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Training and Labor Adjustment to Trade*

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August 2019

Abstract

While there is a large body of literature evaluating how active labor-market policies such as training impact worker outcomes, relatively few studies examine how such policies impact workers who are displaced by trade. The few studies on training and trade-related labor adjustment focus on the impact of trade-specific assistance programs. Most countries in the world, however, do not have assistance programs that are triggered by trade events but instead implement labor-market policies for reasons other than trade. In this paper, we use detailed data on workers' employment histories and training activities to evaluate the impact of an industrial training program in Brazil on workers who are displaced from manufacturing sectors. We find that industrial training increases the probability of re-entry into the formal labor market one year after displacement by about 13.2 percentage points (equivalent to 30%) and is effective for workers who are displaced from sectors of high exposure to import competition. This effect is explained by workers switching sectors and occupations after training. We also find that training has positive effects on employment spells and cumulative earnings in the two years after displacement.

JEL Codes: F14, F16, F61, F66, J00

Keywords: job training, displaced workers, trade exposure, matched employer-employee data

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1. INTRODUCTION

Trade liberalization and other trade shocks impose a burden on specific groups of workers, as documented in a large body of literature.[1] Trade involves a reallocation of production factors that must move from import-competing sectors to sectors with comparative advantage. Although this reallocation process brings efficiency gains at the aggregate level, workers bear significant costs when switching sectors in terms of employment spells (Murphy and Topel, 1987) and wage losses (Neal, 1995). These costs emerge from industry-specific human capital, which cannot be transferred in a frictionless way from one industry to another (Neal, 1995; Dix-Carneiro, 2014; Yi, Mueller, and Stegmaier, 2017).

Active labor-market policies can ease the transition across sectors of workers who are displaced by trade. However, only a few (developed) countries in the world have assistance programs that are triggered by trade events, such as the Trade Adjustment Assistance Program (TAA) in the US and the European Globalization Adjustment Fund (EGF) in Europe. Most countries implement active labor-market policies for reasons other than trade that nevertheless may help workers affected by trade shocks. In principle, some of these policies, such as training programs, can provide workers who are displaced from import-competing sectors with new skills, facilitating their transition to other sectors, even if these programs were not specifically designed to assist trade-related displacements. How do training programs perform when applied to workers who are displaced from trade-exposed sectors?

The objective of this paper is to answer this question in the context of a developing country. We study a large-scale general training program in Brazil administered by the National Service for Industrial Training (*Serviço Nacional de Aprendizagem Industrial*, SENAI) on the labor-market outcomes of workers who are displaced from manufacturing sectors. We build a dataset that allows us to track a worker's employment history (from 2006 to 2015) and training activities (from 2009 to 2014) by merging a matched employer-employee dataset (*Relação Anual de Informações Sociais*, RAIS) that spans the universe of formal firms in Brazil with data at the individual level on training from SENAI.[2] Using this data, we estimate the impact of training on the probability of workers who are displaced from manufacturing sectors being re-employed and we study if training is effective for workers who are displaced from sectors with high import competition.

There are two main challenges to identifying causal effects in our setting. First, employment separation is not strictly exogenous and can be driven by unobservable factors not captured by control variables.[3] Second, the decision to engage in training is voluntary and can be driven by unobservable individual characteristics, which may, in turn, be correlated with the probability of re-employment. To address the first issue, throughout the analysis we focus exclusively on workers that we identify as involuntarily displaced, using information from the RAIS dataset on the reason for separation. To address the second issue, we use an instrumental variable design that exploits variation in the availability of training over time and across geographic areas. We find that training availability is a strong predictor of the individual decision to receive training, implying that the instrument is not weak. The main identifying assumption—which we cannot test—is that once we control for observable characteristics and an array of fixed effects, the geographic availability of training only affects the probability of re-employment through the decision to take a course. We also discard the possibility that pre-existing trends are driving the results by running placebo regressions.

We find, as expected, that workers who are displaced from sectors with high levels of import penetration (IP) face a lower probability of re-employment in the displacing sector than workers who are displaced from low-IP sectors. However, the impact of training on short-term employability for workers who are displaced

[1] For literature reviews on the impacts of globalization on different groups of workers across different countries, see Goldberg and Pavcnik (2007); and Pavcnik (2017).

[2] To our knowledge the only papers using a linked dataset of the RAIS and SENAI datasets are Bastos, Silva, and Proença (2016), Silva, Gukovas, and Caruso (2015), and Corseuil, Fogel, and Gonzaga (2016). However, their research questions are different to ours.

[3] We control for a wide array of fixed effects, including initial sector of employment, and municipality. We also control for a variety of individual and firm characteristics.

from high-IP sectors is higher than average. SENAI training courses increase the probability of re-employment one year after displacement by 13.2 percentage points (p.p.), which is equivalent to an increase of 30.2%. This probability is even higher for workers who are displaced from high-IP sectors, at 19.6 p.p. Importantly, the increase in employability is driven by an increase in the probability of re-employment in a different manufacturing sector and not by increases in employability in the original sector of displacement or in nonmanufacturing. We find analogous results when we focus on occupations: training increases the probability of re-employment in a different occupation and does not have a statistically significant impact on the probability of re-employment in the original occupation. We interpret our results as evidence that SENAI training facilitates transitions into other sectors.

We also explore the existence of heterogeneous effects of training across different groups of workers. We find that the effect of training is higher for high-school graduates, workers in the middle of the age distribution, and workers with longer tenure in their last job. Importantly, we find that shorter courses are more effective in guaranteeing employability than longer courses. When analyzing the characteristics of the manufacturing sectors to which displaced workers transition, we find they are more likely to transition to sectors with high comparative advantage, regardless of the import competition in their initial sector. Although the program does not target a specific pattern of sector reallocation, it can be important to take these features into account if programs like this are considered for a re-design to address trade events. Finally, we conduct a series of tests and show our results are robust to altering the definition of trade-exposed sectors and to including several time-varying controls at the municipality level.

Analyzing the extent to which general training programs facilitate the reallocation of workers who are displaced from trade-exposed sectors is important for various reasons.[4] First, many countries already implement these policies, therefore knowing if these programs work may help inform decisions of whether to launch a new trade-related assistance program or not. This is especially important in developing countries, where resources to create new programs and the ability to execute them are limited. Second, whether governments should assist trade-related labor displacements with trade-specific programs is a subject of debate. For instance, a call for a broader approach is sometimes based on the idea that it can be hard to prove that a change in a labor outcome is the result of a trade-related event as opposed to other shocks (like technology or demand shocks), and thus casting a larger net could be a more effective approach to assisting workers, including those affected by trade shocks. A third argument, based on political economy, states that singling out a trade-specific program could feed negative perceptions about international trade, eroding support for policies such as free trade agreements, making general programs preferable.[5] A related argument states that assistance policies face time-inconsistency problems: governments have incentives to promise a compensation scheme ex-ante (for example, before signing a free trade agreement) but not to carry it out ex-post (Rodrik, 2018). If general programs that are already in place prove to smooth the transition of workers who are displaced from trade-exposed sectors, it may be in countries' interests to stick with them, perhaps with marginal modifications to improve their overall effectiveness.

Our paper contributes to several strands of existing literature. First, by analyzing the impact of training on the employability of workers who are displaced from highly trade-exposed sectors, this study adds to the literature on the impact of trade-related assistance programs. While earlier analyses show that the program has no significant effects on earnings (Decker and Corson, 1995; D'Amico et al., 2007), more recent studies find that the training component has positive effects on participants' earnings (Park, 2009; Barnette and Park, 2016; Hyman, 2017).[6] Our results provide new, complementary evidence of the extent to which general

[4] By general training programs we mean programs that they are not triggered by trade events.

[5] See Rodríguez Chatruc, Stein, and Vlaicu (2019) for experimental evidence on the effect that making employment losses salient has on support for trade.

[6] Cernat and Mustilli (2017) and Claeys and Sapir (2018) provide descriptive evidence on the European Globalization Adjustment Fund (EGF). To the best of our knowledge, impact evaluations of this program do not exist to date.

training programs, as opposed to trade-specific training programs, impact workers who are displaced from manufacturing sectors and how their effectiveness varies with trade exposure.[7]

Second, our study speaks to an increasing body of analyses that link trade episodes with labor-market outcomes (Menezes-Filho and Muendler, 2011; Dix-Carneiro and Kovak, 2017 and 2019; Bernard, Jensen, and Schott, 2006; Autor, Dorn, and Hanson, 2013; Acemoglu et al., 2016). Most of these analyses carefully identify the causal effects of trade on labor outcomes but do not evaluate the role of policies in assisting affected workers. Our paper complements this literature by studying whether an active labor-market policy such as training can ease the impacts of international trade.

Lastly, our paper relates to the large and more general body of literature evaluating the impact of active labor-market policies on worker performance. Many of the analyses have been summarized in different studies, including McKenzie (2017), Card, Kluve, and Weber (2015) and Crépon, Gerard, and Berg (2016), among others. There is no unified message regarding the effectiveness of these programs, as the results from the various evaluations tend to be mixed due to differences in methodologies, the quality of the interventions, and the context in which the interventions are formulated, among other factors. McKenzie (2017), for example, presents a survey based on 24 randomized control trials examining an array of labor-market programs and concludes that many of these policies are much less effective than assumed. Card, Kluve, and Weber (2015) develop a meta-analysis with more than 200 evaluations of active labor-market policies around the world and offer a more nuanced view. The authors suggest that while the average impacts of such policies tend to be close to zero in the short run, they become positive in the medium run, with programs that emphasize some form of human capital accumulation typically showing the best outcomes. Like most of the analyses in this literature, our study evaluates the impact of a general training program but it complements the existing evidence by focusing on the effects that these programs have on workers who are displaced from trade-exposed sectors.

The rest of the paper is divided as follows. Section 2 provides a detailed description of the SENAI institution and its training activities. Section 3 lays out the empirical methodology. Section 4 describes the various datasets used in the analysis and shows descriptive evidence. Section 5 presents and discusses the results of the estimations while section 6 presents the results of robustness exercises. Finally, section 7 concludes.

2. BACKGROUND ON SENAI TRAINING COURSES

SENAI is a network of not-for-profit training centers established by the National Confederation of Industry (*Confederação Nacional da Indústria*, CNI), Brazil's largest business association.[8] SENAI is the largest training provider in the manufacturing sector in Brazil. The programs are funded primarily by the federal government through a 1% payroll tax on manufacturing employment. Accordingly, SENAI is structured as a hybrid organization, funded by the public sector but governed by a business association. Operating through a system of national and regional bodies with delegates from the ministries of education and labor, SENAI has close to a thousand training centers distributed through all the states of Brazil (see figure 1).

Our evaluation focuses on the basic qualification courses offered by SENAI.[9] With an average duration of 200 hours, the objective of these courses is to develop or to perfect skills for a range of occupations.[10]

[7] Hummels et al. (2012) is also related to our paper. They study the adjustment process for workers who are displaced from offshoring firms vis-à-vis those who are displaced from nonoffshoring firms. Instead of estimating the impact of training as we do, they analyze differences in training take-up rates between the two groups.

