International Trade, Job Training, and Labor Reallocation*

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Abstract

A large literature studies the impact of increased import competition on workers' outcomes, however, relatively few studies examine which policies can aid workers displaced by trade. While a few studies focus on the impact of trade-assistance programs, most countries in the world do not have assistance programs that are triggered by trade events, but 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 job training program in Brazil on workers 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 percentage points and is even more effective for workers displaced from sectors exposed to high import competition. This effect is mainly explained by workers switching sectors and occupations after training. We also find positive effects of training on employment spells and cumulative earnings in the two years after displacement.

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1 Introduction

Trade liberalization and other trade shocks can be disruptive for specific groups of workers, as documented in a large literature.[1] Trade involves a reallocation of productive factors that must relocate away from import-competing sectors to other sectors. Although this reallocation process brings efficiency gains at the aggregate level, workers bear significant costs when switching sectors in terms of unemployment 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 et al., 2017).

Active labor market policies can ease the transition of workers displaced by trade across sectors. 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 can help workers affected by trade shocks. In principle, some of these policies, such as job training programs, can provide workers displaced from import-competing sectors with new skills, facilitating their transition to other sectors, even if these programs were not purposely designed to assist trade-related displacements. How do training programs perform when applied to workers 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 training program in Brazil administered by the National Service for Industrial Training (SENAI) on the labor market outcomes of workers displaced from manufacturing sectors. We build a dataset that allows us to track a worker's employment history and training activities 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 re-employment of workers displaced from manufacturing sectors with a special focus on workers displaced from sectors of high-import competition.

There are two main challenges to identifying causal effects in our setting. First, separations from a job are 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 can 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 training availability is a strong predictor of the individual decision to take 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 displaced from high-import penetration sectors face a lower probability of re-employment in the displacing sector than workers displaced from low-import penetration sectors. However, the impact of job training on short-term employability for workers displaced from high-import penetration sectors is higher than average. SENAI training courses increase the probability of re-employment one year after displacement in 13.2 percentage points, which is equivalent to an increase of 30.2 percent. This probability is even higher for workers displaced from sectors of high-import penetra-

[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 studies using a linked dataset of the RAIS and SENAI datasets are Bastos et al. (2016), Silva et al. (2015), and Corseuil et al. (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.

tion, at 19.6 percentage points. 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 non-manufacturing. 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 sectoral transitions.

We also explore the existence of heterogeneous effects of training across different groups of workers. We find that the effect of training is larger for high school graduates and workers in the middle of the age distribution. When analyzing the characteristics of the manufacturing sectors to which displaced workers transition, we find they are more likely to transition to sectors of high (revealed) comparative advantage, regardless of the import competition in their initial sector. Although the program does not target a specific pattern of sectoral 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 alternative measures of import competition and to including time-varying controls at the municipality level.

Our paper contributes to several strands of existing literature. First, by analyzing the impact of training on the employability of workers displaced from highly trade-exposed sectors, this study adds to the literature on the impact of trade-related assistance programs. While earlier analyses show no significant effects of the TAA program on earnings (Decker and Corson, 1995; D'Amico et al., 2007), more recent studies find positive effects of the training component on the earnings of participants (Park, 2012; Barnette and Park, 2016; Hyman, 2018).[4] Our results provide new and complementary evidence of the extent to which general training programs, as opposed to trade-specific training programs, impact workers displaced from manufacturing sectors and how their effectiveness varies with trade exposure.[5]

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, 2019; Bernard et al., 2006; Autor et al., 2013; Acemoglu et al., 2016) . Most of these analyses carefully identify causal effects of trade on labor outcomes, but do not evaluate the role of policies to assist 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 literature evaluating the impact of active labor market policies on worker's performance. Many of the analyses have been summarized in different studies, including McKenzie (2017), Card et al. (2010), and Crépon and Van Den Berg (2016), among others. There is not a 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 et al. (2010) develops a meta-analysis with more than 200 evaluations of active labor market policies around the world and offers a more nuanced view. The authors indicate that while the average impacts 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. Similar to 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 exert on workers displaced from trade-exposed sectors.

Analyzing the extent to which general training programs facilitate the reallocation of workers dis-

[4] Cernat et al. (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.

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

placed from trade-exposed sectors is of utmost policy relevance for various reasons.[6] First, many countries already implement these policies, therefore, knowing if these programs work can inform the decision 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 more effective to assist 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. 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 displaced from trade-exposed sectors, it can be in the interest of the countries to stick with them, perhaps with marginal modifications to improve their overall effectiveness.

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 (National Service for Industrial Training) is a network of not-for-profit training centers established by the National Confederation of Industry (CNI), Brazil's largest business association.[7] SENAI is the largest training provider in the manufacturing sector in Brazil. The programs are funded primarily by the federal government through a one percent 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 located in all the states of Brazil (see Figure 1).

The focus of our evaluation is on the basic qualification courses offered by SENAI.[8] With an average duration of 200 hours, the objective of these courses is to develop or to perfect skills for a range of occupations.[9] Examples of basic qualification courses include: "certified operator of plastic extruder machines", "textile designer assistant", "certified operator of rubber transforming machines", and "installer of vehicular electronic systems". The enrollment of new students in qualification courses increased steadily during most our sample period except for 2014, starting with close to 443,000 students in 2009 with a peak enrollment of almost 870,000 in 2013, as Figure 2 shows.[10] [11]

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

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

[8] SENAI also provides guidance in 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, in the case there was any.

[9] SENAI also offers technical qualification courses, which are of longer duration (600 hours on average). We do not include them in the analysis since they have a much lower enrollment (about 10% the enrollment of basic qualification courses) and therefore, when matching it to the RAIS dataset the number of treated workers is too small to identify 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.

[10] Since our investigation is centered on the role of training for displaced workers who already have a relevant work experience in formal manufacturing, we do not include in the analysis apprenticeship, initiation, and habilitation courses or any internship programs offered by SENAI which generally target first-time job seekers.

