The impact of immigration on the labour market: Evidence from 20 years of cross-border migration to Argentina

Battiston, Diego

London School of Economics, CEP

2013

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Diego Battiston

London School of Economics

Abstract

This paper studies the effects of immigration on the wages of Argentinean native workers over the period 1993-2012. I use a novel micro-dataset which combines household surveys from Argentina and six other Latin American countries. Immigration from these six countries accounts for 95% of the total immigration from Latin American countries. The empirical strategy identifies the effects of the labour supply variation using the "national approach" from Borjas (2003) and a reduced form equation obtained within a CES framework. In order to account for demand/pull shocks, I propose a set of instruments based on labour market conditions in immigrants' home countries. An alternative specification also explores the hypothesis of heterogeneous impact by country of origin. Overall, findings show a significant negative impact of immigration on wages. IV estimates suggest that OLS results are a lower bound for the (partial) causal effect. Thus, if confounding demand factors exist, they bias the results toward zero.

1. Introduction

During the last years there has been an active debate about the effects of immigration on the labour market, particularly on the impact on the wage structure of native population. Borjas (2003) develops a framework to account for such impact evaluating immigration as a labour supply shock for workers with similar characteristics. In two recent works, Manacorda, Manning and Wadsworth (2012) and Ottaviano and Peri (2005) extend the standard setting to allow for imperfect substitution between migrants and natives. Both papers find evidence of imperfect substitution and a low impact of immigration on the wage structure of natives for the UK and the US. Peri and Sparber (2009) conclude that the lack of substitution between natives and immigrants could be driven by differences in linguistic abilities and other cultural dissimilarities. A natural follow-up question arises about the

[1] I thank Alan Manning, Soledad Giardili and Guillermo Cruces for helpful comments and suggestions. I also thank Pablo Gluzmann for helpful support with SEDLAC database. PRELIMINAR VERSION.

effects of immigration in countries with higher rates of immigrants' assimilation and fewer differences with their home cultures.

Most of the academic debate about immigration has been focused on traditional corridors like Mexico-US and other South-North corridors. However, South-South migration has interesting characteristics and may contribute to the debate about the impact of immigration. Particularly, cross-border migration to Argentina has not received much attention in the academic literature. Few descriptive works exists about immigration in this corridor and no work attempted to estimate the causal impact on the local labour market. The magnitude of migration flows to Argentina was significant in the last decades. Jachimowicz (2006) estimates an average inflow of 15.000 permanent migrants per year between 1995 and 2002. According to the 2010 census, approximately 5% of the total population in Argentina is foreign and 81% of this group migrated from Latin American countries. In some areas this value increases notably, for instance, foreign population in Buenos Aires city represents 13.2% of total population.

There are some characteristics that make this corridor an interesting case of analysis. First, all the countries in the region (with few exceptions) have a common language and cultural barriers seem to be lower than in other corridors. Moreover, this characteristic has a methodological advantage: Dustmann and Fabbri (2003) and Dustmann and Preston (2011) conclude that language differences reduce the ability of immigrants to find a job that suits with their education and experience. The "downgrading effect" produced by language violates the identification assumptions of common approaches. Second, legal barriers to immigration are much weaker than the case of US or UK policies and illegal immigration is presumably lower. Third, during the last decades, most immigrants arrived from a small group of countries. Finally, the composition of immigrant population by country of origin has changed drastically over time.

This paper contributes to the existing literature in different ways: First, it is the first empirical work addressing the impact of immigration on the labour market in this important corridor. I address specific problems and characteristics related to the South- South corridors, for instance, internal migration and native emigration are recognised as confounding factors of the causal impact. Second, in order to isolate supply shocks from demand/pull factors, I propose a set of instrumental variables using a novel micro-database with harmonized socioeconomic information from six LAC countries. These countries accounts for 95% of recent Latin American migration toward Argentina. This paper also explores the hypothesis that the effect on wages varies by country of origin under imperfect substitution among immigrants. This is particularly interesting in the case of Argentina since the composition of immigration has been changing during the last 20 years. Indeed, some countries like

Paraguay, Bolivia and Peru have notably increased their share in total Latin-American immigrant population.

