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The effects of immigration on the productive structure of Spanish regions

Joan Martin-Montaner, Francisco Requena and Guadalupe Serrano^{*}

Abstract

Immigrants have increased their participation in Spanish labour supply from less than 3 percent in 1996 to more than 13 percent in 2005. Using the factor proportion model of production, this paper analyses whether this labour supply shock has affected the industrial structure of Spanish regions. Our best specification suggests the need to include time varying region-specific effects to capture differences in technology and prices across regions. Our results confirm that, first, labour endowment differences across regions help to explain the pattern of industry specialisation across region. Second, immigrants and natives act as complementary factors in most industries. Third, the importance of factor endowment changes is relatively small compared to production technique changes and idiosyncratic industry changes in explaining the overall changes in industrial structure over 1996-2005, being only important in the case of Building, a sector where foreign workers represent an important share of its total labour force.

Jel Classification: F22, R11, R13

Keywords: Rybczynski Effect, immigrants, education levels, specialisation patterns, technological change.

Resumen

Los trabajadores extranjeros han incrementado su participación en la oferta de trabajo española pasando de un 3% en 1996 a más del 13% en 2005. En el marco del modelo de producción de proporciones factoriales, este trabajo analiza si este *shock* de oferta de trabajo ha afectado a la estructura productiva de las regiones españolas. Nuestra mejor especificación apunta la necesidad de incluir efectos regionales cambiantes en el tiempo para capturar diferencias interregionales en precios y tecnología. Nuestros resultados confirman, primero, que las diferencias interregionales en la dotación de factor trabajo contribuyen a explicar los patrones de especialización regionales. Segundo, se observa que los trabajadores inmigrantes y nativos actúan como factores complementarios en la mayoría de industrias. Tercero, la importancia de los cambios en las dotaciones factoriales es relativamente pequeña comparada con la de los cambios en las técnicas de producción, y con la de los cambios idiosincráticos en cada industria, a la hora de explicar los cambios en la estructura productiva regional en el periodo 1996-2005. Solo es relevante en Construcción, un sector en el que el trabajo foráneo representa una parte importante de su fuerza de trabajo total.

Palabras clave: Efecto Rybczynski, inmigrantes, niveles de educación, patrones de especialización, cambio tecnológico.

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1. Introduction

The large migration flows from developing countries to developed countries can be viewed as labour supply shocks which affect the relative factor endowments in both the source and the host economy. Since migrant workers' skills endowments may strongly differ from the native's in the host countries, it is likely that the factor intensities in different sectors may be affected. This could be one explanation for the observed differences in wages of more-skilled relative to less-skilled workers in the developed countries over the nineties (Davis and Trevor, 2004). This migratory phenomena may also induce (or prevent) technological adjustments, as the adoption of new capital-intensive technologies could be delayed when low-skilled labour is a relative abundant factor (Lewis, 2004; Gandal et al., 2004).

Explaining the shifts in production composition in an economy requires a general equilibrium framework by its very nature, although this has been often forgotten in the empirical analysis. Harrigan (1995) popularised the production side of the factor proportion theory as an empirical tool. Using country-level data for OCDE countries over the period 1970-1985, he concluded that relative factor endowments have a large influence on industrial specialisation across countries.¹

Bernstein and Weinstein (2002) evaluate the prediction capacity of the standard factor proportions theory using regional and international data. They observe that prediction errors using intra-country data are much larger than using international data and conclude that the standard, factor proportions model of trade does a bad job of explaining production patterns at regional level, making therefore necessary to incorporate technological differences, trade costs, and other sources of specialization. Redding and Vera (2006) follows Harrigan's approach in their analysis of the regional pattern of specialisation in Europe and find out that it is necessary to account for countries' technology to predict accurately the pattern of industrial specialisation of the European regions.

In this paper we analyse the impact of immigration on Spanish regions' industrial composition, its measurement and the quantification of the extent to which an increase in the immigrant labour force could induce shifts in the industrial structure and specialisation patterns of regional economies. To do so, we adopt a general equilibrium

¹ Harrigan's conclusions are showed to be robust to alternative model specifications and estimation techniques by Harrigan (1999), Harrigan and Zakrajšek (2000) and Reeve (2006).

approach –the factor proportions model of international trade²- to explain up to which point changes in industrial structure of economies are driven by shifts in factor endowments, with independence of those specific changes happened in each industry or market. Foreign labour force in Spain has increased from less than 1% of the total labour force in 1997 to an astonishing 9% in 2005. In addition, foreign immigrants are heavily concentrated in some sectors and some regions. Moreover, and despite the strong efforts made by both private and public agents to increase the level of R&D expenditures, the adoption of new technologies in certain manufacturing and services activities in Spain has been slow compared to other European countries (OECD, 2005). A plausible reason is the type of technologies required to accommodate the new inflows of workers in sectors that use more intensively labour. Therefore, knowing whether production in each sector varies because of changes in endowments or because of the adoption of new technologies a key point in the analysis.

The rest of the paper is structured as follows. First, we formalise the production side of the factor proportions model and its extensions to accommodate differences in prices and technology across regions. Second, we present the data and describe the evolution of foreign and native labour force in the period 1996-2005. Third, we estimate the model using different levels of regional and sectoral aggregation and interpret the Rybczynski coefficients. Four, we allow the Rybczynski coefficients to change over time and assess the relative importance of changes in factor endowments and changes in production techniques in explaining changes in industrial specialisation. Finally, we summarize our results in the conclusions section.

2. The production side of the factor proportions model

In this section we describe the factor endowment production function originally proposed by Harrigan (1995) and extended recently by Harrigan and Zakrajšek (2000), Reeve (2006) and Redding and Vera (2006).

2.1. Theoretical foundations

The production side of the factor proportions model of international trade provides the general-equilibrium framework to explain industrial structure. The core insight of the

 $^{^2}$ The key assumption for the present analysis is the existence of a structural relationship between factor endowments and outputs, but for our purposes, we do not need to go further in testing the factor proportions model's assumptions against alternatives and in addressing some of its critics. Thus, the factor proportion model is a good theoretical framework to base on our analysis.

factor proportions model is that regions tend to produce -hence export- relatively more of those goods that intensively use their abundant factors of production. Thus, relative factor endowments become the determinant of industrial structure and the source of comparative advantage.

Under a constant-returns-to-scale technology and perfect competition in good and factor markets, a country's national product is given by its revenue function

$$\Pi(P,V) = \max_{y} \left\{ PY \middle| Y \in Y(V) \right\}$$

where p is an $(N \times 1)$ vector of goods prices, v is an $(M \times 1)$ vector of inelastic factor supplies, y is an $(N \times 1)$ vector of net outputs, and Y(V) is a compact production set. Assuming $\Pi(P, V)$ is twice continuously differentiable, the gradient with respect to P gives the net supply vector,

$$Y = \prod_{p} (P, V)$$

Differentiating again with respect to factor supplies gives the matrix of Rybczynski derivatives,

$$R = \prod_{pv} (P, V)$$

Since the supply function is homogeneous of degree one in v,

$$Y = RV \tag{1}$$

and net output is a linear function of factor endowments.

The underlying condition that allows the R matrix to be identical across regions and thus equation (1) to be used as a model of interregional location of production is that regions must produce the same set of goods with the same techniques. Producing the same set of goods requires that relative factor endowments not be "too" dissimilar across regions. As far as regions use the same techniques of production depends on common technologies and prices. Good prices will be equalized across regions with free trade and zero transport costs. A crucial condition for factor price equalization is that the number of goods exceeds the number of factors, $N \ge M$. However, in order for the supply function to be single-valued, there must be at least as many factors as goods, M $\ge N$. Thus, what is left is the "square" model in which there are equal numbers of goods and factors, N = M. In this case, equation (1) holds for each region and forms the basis for the empirical work to follow. Obviously there are more goods than factors and therefore there does not exist a unique mapping between factor endowments and production. Nevertheless, the existence of a structural relationship between factor endowments and production is all that really matters for the present analysis (see Reeve, 2006, for a deeper discussion on this topic).³

2.2. Empirical model

Equation (1) is defined for each industry in each year. It can be rewritten with an additive error term,

$$Y_{ct}^{i} = v_{ct}R_{t}^{i} + \varepsilon_{ct}^{i}$$
⁽²⁾

Here, Y_{ct}^i is region *c*'s value added in industry *i* in year *t*. Region *c*'s (1 × M) vector of factor endowments in year *t* is given by v_{ct} . The (M × 1) vector R_t^i represents the factor proportions mapping from endowments to outputs for industry *i*. Collecting observations across regions and years, we get:

$$Y^{i} = V \ R^{i} + \varepsilon^{i} \tag{3}$$

for industry *i*. Now, Y_i and ε_i are (CxT × 1) vectors and *V* is the (CxT × M) endowment matrix.

Rather than estimating each equation individually, a multivariate regression model is formed in which each equation represents equation (3) for a particular industry i belonging to the aggregated economy; or belonging to the aggregated sector n when larger sectoral disaggregation in available. The model for sector n is,

$$\begin{bmatrix} Y^{1} \\ \vdots \\ Y^{i} \end{bmatrix} = \begin{bmatrix} V & R^{1} \\ \vdots \\ V & R^{i} \end{bmatrix} + \begin{bmatrix} \varepsilon^{1} \\ \vdots \\ \varepsilon^{i} \end{bmatrix}$$
(4)

³ The structural relationship goes in one-direction since factor endowments are exogenous in the model. However, as far as accumulation depends primarily on broad forces that are largely external to a given sector, this assumption should not be a serious problem. For example, educational attainment seems to be driven largely by demographic characteristics and domestic educational policy and capital accumulation depends on aggregate forces such as life-cycle behaviour, macroeconomic conditions, and tax policy. From a more pragmatic point of view, there are no good instruments available for factor supplies. Indeed many empirical papers use factor endowments as "good" instruments of production output when this variable is included in the regression as explanatory variable under the assumption that they are exogenous.