[11] In 2010 SENAI reclassified basic qualification courses of a duration of less than 160 hours as upgrading courses – which are

SENAI qualification courses are open to the general public aged 16 years old and above, regardless of educational achievement. The courses can be either offered for a fee or can be subsidized through public programs. Although we do not have information on the amount of the fee paid by the students, we do have information on which students were subsidized by those public programs and which students were not. We exploit this information in the empirical analysis (see the Appendix).

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 not specifically designed to assist trade-related displacements.

There are two critical periods for workers in our analysis, the end of period t when we observe if a worker previously employed in manufacturing is displaced (or not) and the end of period $t+1$ when we assess if re-entry in 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 roughly at similar times and have been out of the labor market for no more than a year.[12] During this time (i.e. period t), some workers took a SENAI training course while others did not. Then, we observe the workers in December of period $t+1$ to check whether they were re-hired (in manufacturing or in other sectors). A limitation of RAIS data is that not observing a worker in $t+1$ could be due to a variety of reasons that we cannot distinguish: the worker could be unemployed and actively searching, she could be inactive, she could be self-employed, or she could be working in an informal (i.e. unregistered) job.

To estimate the effect of training, we employ the following linear probability model

$$Y_{ism,t+1} = \beta T_{i,t} + X'_{i,t}\gamma + \theta_{s,t} + \theta_m + \epsilon_{i,t} \tag{1}$$

where $Y_{ism,t+1}$ 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 zero 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 zero otherwise; $X_{i,t}$ is a vector of characteristics of individual *i's* such as her age, gender, and education, of characteristics of her last job, such as tenure, and of her last firm, such as its size (number of employees). Finally, $\theta_{s,t}$ are sector-year fixed-effects to control for sectoral shocks and θ_m are municipality fixed-effects to control for invariant municipality characteristics.

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

aimed at perfecting already acquired skills – regardless of the content of the course. In order to keep track of these courses and include them in our analysis, we classify as qualification courses those courses of less than 160 hours of duration that in 2009 were labelled as basic qualification but that from 2010 onward were reclassified by SENAI as upgrading courses. Reassuringly, all the main results in the paper are qualitatively similar if courses are not reclassified

[12] 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.

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 increased 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 of displacement, the probability of being re-employed in a different manufacturing sector, and the probability of being re-employed in non-manufacturing. 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 displaced from manufacturing and then we split the sample into high and low-import penetrated sectors. This allows to see if the effectiveness of the courses varies with trade exposure.[13]

A 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 define as those workers that have been either dismissed or whose contracts ended.[14]

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.[15] Our preferred instrument is the number of SENAI qualification courses that are available in the municipality where the individual was last employed and in its neighboring (i.e. contiguous) municipalities per one-thousand population.[16] 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 localities with a larger supply of SENAI courses are also more populated, limiting the ability of individuals 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

$$T_{i,t} = \alpha Z_{m,t} + X'_{i,t}\gamma + \theta_{s,t} + \nu_{i,t} \tag{2}$$

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 contiguous municipalities to municipality m. Therefore, the numerator is the total number of SENAI qualification courses offered in municipality m and its 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 population instead of in *per capita* terms for ease of interpretation of the

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

[14] 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.

[15] 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 Do (2004). Spiess and Wrohlich (2010) find that the probability to enroll in higher education decreases with distance. In the context of evaluating training programs, Brunello et al. (2012) use regional variation in training policies.

[16] Although SENAI does not provide the individual's home address when training was taken, we use RAIS to recover the information on which municipality the individual was last employed. 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.

coefficients and the descriptive statistics but this does not alter the estimated regression coefficients of the second stage.

The identifying assumption is that, once we control for observable characteristics and fixed effects, the number of SENAI courses per one-thousand 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 as control variables the municipality's per capita GDP, its level of manufacturing employment, and its trade exposure as defined in Autor et al. (2013). 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). Also, there are areas that have a high concentration of courses in 2009 that end up having a relatively lower concentration in 2014 and vice versa. Panels B and D allow to compare the variation in the instrument with the variation in the share of people taking SENAI qualification training, a 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 mechanic since our sample consists of workers displaced from formal manufacturing and not of all possible trainees.

Another potential source of bias in our results could be due to workers participating in training programs other than SENAI qualification courses. To deal with this, we exclude from our sample workers that were ever in other SENAI training programs such as the ones mentioned in section 2. Although SENAI is responsible for 80 percent of Brazil's industrial vocational training, we cannot rule out that workers participated in non-SENAI programs.[17] However, if workers in the control group participated in other programs, and these programs increased their employability, this would likely bias our results downwards and our effects should be interpreted as a lower bound.

A great part of our analysis is devoted to analyzing the impact of training on workers displaced from sectors of high-import penetration. For example, we estimate equation 1 for the subsample of workers displaced from sectors that in Brazil have an import penetration above the median. For this purpose, we use the standard definition of import penetration (IP)

$$IP_{st} = \frac{Imports_{s,t}}{Output_{s,t} + Imports_{s,t} - Exports_{s,t}} \tag{4}$$

where s is a four-digit sector of the CNAE version 2 classification. The numerator are imports of 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 percentage points – equivalent to 25 percent – as Figure 4 shows. In order to prevent sectors from switching across categories of high and low IP during the estimation period, we take the average import penetration for each sector, *before* our sample period – between 2005 and 2007 – and we classify a sector as high-import penetration if its IP is above the median and as low, otherwise.

[17] The 80 percent figure was obtained in conversations with SENAI officials.

