



Economic geography and wages in Brazil: Evidence from micro-data

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ABSTRACT

This paper estimates the impact of market and supplier access on wage disparities across Brazilian states, incorporating the control for individual characteristics into the new economic geography methodology. We estimate market and supplier access disaggregated by industry, and we compute access to local, national and international markets separately. We find a strong correlation between market access and wage differentials, even after controlling for individual characteristics, market access level (international, national or local), and using instrumental variables.

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1. Introduction

Brazil, the world's fifth largest country in surface area, also has one of the highest levels of inequality. Its inequality is reflected not only at the individual level, but also in its geographic distribution. Lall et al. (2004) report that per capita income in São Paulo, the wealthiest Brazilian state, is 7.2 times higher than in Piauí, the poorest north-eastern state. In addition, population density and market size vary substantially across regions. Most of the population lives in the coastal areas of the north-east and south-east. While the average density in the south-east of Brazil is over 150 inhabitants per square kilometer, this number drops below 4 for the states in the north.

New economic geography (NEG) models focus on the impact of market proximity on economic outcomes, hence providing an interesting framework to study regional wage inequalities in Brazil. An important relationship put forward by NEG models is the impact of trade costs on firm profits. Trade costs are captured by two structural terms referred to in the literature as “market access” and “supplier access”. The first term measures access to potential consumers, while the latter refers to access to intermediate inputs. Since market and supplier access have a positive impact on profits, the maximum wages that firms can afford to pay are positively related to these variables.

This paper estimates a structural NEG model in order to study wage disparities across states and industries in Brazil. We use estimates of market and supplier access to explain regional wages, as in Redding and Venables (2004), and Head and Mayer (2006). We draw on industry-level trade data across states and control for individuals' characteristics in our estimations. Thereby, we are able to isolate the impact of location on wage inequality from other sources of wage inequality such as differences in the composition of the labor force or the local diversity of industries.

In two seminal works, Hanson (2005) and Redding and Venables (2004) test structural models of the new economic geography. The first is applied to US counties and the second to a sampling of countries. Both find a significant impact of trade costs on wages. Inspired by this approach, intranational studies have looked at European NUTS regions (Head and Mayer, 2006), US states (Knaap, 2006) and Chinese provinces (Hering and Poncet, forthcoming).¹

Our empirical framework makes two noteworthy methodological contributions. First, we control for individual characteristics. The spatial distribution of individuals could be such that their characteristics are correlated with structural NEG variables, thus leading to

¹ All these papers use the methodology proposed by Redding and Venables (2004), performing a structural estimation of NEG models. Other empirical studies use alternative frameworks, such as Mion and Naticchioni (2005) for Italy, Combes et al. (2008) for France, and Lederman et al. (2004) and Da Mata et al. (2007) for Brazil.

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spurious results in the estimation of the NEG wage equation.² Such controls are particularly important in the case of Brazil, since individual diversity is vast and it is an important determinant of wage inequalities in the country. For instance, Barros et al. (2000) show that the distribution of education and its return account for about half of the wage inequality from observed sources in Brazil. In addition, we observe large differences in human capital distribution across regions: workers from southern regions are on average more educated than those from northern regions. Ferreira et al. (2006) show that over 55% of the difference in the return to labor between the north-eastern and the south-eastern regions are due to differences in educational attainment. This substantial difference in the workforce's level of education across regions may be explained by sorting (Combes et al., 2008) or endogenous differences in returns to schooling (Redding and Schott, 2003). In any case, by controlling for education we correct for the bias induced by the differences in workforce composition across regions.

The second methodological contribution is an estimation of market and supplier access using trade flows at industry level. Other studies use aggregate trade flows.³ This procedure alleviates the colinearity problem found in the literature when attempts are made to estimate these two variables simultaneously. While it is true that supply and demand should be naturally correlated at aggregate level, since workers are also consumers, it is less likely to be true at industry level. A firm may rely intensively on inputs from a particular industry, while selling its product to consumers at large. Supplier access will then be higher for regions specialized in that particular industry. Hence, by adopting this procedure we are better equipped to disentangle the effects of market and supplier access. As a matter of fact, in the case of Brazil, the distribution of economic activity across regions varies a great deal across industries. Chemicals, for example, are mainly produced in Bahia, whereas transportation industries are mostly located in São Paulo.

With data on intranational and international trade flows, all disaggregated at industry level, we are also able to isolate local, national and international market and supplier access. Consequently, we are able to establish which kinds of trade (intranational or international) have the greatest impact on wages using a NEG mechanism.

Our empirical strategy uses a three-step procedure. Firstly, wages are regressed on worker characteristics, controlling for state–industry fixed effects. Secondly, we estimate gravity equations by industry in order to calculate market and supplier access for each industry in each state. We can also compute access to international, national and local markets separately. Lastly, market access and supplier access derived in the second step are used as explanatory variables for the wage disparities captured by the state–industry fixed effects in the first step.

We find a positive and significant effect of market and supplier access on the state–industry wage premium, with the impact of market access being stronger than the effect of supplier access. International market access turns out to have a greater impact than national or local market access. The positive impact of market access on wages is robust after controlling for several variables, such as firm productivity, taxes, regulation, endowments, and after using instrumental variables. The results are also unchanged in regressions at municipal level, where we are able to further control for local amenities and endowments.

The paper is organized as follows. Section 2 describes the methodology, with a brief summary of the theoretical background and a description of the empirical strategy used. The data are de-

scribed in Section 3, while Sections 4 and 5 discuss the results and the main robustness checks. Section 6 concludes.

2. Methodology

2.1. Theoretical framework

In economic geography models, transport costs make the geographic distribution of demand an important determinant of profits. We follow in the footsteps of Head and Mayer (2006) and Redding and Venables (2004) and derive profits and market and supplier access from Dixit–Stiglitz preferences. We present a brief description of the main hypothesis and results, rather than a full-fledged model, since such models are now standard in the literature.

As in the standard version of the Dixit–Stiglitz–Krugman model of trade, we assume preferences have a constant elasticity of substitution across product varieties. Each variety is produced by a single firm under monopolistic competition. Producers and consumers are spread over different regions, and we assume *ad valorem* trade costs, τ_{rsi} , between any two regions r and s .

Given these assumptions, in a symmetric equilibrium with n_{ri} firms in region r and industry i , the value of total sales from region r to region s , in industry i , X_{rsi} , can be shown to be:

$$X_{rsi} \equiv n_{ri} p_{ri} x_{rsi} = \frac{n_{ri} (p_{ri} \tau_{rsi})^{1-\sigma}}{P_{si}^{1-\sigma}} E_{si}, \quad (1)$$

where x_{rsi} represents sales of a firm in region r to region s , in industry i , p_{ri} is the price received by the firm, so that $p_{ri} \tau_{rsi}$ is the price paid by a consumer in region s for a good from region r in industry i , σ is the elasticity of substitution between product varieties, and E_{si} is the total region s spending on industry i . P_{si} is the price index for industry i in region s , defined as:

$$P_{si} \equiv \left[\sum_r n_{ri} (p_{ri} \tau_{rsi})^{1-\sigma} \right]^{1/1-\sigma}. \quad (2)$$

As for production costs, we assume that firms use labor and intermediate goods as inputs, and incur a fixed cost. More precisely, in industry i , intermediate inputs consist in a composite of goods from all industries where ϖ_{ji} is the share of expenditure on inputs from industry j , and, for each industry i , $\sum_j \varpi_{ji} = 1$. The total price index of intermediate inputs is equal to $\prod_j P_{rj}^{\varpi_{ji}}$.⁴ 'Supplier access' for a firm in region r and sector i , SA_{ri} , is defined as the price index of intermediate inputs, raised to the power $1 - \sigma$, as in:

$$SA_{ri} \equiv \prod_j (P_{rj}^{1-\sigma})^{\varpi_{ji}} \quad (3)$$

It is worth noting that, in this paper, we adopt a more precise definition of supplier access than the NEG literature, by computing supplier access separately for each industry, and taking into account inter-industry linkages. This procedure helps to disentangle supplier access from market access. Given the definition of supplier access, total costs of a firm in region r and industry i may be represented by $SA_{ri}^{\alpha/(1-\sigma)} w_{ri}^{\beta} (f_i + \sum_s x_{rsi})$, where α and β are parameters, f_i indicates the fixed cost in industry i , and w_{ri} is the wage in region r and industry i .⁵ Supplier access is a measure of the firm's access to intermediate inputs, and it is negatively related to trade costs. The greater the supplier access, the lower the cost of intermediate inputs.

² To our knowledge, only Hering and Poncet (forthcoming) control for worker characteristics in a NEG framework, and no other study has introduced firm productivity. Mion and Naticchioni (2005) also control for individual characteristics, but in a different framework.

³ Head and Mayer (2006) also use industry-level data, but they compute market access only.

⁴ This specification of the price index of intermediate inputs may be derived from a Cobb–Douglas production function, using input from all other industries.

⁵ We assume that labor migration across regions is not high enough to arbitrage away all regional wage disparities.

In maximizing profits, prices are set as a constant mark-up over marginal cost. Profits, then, can be shown to be given by:

$$\Pi_{ri} = \frac{1}{\sigma} \left(SA_{ri}^{\alpha/(1-\sigma)} w_{ri}^{\beta} \right)^{1-\sigma} MA_{ri} - f_i SA_{ri}^{\alpha/(1-\sigma)} w_{ri}^{\beta} \quad (4)$$

where MA_{ri} is ‘market access’, or ‘real market potential’, as referred to by [Head and Mayer \(2006\)](#), defined as:

$$MA_{ri} \equiv \sum_s \left(\frac{\tau_{rsi}^{1-\sigma} E_{si}}{P_{si}^{1-\sigma}} \right) \quad (5)$$

Market access will be greater when trade costs are lower and the real expenditure of the importing region is larger. The greater the market access, the higher the potential demand for the region’s products in industry i .