The main advantage of this approach is the ability to test homogeneity hypotheses across equations, i.e. across industrial branches belonging to the same sector. Moreover, since it is likely that the disturbances across equations are correlated, the multivariate approach may lead to efficiency gains and account for inter-industry externalities, an issue that has not been addressed in previous studies up to our knowledge. This framework is a Seemingly Unrelated Regression (SUR) model. Typically, the SUR framework defines a separate equation for the cross-sectional units, each of which contains observations over time. Here, each equation contains cross-sectional observations over time with the industrial disaggregation considered defining the number of equations. Thus the double cross-sectional and temporal perspective of information will allow us to go further in the analysis.

Despite the empirical advantages of the Heckscher-Ohlin model, the adequacy of its assumptions on homothetic preferences, identical technologies and no barriers to trade has been questioned and used as arguments supporting the poor performance of the model to explain countries' production patterns. In our case, the use of infra-national information makes more plausible the irrelevance of measurement errors and technological differences across regions and the exogeneity of variations in relative prices. However the use of regional data implies that the exogeneity and immobility of factor endowments assumption does not stand in that sample.⁴ Nevertheless, we derive and use a general equilibrium relationship between production structure, relative prices, technology and factor endowments that hold irrespective of the degree of factor mobility.⁵ Following that approach, we conduct a more flexible empirical analysis by specifying a model that relaxes the assumptions on identical prices and technology among regions. The model becomes (4a).

$$\begin{bmatrix} Y^{1} \\ \vdots \\ Y^{i} \end{bmatrix} = \begin{bmatrix} V & R^{1} \\ \vdots \\ V & R^{i} \end{bmatrix} + \begin{bmatrix} D_{t} \phi_{t}^{1} \\ \vdots \\ D_{t} \phi_{t}^{i} \end{bmatrix} + \begin{bmatrix} \varepsilon^{1} \\ \vdots \\ \varepsilon^{i} \end{bmatrix}$$
(4a)

⁴ Devillanova and García-Fontes (2004) observe over the period that active population is more mobile than non-active population and obtain slightly higher migration rates as regional units become more disaggregated (specially among high skilled workers), both of them being relative low (2.25% and 1.68% migrants over total social security registered workers, respectively).

⁵ Redding and Vera (20006) show that the production-factor endowment relationship holds without factor price equalisation given that both differences in relative prices and technology are controlled for in the model, and holds under factor mobility. However the interpretation of this general equilibrium relationship changes depending on the mobility of factors. When factor immobility holds, the model can be interpreted in supply-side terms (external changes in factor endowments cause production structure changes). When factors are perfectly mobile across regions, there is also a demand-side interpretation (external changes in factor endowments).

Time dummies, D_t , approximate industry-specific impact of changes in prices and technology on sector production in the context of identical prices and technology across regions.

If we allow for time-invariant regional differences in relative prices and technology, we add to the initial SUR model a time-invariant regional fixed effect, D_z , with dimension (CxT x Z), and its correspondent vector of (Z x 1) parameters, ϕ_z . This is illustrated in model (4b).

$$\begin{bmatrix} Y^{1} \\ \vdots \\ Y^{i} \end{bmatrix} = \begin{bmatrix} V & R^{1} \\ \vdots \\ V & R^{i} \end{bmatrix} + \begin{bmatrix} D_{t} \phi_{t}^{1} \\ \vdots \\ D_{t} \phi_{t}^{i} \end{bmatrix} + \begin{bmatrix} D_{Z} \phi_{Z}^{1} \\ \vdots \\ D_{Z} \phi_{Z}^{i} \end{bmatrix} + \begin{bmatrix} \varepsilon^{1} \\ \vdots \\ \varepsilon^{i} \end{bmatrix}$$
(4b)

Finally we can allow region-specific differences in prices and technology vary over time, by including a set of region-time dummy variables, D_{Zt} , with dimension (CxT x ZxT), and its correspondent vector of (ZxT x 1) parameters, ϕ_{Zt} , as shown in model (4c).

$$\begin{bmatrix} Y^{1} \\ \vdots \\ Y^{i} \end{bmatrix} = \begin{bmatrix} V & R^{1} \\ \vdots \\ V & R^{i} \end{bmatrix} + \begin{bmatrix} D_{t} \phi_{t}^{1} \\ \vdots \\ D_{t} \phi_{t}^{i} \end{bmatrix} + \begin{bmatrix} D_{Zt} \phi_{Zt}^{1} \\ \vdots \\ D_{Zt} \phi_{Zt}^{i} \end{bmatrix} + \begin{bmatrix} \varepsilon^{1} \\ \vdots \\ \varepsilon^{i} \end{bmatrix}$$
(4c)

3. Data

The dependent variable in our study is production by geographical unit, type of activity and year. Industry's output is measured by means of sector GAV (gross added values) at 2000 current market prices from the homogeneous series of INE's *Regional Accounts*. The database provides regional value added at two different geographical levels: 17 regions (NUTS 2)⁶ which can be disaggregated into 52 provinces (NUTS 3). The number of sectors defined varies depending on the level of geographical aggregation. There are 21 sectors (S-21) for NUTS 2 (see Appendix Table A-1) which

⁶ The Spanish *autonomous communities* (EUROSTAT NUTS 2 classification) represent the most important administrative units at the regional level, most of them including more than one province.

are reduced to 5 sectors (S-5) for NUTS 3: Agriculture, Energy, Manufacturing, Construction and Services.⁷ The period of analysis is 1996-2005.

Endowment data include three primary factors: arable land, capital stock and labour. Labour is split in native and foreign workers and in three educational categories: low, medium, and high-educated workers, to account for differences in human capital in the labour force. Data on arable land is provided by INE's *Statistical yearbook of Spain* and data on capital stock is provided by the BBVA Foundation and IVIE. Labour endowments come from INE's Spanish Labour Force Survey (EPA, 2005 methodology) on active population. Low educated workers include illiterates and workers with primary education. Medium-educated workers have completed secondary school. High-educated workers have at least enrolled in a high education degree.⁸

Figure 1 shows that the massive arrival of immigrants to Spain starts in the second half of the nineties. Besides, Table 1 shows that the newly arrived foreign population poses a different composition of education levels compared to natives. Over the period 1996-2005, the percentage of natives have decreased among low-educated and have increased among high-educated actives; meanwhile the percentage of immigrants among low educated stayed the same and has decreased among high educated actives. Skill upgrading in the immigrants group occurred only in the medium-education level in which the share of immigrants increased 4 percent from 1996 to 2005. Table 1 also shows that foreign labour force is more heterogeneously distributed across Spanish provinces than native labour force. While medium-educated actives are the less unequally distributed foreign actives in the territory, natives with low education are the less homogenously distributed. Those differences in the distribution of foreign active population could change the composition of labour force in the Spanish provinces, especially if we focus in the level of skills of foreign actives that arrive to each province.

Figures 2 to 7 show the composition of native and foreign labour force by educational attainment. Between 1996 and 2005 the number of foreign residents in Spanish regions increased, especially in Andalucia, Cataluña, Comunidad Valenciana and Madrid (see Figures 2 and 3). Nevertheless, the share of foreign actives is still very low compared to native actives in most cases: only Madrid, Baleares, Murcia, Comunidad Valenciana and Canarias account a share of foreign actives higher than 18 percent. The highest concentration can be found, at NUTS 3 level, in Alicante, Almeria, Baleares, Castellon, Gerona and Madrid, where the share of foreign actives ranges

⁷ See Table A-1 for the equivalences between sectors at the different levels of aggregation

⁸ Here we describe briefly the sources of the data. For details about its construction, see Appendix.

between the 20 and 30 percent. Medium-educated workers are the prevailing educational level for both native and foreign actives in all the regional units, as it is shown in Figures 6 and 7.





		Total	Low-edu	Medium-edu	High-edu
Total	1996	100	34,1	50,2	15,7
	2005	100	17,2	60,6	22,2
Immigrants	1996	2,7	20,9	55,7	23,5
	2005	13,3	20,9	59,5	19,6
Rest of labour	1996	97,3	34,5	50,0	15,5
force	2005	86,7	16,6	60,8	22,6
Dispersion* of labour shares by educ	ation level	and national	ity across Spanis	sh provinces in 20	005
Immigrants		1,70	1,02	1,68	1,75
Rest of Labour force		14,03	2,77	8,65	4,20
Total			0,86	0,78	0,59
Dispersion* of labour shares by educ	ation level	and national	ity across Spanis	sh regions in 2005	
Immigrants		2,04	1,55	1,86	2,10
Rest of Labour force		14,79	4,26	10,58	4,43
Total		-	4,53	15,71	5,20

Table 1. Composition of Labour Supply by Education Levels and Nationality

Notes: Own elaboration using Encuesta Población Activa (EPA). Education levels: Low=primary education or less; Medium=high school or equivalent; High=university degree or equivalent. *Coefficient of variation of shares of actives by education level

Source: INE's Statistical yearbook of Spain.

Figure 2. Foreign Residents in Spanish provinces. Years 1996 and 2005



Figure 3. Foreign Residents in Spanish regions. Years 1996 and 2005





Figure 4. Participation (%) of Foreign Actives in Total Labour Force. Year 2005

Figure 5. Participation (%) of Foreign Actives on Total Labour Force. 2005





Figure 6. Composition of Labour Force by Education Level. 2005

Figure 7. Composition of Labour Force by Education Level. 2005



Sectors that employ more foreign workers are *Agriculture, Building* and, *Services* (mostly *Trade and Hotels* and *Household Services*). Additionally, as it is shown in Figure 8, the distribution of natives and immigrants is slightly different across sectors. The share of native workers in *Industry* is larger than in *Building*, while the opposite holds for immigrant workers. Only in *Agriculture* both types of workers are almost equally distributed.