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.[18] 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 four-digit industry 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.[19] We work at the most detailed level in terms of sector aggregation that the data allow, which is the four-digit level of the Brazilian National Classification of Economic Activities (CNAE version 2).[20] We keep in our sample workers aged 18 to 65 that were displaced from a manufacturing sector anytime during the period 2009-2014. For these workers, we can recover their employment histories up to three years before 2009 and a year after 2014, since the RAIS dataset that we have access to spans the period 2006-2015. So, for example, we can know if someone who took training in 2014 was re-employed in 2015 or if someone who took training in 2009, was previously employed in 2008, 2007, or 2006.[21]

We start by examining whether workers displaced from highly trade-exposed sectors have a lower chance of re-entering the labor market. Table 1 presents the probability of re-employment, after displacement, in the same sector of origin according to this sector's exposure to import competition. The results for workers displaced from high trade-exposed sectors and low trade-exposed sectors are presented in columns 1 and 2, respectively. The first row in the table shows unconditional probabilities: 10.8 percent of the workers displaced from high-exposure sectors were re-hired in the same four-digit sector in period *t+1*, as compared to 14.7 percent for workers displaced from low-exposure sectors. When performing the comparison at the two-digit level, we obtain probabilities of 14.5 percent versus 17.5 percent respectively. The second row shows conditional probabilities, were 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 in the same sector is 11.3 percent for workers displaced from high-exposure sectors and 14.4 percent for workers displaced from low-exposure sectors. The difference is 1pp smaller when we analyze it at the two-digit level (15.0 versus 17.2 percent). The results support the notion that because trade shocks tend to be sectorial in nature, workers displaced from highly trade-exposed sectors are less likely to return to the same sector and because they can encounter frictions when switching sectors, their re-employment might take time. The question is whether training can aid in this process.

SENAI training courses are associated with an increased chance of switching sectors, as shown in Table 2. The table reports (unconditional) transition probabilities of displaced workers according to 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 percent) than non-trainees (56.9 percent) and a lower probability of transitioning into the same (two-digit) sector that displaced them (12.7 percent) than non-trainees (16.4 percent). This is compensated by trainees having a higher probability of transitioning into a different sector in manufacturing or to non-manufacturing than

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

[19] Other studies linking SENAI and RAIS datasets include:Bastos et al. (2016),Corseuil et al. (2016), and Silva et al. (2015).

[20] There are 234 four-digit manufacturing sectors in our sample.

[21] To keep the sample size manageable, we do not work with the full RAIS dataset but instead we take a random sample of 10 percent of individual IDs in RAIS.

non-trainees.[22] For workers displaced from high import-penetration sectors, the probability of remaining jobless is also lower for trainees but they have overall a lower probability of returning to the sector of displacement, as compared with the whole sample. Overall, the descriptive evidence in Table 2 suggests that SENAI training is positively correlated with re-employment in sectors other than the displacing sector. 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 the workers displaced from manufacturing separating by training status. Table 3 shows these results for all manufacturing sectors and for trade exposed sectors. On average, trainees are around three years younger than non-trainees, have about one year more education, are less likely to be female, and have similar tenure. This same pattern holds for workers displaced from sectors with high import penetration with the exception of tenure, for which the difference by training status is significant, albeit small.

5 Estimation Results

5.1 Baseline Estimates

We start by exploring the impact of training on the probability of re-employment of displaced manufacturing workers in Table 4. According, to the OLS estimate of Equation 1 (column 1, Table 4), displaced workers who took training have a higher probability (9.9 percentage points) of being employed in the period after displacement than workers who did not took training. This increase in the probability of re-employment is similar for sectors of high import-penetration (column 2). 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 with the number of employees of 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 one and implies an impact—in our preferred specification in column 7—of training of 13.2 percentage points.[23] This coefficient is larger for workers displaced from sectors with above-median IP (column 8), with an increase in the probability of re-employment associated with training of 19.6 percentage points. The impact on workers displaced from low-import penetration sectors—not reported here—, is smaller (at 8.4 p.p.) and less precisely estimated. The number of courses per 1,000 inhabitants is a strong predictor of the probability of training, with a first-stage F-statistic above 80. The coefficient of 0.4 (bottom of column 7) implies that an individual in a municipality in the 75th percentile of the course (per 1,000 inhabitants) distribution has a 3.4 pp. higher probability of taking a training course than an individual in a municipality in the 25th percentile.[24] Given that the overall probability of re-entry into the formal labor market for non-trainees is 43.1 percent, our baseline estimate of 13.2 pp implies an increase of 30.6 percent in this probability for trainees. Our results overall suggest that training is effective among workers displaced from high-import penetration sectors.[25]

Our results imply that OLS estimates underestimate the impact of training on the probability of re-employment. If taking training is correlated with unobservable individual traits such as motivation–which can correlate positively with both training and with the error term–, we would expect OLS to be upward, not downward-biased. In the returns to schooling literature, the finding that OLS is downward-biased is quite frequent (Ashenfelter et al., 1999). A possible explanation is that the IV coefficient is reflecting the effect of training on a subset of the population, those induced to change behavior by the instrument. In this sense, IV identifies a local average treatment effect (Angrist and Imbens, 1995). This subgroup may have a higher return to training in terms of the probability of finding employment than the rest of the

[22] Non-manufacturing is comprised of agriculture, mining, and services.

[23] In the robustness section we explore the performance of alternative instruments and we obtain qualitatively similar results.

[24] The interquartile range change in courses per 1,000 inhabitants is 0.083.

[25] These results are robust to changing the definition of high-IP sector (see Robustness section).

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 our setting would imply that areas with a higher supply of courses also have more job creation. We address this possibility in two ways. First, by including the 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 Robustness section). 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 take training while unemployed can arguably be less financially constrained than non-trainees and may have a higher reservation wage, implying they are more likely to forgo job offers with lower wages, and therefore, less likely to be employed in t+1. If our IV is correcting for this type of endogeneity, then we would expect the 2SLS coefficient to be larger than the OLS one.