We are able to relate regional wages to market access and supplier access (hereafter, MA and SA, respectively). With free entry, profits are necessarily zero in equilibrium. Given the profit function in Eq. (4), this equilibrium condition yields:

$$w_{ri} = \left(\frac{MA_{ri}}{\sigma f_i} \right)^{\frac{1}{\beta\sigma}} SA_{ri}^{\frac{\alpha}{\beta(1-\sigma)}} \quad (6)$$

Hence, wages are higher in regions with greater MA, that is, with low trade costs to importing regions with high spending. Also, wages are higher in regions with greater SA, that is, where inputs can be bought at low prices due to low transport costs to suppliers.

2.2. Empirical strategy

Our empirical use of the theoretical framework described above involves a three-step strategy in a cross-sectional analysis for 1999.⁶ Firstly, wages are regressed on worker characteristics, including state–industry fixed effects. The wage premium captured by these fixed effects is the variable to be explained by market and supplier access. Secondly, in keeping with the new economic geography literature, we estimate gravity equations in order to calculate market and supplier access for each state and industry pair. Finally, market access and supplier access derived in the second step are used as explanatory variables for wage disparities captured by state–industry fixed effects from the first step.⁷ We explain each step in turn.

2.2.1. First step

Although the theoretical framework described in the previous subsections treats labor as a homogeneous factor of production, we know that this is not the case. There is extensive literature explaining wage differences across individuals by means of their characteristics, such as educational attainment, experience in years, gender and marital status, among many other variables. For Brazil, in particular, [Langoni’s seminal work \(1973\)](#) presents evidence of the importance of worker heterogeneity in income inequality. If patterns of diversity among individuals in the labor force were similar across regions, we could still explain average regional wages by regional market and supplier access differences, as proposed in Eq. (6). Previous empirical work, however, has identified substantial differences in the composition of the labor force across Brazilian regions, especially with respect to educational attainment (see [Ferreira et al., 2006](#)). Thus, our results would be biased if we did not control for individual char-

acteristics and sorting across regions and sectors. The first step of our empirical study consists in estimating the following equation:

$$\log w_{l,ri} = \lambda_1 \text{age}_{l,ri} + \lambda_2 \text{age}_{l,ri}^2 + \sum_{m=1}^9 \mu_m \text{ed}_{l,ri}^m + \omega_{ri} + \zeta_{l,ri} \quad (7)$$

where $w_{l,ri}$ is the wage of a male⁸ worker l working in industry i , of region r , $\text{age}_{l,ri}$ is the worker’s age, $\text{ed}_{l,ri}^m$ is a dummy variable for each of the nine educational levels (see [Appendix A1](#)), and ω_{ri} are dummy variables for each state–industry pair.⁹

State–industry fixed effects capture wage disparities that are not explained by worker characteristics. In the third step of our empirical procedure, these fixed effects will be explained by market access and supplier access.

2.2.2. Second step

The second step consists in estimating MA and SA as follows. Total sales from region r to region s in industry i , from Eq. (1), can be written as:

$$\log X_{rsi} = \log(n_{ri} p_{ri}) + (1 - \sigma) \log \tau_{rsi} + \log \frac{E_{si}}{P_{si}^{1-\sigma}} \quad (8)$$

The first term in the right-hand side of Eq. (8) comprises variables related to the exporting region, while the third term involves variables exclusively from the importing region. Hence, these two terms are captured empirically by exporting and importing region fixed effects, FX_{ri} and FM_{si} , respectively. As for the second term, there is no single variable to capture trade costs between two regions. Trade costs will then be captured by a set of variables, $TC_{k,rs}$, such as the distance between the regions (in log), whether they share borders, a language, or whether they have a colonial link.¹⁰ In sum, Eq. (8) is estimated by means of a gravity equation as follows:

$$\log X_{rsi} = FX_{ri} + \sum_k \delta_{ki} TC_{k,rs} + FM_{si} + \varepsilon_{rsi} \quad (9)$$

where X_{rsi} stands for exports from region r to region s in industry i , and ε_{rsi} is an error term. A region may be defined as either a Brazilian state or one of the 210 countries in our dataset.

In order to render our results comparable to those in the literature, we have also estimated Eq. (9) for aggregate trade flows, instead of disaggregating by industry. In this way, we can compute MA and SA measures comparable to those in [Redding and Venables \(2004\)](#), [Knaap \(2006\)](#), [Head and Mayer \(2006\)](#), and [Hering and Poncet \(forthcoming\)](#).

We would like to note that an estimation based on gravity regressions has the advantage of using information on the economic mechanism that our theoretical model intends to stress, namely, spatial interactions arising from trade. We would thus be less prone to capture other effects of proximity, such as technological or urban externalities. Nevertheless, we will perform a number of robustness checks to investigate a potential correlation between the trade channel and other covariates and competing explanations.

⁸ In keeping with most of the labor literature, we focus on male workers between the ages of 25 and 65, because the wage dynamics and labor supply of the female workforce are often affected by non-economic factors, such as fertility decisions.

⁹ In Section 5.4, on robustness checks, this equation will be estimated adding in productivity as the explanatory variable. In that case, the regression will incorporate the firm dimension.

¹⁰ A number of alternative sets of variables could be chosen, but changing gravity equation specifications makes little difference to the final-step results. Similar results are obtained, for example, when we introduce a dummy for pairs of countries belonging to MERCOSUR, when we introduce distances by road (for intranational trade only) instead of physical distance, and when we estimate differentiated distance coefficients for intranational versus international trade. Lastly, [Paillacar \(2007\)](#) shows that Gamma PML yields similar results to OLS.

⁶ We limit our analysis to 1999 due to the lack of intranational trade data for other periods in Brazil, as explained in Section 3.

⁷ We thank an anonymous referee for suggesting an empirical procedure where fixed effects from the wage equation are regressed on market and supplier access.

Despite their empirical success in explaining trade flows, gravity equations have an important caveat: they treat the size of regions as exogenous (Knaap, 2006). We acknowledge this limitation in explaining the long-term evolution of a country's economic geography, and we see our work as an effort to uncover the impact of market access on wages, taking the spatial distribution of economic activity as given.

From Eq. (5), the estimated coefficients in Eq. (9) can be used to compute market access as in:

$$\hat{MA}_{ri} \equiv \sum_s \left[\left(\exp FM_{si} \right) \prod_k \left(\exp TC_{k,rsi} \right)^{\delta_{ki}} \right] \quad (10)$$

We have, then, a market access measure for each separate industry in each Brazilian state.

The estimated value of SA, defined in Eq. (3), is computed in a similar fashion, but using the coefficient from the exporting region dummy variables. To account for vertical linkages across industries, we use coefficients from the input–output matrix, ϖ , to weigh the impact of each industry in supply access. We, then, compute:

$$\hat{SA}_{ri} \equiv \prod_j \left\{ \sum_s \left[\left(\exp FX_{sj} \right) \prod_k \left(\exp TC_{k,rsj} \right)^{\delta_{kj}} \right] \right\}^{\varpi_{ji}} \quad (11)$$

which yields an SA measure for each industry in each Brazilian state.

This paper is the first to weigh industry supplier access using an input–output matrix in the structural approach proposed by Redding and Venables (2004). Amiti and Cameron (2007) also take into account industry vertical linkages in a study for Indonesia, but with a somewhat different empirical strategy. In their computation of SA, they use the shares of GDP by industry for each Indonesian district instead of exporter fixed effects derived from gravity equations.

2.2.3. Third step

Lastly, the MA and SA values estimated in the second step are used to explain wage differences across states and industries. Wage Eq. (6) can be written as:

$$\log w_{ri} = -\frac{1}{\beta\sigma} \log \sigma f_i + \frac{1}{\beta\sigma} \log MA_{ri} + \frac{\alpha}{\beta(\sigma-1)} \log SA_{ri} \quad (12)$$

As previously discussed in the beginning of this section, differences in human capital allocation across regions may distort the impact of market and supplier access on regional wages, and previous empirical studies suggest that this is a relevant issue for Brazil. Therefore, instead of adopting wages as a dependent variable, we use the state–industry fixed effects estimated in Eq. (7). They represent the wage differentials across states and industries that are not explained by age and education, thus controlled for composition of labor force with respect to these variables. We estimate the equation as follows:

$$\hat{\omega}_{ri} = \theta_0 + \theta_1 \log \hat{MA}_{ri} + \theta_2 \log \hat{SA}_{ri} + \theta_3 D_i + \zeta_{ri} \quad (13)$$

where D_i are the industry dummies, $\hat{\omega}_{ri}$ are the state–industry fixed effects estimated in the wage regression (7), and ζ_{ri} is an error term.¹¹

Two issues arise from the use of estimated values for the variables in the NEG wage equation.

Firstly, the use of estimated wage premia means that the error term ζ_{ri} in the NEG equation will contain part of the variance of the error term from the wage premium estimation (Eq. (7)), which can

¹¹ Combes et al. (2008) employ similar methodology, but they estimate location and industry fixed effects separately due to computational problems and insufficient data (they have 341 locations and 99 industries, see p. 727, footnote 7). Our aggregation level, with 27 Brazilian states and 22 industries, precludes such problems. The only exception is in Section 5.5, where we adopt municipalities and not states as regional units. For 3439 municipalities (instead of 27 Brazilian states), we only consider the spatial dimension.

generate heteroskedasticity. This has led some researchers to use weighted least squares (WLS), using as weights the inverse of the standard error of the wage premium estimates from the first stage (see, for example, Pavcnik et al., 2004). Nevertheless, Monte Carlo experiments by Lewis and Linzer (2005) suggest that WLS can only surpass White standard error estimates in efficiency when a very high proportion (80% or more) of the residual in the final regression results from errors in the dependent variable estimation. Moreover, they find that WLS can actually produce biased standard error estimates if the contribution of the error term is low in the first stage. In our case, we have a very high number of individual observations, yielding highly precise estimations of the wage premium. Consequently, we choose to report regressions with robust standard errors.