Figure 8. Share of Workers by Sector and Nationality. 2005

4. Model specification and estimation

We conduct the analysis in the two different datasets referred to different geographic units in Spanish economy. As we can also aggregate Spanish provinces from NUTS-3 to NUTS-2, we can perform our analysis both for S-5 and S-21 classifications. This latter possibility allows us to get deeper understanding of the aggregation problem pointed out by Redding and Vera-Martin (2006) using European regional data.⁹

Source: Spanish INE's Spanish Labour Force Survey

⁹ The authors find larger within sample average absolute prediction errors in disaggregated manufacturing industries, and relate it to the production indeterminacy problem given the larger number of industries relative to production factors. Moreover, and related to the empirical analysis of HO model at a regional framework, the authors obtain evidence supporting the significant and quantitatively relevant role of factor endowment in determining production structure in European regions. They relate the larger prediction errors obtained by Bernstein and Weinstein (2002) in the regional relationship between output shares and factor endowments, than in the cross-country model to the possibility of production

Models (4a)-(4c) are estimated considering the eight productive factors described in the previous section. When data correspond to S-5 disaggregation, we estimate two five-equation SUR models both for provincial and regional data. Nevertheless, computational capabilities do not allow the estimation of a 21-equation SUR model. Because of this, we estimate a single equation model for *Agriculture* and *Building* whereas SUR specifications are estimated for *Energy* (two equations), *Industry* (ten equations) and *Services* (seven equations).

Through the analysis, sector Gross Added Value (GAV) for each region and the regional gross capital stock are measured in current prices. To control for scale effects due to differences in the size of region, sectoral output and regional inputs are expressed in relative terms respect to regional GDP, measured in current prices. Moreover, to avoid heteroskedasticity problems in each equation, we specify a SUR model with weighted equations, where each weight is obtained from the equation's robust estimation. Then, the estimates of the cross-equation covariance matrix are based upon GLS parameter estimates of the unweighted system.

Our first purpose is to select the most adequate specification out of all three models available. Therefore, Table 2 reports the mean absolute percentage prediction errors by industry and regional units for the models (4a), (4b) and (4c) in columns *(ii)*, *(iv)* and *(v)* respectively. As a crude benchmark for comparison, these prediction errors are contrasted with those based on the prediction of relative production using the cross-sectional mean. This naïve estimator, in the estimation without dummy variables, column *(i)*, has an overall mean absolute prediction error of 66.5 percent for provinces, and a 66.4 percent for regions, 30 percentage points larger than the average error based on the factor proportions model. Besides, the naïve estimator is larger than the overall mean absolute prediction error is quite different among sectors.¹⁰

Let us focus therefore in the Heckscher-Ohlin specification. As it was expected, the model performs better at regional level (NUTS-2) than at province level (NUTS-3). Thus, in the estimation without regional dummies (column (i)) the overall average absolute prediction error is 35.3 percent for provinces, higher than the 26.9 and 27.2 percent achieved in the specification for regions. Following the same trend, in those models including time and regional dummies, the average prediction error is smaller

indeterminacy, "which is likely to be larger for the lower values of trade costs observed across regions within a country" (page 4).

¹⁰ The exceptions are *Wood Products* in all the specifications and *Financial Services* in the estimation without regional dummies.

 Table 2. Model Specification and evaluation

	SURE EST	IMATION.	5 SECTOR	S. PROVIN	ICIAL DATA	SURE EST	IMATION.	5 SECTOR	S. CCAA I	DATA	GLS & SU	RE ESTIM	. 21 SECT	ORS. CCA	A DATA
	(i)	(ii)	(iii)	(iv)	(v)	(i)	(ii)	(iii)	(iv)	(v)	(i)	(ii)	(iii)	(iv)	(v)
Prediction Error Naïve	model														
Agriculture	158,93	158,93	158,93	158,93	158,93	201,60	201,60	201,60	201,60	201,60	201,60	201,60	201,60	201,60	201,60
Energy	91,49	91,49	91,49	91,49	91,49	37,27	37,27	37,27	37,27	37,27	37,27	37,27	37,27	37,27	37,27
Manufacturing	56,25	56,25	56,25	56,25	56,25	52,23	52,23	52,23	52,23	52,23	52,23	52,23	52,23	52,23	52,23
Construction	16,81	16,81	16,81	16,81	16,81	11,79	11,79	11,79	11,79	11,79	11,79	11,79	11,79	11,79	11,79
Services	9,25	9,25	9,25	9,25	9,25	9,09	9,09	9,09	9,09	9,09	9,09	9,09	9,09	9,09	9,09
MEAN	66,55	66,55	66,55	66,55	66,55	62,39	62,39	62,39	62,39	62,39	62,39	62,39	62,39	62,39	62,39
Absolute prediction err	or														
Agriculture	55,28	47,01	25,85	26,00	23,96	53,47	42,33	13,03	12,99	6,89	48,08	33,04	13,58	14,58	7,61
Energy	52,99	53,05	42,09	41,57	41,20	27,32	27,31	7,92	7,88	4,97	26,42	26,65	7,13	7,02	4,34
Manufacturing	45,41	44,04	23,27	23,41	22,50	34,98	33,20	2,99	2,98	1,81	43,98	42,66	5,52	5,51	3,94
Consruction	16,10	14,10	10,78	10,77	10,11	12,64	9,67	3,14	3,11	1,94	12,43	9,92	3,58	3,48	2,50
Services	6,62	6,66	3,61	3,52	3,40	5,95	5,95	0,70	0,66	0,47	5,31	5,41	0,77	0,70	0,51
MEAN	35,28	32,97	21,12	21,06	20,23	26,87	23,69	5,56	5,52	3,21	27,24	23,53	6,12	6,26	3,78
Averaged R-squared	,		,	,	,	,	,	,	,		,	,	,		
Agriculture	0,92	0,93	0,97	0,97	0,98	0,93	0,94	1,00	1,00	1,00	0,87	0,92	0,99	0,99	1,00
Energy	0,81	0,81	0,88	0,88	0,89	0,92	0,92	0,99	0,99	1,00	0,75	0,75	0,97	0,97	1,00
Manufacturing	0.88	0.89	0.97	0,97	0,98	0,93	0,93	1.00	1,00	1.00	0,75	0.76	1,00	1,00	1,00
Construction	0,97	0,98	0,99	0,99	0,99	0,98	0,99	1,00	1,00	1,00	0,43	0,67	0,96	0,96	0,99
Services	0.99	0,99	1,00	1,00	1,00	0,99	0.99	1.00	1,00	1,00	0,96	0.96	1,00	1,00	1,00
MEAN	0.91	0.92	0.96	0.96	0,97	0,95	0.95	1.00	1.00	1.00	0.75	0.81	0,98	0,98	1,00
Akaike info. Criterion	-,	-,	-,	-,	-,	-,	-,	.,	.,	.,	-,	-,	-,	-,	.,
Agriculture											-5,77	-6,25	-8.13	-8.10	-9,12
Energy											-14.88	-14.88	-19.10	-19.11	-23,39
Manufacturing											-78,30	-78.68	-118,15	-118,36	-134,35
Construction											-5,64	-6.16	-8,52	-8,48	-9,06
Services											-50,82	-51,29	-71,12	-71,67	-76,78
AIC Total model	-25,68	-26,09	-30,22	-30,35	-30,90	-28,54	-29,06	-45,03	-45,35	-50,58	00,02	01,20	,	,	. 0,. 0
Breusch-Pagan test	443,65	433,16	268,00	267,14	278,32	213,08	202,20	124,51	138,78	38,63					
(P-value)	0,00	0,00	0,00	0,00	0,00	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)					
Energy SURE	0,00	0,00	0,00	0,00	0,00	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	1,12	1,23	39,78	41,42	2,71
(P-value)											(0,29)	(0,27)	(0,00)	(0,00)	(0,10)
Manufacturing SU	RF										1076,27	972.63	637.48	639.80	410.55
(P-value)											(0,00)	(0,00)	(0,00)	(0,00)	(0,00)
Services SURE											374,30	370,31	130,88	129,53	101,75
(P-value)											(0,00)	(0,00)	(0,00)	(0,00)	(0,00)
Time dummies	No	Yes	No	Yes	Yes	No	Yes	No	Yes	Yes	(0,00) No	Yes	(0,00) No	Yes	Yes
Regional dummies	No	No	Yes	Yes	No	No	No	Yes	Yes	No	No	No	Yes	Yes	No
Time-varying Reg. dum.	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes
1 Wald test. Non sigf. R.D.	-	-	Rejected	Rejected	Rejected	-	-	Rejected	Rejected		-	-	Rejected	Rejected	Rejected
2 Wald test. Constant R.D.	-	-	-	-	Rejected*	-	-	-	-	Rejected	-	-	-	-	Rejected
- maia toot. oonstant N.D.															

Note: P-values in parenthesis. 1Wald test for the Null of non significance of regional effects. . 2Wald test for the Null of temporal stability of regional effects * Rejected at 8% of significance level.

across regions rather than across provinces. Our results are in line with those of Bernstein and Weinstein (2002), which point to the worse performance of the model with larger spatial disaggregation, given the larger production indeterminacy when the lower values of trade costs are across regional economies.¹¹

Table 2 also reports the averaged R^2 measures for goodness of fit by large sector and model. Their values range between 0.75 (for specification *(i)* in the S-21 case) and 0.99 (specification *(v)* for both S-5 and S-21), which are substantially higher than the average of 0.38 reported by Bernstein and Weinstein (2002).¹² According to the goodness of fit and the AIC selection criterion, the better specification is (4c) in both S-5 and S-21 cases. This conclusion is confirmed by two additional tests. First, we reject the non significance of the regional dummies in all cases. Second, we have tested whether the coefficients for the regional dummy variables are constant over time (model 4b vs 4c), being the hypothesis rejected in all cases. This specification, which corresponds to an augmented factor proportion model of production such that regional dummies capture differences in technology and prices that are not permanent but change over the time is also preferred in Redding and Vera (2006) using European regional data.

Finally, we analyse the validity of the SUR specification by testing the null hypothesis of non correlation across the residuals of each equation in the model. The results of the Breusch-Pagan test point to the rejection of the null hypothesis, confirming the adequacy of the SUR estimation of the model (being the exception *Energy* in the specifications *(i)* and *(ii)* with 21 sectors).

