.74	43.608	9.59
Education (in years)	12.042	2.80	11.522	2.84	12.087	2.75	11.640	2.74	12.082	2.76	11.648	2.73
Experience (in years)	23.522	10.60	23.680	10.74	25.724	10.14	25.994	10.19	25.658	10.08	25.960	10.12
Spanish	0.068	0.25	0.100	0.30	0.069	0.25	0.093	0.29	0.069	0.25	0.092	0.29
Black	0.108	0.31	0.193	0.39	0.108	0.31	0.199	0.40	0.108	0.31	0.200	0.40
Asian	0.044	0.21	0.044	0.21	0.044	0.20	0.044	0.20	0.043	0.20	0.042	0.20
Native American	0.009	0.09	0.011	0.10	0.009	0.09	0.010	0.10	0.009	0.09	0.010	0.10
Hawaiian	0.004	0.06	0.003	0.05	0.004	0.06	0.003	0.05	0.004	0.06	0.003	0.05
Veteran	0.790	0.41	0.799	0.40	0.774	0.42	0.775	0.42	0.768	0.42	0.769	0.42
Limited English	0.039	0.19	0.060	0.24	0.039	0.19	0.057	0.23	0.039	0.19	0.056	0.23
Outcomes												
Earnings (in U.S. $)	9310.255	5380.54	5981.281	3792.87	6661.535	4429.81	4604.949	3193.48	6938.799	4331.11	4780.952	3127.59
Log (Earnings)	8.958	0.73	8.508	0.71	8.487	1.01	8.135	0.96	8.581	0.91	8.222	0.86
Employed					0.906	0.29	0.921	0.27				
Program Characteristics												
Received Training					0.946	0.23	0.904	0.29	0.946	0.23	0.905	0.29
Training Duration (in days)					327.379	240.01	394.978	237.69	330.142	241.09	397.776	238.00
Completed Training					0.747	0.43	0.720	0.45	0.751	0.43	0.723	0.45
Travel While in Training					0.134	0.34	0.122	0.33	0.135	0.34	0.123	0.33
Training Waiver					0.204	0.40	0.186	0.39	0.207	0.41	0.187	0.39
TRA					0.452	0.50	0.489	0.50	0.449	0.50	0.491	0.50
Job Search Allowance					0.008	0.09	0.003	0.06	0.008	0.09	0.003	0.05
Program Duration (in days)					396.743	250.30	452.991	245.21	398.837	251.58	454.715	245.74
Subsistence Allowance					0.041	0.20	0.012	0.11	0.042	0.20	0.012	0.11
Number of Observations (N)	40,555		45,472		35,295		38,972		31,991		35,880	

Notes: This table offers descriptive statistics using our data from 1999 to 2005 for the main variables that are employed in our analysis. The descriptive statistics is based on the individuals who were laid off from the manufacturing sectors only. Column *Before* contains descriptive statistics for individuals three quarters before they lost their jobs due to international trade. Column *After* provides descriptive statistics for individuals three quarters after their participation in the TAA program. See text for further details.

Table 3: **Gender Differences in Employment**

Additional Controls:	State and Sector		
		State × Female	Sector × Female
	(1)	(2)	(3)
	Panel A: Individual Characteristics: Men		
Experience	0.020***	0.020***	0.020***
	(0.004)	(0.004)	(0.004)
Experience^2	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Education	-0.008**	-0.009**	-0.008**
	(0.004)	(0.004)	(0.004)
Spanish	0.006	0.010	0.009
	(0.042)	(0.043)	(0.042)
Black	-0.007	-0.009	0.000
	(0.032)	(0.033)	(0.032)
Asian	0.119**	0.103**	0.110**
	(0.051)	(0.051)	(0.051)
Native American	-0.059	-0.056	-0.053
	(0.094)	(0.094)	(0.094)
Hawaiian	-0.141	-0.108	-0.149
	(0.139)	(0.139)	(0.139)
Veteran	-0.203***	-0.196***	-0.202***
	(0.027)	(0.028)	(0.027)
Limited English	-0.046	-0.022	-0.040
	(0.055)	(0.055)	(0.055)
	Panel B: Individual Characteristics: Women vs. Men		
Female	-0.111		
	(0.098)		
(Experience $-\mu$)	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)
(Experience $-\mu)^2$	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Education	0.005	0.006	0.005
	(0.005)	(0.006)	(0.005)
Spanish	-0.058	-0.066	-0.059
	(0.054)	(0.062)	(0.055)
Black	-0.015	-0.008	-0.028
	(0.040)	(0.043)	(0.041)
Asian	-0.083	-0.040	-0.065
	(0.069)	(0.074)	(0.070)
Native American	0.154	0.164	0.137
	(0.134)	(0.135)	(0.134)
Hawaiian	0.169	0.084	0.181
	(0.216)	(0.218)	(0.217)
Veteran	-0.055	-0.079*	-0.061
	(0.038)	(0.042)	(0.038)
Limited English	-0.029	-0.066	-0.041
	(0.070)	(0.072)	(0.070)