The rest of the paper is organized as follows. Section 2 discusses the CES framework and the wage equations for natives and immigrants. Section 3 describes Data. Section 4 briefly summarizes the evolution of immigrant flows to Argentina and discusses some facts and evidence of this process. Section 5 discusses the baseline empirical setting and alternative identification strategies like IV and geographical stratification. Section 6 presents all the results and Section 7 summarizes the main conclusions of this work.

2. Theoretical framework

2.1. The basic model

Consider a version of the model proposed in Manacorda, Manning and Wadsworth (2012) which in turn is based on the model in Card and Lemieux (2001). Firms produce using a neoclassical production function that combines labour and capital. For simplicity, assumes that it can be represented by a Cobb-Douglas function with neutral technological change:

(1) $$Y_t = A_t K_t^{1-\alpha} L_t^{\alpha}$$

Capital can be assumed either fixed in the short run or endogenous in the long run but exogenous from the point of view of a firm deciding the composition of the bundle of labour inputs. Labour is a composite input that aggregates different skill groups (indexed by *e*) using a CES technology:

(2) $$L_t = \left[\sum_{e=1}^{E} \theta_{et} L_{et}^{\rho} \right]^{\frac{1}{\rho}}$$

where $\theta_{1t} = 1$ is the usual normalization for the relative efficiency parameters. Substitution between different education groups is measured by the elasticity of substitution $\sigma_E = 1/(1-\rho)$. Similarly, L_{et} is composited by different experience groups *a=1,..,A*.

(3) $$L_{et} = \left[\sum_{a=1}^{A} v_{ea} L_{eat}^{\eta} \right]^{\frac{1}{\eta}}, \qquad e = 1,\ldots,E \quad ; \quad a = 1,\ldots,A$$

The relative efficiency parameter v_{ea} is assumed to be time invariant and v_{e1} is normalized to one. The elasticity of substitution across experience groups is equal to

$\sigma_A = 1/(1-\eta)$. Finally, native and immigrant sub-population are (potentially) imperfect substitutes:

(4) $$L_{eat} = \left[L_{neat}^{\delta} + b_{eat} L_{meat}^{\delta} \right]^{\frac{1}{\delta}} , \qquad e = 1,...,E \;\; ; \;\; a = 1,...,A$$

where L_n is the native sub-population and L_n is the immigrant sub-population and parameter b_{eat} accounts for differences in efficiency units provided by immigrants. Substitution between natives and immigrants is equal to $\sigma_M = 1/(1-\delta)$. Assuming competitive markets, wages are equated to marginal productivity for each type of worker.

(5) $$w_{neat} = \alpha Y_t \theta_{et} L_t^{-\rho} L_{et}^{\rho-\eta} v_{ea} L_{eat}^{\eta-\delta} L_{neat}^{\delta-1}$$

(6) $$w_{meat} = \alpha Y_t \theta_{et} L_t^{-\rho} L_{et}^{\rho-\eta} v_{ea} L_{eat}^{\eta-\delta} b_{eat} L_{meat}^{\delta-1}$$

The empirical version of equations (5) and (6) can be easily derived, consider for example the log-transformation of (5):

(7) $$\log w_{neat} = \tilde{\alpha} + \tilde{Y}_t + \tilde{\theta}_{et} + \tilde{v}_{ea} - \rho \log L_t + (\rho-\eta)\log L_{et} + (\eta-\delta)\log L_{eat} + (\delta-1)\log L_{neat}$$

where $\tilde{\alpha} = \log \alpha$, etc. Even though the terms $\tilde{\alpha}$, $\tilde{Y}_t$, $\tilde{\theta}_{et}$ and $\tilde{v}_{ea}$ can be absorbed by a set of dummies and interactions, equation (7) cannot be directly estimated by OLS since for example L_{eat} only can be calculated when there is an available estimation of δ. Manacorda, Manning and Wadsworth (2012) propose an econometric procedure to estimate the structural version of a similar model in several steps, that approach is briefly discussed in section 5 but beyond the scope of this paper.[2]