The analysis of the absolute prediction errors obtained in the S-5 model and in the S-21 model show negligible differences. Then our results do not point to the production indeterminacy due to the larger number of goods than factors. Under these conditions it is not possible to discard one specification against the other. Some additional work is therefore needed. The estimated coefficients of models (4a), (4b) and (4c) using both sets of regional data are displayed in Table A-2 and A-3. We test the equality of Rybczinsky parameters across S-21 branches belonging to the same S-5

¹¹ Using data on Japanese regions, Bernstein and Weinstein (2002) report an absolute prediction error of 310 percent, which is substantially larger than the one we find in the case of the Spanish provinces and regions. We find that our larger absolute prediction error, 35.28 percent in the provincial model without dummies, is very similar to the one reported by papers using international data: Harrigan (1995) reports a 40 percent, Bernstein and Weinstein (2002) a 67 percent, and Reeve (2006) a 52 percent. In the regional models, the larger absolute prediction error is clearly lower that the ones reported in international data. This better performance of the Hecksher-Ohlin model in an interregional sample supports the larger plausibility of its assumptions.

¹² This is a temptative comparison given that R^2 only allows comparing nested models with the same endogenous variable.

sector. The results displayed in Table A-2 show that the equality of Rybczinsky coefficients is rejected for branches belonging to *Energy*, *Industry* and *Services*. Because of this result, we will focus our analysis in the S-21 framework for the rest of the paper.

5. Immigration in the factor proportion model of production

Once we have established specification (4c) using regional data (NUTS 2) and 21 sectors, we can use the Rybczinsky coefficients to investigate the impact of immigration on the production structure of Spanish regions. Since the work of Learner (1984) and Harrigan (1995), the sign and significance of the coefficients can be interpreted in terms of comparative advantage. Thus, a positive and statistically significant coefficient indicates that the associated factor is a source of comparative advantage for that industry; conversely for a negative coefficient. ¹³ The actual coefficient estimates presented in Tables A-2 and A-3, however, are difficult to interpret in terms of the underlying economic variables of the model. The economic significance of the parameter estimates is better reflected in standardised or beta coefficients. Beta coefficients indicate the relevance of the explanatory variable in the regression, since they measure the expected change in the standardised dependent variable induced by a unitary change in the standardised independent variable, conditional on the other standardised regressors. ¹⁴

We compute the beta coefficient estimates in Table 3. Capital is significant in most sectors, although only displays a positive effect in branches 3 (*Electricity, gas and water*), 4 (*Food, drink and tobacco*), 14 (*Building*), 19 (*Renting and business services*) and 20 (*Education, health and other services*). Land is also significant in most branches, playing a positive role in branch 1 (*Agriculture*), 6 (*Wood Products*), 14 (*Building*), 18 (*Financial Services*), 19 (*Renting and business services*) and 20 (*Education, health and other services*) and 20 (*Education, health and other services*). With regard to native work, medium-skilled workers appear to be a relevant productive factor in most sectors (17 branches out of 21). High-educated

¹³ There is a high correlation between native and foreign actives by education categories. This multicollinearity problem implies higher standard error in coefficient estimates that tend to not refuse the null of no significance of parameters. Because of this, we are flexible with p-values to refuse the null hypothesis both in testing the significance of factor endowments or the null of equality of the Rybczynski coefficients between natives and immigrants.

¹⁴ Standardised or beta coefficients, discussed in Leamer (1984), are formed by multiplying the regression slope by the standard deviation of the explanatory variable and dividing by the standard deviation of the dependent variable.

Table 3. Standardised Coefficient Estimates (1996-2005). Beta Coefficients

Sectors		1	2	3	4	5	6	7	8	9	10	11
R-squared		0,997	0,997	0,998	1,000	0,999	0,996	0,999	0,999	0,999	1,000	1,000
Absolute Prediction error		7,608	13,147	4,519	1,8476	12,134	129,87	3,444	6,44	7,11	1,49	3,58
Beta-coefficients												
Native work	High-edu	-0,004	0,158 ***	0,192 ***	0,015	-0,005	-0,051	0,047 **	-0,014	-0,008	-0,018	-0,014
	Medium-edu	0,086 ***	0,261 ***	0,512 ***	0,062 **'	0,097 ***	0,185 ***	0,108 ***	0,121 ***		0,035 **	0,061
	Low-edu	0,147 ***	0,049	0,610 ***	0,107 ***	0,009	0,004	0,019	-0,006	-0,034 **	-0,028 ***	0,005
Immigrant work	High-edu	-0,011	-0,004	-0,002	-0,001	0,008	-0,040 *	0,033 ***	-0,008	-0,011	-0,004	-0,012
	Medium-edu	0,063 ***	0,105	0,100 ***	-0,037 ***	-0,090 ***	-0,074 **	-0,035 **	-0,010	-0,031 **	-0,037 ***	-0,010
Capital	Low-edu	0,015 -0,090 ***	0,059 *** 0,000	-0,008 1,071 ***	-0,040 *** 0,240 ***	-0,025 *** -0,183 ***	-0,053 ** -0,297 **	-0,020 ** -0,211 ***	-0,016 -0,206 **	-0,054 *** -0,228 ***	-0,029 *** -0,077 **	-0,007 -0,249
Land		-0,090 0,107 **	-0,019	-0,503 ***	-0,165 **'	-0,183	-0,297 0,016	-0,211	-0,208	-0,228	-0,077	-0,249
Land		0,107	-0,019	-0,505	-0,105	-0,040	0,010	-0,177	-0,007	-0,090	-0,100	-0,080
Wald test												
Temporal stability of Rybcz.												
Coeffs		12,62	27,63	465,03	77,71	319,66	21,11	178,44	66,97	159,53	331,5	54,56
p-value		(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
Sectors		12	13	14	15	16	17	18	19	20	21	
Sectors R-squared		12 0,999	13 0,999	14 0,986	15 1,000	16 0,999	17 1,000	18 0,999	19 1,000	20 1,000	21 0,999	
R-squared Absolute Prediction error		0,999	0,999	0,986	1,000	0,999	1,000	0,999	1,000	1,000	0,999	
R-squared	High-edu	0,999	0,999	0,986	1,000	0,999	1,000 1,6589	0,999	1,000	1,000	0,999 2,6942	
R-squared Absolute Prediction error Beta-coefficients	High-edu Medium-edu	0,999 5,52	0,999 3,36	0,986 2,503	1,000 1,7997	0,999 2,6291	1,000	0,999 2,4142	1,000 1,2599	1,000 0,8217	0,999	
R-squared Absolute Prediction error Beta-coefficients		0,999 5,52 0,034 *	0,999 3,36 0,043 *	0,986 2,503 -0,052	1,000 1,7997 0,020	0,999 2,6291 -0,058 *	1,000 1,6589 0,058 ***	0,999 2,4142 0,220 ***	1,000 1,2599 0,069 ***	1,000 0,8217 0,007	0,999 2,6942 0,064	
R-squared Absolute Prediction error Beta-coefficients	Medium-edu	0,999 5,52 0,034 * 0,057 **	0,999 3,36 0,043 * -0,082 **	0,986 2,503 -0,052 -0,523 ***	1,000 1,7997 0,020 0,075 **	0,999 2,6291 -0,058 * -0,087 **	1,000 1,6589 0,058 *** 0,084 ***	0,999 2,4142 0,220 *** 0,056	1,000 1,2599 0,069 *** -0,046	1,000 0,8217 0,007 0,084 ***	0,999 2,6942 0,064 0,000	
R-squared Absolute Prediction error Beta-coefficients Native work	Medium-edu Low-edu	0,999 5,52 0,034 * 0,057 ** -0,001	0,999 3,36 0,043 * -0,082 ** -0,038 **	0,986 2,503 -0,052 -0,523 *** -0,489 ***	1,000 1,7997 0,020 0,075 ** 0,081 ***	0,999 2,6291 -0,058 * -0,087 ** -0,016	1,000 1,6589 0,058 *** 0,084 *** 0,049 ***	0,999 2,4142 0,220 *** 0,056 0,043	1,000 1,2599 0,069 *** -0,046 0,010	1,000 0,8217 0,007 0,084 *** 0,101 ***	0,999 2,6942 0,064 0,000 0,145 ***	
R-squared Absolute Prediction error Beta-coefficients Native work	Medium-edu Low-edu High-edu	0,999 5,52 0,034 * 0,057 ** -0,001 0,010	0,999 3,36 0,043 * -0,082 ** -0,038 ** 0,045 ***	0,986 2,503 -0,052 -0,523 *** -0,489 *** -0,073 **	1,000 1,7997 0,020 0,075 ** 0,081 *** -0,009	0,999 2,6291 -0,058 * -0,087 ** -0,016 -0,010	1,000 1,6589 0,058 *** 0,084 *** 0,049 *** 0,035 **	0,999 2,4142 0,220 *** 0,056 0,043 -0,011	1,000 1,2599 0,069 *** -0,046 0,010 0,005	1,000 0,8217 0,007 0,084 *** 0,101 *** 0,017 *	0,999 2,6942 0,064 0,000 0,145 *** 0,049 **	
R-squared Absolute Prediction error Beta-coefficients Native work	Medium-edu Low-edu High-edu Medium-edu	0,999 5,52 0,034 * 0,057 ** -0,001 0,010 -0,008	0,999 3,36 -0,082 ** -0,038 ** 0,045 *** -0,058 ***	0,986 2,503 -0,052 -0,523 *** -0,489 *** -0,073 ** 0,021 0,022	1,000 1,7997 0,020 0,075 ** 0,081 *** -0,009 -0,038 *	0,999 2,6291 -0,058 * -0,087 ** -0,016 -0,010 -0,041 **	1,000 1,6589 0,058 *** 0,084 *** 0,049 *** 0,035 ** -0,082 ***	0,999 2,4142 0,220 *** 0,056 0,043 -0,011 -0,003	1,000 1,2599 -0,046 0,010 0,005 0,050 **	1,000 0,8217 0,084 *** 0,101 *** 0,017 * 0,020 *	0,999 2,6942 0,064 0,000 0,145 *** 0,049 ** -0,074 ***	
R-squared Absolute Prediction error Beta-coefficients Native work Immigrant work	Medium-edu Low-edu High-edu Medium-edu	0,999 5,52 0,034 * 0,057 ** -0,001 0,010 -0,008 0,001	0,999 3,36 -0,082 ** -0,038 ** 0,045 *** -0,058 *** -0,004	0,986 2,503 -0,052 -0,523 *** -0,489 *** -0,073 ** 0,021 0,022	1,000 1,7997 0,020 0,075 ** 0,081 *** -0,009 -0,038 * 0,019	0,999 2,6291 -0,058 * -0,087 ** -0,016 -0,010 -0,041 ** 0,010	1,000 1,6589 0,058 **** 0,084 *** 0,049 *** 0,049 *** 0,035 ** -0,082 ***	0,999 2,4142 0,220 *** 0,056 0,043 -0,011 -0,003 0,071 ***	1,000 1,2599 -0,046 -0,046 0,010 0,005 0,050 ** 0,024 *	1,000 0,8217 0,007 0,084 *** 0,017 * 0,020 * -0,002	0,999 2,6942 0,064 0,000 0,145 *** 0,049 ** -0,074 *** 0,032	
R-squared Absolute Prediction error Beta-coefficients Native work Immigrant work Capital Land	Medium-edu Low-edu High-edu Medium-edu	0,999 5,52 0,034 * 0,057 ** -0,001 0,010 -0,008 0,001 -0,236 ***	0,999 3,36 0,043 * -0,082 ** -0,038 ** 0,045 *** -0,058 *** -0,004 -0,309 ***	0,986 2,503 -0,523 *** -0,489 *** -0,073 ** 0,021 0,022 0,328 **	1,000 1,7997 0,020 0,075 ** 0,081 *** -0,009 -0,038 * 0,019 -0,206 ***	0,999 2,6291 -0,058 * -0,087 ** -0,016 -0,010 -0,041 ** 0,010 -0,046	1,000 1,6589 0,058 *** 0,084 *** 0,049 *** 0,035 ** -0,082 *** -0,004 -0,287 ***	0,999 2,4142 0,220 *** 0,056 0,043 -0,011 -0,003 0,071 *** -0,314 ***	1,000 1,2599 0,069 **** -0,046 0,010 0,005 0,050 ** 0,024 * 0,303 ***	1,000 0,8217 0,007 0,084 *** 0,101 *** 0,017 * 0,020 * -0,002 0,308 ***	0,999 2,6942 0,064 0,000 0,145 *** 0,049 ** -0,074 *** 0,032 -0,517 ***	
R-squared Absolute Prediction error Beta-coefficients Native work Immigrant work Capital Land Wald test	Medium-edu Low-edu High-edu Medium-edu	0,999 5,52 0,034 * 0,057 ** -0,001 0,010 -0,008 0,001 -0,236 ***	0,999 3,36 0,043 * -0,082 ** -0,038 ** 0,045 *** -0,058 *** -0,004 -0,309 ***	0,986 2,503 -0,523 *** -0,489 *** -0,073 ** 0,021 0,022 0,328 **	1,000 1,7997 0,020 0,075 ** 0,081 *** -0,009 -0,038 * 0,019 -0,206 ***	0,999 2,6291 -0,058 * -0,087 ** -0,016 -0,010 -0,041 ** 0,010 -0,046	1,000 1,6589 0,058 *** 0,084 *** 0,049 *** 0,035 ** -0,082 *** -0,004 -0,287 ***	0,999 2,4142 0,220 *** 0,056 0,043 -0,011 -0,003 0,071 *** -0,314 ***	1,000 1,2599 0,069 **** -0,046 0,010 0,005 0,050 ** 0,024 * 0,303 ***	1,000 0,8217 0,007 0,084 *** 0,101 *** 0,017 * 0,020 * -0,002 0,308 ***	0,999 2,6942 0,064 0,000 0,145 *** 0,049 ** -0,074 *** 0,032 -0,517 ***	
R-squared Absolute Prediction error Beta-coefficients Native work Immigrant work Capital Land	Medium-edu Low-edu High-edu Medium-edu	0,999 5,52 0,034 * 0,057 ** -0,001 0,010 -0,008 0,001 -0,236 ***	0,999 3,36 0,043 * -0,082 ** -0,038 ** 0,045 *** -0,058 *** -0,004 -0,309 ***	0,986 2,503 -0,523 *** -0,489 *** -0,073 ** 0,021 0,022 0,328 **	1,000 1,7997 0,020 0,075 ** 0,081 *** -0,009 -0,038 * 0,019 -0,206 ***	0,999 2,6291 -0,058 * -0,087 ** -0,016 -0,010 -0,041 ** 0,010 -0,046	1,000 1,6589 0,058 *** 0,084 *** 0,049 *** 0,035 ** -0,082 *** -0,004 -0,287 ***	0,999 2,4142 0,220 *** 0,056 0,043 -0,011 -0,003 0,071 *** -0,314 ***	1,000 1,2599 0,069 **** -0,046 0,010 0,005 0,050 ** 0,024 * 0,303 ***	1,000 0,8217 0,007 0,084 *** 0,101 *** 0,017 * 0,020 * -0,002 0,308 ***	0,999 2,6942 0,064 0,000 0,145 *** 0,049 ** -0,074 *** 0,032 -0,517 ***	