Continued on next page

Table 3 – continued from previous page

	Panel C: Program Characteristics: Men		
Received Training	-0.031	-0.027	-0.041
	(0.047)	(0.047)	(0.047)
Training Duration	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Completed Training	0.086***	0.093***	0.084***
	(0.022)	(0.023)	(0.022)
Travel While in Training	0.003	0.008	0.010
	(0.032)	(0.034)	(0.032)
Training Waiver	0.071***	0.101***	0.065**
	(0.027)	(0.028)	(0.028)
TRA	-0.148***	-0.150***	-0.147***
	(0.020)	(0.021)	(0.020)
Job Search Allowance	0.019	0.017	0.018
	(0.112)	(0.112)	(0.112)
Program Duration	0.000***	0.000**	0.000**
	(0.000)	(0.000)	(0.000)
	Panel D: Program Characteristics: Women vs. Men		
Received Training	0.126**	0.123**	0.143**
	(0.057)	(0.058)	(0.057)
Training Duration	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Completed Training	0.023	0.011	0.027
	(0.030)	(0.032)	(0.030)
Travel While in Training	-0.067	-0.079	-0.083*
	(0.044)	(0.050)	(0.044)
Training Waiver	-0.050	-0.115***	-0.036
	(0.037)	(0.040)	(0.038)
TRA	0.138***	0.146***	0.135***
	(0.028)	(0.030)	(0.028)
Job Search Allowance	-0.168	-0.197	-0.175
	(0.192)	(0.194)	(0.193)
Program Duration	-0.000**	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)
Subsistence Allowance	0.120**	0.114*	0.129**
	(0.057)	(0.059)	(0.058)
Female×Subsistence Allowance	0.044	0.077	0.011
	(0.110)	(0.115)	(0.111)
Observations	74,267	74,267	74,267

Notes: This table offers estimation results for the gender differences in employment using 2002 through 2006 waves of the TAPR data containing information on every certified TAA participant starting from 1999 to 2005. The dependent variable is the indicator for whether a person is employed in the third quarter after the TAA program or not. The estimator is profit and the reported probit coefficient estimates are based on the manufacturing sectors only. Specifications (1)-(3) include state and sector fixed effects. Specifications (2) and (3) additionally allow for gender heterogeneity across states and sectors, respectively. Standard errors are reported in parenthesis. Standard errors for the coefficient estimates are robust to heteroskedasticity. * p<0.10, ** p<0.05, *** p<0.01. See text for further details.

Table 4: **Gender Gap in Employment Across States**

State	Marginal Effect
Indiana	0.046**
Kentucky	-0.064*
Minnesota	0.083***
New York	-0.037**
Ohio	0.041***
Oklahoma	0.045*

Notes: This table reports the gender differences in employment for women relative to men across certain U.S. states based on information for the years 1999 to 2005. The APEs are obtained from specification (2) in Table 3. Only statistically significant estimates are reported. The rest of the estimates are omitted for brevity. * p<0.10, ** p<0.05, *** p<0.01. See text for further details.

