Task trade and the employment pattern: the offshoring and onshoring of Brazilian firms

Philipp Ehrl *
University of Würzburg

July 2013
Preliminary version

Abstract

This paper studies the effect of an expansion of imported intermediate inputs on establishments' average task intensities and employment size in a middle-income country. I use confidential matched employer-employee data and information on trade transactions for the universe of Brazilian firms. Propensity Score Matching shows that import expansion leads to an overall employment growth, higher intensities in routine and non-routine manual tasks and an increased share of intermediates exports. Thus, our findings point out that intermediates imports represent onshored instead of offshored tasks. Distinguishing between the origin of imports, the following pattern is observed: onshoring is more pronounced for imports from high-wage countries, whereas the low-wage country imports remain inconsistent with offshoring.

Keywords: Task trade, offshoring, onshoring, Brazil
JEL Classification: F16, J24, O54

*First and foremost, I thank Bruno Oliveira Cruz, who made the realization of this research possible. I am grateful to Massimiliano Bratti, Bohdan Kukharskyy, Lucas Ferreira Mattion, Rafael Moraes Pereira, Aguinaldo Nogueira Maciente, Michael Pflüger, John Weche Gelübcke and participants at the University of Passau, the IPEA in Brasília, the AIEL/ITSG Conference in Padova and RIEF in Paris for fruitful discussions and comments. The author also acknowledges the hospitality of the IPEA, where most of the research was conducted, and the DAAD for financial support. Contact: *philipp.ehrl@uni-wuerzburg.de*, University of Würzburg, Sanderring 2, 97070 Würzburg, Germany.

1 Introduction

The most distinctive feature between trade some 40 years ago and trade nowadays is the fragmentation of the value chain. Intermediate goods and services are increasingly exchanged across borders, and this development is far from over yet.[1] The new possibilities to relocate parts of the production naturally started a discussion about the types of affected jobs. It turned out that the conventional dichotomy of high- and low-skilled labor is ill-suited. More decisive for a job's offshorability is which tasks the worker is actually performing. Whether a task is easily offshorable depends on its codifiability and coordination requirement inside the firm (Grossman and Rossi-Hansberg 2008, 2012).[2] While the understanding of labor heterogeneity has changed, fostered by the disaggregation of data sources from industry to firm to the worker level, the focus of investigation has remained the same over time. Most papers study the effects of offshoring on wages, productivity and employment.[3] Moreover, with some exceptions, e.g., Feenstra and Hanson (1997), the focus lies on those countries where offshoring originates, i.e., high-wage countries.

The present paper takes a different route and studies the impact of the increased fragmentation of production in a middle-income country: Brazil. Precise theoretical predictions just like empirical research about trade involving middle-income countries are scarce, despite their steadily rising fraction of global trade (Hanson 2012). Hanson emphasizes that comparative advantage and relative endowments deserve a reconsideration to explain the observed trade patterns. Brazil is well endowed with low-skilled labor. While it recently expanded its automotive, aircraft and chemical industry, the economy's core is yet on products involving much manual labor (De Negri 2005b). Finally, the fact that the Brazilian wage level is higher than in China or India, but still far below the developed countries, makes Brazil a very interesting object of study. The country is a potential destination for offshoring. At the same time, it hosts some innovative highly productive, large firms, which are able sell to high-wage countries and might be originators of offshoring (De Negri 2005a). Hence, intermediate goods imported into Brazil can be onshored tasks from developed countries or can be offshored tasks, as in the usual perspective.

The present paper investigates the effect of increased intermediate goods imports on plants' employment and characterizes won and lost jobs by their task content. The main contribution is to answer the following questions: Are tasks lost in developed countries really similar to those offshored from and onshored to Brazilian firms? Is offshoring or onshoring more prevalent in the economy? What is the overall employment effect on firms? To the best of our knowledge, this paper is the first approach from a tasks perspective, not only for Brazil, but for any middle-income country.

Using confidential but not exclusive matched employer-employee data on the universe of Brazilian workers and plants, we can precisely characterize both by the tasks they perform.

[1] See Hummels *et al.* (2001), Hanson *et al.* (2005) and Amiti and Wei (2005).

[2] Besides, theory predicts that tasks with the lowest offshoring costs are relocated from high to low-wage countries, as long as the savings on labor costs outweigh the coordination expenses. Blinder (2009) stresses personal delivery as the most important determinant and argues that skill is entirely irrelevant.

[3] See Crinò (2009) or Feenstra (2010) for an ample review of the literature.

The concept of tasks in economic analysis has been popularized by Autor *et al.* (2003). The authors find that labor market effects of technological progress are better described by tasks than by workers' skills. In particular, workers who perform "a limited and well-defined set of cognitive and manual activities", termed routine tasks, are likely to be substituted by computers (Autor *et al.* 2003: 1280). Precisely those routine tasks should be most offshorable. Indeed, Goos *et al.* (2010) find that technological progress and offshoring have caused the large loss of routine jobs in 16 European countries. Firpo *et al.* (2011) link observed changes in the U.S. wage structure to the decrease in demand for routine tasks. Besides their first empirical successes, tasks are elegant and yet informative. Since a task measure is a continuous variable, it concentrates extensive information across all occupations and thus preserves this variation, while it allows to keep the empirical analysis manageable and well-arranged. Autor *et al.* (2003) use five task classifications: routine manual, routine cognitive, non-routine manual, non-routine cognitive and analytical. We complement these by an offshorability measure as suggested in Acemoglu and Autor (2011). To investigate the effects of offshoring and onshoring on the employment pattern in greater detail, we calculate averages of those task measures at the plant level.

Our identification strategy mainly relies on Propensity Score Matching (PSM). This approach matches similar establishments and then compares establishments with and without an expansion in their range of imported intermediate goods.[4] The indicator for this expansion is novel in the literature. Here, offshoring corresponds to a discrete change in the organization of the firm. One advantage is that the indicator is orthogonal to variations in the value of imported inputs which can be blended by fluctuations in production, demand or currencies. PSM is frequently used in the context of offshoring, because firms involved in international trade perform different than the average domestic producer (Bernard *et al.* 2007; Laplane and De Negri 2004). Nevertheless, two control groups are used: purely national firms and importers without an increase in imports. Besides the usual comparison in levels, a difference-in-difference estimator is employed. The latter estimator additionally eliminates any constant differences between treated and control firms. In an extension, establishments are distinguished according to whether imports originate from low- or high-wage countries. When matching is performed adequately, this strategy provides causal effects in the absence of experimental data. To check the robustness, the task content is analyzed at the level of occupations in all affected establishments and different definitions for the increase in imported intermediates are used.

Both matching estimators in levels and differences reveal that an expansion of imported intermediates raises the intensity of routine and non-routine manual tasks. There is also an increase in plant size by about 12 employees and a higher share in exported intermediate goods. Taken together, this evidence suggests that Brazilian plants onshore rather than offshore tasks. At the level of occupations a somewhat surprising pattern emerges. Still, the manual intensive tasks are most affected by trade and the overall employment gain is visible across all manufacturing sectors. However, no significant difference with respect to the task content between created and lost jobs is observed. Only when plants are

[4] We will also refer to this expansion as an 'increase in (intermediate) imports'.

distinguished according to the origin of imports, some differences between lost and won jobs emerge. Particularly, there is some evidence, that dismissed workers in importers from low-wage countries are performing more offshorable and routine tasks than their newly recruited workers. However, this finding vanishes, once these importers are compared to matched national establishments. At last, even with this differentiation, the pointers for offshoring remain rare. Regarding the imports from high-wage countries, more significant and larger effects in favor of onshoring emerge, as expected.

For the developed world the evidence on employment effects from firm level data is mostly positive. Barba Navaretti *et al.* (2010) and Hijzen *et al.* (2007) apply PSM and find employment size to be positively affected for plants that conduct foreign direct investment (FDI). An exception is Crinò (2010) who reports no significant employment effects after service offshoring. Moser *et al.* (2010) investigate the reason for positive employment effect in more depth with data on German firms. Again, a PSM approach is used, but offshoring is captured by a qualitative indicator for the increase of imported intermediate inputs. In line with common intuition, Moser *et al.* (2010) identify a negative effect on employment due to the restructuring inside the plant. However, an even larger, positive productivity effect leads to an overall increase in the number of workers. This productivity effect has first been pointed out in a model by Grossman and Rossi-Hansberg (2008).

Once the task content of offshored jobs is considered, one recognizes that the situation in the developed world is entirely different. Two other firm level studies examine the employment pattern in the aftermath of offshoring using task classifications: Hakkala and Huttunen (2010) provide weak evidence for a decrease in routine tasks. Compared to the present paper, the authors distinguish only 15 different occupations, and the share of imported intermediates is calculated at the industry level. Using a shift-share analysis and regressions on the wage bill share, Becker *et al.* (2013) find that more offshoring increases a plant's proportion of non-routine and interactive tasks. This contrary result is consistent with theoretical predictions as well as with our findings, because the perspective from the originators of offshoring is taken.

As expected, stronger responses regarding the task intensities are found for offshoring to less developed countries, cf. Biscourp and Kramarz (2007), Becker *et al.* (2013). Such destinations invoke insignificant or negative employment effects, because the productivity effect is increasingly overturned by the relocation itself (Barba Navaretti *et al.* 2010; Moser *et al.* 2010). Completing the mirror-image, we obtain stronger results when imports are coming from high-wage countries. Somewhat surprisingly, our findings for imports from low-wage countries are inconsistent with offshoring by Brazilian firms. Rising employment and exports of intermediate goods rather suggest that those plants are part of an international production network. Such a view is given in Costinot *et al.* (2013), where differences in absolute comparative advantages predict the order in a sequential production chain. Their model assigns intermediate production stages to a middle-productivity country like Brazil. That is, similar impacts of imports from high- and low-income countries pertain to different design options for a fragmented production.