1. Sector classification according to TableA1. The model specification includes time-varying dummy variables. ***, **,* significant at 1%, 5% and 10% respectively Standard errors are in parentheses. Wald test for the null of temporal stability of coefficients

workers are significant mostly in *Energy* and *Services* branches, whereas significance for low-educated workers is more scattered across sectors.

1 ((0,33 0,5672)	4,5	0,04
	0,5672)	,	
(. ,	(0,0358)	(0,8427)
2	1,1	5,94	9,04
()	0,2945)	(0,0148)	(0,0026)
3	1,43	0,57	8,24
()),2323)	(0,4496)	(0,0041)
4	0,14	24,32	55,69
()	0,7093)	(0,000)	(0,000)
5	0,72	75,13	9,71
()	0,3966)	(0,000)	(0,0018)
6	1,59	11,34	6,62
()	0,2072)	(0,0008)	(0,0101)
7	4,15	10,83	5,03
()	0,0417)	(0,001)	(0,0249)
8	0,25	3,43	2,44
()	0,6145)	(0,0638)	(0,1179)
9	0,82	6,84	35,68
()	0,3648)	(0,0089)	(0,000)
10	0,15	38,64	28,35
((0,6988)	(0,000)	(0,000)
11	1,53	3,88	1,52
((0,2162)	(0,0489)	(0,2179)
12	0,25	1,53	0,01
()	0,6194)	(0,2161)	(0,9206)
13	6,88	8,9	0,01
()	0,0087)	(0,0029)	(0,9249)
14	2,62	11,46	4,66
()	0,1082)	(0,0009)	(0,0327)
15	0,5	6,27	0,7
(0,4789)	(0,0123)	(0,4016)
16	0,05	3,72	0,95
((0,8274)	(0,0537)	(0,329)
17	2,26	24,65	0,37
((0,1326)	(0,000)	(0,5448)
18	3,21	0,12	7,83
	(0,073)	(0,7254)	(0,0051)
19	0,2	8,7	3,22
	0,6566)	(0,0032)	(0,0727)
20	2,48	0,26	1,65
	0,1153)	(0,6123)	(0,1996)
21	2,74	6,8	0,95
() Note: Wald tests	0,0978)	(0,0091)	(0,3286)

Table 4. Hypothesis Tests for Equality in the Marginal Effects of Native and Foreign Actives by Education Categories

Note: Wald tests. P-values in parenthesis

With regard to immigrants, our results display a high degree of heterogeneity in terms of significance. Thus, medium-skilled workers are significant in 14 branches (in most cases showing a negative sign), whereas high-skilled workers have a significant effect only in 6 branches. Low-skilled workers are in an intermediate position, being significant in 9 branches, most of them in *Industry*. The unexpected absence of significance of less skilled immigrants in *Agriculture* and *Building* could perhaps be explained by the fact that our data do not include undocumented workers which likely enlarge the amount of foreign workers in that sector. Despite several regularisations of illegal immigrants in the last years, they cannot translate into our data ending up in 2005. Another striking result comes from the *Industry* case, where the impact of low and medium educated foreign workers is negative in all its branches. This negative impact can be interpreted as foreign workers constituting a source of comparative disadvantage. This could explain both the small number of overall immigrants in *Industry* and the fact that they are medium-qualified (some qualifications are required, but not as much as to require high-qualified workers).

Next, we analyse which type of relationship, if any, can be found between foreign and native workers. Some mixed results, shown in Table 5, are achieved when the equality of the parameters for native and immigrants workers at the different skill levels is tested. We only reject the hypothesis of equal parameters for high-qualified workers in two cases: sectors 7 (*Paper and printing*) and 13 (*Miscellaneous*). This is not surprising as both native and foreign high-qualified workers are only significant in both sectors. The equality of the parameters for medium-qualified workers is rejected in all the cases in which both native and foreign workers are significant (sectors 1, 2, 4, 5, 6, 7, 10, 13, 15 and 17) and it is accepted in two cases: 3 (*Electricity, gas and water*) and 20 (*Education health and other services*), both with a positive sign. Finally, in the case of low-qualified workers, equality is rejected in the three possible cases: branches 4 (*Food drink and tobacco*), 9 (*Plastic and Rubber*) and 10 (*Metal industries and non metallic products*).

In general, it can be observed that immigrant work is not significant unless native work is also significant in a number of cases: the significant parameter for immigrant workers corresponds to an educational level for which the native counterpart is not significant only in 9 cases out of 63. Moreover, this outcome should be due in part to high standard errors in the case of the estimates for the parameters associated to the immigrant workers variables (see Tables A-2 and A-3). Given the asymmetry of estimated effects for native and foreign workers in most sectors, it is not possible to point to any accumulation or compensation effect of foreign workers relative to native

ones, but a sort of interrelation between both types of labour, especially for medium qualified workers.