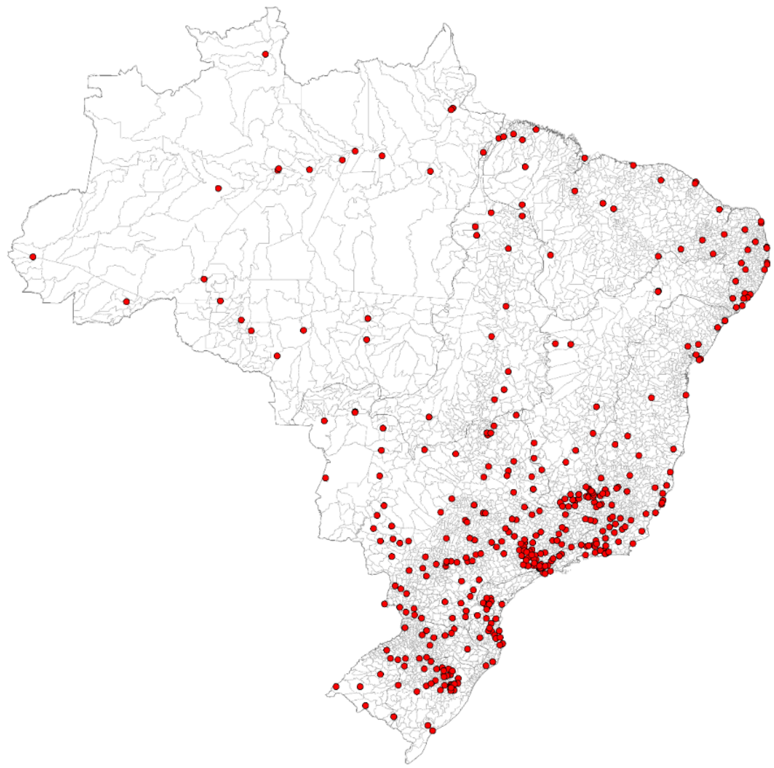
[8] CNI is the highest-level official organization representing private Brazilian industry.

[9] SENAI also provides guidance on the job search process by forming partnerships with employment services agencies at the subnational level. Unfortunately, we do not have individual-level data on who uses these services, so the effects we estimate include both the effects of the training and the effect of job search assistance, if any was provided.

[10] SENAI also offers longer technical qualification courses (600 hours on average). We are not including these in the analysis since they have a much smaller enrollment rate (about 10% of the enrollment rate for the basic qualification courses), so when matching this to the RAIS dataset, the number of treated workers is too small to identify the effects separately. If we include these courses in the analysis and consider as treated a worker that took either a basic or technical qualification course, none of the main conclusions reached in the paper are altered.

Examples of basic qualification courses include programs to become a certified operator of plastic extruder machines, a textile design assistant, a certified operator of rubber transforming machines, and an installer of electronic vehicular systems. The enrollment of new students in qualification courses increased steadily during most of our sample period except for 2014, starting with close to 443,000 students in 2009, reaching peak enrollment levels of almost 870,000 in 2013, as figure 2 shows.[11, 12]

FIGURE 1. LOCATION OF SENAI TRAINING CENTERS, 2015

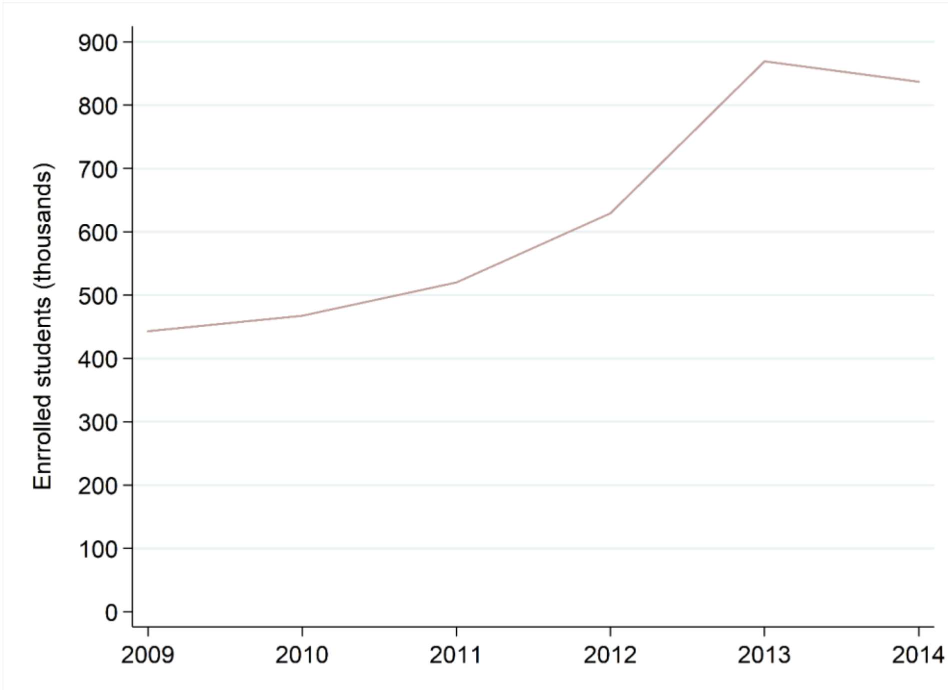


Source: Compiled by the authors based on data shared by SENAI.

[11] Since our investigation centers on the role of training for displaced workers who already have relevant work experience in formal manufacturing, we are not including the apprenticeship, initiation, and habilitation courses or any internship programs offered by SENAI in our analysis, as these generally target first-time job seekers.

[12] In 2010 SENAI reclassified basic qualification courses of a duration of less than 160 hours as upgrading courses—which are aimed at perfecting skills workers had already acquired—regardless of the content of the course. To keep track of these courses and include them in our analysis, the courses we classify as "qualification courses" are those lasting less than 160 hours which were labelled as a basic qualification in 2009 but were reclassified by SENAI from 2010 onwards as upgrading courses. Reassuringly, all the main results in the paper are qualitatively similar if courses are not reclassified.

FIGURE 2. ENROLLMENT IN SENAI QUALIFICATION COURSES, 2009–2014



Notes: The graph shows the number of newly enrolled students in SENAI qualification courses as we define them in this paper. In 2010 SENAI reclassified basic qualification courses of less than 160 hours as upgrading courses. From 2010 onwards, we use the classification of "basic qualification" for courses of less than 160 hours that were listed in 2009 as a basic qualification but have recently been reclassified by SENAI as upgrading courses.

SENAI qualification courses are open to the general public aged 16 years and over, regardless of their prior education level. Courses can either be offered for a fee or can be subsidized through public programs (such as PRONATEC). Although we do not have information on the monetary fee paid by the students, we do have information on which students were subsidized by public programs and which students were not. We exploit this information in the empirical analysis (see section 5).

3. EMPIRICAL STRATEGY

The objective of our study is to assess the extent to which general training programs can ease the transition to new employment after displacement for workers who previously held jobs in highly trade-exposed manufacturing sectors. Here, the term "general training programs" refers to training programs that are not specifically designed to deal with trade-related displacements.

There are two critical periods for workers in our analysis: the end of period t, when we observe if a worker who was previously employed in manufacturing is displaced (or not), and the end of period $t+1$, when we assess if re-entry into the (formal) labor market has occurred. Each period corresponds to calendar years, and the end of the period corresponds to the month of December. An advantage of this strategy is that it allows us to compare workers with relatively similar work histories. In other words, we avoid mixing workers who have been out of the labor market for a short period of time with those who have been out of the labor market for many years. In our analysis, the comparison is among workers who were employed in the manufacturing sector at roughly similar times and have been out of the labor market for no more than a year.[13] During this time (i.e., period t), some workers took a SENAI training course, while others did not. We observe the workers in December of period $t+1$ to check whether they were re-hired (in manufacturing or in other

[13] When we say an individual is out of the labor market or unemployed, we actually mean that they are out of the *formal* labor market. Since RAIS only surveys formal firms, we cannot track individual trajectories in the informal labor market.

sectors). One limitation of the RAIS data is that a worker not being observed in *t*+1 could be due to a variety of reasons that we cannot distinguish. For example, the worker could be unemployed and actively searching for employment, or she could be inactive, self-employed, or employed in an informal (i.e., unregistered) job.[14]

We employ the following specification to evaluate the impact of training:

$$Y_{i,t+1} = \beta T_{i,t} + \gamma X_{i,t} + \theta_{s,t} + \theta_m + \varepsilon_{i,t}, \qquad (1)$$

where $Y_{i,t+1}$ is a binary variable that is equal to 1 if individual *i*, who previously worked in manufacturing sector *s* in a plant located in municipality *m,* is employed in the formal labor market at period *t+1* and equal to 0 otherwise; $T_{i,t}$ is a dummy variable that is equal to 1 if individual *i* took a SENAI training course in period *t* (while unemployed) and equal to 0 otherwise; $X_{i,t}$ is a vector of characteristics of individual *i*, such as her age, gender, and education, and the characteristics of her last job, such as tenure, and her last firm, such as its size (number of employees). Finally, θ_{st} are sector-year fixed effects and θ_m are municipality fixed effects.

Workers who are displaced from highly trade-exposed sectors likely need to find jobs in a different sector. Below, we show that workers who are displaced from sectors more exposed to import competition have indeed a lower probability of being re-employed in the same sector than workers who are displaced from relatively less exposed sectors. Since the literature has shown that switching sectors is costly for workers (Neal, 1995; Dix-Carneiro, 2014; Yi, Mueller, and Stegmaier, 2017), an important question is whether there are policies that can facilitate this transition process.

In order to examine this issue, the dependent variable in equation (1) is decomposed to analyze not only whether training improves the chances of returning to the labor market in general, but also whether training is related to employability in a different sector. To this end, we decompose the probability of being re-hired into the probability of returning to the same manufacturing sector from which they were displaced, the probability of being re-employed in a different manufacturing sector, and the probability of being re-employed in nonmanufacturing. Likewise, we also decompose that probability into the probability of returning to the same occupation and to a different occupation. We evaluate this impact for the whole sample of workers who are displaced from manufacturing and then we split the sample into high- and low-IP sectors. This allows us to see if the effectiveness of the courses varies with trade exposure.[15]

One challenge when analyzing the trajectories of displaced workers is to find an effective way to separate genuine displacements from voluntary quits and separations. We exploit the fact that RAIS contains a variable that specifies the reason for separation (dismissal, quit, end of contract, retirement, death, etc.). We keep in our sample workers that have been involuntarily displaced, which we defined as those workers that have been either dismissed or whose contracts ended.[16]

The main challenge in evaluating training programs is to control for selection into training. The decision to engage in training is likely driven by unobservable individual characteristics, which can, in turn, be correlated with the probability of re-employment. To address this issue, we use an instrumental variable design that exploits variation in the availability of training over time and across geographic areas.[17] Our preferred instrument is the number of SENAI qualification courses that are available in the municipality where the

[14] However, the SENAI dataset does provide information on employment status. We do therefore know if the trainee was employed or unemployed when she registered for training. In section 5.C, we exploit this information to analyze if trainees that are unemployed during training have a different return from training than trainees that are not.

[15] Table A1 shows the list of the 20 most and 20 least trade-exposed sectors and includes details about the calculations.

[16] The main results presented in the paper are robust to using other definitions of displacement that exclude the end of contract and that exclude dismissals with cause.