5.2 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 of displacement, in a different manufacturing sector, and in non-manufacturing. Second, we decompose it into the probability of entering the same occupation and a different occupation. Sectors and occupations of destination for the purpose of this exercise are defined at the two-digit level, but results are similar when they are defined at the four-digit level. Panel A of Table 5 shows the decomposition, where each cell displays the estimated 2SLS coefficient for 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 import penetration of the displacing sector.[26] What these results point to is that this type of training facilitates sectoral and occupational reallocation of displaced workers. As mentioned earlier, the sectoral nature of trade shocks implies that workers 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.

5.3 Heterogeneous Effects

We can further examine how training impacts the probability of returning to the labor market, according to worker characteristics. In Panels B to D 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 sectors of high-IP, 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 highly import penetrated sectors (Panel C).[27] The program has overall negative – although non-significant – effects for individuals with less than high school. Third, for the whole sample SENAI training has a 2 percentage points higher point estimate for men than for women, although the estimate for women is imprecise and therefore, insignificant (Panel D). However,

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

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

women do have a positive and significant increase in the probability of re-employment in a different manufacturing sector (column 3, Panel D).

5.4 Patterns of Sectoral Reallocation

What are the characteristics of destination sectors in terms of comparative advantage? Table 6 displays the coefficient of training in a regression where the dependent variable is the probability of transitioning to a sector of high or low comparative advantage, as measured by the index of revealed comparative advantage (RCA).[28] The sample is split according to the import penetration of the displacing sector. The table shows that workers who took training and were displaced from both high-IP or low-IP sectors are more likely to transition to sectors of high-RCA than workers who did not take training. These results imply that training increases the probability that displaced workers transition to high-RCA sectors, something that is desirable to reallocate workers towards more competitive sectors.[29]

5.5 Other Outcomes: Employment Spells and Earnings

A large literature analyzes the impacts of workers' displacements on medium or long-run outcomes such as employments 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. Therefore, we estimate the impact of SENAI training on the employment spell and the cumulative earnings one year and two years after displacement. We use the following definition of the employment spell of worker i displaced in year t

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

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 zero, 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.[30]

[28] 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 one in sector **s**, means Brazil's exports in sector **s** more intensively than the rest of the world, and therefore, has a revealed comparative advantage in this sector. As we do with import penetration, we calculate RCA yearly for 2005-2007, we take averages, and then we classify sector as high-RCA if their average is above the median and as low-RCA otherwise.

[29] It is worth noting that the correlation coefficient between IP and RCA is slightly negative and equal to -0.12. Therefore, it is not the case that competitive RCA sectors have systematically higher import penetration due to using a high share of imported inputs.

[30] Note that both the measure of employment spells and of cumulative earnings include zeroes, this 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 to avoid sample selection issues.

For this estimation we focus on the subsample of workers that were full-year workers during the two years prior to displacement. This guarantees we are comparing workers of similar employment trajectories.[31]

Both the OLS and 2SLS estimates suggest that training increases employment spells (Table 7). The IV estimates yield an effect of training of 1.35 extra months of employment 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 Panels C and D show. Trainees have earnings that are 20 percent higher in the year after displacement (Column 2, Panel C) and 25 percent higher, on average, in the two year-period after displacement (Column 2, Panel D) 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). Therefore, these estimates are larger than the effect we would expect on outcomes like the hourly wage, which is undefined for workers out of the formal labor force and therefore, we do not focus on it. Both effects on employment spells and on earnings are even larger for workers displaced from high-import penetration sectors.

5.6 Comparison with Existing Estimates

Putting our results in perspective is not easy because – due to the nature of our question – we focus on a narrow group: workers displaced from manufacturing. In addition, due to data limitations, we only analyze formal workers. Therefore, our estimates cannot be compared to those related to broader populations or to on-the-job training programs. To the best of our knowledge, there are no studies focusing on a population and a training program like ours. However, the positive impact we find of SENAI on employability and earnings is in line with Silva et al. (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 focused on adult training programs finds that training increases employability on average by 2.6 percentage points but there is substantial heterogeneity with several studies finding effects larger than 10 percentage points (Busso and Messina, 2019). Our estimates tend to be higher than those reported in most 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 we perform to test the robustness of our results.

6.1 Alternative Instruments

A potential concern with our instrument is that we consider courses in neighboring municipalities, but municipalities vary in area size. Typically, municipalities in the Northwest are larger in area than municipalities in the Southeast. Therefore, courses in contiguous municipalities might be harder to access in the Northwest since the travel distance is larger. To address this, we construct two alternative IVs that consider instead the number of courses per capita in a radius of 25 and 50 miles respectively, from the municipality

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

of the worker. Since we do not have the exact geolocation of the initial plant of the worker or of the facilities where the 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. Then, we add all the courses within the radius and divide them by the population of the own municipality and of the municipalities whose centroids are within the radius.

Results using these two alternative instruments are in line with the baseline estimates, as Table 8 shows. The impact of training on employability is of 11.7 pp using the 25-mile radius IV and of 16.3 pp using the 50-mile radius one. Our baseline estimate (13.2 pp) lies in between these two estimates. In both cases the first stage has a high F-statistic and the impact of training is larger for workers displaced from high-IP sectors. Estimates are more precise when using the 50-mile definition than the 25-mile version.

6.2 Alternative Measures of Import Penetration

Another concern to address is that our results are not driven by the definition of a sector as high-import penetration. Columns 1 to 4 in Table 9 reproduce the baseline regressions of Table 4 using the same measure of IP but defining as high-IP those sectors that are above the 75th percentile. 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 pp. and significant, and of a similar magnitude to the effect for industries above the median reported in Table 5 (15 pp.). In columns 3 and 4 of Table 9 we use a different measure of IP that considers the change in IP occurring between the current period and five years before. We classify sectors as high-IP if they are above the median of this measure in each year.[32] We find that training also increases employability when we define IP in changes.