This simple CES framework is the base of the empirical strategy discussed in Section 5 and is has been widely used in recent literature because it allows for a high degree of flexibility in terms of substitution across education and age dimension but only imposes a low number of parameters to estimate. The main disadvantage of the nested CES approach is that substitution within education or age dimension is constant, for instance, the substitution degree between workers with high and medium education is assumed to be the same than substitution between workers with high and low education. Section 5 describes an empirical strategy to identify

[2] An analogous wage equation to (7) holds for immigrants under the assumption of no market discrimination against them. However, if this (negative) discrimination premium is assumed to be proportional to the counterfactual wage in a scenario without discrimination, a simple reinterpretation of the constant term can accommodate this problem. In other words, $\tilde{\alpha}_m = \log \alpha + \log D$, where D is the proportional discrimination adjustment.

some aspects of this model without relying on the structural estimation of all the parameters.

2.2. Accounting for heterogeneity by country of origin

The basic model assumes that immigrants are perfect substitutes independently of the country of origin. There are many reasons to believe that migrants from different countries are not perfect substitutes. First, countries of origin are heterogeneous in terms of culture, education quality, and other unobserved variables. Second, even though this model takes into account differences in education and experience, selection in unobservables (Borjas, 1987) is a potential source of heterogeneity between workers from different countries. For example, sorting across sectors seems to be very different for workers from different countries, indicating some unobserved differences between migrants with same education/experience but different nationality (Patel and Vella, 2007, Toussaint-Comeau, 2007).

To allow for imperfect substitution across nationalities, I assume that immigrant population can be aggregated by means of a CES technology with substitution[3] $\sigma_J = 1/(1-\pi)$:

(8) $$L_{meat} = \left[\sum_{j=1}^{J} c_{jmeat} L_{jmeat}^{\pi} \right]^{\frac{1}{\pi}}$$

with c_{1meat} normalized to one. In this case, theoretical wages also varies within cells with the supply of workers from countries of origin *j=1,…,J*. The reason to allow c_{jmeat} to vary along time is that immigration waves from the same country can change in terms of efficiency units because different economic or legal conditions in origin and destination can change the self-selection patterns (Longhi and Rokicka, 2012). First order conditions, assuming no discrimination against immigrants, imply that wages for each education-age-immigrant group are given by:

(9) $$w_{jmeat} = \alpha Y_t L_t \theta_{et} L_t^{-\rho} L_{et}^{\rho-\eta} a_{ea} L_{eat}^{\eta-\delta} b_{eat} L_{meat}^{\delta-\pi} c_{jmeat} L_{jmeat}^{\pi-1}$$

Although there is an extensive literature estimating the impact of immigration on wages, there are no attempts to identify heterogeneity of this impact by country of origin. The only exception (to my knowledge) is Bratsberg et al. (2011) who use a

[3] Alternatively, it can be assumed that $L_{eat} = (L_{neat}^{\delta} + \sum_{m=1}^{M} b_{eat} L_{meat}^{\delta})^{\frac{1}{\delta}}$ with m indexing the immigrant nationality. This specification means that substitution between natives and immigrants is the same than substitution between two groups of immigrants.

panel dataset from Norway to test if immigration from Nordic and high income countries had a different effect than immigration from developing countries.

3. Data

The main source of data for this paper is the Socioeconomic Database for Latin America and the Caribbean (SEDLAC), jointly developed by CEDLAS at the Universidad Nacional de La Plata (Argentina) and the World Bank's LAC poverty group (LCSPP). This database contains information on more than 200 official household surveys in 25 LAC countries. All variables in SEDLAC are constructed using consistent criteria across countries and years, and identical programming routines[4]. In this paper I use micro-data for Argentina and a set of six Latin American countries that account for more than 95% of immigrant flows from the region. Most of the analysis is done using the Argentinean sub-sample but the IV strategy uses information at the level of the country of origin of the immigrants.