[17] Our choice of instrument relates to a large literature using geographic variation in the accessibility of public services to identify casual effects. Card (1995) introduced this idea by using geographic distance to college as an instrument for years of schooling in an earnings equation. Related approaches are used by Currie and Moretti (2003), Nybom (2017), and Chau (2004). Spiess and Wrolich (2010) find that the probability of enrolling in higher education decreases with distance. In the context of evaluating training programs, Brunello, Comi, and Sonedda (2012) use regional variation in training policies.

individual was last employed and in the neighboring (i.e., contiguous) municipalities per 1,000 people.[18] The intuition behind this choice of instrument is that training take-up is more likely when the worker is geographically closer to a larger supply of courses, given that this reduces the commuting cost as well as the cost of acquiring information about courses. However, it is possible that places with a larger supply of SENAI courses are also more populated, limiting individuals' ability to obtain a vacancy for a course. To capture this possibility, we normalize by the population of the municipality and the contiguous municipalities. The first-stage equation is therefore given by

$$T_{i,t} = \alpha Z_{m,t} + \gamma \cdot X_{i,t} + \theta_{s,t} + \theta_m + \nu_{i,t}, \tag{2}$$

where $Z_{m,t}$ is our instrument, which is given by

$$Z_{m,t} = \frac{courses_{m,t} + \sum_{n \in C_m} courses_{n,t}}{population_{m,t} + \sum_{n \in C_m} population_{n,t}}, \tag{3}$$

where $courses_{m,t}$ ($courses_{n,t}$) is the number of SENAI qualification courses offered in municipality *m* (*n*) in year *t*; $population_{m,t}$ ($population_{n,t}$) is the population of municipality *m* (*n*); and C_m is the set of municipalities that are contiguous to municipality *m*. The numerator is therefore the total number of SENAI qualification courses offered in municipality *m* and the contiguous municipalities and the denominator is the total population in municipality *m* and its contiguous municipalities. We divide the denominator by 1,000 to express the measure per 1,000 inhabitants instead of in per-capita terms to make the coefficients and descriptive statistics easier to interpret, but this does not alter the estimated regression coefficients for the second stage.

The identifying assumption is that, once we control for observable characteristics and fixed effects, the number of SENAI courses per 1,000 inhabitants only affects the probability of re-employment through the decision of taking a course. This assumption can be violated if there are other factors varying at the municipality and time level (the level of variation of our instrument) that affect the supply of courses but also affect the probability of finding a job, such as changes in the overall level of economic activity. To address this issue, in robustness tests, we include the municipality's per-capita GDP, the level of manufacturing employment, and trade exposure as defined in Autor, Dorn, and Hanson (2013) as control variables. SENAI officials told us that the location of the training centers is driven by the presence of a manufacturing industry in the municipality or in its vicinity that might demand the skills provided by the courses. In addition, we discard the possibility that pre-existing trends are driving the results by running placebo regressions.

Our instrument exhibits variation across space and time, as panels A and C of figure 3 show. While some municipalities have no courses, others have more than 1 course per 1,000 inhabitants (including in contiguous municipalities). There are also areas with a high concentration of courses in 2009—for example, those in the southeast—that end up having a relatively lower concentration in 2014, while some municipalities that had qualification courses in 2009 end up having a medium level of concentration in 2014—such as those in the northwest. Panels B and D allow us to compare the variation in the instrument with the variation in the share of people taking SENAI qualification training, which provides visual proof that the instrument is not weak. By comparing panel A with B and panel C with D, we can see that areas that have a higher concentration of courses tend to have a higher concentration of trainees in our sample. This correlation is not mechanical,

[18] Although SENAI does not provide the individual's home address when training was taken, we use RAIS to recover information on which municipality the individual was last employed in. Implicitly, we are assuming individuals do not move beyond contiguous municipalities in the months that go between displacement and training. If they did move, this would imply our instrument is weak, however, this is not what we find empirically, given that the first stage of our regressions has an F-statistic well above 10.

since our sample consists of workers who are displaced from formal manufacturing, rather than being made up of all possible trainees.

Another potential source of bias in our results could be due to workers participating in training programs other than the SENAI qualification. To deal with this, we exclude workers that took part in other SENAI training programs such as the ones mentioned in section 2. Although SENAI is responsible for 80% of Brazil's industrial vocational training, we cannot rule out that workers participated in non-SENAI programs.[19] However, if workers in the control group participated in other programs, and these programs increased their employability, this would likely bias our results downward and our effects should be interpreted as a lower bound.

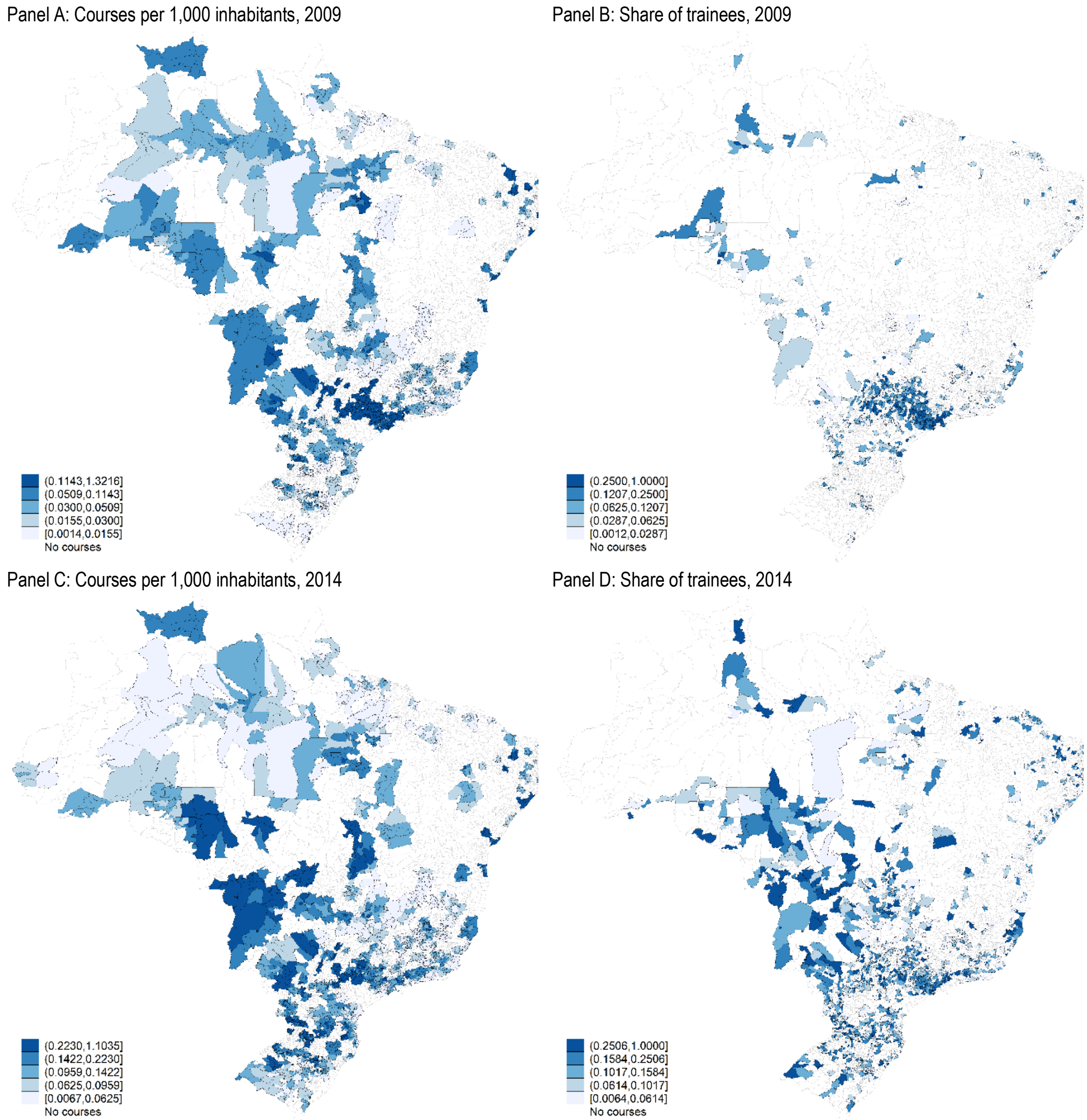
Much of our analysis is devoted to analyzing the impact of training on workers who are displaced from high-IP sectors. For example, we estimate equation 1 for the subsample of workers who are displaced from sectors where IP in Brazil is above the median. For this purpose, we use the standard definition of IP:

$$IP_{s,t} = \frac{Imports_{s,t}}{Output_{s,t} + Imports_{s,t} - Exports_{s,t}} \quad (4),$$

where *s* is a 4-digit sector of the CNAE version 2 classification. The numerator is imports from sector *s* and the denominator is the apparent consumption of sector *s*, which is equal to the output plus the imports of the sector minus its exports. Our sample period for the estimations—2009 to 2014—coincides with an increase in IP in manufacturing in the Brazilian economy of around 4 p.p.—equivalent to 25%—as shown in figure 4. In order to prevent sectors from switching across high- and low-IP categories during the estimation period, we take the average IP for each sector from *before* our sample period (between 2005 and 2007) and we classify a sector as high-IP if it is above the median and as low otherwise.

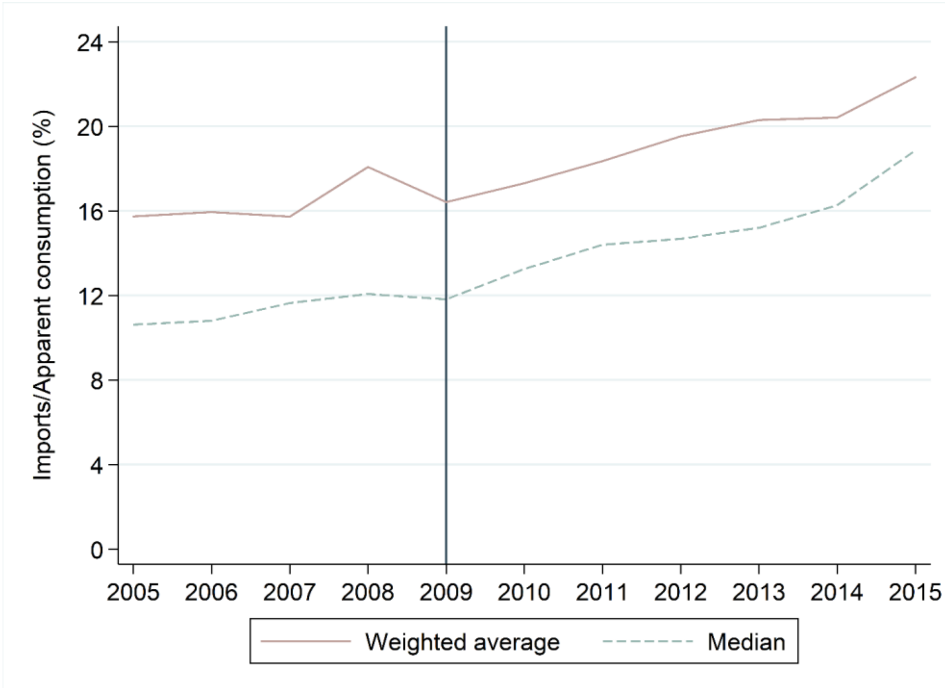
[19] The 80% figure was obtained in conversations with SENAI officials.

FIGURE 3. BRAZILIAN MUNICIPALITIES' SENAI QUALIFICATION COURSES PER 1,000 INHABITANTS AND SHARE OF TRAINEES, 2009 AND 2014



Notes: The figure displays maps at the municipality level (N=5,570). Panels A and C display our instrumental variable in 2009 and 2014, respectively. The instrument is the total number of SENAI qualification courses offered in a municipality and the contiguous municipalities normalized by the total population (in thousands). Panels B and D display the share of workers in our sample that took SENAI qualification training in 2009 and 2014, respectively.