6.3 Time-varying Factors at the Municipality Level

A concern we mentioned in the empirical strategy section is that factors varying at the municipality level could be correlated with the supply of courses and 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. Therefore, we check our results are robust to including time-varying characteristics of the municipalities. In Table 10, we show that training has a similar impact in the whole sample when controlling for the logarithm of the municipalities' per capita GDP, trade exposure, and the logarithm of (formal) manufacturing employment.[33] We also add more controls at the individual level (indicators for manager or production worker in the job before displacement) and at the firm level (share of skilled workers). Reassuringly, the point estimates for the whole sample as well as 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. We show in columns 5 and 6 of Table 10 that OLS estimates are still around 10 pp. when we include these fixed effects, which is reassuring of our results not being driven by time-varying unobservables at the municipality level.

[32] 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.

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

6.4 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 11, 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.

6.5 Differential Impacts for Unsubsidized Trainees and for Graduates

One potential concern with our estimations is that we are combining trainees that pay for the courses with trainees that are not and that the impact of training could be different across both groups. We address this concern in Table A2. In columns 1 and 2, we interact the training indicator with an indicator equal to one if the student paid a fee for training and equal to zero if the training was subsidized.[34] Students that were unsubsidized seem to have higher returns in terms of employability, but training still has a positive impact of 7.3 p.p. for unsubsidized students.

Another potential concern is that we are combining students who may have finished their courses with others that did not. In columns 3 and 4 we show that for those who do not graduate, training increases employability by 3.4 p.p. but graduating from the training course adds an extra 12.4 p.p. to the return from training. This is supportive evidence that our estimates are not merely driven by selection into training but that finishing the courses matters.[35]

7 Concluding Remarks

It has been widely studied that trade shocks impose a burden on specific groups of workers because industry-specific human capital cannot be transferred in a frictionless way from one industry to another. However, analyses about 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 non-trade related (i.e. general) training program in Brazil on workers displaced from manufacturing sectors.

The estimations show SENAI training facilitates the transition to new employment while having positive effects on earnings. Training does not ease re-entry in the same sector or occupation, but it does help re-entry in a different manufacturing sector or in a different occupation. These results hold for workers displaced from sectors of high-import penetration as well. We interpret these results as providing support to 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, finding that general training programs can facilitate the reallocation of workers affected by import competition has important policy implications. Countries could potentially use their existing general labor market programs on training, or small adjustments to them, to smooth the transition to new employment of workers displaced by trade, instead of having to design new full-fledged trade-related assistance programs from scratch.

[34] In the sample, 63 percent of trainees paid a fee.

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

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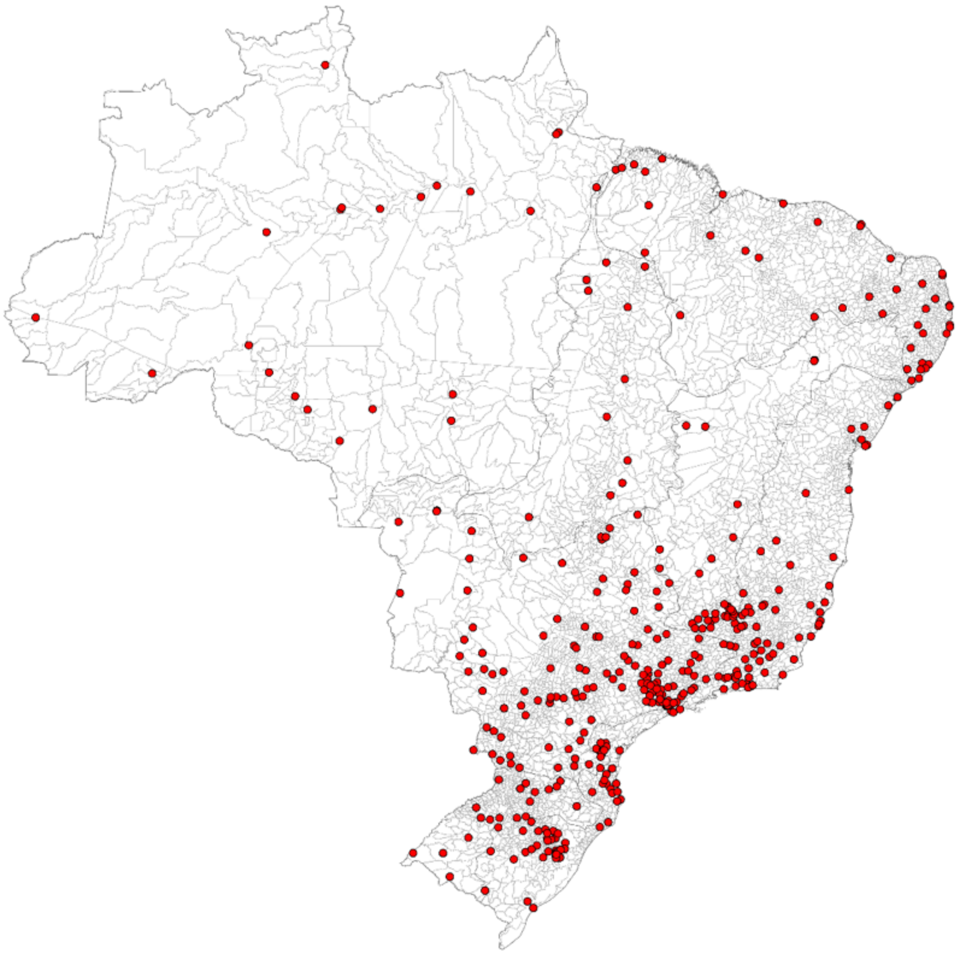
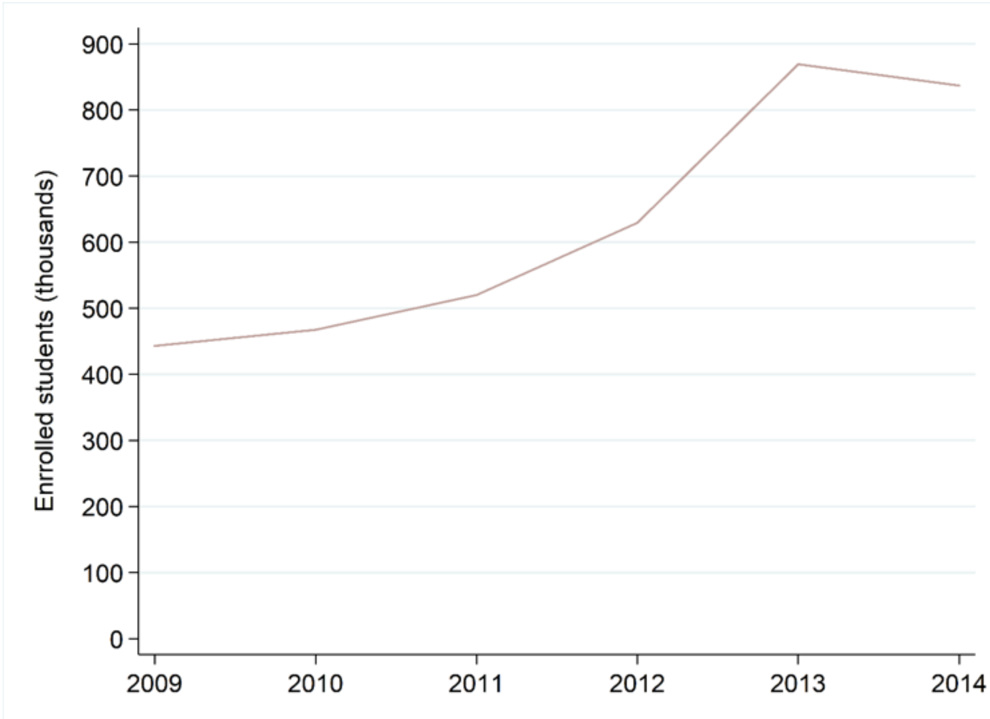
Figure 1
Location of SENAI training centers, 2015