Table 5: **Gender Gap in Employment Across Manufacturing Industries**

SIC Industry (2 Digit)	Industry	Marginal Effect
20	Food & Kindred Products	0.0040*
22	Textile Mill Products	0.0038*
23	Apparel & Other Textile Products	0.0039*
24	Lumber & Wood Products	0.0042*
25	Furniture & Fixtures	0.0039*
26	Paper & Allied Products	0.0041*
27	Printing & Publishing	0.0041*
28	Chemical & Allied Products	0.0036*
29	Petroleum & Coal Products	0.0049
30	Rubber & Miscellaneous Products	0.0046*
31	Leather & Leather Products	0.0038*
32	Stone, Clay & Glass Products	0.0043*
33	Primary Metal Products	0.0037*
34	Fabricated Metal Products	0.0041*
35	Industrial Machinery & Equipment	0.0037*
36	Electronic & Other Electric Equipment	0.0041*
37	Transportation Equipment	0.0049*
38	Instruments & Related Products	0.0037*
39	Miscellaneous Manufacturing Industries	0.0033*

Notes: The table reports the gender differences in employment for women relative to men across manufacturing sectors using information for the years 1999 to 2005. It is based on specification (3) from Table 3. * p<0.10, ** p<0.05, *** p<0.01. See text for further details.

Table 6: **Estimating the Gender Wage Gap**

Additional Controls:	Main	(1)+ Subst. Allow.	Empl. & Wage Data	(3)+ Subst. Allow.	Sample Selec.	Bootstr. std.err.	St. × Fem.	Sec. × Fem.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Subsistence Allowance		-0.000		0.001				
		(0.027)		(0.027)				
Female×Subsist. Allowance		-0.057		-0.054				
		(0.055)		(0.054)				
IMR × Q(uarter)D(ummy)					-1.054***	-1.054***	-0.994***	-1.031***
					(0.075)	(0.135)	(0.121)	(0.133)
	Panel A: Individual Characteristics for Men Before the Program:							
Experience	0.028***	0.028***	0.028***	0.028***	0.028***	0.028***	0.028***	0.028***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Experience^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.030***	0.030***	0.029***	0.029***	0.028***	0.028***	0.027***	0.028***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Spanish	-0.091***	-0.091***	-0.086***	-0.086***	-0.086***	-0.086***	-0.082***	-0.087***
	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.021)	(0.024)	(0.024)
Black	-0.109***	-0.109***	-0.118***	-0.118***	-0.114***	-0.114***	-0.132***	-0.116***
	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)	(0.018)	(0.019)	(0.018)
Asian	0.031	0.031	0.053**	0.053**	0.021	0.021	0.039	0.024
	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.031)	(0.029)	(0.032)
Native American	0.003	0.003	0.017	0.017	-0.000	-0.000	-0.002	0.001
	(0.030)	(0.030)	(0.032)	(0.032)	(0.032)	(0.050)	(0.049)	(0.050)
Hawaiian	0.123**	0.123**	0.080	0.080	0.066	0.066	0.080	0.070
	(0.053)	(0.053)	(0.058)	(0.058)	(0.058)	(0.082)	(0.094)	(0.084)
Veteran	0.101***	0.102***	0.103***	0.103***	0.103***	0.103***	0.104***	0.103***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.014)	(0.015)	(0.015)
Limited English	-0.163***	-0.163***	-0.167***	-0.166***	-0.162***	-0.162***	-0.173***	-0.166***
	(0.022)	(0.022)	(0.024)	(0.024)	(0.024)	(0.036)	(0.037)	(0.036)
	Panel B: Individual Characteristics for Women Compared to Men Before the Program:							
Female	-0.331***	-0.331***	-0.362***	-0.362***	-0.362***	-0.362***		
	(0.025)	(0.025)	(0.028)	(0.028)	(0.027)	(0.040)		
(Experience − μ)	-0.004***	-0.004***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
(Experience − μ)^2	-0.000	-0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.002	-0.002	0.001	0.001	0.001	0.001	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Spanish	-0.013	-0.013	-0.020	-0.020	-0.024	-0.024	-0.032	-0.021
	(0.018)	(0.018)	(0.020)	(0.020)	(0.020)	(0.030)	(0.030)	(0.030)
Black	0.035**	0.035**	0.032**	0.032**	0.032**	0.032	0.065***	0.036
	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.024)	(0.025)	(0.023)
Asian	0.127***	0.127***	0.116***	0.116***	0.123***	0.123***	0.087*	0.119**
	(0.028)	(0.028)	(0.030)	(0.030)	(0.029)	(0.045)	(0.046)	(0.049)
Native American	0.012	0.012	-0.019	-0.019	-0.011	-0.011	-0.004	-0.011
	(0.043)	(0.043)	(0.049)	(0.049)	(0.049)	(0.077)	(0.081)	(0.079)
Hawaiian	0.075	0.075	0.128	0.128	0.139*	0.139	0.116	0.133
	(0.073)	(0.073)	(0.083)	(0.083)	(0.083)	(0.118)	(0.125)	(0.132)
Veteran	0.051***	0.051***	0.052***	0.052***	0.057***	0.057***	0.055***	0.062***
	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.020)	(0.021)	(0.022)
Limited English	0.018	0.018	0.025	0.025	0.020	0.020	0.035	0.025
	(0.026)	(0.026)	(0.029)	(0.029)	(0.029)	(0.046)	(0.048)	(0.045)
	Panel C: Individual Characteristics for Men After the Program:							
(Experience − μ)	-0.004*	-0.004*	-0.004*	-0.004*	-0.010***	-0.010***	-0.009***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
(Experience − μ)^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.025***	-0.025***	-0.024***	-0.024***	-0.019***	-0.019***	-0.020***	-0.020***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Spanish	0.023	0.022	0.017	0.017	0.013	0.013	0.011	0.013
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.029)	(0.033)	(0.029)