FIGURE 4. IMPORT PENETRATION IN MANUFACTURING, 2005–2015



Notes: The figure displays IP in Brazil for the manufacturing sector as a whole. IP is the ratio of imports to apparent consumption (gross output + imports - exports) multiplied by 100. We obtain the imports, exports, and output for each CNAE v2 4-digit sector annually. For each year, the figure shows the weighted average (the sum of imports for all 4-digit sectors divided by the sum of their apparent consumption) and the median value.

4. DATA AND DESCRIPTIVE EVIDENCE

We use two main datasets in this paper. First, we use administrative data from SENAI from 2009 to 2014. The SENAI dataset includes individual-level information on the workers trained each year, the municipality of the training facility, the type of course taken, the course duration and the enrollment and completion dates. As explained in section 2, we focus on the basic qualification courses offered by SENAI.

Second, we use the matched employer-employee dataset, *Relação Anual de Informações Sociais* (RAIS) for 2006–2015.[20] The RAIS dataset is collected annually by the Ministry of Labor and Employment of Brazil and covers the universe of formal firms in the country and their registered workers. RAIS provides a battery of information on the workers (age, gender, education) and on their jobs (occupation, wage, tenure), as well as information on hiring and termination dates. Additionally, RAIS collects information on the worker's plant, including its 4-digit industry category and the municipality where it is located.

We merge the RAIS dataset with the SENAI dataset using the worker's identification number, making it possible to track workers' formal employment and training history.[21] We work at the most detailed level of sector aggregation that the data allows, which is the 4-digit level of the Brazilian National Classification of Economic Activities (*Classificação Nacional de Atividades Econômicas*, CNAE, version 2).[22] We keep workers aged 18 to 64 that were displaced from a manufacturing sector at any time from 2009 to 2014 in our sample. We can retrieve these workers' employment histories up to three years before 2009 and a year after 2014, since the RAIS dataset that we have access to covers 2006–2015. So, for example, we know if someone who

[20] RAIS has been extensively used in the literature that estimates the impacts of trade liberalization on worker outcomes. See for example, Menezes-Filho and Muendler (2011), Dix-Carneiro (2014), and Dix-Carneiro and Kovak (2017).

[21] Other studies linking SENAI and RAIS datasets include Bastos, Silva, and Proença (2016), Corseuil, Foguel, and Gonzaga (2016), and Silva, Gukovas, and Caruso (2015).

[22] There are 234 4-digit manufacturing sectors in our sample.

received training in 2014 was re-employed in 2015 or if someone who received training in 2009 was previously employed in 2008, 2007, or 2006.[23]

We start by examining whether workers who are displaced from highly trade-exposed sectors do indeed have a harder time re-entering the labor market. Table 1 presents the probability of re-employment in the same sector of origin after displacement by the sector's exposure to import competition. The results for workers who are displaced from sectors that are highly exposed to trade and sectors that are less exposed are presented in columns 1 and 2, respectively. The first row in the table shows unconditional probabilities: 10.8% of the workers who were displaced from high-exposure sectors were re-hired in the same 4-digit sector in period $t+1$, as compared to 14.7% for workers who were displaced from low-exposure sectors. When performing the comparison at the 2-digit level, we obtain probabilities of 14.5% versus 17.5%, respectively. The second row shows conditional probabilities, where the predicted probability of re-entry is conditioned on individual characteristics and year fixed effects. The results confirm the findings in the first row. The conditional probability of re-entry into the same sector is 11.3% for workers who are displaced from high-exposure sectors and 14.4% for workers who are displaced from low-exposure sectors. The difference is 1 p.p. smaller when we analyze it at the 2-digit level (15.0% versus 17.2%). The results support the notion that because trade shocks tend to be sector-specific in nature, workers who are displaced from highly trade-exposed sectors are less likely to return to the same sector. Because they may encounter frictions when switching sectors, their re-employment might take time. The question is whether training can aid this process.

SENAI training courses are associated with an increased chance of switching sectors, as shown in table 2. The table reports the (unconditional) transition probabilities of displaced workers by their training status. Even though these are not causal estimates, some suggestive messages emerge. Overall, trainees have a 13.4 pp. lower probability of remaining out of the formal labor force in t+1 (43.5%) than nontrainees (56.9%) and a lower probability of transitioning into the same (2-digit) sector that displaced them (12.7%) than nontrainees (16.4%). This is compensated by trainees having a higher probability of transitioning into a different sector in manufacturing or to nonmanufacturing than nontrainees.[24] For workers who are displaced from high-IP sectors, the probability of remaining jobless is also lower for trainees but overall they have a lower probability of returning to the sector from which they were displaced, as compared with the whole sample. Overall, the descriptive evidence in table 2 indicates that SENAI training is positively correlated with re-employment in sectors other than the displacing sector. This suggests that training can aid in the sectoralreallocation of workers who are displaced from trade-exposed sectors. The next section examines whether this link is causal.

Before moving to the results section, it is worth reviewing differences in the individual characteristics of workers who are displaced from manufacturing separating by training status. Table 3 shows the results for all manufacturing sectors and for trade-exposed sectors. On average, trainees are around three years younger than nontrainees, have about one year more of education, are less likely to be female, and have similar tenure. This same pattern holds for workers who are displaced from sectors with high levels of IP, with the exception of tenure, for which the difference by training status is significant, albeit small.

[23] To keep the sample size manageable, we do not work with the full RAIS dataset but instead take a random sample of 10% of individual IDs in RAIS.
[24] Nonmanufacturing comprises agriculture, mining, and services.

5. ESTIMATION RESULTS

A. Baseline estimates

We start by exploring the impact of training on the probability of re-employment for displaced manufacturing workers in table 4. According to the OLS estimate of equation 1 (column 1, table 4), displaced workers who received training have a higher probability (9.9 p.p.) of being employed in the period after displacement than workers who did not receive training. This increase in the probability of re-employment is similar for sectors with high and low levels of IP (columns 2 and 3). Regarding the covariates, the estimates imply that the probability of transitioning to a new job after displacement increases with education and with tenure (concavely), decreases with age and the number of employees at the displacing firm, and is smaller for women.

The 2SLS estimate, using the number of courses per 1,000 inhabitants in the vicinity of the individual's municipality as an instrument, is larger than the OLS estimate and implies that training has an impact of 13.2 p.p.[25] Contrary to the OLS estimation, however, this coefficient is larger for workers who are displaced from sectors with above-median IP (column 5), with a 19.6 p.p. increase in the probability of re-employment associated with training. The number of courses per 1,000 inhabitants is a strong predictor of the probability of having received training, with a first-stage F-statistic above 80. The coefficient of 0.4 (at the bottom of column 4) implies that an individual in a municipality in the 75th percentile of the course distribution (per 1,000 inhabitants) has a 3.4-p.p. higher probability of taking a training course than an individual in a municipality in the 25th percentile.[26] Given that the overall probability of re-entry into the formal labor market for nontrainees is 43.1%, our baseline estimate of 13.2 p.p. implies an increase of 30.6% in this probability for trainees. Our results overall suggest that training is effective among workers who are displaced from high-IP sectors.[27] The impact on workers who are displaced from low-IP sectors is smaller and less precisely estimated.

Our results imply that OLS estimates underestimate the impact of training on the probability of re-employment. If receiving training is correlated with unobservable individual traits such as motivation—which can correlate positively with both training and the error term—we would expect OLS to be upward-biased rather than downward-biased. In the returns to schooling literature, the finding that OLS is downward-biased is quite frequent (Ashenfelter, Harmon, and Oosterbeek, 2000). One possible explanation is that the IV coefficient is reflecting the effect of training on a subset of the population, namely, those induced to change behavior by the instrument. In this sense, IV identifies a local average treatment effect (Imbens and Angrist, 1994). This subgroup may have a higher return to training in terms of the probability of finding employment than the rest of the population, explaining the downward bias. However, given that the level of variation of the instrument is the municipality-time and not the individual, the existence of heterogeneous returns to training in this context implies that there would be more job creation in areas with a higher supply of courses. We address this possibility in two ways. First, by including municipality fixed effects, which capture any systematic differences in returns to training across municipalities. Second, by including time-varying variables at the municipality level that could explain changes in the returns to training within municipalities, such as employment in (formal) manufacturing, GDP per capita, or trade exposure (see section 6). A different explanation for the downward bias of OLS is that there are unobservable characteristics other than motivation that correlate with the error term but in a negative way. For example, individuals who receive training while unemployed may arguably be less financially constrained than nontrainees and may have a higher reservation wage, implying that they are more likely to forgo job offers with lower wages and are therefore less likely to

[25] In the robustness section, we explore the performance of other instruments and we obtain qualitatively similar results.
[26] The interquartile range change in courses per 1,000 inhabitants is 0.083.
[27] These results are robust to changing the definition of high-IP sector (see section 6).

be employed in t+1. If our IV corrects for this type of endogeneity, then we would expect the 2SLS coefficient to be larger than the OLS coefficient.

B. Decomposition across sectors and occupations

Next, we evaluate the extent to which trainees relocate to other sectors and occupations. For this purpose, we first decompose the overall probability of re-employment mentioned in the previous paragraph into the probability of re-employment in the same manufacturing sector from which the worker was displaced, in a different manufacturing sector, and in nonmanufacturing. Second, we decompose this into the probability of entering the same occupation and a different occupation. For the purpose of this exercise, destination sectors and occupations are defined at the 2-digit level, but results are similar when they are defined at the 4-digit level. Panel A of table 5 shows the decomposition, where each cell displays the estimated 2SLS coefficient of training from a separate regression that includes the same controls and fixed effects as the baseline estimates from table 4. For reference, the first column displays the overall impact (displayed previously in table 4). The main message that arises from panel A is that the overall impact of SENAI training is explained overwhelmingly by workers switching manufacturing sectors or occupations, independently of the IP of the displacing sector.[28] What these results point to is that this type of training facilitates the reallocation of displaced workers into different sectors and occupations.[29] As mentioned earlier, the sector-specific nature of trade shocks implies that workers who are displaced from trade-exposed sectors are most likely expected to find jobs in a different sector, a process that can be slow and costly. By showing that training improves the probability of finding jobs in different sectors, the results suggest that training helps reduce the time it takes for workers to reallocate.

C. Heterogeneous effects

We can further examine how training impacts the probability of returning to the labor market by worker, initial job, and course characteristics. In panels B to G of table 5, we repeat the regressions from panel A but splitting the sample according to those characteristics. The exercise reveals important insights regarding the effectiveness of SENAI courses across different groups. First, for the whole sample, training seems to be more effective for workers in the second tercile of the age distribution (28–36 years) than in the other two age groups (panel B, table 5). However, for high-IP sectors, the effectiveness of training seems to increase with age. Second, the overall effectiveness in terms of re-entry is explained by high-school graduates switching sectors and occupations, which also holds for sectors with high levels of IP (panel C).[30] The program has overall negative—although nonsignificant—effects for individuals with less than high school. Third, for the whole sample, SENAI training has a 2 p.p. higher point estimate for men than for women, although the estimate for women is imprecise and therefore insignificant (panel D). However, women do have a positive and significant increase in the probability of re-employment in a different manufacturing sector (column 3, panel D). Fourth, the impact is larger for those with longer tenure in their predisplacement job (panel E) and those who come from small firms (less than 99 employees). Fifth, the courses that SENAI categorizes as short have a greater impact than longer courses over the sample as a whole, whereas for high-IP sectors the impacts are more similar. There are two potential explanations for this pattern. The first is that long and short courses provide different kinds of skills. It would be interesting to distinguish by the content of course but unfortunately, we do not have systematic information about course content, just a general title for each course. The second has to do with students of different characteristics self-selecting into courses of different durations.