Secondly, the use of MA and SA estimates from trade equations as independent variables implies that trade equation residuals also affect ζ_{ri} . As Head and Mayer (2006) point out, this invalidates standard errors, but it has no impact on the estimated coefficient. In this case, a number of researchers (Redding and Venables, 2004; Hering and Poncet, forthcoming) have used bootstrap to obtain unbiased confidence intervals in order to make inferences. We, therefore, have also computed bootstrapped standard errors.

Furthermore, there are additional potential problems with the estimation of Eq. (13) due to the simultaneous impact of other variables on both wage differentials and MA, and the possibility of the endogeneity of MA. We discuss and deal with these issues in Section 5, where we perform a number of robustness checks.

3. Data

In this paper, we use three sets of data: individual characteristics, trade flows and country characteristics. We perform a cross-sectional analysis for 1999, since intranational trade data by industry for Brazil is only available for that year (Vasconcelos and Oliveira, 2006).

Individual characteristics are drawn from the RAIS database (Relação Anual das Informações Sociais issued by the Brazilian Labor Ministry), which covers all workers in the formal sector.¹² We focus on the manufacturing sector for compatibility with the trade data. When more than one job is recorded for the same individual, we select the highest paying one.¹³ The database provides a number of individual characteristics (wages, educational level, age, gender, etc.) as well as worker and firm identification numbers, which allows us to match the RAIS database with the manufacturing survey.

The manufacturing survey, PIA (Pesquisa Industrial Anual produced by IBGE, the Instituto Brasileiro de Geografia e Estatística), includes all firms with thirty employees or more from 1996 to 2003, covering the majority of the workforce in the manufacturing sector. This dataset provides a wide range of variables on production, including sales, labor, materials, energy and investments, which allows for the measurement of productivity (see Appendix A3). We round out the PIA with IBRE-FGV (Instituto Brasileiro de Economia – Fundação Getulio Vargas) balance sheet data from 1995, from which we draw initial fixed capital, and with patent data from INPI (Instituto Nacional da Propriedade Industrial). All datasets can be matched due to firm identification numbers.¹⁴

¹² Because of the huge number of observations, we run our regressions on random samples of 500,000 or 800,000 employees (out of 2,786,852 employees in the full sample). Changing the size of the sample does not affect our coefficients nor does it particularly affect the estimation of state–industry fixed effects. Table A1 provides summary statistics of individual characteristics.

¹³ For example, a worker may change occupation or place of work over time, or may even hold two recorded jobs at the same time. To assess the robustness of our results, we alternatively choose the average wage, the total wage, in December or over the year, and the choice does not affect the results.

¹⁴ Note that firm-level data is employed exclusively to compute the productivity measure used in one of the robustness checks in Section 5.4. Otherwise, we use worker- and industry-level data.

In order to estimate the gravity equation, we need three sets of trade data: (1) data on trade among Brazilian states, which is drawn from Vasconcelos and Oliveira (2006) who processed value-added tax information provided by the National Council of Financial Policy (CONFAZ, Conselho Nacional de Política Fazendária) attached to the Ministry of Finance (Ministerio da Fazenda); (2) data on trade between Brazilian states and foreign countries, taken from Secretaria de Comércio Exterior, Ministry of Trade; and (3) data on trade among foreign economies, from BACI: Base pour l'Analyse du Commerce International, CEPII. Moreover, we use total sales by region and industry from the PIA database to compute internal flows within state by subtracting intranational and international exports. These sets of data provide a complete and consistent picture of all trade flows, defined at the 2-digit ISIC Revision 3 level (which corresponds to the Brazilian CNAE 2-digit industry classification).

We round out the trade and individual information with additional data on geography, infrastructure and regulations. Distances, colonial links, languages, coordinates, GDP, areas and demographic densities are provided by CEPII (Centre d'Etudes Prospectives et d'Informations Internationales) and IBGE. The distance between states is measured in geodesic distance between their respective capitals (computed in km using the coordinates).

We construct an international border dummy that equals zero if both the origin and the destination of the trade are within the same country, and equals 1 otherwise. Likewise, the internal border dummy equals zero if the trade is within one Brazilian state, and equals 1 otherwise. In addition, we construct a dummy for international contiguity that equals 1 if the international border dummy equals 1 and if both countries (or the country and the Brazilian state) share a border. Likewise, the dummy for internal contiguity equals 1 when both Brazilian states share a border. The language dummy equals one if the trade is between two different countries (that is, the international border dummy equals 1) and they share the same language (more precisely, if the official language is the same or if the same language is used by at least 20% of the population). Lastly, the colonial link dummy equals 1 if the trade is between two different countries and one of them has been colonized by the other in the past.

Census 2000 (IBGE) provides data on migration rates per municipality. The input–output matrix is constructed by the OECD and IBGE across ISIC Rev3 2-digit industries. The cost of starting a business is measured by the World Bank for 13 Brazilian states (Doing Business database). An index of tax pressure across Brazilian states is constructed using the PIA data. The data on harvested agricultural area in 1996 are taken from the Agricultural Census. The Anuário Mineral Brasileiro 1999 (Table 8 page 51) is our source for regional shares of mineral production. Municipality data on natural endowments come from Timmins (2006).

4. Results

We organize the results into three subsections. We start, in Subsection 4.1, by presenting the results of the first and second steps of our empirical procedure, that is, the estimation of the state–industry wage differentials and market and supplier access using gravity equations. Subsection 4.2 presents the results of the regressions of MA and wage differentials, while 4.3 incorporates SA into the analysis.

4.1. Preliminary regressions

4.1.1. First step: wage premium

The first step of the empirical procedure consists in estimating wage differentials across states and industries that are not driven by individual characteristics. We regress wages on educational attainment, experience, and state–industry fixed effects, as described in Eq. (7). We use individual data for male workers between the ages of 25 and 65. This group of workers was chosen to render the sample more homogeneous, thus eliminating possible effects from differences in variables such as early school dropouts and female participation.

We measure education by means of dummy variables for nine levels of education (as described in Appendix A1). Age and age squared are used as proxies for experience. Table 1 presents the results.

We should note that the *R*-squared (adjusted or not) is very high. If worker characteristics are excluded, state–industry dummies explain 83.1% of wage variance (not shown in the table). However, if state–industry dummies are excluded, still 34.1% of the variance is explained by worker characteristics, suggesting that the explanatory power of state–industry dummies is partly due to differences in labor force composition.

4.1.2. Second step: market and supplier access

In order to compute estimated values of market and supplier access, we start by estimating gravity Eq. (9), where bilateral trade flows are explained by exporter and importer fixed effects, and a set of variables capturing trade costs. We define each Brazilian state as a region, and apply two procedures. In the first, we take the coefficients to be the same for all industries, in keeping with the literature, and use them to compute aggregate measures of MA and SA. In the second procedure, a regression is run separately for each industry, estimating different coefficients for each of them. We are thereby able to compute market and supplier access measures for each state–industry pair.

The first column of Table 2 presents the regression coefficients using aggregate trade flows, with the corresponding standard errors in the second column. The next three columns of the table show some summary statistics for the 22 regressions by industry: average values of the estimated coefficient across industries (third column), average values of the standard errors of each regression in square brackets beneath each coefficient (fourth column), and the standard deviation of the 22 coefficients in parentheses (fifth column). The coefficients' standard deviations are generally larger than average standard errors, indicating marked differences in transport cost coefficients across industries.

Taking the estimated coefficients from Eq. (9) (presented in Table 2), we use Eqs. (10) and (11) to compute estimated values for MA and SA respectively for each state–industry pair. Note that, when calculating MA, we take the sum over all states and countries with which a particular state trades. We can then construct a market access

Table 1
Wages and individual characteristics.

Dependent variable: wages	
	(1)
Age	0.072** [0.001]
Age squared/100	−0.072** [0.001]
Education (level 5 = 0):	
Level 1	−0.365** [0.005]
Level 2	−0.239** [0.003]
Level 3	−0.149** [0.002]
Level 4	−0.075** [0.002]
Level 6	0.156** [0.003]
Level 7	0.419** [0.002]
Level 8	0.852** [0.004]
Level 9	1.240** [0.003]
State × industry FE	yes
<i>R</i> -squared	0.880
Observations	798494

Notes: OLS regressions with robust standard errors.
Statistical significance: *5% and **1% levels.

Table 2
Gravity equations.

Dependent variable: trade flows					
Statistics	Aggregated		By industry		
	Coefficient	Standard error	Average of coefficients	Average of standard errors	Standard dev. of coefficients
Physical distance	−1.448**	[0.018]	−1.359	[0.031]	(0.180)
International border	−4.326**	[0.116]	−4.534	[0.563]	(0.983)
International contiguity	1.001**	[0.095]	0.785	[0.249]	(0.184)
Internal border	−2.594**	[0.386]	−3.212	[0.224]	(0.968)
Internal contiguity	0.128	[0.225]	0.205	[0.118]	(0.469)
Language	0.839**	[0.043]	0.604	[0.071]	(0.263)
Colonial link	0.832**	[0.100]	0.903	[0.115]	(0.140)
Exporter FE	Yes		Yes		
Importer FE	Yes		Yes		
Industries			22 Regressions		
R-squared	0.982				
Observations	25315		Total: 246833		

Notes: OLS regressions with robust standard errors. Dependent variable: trade flows (aggregated or by industry). Statistical significance in the first column: *5% and **1% levels.

measure from a subgroup of trade partners, which is exactly what we do to investigate the varying impact of local, national and international market access.