The remainder of the paper is organized as follows. Section 2 presents the data at use and the task classifications. Section 3 describes the PSM approach. Section 4 contains the results and section 5 concludes.

2 Data

2.1 Employer-employee data

The backbone of this analysis is the linked employer-employee data set RAIS (Relação Anual de Informações Sociais) which comprises the universe of the formal Brazilian labor market.[5] On a yearly basis, all establishments are required to report to the Ministry of Labor about every worker registered throughout the calender year. The data is employment spell-specific and also contains basic information about the establishments activities. Since the information is extracted from official records, its quality is excellent. Furthermore, plants are fined for late- or non-submission and very few entries have missing values. Workers as well as plants are characterized by a unique identifier, so each can be traced over the years. We extract the information yearly on December 31 and keep all plants with at least five employees. Multiple spells for workers, even in the same establishment, are distinguished and kept for the following analysis. Data constraints restrict the period of this investigation to the years 2003 to 2006. We focus on privately owned plants from the manufacturing industry, because international trade models are more relevant here. Still, there are around 6 million spells per year.

Throughout the paper we weight spell-specific information by the number of hours worked per week. Likewise, employment size is calculated as the total of hours worked in that plant relative to the grand mean of hours per job in the data. In addition, the annual mean wage, education and the occupation of each worker are known. The latter is taken at the 5-digit level, where more than 2500 different jobs are recorded. Since occupations and their mapping to tasks are key variables in this paper, this most disaggregated level is kept throughout the analysis. Unfortunately, a severe break in the classification impedes the mapping before 2003 and thus limits the observation period in this study. Education is reported in 10 categories which we aggregate to four, corresponding to: (1) less than high school, (2) high school, (3) college and (4) higher education.

At the plant level we use the region[6], industry (IBGE subsectors 1-13)[7], legal form and an indicator, whether the plant is considered small from a fiscal point of view, i.e., its annual revenue is less than 1.2 million Reais. Because the affiliation of establishments is known, controlling for the overall firm size is possible. Apart from the disaggregated labor input,

[5] Access to this data is confidential and was granted while the author visited the IPEA Institute in Brasília.

[6] We found in the PSM procedure that the five Brazilian regions (North, North-East, Central-West, South-East and South) already capture most of the interstate heterogeneity, which is obviously existing.

[7] Industries are aggregated to the 2-digit level. This IBGE (Brazilian Institute of Geography and Statistics) classification is roughly conform to the 2-digit ISIC (International Standard Industrial Classification) industries (Helpman *et al.* 2012). Those sectors are listed in figure 3, but we found no relevant differences between sectors, so a further discussion is of less importance.

no more information about the production side is given. Nevertheless, we are confident that the way the outcome and offshoring variables are defined, this paper provides robust and valuable insights about the effects of importing intermediates.

2.2 Trade data

This subsection describes our data about trade transactions and the construction of the offshoring indicator. We also motivate, which variables are adequate controls for firms' performance in the absence of output and productivity.

For each establishment, the Ministry of Development, Industry and Foreign Trade (MDIC) records all commodity transactions at the level of product and countries.[8] This sums to around 0.5 million observations per year. Via the unique plant identifier this information is merged into the RAIS.

As shown theoretically and empirically in Bernard *et al.* (2010, 2011) with U.S. data, the extensive margin of exporters is a good indicator for productivity. Using data from India, Goldberg *et al.* (2010) document that multi-product firms have superior performance in the developing world, too. Despite this recent interest in multi-product firms, evidence on their import behavior is still rare. An exception is Bernard *et al.* (2007) who find that importers are even more scarce than exporters. While both outperform plants that only serve the domestic market, importers have almost twice the total factor productivity of exporters. Silva *et al.* (2012) report a positive relation between import volume and the hourly labor productivity in the Brazilian economy employing Granger causality tests and a vector autoregressive model. Even in a model with plant fixed effects, Laplane and De Negri (2004) find a positive relation between the labor productivity and the export or import volume.

Consequently, we aggregate the number of products, the number of destinations and the total value for establishments' imports and exports in each year to use these variables as productivity proxies. Summary statistics are displayed in table 1, where, for now, only the first four columns are of interest. Note that all the trade variables exhibit a huge heterogeneity across establishments. Our data support the previous findings on trade and productivity. Firms engaged in international trade are much larger. They also use a higher share of skilled labor in production. Mere exporters have a much smaller scope of products and destinations than firms which export and import. Finally, the latter's export value per product is higher by 156.000 Reais.

De Negri (2005a) divides Brazilian imports according to their technological content and country of origin. She finds that products from the EU or North America have a higher technological content, whereas the majority of imports from Asia and Latin America are labor and resource intensive. Furthermore, foreign firms are on average more productive than Brazilian firms, and they are more likely to import from the EU or North America.

[8] MDIC data was available until 2006, which has set the upper time bound in this study.

This gives reason to believe that the purpose of imported intermediate goods is different depending on their country of origin. We pick up this differentiation for a detailed analysis after the pooled baseline results. Brazil's most important high-wage trading partners are the EU 15, the U.S., Canada and Japan. Their low-wage counterpart are Russia, India, China (RIC) and the countries in Latin America (LA). For convenience, we denote the high income countries by 'EU' and the second trade bloc simply by 'LA'.

The final four columns in table 1 contain summary statistics according to whether more than 50% of a plant's total value of intermediates imports is from one of the two trading blocs. The findings from De Negri (2005a) are reflected in our data. EU-importers seem more productive as their export and import volumes are much higher. Even though they are not larger in terms of employment, their number of import products and destinations is more extensive. Finally, EU-importers are more likely to export.

Since there is no direct information whether a plant has engaged in offshoring, it is non-trivial to define an adequate indicator, however, the data is detailed enough to do so. The IBGE provides a mapping of the 5-digit product codes (NCM) in our MDIC data to the international BEC (Broad Economic Classification) classification. With the BEC the products can be divided according to their stage of production into: (i) primary products, (ii) intermediate goods and (iii) final goods (Calfat *et al.* 2008). The intermediate goods can be further divided into 'semi-finished goods' and 'parts and components'. Typically, the famous examples for offshoring from the automotive, aircraft or toy industry deal with the assembly of parts and components. Semi-finished goods are admittedly less dazzling, but we see no reason to restrict our definition of offshoring to the latter category. Most related studies either use all imports or do not discuss this distinction of intermediate goods at all. All following steps of our analysis were conducted for the entire intermediate goods classification and only for 'parts and components'. The results for the latter category were largely similar. Following Feenstra and Hanson (1999), we also check whether a restriction to imports within the same 2-digit sector (narrow offshoring) alters the results. Both cases are reported in the robustness checks section.

We now define the indicator for an increase in imports, which is central for this paper. The indicator takes the value 1, when a plant imports a new intermediate good in a period t, subject to the following constraints. New products are products which the establishment has not purchased over the last two years and the product is at least purchased for three consecutive years or rather two years in case the import only begins in 2005. We thereby separate stable offshoring relations from one-off investments, fluctuations in productions, etc. However, the indicator for increased imports is not restricted to the number of products. Thus, in case a plant starts to import two or more new products in a given year, it would still be classified as an offshorer. Imports with an annual volume of less than 2000 Reais are regarded as being irrelevant and unlikely to cause any labor substitution. At last, plants with an increase in two consecutive years and import newcomers are excluded from the analysis to get clean effects. For more than 90% of observations the increase in the number of products is synonymous with an increase in the total value of imports or the number of products.[9]

Most prior studies have struggled with the definition of offshoring. In the absence of managers' direct responses it is almost impossible to discover doubtlessly from data whether or not a firm conducted offshoring. Vertical FDI can capture the offshoring flows inside a multinational firm. Apart from the difficulty to disentangle vertical and horizontal FDI, this proxy is at best incomplete. The share of imported intermediates in total inputs is a reasonable measure, however it is exposed to currency fluctuations, shifts in lines of domestic production which are unrelated to the imported intermediates and so on. This paper is not the only one lacking data to construct the share of imported in total inputs. Becker *et al.* (2013) use the employment in offshore plants, Moser *et al.* (2010) have a categorical variable with three values and Hakkala and Huttunen (2010) rely on the share of imported intermediates in production. The approach here is novel. Offshoring corresponds to a discrete event and we aim to capture the beginning of a new and stable relationship to a foreign supplier. Our indicator suffers less from the undesired fluctuations addressed above, yet it is narrower, because it disregards expansions of existing offshoring.

2.3 Tasks in Brazil

In the following we introduce six task dimensions by which we characterize employment fluctuations. Unfortunately, there is no Brazilian workforce survey of tasks for a detailed classification of occupations, but we rely on U.S. data from the O*NET (Occupational Information Network). Maciente (2013) conducted a mapping between the U.S. and Brazilian occupations at the 5-digit level.[10] The existence of different synonyms for many Brazilian and U.S. occupations (so called lay titles) facilitates the mapping. Moreover, Maciente (2013) compared the score distribution of the O*NET measures for matched occupations. In some cases where the mapping was ambiguous, the occupation is disregarded. The same is true for some occupations where the O*NET categories appeared obviously inappropriate for the Brazilian job. Therefore, not all occupations could be matched with task measures.[11]

The O*NET survey asks workers to state the importance of various ability requirements and activities performed in their job. Acemoglu and Autor (2011) group some of those O*NET measures to reproduce the five categories introduced the seminal article by Autor *et al.* (2003), which was based on the DOT, the predecessor of O*NET. These categories are: analytical, routine cognitive, routine manual, non-routine cognitive and non-routine manual. The authors add one more category that should capture the offshorability of

[9] However, we prefer not to restrict the indicator to these cases, because the overall level of inputs could drop simultaneously. That is, a decrease in the total value of (intermediate) imports is not inconsistent with offshoring.