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[28] The fact that SENAI training does not significantly increase the probability of transitioning to nonmanufacturing is not surprising given that the courses teach skills that are mostly applicable in the manufacturing sector.

[29] An alternative explanation is that the results are due to a sorting pattern according to which displaced workers who decide to take a SENAI training course do so with the purpose of changing sectors or occupations.

[30] Trainees are more likely to be high-school graduates than nontrainees. The share of high-school graduates in the whole sample (of workers who are displaced from manufacturing) is 56.2%. The share of trainees that are high-school graduates is 77.4%.

In table A2, we provide the means of individual characteristics by course duration. Trainees who enrolled in short courses tend to be younger, more educated, less likely to be female, and to have had longer tenure in their previous jobs than students taking long courses. Importantly, the share of high-school graduates in short courses is 10 p.p. larger than in long courses and, as we saw previously, high-school graduates drive the overall impact of training on employability (panel C). Self-selection could therefore be playing a role. A related explanation that we cannot rule out is that students of different *unobservable* characteristics self-select into courses of different duration. Finally, a general insight from table 5 is that these heterogeneous effects do not seem to be so prevalent for workers who are displaced from high-IP sectors, where the impacts are more similar across groups.

We also explore heterogeneous effects by characteristics of the trainees in table 6. In columns 1 and 2, we interact the training indicator with an indicator equal to 1 if a fee was paid for training and equal to 0 if the training was subsidized.[31] Students that were unsubsidized seem to have higher returns in terms of employability, although the interaction is not significant. In columns 3 and 4, we show that graduating from the training course has a differential effect on the return on training of 12.4 p.p. This evidence supports the argument that our estimates are not merely driven by self-selection into training but that finishing courses does add value.[32] Finally, we explore the differential effect for individuals that were unemployed while they received training. As we explained earlier, we cannot know the employment status of individuals who do not appear in RAIS but we do have information on this for individuals who received training. Columns 5 and 6 show that unemployed trainees reap higher overall returns from training but that this is not estimated precisely.

D. Patterns of sector-related reallocation

What are the characteristics of destination sectors in terms of comparative advantage? Table 7 displays the coefficient of training in a regression where the dependent variable is the probability of transitioning to a sector with high or low comparative advantage, as measured by the index of revealed comparative advantage (RCA).[33] The sample is split according to the IP of the displacing sector. The table shows that workers who received training and were displaced from either high- or low-IP sectors are more likely to transition to high-RCA sectors than workers who did not receive training. These results imply that training increases the probability of displaced workers transitioning to high-RCA sectors, which is desirable as it implies workers reallocating toward more competitive sectors.[34]

E. Other outcomes: employment spells and earnings

A large body of literature analyzes the impacts of workers' displacements on medium- or long-run outcomes such as employment spells and cumulative earnings. Since our data on training starts in 2009 and our data on employment outcomes ends in 2015, we can only estimate the impact of the program on short-term outcomes. We therefore estimate the impact of SENAI training on employment spells and the cumulative

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[31] In our sample, 63% of trainees paid a fee.

[32] SENAI provides certification to students who graduate from courses, which is validated by the Ministry of Education.

[33] The index of revealed comparative advantage is calculated in the standard way as: $RCA_s^{BRA} = \frac{X_s^{BRA}/X^{BRA}}{X_s^{WLD}/X^{WLD}}$, where the numerator is the share of sector *s* in total Brazilian exports and the denominator is the share of sector *s* in total world exports. An RCA greater than 1 in sector *s* means that Brazil exports more intensively in sector *s* than the rest of the world and therefore has an RCA in this sector. As with IP, we calculate RCA yearly for 2005–2007, take averages, and then classify the sector as having high levels of RCA if its average is above the median and as having low levels of RCA otherwise.

[34] It is worth noting that the correlation coefficient between IP and RCA is slightly negative and equal to -0.12. It is therefore not the case that competitive RCA sectors have systematically higher levels of IP due to using a large share of imported inputs.

earnings one year and two years after displacement. We use the following definition of the employment spell of worker *i* displaced in year *t*:

$$EmpSpell_{it} = \frac{1}{T-t}\sum_{y=t+1}^{T}\sum_{m}\mathbf{1}\left[Emp_{imy}\right], \tag{5}$$

where Emp_{imy} is a dummy variable equal to 1 if the worker is employed in the formal sector in month *m* of year *y* (and 0, otherwise) and $\mathbf{1}[.]$ is the indicator function. We perform this sum up to two years ($T-t=2$) after displacement. Additionally, we use the following definition for (normalized) cumulative earnings of worker *i* displaced in year *t*:

$$CumEarnings_{it} = \frac{\frac{1}{T-t}\sum_{y=t+1}^{T} AveEarnings_{iy} \times EmpSpell_{iy}}{\frac{1}{2}\sum_{y=t-2}^{t-1} AveEarnings_{iy} \times EmpSpell_{iy}}, \tag{6}$$

where $AveEarnings_{iy}$ are average monthly earnings as reported in RAIS, which we multiply by the number of months employed to obtain annual earnings. We perform this sum up to two years ($T-t=2$) after displacement and we normalize it by the cumulative earnings in the two years before displacement.[35] For this estimation, we focus on the subsample of workers that were employed year-round for the two years prior to displacement. This guarantees that we are comparing workers with similar employment trajectories.[36]

Both the OLS and 2SLS estimates suggest that training increases employment spells (table 8). The IV estimates yield an effect of training of 1.35 extra months of employment in the first year after displacement (column 2, panel A) and of 1.66 extra months per year in the two-year period after displacement (column 2, panel B). Training is also associated with increases in cumulative earnings, as table 9 shows. Trainees have earnings that are 20% higher in the year after displacement (column 2, panel A) and 25% higher, on average, in the two-year period after displacement (column 2, panel A) compared to their earnings before displacement. Note that the effect on earnings also comprises the effect on employability since the sample includes workers with zero earnings (i.e., out of the formal labor force). These estimates are therefore larger than the effect we would expect on outcomes like the hourly wage, which is undefined for workers who are out of the formal labor force, so we therefore do not focus on it. Both effects on employment spells and on earnings are even larger for workers who are displaced from high-IP sectors.

F. Comparison with existing estimates

Putting our results in perspective is not easy because—due to the nature of our question—we are focusing on a narrow group: workers who are displaced from manufacturing. In addition, due to data limitations, we only analyze formal workers. Our estimates cannot therefore be compared to those relating to broader populations or to on-the-job training programs. To the best of our knowledge, there are no studies focusing on a population or training program like ours. However, the positive impact we find that SENAI training has on employability and earnings is in line with Silva, Gukovas, and Caruso (2015), who use similar data for a similar time period but for a broader population.

Estimates of the effects of job training programs vary substantially in magnitude (and precision) across different studies. A recent meta-analysis focusing on adult training programs finds that training increases employability by 2.6 p.p. on average, but there is substantial heterogeneity, and several studies find effects greater than 10 p.p. (Busso and Messina, 2019). Our estimates tend to be higher than those reported in most

[35] Note that both the measure of time in employment and of cumulative earnings include zeroes, that is, the estimation sample includes individuals who were out of the formal labor force after displacement. This is done following others in the literature (Autor et al., 2014) and allows us to avoid sample selection issues.

[36] When we perform the estimation on the whole sample, the estimates are imprecise and much larger. This is caused by some individuals having spent a very short time in employment before displacement, causing the denominator to be very small and the measure of cumulative earnings extremely large.

studies, but we attribute this to our focus on a relatively narrow group. Workers that were employed in formal manufacturing and were out of the formal labor force for a short period of time are likely to be more employable and thus may have higher returns to training than the average worker.

6. ROBUSTNESS

In this section, we describe several exercises that we perform to test the robustness of our results.

A. Alternative instruments

A potential concern around our instrument is that we consider courses in neighboring municipalities, but municipalities vary in size. Typically, municipalities in the northwest are larger in area than municipalities in the southeast. Consequently, courses in contiguous municipalities might be harder to access in the northwest since reaching them would imply traveling longer distances. To address this, we construct two alternative IVs that consider the number of courses per capita in a radius of 25 and 50 miles, respectively, from the worker's municipality. Since we do not have the exact geolocation of the worker's initial plant or of the facilities where courses take place, we consider a course to be within 25 (or 50) miles of the plant if the centroid of the municipality where the plant is located is at a distance of 25 (or 50) miles or less from the centroid of the municipality where the courses are offered. We then add up all the courses within the radius and divide them by the population of the municipality they pertain to and that of the municipalities whose centroids are within the radius.

Results using these two alternative instruments are in line with the baseline estimates, as table 10 shows. The impact of training on employability is 11.7 p.p. using the 25-mile-radius IV and 16.3 p.p. using the 50-mile-radius IV. Our baseline estimate (13.2 p.p.) lies between these two estimates. In both cases, the first stage has a high F-statistic and the impact of training is larger for workers who are displaced from high-IP sectors. Estimates are more precise when using the 50-mile definition than the 25-mile version.

B. Alternative measures of import penetration

Another concern to address is that our results are not driven by the definition of a sector as being high-IP. Columns 1 to 4 in table 11 reproduce the baseline regressions of table 4 using the same measure of IP but defining sectors that are above the 75th percentile as being high-IP. Although the overall effect is not significant (column 1), the effect on the probability of switching to a different manufacturing sector is equal to 17.8 p.p., significant, and of a similar magnitude to the effect for industries above the median reported in table 5 (15 p.p.). In columns 3 and 4 of table 11, we use a different measure of IP that considers the change in this between the current period and five years earlier. We classify sectors as high-IP if they are above the median for this measure each year.[37] We find that training also increases employability when we define IP in changes.

C. Time-varying factors at the municipality level

A concern we mentioned in the empirical strategy section is that factors that vary at the municipality level could be correlated with course supply and may also help explain employability, such as the municipality's general level of economic activity. A limitation of our IV strategy is that the instrument varies at the municipality-year level, preventing us from controlling for municipality-year fixed effects. We therefore check that our results are robust to including time-varying characteristics of the municipalities. In table 12, we show that training has a similar impact on the whole sample when controlling for the logarithm of the municipalities' per-capita GDP, trade exposure (as defined in Autor, Dorn, and Hanson, 2013), and the logarithm of (formal) manufacturing

[37] This measure is not only different to our baseline measure in that it considers changes but also in that a sector can switch from high to low or vice versa.

employment.[38] We also add more controls at the individual level (indicators for whether the predisplacement position was as a manager or production worker) and at the firm level (share of skilled workers). Reassuringly, the point estimates for the whole sample and for the sample of high-IP sectors are similar to those in table 4.

Another way to show that results are robust to unobservables that vary at the municipality and time level is to include municipality-year fixed effects in the OLS estimation. In columns 5 and 6 of table 12, we show that the OLS estimates remain at around 10 p.p. when we include these fixed effects, which is reassuring in terms of our results not being driven by time-varying unobservables at the municipality level.

D. Falsification test

As a robustness test that pre-existing trends are not driving the results, we run placebo regressions. We relate current training with the probability of being employed in the past. If there is a systematic correlation between training and employment this should show up in the probability of past employment. In table 13, we report results from running the baseline specification, but the dependent variables are now dummy variables that take the value of 1 if the individual is employed by the end of period t-2 or at end of period t-3 (where t is the period of displacement). Reassuringly, the coefficient estimates for the training variable are not significantly different from zero.