	Techniques	Factor Endowments	Residual
Sector	$\overline{V}\left(\hat{R}_{i}^{t}-\hat{R}_{i}^{t-n}\right)$	$\left(V^t - V^{t-n}\right)\hat{\overline{R_i}}$	$\left(\hat{\varepsilon}_{i}^{t}-\hat{\varepsilon}_{i}^{t-n}\right)$
1	47,5	6,7	45,8
2	50,4	0,9	48,7
3	44,5	8,9	46,5
4	47,9	2,1	50,0
5	48,1	1,9	50,0
6	47,8	2,2	50,0
7	47,7	2,3	50,0
8	48,0	2,0	50,0
9	47,9	2,1	50,0
10	46,2	3,8	50,0
11	49,8	0,2	50,1
12	47,7	2,2	50,0
13	47,6	2,4	50,0
14	31,9	57,4	10,8
15	47,9	2,1	50,0
16	47,7	2,3	50,0
17	48,0	2,0	50,0
18	45,0	6,5	48,5
19	48,6	1,2	50,2
20	70,2	28,0	1,8
21	36,6	13,3	50,1
Mean	47,5	7,2	45,4

Table 5. Decomposition of Output Change between 1996 and 2005

Note: Values indicate the cross-region average percentage contributions of the three effects in terms of relative magnitudes, normalised to sum to 100 percent (aside from rounding).

6. Factor accumulation and industrial structure changes from 1996 to 2005

As the final step in the analysis carried out in this paper, the stability of the Rybczinsky parameters over the years has been tested. Although factor endowments have been proved to be significant to determine the value added for the different sectors, changes in the productive structure can be caused by both changes in the level of those endowments or in the way they are combined to produce. In order to incorporate the possibility of changes in production techniques, we need to know about the existence of significant shifts in the estimated parameters of Equation (4) over time. Wald test statistics for the null hypothesis of equality of coefficient estimates for the periods

1996-2000 and 2001-2005 are reported in Table 3. The null hypothesis of constant coefficients can be rejected at standard levels of significance in all the cases. Therefore changes in the techniques of production over the entire period 1996-2005, as measured by the parameter estimates, could be an important source of change in industrial structure.

In order to identify the relative importance of the forces acting on production structures, the estimation results from Equation (4) can be used to decompose the change in output from t-n to t as:

$$Y_i^t - Y_i^{t-n} = \left(V^t - V^{t-n} \right) \widehat{\overline{R}}_i + \overline{V} \left(\hat{R}_i^t - \hat{R}_i^{t-n} \right) + \left(\hat{\varepsilon}_i^t - \hat{\varepsilon}_i^{t-n} \right)$$
(5)

where \overline{V} is the average value of factor endowments in years t and t-n, and \hat{R}_i is the average estimated coefficient matrix in periods t and t-n for industry i. The first term, $\Delta_n V \hat{R}_i$ captures the contribution of changes in factor endowments, holding fixed \hat{R}_i , the estimated techniques of production. The Rybczynski theorem characterises how output responds to changes in endowments at fixed prices and technology, i.e. at fixed techniques of production. Hence, the term $\Delta V \hat{R}_i$ can also be interpreted as the Rybczynski effect. The second term in Equation (5) $\overline{V}\Delta_n \hat{R}_i$ is the effect that changes in production techniques have on shifts in production, holding fixed endowments. Here, "technique" refers to factor usage which depends on technology (i.e. the production function) as well as relative factor prices.¹⁵ The reasons of change in techniques cannot be distinguished in the present framework. However, explaining the changes in the techniques is not our goal, but merely distinguishing them from the factor endowment effect. The final term, $\Delta_n \hat{\varepsilon}_i$, is the difference in the residuals.

Table 5 shows the decomposing analysis in equation (5), to study the percentage contribution of changes in factor endowments and technology to variations in value added between 1996-2000 and 2001-2005. The values reported are the percentage contributions of the terms in Equation (5), expressed as cross-country averages.¹⁶ The overall contribution of factor accumulation, across all industries and years, is about 7.2

¹⁵ Techniques can change for a wide variety of reasons. These include changes in the more primitive forces of technology and preferences. Other sources of change include trade liberalization with the rest of the world, the emergence of new industrialized trading partners, overall factor accumulation within the sample, and even industry-specific shocks.

¹⁶ Since the terms in Equation (5) can be of either sign, a simple average obscures their true contributions. Therefore, the averages are reported in terms of absolute values. Moreover, these components have been normalized to sum to 100 percent.

percent. Changes in the techniques of production contribute about the 47.5 percent. The residual term comprises the remaining 45.4 percent. In general terms, these results give little room for changes in factor endowments to play a relevant role. In fact, they are the dominant source of change only in the case of branch 14 (*Building*), and represent more than a 10 percent in branches 20 (*Education, health and other services*) and 21 (*Household services*). Nevertheless, changes in techniques appear to have played a larger role in most cases, followed by the region-specific changes of each sector which are included in the residual term. Thus, we observe a little Rybczynski effect while the skill-biased technological change has tended to be one important gross force acting on production patterns.

7. Final Remarks

This paper provides a first evidence of the impact of immigration in the pattern of production specialisation across Spanish regions in the period 1996-2005. The extent to which an increase in the immigrant labour force could induce shifts in the industrial structure of regional economies is also quantified. Based on the factor proportions model of international trade, foreign and native labour force are introduced as two separate inputs in an augmented supply production function to estimate how much sectoral output varies with changes in factor endowments, the so-called Rybczynski coefficients.

The results point out that both the effect of factor endowments and specific timevarying regional characteristics in each industry appear to be important in understanding industrial structure. While a higher spatial disaggregation reveals a production indeterminacy problem and a poor performance of the model, the higher sector disaggregation does not seem to generate this indeterminacy problem.

Our first finding is that the data reject the hypothesis of equality in the impact of native and foreign labour by educational type on industrial shares across Spanish regions. This result holds even when we examine those sectors in which the Rybczynski coefficients for natives and immigrants have the same sign. This can be interpreted as natives and immigrants are not perfect substitutes in the production function.

In terms of the impact of factor endowments and its role as a source of comparative advantage across industries within Spain, the results show a small effect caused by the presence of foreign workers. First, only medium-educated foreign workers present a statistically significant effect in most of sectors, whereas the effect of low and high-educated foreign workers appears to be important in less than half of the branches considered. Second, this effect is positive only in four sectors in the case of high and medium-educated workers, and even less for low-educated workers.

If we connect these results to the idea of complementarities between native and foreign labour, we conclude that the presence of immigrants never implies native workers leaving a sector, as shown by the fact that immigrant work is never statistically significant without native works also being. Native work, however, is significant in some activities where foreign workers are not relevant. In general, results suggest a sort of complementarity between natives and immigrants at the different levels of qualification, especially among the medium educated workers.

To conclude, factor accumulation has tended to be the least important gross force acting on production patterns as reflected in the factor proportions model of production. On the contrary, shifts in the national techniques of production have been the more relevant source of changes in relative outputs in Spanish regions. If we agree that immigration has been one of the most important sources of change in factor endowments in Spain in the last years, a strong conclusion stems from our results: immigration is not important in explaining changes in industrial structure in the period 1996-2005.

Appendix

Data sources and variable computations

Data on Gross Added Value (GAV) of 23 sectoral branches (S-23) (Table A1), have been obtained from INE's information. We use 1995-2006 homogenous information on current GAV and variation rates of volume indexes for 5 large production sectors (S-5) to obtain constant base-2000 GAV.

We obtain current 23 branches GAV by using sector shares from year base 1995 data once those shares have been corrected by year base 2000 database revision, and combine it with those GAV values for 23 branches for the period 2000-2006 provided by INE. The main problem with sectoral branches classification in current euros lies on the services sector. While year base-1995 database distinguish between market services branches and non market services branches, year base-2000 database does not distinguish the non market services. Then, in order to reduce branch shares differentials among both databases, we have to consider those branches mainly from public sectors as an aggregated "Education health, public administration and other services" which is obtained as a rest.

We use data from INE's Spanish Labour Force Survey (EPA, 2005 methodology) on active population to measure native and foreign labour endowments. We use data on the second quarter of each year from 1996 to 2005 given its possibility of actualization using the new 2005 methodology, which is adopted explicitly to account for the large wave of immigrants that arrive to Spain form the second half of the nineties. In order to extrapolate population data from sample data, the EPA compute a "elevation factor" variable (so-called 'facele') from population census data. The elevation factor captures the representativeness of each individual in the EPA sample in total population. The 2005 methodology uses information from the last population census carried out in Spain in 2001 to extrapolate population data from sample data by means of a new elevation factor, which is possible to obtain from INE since 1996. The use of the 2005 EPA methodology over the period 1996-2005 is especially relevant for our immigrants' population database because the INE considers that, due to the unexpected fast increase of such population in Spain, the elevation factor computed using the previous population census (1991) severely underestimates immigrant population in total Spanish population.

Data on arable land is provided by INE's *Statistical yearbook of Spain* and interpolated when a specific year is missing

Data on the gross capital stock in current Euros is obtained from estimations provided by the BBVA Foundation and IVIE. Concretely, we use the gross capital stock in current Euros for the period 1995-2004, which is valued at restoration prices. Data on regional gross capital stock in 2005 has been obtained from a Holt-Winter no seasonal smoothing of the 1964-2004 series of regional shares in national total stock of capital, and its application to the total national stock in 2005. For provinces we use the same methodology but ensuring that shares sum up to 100% for provinces belonging to the same region and thus dividing each previous regional stock among its provinces.