Before moving on to the estimation of the NEG wage equation, it is worth viewing the relationship between wages and MA estimated in steps 1 and 2. In Fig. 1, four maps of Brazil show the spatial distribution of wages and MA. Values are normalized as deviations from the mean across regions, and they are grouped into five classes. The middle group falls between the mean ± 0.5 standard deviations, and the subsequent groups are delimited by 1 standard deviation.

Panel (a) presents regional wages after controlling for individual characteristics. It is clear that, even after skill sorting is taken into account, there are still substantial spatial wage differentials across states. São Paulo is the region with the highest wages, followed by neighboring states (Rio de Janeiro, Paraná and Minas Gerais, among others). Interestingly, the state of Amazonas, a landlocked region in the more sparsely populated north, also posts high wages. We expect these differentials to reflect exogenous regional characteristics, such as amenities and the availability of natural resources, as well as spatial externalities, such as knowledge spillovers and market access.

Panel (b) displays total MA across the regions. Fig. 1 gives the impression that MA and regional wages are indeed related. São Paulo is the state with the greatest MA (followed by Rio de Janeiro). This ties in with the fact that wages are highest in that state. Amazonas' MA, however, does not stand out from the rest of the North. A more in-depth understanding of the factors at work is gleaned by decomposing MA into its national and international aspects.

Panel (c) focuses on the role of inter-state trade, excluding international and local (i.e. own state) MA. As expected, the states neighboring São Paulo exhibit the greatest non-local national MA, while the value for São Paulo itself is lower. More interestingly, this exercise shows that Amazonas and Rio Grande do Sul (the southern region closest to Argentina) are remote from the main sources of demand within the country.

Panel (d) completes the picture by considering only international MA. The international component of market access in these two regions appears to explain their high wages. Rio Grande do Sul is close to Buenos Aires, the other important economic center of MERCOSUR (besides São Paulo). Similarly, the state of Amazonas is close to middle income countries in South America (Colombia and Venezuela), and NAFTA members.¹⁵

¹⁵ The question could be asked as to whether this high market access for Amazonas is just an artifact of the data, since Brazilian trade with Colombia and Venezuela is not very high. In actual fact, exports to Colombia and Venezuela represent 20% of total exports from Amazonas, while this ratio is only 2.4% for Brazil as a whole. Moreover, Amazonas exports a higher proportion of its production compared to the rest of Brazil.

4.2. Wages and market access

The empirical strategy we propose to estimate the impact of MA on wage differentials basically departs from Redding and Venables (2004) in two ways: we control for individual characteristics and we use industry-level data. We introduce each of them in turn.

Firstly, we control for individual characteristics, but still use aggregate data to compute market access. In the first step of the empirical procedure, we use individual characteristics and state fixed effects to explain individual wages in the aggregate version of Eq. (7). These fixed effects serve as dependent variables in the estimation of Eq. (13), where aggregate MA is derived from aggregate trade flows in gravity Eq. (9). As shown in the results presented in the first column of Table 3, the wage differentials are positively and significantly correlated with MA. The coefficient for MA is approximately 0.08, which is lower than the coefficients found by Redding and Venables (2004). Since Redding and Venables (2004) do not control wages for individual variables as we do, their larger estimated coefficient may be capturing different labor force composition patterns across the countries. Our coefficient is closer to that found by Hering and Poncet (forthcoming), who also control for individual characteristics in a study of Chinese regions.

Secondly, the results presented in the second column of the table use industry-level data, but do not control for individual characteristics. Instead of running the first step of the empirical procedure, we simply use average state–industry wages as a dependent variable in the estimation of Eq. (13). The MA coefficient is estimated with greater accuracy, probably due to the use of more disaggregated data. Its estimated value of 0.17 is significantly higher than found in the previous regression, where we control for individual characteristics. This higher coefficient may be capturing part of the impact of spatial sorting of human capital.

Finally, column 3 presents our baseline regression, where we simultaneously control for worker characteristics and use industry-level data. Wage differentials captured by state–industry fixed effects in the first step of our empirical procedure are regressed on MA, as calculated in the second step.¹⁶ The estimated coefficient for MA in this regression is 0.14, which is lower than that found by the previous regression, where there is no control for individual attributes. Here,

¹⁶ Given that the predicted values for market access and wage premiums are generated by prior regressions, we check our results for sensitiveness to bootstrap techniques. Results remain unchanged and the bootstrapped standard errors are slightly lower than the robust standard errors reported in the Tables. Redding and Venables (2004), De Sousa and Poncet (2007) and Hering and Poncet (forthcoming) also find bootstrapped standard errors close to the non-bootstrapped estimate.

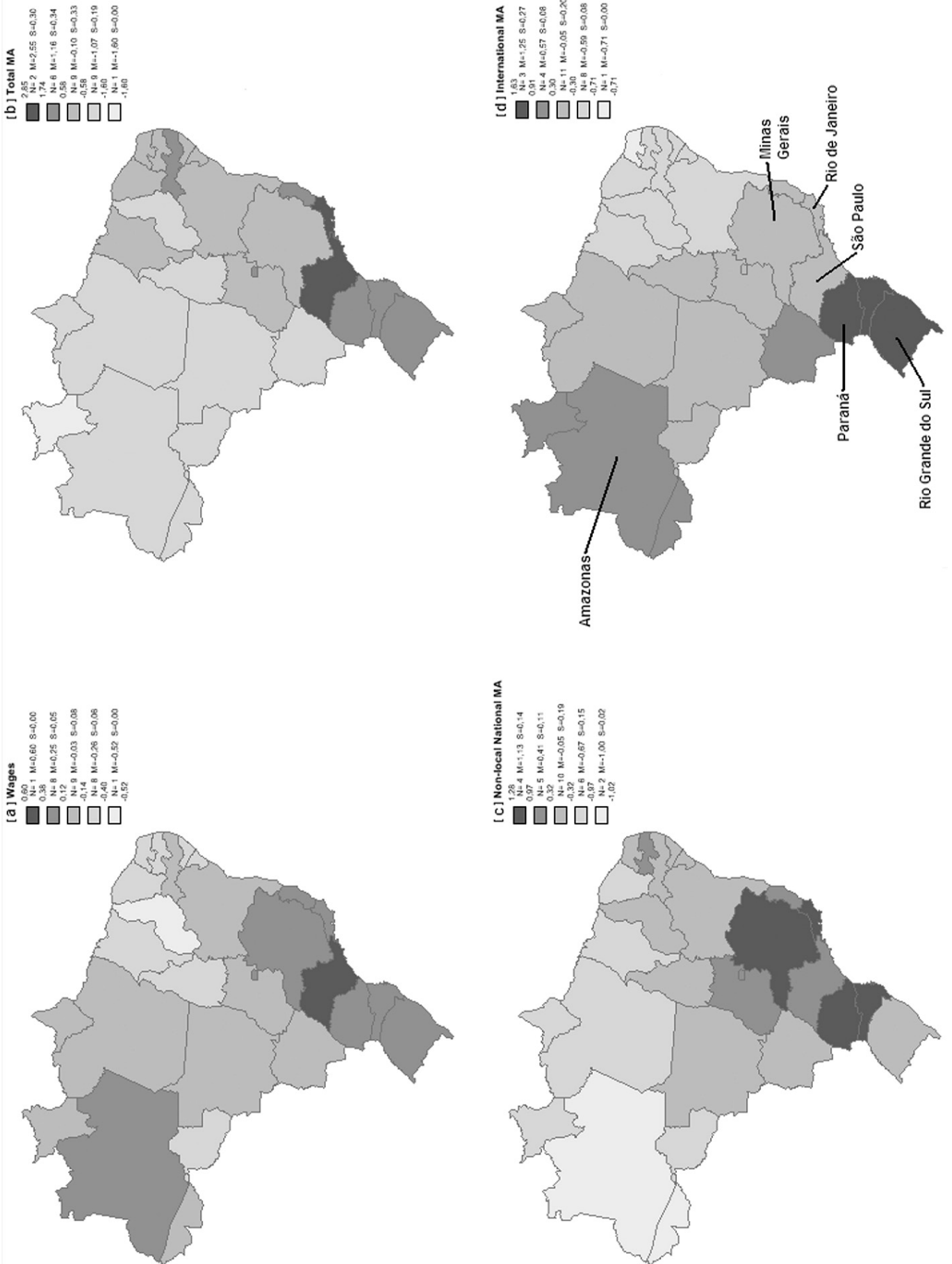


Fig. 1. Market access and wages across Brazilian States.

Table 3
Response of wage premium to market access.

Dependent variable: wage premium						
Measure of MA	(1)	(2)	(3)	(4) (5) (6)		
	Total MA (aggregate)	Total MA	Total MA (baseline)	Components of market access		
				Non-local	National	International
Market access	0.079** [0.026]	0.168** [0.013]	0.140** [0.012]	0.185** [0.022]	0.162** [0.021]	0.228** [0.018]
Controlling for skills in 1st step	Yes	No	Yes	Yes	Yes	Yes
By industry	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
R-squared	0.275	0.432	0.350	0.255	0.248	0.294
Observations	27	540	540	540	540	540

Notes: OLS regressions with standard errors robust to heteroskedasticity and industry fixed effects (except column 1).

Dependent variable: wage premium (see Section 2.2, fixed effects from the regression of individual wages on individual characteristics).

Regressor: market access (see Section 2.2, calculated from a gravity equation on intranational and international trade flows); "non-local": excluding own state; "national": excluding foreign and local markets; "international": foreign countries with a common frontier with Brazil.