[10] The author is very grateful for the provision with this data.

[11] Consequently, we have some missing values when we calculate the average task content for each establishment. To avoid overly imprecise averages, all plants whit more than one-third missing values are dropped. This amounts to 2% of observations.

jobs.[12] Goos *et al.* (2010) provide different task definitions based on the O*NET, distinguishing only analytical, routine and service tasks.

We performed our analysis with both definitions and found the categories used by David Autor to be more selective. One problem with the definition in Goos *et al.* (2010) is that in combination with the Brazilian occupations, service and abstract tasks are quite similar. Nevertheless, their routine category corresponds well with both routine categories in Acemoglu and Autor (2011) and we obtained similar results throughout. To construct the task variables for each occupation, we first take the mean of the relevant O*NET measures and then standardize it to a mean of 10 and a standard deviation of 1. The standardization makes the six tasks variables comparable, independent of the differently scaled O*NET work activities. Once all occupations have positively defined task variables, it is more convenient to interpret changes in the employment pattern. To this end the most important variables will be the average task intensities of plants. Again, in its calculation we weight worker's task values by their hours worked, as is the case in the construction of the following graph.

Figure 1 depicts the average task content of occupations along the entire wage distribution in the sectors used in this study with a lowess smoother for the year 2003. Since the task measures were standardized at the level of occupations, they do not have a mean of 10 anymore in this economy-wide representation. We see, for example, that roughly 10% of workers have above average analytical or non-routine cognitive task content. Jobs on the lower end of the wage distribution are best characterized by their low content of analytical and cognitive skills. These occupations also have a medium manual content and are most easily offshored. They are particularly jobs in sales and in industrial activities, where little skill is required. In the middle of the wage distribution we see industrial jobs which require more skill and the highest intensity of manual skills. Unsurprisingly, the jobs at the top of the wage distribution feature the highest intensity of cognitive and analytical tasks. The offshorability score peaks again at the upper end due to scientists, editors and other creative activities that are not required to be performed in a particular site. To the best of our knowledge, despite the wide spread use of tasks, the only comparable graph can be found in Autor *et al.* (2008). The main difference between the U.S. economy is that the lower end of the wage distribution is marked by service rather than non-routine manual jobs in Brazil. Notwithstanding the task measures seem to make sense. Apart from the precautionary measures with the mapping of occupations explained above, there is no certainty that Brazilian and U.S. occupations have the same content. Presumably, the U.S. is the most technologically advanced nation in the world. Therefore, if anything, the Brazilian occupations are likely to be more manual and less analytic.

As will be clear from the next section, the identification strategy requires information from the period before and after the increase in imports. So essentially the increase can occur either in 2004 or in 2005. Table 1 shows the complete summary statistics for the variables described in this chapter pooled for the periods 2004/5. The first four columns contain the

[12] Exactly the same definitions are used here with one exception. The routine cognitive measure misses two O*NET work activities: 4.C.3.b.7 and 4.C.3.b.8.

mean and the standard deviation, depending on whether the plant is an importer or not. The last four columns subdivide the group of importing plants into those that purchase more than 50% from the EU, the U.S., Canada or Japan. The label 'LA importers' refers to those plants with more than 50% of total value of intermediates imports coming from Latin America, Russia, India and China.

3 Empirical strategy

The purpose of this paper is to investigate the employment effects on establishments due to an increase in imports. Ideally, we would like to observe the same establishment in two situations, where the only exogenous difference is the increase in imports. A propensity score matching (PSM) approach allows to construct a counterfactual situation through which the causal effect on the outcome Y can be estimated. This strategy and its advantages over a simple regression analysis are explained in the following section.

There are two distinct groups of establishments in our sample: those that have expanded their import product range ($D = 1$) in period t and those without an expansion ($D = 0$), according to the indicator described above. In analogy to the program evaluation literature, we refer to the expansion of imports as treatment. Besides its treatment status D, an establishment is characterized by observable characteristics X. Following Heckman *et al.* (1998b) two conditions have to be satisfied for the matching approach to be valid. Conditional on X, the expected outcome without treatment Y^0 has to be the same for establishments in both groups. More formally, this is

$$E(Y^0|D = 1,\ X) = E(Y^0|D = 0,\ X) \tag{1}$$

The RHS refers to the actual observation for the untreated establishments, whereas the LHS refers to the hypothetical outcome of a treated establishment in case it would not have increased its imports. Clearly, this requirement is impossible to verify and has to hold by assumption. To satisfy this assumption, we require establishments in both groups to be as similar as possible in X. This is the heart of the identification strategy: establishments with $D = 1$ are paired with untreated establishments, one at a time, if they are sufficiently similar regarding their pre-treatment characteristics X. Conditional on being matched, the difference in the observed outcome between both groups is the treatment effect we are interested in.[13]

The employment size and the average task intensities are analyzed as outcome variable Y. The response in the latter variables is straightforward to explain. Since all task intensities are positively defined, an increase in their plant average means that either workers are hired with a task intensity above average, or alternatively, that workers with a task intensity

[13] Matching also requires the stable unit treatment value assumption. In the setting here, it means that a firm's import decision has no impact on the employment pattern of other firms. Even tough the matching is performed on regions and sectors, their definition is not so narrow. Furthermore the number of importers is rather low, thus there is no reason to suspect that importers employment changes have an effect on local labor markets in the short run.

below average are dismissed. Thus, it is irrelevant in the first place, whether the total employment rises or falls.

Rosenbaum and Rubin (1983) establish that instead of comparing firms along all variables X, a single statistic $P(X)$ suffices. $P(X)$, the so called propensity score, is defined as the probability of receiving the treatment conditional on X. Here, we estimate $P(X)$ in a Probit model, where X are values from period $t-1$. The pre-treatment value of the outcome variable is also included in X, to obtain similar values of Y_{t-1} in the treatment and control group as well.

The second requirement in the procedure is that $0 < P(X) < 1$. This is a practical matter, to guarantee that all establishments can theoretically be matched. Therefore, the predicting power in the probit estimation should not be too high. Otherwise, it is difficult to find pairs with the same $P(X)$ from treatment and control group, which is of course especially true for perfectly predicted treatment statuses $P(X) = 1$ and $P(X) = 0$. We follow the previous literature and restrict the matching to a common set of $P(X)$-values in both groups (Heckman *et al.* 1998b). In the present application, we are not worried that this common support restriction may confine the representativeness of our findings. Quite the contrary. It is well known that firms involved in international trade, especially importers, are inherently different from national firms (Bernard *et al.* 2007). Therefore, the largest multinationals and the smallest domestic firms do not represent comparable matching partners and should be disregarded.

Even if a similar national control group is found, one might be worried that responses in the outcome are influenced by the participation in international trade. For this reason, we have excluded import newcomers in the definition of the treatment dummy and we work with two distinct control groups. One group is composed of purely national firms and the group other are only importers which did not increase their imports. Matching with the second control group allows to include trade related characteristics into X.

Then the PSM approach proceeds to choose the pairs of firms.[14] It turns out that the best balance of all X variables and Y_{t-1} between treatment and control group are achieved with a simple 1:1 nearest neighbor matching without replacement, where we additionally restrict the maximum distance between observations of a possible pair. Consequently the distributions of $P(X)|D = 1$ and $P(X)|D = 0$ are limited to the common support plus/minus this maximum distance. Firms that remain unmatched are discarded in the following analysis, leading to the satisfaction of the second requirement. Not only the distribution of $P(X)$ and Y_{t-1} but also of each variable in X should now be alike in both groups. These are conditions that can and will be tested. Note that the main findings in this paper are not critical to the matching algorithm. Using a k-nearest neighbor matching with $k = 10$ yields similar effects. However, the number of establishments in the control group is much lower and the balance of covariates in matched sample is much worse than in our 1:1 matching.

[14] Several matching algorithms have been proposed, cf. Ebner (2012), Smith and Todd (2005) for an overview and a discussion. The algorithms differ in how pairs are formed and how the observations in a pair are weighted.

Once treated and untreated firms are accurately matched on the relevant characteristics, the conditional mean independence in equation (1) implies that the *observed* difference in outcomes between treated and control group $E(Y_t^1|D = 1, P(X)) - E(Y_t^0|D = 0, P(X))$ reveals the effect of an increase in imports we are interested in[15]

$$E(Y_t^1 - Y_t^0|D = 1, P(X)) \quad . \tag{2}$$

A potential problem for the identification are unobservable factors that affect the decision to increase imports. In this case, equation (1) does not hold with equality and the estimation is biased. We additionally construct the conditional difference-in-difference (DID) estimator proposed by Heckman *et al.* (1998a) that eliminates biases that are constant over time, which implies a relaxation of the requirement in equation (1).[16]

$$E(Y_t^1 - Y_{t-1}^1|D = 1, P(X)) - E(Y_t^0 - Y_{t-1}^0|D = 0, P(X)) \quad . \tag{3}$$

Alternatively, it is possible to compare changes in Y^1 and Y^0 between $t+1$ and $t-1$. This would be reasonable if restructurings take more than one year to occur. We report both DID_t and DID_{t+1} in the following. However, a preliminary look at the data showed that for the treatment group the largest change in employment (in absolute values) occurs during t and $(t-1)$.