Source: Own elaboration based on data shared by SENAI

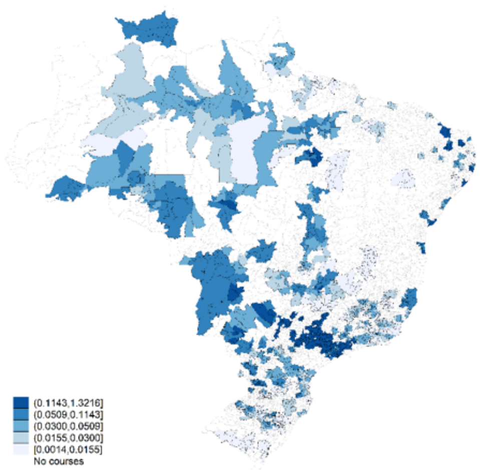
Figure 2
Enrollment in SENAI qualification courses, 2009-2014



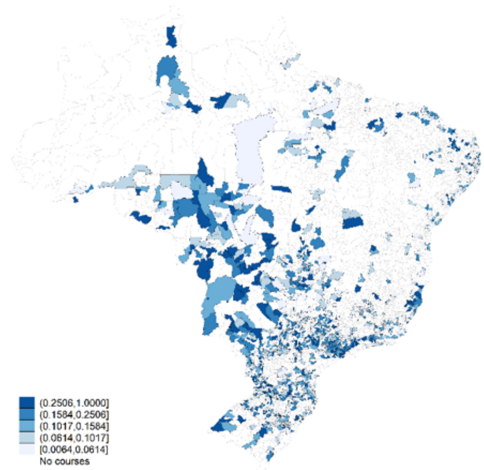
Notes: Newly enrolled students in SENAI qualification courses as we define them in this paper. In 2010 SENAI reclassified basic qualification courses of a duration of less than 160 hours as upgrading courses. From 2010 onwards, we classify as qualification course those courses of less than 160 hours that in 2009 were listed as basic qualification but that were reclassified by SENAI as upgrading courses.

Figure 3
Brazilian municipalities' SENAI qualification courses per 1,000 population and share of trainees, 2009 and 2014

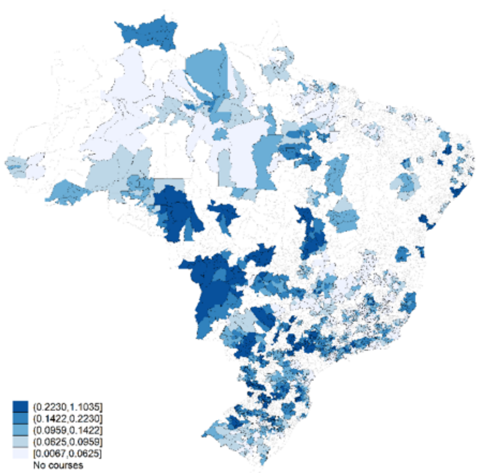
(a) Panel A: Courses per 1,000 population, 2009