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Black	0.037**	0.037**	0.041**	0.041**	0.034*	0.034	0.036	0.034
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.025)	(0.026)	(0.024)
Asian	0.020	0.020	-0.006	-0.006	0.021	0.021	0.018	0.020
	(0.030)	(0.030)	(0.029)	(0.029)	(0.029)	(0.043)	(0.041)	(0.043)
Native American	-0.014	-0.014	-0.032	-0.032	0.015	0.015	0.014	0.013
	(0.055)	(0.055)	(0.055)	(0.055)	(0.056)	(0.085)	(0.081)	(0.087)
Hawaiian	-0.031	-0.031	0.009	0.009	0.076	0.076	0.073	0.071
	(0.096)	(0.096)	(0.097)	(0.097)	(0.097)	(0.127)	(0.108)	(0.126)
Veteran	-0.263***	-0.263***	-0.264***	-0.264***	-0.213***	-0.213***	-0.220***	-0.214***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.021)	(0.022)	(0.021)
Limited English	0.134***	0.134***	0.134***	0.134***	0.139***	0.139***	0.140***	0.139***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.043)	(0.045)	(0.046)
	Panel D: Individual Characteristics for Women Compared to Men After the Program:							
Female	-0.014	-0.014	0.011	0.011	0.043	0.043	0.044	0.044
	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.057)	(0.063)	(0.067)
(Experience $-\ \mu$)	0.006***	0.006***	0.005***	0.005***	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
(Experience $-\ \mu)^2$	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.001	-0.001	-0.003	-0.003	-0.005*	-0.005	-0.005	-0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Spanish	-0.097***	-0.097***	-0.084***	-0.084***	-0.061**	-0.061	-0.058	-0.061
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.040)	(0.043)	(0.038)
Black	-0.025	-0.025	-0.022	-0.022	-0.018	-0.018	-0.021	-0.018
	(0.023)	(0.023)	(0.024)	(0.024)	(0.024)	(0.033)	(0.032)	(0.032)
Asian	-0.094**	-0.094**	-0.079**	-0.079**	-0.067*	-0.067	-0.065	-0.066
	(0.041)	(0.041)	(0.040)	(0.040)	(0.040)	(0.064)	(0.061)	(0.064)
Native American	-0.019	-0.019	0.011	0.011	-0.043	-0.043	-0.042	-0.041
	(0.077)	(0.077)	(0.078)	(0.078)	(0.079)	(0.115)	(0.112)	(0.120)
Hawaiian	-0.118	-0.119	-0.166	-0.166	-0.236**	-0.236	-0.234	-0.228
	(0.115)	(0.115)	(0.117)	(0.117)	(0.117)	(0.151)	(0.150)	(0.167)
Veteran	0.009	0.010	0.006	0.007	0.003	0.003	0.012	0.003
	(0.020)	(0.020)	(0.021)	(0.021)	(0.021)	(0.026)	(0.026)	(0.027)
Limited English	-0.016	-0.016	-0.023	-0.024	-0.005	-0.005	-0.008	-0.006
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.058)	(0.059)	(0.058)
	Panel E: Program Characteristics for Men:							
Received Training	0.004	0.005	0.009	0.009	0.018	0.018	0.026	0.020
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.027)	(0.027)	(0.027)
Training Duration	0.000***	0.000***	0.000***	0.000***	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Completed Training	0.029**	0.029**	0.030**	0.030**	0.003	0.003	0.013	0.004
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)
Travel While in Training	0.083***	0.083***	0.077***	0.076***	0.068***	0.068***	0.058***	0.066***
	(0.014)	(0.015)	(0.014)	(0.015)	(0.014)	(0.016)	(0.016)	(0.014)
Training Waiver	0.030**	0.031**	0.032**	0.032**	0.011	0.011	0.005	0.013
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)	(0.014)
TRA	-0.033***	-0.033***	-0.032***	-0.032***	0.001	0.001	-0.004	-0.001
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.013)	(0.013)
Job Search Allowance	0.092	0.092	0.093	0.092	0.080	0.080	0.088	0.083
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.064)	(0.062)
Program Duration	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Panel F: Program Characteristics for Women Compared to Men:							
Received Training	0.057**	0.057**	0.055*	0.055*	0.026	0.026	0.012	0.023
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.035)	(0.032)	(0.032)
Training Duration	0.000*	0.000*	0.000*	0.000*	0.000	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Completed Training	0.021	0.021	0.020	0.021	0.019	0.019	0.003	0.020
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.018)	(0.018)	(0.017)
Travel While in Training	-0.055***	-0.051***	-0.055***	-0.052***	-0.038**	-0.038*	-0.018	-0.034*
	(0.019)	(0.020)	(0.019)	(0.020)	(0.019)	(0.022)	(0.021)	(0.019)
Training Waiver	-0.038**	-0.038**	-0.037**	-0.037**	-0.023	-0.023	-0.010	-0.026
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.020)	(0.021)	(0.022)