Geographic unit	
Provinces (NUTS 3)	Autonomous Communities (NUTS 2)
Period	
1996-2005	1996-2005
Sectors	
1. Agriculture	1 Agriculture
2. Energy	2 Extractive energy and other energetic minerals, oil and nuclear3 Electricity, gas and water
3. Manufactures	 4 Food, drink and tobacco 5 Textiles, clothing, leather, fur 6 Wood products, excl. furniture 7 Paper, printing and publishing 8 Chemical products 9 Plastic, rubber 10 Metal basic industries and other non-metallic mineral 11 Mechanical mach. & Electric and electronic equipment 12 Transport equipment 13 Miscellaneous
4. Building	14 Building
5. Services	 15 Reparation and commerce 16 Hotels 17 Transport and communication services 18 Financial services 19 Renting and business services 20 Education, health and other services 21 Household services

Table A-1. Geographic units and Sector classification

Time dummies		AGRI	ENER	INDUS	BUILD	SERV
Native work	High-edu	0'777	4'663***	-2'865	3'498***	-8'858*
	0	(1'655)	(1'002)	(4'287)	(1'137)	(4'691)
	Medium-edu	1'990* ^{***}	Ò'081	-12'899***	1'535* ^{**}	8'777***
		(0'645)	(0'365)	(1'597)	(0'422)	(1'710)
	Low-edu	2'971***	1'363***	-0'653	0'183	-2'030
		(0'583)	(0'333)	(1'312)	(0'393)	(1'383)
Immigrant work	Hiah-edu	-32'109***	-9'530	-87'806***	-4'469	137'969***
	g	(10'304)	(6'478)	(28'439)	(6'771)	(29'602)
	Medium-edu	-2'737	0'950	-46'177***	6'091**	37'106***
		(3'796)	(2'389)	(9'997)	(2'490)	(10'464)
	Low-edu	25'773***	-2'514	18'624	-7'553**	-31'364**
		(4'638)	(2'693)	(12'536)	(2'975)	(12'919)
Capital		0'004	0'007***	0'027***	0'011***	-0'051***
		(0'003)	(0'002)	(0'009)	(0'002)	(0'010)
Land		0'420***	-0'015	-0'326***	0'012	-0'102
		(0'029)	(0'017)	(0'073)	(0'018)	(0'076)
Time & Regiona	al dummies	AGRI	ENER	INDUS	BUILD	SERV
Native work	High-edu	-1'504*	2'509***	1'161	-1'051	0'383
	0	(0'847)	(0'697)	(1'208)	(0'881)	(1'286)
	Medium-edu	0'522* [´]	1'111* [*] *	1'825* ^{***}	-2'931 ^{***}	1'617* ^{**}
		(0'268)	(0'234)	(0'399)	(0'270)	(0'417)
	Low-edu	1'552* ^{**} *	1'337***	0'187 [´]	-2'207***	1'053* ^{**}
		(0'152)	(0'132)	(0'207)	(0'161)	(0'207)
Immigrant work	High-edu	2'404	-2'370	-3'902	-2'789	1'975
5	0	(2'865)	(2'483)	(4'118)	(2'865)	(4'352)
	Medium-edu	1'510	1'606*	-2'636*	0'641	-0'373
		(1'013)	(0'902)	(1'424)	(0'990)	(1'468)
	Low-edu	-3'484**	2'212**	-2'134	0'283	9'526***
		(1'391)	(1'103)	(1'977)	(1'533)	(2'003)
Capital		-0'007***	0'005***	-0'019***	0'011***	0'007***
•		(0'002)	(0'001)	(0'002)	(0'002)	(0'002)
Land		Ò'031 ໌	-0'105 ^{***}	-0'235***	0'144* ^{**}	0'192***
		(0'026)	(0'021)	(0'034)	(0'025)	(0'034)
Time-varying R	eg. dum.	AGRI	ENER	INDUS	BUILD	SERV
Native work	High-edu	-0'218	2'004***	0'264	-1'092**	1'455
		(0'474)	(0'433)	(0'661)	(0'489)	(0'914)
	Medium-edu	1'134***	0'788***	1'572***	-3'095***	0'037
		(0'187)	(0'187)	(0'267)	(0'177)	(0'380)
	Low-edu	1'326***	1'926***	0'709***	-2'212***	1'298***
		(0'111)	(0'125)	(0'157)	(0'114)	(0'220)
Immigrant work	High-edu	-1'434	-1'100	4'322*	-6'516***	1'803
		(1'619)	(1'580)	(2'383)	(1'655)	(3'286)
	Medium-edu	3'069***	2'426***	-1'956*	0'591	-0'011
		(0'700)	(0'689)	(1'026)	(0'694)	(1'297)
	Low-edu	1'988*	0'877	-2'494*	0'562	6'419***
		(1'053)	(0'964)	(1'443)	(1'042)	(1'849)
Capital		-0'007***	0'007***	-0'019***	0'013***	0'002
		(0'001)	(0'001)	(0'002)	(0'001)	(0'002)
Land		0'061**	-0'034	-0'276***	0'157***	0'259***
		(0'026)	(0'024)	(0'030)	(0'021)	(0'040)
Homogeneity of	Rybczinsky coeffi	cients across	branches be	longing to the	same sector	
Wald test (df)			454,33 (8	3) 1026,67 (72)	1128,67 (48)
P-value			(0,000			(0,000)
*** ***	-+ 10/ E0/ 1 100/ -	. 1 0.	1 1	· 1 V	W-1-1 + + D 1	

Table A-2. Coefficient Estimates. SUR estimates. (1996-2005)

***, **,* significant at 1%, 5% and 10% respectively Standard errors are in parentheses. Wald test: P-values in parenthesis