7. CONCLUDING REMARKS

It has been widely studied that trade shocks impose a burden on specific groups of workers, partly because industry-specific human capital cannot be transferred in a frictionless way from one industry to another. However, analyses of the effectiveness of active labor-market policies on workers affected by trade shocks are rare. Very few countries implement assistance programs that are triggered by trade events, but many countries have labor-market policies that could potentially help workers affected by trade shocks. In this study, we evaluate the impact of a nontrade-specific (i.e., general) training program in Brazil on workers that are displaced from manufacturing sectors.

The estimations show that SENAI training facilitates the transition to new employment while having positive effects on earnings. Training does not ease re-entry into the same sector or occupation but it does help re-entry into a different manufacturing sector or occupation. These results also hold true for workers who are displaced from high-IP sectors. We interpret these results as providing support for the idea that training can facilitate the reshuffling of labor across sectors.

Caution should be exercised so as not to generalize the results from these estimations to other contexts, particularly because the quality of vocational training programs differs across countries. Nevertheless, we find that general training programs can facilitate the reallocation of workers affected by import competition has important policy implications. Countries could potentially use or adjust their existing general labor-market training programs to smooth the workers' transition to new employment after being displaced by trade, instead of having to design fully-fledged new trade-related assistance programs from scratch.

[38] We define a municipality's exposure to import competition following Autor, Dorn, and Hanson (2013) as the weighted average across (CNAE v2 4-digit) sectors of the change (between year t and the year 2000) in imports per worker, where the weights are the municipality's share in the country's employment in the sector. We use the Brazilian 2000 census to obtain the employment shares.

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TABLES

TABLE 1. PROBABILITY OF RE-EMPLOYMENT IN T+1 IN THE DISPLACING SECTOR, BY THE DISPLACING SECTOR'S TRADE EXPOSURE, PERCENTAGES

	Same 4-digit sector		Same 2-digit sector	
	High-IP	Low-IP	High-IP	Low-IP
Unconditional probability	10.8	14.7	14.5	17.5
Conditional probability	11.3	14.4	15.0	17.2
95% confidence interval	(11.14 11.46)	(14.30 14.55)	(14.83 15.17)	(17.05 17.32)
Observations	160,281	305,235	160,281	305,235

Note: The table shows the probability of workers who are displaced from manufacturing in period *t* and who did not receive training in *t*+1 being employed in the original 4- or 2-digit sector of employment in period *t*+1, by the trade exposure of the displacing sector. The conditional probability is estimated with a linear probability model using age, age-squared, gender, education, and year fixed effects as controls. High- (low)-IP corresponds to sectors with above- (below-) median IP (defined as the ratio of imports to apparent consumption—output plus imports minus exports—for the 4-digit displacement sector calculated during 2005–2007).

TABLE 2. PROBABILITY OF WORKERS WHO ARE DISPLACED FROM MANUFACTURING IN T BEING RE-EMPLOYED IN PERIOD T+1, BY THE DISPLACING SECTOR'S TRADE EXPOSURE TRAINING STATUS, PERCENTAGES

	All manuf. sectors		High-IP	
	Nontrainees	Trainees	Nontrainees	Trainees
Employed in same 2-digit sector	16.4	12.7	14.5	12.0
Employed in another 2-digit manuf. sector	8.1	19.3	10.0	21.1
Employed in nonmanufacturing	18.6	24.5	18.7	24.7
Out of the formal labor market	56.9	43.5	56.8	42.3
Observations	465,516	64,874	160,281	29,002

Note: The table shows the (unconditional) probabilities of a displaced worker being employed in the original sector of employment, in a different manufacturing sector, in nonmanufacturing, or out of the formal labor market a year after being displaced from manufacturing, by training status. The sample consists of workers who are displaced from the formal manufacturing sector any time during the period 2009–2014. High-IP corresponds to sectors with an above-median IP (defined as the ratio of imports to apparent consumption—output plus imports minus exports—of the 4-digit sector of displacement calculated during the period 2005–2007). Trainees are those workers that received training while being displaced.

TABLE 3. INDIVIDUAL CHARACTERISTICS (MEANS), BY TRAINING STATUS AND IMPORT PENETRATION

	All manuf. sectors			High-IP		
	Nontrainees	Trainees		Nontrainees	Trainees	
Age	35.1	31.8	*	35.1	31.6	*
Education	10.6	11.5	*	11.0	11.7	*
Female	0.354	0.206	*	0.359	0.182	*
Tenure	3.44	3.44		3.74	3.61	*
Observations	465,516	64,874		160,281	29,002	

Note: The table displays the sample means of individual characteristics for workers who are displaced from manufacturing anytime during 2009–2014 by training status and IP of the displacing sector. Age and education are in years, female is a binary variable equal to 1 if the worker is female, and tenure is the years of experience in the displacing firm. (*) Indicates the means are different at the 1% significance level. High-IP corresponds to sectors with an above-median IP (defined as the ratio of imports to apparent consumption-output plus imports minus exports—of the 4-digit sector of displacement calculated during the period 2005–2007). Trainees are those workers that received training while being displaced.

TABLE 4. BASELINE ESTIMATES: IMPACT OF TRAINING ON THE PROBABILITY OF RE-EMPLOYMENT OF DISPLACED MANUFACTURING WORKERS. OLS AND 2SLS ESTIMATES

	OLS			2SLS		
	All manuf. sectors	High-IP	Low-IP	All manuf. sectors	High-IP	Low-IP
	(1)	(2)	(3)	(4)	(5)	(6)
Training	0.0992***	0.107***	0.0912***	0.132***	0.196***	0.0842
	(0.00315)	(0.00460)	(0.00359)	(0.0464)	(0.0548)	(0.0685)
Age	-0.00109*	0.000886	-0.00218***	-0.000968	0.00132	-0.00220***
	(0.000577)	(0.000828)	(0.000710)	(0.000610)	(0.000900)	(0.000733)
Age sq.	-7.71e-05***	-0.000112***	-5.84e-05***	-7.71e-05***	-0.000111***	-5.84e-05***
	(7.84e-06)	(1.11e-05)	(9.39e-06)	(7.87e-06)	(1.12e-05)	(9.39e-06)
Education	0.00734***	0.00630***	0.00788***	0.00721***	0.00614***	0.00791***
	(0.000397)	(0.000634)	(0.000471)	(0.000444)	(0.000649)	(0.000588)
Female	-0.0928***	-0.0922***	-0.0931***	-0.0908***	-0.0854***	-0.0934***
	(0.00300)	(0.00511)	(0.00286)	(0.00420)	(0.00681)	(0.00459)
Tenure	0.0145***	0.00875***	0.0182***	0.0145***	0.00870***	0.0182***
	(0.00109)	(0.00133)	(0.00107)	(0.00108)	(0.00132)	(0.00107)
Tenure sq.	-5.13e-06***	-3.66e-06***	-6.07e-06***	-5.10e-06***	-3.61e-06***	-6.08e-06***
	(3.05e-07)	(3.64e-07)	(3.23e-07)	(3.08e-07)	(3.62e-07)	(3.27e-07)
Firm size	-0.00491***	-0.00475***	-0.00403***	-0.00521***	-0.00559***	-0.00396***
	(0.000622)	(0.000899)	(0.000785)	(0.000753)	(0.00103)	(0.00100)
Sector-year FE	Yes	yes	yes	yes	Yes	yes
Municip. FE	Yes	yes	yes	yes	Yes	yes
Observations	530,390	189,283	341,107	530,390	189,283	341,107
R^2	0.069	0.085	0.066	0.068	0.082	0.066
				First-stage estimates		
Courses/1,000 people				0.404***	0.652***	0.313***
				(0.0446)	(0.0633)	(0.0411)
F-stat (1st-stage)				82.18	105.8	58.04

Notes: The estimation sample consists of workers who are displaced from the formal manufacturing sector at time *t* any time during 2009–2014. The dependent variable is the probability of re-entry into the formal labor market, a binary variable that takes the value of 1 if the worker is re-hired in the formal labor market in period *t*+1, and 0 otherwise. Training takes a value of 1 if the worker received training while being displaced. The instrument is the number of courses in the individual municipality and in neighboring municipalities per 1,000 inhabitants. The control variables are the individual's age in years, age-squared, an indicator for whether they are female, years of education, years of tenure at the displacing firm, years of tenure squared, and the size of the displacing firm (i.e. the logarithm of the total number of employees). High- (low-) IP corresponds to sectors with above- (below-) median IP (defined as the ratio of imports to apparent consumption—output plus imports minus exports—for the 4-digit sector of displacement calculated during 2005–2007). All regressions include 4-digit sector-year and municipality fixed effects. Standard errors in parentheses are clustered by municipality. The F-statistic corresponds to the Kleibergen-Paap Wald weak identification test. (***), (**), (*) significant at the 1%, 5%, and 10% level, respectively.

TABLE 5. DECOMPOSITION AND HETEROGENEOUS EFFECTS OF TRAINING: PROBABILITY OF RE-EMPLOYMENT OF DISPLACED MANUFACTURING WORKERS BY WORKER, JOB, AND COURSE CHARACTERISTICS. 2SLS ESTIMATES

		Re-entry	Same sector	Different manuf. sector	Nonmanuf.	Same occupation	Different occupation
		(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample							
	All	0.132***	-0.00776	0.130***	0.00976	-0.0157	0.148***
		(0.0464)	(0.0411)	(0.0257)	(0.0357)	(0.0407)	(0.0333)
	High-IP	0.196***	0.0727*	0.150***	-0.0269	0.0798*	0.117**
		(0.0548)	(0.0428)	(0.0385)	(0.0505)	(0.0461)	(0.0455)
Panel B: Age							
1st tercile (18–28 yrs)	All	0.0854	-0.0243	0.105***	0.00483	-0.0281	0.115**
		(0.0576)	(0.0467)	(0.0390)	(0.0519)	(0.0450)	(0.0513)
	High-IP	0.152**	0.130**	0.0973*	-0.0751	0.112*	0.0421
		(0.0659)	(0.0562)	(0.0540)	(0.0671)	(0.0591)	(0.0680)
2nd tercile (29–36 yrs)	All	0.219**	0.00892	0.177***	0.0339	0.0290	0.188**
		(0.0872)	(0.0675)	(0.0468)	(0.0651)	(0.0661)	(0.0730)
	High-IP	0.231**	0.119*	0.127*	-0.0144	0.151**	0.0807
		(0.103)	(0.0696)	(0.0721)	(0.0862)	(0.0699)	(0.0933)
3rd tercile (37–64 yrs)	All	0.128	0.0256	0.0858*	0.0162	0.0295	0.0981
		(0.110)	(0.0955)	(0.0504)	(0.0823)	(0.102)	(0.0821)
	High-IP	0.311**	0.0286	0.228***	0.0539	0.0387	0.272***
		(0.141)	(0.0957)	(0.0805)	(0.0955)	(0.113)	(0.104)
Panel C: Education							
Less than HS (<12 yrs)	All	-0.0731	-0.122	-0.0186	0.0676	-0.108	0.0345
		(0.137)	(0.122)	(0.0596)	(0.0904)	(0.113)	(0.0965)
	High-IP	0.172	0.0621	0.0419	0.0676	0.0828	0.0887
		(0.162)	(0.117)	(0.0884)	(0.117)	(0.128)	(0.121)
HS graduates (>=12 yrs)	All	0.159***	0.0281	0.152***	-0.0209	0.0123	0.147***
		(0.0404)	(0.0301)	(0.0272)	(0.0363)	(0.0365)	(0.0330)
	High-IP	0.180***	0.0839**	0.152***	-0.0556	0.0926**	0.0889*
		(0.0539)	(0.0395)	(0.0394)	(0.0519)	(0.0452)	(0.0527)
Panel D: Gender							
Female	All	0.112	-0.0622	0.108**	0.0664	-0.0726	0.184**
		(0.102)	(0.0773)	(0.0523)	(0.0773)	(0.0907)	(0.0882)
	High-IP	0.210	0.0390	0.169**	0.00198	0.0526	0.160
		(0.172)	(0.113)	(0.0846)	(0.137)	(0.123)	(0.144)
Male	All	0.137***	0.00786	0.127***	0.00179	0.00527	0.131***
		(0.0521)	(0.0476)	(0.0296)	(0.0411)	(0.0451)	(0.0410)
	High-IP	0.181***	0.0742*	0.130***	-0.0228	0.0813*	0.100*
		(0.0561)	(0.0434)	(0.0439)	(0.0494)	(0.0477)	(0.0520)