Statistical significance: **at 1% level.

again, the difference may be explained by spatial sorting of human capital.

Despite being higher than the coefficient estimated in column (1), the MA coefficient in our baseline regression is still lower than that estimated by Redding and Venables (2004). It is closer to the MA coefficient found for European regions by Head and Mayer (2006), who also control for education.

In this baseline regression, the MA and industry dummies explain 35% of wage disparities across regions and industries. The use of industry dummies alone, without MA, explains only 17.5% of the wage differentials (regression not reported): The explanatory power of the regression increases substantially with the inclusion of MA.

We use separate measures of MA to analyze the different impacts of local, national and international MA. When we drop local market access and consider solely access to other Brazilian states and other countries (results in column 4), we still find a large and significant coefficient. In fact, the coefficient is even higher than the one in the third column, which also includes local market access, but the difference is not statistically significant.

Columns 5 and 6 present the results when considering only national market access (excluding local access) and only international market access, respectively. It is worth noting that international market access alone yields the highest impact on wages and its coefficient is estimated with the smallest standard errors compared to the other market access subgroups. The R-squared of the regression on international market access is also higher when compared to the other subgroups, although it is still lower than total market access (column 3).

This interesting result may be explained by the trade liberalization that took place in the early 1990s. Trade barriers were lowered in the first half of the decade, and the impacts of this may have differed across the country precisely due to the differences in international MA among the regions. On this basis, the impact of trade liberalization should be greater in regions with greater international MA. In a study of Mexican trade liberalization, Chiquiar (2008) shows that, following the second stage of trade liberalization, "regions with a larger exposure to international markets exhibited a relative increase in wage level". We may be capturing a similar pattern for Brazil.

4.3. Market access and supplier access

So far, we have studied the impact of MA on wages. As discussed in Section 2.1, MA captures how close a firm in a given region is to consumers, whereas SA establishes proximity to suppliers of intermediate goods. While MA has a positive impact on wages due to the effect of demand, SA's impact on wages is associated with lower costs and higher productivity.

A common problem with MA and SA measures is that they tend to be closely correlated. To address this issue, Redding and Venables (2004) include additional assumptions on the link between MA and SA. In our procedure, however, this problem is mitigated and there is no need for further restrictions. By calculating MA and SA for each industry, as we do, market and supplier access are less likely to be correlated. Take for instance, the Rubber and Plastic industry, whose output is consumed by consumers at large, while a large fraction of its inputs come from the Chemical industry. Firms in the Rubber and Plastic industry have high supplier access in Bahia, where the Chemical industry is concentrated, while their MA level is high in São Paulo and Rio de Janeiro. In practice, we find a high partial correlation between MA and SA across regions (0.76), although lower than the correlation reported by Redding and Venables (0.88). Still, the correlation appears to be low enough to allow for the inclusion of both variables in a single regression, without any multicollinearity problems.

We apply the same three-step procedure adopted for the MA regressions. In the first step we regress wages on individual characteristics and on state–industry dummies. Secondly, we compute the SA measure using Eq. (11), as described in Section 2.2. Lastly, we use SA as an explanatory variable of the state–industry wage disparities estimated in the first step. The results are presented in Table 4.¹⁷

The first column of Table 4 is equivalent to the baseline regression for MA in the third column of Table 3, but using SA instead of MA as the explanatory variable. It is interesting to note that the estimated coefficient for SA has the same value as that found for MA. We obtain a similar coefficient based solely on non-local SA, as shown in the second column. This could be a sign that our MA and SA measures are actually correlated, so that both variables are capturing the same effect.

In order to investigate whether these two measures affect regional wages independently, we include both simultaneously as explanatory variables of wage differentials. The results presented in the third column show that both variables have a positive and significant impact on wages, with a higher coefficient for MA. Furthermore, beta estimates of 0.242 for SA and 0.467 for MA suggest that MA plays a greater role than SA in explaining wage differentials across states and industries in Brazil. The regression presented in the fourth column looks at non-local MA and SA. In this case, only MA has a positive and significant coefficient. Note the high standard deviations, indicating that colinearity problems may be greater for non-local market and supplier access than local MA and SA.

One concern with the SA measure is that it may be correlated with its own industry characteristics, such as productivity. To account for

¹⁷ Since we need exporter fixed effects for industry inputs, we cannot compute SA for industries using non-industrial inputs. Therefore, the regressions in Table 4 exclude Food and Beverages, Tobacco, Wood and Fuel Refining.

Table 4
Market access and supplier access.

Dependent variable: wage premium					
	(1)	(2)	(3)	(4)	(5)
Supplier access	0.140** [0.010]		0.066** [0.017]		
Non-local SA		0.193** [0.023]		−0.019 [0.078]	
SA (excl. own ind)					0.040* [0.017]
Market access			0.108** [0.021]		0.135** [0.019]
Non-local MA				0.238** [0.079]	
Industry FE	Yes	Yes	Yes	Yes	Yes
Controlling for skills	Yes	Yes	Yes	Yes	Yes
R-squared	0.347	0.222	0.384	0.241	0.382
Observations	441	441	441	441	441

Notes: OLS regressions with robust standard errors and industry fixed effects.
Regressors: supplier and market access (see Section 2.2, calculated from a gravity equation on intranational and international trade flows); “non-local”: excluding own state; “excl. own ind”: supplier access excluding own industry in the input–output matrix.
Statistical significance: *5% and **1% levels.

this possibility, we compute an SA measure that excludes its own industry, that is, we set to zero the input–output matrix coefficient for own industry and normalize the other coefficients so as to obtain a sum equal to one. When this proxy is used in the place of SA (results in the fifth column), we still find positive and significant coefficients for SA and MA. Moreover, the difference between them is larger compared to the results in the third column, using the original SA measure.¹⁸

5. Robustness checks

5.1. Instruments for market access

There may be some concern about the endogeneity of market access. Wages might positively affect individual demand for goods, thus increasing the index of market access. Similarly, a productivity shock in a region would affect both wages and the market access index if productivity were also to affect demand for goods. Such biases are mitigated by the consideration of “non-local” market access constructed by excluding own-market demand, as already done in column (4) of Table 3. In this section, we instrument the MA index using geographical and demographic variables that should have an impact on market access but not directly affect the wage differentials across regions.

We propose two alternative instruments.¹⁹ Firstly, we consider “Harris Market Potential” (HMP, sum of other regions' GDP divided by distance) constructed using GDP by states in 1939:

$$\text{HMP}_r = \sum_s \text{GDP}_s / \text{Dist}_{rs} \quad (14)$$

¹⁸ We also use this measure as an instrument for SA and find similar results. The coefficients for MA and SA are 0.124 and 0.049 respectively. MA is significant at 1%, while SA is significant at 5%.

¹⁹ We also tried the distance to the main economic centers as instruments, as proposed by Redding and Venables (2004). In particular, we estimated regressions using the distance to São Paulo and the distance to Buenos Aires as instruments of national and international MA, respectively. Although the coefficients for MA in the wage equations support our findings (0.20 for national MA and 0.32 for international MA, both highly significant), we share the concerns raised by Head and Mayer (2006) that economic centers may be endogenous themselves. More specifically, the distance to São Paulo may capture effects that are not related to MA, such as the proximity to firm headquarters, and therefore managerial power, which may have a positive impact on wages. Regressions are available on request and in a previous working paper (Fally et al., 2008).

This variable was first used in empirical studies of new economic geography literature by Hanson (2005), in his working paper version of 1998. Using 1939's HMP as an instrument relies on the assumption that wages in 1939 are only indirectly related to current wages (which is a reasonable assumption given technological innovation). As shown in the first row of Table 5,²⁰ this instrument yields a significant and strong coefficient for MA, which is nevertheless smaller than in the baseline OLS specification. We also consider a second instrument, which uses population size (in 1940) instead of GDP in Eq. (14). It provides similar results to HMP (result not reported here).

We also instrument market access by average registration dates of municipalities in the region²¹ (second row of Table 5), and we still obtain a similar coefficient for MA. If we use both HMP and the average registration date as instruments to test for over-identification, the Hansen *J*-test cannot be rejected (as the *P*-value equals 0.229) and the coefficient remains unchanged.

5.2. Differences across skills

One of the underlying assumptions of our methodology is that returns to education are constant across states, that is, they are independent of MA. This assumption allows us to control for education in the first step, independently of the final-step regression. Theoretical papers have shown however, that MA may affect the skill premium and returns to education (see, for example, Redding and Schott, 2003): skilled workers are more mobile, but the concentration of activity may increase the productivity of skilled workers either via increasing returns to scale or via pervasive input–output linkages in skill-intensive sectors. The results in the first two columns of Table 6, however, indicate that this link is not relevant in the Brazilian case: the observed correlation between wages and MA does not appear to vary significantly across educational levels.

In column (1), where the wage premium is constructed from data on skilled workers only (workers who completed high school or beyond), the coefficient for MA is higher but not statistically different from the coefficient in the third column in Table 3 (same specification for all workers). In column (2), the wage premium is constructed using data on unskilled workers only (workers who have not completed high school), and the coefficient obtained for MA is close to the baseline regression in Table 3. Hence, market access appears to have a stronger impact on skilled workers' wages, but the difference is not significant.²² In other words, returns to education are not strongly correlated with market access, which validates our methodology in the first step.