At last, we want to stress some benefits of propensity score matching over regression analysis. The PSM does not include all firms, but only similar candidates, for the calculation of the treatment effect. In the context of trade, this exclusion is certainly important, since few nationals perform like international companies. Furthermore, PSM equalizes the pre-treatment mean of the outcome variable in both groups. Thereby, differences in Y in later periods mirror the causal effect of the treatment, contrary to a linear regression on the treatment dummy. The downside of the PSM is that some information is lost due to unmatched establishments. Depending on the sample size, this can induce difficulties to obtain significant results.

4 Results

4.1 Propensity Score Matching

This section presents the estimation and balance properties of the propensity scores (PS) and finally shows the treatment effects. The PS is estimated in a Probit model, where the dependent variable is the indicator for an increase in imported intermediates during period t. We try two specifications with different control groups to fortify the robustness of the results. In version 1 the plants without treatment are the ones without imports in *t and*

[15]This effect is correctly called the average treatment effect on the treated (ATT).

[16]Compare Smith and Todd (2005) for more details about why the authors prefer this conditional DID estimator.

$t-1$. Version 2 contains only importers, but still amounts to 14203 observations in the years 2004 and 2005. The covariates on which the PS is conditioned also differ between both versions. Obviously, the number of different import countries, import products and their value appear exclusively in version 2. As argued above, these variables are proxies for a plant's productivity. Having a much higher dispersion in plant size in version 1, we obtain a satisfactory balance between treated and control group, with a quadratic in log plant employment size and the overall log size of the entire firm. In the other sample we obtain better results with dummies for employment size ranges. Moreover, both versions contain employment shares for workers with high school (2), college (3) and higher education (4). The omitted reference group is the share of workers without high school degree. These variables take up differences in the production technology. Their coefficients are positive, increasing in the level of education and significant in both models, cf. table 2. Finally, both estimations condition on region fixed effects, an indicator for less than 1.2 million Reais annual revenue and a quadratic in the outcome variable, whose response we will test in the next step. Recall that all covariates contain pre-treatment values from $t-1$. For each outcome variable a different Probit model is estimated. Coefficients are very similar across the models, thus to save on space, table 2 exemplarily shows the results with the routine manual task index.

Only after the estimation of the probability for an import expansion we condition plants to be in the same 2-digit sector and observations years to be equal.[17] Then, a 1:1 nearest neighbor matching without replacement is performed by the STATA routine *psmatch2*.[18] Balancing properties of both versions are reported, exemplarily for the case where the outcome variable is the routine manual task intensity, in tables 3 and 4, respectively. The matching yields reasonable bias reductions and the difference in means is insignificant for most of the covariates. Most importantly, the plant's task content, i.e. the outcome variable in the pre-treatment period, is also quite even in treatment and control group. Their PS distributions confirm the good balancing, which is again true for both control groups, compare panel (a) and (b) in figure 2. We also observe that the after conditioning on the common support, the remaining overlap of $P(X)$ is quite large. The low pseudo R^2 in the Probit estimation for version 2 (in table 2), before the exact matching on year and sector, is not necessarily bad news. It means that, given the available variables, it is difficult to predict which *importer* will increase its foreign activities in the next period. Either this is a sign that the conditional independence assumption in equation (1) is likely to hold. Or it means that the data set is not rich enough and the selection into treatment is based on unobservables. Finally, note that neither the matching algorithm (as already mentioned above), nor the choice of covariates is critical to obtain the results in this paper. Matching on less variables X deteriorates the balance between importer and control group while most outcome differences have the same sign and similar magnitude.

[17] Given the caliper matching, the forcing of exact matches is done by adding 10∗year and 100000∗sector to the predicted probability, cf. Ebner (2012).

[18] Propensity scores of matched pairs may not exceed a distance of 0.005 in version 1 and 0.1 in version 2 (caliper matching). A larger distance is allowed in the version with only importers, because the firms are inherently more similar and there are much less possible matching partners available.

The following two tables, which contain the effects for all outcome variables, repeat the pre-treatment differences. Table 5 and 6 are created with the national and the importer control group, respectively. The first column, each, shows the difference in means between treated and control plants, while the second and third column refer to the difference-in-difference estimators. The comparable treatment effects, across estimators and the two control groups confirm that matching is accurate. Unfortunately, not all of the pre-treatment differences are completely balanced and we will desist from interpreting these cases. Nevertheless, we prefer this situation over a mixing of matching algorithms to maintain comparability and tractability.[19]

For the average task contents of a plant, reported in the first six rows in table 5 and 6, the strongest results emerge for routine and non-routine manual tasks. The comparisons in levels and both DID estimators show that an increase in imports raises the intensity of manual tasks in production. The mirror-image is that there is also some evidence for a reduction of the non-routine cognitive task intensity. However, routine cognitive tasks do not seem to be much affected by trade in intermediate products. In line with observations from Becker *et al.* (2013), routine manual tasks are among the most tradable.

The novelty is that apparently also non-routine manual tasks are affected and, what is more, an increase of their intensity is observed, instead of a reduction. This finding is consistent with the overall predominance of manual tasks in the Brazilian economy (De Negri 2005b). Tables 5 and 6 also show that the increase in imports implies a clear increase in employment, by about 12 workers on average. Importing more intermediates also increases the share of intermediate goods exports. This paints the following picture: On average, establishments process the imported intermediates using manual tasks intensively and then proceed to export them. In other words, onshoring is prevalent in the Brazilian economy.

The following highly stylized example intents to provide a feeling about the size of the treatment effects. Table 3 shows that the average size of matched plants in the sample is approximately 163 in period $t-1$. The average value of routine manual tasks is 10.32 for the treated firms and 10.29 for the control group. The DID_t effects amount to 0.025 for the routine manual task measure and to 12 for the employment size, cf. table 5. For simplicity, we assume that plants' characteristics in the control group remain constant. Consequently, after the treatment, the task value for the treated firms increased to 10.345. If we assume that these firms keep all previous employees, the 12 additional workers have an average task score of 10.68. That is, the new positions are significantly more routine manual intensive. The task scores may still be an abstract number, but we select a few of the 2511 different jobs to illustrate this scale: Weaver (11.02), maintenance technician (10.74), machine assembler (10.57), production supervisor (10.27), truck driver (10.22), automotive engineer (9.47); The spread of about 1.5 may seem large, but one has to bear in mind that the task values are firm-level averages and that firm sizes are also quite large. Therefore, the changes in these average values are much smaller, as observed in our results.

[19]By this, we also mean, e.g., changing the maximum distance of the caliper or the specification of the X variables. On average, the best balancing results are obtained with the algorithm described above, even it may not be perfect in each single estimation.

As argued in section 2.3, in case of possible inaccuracies, the Brazilian occupations are without much doubt more manual and less analytic than their U.S. counterparts. In this case, we expect the additionally employed workers to attain even higher scores in the manual task categories. So, the good news is that the PSM estimates, if anything, represent lower bounds. One might also be worried that due to the definition of our treatment variable, we principally capture new innovations. In this case, the increase in the size of the plant would come about naturally. Colantone and Crinò (2012) show that new imported intermediates foster the development of new final products. However, their definition of new products is much more stringent because 'new' refers to latest technological innovations. In addition, the fact that the share of exported intermediates also rises, makes us confident that the evidence is consistent with onshoring, rather than with the effects of adopting new technologies from abroad.

4.2 Won and lost jobs

The aim of this subsection is a closer examination of the results obtained by the PSM. In particular, it is compelling to see if offshoring is not present at all, or if certain tasks are being substituted by imported intermediates.

The changes in the average manual task content do not definitely reveal whether their cause is an increase in manual tasks or whether jobs are lost which use manual labor un-intensively. For this reason, the analysis is shifted to the level of occupations keeping only those establishments that experienced an expansion in imports in period t. This view might also uncover occupation-specific changes within importers compared to average task intensities in establishments. First, we count the number of employees (weighted by hours worked) in each plant for each of the 5-digit occupations. Then, we calculate and depict the change in the stock of workers between t and $t-1$ in treated establishments.[20]

Figure 3 plots these changes aggregated by sector. In all of the 13 industries more jobs are created then are lost, hence no industry is particularly engaged in offshoring. The same picture emerges from the distribution by 1-digit occupation groups in figure 4. It is striking that the vast majority of churning occurs in industrial and technical jobs. Sales, maintenance and administrative jobs seem much less involved. Although one would have suspected these jobs to be in danger of being moved abroad, they gain. Obviously, not all of these changes are caused by the increase in imports, but are overlaid with the usual job flows, which are traditionally quite large in the Brazilian economy. Note that the sectoral distribution of jobs in figure 3 corresponds quite well with the structure of the entire stock of jobs in manufacturing.[21] Even though the partitioning of occupied vacancies into occupation groups is unexceptional, the specific types of those new jobs seem to be more manual intensive.

[20] Some plants are excluded from the analysis, that report large increases or decreases in a certain occupation, whereupon this change is almost reversed in the following period. We suppose that these dismissals are merely intended to bypass certain consequences of labor legislation.

[21] The economy-wide numbers are borrowed from Muendler (2008: 290).

In the next consideration, the employment changes in establishments are aggregated to 5-digit occupations. We want to examine if occupations with an overall decrease of employment are different from growing occupations regarding their task content. Figure 5 plots the task content against employment change (in logarithmic scale) using a kernel-weighted local regression smoother. For negative employment changes, the *absolute* values were transformed in log and then multiplied by minus one. For the ease of exposition, only four of the six task measure are depicted here.[22] The task contents of occupations with small employment changes are close to their original mean of 10. Further to the edges, the manual task intensity increases steadily, while the analytical intensity decreases. The curve for the routine cognitive intensity shows no clear direction and stays close to its mean. Apparently, jobs that are most affected by imports are manual intense and hence less analytic. Most astonishing is that the task contents of occupations with the largest absolute change are almost equal. Thus, from this perspective, there is no difference between lost and won jobs. Note however, that the maximum value of employment change is much larger for created occupations reflecting the overall employment gain.