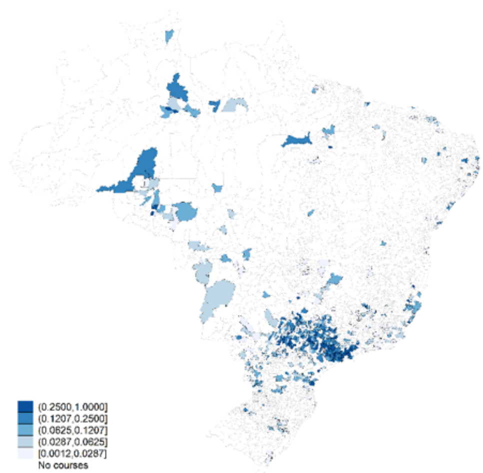
(b) Panel B: Share of trainees, 2009



(c) Panel C: Courses per 1,000 population, 2014

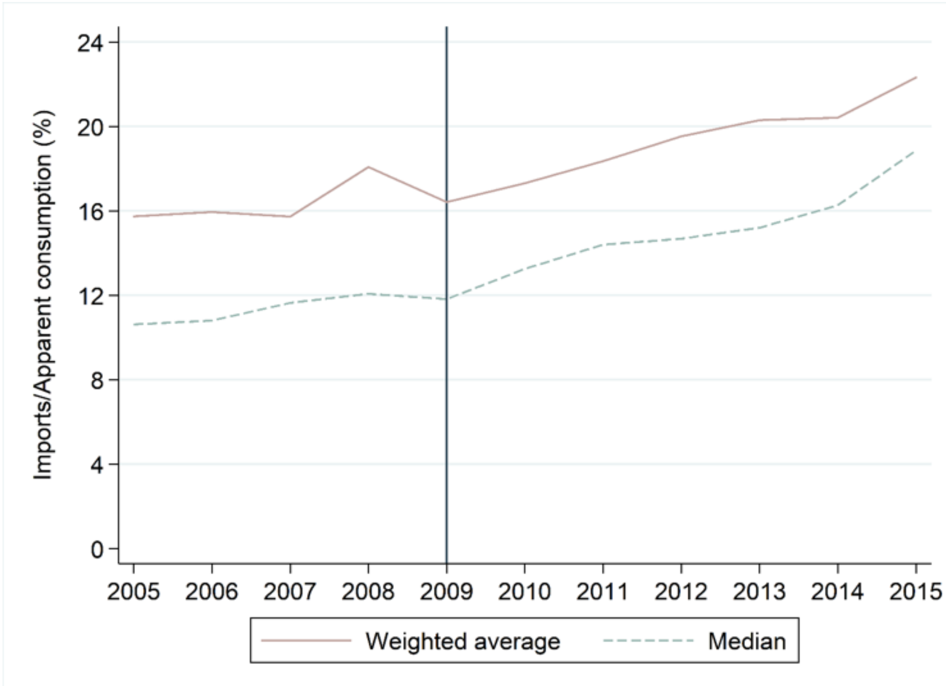


(d) Panel D: Share of trainees, 2014



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 its 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 import penetration in Brazil for the manufacturing sector as a whole. Import penetration is the ratio of imports to apparent consumption (gross output + imports - exports) times 100. We obtain imports, exports, and output of each CNAE v2 four-digit sector annually. The figure shows for each year the weighted average (the sum of imports of all four-digit sectors divided by the sum of their apparent consumption) and the median value.

Table 1
Probability of re-employment in t+1 in the same sector of displacement, according to the displacing sector's trade exposure, percent.

	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 being employed in the original 4 or 2-digit sector of employment in period t+1 for workers displaced from manufacturing in period t and who did not take training in t+1, according to the trade-exposure of the displacing sector. The conditional probability is estimated with a lineal probability model using age, age squared, gender, education, and year fixed effects as controls. High (Low)-IP corresponds to sectors with an above (below)-median import penetration (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).

Table 2
Probability of re-employment in period t+1 of workers displaced from manufacturing in t, according to the displacing sector's trade exposure and training status, percent.

	All manuf. sectors		**High-IP**	
	Non-trainees	**Trainees**	**Non-trainees**	**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 non-manufacturing	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 being employed in the original sector of employment, in a different manufacturing sector, in non-manufacturing or out of the formal labor market a year after of being displaced from manufacturing, according to training status. The sample consists of workers displaced from the formal manufacturing sector anytime during the period 2009-2014. High-IP corresponds to sectors with an above-median import penetration (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 took training while being displaced.

Table 3
Individual characteristics (means), by training status and import penetration

	All manuf. sectors			**High-IP**		
	Non-trainees	**Trainees**		**Non-trainees**	**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 displaced from manufacturing anytime during 2009-2014 by training status and import penetration 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 are 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 import penetration (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 took 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**	**All manuf sectors**	**High-IP**	**All manuf sectors**	**High-IP**	**All manuf sectors**	**High-IP**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Training	0.0992***	0.107***	0.189***	0.237***	0.206***	0.225***	0.132***	0.196***
	(0.00315)	(0.00460)	(0.0455)	(0.0671)	(0.0452)	(0.0581)	(0.0464)	(0.0548)
Age	-0.00109*	0.000886			-0.00354***	-0.000792	-0.000968	0.00132
	(0.000577)	(0.000828)			(0.000748)	(0.00108)	(0.000610)	(0.000900)
Age sq.	-7.71e-05***	-0.000112***			-4.27e-05***	-8.20e-05***	-7.71e-05***	-0.000111***
	(7.84e-06)	(1.11e-05)			(9.64e-06)	(1.31e-05)	(7.87e-06)	(1.12e-05)
Education	0.00734***	0.00630***			0.00355***	0.00135	0.00721***	0.00614***
	(0.000397)	(0.000634)			(0.000820)	(0.00118)	(0.000444)	(0.000649)
Female	-0.0928***	-0.0922***			-0.0693***	-0.0632***	-0.0908***	-0.0854***
	(0.00300)	(0.00511)			(0.00481)	(0.00841)	(0.00420)	(0.00681)
Tenure	0.0145***	0.00875***			0.0129***	0.00646***	0.0145***	0.00870***
	(0.00109)	(0.00133)			(0.00117)	(0.00140)	(0.00108)	(0.00132)
Tenure sq.	-5.13e-06***	-3.66e-06***			-5.00e-06***	-3.46e-06***	-5.10e-06***	-3.61e-06***
	(3.05e-07)	(3.64e-07)			(2.79e-07)	(3.37e-07)	(3.08e-07)	(3.62e-07)
Firm size	-0.00491***	-0.00475***			-0.0102***	-0.0128***	-0.00521***	-0.00559***
	(0.000622)	(0.000899)			(0.00104)	(0.00181)	(0.000753)	(0.00103)
Sector-year FE	yes	yes	no	no	no	no	yes	yes
Municip. FE	yes	yes	no	no	no	no	yes	yes
Observations	530,390	189,283	530,390	189,283	530,390	189,283	530,390	189,283
R2		0.085	0.006	0.007	0.036	0.041	0.068	0.082
			First-stage estimates					
Courses/1000 pop.			0.510***	0.652***	0.471***	0.604***	0.404***	0.652***
			(0.0524)	(0.0623)	(0.0476)	(0.0590)	(0.0446)	(0.0633)
F-stat(1st-stage)			94.44	109.5	97.68	104.8	82.18	105.8