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		Re-entry	Same sector	Different manuf. Sector	Nonmanuf.	Same occupation	Different occupation
		(1)	(2)	(3)	(4)	(5)	(6)
Panel E: Tenure							
Below-median (<2.1 yrs)	All	0.0921	-0.0210	0.105***	0.00820	-0.0431	0.136***
		(0.0605)	(0.0527)	(0.0301)	(0.0492)	(0.0550)	(0.0416)
	High-IP	0.174***	0.0853*	0.142***	-0.0531	0.0748	0.1000*
		(0.0592)	(0.0464)	(0.0419)	(0.0552)	(0.0522)	(0.0516)
Above-median (>=2.1 yrs)	All	0.264***	0.0507	0.176***	0.0373	0.0686	0.193***
		(0.0739)	(0.0566)	(0.0439)	(0.0569)	(0.0562)	(0.0593)
	High-IP	0.247***	0.0673	0.175***	0.00491	0.0755	0.172**
		(0.0948)	(0.0699)	(0.0630)	(0.0736)	(0.0729)	(0.0805)
Panel F: Firm size							
Small (1–99 employees)	All	0.203***	-0.00964	0.154***	0.0583	0.0376	0.164**
		(0.0765)	(0.0693)	(0.0419)	(0.0538)	(0.0704)	(0.0644)
	High-IP	0.365***	0.0718	0.156**	0.137	0.159	0.205*
		(0.122)	(0.0939)	(0.0750)	(0.0934)	(0.0978)	(0.110)
Medium (100–499 employees)	All	0.0816	0.0388	0.0897*	-0.0469	0.0240	0.0580
		(0.0649)	(0.0537)	(0.0503)	(0.0526)	(0.0565)	(0.0590)
	High-IP	0.0668	0.0610	0.206***	-0.200**	0.0500	0.0170
		(0.0858)	(0.0611)	(0.0704)	(0.0804)	(0.0704)	(0.0745)
Large (500+ employees)	All	0.0587	-0.0351	0.111***	-0.0170	-0.0857	0.144**
		(0.0849)	(0.0711)	(0.0423)	(0.0639)	(0.0678)	(0.0608)
	High-IP	0.176**	0.106	0.0904*	-0.0207	0.0497	0.127*
		(0.0850)	(0.0693)	(0.0541)	(0.0757)	(0.0741)	(0.0708)
Panel G: Course duration							
Short (< 160 hours)	All	0.205***	0.0124	0.188***	0.00533	-0.0114	0.216***
		(0.0664)	(0.0584)	(0.0354)	(0.0507)	(0.0570)	(0.0469)
	High-IP	0.289***	0.0976*	0.225***	-0.0336	0.0943	0.196***
		(0.0757)	(0.0553)	(0.0504)	(0.0667)	(0.0632)	(0.0624)
Long (>= 160 hours)	All	0.124	-0.126	0.155*	0.0948	-0.142	0.264**
		(0.147)	(0.132)	(0.0837)	(0.108)	(0.135)	(0.118)
	High-IP	0.347*	0.105	0.208	0.0344	0.104	0.244
		(0.195)	(0.154)	(0.134)	(0.166)	(0.158)	(0.163)

Notes: Each cell shows the coefficient for training in a separate regression. The probability of re-entry into the formal labor market is decomposed in two ways: (i) across sectors into the probability of re-entering the same 2-digit manufacturing sector, the probability of entering a different 2-digit manufacturing sector, and the probability of entering nonmanufacturing (agriculture, mining, or services); (ii) across occupations, into the probability of re-entering the same 2-digit occupation and the probability of entering a different 2-digit occupation. For the case of occupations, the decomposition is not exact due to missing values in the occupation variable. See notes in table 4 for details on the estimation sample and variable definitions. Panel A: same sample as table 4. Panel B: split sample by age terciles. Panel C: split sample by education levels (less than high-school diploma and high-school diploma or more). Panel D: split sample by gender. Panel E: split sample by tenure in the job prior to displacement. Panel F: split sample by size of the displacing firm (following the IBGE classification of industrial firms by size). Panel G: split sample by course duration. Standard errors in parentheses are clustered by municipality. (***), (**), (*) significant at the 1%, 5%, and 10% level, respectively.

TABLE 6. HETEROGENEOUS EFFECTS BY TRAINEE CHARACTERISTICS. 2SLS ESTIMATES

	Re-entry	Different manuf. sector	Re-entry	Different manuf. sector	Re-entry	Different manuf. sector
	(1)	(2)	(3)	(4)	(5)	(6)
Training	0.0728***	0.0558***	0.0342***	0.0470***	0.103***	0.0861***
	(0.00972)	(0.00576)	(0.0131)	(0.00802)	(0.0104)	(0.00643)
Training X Fee	0.0920	0.115***				
	(0.0602)	(0.0321)				
Training X Graduate			0.124***	0.105***		
			(0.0446)	(0.0241)		
Training X Unemployed					0.0683	0.104**
					(0.0870)	(0.0491)
Observations	530,390	530,390	530,390	530,390	530,390	530,390
R2	0.068	0.065	0.068	0.064	0.068	0.063
F-stat (1st-stage)	32.14	32.14	39.56	39.56	27.35	27.35

Notes: See notes in table 4 for details on the estimation sample and variable definitions. Fee is a binary variable taking the value of 1 if the trainee paid a fee for the training, and 0 otherwise. Graduate is a binary variable taking the value of 1 if the trainee graduated from the course, and 0 otherwise. Unemployed is a binary variable taking the value of 1 if the trainee declared that they were unemployed when signing up for training, and 0 otherwise. Whenever training is interacted with a new variable, we add to the set of instruments the interaction of the instrument and the new variable. The control variables are those of table 4. All the regressions include 4-digit sector-year and municipality fixed effects. Standard errors in parentheses are clustered by municipality. The F-statistic corresponds to the Kleibergen-Paap Wald weak identification test. (***), (**), (*) significant at the 1%, 5%, and 10% level, respectively.

TABLE 7. IMPACT OF TRAINING ON THE PROBABILITY OF TRANSITIONING TO A DIFFERENT MANUFACTURING SECTOR, BY RCA OF THE NEW SECTOR, 2SLS ESTIMATES

	Sector of re-entry	
Sector of displacement	Low-RCA	High-RCA
	(1)	(2)
Low-IP	0.0339	0.0657**
	(0.0257)	(0.0271)
High-IP	0.0426	0.118***
	(0.0295)	(0.0345)

Notes: Each cell shows the coefficient for training in a separate regression. See notes in table 4 for details on the specification, estimation sample, and variable definitions. The probability of re-entry is decomposed across sectors of high and low revealed comparative advantage (RCA). Standard errors in parentheses are clustered by municipality. (***), (**), (*) significant at the 1%, 5%, and 10% level, respectively.

TABLE 8. IMPACT OF TRAINING ON THE EMPLOYMENT SPELLS OF DISPLACED MANUFACTURING WORKERS. OLS AND 2SLS ESTIMATES

	All sectors		High-IP	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Panel A. Employment spell in *t*+1				
Training	0.881***	1.351***	0.937***	1.402***
	(0.0262)	(0.338)	(0.0414)	(0.459)
Observations	530,390	530,390	189,283	189,283
R2	0.073	0.072	0.092	0.091
F-stat (1st-stage)		82.18		105.8
Panel B. Employment spell in *t*+1 and *t*+2				
Training	0.965***	1.662***	1.022***	1.830***
	(0.0315)	(0.458)	(0.0488)	(0.572)
Observations	440,938	440,938	157,663	157,663
R2	0.088	0.086	0.107	0.103
F-stat (1st-stage)		55.85		66.31

Notes: See notes in table 4 for details on the estimation sample and variable definitions. The dependent variables are: the employment spell (in months) in the year after displacement (panel A), and the average employment spell in the two years after displacement (panel B). For those individuals out of the formal labor force, the employment spell is zero. The control variables are those of table 4. The F-statistic corresponds to the Kleibergen-Paap Wald weak identification test. All the regressions include 4-digit sector-year and municipality fixed effects. Standard errors in parentheses are clustered by municipality. (***), (**), (*) significant at the 1%, 5%, and 10% level, respectively.

TABLE 9. IMPACT OF TRAINING ON THE CUMULATIVE EARNINGS OF DISPLACED MANUFACTURING WORKERS. OLS AND 2SLS ESTIMATES

	All sectors		High-IP	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Panel A. Cumulative earnings in *t*+1				
Training	0.0823***	0.202***	0.0895***	0.252***
	(0.00434)	(0.0723)	(0.00649)	(0.0967)
Observations	219,317	219,317	82,617	82,617
R^2	0.121	0.113	0.149	0.132
F-stat (1st-stage)		92.68		43.55
Panel B. Cumulative earnings in *t*+1 and *t*+2				
Training	0.104***	0.253**	0.111***	0.284**
	(0.00560)	(0.101)	(0.00840)	(0.140)
Observations	178,521	178,521	67,456	67,456
R^2	0.145	0.136	0.176	0.160
F-stat (1st-stage)		57.81		24.95

Notes: See notes in table 4 for details on the estimation sample and variable definitions. The dependent variables are: the normalized earnings in the year after displacement (panel A) and the normalized average annual earnings in the two years after displacement (panel B). Normalization is done by dividing earnings after displacement by the average earnings in the two years prior to displacement. We only include workers employed year-round before displacement in this estimation. For those individuals who are out of the formal labor force, earnings are zero. The control variables are those of table 4. The F-statistic corresponds to the Kleibergen-Paap Wald weak identification test. All the regressions include 4-digit sector-year and municipality fixed effects. Standard errors in parentheses are clustered by municipality. (***), (**), (*) significant at the 1%, 5%, and 10% level, respectively.