Table A-3. Coefficient Estimates. GLS and SUR estimates.	(1996-2005).	[Continues]	
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Time dummies	s	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Native work	High-edu	6'3293***	1'147	3'226***	-3'155***	-4'144***	-3'618***	1'535***	0'349	-0'550	0'629	2'365**	1'395	-0'698*	3'223**	4'438***	-31'637***	0'184	4'113***	3'180**	13'872***	0'816***
		(1'2606)	(0'769)	(0'779)	(1'123)	(0'702)	(0'752)	(0'455)	(0'693)	(0'455)	(1'587)	(0'993)	(1'198)	(0'384)	(1'319)	(1'082)	(2'883)	(0'983)	(0'661)	(1'521)	(1'483)	(0'161)
	Medium-edu	4'4128***	0'187	-0'064	-1'269***	-0'303	-0'093	-0'904***	0'305	-0'745***	-2'893***	-1'793***	-2'375***	-0'324**	1'591***	1'954***	3'450***	-0'097	-0'892***	-0'533	3'038***	0'098
		(0'4667)	(0'285)	(0'275)	(0'409)	(0'260)	(0'292)	(0'170)	(0'251)	(0'175)	(0'633)	(0'350)	(0'463)	(0'137)	(0'488)	(0'381)	(1'015)	(0'380)	(0'241)	(0'546)	(0'581)	(0'061)
	Low-edu	1'7337***	0'271	0'956***	1'417***	0'253	0'075	-0'901***	-0'985***	-0'274*	-0'228	-2'014***	-0'889**	-0'230*	0'412	0'093	-1'335	-0'565*	-0'182	0'543	2'316***	0'093*
		(0'4099)	(0'246)	(0'248)	(0'367)	(0'229)	(0'251)	(0'149)	(0'211)	(0'148)	(0'547)	(0'304)	(0'410)	(0'121)	(0'429)	(0'341)	(0'917)	(0'321)	(0'204)	(0'488)	(0'497)	(0'054)
Immigrant work	High-edu	-38'3276***	-3'085	-5'183	-3'889	7'772*	9'129**	2'448	11'671***	-6'698**	-44'856***	-21'729***	-40'828***	-4'074*	-1'962	28'987***	23'697	43'331***	14'713***	78'209***	-1'533	2'165**
		(7'7795)	(5'062)	(4'628)	(7'214)	(4'389)	(4'632)	(2'838)	(4'014)	(2'811)	(10'217)	(5'903)	(7'520)	(2'245)	(8'142)	(6'335)	(16'822)	(6'280)	(4'073)	(9'381)	(8'560)	(0'991)
	Medium-edu	6'6563**	-0'754	1'908	-10'961***	-6'321***	-6'233***	-1'669	-8'259***	-3'724***	-13'025***	-3'481	5'021*	-0'742	4'696	-0'294	21'447***	2'946	-3'061**	-7'965**	12'614***	0'434
		(2'8498)	(1'858)	(1'709)	(2'628)	(1'605)	(1'687)	(1'046)	(1'483)	(1'035)	(3'782)	(2'175)	(2'745)	(0'821)	(2'983)	(2'306)	(6'256)	(2'319)	(1'467)	(3'454)	(3'161)	(0'365)
	Low-edu	15'3771***	3'495	-8'206***	19'203***	8'704***	8'310***	0'090	9'908***	1'247	-9'675**	-1'867	-4'788	6'115***	-6'948*	11'814***	-27'512***	-8'905***	-0'066	1'271	-9'272**	-0'292
		(3'3811)	(2'474)	(1'974)	(3'204)	(1'927)	(2'017)	(1'230)	(1'792)	(1'270)	(4'419)	(2'585)	(3'248)	(1'047)	(3'539)	(2'742)	(7'192)	(2'711)	(1'767)	(4'055)	(3'711)	(0'422)
Capital		-0'0012	0'003	0'003*	0'006***	0'006***	0'007***	-0'004***	0'001	0'001	0'021***	-0'006***	-0'008***	0'002***	0'0120***	-0'009***	-0'024***	-0'013***	0'001	0'009***	-0'011***	0'000
		(0'0024)	(0'002)	(0'001)	(0'002)	(0'001)	(0'001)	(0'001)	(0'001)	(0'001)	(0'003)	(0'002)	(0'002)	(0'001)	(0'00256)	(0'002)	(0'006)	(0'002)	(0'001)	(0'003)	(0'003)	(0'000)
Land		0'4504***	0'012	-0'029**	0'009	-0'012	-0'018	0'005	-0'020*	-0'026***	-0'219***	-0'016	-0'003	0'002	0'000714	-0'053***	0'016	-0'017	0'028**	-0'253***	0'158***	-0'007**
		(0'0210)	(0'014)	(0'013)	(0'018)	(0'012)	(0'013)	(0'008)	(0'011)	(0'008)	(0'029)	(0'016)	(0'020)	(0'006)	(0'0219)	(0'017)	(0'046)	(0'016)	(0'011)	(0'025)	(0'025)	(0'003)
Time & Region	al dummies	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Native work	High-edu	-0'2189	1'442**	0'543	-0'564	-0'028	-0'642	-0'034	-0'225	0'029	-0'237	0'049	0'566	-0'013	0'418	1'072	-0'859	0'838*	1'767***	1'157	0'365	0'012
		(1'2395)	(0'673)	(0'730)	(0'381)	(0'300)	(0'427)	(0'202)	(0'201)	(0'109)	(0'364)	(0'314)	(0'449)	(0'124)	(1'023)	(0'907)	(0'993)	(0'432)	(0'421)	(0'891)	(0'870)	(0'093)
	Medium-edu	0'8671**	0'684***	0'272	0'361***	-0'098	0'054	0'214***	0'337***	0'081**	0'249**	0'395***	0'196	-0'069*	-2'676***	-0'033	-0'055	0'298**	0'074	-0'299	1'979***	0'073**
		(0'3932)	(0'215)	(0'240)	(0'121)	(0'097)	(0'137)	(0'061)	(0'064)	(0'035)	(0'119)	(0'095)	(0'141)	(0'038)	(0'324)	(0'282)	(0'333)	(0'138)	(0'133)	(0'274)	(0'281)	(0'031)
	Low-edu	1'7640***	0'090	1'339***	0'310***	0'032	0'061	-0'024	-0'097***	-0'037*	0'011	-0'064	-0'082	-0'035*	-1'961***	0'362**	-0'433***	0'406***	0'196***	0'149	0'954***	0'123***
		(0'2077)	(0'118)	(0'123)	(0'062)	(0'052)	(0'070)	(0'032)	(0'033)	(0'019)	(0'060)	(0'051)	(0'081)	(0'020)	(0'171)	(0'146)	(0'162)	(0'073)	(0'069)	(0'147)	(0'149)	(0'018)
Immigrant work	High-edu	7'3363*	-1'621	0'359	0'809	-1'933*	-3'663***	1'337**	-0'243	-0'161	-2'520**	-0'367	1'856	0'271	-2'835	-1'561	0'237	2'532*	1'499	-0'259	1'418	1'156***
		(4'1258)	(2'266)	(2'450)	(1'241)	(1'038)	(1'356)	(0'653)	(0'645)	(0'352)	(1'192)	(1'058)	(1'466)	(0'411)	(3'404)	(2'919)	(3'215)	(1'483)	(1'387)	(2'879)	(2'787)	(0'319)
	Medium-edu	-0'5532	3'748***	-2'084**	-0'108	-1'782***	-1'799***	-0'491**	0'047	0'043	-0'465	0'048	-0'157	-0'554***	1'949*	0'882	-3'978***	-1'420***	0'911*	1'879*	1'390	-0'167
		(1'4213)	(0'832)	(0'827)	(0'439)	(0'355)	(0'486)	(0'226)	(0'230)	(0'121)	(0'413)	(0'355)	(0'501)	(0'138)	(1'172)	(1'000)	(1'156)	(0'500)	(0'479)	(0'986)	(0'966)	(0'110)
	Low-edu	-1'5562	1'881	0'816	-3'676***	-1'032**	-1'339**	-0'273	1'310***	-0'513***	0'873	0'606	-0'227	0'068	-0'601	-3'699***	7'139***	0'916	2'213***	1'972	-2'345*	0'438***
		(1'9604)	(1'165)	(1'091)	(0'667)	(0'493)	(0'680)	(0'294)	(0'311)	(0'175)	(0'539)	(0'485)	(0'676)	(0'201)	(1'617)	(1'423)	(1'438)	(0'668)	(0'664)	(1'312)	(1'364)	(0'148)
Capital		-0'0057**	-0'004***	0'009***	-0'001	-0'000	-0'001	-0'001**	-0'001**	-0'001***	-0'000	-0'002***	-0'003***	-0'001***	0'0114***	-0'007***	0'002	-0'004***	-0'004***	0'009***	0'015***	-0'001***
		(0'0024)	(0'001)	(0'001)	(0'001)	(0'001)	(0'001)	(0'000)	(0'000)	(0'000)	(0'001)	(0'001)	(0'001)	(0'000)	(0'00200)	(0'002)	(0'002)	(0'001)	(0'001)	(0'002)	(0'002)	(0'000)
															01440444							01004
Land		0'0806**	-0'052**	-0'079***	-0'073***	0'015	0'015	-0'021***	0'011*	-0'012***	-0'078***	-0'019**	-0'027**	-0'002	0'113***	-0'003	0'043	-0'009	0'047***	0'024	0'048*	-0'004

***, **,* significant at 1%, 5% and 10% respectively Standard errors are in parentheses

Table A-3 [continue]. Coefficient Estimates. GLS and SUR estimates. (1996-2005)

Time-varying R	leg. dum.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Native work	High-edu	-0'1699	0'623***	1'199***	0'116	-0'027	-0'311	0'210**	-0'064	-0'029	-0'219	-0'112	0'285*	0'124*	-1'194	0'401	-1'243*	0'892***	1'826***	1'905***	0'255	0'115
		(0'7565)	(0'194)	(0'277)	(0'130)	(0'100)	(0'262)	(0'100)	(0'098)	(0'073)	(0'154)	(0'128)	(0'168)	(0'073)	(0'779)	(0'558)	(0'664)	(0'345)	(0'347)	(0'699)	(0'575)	(0'071)
	Medium-edu	1'0502***	0'306***	0'954***	0'148***	0'145***	0'331***	0'137***	0'164***	0'016	0'132**	0'138***	0'136**	-0'069**	-3'133***	0'440**	-0'576**	0'368***	0'134	-0'366	0'940***	-0'000
		(0'2949)	(0'078)	(0'120)	(0'047)	(0'040)	(0'102)	(0'037)	(0'040)	(0'027)	(0'062)	(0'047)	(0'063)	(0'027)	(0'304)	(0'211)	(0'263)	(0'137)	(0'135)	(0'265)	(0'240)	(0'029)
	Low-edu	1'3711***	0'075	1'387***	0'338***	0'016	0'008	0'028	-0'010	-0'041**	-0'136***	0'015	-0'004	-0'037**	-2'237***	0'539***	-0'143	0'210***	0'099	0'086	1'227***	0'087***
		(0'1717)	(0'049)	(0'077)	(0'027)	(0'024)	(0'060)	(0'021)	(0'022)	(0'016)	(0'037)	(0'027)	(0'039)	(0'016)	(0'177)	(0'124)	(0'139)	(0'077)	(0'079)	(0'152)	(0'143)	(0'018)
Immigrant work	High-edu	-1'8056	-0'136	-0'061	-0'057	0'310	-1'487*	0'935***	-0'248	-0'269	-0'434	-0'722	0'602	0'858***	-5'947**	-1'030	-1'751	2'840**	-0'435	0'806	3'514*	0'566**
		(2'6278)	(0'677)	(0'971)	(0'417)	(0'370)	(0'866)	(0'327)	(0'340)	(0'242)	(0'522)	(0'450)	(0'578)	(0'258)	(2'707)	(1'829)	(2'124)	(1'211)	(1'172)	(2'292)	(1'892)	(0'253)
	Medium-edu	3'2888***	1'051***	1'269***	-0'730***	-1'108***	-0'876**	-0'321**	-0'101	-0'237**	-1'182***	-0'200	-0'147	-0'358***	0'549	-1'364*	-2'298**	-2'081***	-0'035	2'541**	1'347*	-0'271***
		(1'0806)	(0'311)	(0'426)	(0'178)	(0'147)	(0'370)	(0'144)	(0'147)	(0'099)	(0'220)	(0'177)	(0'237)	(0'101)	(1'113)	(0'741)	(0'908)	(0'502)	(0'488)	(1'006)	(0'806)	(0'105)
	Low-edu	1'6821	1'454***	-0'220	-1'910***	-0'676***	-1'435**	-0'407**	-0'364	-0'924***	-1'990***	-0'288	0'028	-0'051	1'243	1'500	1'125	-0'235	2'083***	2'676*	-0'247	0'230
		(1'5596)	(0'460)	(0'561)	(0'301)	(0'222)	(0'560)	(0'194)	(0'226)	(0'147)	(0'349)	(0'246)	(0'319)	(0'150)	(1'607)	(1'136)	(1'292)	(0'732)	(0'707)	(1'437)	(1'141)	(0'145)
Capital		-0'0067***	-0'000	0'007***	0'002***	-0'001***	-0'002**	-0'001***	-0'001**	-0'001***	-0'001**	-0'002***	-0'002***	-0'001***	0'012***	-0'004***	-0'001	-0'005***	-0'003***	0'009***	0'012***	-0'001***
		(0'0020)	(0'001)	(0'001)	(0'000)	(0'000)	(0'001)	(0'000)	(0'000)	(0'000)	(0'000)	(0'000)	(0'000)	(0'000)	(0'002)	(0'001)	(0'002)	(0'001)	(0'001)	(0'002)	(0'002)	(0'000)
Land		0'0775**	-0'003	-0'101***	-0'046***	-0'008	0'003	-0'023***	-0'001	-0'010***	-0'077***	-0'021***	-0'017**	-0'002	0'154***	-0'077***	-0'028	-0'033**	0'043***	0'087***	0'105***	-0'003
		(0'0339)	(0'010)	(0'013)	(0'005)	(0'005)	(0'012)	(0'004)	(0'005)	(0'003)	(0'007)	(0'005)	(0'007)	(0'003)	(0'035)	(0'026)	(0'027)	(0'015)	(0'016)	(0'030)	(0'028)	(0'003)

Note: ***, **,* significant at 1%, 5% and 10% respectively. Standard errors are in parentheses.

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