When we consider international MA only, we obtain different and very interesting results. The coefficient for international MA on wage differences across state–industry is significantly higher among unskilled than skilled workers (results in columns 3 and 4 of Table 6). This result means that higher international MA raises the wages of unskilled workers relatively more. Given that our study corresponds to a period of just a few years after a massive trade liberalization program, this result could actually be a sign that the Stolper–Samuelson mechanism is at work. This mechanism posits that trade liberalization in Brazil, a country where unskilled labor is relatively abundant,²³ increases relative returns to this factor of production. When viewed through the prism of economic geography, such an impact would not be homogeneous across the country: it would be greater in regions with higher international MA. This interpretation is in line with the findings of Gonzaga et al. (2006), who present evidence for Brazil of relative wage changes compatible with Stolper–Samuelson predictions.

²⁰ Appendix A2 presents the first-stage regressions behind Table 5.

²¹ We thank an anonymous referee for suggesting this instrument.

²² Alternatively, we also directly regress the skill premium on MA (results not reported). The coefficient has the expected sign, but it is not significant.

²³ Muriel and Terra (2009) present evidence that Brazil is relatively abundant in unskilled labor.

Table 5
Response of wage premium to market access, instrumented.

Market access variable:	Estimated coefficient	Robust std. error	Hansen <i>J</i> -test	Number of observations
MA, instrumented by HMP in 1939	0.145**	0.015	\	540
MA, instrumented by av. date of registration	0.119**	0.024	\	540
MA, instrumented by HMP and date of registration	0.144**	0.014	0.229	540

Notes: 2SLS regressions with standard errors robust to heteroskedasticity and industry fixed effects.

Wage premium regressed on market access. Instruments: HMP: Harris Market Potential = sum(GDP/distance) in 1939; average date of registration of municipalities within the state.

Statistical significance: **at 1% level.

5.3. Controlling for additional covariates across states

Endowments are unequally distributed across Brazilian states and play an important role in explaining wage differentials. In addition, endowments may be correlated with market access, thus biasing our coefficient. Notice that in Section 4.3, the correlation between wages and MA was not affected when we restricted our analysis to sectors that do not depend on natural resources (see footnote 17). We now perform another robustness check in which we directly control for endowments. In Table 7, column (1), we control for minerals, harvested land area, access to the sea and dummies for macro regions.²⁴ As expected, wages are positively correlated with the presence of natural resources: the coefficient for harvested land is positive and significant; minerals (share of total national extraction) have a positive and significant coefficient; access to the sea (excluding landlocked areas) has a positive albeit not strongly significant effect on wages. Among the macro-region dummy variables, only the north-east is significant at the 1% level: its value is -0.22 (with an estimated standard error of 0.06). This may be partially explained by its harsh climate (e.g. frequent droughts). In spite of the inclusion of these controls, the coefficient for MA remains large and significant.²⁵

Brazilian states also exhibit marked differences in tax rates. Successive governments have adopted fiscal incentives to promote industrial development in lagging regions, with varying degrees of effectiveness. If tax rates are positively or negatively correlated with market access, omitting this control might bias our results. We should also note that Manaus, the capital of the state of Amazonas, is a Free Trade Zone. Thus, we check the sensitiveness of our results to the inclusion of a dummy for the state of Amazonas. Finally, as both market access and wage premium are highest for São Paulo, a reasonable concern is whether wages are high in São Paulo for reasons unrelated to MA. As a robustness check, we estimate the response of wages to MA including a dummy for São Paulo to isolate potential measurement errors or an outlier effect. In column (2) of Table 7, we regress the wage premium on market access, tax rates estimated at firm-level data (sum of taxes paid by each firm divided by total sales), and dummies for Amazonas and São Paulo. We obtain significant coefficients for all controls, and the coefficient for market access is not affected.²⁶

²⁴ The Brazilian states are grouped into five macro-regions based on geographical characteristics. They are: north, north-east, south-east, south and center-west. Our reference category is the south-east.

²⁵ As climate and land seem to have the strongest impact among the different types of endowments, we perform further robustness checks using more detailed data. This analysis is discussed in Section 5.5 as these variables are available by municipality.

²⁶ The coefficient for MA remains unchanged in similar robustness checks on international MA. In Fally et al. (2008), we also control for the cost of starting a business in 13 states, using data from the World Bank (*Doing Business in Brazil*).

Table 6
Wage premium to market access – skilled versus unskilled workers.

Dependent variable: wage premium				
	(1)	(2)	(3)	(4)
Workers:	Skilled	Unskilled	Skilled	Unskilled
Market access	0.160** [0.014]	0.134** [0.011]		
International MA			0.196** [0.023]	0.229** [0.017]
Industry FE	Yes	Yes	Yes	Yes
R-squared	0.373	0.387	0.278	0.344
Observations	504	532	504	532

Notes: OLS regressions with standard errors robust to heteroskedasticity and industry fixed effects.

Skilled workers: educational level higher than high school.

Statistical significance: **at 1% level.

5.4. Controlling for productivity and technology

Recent models on international trade and the selection of firms show that access to foreign markets may have a positive impact on average firm productivity, which in turn has a positive impact on wages (Melitz, 2003, and Melitz and Ottaviano, 2008). Baldwin and Okubo (2006) describe in a model how MA may impact on productivity across regions. It is thus possible that the impact of MA on wage differentials is due to its impact on productivity, rather than the NEG labor demand channel.

Hence in the same way as we control for laborers' individual characteristics, we can also control for productivity when estimating wage differentials in the first step. Our dataset allows for this control since we are able to match the data on workers with the data on firms with more than 30 employees. In particular, these firm-level data provide information on labor, wages, investment, capital, materials and energy.²⁷ We measure total factor productivity using a cost-share approach (see Foster et al., 2008, and Syverson, 2004, for similar measures of productivity using US data). Details are provided in Appendix A3. In short, productivity is measured by the logarithm of total sales at firm level, minus the log of labor, capital, energy and materials with respective coefficients given by the share of each input in total costs. In addition to its simplicity, this methodology is extremely robust to measurement errors and misspecifications compared to alternative methods (Van Biesebroeck, 2007). Moreover, using alternative measures of productivity yields similar results (see Appendix A3).

A major concern is that productivity is measured on the basis of revenue and expenditure on inputs (except for labor), since we do not have data on quantities and prices. Our productivity measure may be capturing mark-ups, which vary endogenously across regions depending on market access and competition. Thus, we use data on patents in order to control for technology in a way that is not affected by price levels. The data made available by INPI (Instituto Nacional da Propriedade Industrial) list all patents recorded in the 1990s. Our first variable is a dummy for innovative firms, which equals one when there is at least one patent recorded for a given firm. The second variable is the number of patents, in log.²⁸

Table 8 presents the results of the impact of MA on state–industry wage differentials, controlling for productivity and patents. The first column of Table 8 is equivalent to the baseline regression in the third column of Table 3, but using a version of the wage regression in the first step (Eq. (7)) that also controls for firm productivity. The wage

²⁷ Productivity is measured at firm level. We assume that productivity is related to firm characteristics, which should be similar across establishments within the same business unit.

²⁸ The number of patents is discounted at a 15% yearly rate, but results are not sensitive to moderate changes in the discount rate. This variable is normalized to zero for non-innovative firms.

Table 7
Additional controls.

Dependent variable: wage premium		
	(1)	(2)
Market access	0.116** [0.016]	0.138** [0.013]
Harvested land	0.027* [0.011]	
Minerals	0.028* [0.012]	
Landlocked	−0.039 [0.055]	
Taxes		−0.234** [0.038]
Amazonas dummy		0.446** [0.048]
São Paulo dummy		0.219** [0.043]
Industry FE	Yes	Yes
Macro-region FE	Yes	No
Controlling for skills	Yes	Yes
R-squared	0.875	0.432
Observations	540	540

Notes: OLS regressions with robust standard errors and industry fixed effects. Controls: minerals: regional share of mineral production (source: Anuario Mineral Brasileiro 1999); harvested land area in 1999 (source: Agricultural Census); taxes: average taxes/sales ratio of industrial firms in the state. Statistical significance: * 5%; **1% levels.

premium corrected for productivity is still highly correlated with MA, although the coefficient is slightly lower: 0.11 instead of 0.14. The same comparison is true for the regressions comprising solely national and solely international MA (in columns 2 and 3, respectively). When we control for productivity in the first step, the MA coefficient decreases in the third step. Additionally, the R-squared of the regressions controlling for firm productivity is higher than in the regressions without such a control.

Note that, in the first step, we find a positive and significant elasticity of wages to productivity, close to 0.3, as shown in the second part of Table 8. Rather than controlling for productivity in the first step, we can control for it directly in the third step taking industrial and regional averages. The estimated effect of MA remains similar (results not reported).

The first-stage regression in the fourth column of Table 8 shows that wages are strongly correlated with both variables on patents. Since the use of patents (access to technology) may also be correlated with market access, controlling for patents affects the market access coefficient. The impact, however, is small: the coefficient of MA in the regression in the fourth column of Table 8 is not all that different from that in the third column of Table 3. We find the same result if we use aggregate data on patents across states and industries.

5.5. Per municipality: local amenities and spillovers

The results found so far are consistent with the NEG explanation for regional wage disparities. However, other explanations could well fit in with these results too. More specifically, our MA measure could be also capturing short-distance interactions as modeled by the urban economics literature. If that were the case, the relation between wages and MA found in this paper would actually reflect urban economics explanations of wage disparities, rather than the explanations proposed by NEG. In addition, natural endowments and local attractiveness could well play a role in explaining wage premiums across regions, and we should check whether our results still hold after controlling for these features.

We use our dataset on individual workers to refine our analysis at municipal level, which is the smallest administrative unit in Brazil

Table 8
Controlling for productivity and technology.