TABLE 10. BASELINE USING ALTERNATIVE INSTRUMENTS. 2SLS ESTIMATES

	Courses 25-miles/1000 pop.			Courses 50-miles/1000 pop.		
	All manuf. sectors	High-IP	Low-IP	All manuf. sectors	High-IP	Low-IP
	(1)	(2)	(3)	(4)	(5)	(6)
Training	0.117**	0.162***	0.0949	0.163***	0.206***	0.136**
	(0.0492)	(0.0584)	(0.0739)	(0.0415)	(0.0607)	(0.0573)
Sector-year FE	yes	yes	yes	yes	yes	yes
Municip. FE	yes	yes	yes	yes	yes	yes
Observations	530,390	189,283	341,107	530,390	189,283	341,107
R^2	0.068	0.084	0.066	0.067	0.081	0.066
	First-stage estimates			First-stage estimates		
Courses 25-miles/1000 pop	0.443***	0.712***	0.346***			
	(0.0560)	(0.0654)	(0.0547)			
Courses 50-miles/1000 pop				0.638***	0.832***	0.548***
				(0.0569)	(0.0697)	(0.0569)
F-stat (1st-stage)	62.60	118.4	40.10	125.5	142.5	92.82

Notes: See notes in table 5 for details on the estimation sample and variable definitions. The instruments are the number of courses within a 25- or 50-mile radius of the centroid of the municipality of last employment per 1,000 inhabitants. We consider a course to be within that radius if the centroid of the plant's municipality is at a distance of 25 (or 50) miles or less from the centroid of the municipality where the courses are offered. The control variables are those of table 5. Standard errors in parentheses are clustered by municipality. The F-statistic corresponds to the Kleibergen-Paap Wald weak identification test. (***), (**), (*) significant at the 1%, 5%, and 10% level, respectively.

TABLE 11. BASELINE AND TRANSITION TO OTHER SECTORS UNDER ALTERNATIVE IP DEFINITIONS AND MODEL SPECIFICATIONS.2SLS ESTIMATES

	High-IP (4th quartile)		High-IP (5-y change)	
	Re-entry	Different manuf. sector	Re-entry	Different manuf. sector
	(1)	(2)	(3)	(4)
Training	0.107	0.178***	0.157**	0.190***
	(0.0678)	(0.0466)	(0.0799)	(0.0497)
Sector-year FE	yes	yes	yes	yes
Municip. FE	yes	yes	yes	yes
Observations	60,991	60,991	233,649	233,649
R^2	0.094	0.057	0.076	0.058
F-stat (1st-stage)	66.13	66.13	86.29	86.29

Notes: See notes in table 5 for details on the estimation sample and variable definitions. Columns 1 and 2 estimate the model for the sample workers who are displaced from sectors in the 4th quartile of IP. Columns 2 and 3 estimate the sample of above-median IP but where IP is measured in five-year changes. The control variables are those of table 5. Standard errors in parentheses are clustered by municipality. The F-statistic corresponds to the Kleibergen-Paap Wald weak identification test. (***), (**), (*) significant at the 1%, 5%, and 10% level, respectively.

TABLE 12. ADDITIONAL CONTROLS AND FIXED EFFECTS. OLS AND 2SLS ESTIMATES

	2SLS				OLS	
	All sectors		High-IP		All sectors	High-IP
	Re-entry	Different manuf. sector	Re-entry	Different manuf. sector	Re-entry	Re-entry
	(1)	(2)	(3)	(4)	(5)	(6)
Training	0.135***	0.130***	0.179***	0.146***	0.0979***	0.105***
	(0.0446)	(0.0257)	(0.0565)	(0.0390)	(0.00320)	(0.00467)
Manager	-0.0688***	-0.00912***	-0.0708***	-0.00618	-0.0720***	-0.0780***
	(0.00539)	(0.00255)	(0.00723)	(0.00479)	(0.00500)	(0.00644)
Production worker	0.0102***	0.0186***	0.00770*	0.0284***	0.0117***	0.00999***
	(0.00269)	(0.00166)	(0.00404)	(0.00313)	(0.00218)	(0.00332)
Firm size	-0.00527***	0.00509***	-0.00525***	0.00584***	-0.00500***	-0.00475***
	(0.000732)	(0.000406)	(0.00103)	(0.000671)	(0.000650)	(0.000993)
Share HS grad.	-0.0289***	0.00909***	-0.0366***	0.0137***	-0.0280***	-0.0334***
	(0.00401)	(0.00250)	(0.00879)	(0.00439)	(0.00376)	(0.00853)
Manuf. Emp.	-0.00577	-0.00326	-0.0245*	-0.00913		
	(0.00662)	(0.00326)	(0.0130)	(0.00772)		
Per-capita GDP	0.00310	0.00704	0.0105	0.0154		
	(0.00872)	(0.00560)	(0.0151)	(0.0116)		
Trade exposure	-0.00180**	-0.000635	-0.00432***	-0.000518		
	(0.000860)	(0.000528)	(0.00140)	(0.00109)		
Sector-year FE	Yes	yes	yes	Yes	yes	yes
Municip. FE	Yes	yes	yes	Yes	No	no
Municip-year FE		no	no	No	yes	yes
Observations	529,595	529,595	189,202	189,202	527,271	187,103
R2	0.069	0.066	0.084	0.066	0.091	0.113
F-stat (1st-stage)	93.02	93.02	97.97	97.97		

Notes: See notes in table 5 for details on the estimation sample and variable definitions. Besides the controls shown, the regression also includes all the control variables in table 5. Manager is a dummy variable equal to 1 if the worker had previous to displacement a managerial occupation (Brazilian Classification of Occupations, CBO, group 1). Production worker is a dummy variable equal to 1 if the worker had a production occupation before displacement (CBO groups 7, 8, and 9). Share HS Grad is the share of workers with a high-school diploma or more in the firm from which the worker was displaced. Manuf Emp is the municipality total manufacturing employment (in logs). Per-capita GDP is the real GDP per capita of the municipality (in logs). Trade exposure is municipality trade exposure (calculated as in Autor, Dorn, and Hanson 2013). Standard errors in parentheses are clustered by municipality. The F-statistic corresponds to the Kleibergen-Paap Wald weak identification test. (***), (**), (*) significant at the 1%, 5%, and 10% level, respectively.

TABLE 13. PLACEBO TESTS: IMPACT OF TRAINING IN T ON THE PROBABILITY OF BEING EMPLOYED IN T-2 AND T-3

	All sectors	High-IP	All sectors	High-IP
	Employed in *t*-2	Employed in *t*-2	Employed in *t*-3	Employed in *t*-3
	(1)	(2)	(3)	(4)
Training	-0.0193	-0.0697	-0.0409	-0.0841
	(0.0418)	(0.0537)	(0.0451)	(0.0525)
Age	0.00620***	0.00481***	0.0205***	0.0217***
	(0.000537)	(0.000878)	(0.000625)	(0.00113)
Age sq.	-7.87e-05***	-6.72e-05***	-0.000251***	-0.000276***
	(6.51e-06)	(1.10e-05)	(7.75e-06)	(1.44e-05)
Education	0.00677***	0.00782***	0.00772***	0.00903***
	(0.000349)	(0.000590)	(0.000408)	(0.000652)
Female	-0.0166***	-0.0151***	-0.0559***	-0.0566***
	(0.00304)	(0.00465)	(0.00390)	(0.00494)
Tenure	0.107***	0.0978***	0.104***	0.0952***
	(0.00235)	(0.00297)	(0.00185)	(0.00245)
Tenure sq.	-2.35e-05***	-2.09e-05***	-2.15e-05***	-1.93e-05***
	(7.49e-07)	(9.41e-07)	(5.72e-07)	(7.48e-07)
Firm size	0.0136***	0.0150***	0.0129***	0.0120***
	(0.000685)	(0.00141)	(0.000783)	(0.00118)
Sector-year FE	yes	Yes	yes	Yes
Municip. FE	yes	Yes	yes	Yes
Observations	530,390	189,283	530,390	189,283
R2		0.247	0.241	0.233
F-stat (1st-stage)	82.18	105.8	82.18	105.8

Notes: See notes in table 5 for details on the estimation sample and variable definitions. The dependent variables are binary variables that take the value of 1 if the worker was employed in the formal manufacturing sector in *t*-2 and *t*-3, alternatively, and 0 otherwise. Standard errors in parentheses are clustered by municipality. The F-statistic corresponds to the Kleibergen-Paap Wald weak identification test. (***), (**), (*) significant at the 1%, 5%, and 10% level, respectively.

APPENDIX

TABLE A1. LEAST AND MOST IMPORT EXPOSED SECTORS

CNAE code	Description	IP (%)
Bottom 15 least exposed sectors		
1063	Manufacture of manioc flour and its derivatives	0.001
1013	Manufacture of meat products	0.017
1064	Manufacture of corn meal and its derivatives, other than maize	0.042
1071	Manufacture of raw sugar	0.042
1931	Alcohol manufacturing	0.072
1051	Preparation of milk	0.080
1081	Coffee roasting and grinding	0.095
1082	Manufacture of coffee products	0.106
2411	Production of pig iron	0.139
1121	Manufacture of bottled water	0.199
2452	Casting of nonferrous metals and their alloys	0.204
2392	Manufacture of lime and plaster	0.281
1540	Manufacture of parts of footwear of any material	0.347
1732	Manufacture of cardboard packaging and card stock	0.430
1069	Grinding and manufacture of products of vegetable origin nes	0.491
Top 15 most exposed sectors		
2710	Manufacture of generators, transformers, and electric motors	64.87
2813	Manufacture of valves, registers, and similar devices	66.85
3012	Construction of boats for sport and leisure	70.89
2865	Manufacture of machinery and equipment for the pulp, paper, and cardboard industries and artifacts	72.95
2651	Manufacture of measuring, testing, and control apparatus, and equipment	81.42
2864	Manufacture of machinery and equipment for the clothing, leather and footwear industries	82.16
2811	Manufacture of engines and turbines, except for airplanes and road vehicles	84.70
2869	Manufacture of machinery and equipment for specific industrial use	84.72
2815	Manufacture of transmission equipment for industrial purposes	84.86
2863	Manufacture of machinery and equipment for the textile industry	84.87
1910	Manufacture of petroleum coke	87.24
2852	Manufacture of other machinery and equipment for use in mineral extraction, except for oil extraction	87.88
2670	Manufacture of optical, photographic, and cinematographic equipment and instruments	91.81
2840	Machine tool manufacturing	94.37
2110	Manufacture of pharmaceutical products	97.11

Note: the table displays the 20 most and least import exposed CNAE (version 2) 4-digit sectors. We calculate the IP of each sector annually by taking the ratio of imports to apparent consumption (gross output + imports - exports) times 100. We take simple averages for each sector over the period 2005–2007. Imports and exports come from UN COMTRADE at the HS 1996 classification. We converted them to the HS 2012 classification by using the mapping from UN and then from HS 2012 to CNAE version 2 by using mapping from the IBGE (https://concla.ibge.gov.br/classificacoes/correspondencias/atividades-economicas.html), the Brazilian Institute of Geography and Statistics. Output data comes from the Annual Industrial Survey (Pesquisa Industrial Anual, PIA) which is available online at the 4-digit CNAE version 2 level (https://www.ibge.gov.br/estatisticas-novoportal/economicas/industria/9042-pesquisa-industrial-anual.html?edicao=17128&t=downloads). Before 2008, the survey is available at the 4-digit CNAE version 1 classification, so we used a mapping from IBGE's website to convert it to CNAE version 2.

TABLE A2. INDIVIDUAL CHARACTERISTICS (MEANS), BY LENGTH OF COURSE

	Short	Long	
Age	31.3	32.1	*
Education	11.8	11.3	*
HS graduate	0.831	0.727	*
Female	0.134	0.266	*
Tenure	3.87	3.09	*
Observations	29,451	35,423	

Note: The table displays the mean of individual characteristics for workers who are displaced from manufacturing in the year they received training. Age and education are in years, HS graduate is a dummy variable equal to 1 if the worker has a high-school diploma or more education, female is a binary variable equal to 1 if the worker is female, and tenure is the number of years the worker spent at the displacing firm. (*) Indicates the means are different at the 1% significance level. Short corresponds to the sample of trainees who took courses less than 160 long, and long to the sample who took courses less than 160 hours long.