4.3 Imports from high- and low-wage countries

What could be the reason for the almost symmetric change at the level of occupations? Notwithstanding, we are still confident that the task classification is appropriate, given that the routine manual index shows the largest dispersion and seems to be most associated with the tradability of jobs. As mentioned in section 2.2, the origin of imports reflects fundamental differences between the performance of Brazilian firms. One possibility is that a division of importers from high-wage countries, such as the EU, Canada, Japan and the U.S. (labeled EU), and low-wage countries, such as Russia, India, China and Latin American countries (LA), might reveal differences which are disguised in the pooled sample. This distinction between high- and low-wage countries is frequently made in the context of FDI. Concerning imports, e.g., Becker *et al.* (2013) found that interrelations with low-wage countries generate larger effects. Since the basic intention of offshoring is to save labor costs, our working hypothesis is: intermediates imports from high-wage countries represent onshored tasks, while imports coming from developing countries are offshored tasks.

Figure 6 presents the entire distribution along the log employment change per occupation for each of the task measures. The only difference between figure 5 and the construction of these graphs is that the employment changes are first divided according to the origin of the plant's imports and then aggregated to the level of occupations for both groups of importers. For the two categories analytical and non-routine cognitive, a difference in the entire employment change distribution is observed in panel a) and d) in figure 6. This is consistent with the view in De Negri (2005a) that high-wage country importers are technologically advanced. Similar mean differences are observed for the offshorability task

[22] Non-routine cognitive were quite alike the analytical tasks in this diagram, as was the case in figure 1. The offshorablity measure is omitted, because its results were insignificant before.

index, however this impression is not confirmed in the graphical representation. In panel f) the lines cross twice. Consistent with our hypothesis, displaced workers in LA importers show a higher value of offshorability than laid off workers from EU importers, and the pattern is reversed for new workers except for those occupations with the highest employment changes. Systematic differences in the two dimensions lost vs. won employment and EU vs. LA imports, for the routine cognitive and routine manual tasks also support the working hypothesis. EU importers shift their employment towards routine tasks, whereas the low-wage country importers rather reduce those tasks. To complete the picture, LA importers seem to shift away from non-routine manual tasks, whereas the direction for the EU importers is ambiguous given the information in the graph.

Our interpretation of these patters is the following: Some inherent differences between importers are due to a technological edge. Jobs created in consequence of more imported intermediates from the EU, U.S., Canada and Japan are more tradable and routine intensive. On the other hand, reduced tasks in plants with imports from low-wage countries are also easier to offshore and more routine manual intensive than those tasks reduced by EU importers. All in all, this is consistent with EU importers performing onshored work, whereas LA imports look more like offshored tasks. The reader is reminded that, since this evidence is on the level of occupations, it is too early to draw evident conclusions about the behavior of firms, but we turn to this in the following.

An advantage of this graphical assessment is that one has an overview of all occupations and everywhere in the distribution of employment changes. The downside is that we do not control for differences other than the origin of imports. We provide some regressions at the occupation-establishment level in table 7 to mitigate that concern. As expected, only large differences along the entire axis of positive or negative employment changes turn out to be significant. That is, LA importers reduce tasks which are significantly less abstract and more routine manual intensive. EU importers increase routine cognitive intensive tasks, thus confirming the prior findings.

The last piece of evidence stems from Propensity Score Matching. Again, we separate the treated importers according to the origin of their foreign intermediates and compare both groups with the sample of purely national plants. The PSM procedure is just like before in version 1.[23] Table 8 shows those outcome variables with significant results and an acceptably low pre-treatment difference. Focus first on panel B with the importers from low-wage countries. This perspective does not provide any evidence for offshoring. Instead, plants increase the share of intermediates in their exports, and plants are on average growing faster than their national counterparts. We do not observe that treated plants reduce their routine and manual intensive tasks. In contrast, the only significant result for the task measures is an increase in the routine manual intensity. Thus, the average establishment in this group does not seem to be involved in offshoring but rather in onshoring. Because the intermediate input was processed in low-wage countries and is likely to be passed on to other countries, Brazil is somewhere in the middle of a global production chain. This is consistent with the multi-country model in Costinot *et al.* (2013).

[23]Probit results and balancing properties are omitted for brevity but are quite like the prior ones.

An even larger increase in intermediates exports is visible in panel A. Recall that import increases from high-wage countries represent the majority of observations, which might partly explain the higher significance of results in panel A of table 8. In line with the prior results, the EU importers significantly raise their manual task intensity and overall employment size. The higher share of intermediate goods exports again completes the case for onshoring. The only aspect contrary to our expectations is that importers appear to trade tasks with an offshorability score below average. This might be explained by the fact that the construction of this task measure is aimed at personal interactions, which is not in accord with those onshored manufacturing activities. In the end, it seems to make no difference where the intermediates are imported from. One case is consistent with a back and forth task trade, the other case is suggestive of a sequential international production chain. Baldwin and Venables (2011) construct a two-country framework that embeds these two types of assembly modes. Since this paper has focused on shifts in the task compositions and not on the actual flow of intermediates, this last conclusion should be seen as a preliminary indication. We leave these questions about the organizational production structure for future research.

4.4 Robustness checks

The main evidence from PSM was complemented by a finer division of importing plants and by the perspective of won and lost occupations. It was mentioned earlier that the classification of tasks, the choice of the control group, the timing of the effects either in t or $t+1$ and the matching algorithm do not change the conclusions obtained so far. One of the crucial variables in the entire paper has not been examined more closely: the increase in imported intermediates. This section briefly shows that the findings remain robust to variations in the definition of this treatment indicator.

Recall that the definition was based on the purchase of any new intermediate good(s) from abroad, subject to some constraints which ensure that the relation is stable and economically important. Firstly, we follow Feenstra and Hanson (1999) and restrict the indicator to cases, where the expanded imports correspond to the importing plant's 2-digit industry class. This narrow definition is intended to separate imports, which the plant could potentially produce itself, from other inputs which are less related to its core competences. The robustness check also lends itself to onshoring, because it can reduce the concern that the observed pattern is merely caused by so-called carry-along trade or by supplementary material for new innovations. That is, maybe imported inputs are not even processed, because they do not belong to the plant's business activity. Table 9 shows that the responses are even stronger than before. Only outcome variables which were most affected so far are displayed. While the sample size is reduced by about one half, our estimators in levels and differences are positive and highly significant for routine manual tasks, the share of exported intermediates and employment size.

Secondly, imports of semi-finished products are disregarded and we focus only on 'parts and components'. Obviously, the latter category is closely linked to industrial manufacturing activities.[24] Except for a decrease in the significance of the effect on the routine manual task intensity, the results are similar to the previous ones, cf. table 10. The drop in significance points out that even for semi-finished products routine manual tasks are used intensively. Therefore, both robustness checks confirm the perceived onshoring of Brazilian firms.

5 Conclusion

This paper evaluates the impact of an expansion in the range of imported intermediate inputs on establishments in Brazil. It is the first study to look at the employment effects in a middle-income country from a task perspective. Changes in the average task intensities of plants' workforces allow to identify that the imported inputs correspond to offshored tasks. In other words, Brazil is onshoring jobs that were relocated from other countries. Then again, there were only few signs that Brazilian plants offshore themselves.

Applying Propensity Score Matching on plants with and without an expansion in intermediates imports the following suggestive pattern emerged: Mainly manual tasks are traded. Importers experience an overall employment growth and they increase their share of exported intermediate inputs. This pattern is more pronounced when plants receive their imports from high-wage countries. Although there are some differences in the production technology, the characterization according to the origin of imports is far from the expected stereotype. Even for imports from low-wage countries the onshoring pattern is prevalent. We hypothesize that those plants might be part of international production networks, i.e., the destination of the imported and processed intermediates is elsewhere. While the total impact is apparently positive for the Brazilian economy, the generated jobs do not promote qualitative advances along the value chain, because the expansion is in manual intensive work. However, the growth of such jobs might be one explanation for the observed reduction of wage inequality (Cruz and Naticchioni 2012). A profound investigation of the wage effects as well as of the actual flow of intermediate inputs constitute logical extensions of this research.

References

Acemoglu, D. and Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In O. Ashenfelter and D. Card (eds.), *Handbook of Labor Economics*, vol. 4, Amsterdam: Elsevier-North Holland, pp. 1043–1171.

Amiti, M. and Wei, S. (2005). Fear of service outsourcing: Is it justified? *Economic Policy*, pp. 307–347.

[24] Plotting the distribution of won and lost jobs, analogous to figure 3, confirms this. However, the seven industries displayed in the lower part of the figure are considerably affected as well. Just as before, not a single industry experiences overall employment losses due to the expansion of imports.

Autor, D., Katz, L. and Kearney, M. (2008). Trends in us wage inequality: Revising the revisionists. *Review of Economics and Statistics*, **90** (2), 300–323.

—, Levy, F. and Murnane, R. (2003). The skill content of recent technological change: An empirical investigation. *Quarterly Journal of Economics*, **118** (4), 1279–1333.

Baldwin, R. and Venables, A. (2011). Relocating the value chain: Off-shoring and agglomeration in the global economy. *University of Oxford Discussion Paper No. 544*.