Dependent variable: wage premium				
	(1)	(2)	(3)	(4)
Market access	0.112** [0.011]			0.126** [0.010]
National, non-local MA		0.134** [0.018]		
International MA			0.201** [0.017]	
R-squared	0.403	0.328	0.388	0.343
Observations	466	466	466	534
First-step regression:	col. (1)–(3)			col. (4)
Firm productivity		0.297** [0.002]		
Innovative firm				0.259** [0.002]
Patent stock				0.044** [0.001]
Controlling for skills		Yes		Yes
Region × industry FE		Yes		Yes
R-squared in first step		0.899		0.886
Observations in first step		499144		499878

Notes: OLS regressions with robust standard errors and industry fixed effects. See Appendix A3 for the measure of productivity. Statistical significance: *5% and **1% levels.

(firm location is given by municipality). Honing in this way means that we can control for additional variables relating to these alternative explanations.

Firstly, we estimate wage premiums across municipalities by running a first-step regression of wages on individual characteristics (education and age for males between 25 and 65 years old). The corrected wage premium is obtained by taking the mean of the residual for each municipality.²⁹

In order to estimate MA per municipality, we would need to regress the gravity equations of the trade flows between them, as specified in Eq. (9). Since we do not have these data, we use aggregate trade flows across states to estimate the importer fixed effects per state, and the coefficients for distance, language, colonial link, border effects (internal and international) and international contiguity.³⁰ Our estimation of trade costs takes in the coefficients estimated in the gravity equation and the physical distance between municipalities. If we further assume that price levels are relatively similar within states, we can construct pseudo-importer fixed effects per municipality by multiplying state importer fixed effects by the industrial GDP share of the municipality in the state. Formally, market access per municipality is computed as follows:³¹

$$\hat{MA}_r = \sum_s \left[\left(\frac{GDP_s}{GDP_{S(s)}} \right) (expFM_{S(s)}) \prod_k (expTC_{k,rs})^{\delta_k} \right] \quad (15)$$

where *s* refers to the municipality or foreign country and *S(s)* stands for the state to which municipality *s* belongs in the first case or the foreign country itself in the latter.

²⁹ This simplified method saves us from having to estimate thousands of fixed effects by municipalities, which we would have had to do had we strictly followed the same methodology we used across states. This may lead to an underestimation of the correlation between wages and MA since we overestimate the effects of age and education. Nevertheless, the estimated coefficients for age and education are very close to the results obtained previously in Table 1.

³⁰ The estimated gravity equation is similar to the column (1) specification in Table 2, but excludes the “internal” contiguity variable which is insignificant and has no meaning at municipality level.

³¹ We exclude the municipality’s internal demand from the calculation of MA. Excluding large cities from the regression does not affect the results.

Table 9
By municipalities.

Dependent variable: wage premium by municipality						
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	0.162** [0.016]	0.086** [0.013]	0.091** [0.012]	0.107** [0.012]	0.091** [0.010]	0.095** [0.011]
Controls in final step			State fixed effects	Density av. age, av. age ² education (% workers by level)	New residents (%)	Erosion type Soil type Temperatures Precipitation Land by type of agriculture
Controlling for individual skills (1st step)	No	Yes	Yes	Yes	Yes	Yes
Spatially corrected SE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.242	0.109	0.301	0.151	0.170	0.255
Observations	3439	3439	3439	3439	3439	3439

Notes: OLS regressions with standard errors corrected for spatial dependence (Conley, 1999).

The proportion of new residents is from the Census 2000; endowments are from Timmins (2006).

Statistical significance: **1%.

Besides MA, other factors are likely to influence wages and their spatial correlation across municipalities, such as, in particular, the interactions between municipalities and spillovers. In order to correct for spatial autocorrelation, which induces underestimated standard errors via OLS, we employ the GMM methodology reported by Conley (1999). We specify a cut-off point for spatial interactions at 1.5° in latitude or longitude, i.e. 100 miles. This means that we disregard interactions between cities at distances of over 100 miles. Specifying other cut-off points does not increase the standard error. This approach is robust to misspecification of the degree of spatial correlation among geographical units and allows us to obtain robust standard errors for coefficients estimated through OLS.

Our results are reported in Table 9, where average wages by municipality are regressed on MA and controls. The correlation between wages and MA still holds for this more detailed spatial scale. The first column shows the results when wages are not controlled for skills in the first step, while the dependent variable in the second column is the wage premium corrected by worker skills. This last result is very close to the corresponding finding in the regressions by state, presented in the first column of Table 3 (using aggregate MA). It should also be noted that the standard error corrected for spatial autocorrelation is three times higher than that estimated using traditional OLS across municipalities, which confirms that OLS standard errors are underestimated. The corrected standard error is closer to that estimated in the regressions across states.

In the results presented in the third column, wages are regressed on MA plus state fixed effects in order to capture within-state variations. The estimated coefficient is similar to that obtained from the corresponding regression at state level (Table 3, column 3). This is consistent with MA having a similar impact on wages at different geographical scales.

In order to investigate whether short-distance interactions are driving our results, that is, in an attempt to disentangle the urban economics and NEG explanations for the regional wage premium, we control for some of the variables used in the literature (Rosenthal and Strange, 2004). Specifically, our controls are demographic density, the average age of workers and the proportion of workers at each level of educational attainment (our reference is level 5: complete primary education) (see Acemoglu, 1996, and Combes et al., 2008).

It is interesting to note that the coefficients for the highest levels of education in the final step are positive (not shown), even after controlling for this variable in the first step. This result suggests that education has an additional impact on average wages, besides the effect arising from its spatial composition of the labor force. A possible explanation could be the existence of positive externalities for workers with higher education. The resulting coefficient for MA in

column (4) is slightly lower than in the first specification in column (1), but it remains significant. This result suggests that, while local interactions go some way to explaining local wages, the NEG approach also plays an important role.

We control for the attractiveness of each municipality in column (5). A variety of regional amenities may influence individual location decisions and may, ultimately, be reflected in compensating wage differentials. Since the role of amenities is not easy to assess and is a research topic in itself, we do not pretend to fully investigate it. In this article, we simply use recent migration as a (raw) indicator of revealed attractiveness in the wage regression. Our regression includes the proportion of new residents in the municipality.³² The market access coefficient remains unchanged. We are aware that recent migration may also capture decisions driven by differences in market access itself. Nevertheless, it is not easy to disentangle these two effects. We refer to Hering and Paillacar (2008) for a study on the relation of market access differentials and migration.

Lastly, we add a number of controls for local amenities and endowments (altitude, temperatures, rainfall, soil quality, and land by type of agriculture). The coefficient for MA remains large and significant, as shown in column (6).

6. Concluding remarks

Migration within a country may well largely offset regional advantages derived from market and supplier access, in which case wage disparities would be the result of diversity in individual, industry and firm characteristics. Our results, however, indicate that labor mobility has not arbitrated away all cross-regional wages differences in Brazil. We find that market access and supplier access have a positive and significant impact on wages, even stronger than has been found for the European regions. Nevertheless, there are no restrictions on internal migration in Brazil, as opposed to, for instance, the case of China. In fact, migration levels in the country are even higher than in Europe. Menezes-Filho and Muendler (2007) find evidence of large labor displacements out of import-competing industries due to Brazilian trade liberalization in the 1990s. This does not mean, though, that labor reallocation moved in the expected direction.³³

³² The proportion of new residents refers to the proportion of males between 25 and 65 years old who have moved from another municipality within the past five years.

³³ The detailed study on labor adjustment by Menezes-Filho and Muendler (2007) is particularly striking: "Brazil's trade liberalization triggers worker displacements particularly from protected industries, as trade theory predicts and welcomes. But neither comparative-advantage industries nor exporters absorb trade-displaced workers for years" (p. 2).

Although NEG models can be proposed for migration and spatial wage inequality (see Hanson, 2005), a more complex phenomenon appears to be afoot, one that needs to take into account labor market frictions, migration dynamics (especially preferences and spatial variations in skill rewards), and the match between worker heterogeneity and firm heterogeneity. A step in that direction has been taken by Hering and Paillacar (2008).

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Appendix A

A1. Data appendix

Education

Educational variables are nine dummies, one for each schooling level:

- Level 1: Illiterate
- Level 2: Primary School (incomplete)
- Level 3: Primary School (complete)
- Level 4: Middle School (incomplete)
- Level 5: Middle School (complete)
- Level 6: High School (incomplete)
- Level 7: High School (complete)
- Level 8: College (incomplete)
- Level 9: College (complete).

Table A1
Summary statistics of individual characteristics.

Variable	Mean	Std. dev.
Log wage	1.508	0.852
Age	36.38	8.639
Age squared/100	13.98	6.927
Educ. level 1	0.026	0.161
Educ. level 2	0.098	0.297
Educ. level 3	0.168	0.374
Educ. level 4	0.203	0.402
Educ. level 5	0.193	0.394
Educ. level 6	0.076	0.264
Educ. level 7	0.151	0.358
Educ. level 8	0.027	0.162
Educ. level 9	0.059	0.235
N obs	798494	

Notes: Summary statistics for the random sample; statistics for the full sample do not differ by more than 0.001.

A2. First-step regressions for the instrumental variable approach

Table A2 presents the first-step estimations of the 2SLS regressions in Table 5. The *P*-value for the test of excluded instruments is less than 0.01 for all regressions.

Table A2
First-stage regressions corresponding to Table 5.

Instruments for market access:	Coefficient	Std. error	Observations
HMP in 1939	1.707**	0.056	540
Av. date of registration	−0.027**	0.002	540
HMP 1939 & av. date of registration	1.616**	0.064	
	−0.005**	0.001	540

Notes: First-stage regressions for Table 5, with industry fixed effects. Market access *i* instrumented by: HMP: Harris Market Potential = sum(GDP/distance) in 1939; average date of registration of municipalities within the state. Statistical significance: ** at 1% level.