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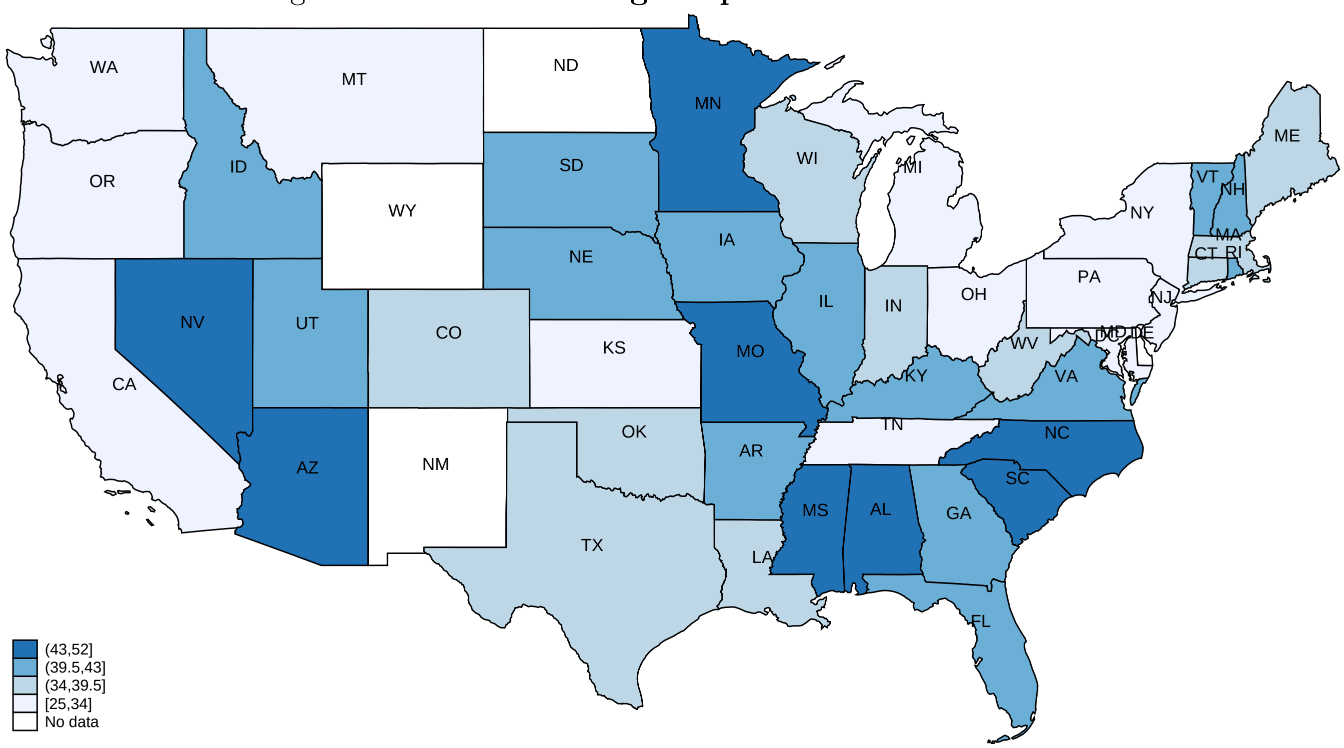
TRA	0.052***	0.051***	0.051***	0.051***	0.018	0.018	0.025	0.020
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.018)	(0.016)
Job Search Allowance	-0.255**	-0.249**	-0.254**	-0.248**	-0.196*	-0.196	-0.197	-0.197
	(0.112)	(0.113)	(0.112)	(0.113)	(0.112)	(0.126)	(0.127)	(0.121)
Program Duration	-0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	153,898	153,898	136,844	136,844	136,844	136,844	136,844	136,844