Barba Navaretti, G., Castellani, D. and Disdier, A. (2010). How does investing in cheap labour countries affect performance at home? Firm-level evidence from France and Italy. *Oxford Economic Papers*, **62** (2), 234–260.

Becker, S., Ekholm, K. and Muendler, M. (2013). Offshoring and the onshore composition of tasks and skills. *Journal of International Economics*, **90** (1), 91–106.

Bernard, A., Jensen, J., Redding, S. and Schott, P. (2007). Firms in international trade. *Journal of Economic Perspectives*, **21** (3), 105–130.

—, Redding, S. and Schott, P. (2010). Multiple-product firms and product switching. *American Economic Review*, **100** (1), 70–97.

—, — and — (2011). Multiproduct firms and trade liberalization. *Quarterly Journal of Economics*, **126** (3), 1271–1318.

Biscourp, P. and Kramarz, F. (2007). Employment, skill structure and international trade: Firm-level evidence for France. *Journal of International Economics*, **72** (1), 22–51.

Blinder, A. (2009). How many us jobs might be offshorable? *World Economics*, **10** (2), 41–78.

Calfat, G., Cassimon, D., Flôres, R. and Rivas, A. (2008). Far from champions, close to midgets–international production sharing in central and south america. *IOB Working Papers No. 2008-01*.

Colantone, I. and Crinò, R. (2012). New imported inputs, new domestic products, mimeo.

Costinot, A., Vogel, J. and Wang, S. (2013). An elementary theory of global supply chains. *Review of Economic Studies*, **80**, 109–144.

Crinò, R. (2009). Offshoring, multinationals and labor market: A review of the empirical literature. *Journal of Economic Surveys*, **23** (2), 197–249.

Crinò, R. (2010). Employment effects of service offshoring: Evidence from matched firms. *Economics Letters*, **107** (2), 253–256.

Cruz, B. and Naticchioni, P. (2012). Falling urban wage premium and inequality trends: evidence for Brazil. *Investigaciones Regionales*, **24**, 91–115.

De Negri, F. (2005a). Conteúdo tecnológico do comércio exterior brasileiro: O papel das empresas estrangeiras. *IPEA Texto para discussão No. 1074.*

— (2005b). Padrões tecnológicos e de comércio exterior das firmas brasileiras. In J. De Negri and M. Salerno (eds.), *Inovações, padrões tecnológicos e desempenho das firmas industriais brasileiras*, IPEA Brasília.

Ebner, S. (2012). *Essays on the economics of mergers & acquisitions*. Ph.D. thesis, University of Passau.

Feenstra, R. (2010). *Offshoring in the global economy: microeconomic structure and macroeconomic implications*. Cambridge University Press.

— and Hanson, G. (1997). Foreign direct investment and relative wages: Evidence from Mexico's maquiladoras. *Journal of International Economics*, **42** (3-4), 371–393.

Feenstra, R. C. and Hanson, G. H. (1999). The impact of outsourcing and high-technology capital on wages: estimates for the United States, 1979–1990. *Quarterly Journal of Economics*, **114** (3), 907–940.

Firpo, S., Fortin, N. and Lemieux, T. (2011). Occupational tasks and changes in the wage structure. *IZA Discussion Paper No. 5542.*

Goldberg, P., Khandelwal, A., Pavcnik, N. and Topalova, P. (2010). Multiproduct firms and product turnover in the developing world: Evidence from india. *Review of Economics and Statistics*, **92** (4), 1042–1049.

Goos, M., Manning, A. and Salomons, A. (2010). Explaining job polarization in europe: the roles of technology, globalization and institutions. *CEP Discussion Paper No. 1026.*

Grossman, G. and Rossi-Hansberg, E. (2008). Trading tasks: A simple theory of offshoring. *American Economic Review*, **98** (5), 1978–97.

— and — (2012). Task trade between similar countries. *Econometrica*, **80** (2), 593–629.

Hakkala, K. and Huttunen, K. (2010). Offshored job tasks and displaced workers, mimeo.

Hanson, G. (2012). The rise of middle kingdoms: Emerging economies in global trade. *Journal of Economic Perspectives*, **26** (2), 41–63.

—, Mataloni Jr, R. and Slaughter, M. (2005). Vertical production networks in multinational firms. *Review of Economics and Statistics*, **87** (4), 664–678.

Heckman, J., Ichimura, H., Smith, J. and Todd, P. (1998a). Characterizing selection bias using experimental data. *Econometrica*, **66** (5), 1017–1098.

—, — and Todd, P. (1998b). Matching as an econometric evaluation estimator. *Review of Economic Studies*, **65** (2), 261–294.

HELPMAN, E., ITSKHOKI, O., MUENDLER, M. and REDDING, S. (2012). Trade and inequality: From theory to estimation. *NBER Working Paper No. 17991.*

HIJZEN, A., TOMOHIKO, I. and TODO, Y. (2007). The effects of multinational production on domestic performance: Evidence from Japanese firms. *RIETI Discussion Paper Series No. 07-E-006.*

HUMMELS, D., ISHII, J. and YI, K. (2001). The nature and growth of vertical specialization in world trade. *Journal of International Economics*, **54** (1), 75–96.

LAPLANE, M. and DE NEGRI, F. (2004). Impactos das empresas estrangeiras sobre o comércio exterior brasileiro: evidências da década de 90. *Revista de Economia*, **30** (1), 31–48.

MACIENTE, A. N. (2013). *The determinants of agglomeration in Brazil*. Ph.D. thesis, University of Illinois at Urbana.

MOSER, C., URBAN, D. and WEDER DI MAURO, B. (2010). Offshoring, firm performance and establishment-level employment: Identifying productivity and downsizing effects, mimeo.

MUENDLER, M. (2008). Trade and workforce changeover in Brazil. In S. Bender, J. Lane, K. Shaw, F. Andersson and von Wachter T. (eds.), *The Analysis of Firms and Employees: Quantitative and Qualitative Approaches*, *9*, University of Chicago Press, pp. 269–308.

ROSENBAUM, P. and RUBIN, D. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, **70** (1), 41–55.

SILVA, I. M., BEZERRA, J. F. and LIMA, R. C. (2012). Análise da relação entre importações e produtividade. *Revista de Economia Contemporânea*, **16**, 62 – 87.

SMITH, A. and TODD, E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics*, **125** (1), 305–353.

Tables and figures

Table 1: Summary statistics pooled for 2004 and 2005

	national		international		EU importers		LA importers	
	mean	std	mean	std	mean	std	mean	std
production								
size	22.9	87.3	208.6	371.0	207.1	348.1	209.9	412.1
Δsize	1.04	28.24	15.37	95.58	12.29	82.33	16.01	84.26
firm size	115	1028	672	2485	729	2670	552	1975
educ.sh.[1]	0.148	0.235	0.079	0.119	0.070	0.107	0.097	0.132
educ.sh.[2]	0.428	0.302	0.254	0.194	0.234	0.184	0.298	0.201
educ.sh.[3]	0.380	0.305	0.490	0.217	0.498	0.208	0.474	0.221
educ.sh.[4]	0.044	0.120	0.176	0.187	0.197	0.193	0.130	0.151
low revenue dummy	0.723	0.448	0.027	0.162	0.024	0.152	0.030	0.171
trade								
imp.countries	-	-	27.9	55.3	31.4	58.6	16.5	34.8
imp.products	-	-	19.8	28.7	22.8	31.0	11.9	18.3
imp.value	-	-	3.225	21.90	3.421	26.30	1.830	6.620
exp.value	1.865	18.10	6.350	32.30	6.295	35.00	4.858	25.30
exp.products	3.3	5.9	8.8	18.1	8.7	18.4	8.4	18.6
exp.countries	7.6	28.5	28.8	108.3	27.9	121.1	27.7	83.9
tasks								
analytical	9.301	0.363	9.489	0.346	9.534	0.340	9.406	0.340
r.cognitive	9.921	0.633	9.921	0.517	9.944	0.505	9.859	0.546
r.manual	10.37	0.662	10.32	0.538	10.32	0.539	10.36	0.530
non-r.cognitive	9.378	0.444	9.570	0.375	9.607	0.374	9.497	0.369
non-r.manual	10.19	0.603	10.11	0.440	10.11	0.441	10.14	0.446
offshorability	10.02	0.539	10.07	0.409	10.07	0.402	10.06	0.407
obs.	271427		2497		1528		599	
obs. (exporters)	8826		1678		1077		383	

Notes: The production and task specific variables (except for the low revenue dummy) are weighted by the number of hours worked by each employee. Column 1 and 2 refer to purely national firms, column 3 and 4 to all importers. The last 4 columns sub-divide importers into those that acquire more than 50% of the value of their imports from the EU, US, Canada or Japan (EU) and those plant which mainly import from Russia, India, China or Latin America (LA). Export and import values are in million Reais.

Table 2: PSM Probit estimation

	all plants [1]		importers only [2]	
	coef.	std. error	coef.	std. error
$educ.share[2]_{t-1}$	0.50	0.08***	0.20	0.12*
$educ.share[3]_{t-1}$	1.50	0.07***	0.54	0.10***
$educ.share[4]_{t-1}$	2.83	0.09***	0.70	0.12***
$\ln(size_{t-1})$	0.28	0.03***		
$(\ln(size_{t-1}))^2$	0.03	0.00***		
$\ln(firmsize_{t-1})$	-0.13	0.01***		
$small_{t-1}$	-1.21	0.04***	-0.25	0.07***
$imp.\text{-}countries_{t-1}$			9.8e-04	9.9e-04
$imp.\text{-}products_{t-1}$			1.9e-03	1.7e-03
$imp.\text{-}value_{t-1}$			1.2e-03	9.8e-04
$r\text{-}manual_{t-1}$	8.65	0.53***	1.52	0.67***
$(r\text{-}manual_{t-1})^2$	-0.41	0.03***	-0.07	0.03***
$constant$	-48.82	2.70***	-9.47	3.42***
size dummies	✗		✓	
region FE	✓		✓	
observations	273780		14203	
pseudo R^2	0.383		0.021	

Notes: The dependent variable is the indicator for an increase in imports. * significance at ten, ** five, *** one percent. This table is exemplarily and corresponds to the version where the outcome variable is the mean routine manual task intensity.