A3. Measurement of productivity

Data

Data by workers and firms are matched using the firm identification number (CNPJ). Labor corresponds to the yearly average number of workers in the firm. Capital stock is estimated using the perpetual inventory method with a discount rate of 15% (results are not sensitive to changes in discount rate between 5% or 25%).

The manufacturing survey (PIA after 1996) does not have any information on capital stock, but the initial capital stock in 1995 can be imputed from IBRE data (Fundação Getulio Vargas) for a large subset of firms. For the other firms, we estimate the initial capital stock using capital stock data by industry obtained from the old PIA (corrected by the sampling rate in terms of labor) and other firm characteristics from the new PIA database, including investments and capital stock depreciation.

Index of productivity

We use a cost-share approach to measure productivity (see Foster et al., 2008, and Syverson, 2004, for similar measures of productivity using US data). Our index of productivity θ_{ih} for firm *h*, in industry *i*, is defined by:³⁴

$$\log \theta_{ih} = \log Y_{ih} - sh_{Li} \log L_{ih} - sh_{Ki} \log K_{ih} - sh_{Ei} \log E_{ih} - sh_{Mi} \log M_{ih} \quad (16)$$

where *Y* refers to revenues, *L*, *K*, *E* and *M* refer to labor, capital, energy and materials, respectively, and sh_{zi} denotes the share of input *Z* in annual costs for firms in industry *i*, taken as the average of the period between 1996 and 2003 across all firms in the industry, for $Z=L, K, E, M$. Total costs equal the cost of labor (wages), capital (investments), energy (electricity, fuel and gas expenditure) and materials (materials expenditure). This methodology is relatively simple to implement and very robust to measurement errors and misspecifications compared to alternative methods (Van Biesebroeck, 2007).

Alternative measures

We constructed alternative measures of productivity using either the residual of OLS regressions or the Levinsohn and Petrin (2003) methodology. Table A3 shows how the main results are affected by the choice of productivity measure. OLS regressions yield very similar results in the intermediary and final-step regressions. Levinsohn and Petrin estimations yield lower correlations between productivity and wages, but closer correlations between productivity and market access. As a result, the correlation between wages and market access is less affected by controlling for productivity using the OLS and the Levinsohn and Petrin measure.

³⁴ This formula can be derived from the optimization of a Cobb–Douglas production function with constant returns to scale. Note that our results are not sensitive to small changes in returns to scale (multiplying the coefficients sh_{zi} by the same factor, between 0.90 and 1.10). Moreover, we should note that our measure is robust to differences in wages across regions. The share of labor in total cost remains constant across firms in the same industry as long as the coefficient in the Cobb–Douglas production function is constant.

Table A3

Main results with alternative measures of productivity.

Measure of productivity	Cost share	OLS	LP
Productivity in first step	0.297 [0.002]**	0.227 [0.002]**	0.045 [0.001]**
MA in final step	0.112 [0.011]**	0.116 [0.012]**	0.120 [0.013]**

Notes: The first line corresponds to the coefficient of productivity in the first step of Table 8; the second line corresponds to the main coefficient of MA in Table 8 (final step). The columns correspond to the different measures of productivity.

A4. Correlation between productivity and market access

As an additional result, we explore the relationship between our chosen measure of productivity and MA. The results in the first column of Table A4 indicate that there is no significant correlation between productivity and global MA at 5% (although it is significant at the 10% level). When splitting MA between national and international (results in the second column), we find a non-significant coefficient for national MA, while the coefficient for international MA is positive and significant at the 1% level.

Table A4

Productivity and market access.

Dependent variable:	Productivity	
	(1)	(2)
Market access	0.022 [0.012]	
National MA		–0.012 [0.019]
International MA		0.062** [0.020]
Industry FE	Yes	yes
R-squared	0.079	0.087
Observations	420	420

Notes: OLS regressions with robust standard errors and industry fixed effects. Statistical significance: *5% and **1% levels.

References

- Acemoglu, D., 1996. A microfoundation for social increasing returns in human capital accumulation. *Quarterly Journal of Economics* 111 (3), 779–804.
- Amiti, M., Cameron, L., 2007. Economic geography and wages. *Review of Economics and Statistics* 89 (1), 15–29.
- Baldwin, R., Okubo, T., 2006. Heterogeneous firms, agglomeration and economic geography: spatial selection and sorting. *Journal of Economic Geography* 6 (3), 323–346.
- Barros, R., Henriques, R., Mendonça, R., 2000. Education and equitable economic development. *Economia* 1, 111–144.
- Chiquiar, D., 2008. Globalization, regional wage differentials and the Stolper–Samuelson Theorem: evidence from Mexico. *Journal of International Economics* 74 (1), 70–93.
- Combes, P., Duranton, G., Gobillon, L., 2008. Spatial wage disparities: sorting matters! *Journal of Urban Economics* 63 (2), 723–742.

- Conley, T., 1999. GMM estimation with cross sectional dependence. *Journal of Econometrics* 92 (1), 1–45.
- Da Mata, D., Deichmann, U., Vernon-Henderson, J., Lall, S., Wang, H.G., 2007. Determinants of city growth in Brazil. *Journal of Urban Economics* 62 (2), 252–272.
- De Sousa, J., Poncet, S., 2007. How are wages set in Beijing? CEPII Working paper, vol. 13.
- Fally, T., Paillacar, R., Terra, C., 2008. Economic geography and wages in Brazil: evidence from micro-data. THEMA Working papers, vol. 23. University of Cergy-Pontoise.
- Ferreira, P., Duarte, A., Salvato, M., 2006. Disparidades Regionais ou Educacionais? Um Exercício Contrafactual. In: Teixeira, Eryl Cardoso, Barbosa, Marcelo José (Eds.), *Investimento e Crescimento Econômico no Brasil*, Editora da UFV, pp. 333–369.
- Foster, L., Haltiwanger, J., Syverson, C., 2008. Reallocation, firm turnover, and efficiency: selection on productivity or profitability? *American Economic Review* 98 (1), 394–425.
- Gonzaga, G., Menezes-Filho, N.A., Terra, C., 2006. Trade liberalization and the evolution of skill earnings differentials in Brazil. *Journal of International Economics* 68 (2), 345–367.
- Hanson, G., 2005. Market potential, increasing returns, and geographic concentration. *Journal of International Economics* 67 (1), 1–24.
- Head, K., Mayer, T., 2006. Regional wage and employment responses to market potential in the EU. *Regional Science and Urban Economics* 36 (5), 573–594.
- Hering, L. and Paillacar, R., (2008). “How Does Market Access Shape Internal Migration? The Brazilian Case”, unpublished manuscript, University of Paris I.
- Hering, L. and Poncet, S., forthcoming. “Market Access Impact on Individual Wages: Evidence from China”, *Review of Economics and Statistics*.
- Knaap, T., 2006. Trade, location and wages in the United States. *Regional Science and Urban Economics* 36 (5), 595–612.
- Lall, S., Funderburg, R., Yepes, T., 2004. Location, concentration, and performance of economic activity in Brazil. World Bank Policy Research Working Paper 3268, World Bank.
- Langoni, Carlos G., 1973. *Distribuição da renda e desenvolvimento econômico do Brasil*. Ed. Expressão e Cultura, Rio de Janeiro. 320p.
- Lederman, D., Bravo-Ortega, C., and Fajnzylber, P., (2004). “The Wage Geography of Brazil After the Reforms”, unpublished manuscript.
- Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. *Review of Economic Studies* 70 (2), 317–341.
- Lewis, J., Linzer, D., 2005. Estimating regression models in which the dependent variable is based on estimates. *Political Analysis* 13 (4), 345–364.
- Melitz, M., 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica* 71 (6), 1695–1725.
- Melitz, M., Ottaviano, G.I.P., 2008. Market size, trade, and productivity. *Review of Economic Studies* 75 (1), 295–316.
- Menezes-Filho, N.A. and Muendler, M., (2007). “Labor Reallocation in Response to Trade Reform”, unpublished manuscript.
- Mion, G., Naticchioni, P., 2005. Urbanization externalities, market potential and spatial sorting of skills and firms. CEPR Discussion Paper 5172.
- Muriel, B., Terra, C., 2009. Sources of comparative advantages in Brazil. *Review of Development Economics* 13 (1), 15–27.
- Paillacar, R., (2007). “Market Potential and Worker Heterogeneity as Determinants of Brazilian Wages”, unpublished manuscript.
- Pavcnik, N., Blom, A., Goldberg, P., Schady, N., 2004. Trade policy and industry wage structure: evidence from Brazil. *World Bank Economic Review* 18 (3), 319–344.
- Redding, S., Schott, P., 2003. Distance, skill deepening and development: will peripheral countries ever get rich? *Journal of Development Economics* 72 (2), 515–541.
- Redding, S., Venables, A.J., 2004. Economic geography and international inequality. *Journal of International Economics* 62 (1), 53–82.
- Rosenthal, S., Strange, W., 2004. Evidence on the nature and sources of agglomeration economies. In: Henderson, V., Thisse, J.F. (Eds.), *Handbook of Regional and Urban Economics*, vol. 4. Elsevier, Amsterdam, pp. 2119–2171.
- Syverson, C., 2004. Product substitutability and productivity dispersion. *Review of Economics and Statistics* 86 (2), 534–550.
- Timmins, C., 2006. Estimating spatial differences in the Brazilian cost-of-living with household location choices. *Journal of Development Economics* 80 (1), 59–83.
- Van Biesebroeck, J., 2007. Robustness of productivity estimates. *Journal of Industrial Economics* 55 (3), 529–569.
- Vasconcelos, J.R., Oliveira, M.A., 2006. *Análise da Matriz por Atividade Econômica do Comércio Interestadual no Brasil - 1999*. IPEA, Texto para Discussão 1159.