Notes: This table offers estimation results for the gender differences in wages using information for the years 1999 to 2005. The dependent variable is log earnings. The reported coefficient estimates are based on manufacturing sectors only. Two time periods – the third quarter before and the third quarter after the TAA program – are used. Specifications (1) and (2) are based on a sample of individuals with earnings >1$ but <300,000$. Specifications (3)-(8) are based on a sample of individuals who in addition to reporting their earnings also report their employment status in the third quarter after the TAA program. Specifications (1)-(8) include state and sector fixed effects. Specifications (7) and (8) additionally allow for gender heterogeneity across states and sectors, respectively. Standard errors reported in parenthesis for specifications (1)-(5) are robust to heteroskedasticity and serial correlation. Standard errors reported in parenthesis for specifications (6)-(8) are bootstrapped standard errors. * p<0.10, ** p<0.05, *** p<0.01. See text for further details.

Figure 2: **Gender Earnings Gap Across States**



Notes: This "heat" map presents the gender differences in earnings for women relative to men across states. The APEs are obtained from specification (7) in Table 6. The darker shades imply lower earnings for women compared to men (and hence higher gender earnings gap) for those individuals who were laid off due to trade. The absolute value of the APEs are used in the map. We obtain significant differential (negative) effect on women earnings relative to men, for all states used in the sample. See text for further details.