Table 3: Balance of covariates in matched sample - national control group

		Mean			%reduct.		
Variable	Sample	Treated	Control	%bias	|bias|	t-value	p>|t|
$educ.share[1]_{t-1}$	Unmatched	0.090	0.158	-34.7		-13.4	0.000
	Matched	0.093	0.083	5.0	85.5	2.35	0.019
$educ.share[2]_{t-1}$	Unmatched	0.274	0.442	-64.3		-26.4	0.000
	Matched	0.282	0.279	1.3	98.0	0.51	0.610
$educ.share[3]_{t-1}$	Unmatched	0.465	0.358	40.5		17.0	0.000
	Matched	0.458	0.458	0.4	99.1	0.13	0.895
$educ.share[4]_{t-1}$	Unmatched	0.171	0.042	81.5		51.7	0.000
	Matched	0.166	0.180	-9.0	88.9	-2.06	0.039
$size_{t-1}$	Unmatched	199.0	21.89	70.4		99.1	0.000
	Matched	162.9	163.1	-0.1	99.9	-0.03	0.980
$firmsize_{t-1}$	Unmatched	641.6	107.9	30.1		27.0	0.000
	Matched	527.4	633.4	-6.0	80.1	-1.56	0.118
$r\text{-}manual_{t-1}$	Unmatched	10.33	10.37	-8.2		-3.61	0.000
	Matched	10.32	10.29	4.4	46.1	1.51	0.131
$region_{t-1}$	Unmatched	3.986	3.907	8.1		3.78	0.000
	Matched	3.993	4.022	-3.0	63.2	-1.07	0.284

Table 4: Balance of covariates in matched sample - importer control group

Variable	Sample	Mean Treated	Mean Control	%bias	%reduct. |bias|	t-value	p>|t|
$educ.share[1]_{t-1}$	Unmatched	0.090	0.110	-14.1		-6.0	0.000
	Matched	0.091	0.087	3.3	76.5	1.24	0.214
$educ.share[2]_{t-1}$	Unmatched	0.274	0.308	-16.4		-7.1	0.000
	Matched	0.278	0.279	-0.9	94.5	-0.31	0.758
$educ.share[3]_{t-1}$	Unmatched	0.465	0.432	14.9		6.6	0.000
	Matched	0.463	0.471	-3.8	74.7	-1.28	0.200
$educ.share[4]_{t-1}$	Unmatched	0.171	0.150	11.7		5.3	0.000
	Matched	0.168	0.163	3.0	74.7	0.99	0.322
$size_{t-1}$	Unmatched	199.0	157.6	12.4		5.6	0.000
	Matched	192.5	170.8	6.5	47.7	2.27	0.024
$firmsize_{t-1}$	Unmatched	641.6	601.1	1.7		0.8	0.449
	Matched	605.5	587.4	0.8	55.3	0.29	0.774
$r\text{-}manual_{t-1}$	Unmatched	10.33	10.31	2.3		1.02	0.308
	Matched	10.32	10.33	-0.9	61.7	-0.3	0.762
$region_{t-1}$	Unmatched	3.986	4.043	-6.1		-2.76	0.006
	Matched	3.996	3.985	1.2	81.0	0.4	0.693
$imp.countries_{t-1}$	Unmatched	20.92	13.44	20.0		10.2	0.000
	Matched	17.95	16.12	4.9	75.6	1.92	0.055
$imp.products_{t-1}$	Unmatched	14.86	10.23	21.9		10.6	0.000
	Matched	13.31	12.08	5.8	73.4	2.09	0.037
$imp.value_{t-1}$	Unmatched	2.4	1.6	4.4		1.99	0.047
	Matched	2.0e+6	1.6e+6	2.7	38.2	1.19	0.234

Table 5: PSM results - national control group

	treatment effect level	treatment effect DID_t	treatment effect DID_{t+1}	pre-treatment difference	obs
analytical	-0.005	-0.004	0.003	-0.001	2213
	[0.623]	[0.453]	[0.634]	[0.821]	
r.cognitive	-0.060	-0.010	-0.002	-0.050	2226
	[0.000]	[0.191]	[0.866]	[0.002]	
r.manual	0.052	0.025	0.027	0.027	2183
	[0.002]	[0.002]	[0.003]	[0.131]	
non-r.cognitive	-0.004	-0.017	-0.009	0.012	2225
	[0.722]	[0.011]	[0.267]	[0.323]	
non-r.manual	0.030	0.013	0.004	0.017	2189
	[0.056]	[0.035]	[0.634]	[0.249]	
offshorability	-0.046	-0.017	-0.013	-0.030	2185
	[0.001]	[0.008]	[0.110]	[0.038]	
exp.sh.int	0.110	0.084	0.073	0.025	1971
	[0.000]	[0.000]	[0.000]	[0.075]	
size	12.03	12.28	11.10	-0.24	2183
	[0.056]	[0.000]	[0.001]	[0.980]	

Notes: The control group are purely national plants, and the treatment group are plants with an increase in intermediate imports. P-values in parenthesis are based on bootstrapped standard errors with 100 replications. The last column quotes the number of treated plants.

Table 6: PSM results - importer control group

	treatment effect			pre-treatment	
	level	DID_t	DID_{t+1}	difference	obs
analytical	-0.009	-0.008	0.002	-0.002	2315
	[0.241]	[0.108]	[0.688]	[0.849]	
r.cognitive	-0.023	-0.007	-0.012	-0.016	2310
	[0.116]	[0.257]	[0.177]	[0.280]	
r.manual	0.017	0.022	0.018	-0.005	2311
	[0.249]	[0.002]	[0.043]	[0.762]	
non-r.cognitive	-0.013	-0.013	-0.010	-0.001	2314
	[0.126]	[0.014]	[0.130]	[0.955]	
non-r.manual	0.007	0.011	0.007	-0.004	2320
	[0.531]	[0.061]	[0.288]	[0.761]	
offshorability	-0.002	-0.007	-0.004	0.005	2316
	[0.840]	[0.172]	[0.615]	[0.696]	
exp.sh.int	0.032	0.027	0.036	0.005	2304
	[0.002]	[0.001]	[0.000]	[0.716]	
size	36.32	14.66	20.2	21.65	2311
	[0.000]	[0.000]	[0.000]	[0.024]	

Notes: The control group are importers with out an increase in intermediates imports plants, and the treatment group are plants with such an increase. P-values in parenthesis are based on bootstrapped standard errors with 100 replications. The last column quotes the number of treated plants.

Table 7: Task content of won and lost jobs - EU and LA importers

	analytical	r.cognitive	r.manual	non-r.cognitive	non-r.manual	offshorability
A) won jobs						
LA imports	-0.043	-0.175	0.005	-0.029	-0.008	-0.004
	[0.260]	[0.000]	[0.919]	[0.354]	[0.854]	[0.938]
R^2	0.05	0.06	0.04	0.05	0.06	0.04
B) lost jobs						
LA imports	-0.081	0.058	0.122	-0.017	0.069	-0.012
	[0.009]	[0.400]	[0.034]	[0.720]	[0.119]	[0.788]
R^2	0.09	0.04	0.06	0.11	0.09	0.07

Notes: Each column pertains to a regression, where the dependent variable is the task content of either won or lost occupations in establishments with an increase in intermediates imports. The variable of interest is a dummy for firms with imports from low-wage countries, below are p-values in parenthesis. Regressions control for sector, region and size class dummies and whether the plant has annual revenue below 1.2 Mio. Reais. Panel A has 26990 observations, panel B has 12120.

Table 8: PSM results - EU and LA imports

	A) EU imports			*B) LA imports*		
	level	DID_t	pre-tr.-diff.	level	DID_t	pre-tr.-diff.
r.manual	0.070	0.033	0.038	0.030	0.032	-0.006
	[0.002]	[0.001]	[0.088]	[0.326]	[0.048]	[0.865]
non-r.manual	0.030	0.013	0.016	0.001	0.018	-0.025
	[0.089]	[0.127]	[0.419]	[0.960]	[0.238]	[0.420]
offshorability	-0.040	-0.017	-0.013	-0.008	-0.023	0.019
	[0.032]	[0.059]	[0.493]	[0.792]	[0.122]	[0.493]
exp.sh.int	0.127	0.095	0.032	0.092	0.052	0.048
	[0.000]	[0.000]	[0.085]	[0.000]	[0.000]	[0.076]
size	34.09	9.867	24.23	23.32	10.42	12.91
	[0.000]	[0.000]	[0.024]	[.094]	[0.011]	[0.631]

Notes: The label 'EU' pertains jobs in establishments that acquire more than 50% of the value of their increased imports from the EU, U.S., Canada or Japan. Accordingly, 'LA' marks jobs in plant which mainly import from Russia, India, China or Latin America. The number of observations oscillates around 2750 in panel A and 1090 in panel B. Both have the purely national plants as control group and matching is performed analogous to version 1 before.