Notes: The estimation sample consists of workers displaced from the formal manufacturing sector at time t anytime during the period 2009-2014. The dependent variable is the probability of re-entry in the formal labor market, a binary variable that takes the value of one if the worker is re-hired in the formal labor market in period t+1, and zero otherwise. Training takes a value of one if the worker took training while being displaced. The instrument is the number of courses in the individual municipality and in its neighboring municipalities per 1,000 inhabitants. The control variables are the individual's age in years, age-squared, an indicator for female, years of education, years of tenure at the displacing firm, years of tenure squared, and the size (i.e. the logarithm of the total number of employees) of the displacing firm. High(Low)-IP corresponds to sectors with an above (below)-median import penetration (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). 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 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 (1)	Same sector (2)	Different manuf. sector (3)	Non-manuf. (4)	Same occupation (5)	Different occupation (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 (16-28 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 (28-36 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)

Notes: Each cell shows the coefficient for training in a separate regression. The probability of re-entry in 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 into non-manufacturing (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 two-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. All the regressions include covariates, 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 6
Impact of training on the probability of transitioning to a different manufacturing sector, by characteristics 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 in two ways: (i) across sectors of high and low import penetration (IP) (ii) across sectors of high and low revealed comparative advantage (RCA). All the regressions include covariates, 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 7
Impact of training on the employment spell and cumulative earnings of displaced manufacturing workers. OLS and 2SLS estimates.

	All sectors		High-IP	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (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
Panel C. 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
R2	0.121	0.113	0.149	0.132
F-stat (1st-stage)		92.68		43.55
Panel D. 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
R2	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 employment in spell (in months) in the year after displacement (Panel A), the average employment spell in the two years after displacement (Panel B), the normalized earnings in the year after displacement (Panel C) and the normalized average annual earnings in the two years after displacement (Panel D). In panels C and D we keep only full year workers before displacement. 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 8
Robustness–Baseline using alternative instruments. 2SLS estimates

	Courses 25-miles/1000 pop.		**Courses 50-miles/1000 pop.**	
	All manuf. sectors **(1)**	High-IP **(2)**	All manuf. sectors **(3)**	High-IP **(4)**
Training	0.117**	0.162***	0.163***	0.206***
	(0.0492)	(0.0584)	(0.0415)	(0.0607)
Sector-year FE	yes	yes	yes	yes
Municip. FE	yes	yes	yes	yes
Observations	530,390	189,283	530,390	189,283
R2	0.068	0.084	0.067	0.081
	First-stage estimates		First-stage estimates	
Courses 25-miles/1000 pop	0.443***	0.712***		
	(0.0560)	(0.0654)		
Courses 50-miles/1000 pop			0.638***	0.832***
			(0.0569)	(0.0697)
F-stat (1st-stage)	62.60	118.4	125.5	142.5

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 9
Robustness—Baseline and transition to other sectors under alternative IP definitions. 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
R2	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 on the sample workers displaced from sectors in the 4th quartile of import penetration. Columns 3 and 4 estimate the model on the sample workers displaced from sectors of above-median import penetration but where import penetration is measured in 5-year changes. The covariates are those of Table 4. 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 10
Robustness—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
Municipality-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 one 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 one if the worker had previous to displacement a production occupation (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 municipality real GDP per capita (in logs). Trade exposure is the municipality trade exposure (calculated as in Autor et al., 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 11
Robustness—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 **(1)**	Employed in t-2 **(2)**	Employed in t-3 **(3)**	Employed in t-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 one if the worker was employed in the formal manufaturing sector in t-2 and t-3., alternatively. and zero 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 20 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 non-ferrous 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
1033	Manufacture of fruit, vegetables, and vegetable juices	0.492
1092	Manufacture of biscuits and wafers	0.524
2014	Manufacture of industrial gases	0.541
2330	Manufacture of articles of concrete, cement, asbestos-cement, gypsum and similar materials	0.574
1733	Manufacture of corrugated cardboard sheets and cartons	0.576
	Top 20 most exposed sectors	
2822	Manufacture of machines and equipment for transport, and lifting loads and people	59.71
2610	Manufacture of electronic components	62.87
2660	Manufacture of electromedical and electrotherapeutic equipment and irradiation equipment	63.05
2829	Manufacture of organic chemicals nec	64.08
3042	Manufacture of turbines, engines and other components and parts for aircraft	64.24
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-sigit sectors. We calculate the import penetration 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 a 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
Robustness—Heterogeneous effects for unsubsidized trainees and for graduates

	Re-entry	**Different manuf. sector**	**Re-entry**	**Different manuf. sector**
	(1)	**(2)**	**(3)**	**(4)**
Training	0.0728***	0.0558***	0.0342***	0.0470***
	(0.00972)	(0.00576)	(0.0131)	(0.00802)
Training X Fee	0.0920	0.115***		
	(0.0602)	(0.0321)		
Training X Graduate			0.124***	0.105***
			(0.0446)	(0.0241)
Observations	530,390	530,390	530,390	530,390
R2	0.068	0.065	0.068	0.064
F-stat (1st-stage)	32.14	32.14	39.56	39.56

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 zero otherwise. Graduate is a binary variable taking the value of 1 if the trainee graduated from the course, and zero otherwise. Unemployed is a binary variable taking the value of 1 if the trainee declared to be unemployed when signing up for training, and zero otherwise. Whenever training is interacted to 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 5. 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.