Table 7: **Gender Earnings Gap Across States**

State	Marginal Effect
Alabama	-0.525***
Arkansas	-0.426***
Arizona	-0.48***
California	-0.301***
Colorado	-0.391***
Connecticut	-0.375***
Florida	-0.418***
Georgia	-0.399***
Iowa	-0.422***
Idaho	-0.408***
Illinois	-0.403***
Indiana	-0.346***
Kansas	-0.305***
Kentucky	-0.411***
Louisiana	-0.354***
Massachusetts	-0.382***
Maryland	-0.26***
Maine	-0.382***
Michigan	-0.332***
Maine	-0.382***
Minnesota	-0.468***
Missouri	-0.478***
Montana	-0.292***
Mississippi	-0.462***
North Carolina	-0.439***
Nebraska	-0.397***
New Hampshire	-0.397***
New Jersey	-0.256***
Nevada	-0.448*
New York	-0.249***
Ohio	-0.344***
Oklahoma	-0.369***
Oregon	-0.254***
Pennsylvania	-0.303***
Rhode Island	-0.422***
South Carolina	-0.476***
South Dakota	-0.432***
Tennessee	-0.341***
Texas	-0.39***
Utah	-0.408***
Virginia	-0.429***
Vermont	-0.434***
Washington	-0.333***
Wisconsin	-0.386***
West Virginia	-0.357***

Notes: This table offers the gender differences in earnings for women relative to men across different states based on information for the years 1999 to 2005. The APEs are obtained from specification (7) in Table 6. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. See text for further details.

Table 8: **Gender Earnings Gap Across Manufacturing Industries**

SIC Industry (2 Digit)	Industry	Earning Gap
22	Textile Mill Products	-0.25***
23	Apparel & Other Textile Products	-0.27***
24	Lumber & Wood Products	-0.11***
25	Furniture & Fixtures	-0.17***
26	Paper & Allied Products	-0.26***
27	Printing & Publishing	-0.25***
28	Chemical & Allied Products	-0.21***
29	Petroleum & Coal Products	-0.45**
30	Rubber & Miscellaneous Products	-0.34***
31	Leather & Leather Products	-0.2***
32	Stone, Clay & Glass Products	-0.19***
33	Primary Metal Products	-0.23***
34	Fabricated Metal Products	-0.19***
35	Industrial Machinery & Equipment	-0.25***
36	Electronic & Other Electric Equipment	-0.27***
37	Transportation Equipment	-0.21***
38	Instruments & Related Products	-0.28***
39	Miscellaneous Manufacturing Industries	-0.29***

Notes: This table represents the gender differential in earnings across sectors by interacting the female and sector dummies after controlling for state and sectors separately based on information for the years 1999 to 2005. Larger estimates (in absolute value) imply lower earnings for women compared to men by sector (and hence higher gender earnings differential) for those individuals who were laid off due to trade. The APEs are obtained from specification (8) in Table 6. * p<0.10, ** p<0.05, *** p<0.01. See text for further details.

Table 9: **Gender Wage Gap: Robustness Results**

	All individuals	> 10%	> 20%
	(1)	(2)	(3)
Female Dummy	-0.331***	-0.308***	-0.289***
	(0.0251)	(0.0253)	(0.0259)
Female x After	-0.014	0.025	0.038
	(0.0509)	(0.0363)	(0.0335)
State Fixed Effect	✓	✓	✓
Sector Fixed Effects	✓	✓	✓
No of women	45,472	41,680	37,375
No of men	40,555	37,731	35,361
Observations	153,898	142,569	129,957

Notes: The dependent variable is log earnings. The reported coefficient estimates are based on the years 1999 to 2005 and the manufacturing sectors only. Two time periods – the third quarter before and the third quarter after the TAA program – are used. All specifications include demographic controls similar to what has been used in Table 6. Standard errors reported in parenthesis are robust to heteroskedasticity and serial correlation. * p<0.10, ** p<0.05, *** p<0.01

Table 10: **Gender Differences in Employment: Robustness Results**

	All individuals	> 10%	> 20%
	(1)	(2)	(3)
Female Dummy	-0.111	-0.169	-0.151
	(0.0983)	(0.1171)	(0.1407)
State Fixed Effect	✓	✓	✓
Sector Fixed Effects	✓	✓	✓
No of women	38,972	34,953	30,324
No of men	35,295	32,320	29,813
Observations	74,267	67,273	60,137

Notes: The dependent variable is the indicator for whether a person is employed in the third quarter after the TAA program or not. The reported probit coefficient estimates are based on the years 1999 to 2005 and the manufacturing sectors only. All specifications include demographic controls similar to what has been used in Table 3. Standard errors for the coefficient estimates are robust to heteroskedasticity.
* p<0.10, ** p<0.05, *** p<0.01