Table 9: PSM robustness - narrow intermediate imports

	treatment effect			pre-treatment	
	level	DID_t	DID_{t+1}	difference	obs
r.manual	0.086	0.032	0.037	0.053	1164
	[0.000]	[0.003]	[0.007]	[0.037]	
non-r.manual	0.026	0.013	0.019	0.012	1161
	[0.194]	[0.129]	[0.087]	[0.534]	
exp.sh.int	0.123	0.102	0.115	0.021	1048
	[0.000]	[0.000]	[0.000]	[0.299]	
size	42.03	16.63	11.21	33.55	1204
	[0.007]	[0.000]	[0.086]	[0.033]	

Notes: The control group are purely national plants. In contrast to table 5, the indicator variable has the value 1 if the increased imported intermediate inputs correspond to the 2-digit sector of the importing plant.

Table 10: PSM robustness - parts and components imports

	treatment effect			pre-treatment	
	level	DID_t	DID_{t+1}	difference	obs
r.manual	0.043	0.020	0.006	0.022	1015
	[0.087]	[0.062]	[0.698]	[0.401]	
non-r.manual	0.013	0.004	0.013	0.009	1007
	[0.521]	[0.677]	[0.315]	[0.670]	
exp.sh.int	0.130	0.088	0.082	0.042	898
	[0.000]	[0.000]	[0.000]	[0.051]	
size	39.18	15.26	19.47	23.92	1015
	[0.007]	[0.000]	[0.002]	[0.069]	

Notes: The control group are purely national plants. In contrast to table 5, the indicator variable has the value 1 if the increased imported intermediate inputs correspond to the sub-group 'parts and components'.

Figure 1: Average task content of occupations along the wage distribution

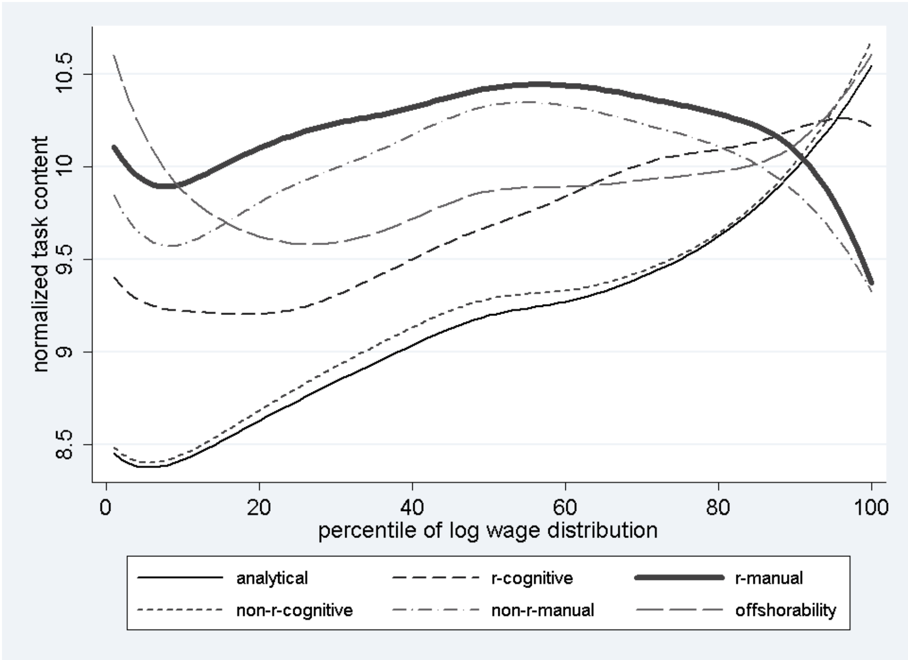

Figure 2: Distribution of matched propensity scores

(a) national control group

(b) importer control group

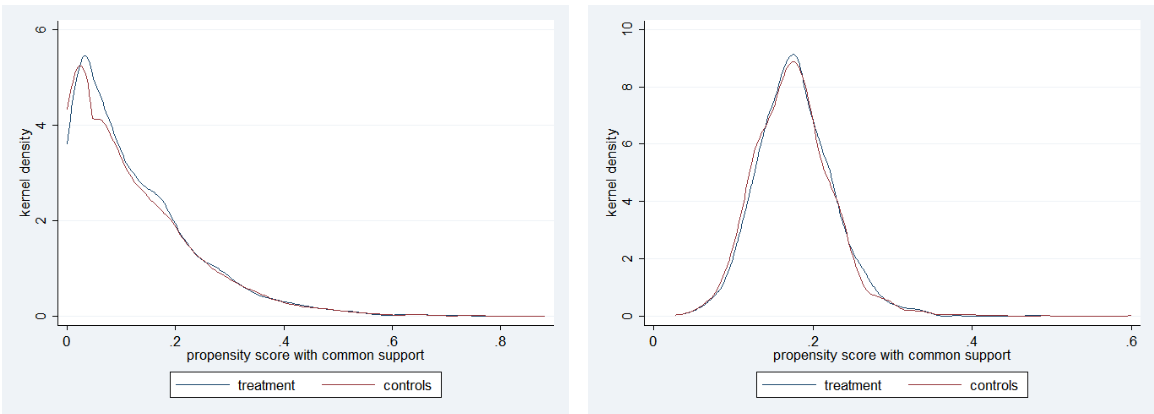

Figure 3: Distribution of won and lost jobs by sector

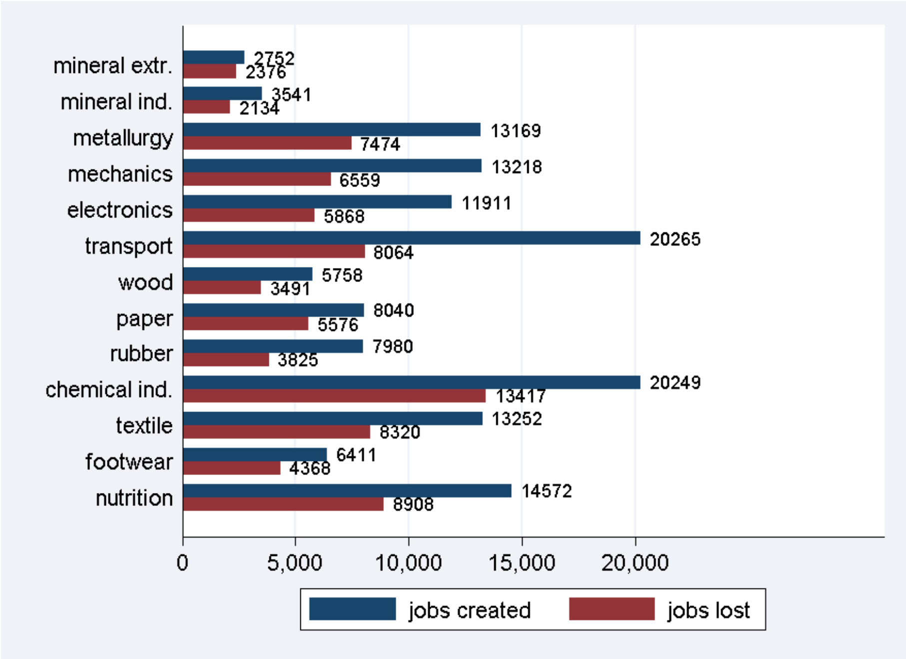

Figure 4: Distribution of won and lost jobs by occupational group

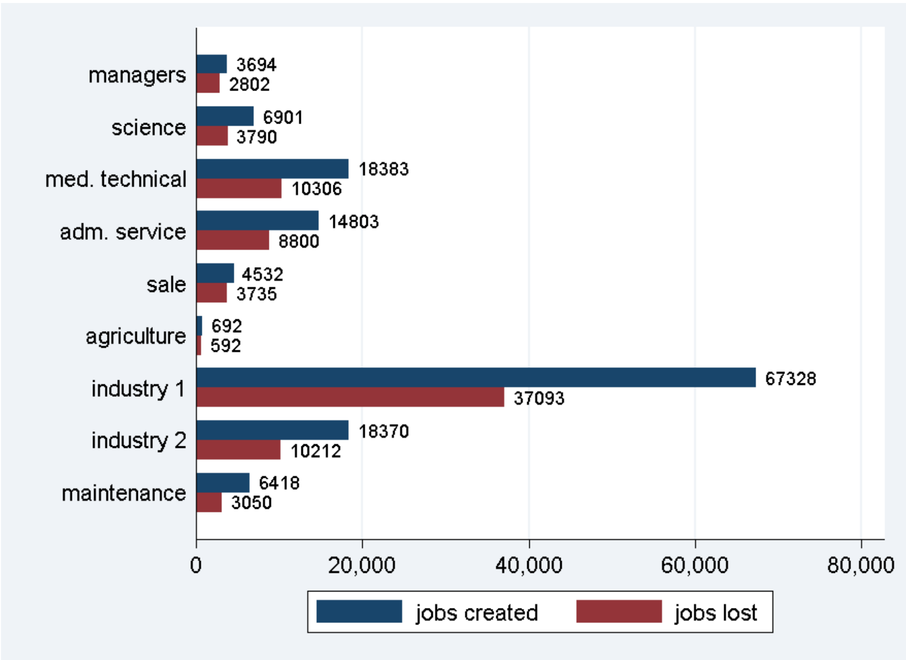

Figure 5: Task content and the employment change by occupation

Notes: The employment change is calculated as the net change of employees in each 5-digit occupation between t and $t-1$ considering all establishments with an increase in intermediates imports. The absolute value of this net change is transformed in logs. Employment losses are multiplied by -1 and consequently displayed on the negative part of the x-axis.

Figure 6: Task content and the employment change by occupation - EU and LA imports