The data covers the period 1993-2012. For comparison purposes, I restrict the sample for each country to those areas covered by the national household survey in the whole period of analysis. In the case of Argentina, only 18 large urban areas had information on immigration in the 1993 survey and I restrict subsequent years to the same geographical coverage.[5] Micro-data for Argentina in the SEDLAC database corresponds to the *Encuesta Permanente de Hogares* officially carried out by the *Instituto Nacional de Estadística y Censos* (INDEC) since the 1980s. In the case of Brazil I exclude Rural-North areas included since 2004 and I only use urban areas from Uruguay since rural areas were added in 2006. The case of Bolivia is more restrictive since only regional capital cities and the city of El Alto, were covered in 1993 and I restrict the sample to these cities for all the available years. Since there is no available information for Peru before 1997, I use the 10% census IPUMS extract for 1993. To keep consistency and comparability across years I harmonize the Census data applying the same methodology and definitions than SEDLAC database. Unfortunately, income information is not available for Peru 1993 Census data. Table 1 reports data availability for each year and country included in the sample.

It is worth mentioning that the official EPH survey from Argentina was carried out in two rounds (May and October) until 2003 but SEDLAC database only contains the October round for that period. On the other hand, SEDLAC micro-data is

[4] A detailed description of the methodology and definitions is available at http://sedlac.econo.unlp.edu.ar/eng/methodology.php

[5] The geographical coverage of the survey was extended from 15 urban areas in 1992 to 31 urban areas in 2003. Nevertheless, the 18 areas included in 1993 account for 85% of the population in the latest years of the survey (which represents 70% of the total urban population in the country). On the other hand, the share of urban population is estimated to be 87%.

available for both semesters since 2003[6]. In order to keep consistency and exploit all the information available, I process and harmonize the May round of the EPH for each year within the period 1993-2003 using the same definitions and methodology than the SEDLAC database.

Table 1: Micro-data available for the covered period

Country/Year	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Argentina	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**
Bolivia	x				x		x	x	x	x	x	x	x	x	x	x			x	
Brazil	x		x	x	x	x	x		x	x	x	x	x	x	x	x	x		x	
Chile		x		x		x		x			x			x			x		x	
Paraguay			x		x		x		x	x	x	x	x	x	x	x	x			
Peru	x				x	x	x	x	x	x	x	x	x	x	x	x	x	x		
Uruguay			x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	

Notes: ***Argentina***: Each year pool first and second semester data except for 1993 and 2012 with only one semester available. ***Bolivia***: 2003 and 2004 unified survey. ***Chile***: 1992 survey also included in the sample. ***Peru***: 1993 correspond to the IPUMS 10% census sample. ***Uruguay***: 1992 survey also included

Another difference between SEDLAC and the data I use in this work is that the former does not have detailed information on immigration. For that purpose, I identify immigrants by country of origin and year of arrival from the original EPH survey and match this information at individual level with the SEDLAC dataset.

4. Immigration in Argentina during the last decades

Argentina is a country with a long tradition in immigration inflows. European mass migration during the late 19th and the early 20th century has been considered among the largest population inflows experienced by a country (Hatton and Williamson, 1998). During that period Argentina implemented a set of active policies to incentive immigration. For instance, the Constitution from 1853 prohibited any barrier, tax or quota to European immigration. Census records show that the immigrant population increased from 210 thousands to 2.3 million between 1869 and 1914. By that time, the immigrant share over total population reached 30%. European inflows started to decline after 1914 and virtually stopped in the late 1950s after a short period of high inflows during the 5 years following the Second World War (Solimano, 2003).

In the last decades, immigration from Latin American countries, particularly from Bolivia, Chile, Paraguay, Peru and Uruguay, shifted the older European waves. As discussed in Pacceca and Courtis (2008) there was an important shift in the destination of Latin American immigrants before and after the 60s. The inflows of

[6] There is a methodological change from 2003 and now the survey is conducted over the whole year and reported in quarterly sub-samples. SEDLAC database groups the 4 subsamples in first and second semester respectively.

workers before 1960 were concentrated in rural areas where the labour supply had dropped due to internal migration toward urban areas. Immigrants usually moved between locations and most of them frequently returned to their home countries. After 1960, most of the immigrants arrived to large urban areas and stay permanently. Political instability during the 70's and 80's in Uruguay and Chile[7] suddenly increased the share of immigrants from these countries whereas inflows from Bolivia and Paraguay have been continuously increasing since the 50s and in the case of Peru since the 80s in (Maurizio, 2007).

During the last two decades, according with Census data, the number of immigrants born in Bolivia, Brazil, Chile, Paraguay, Peru and Uruguay increased from 817 thousands in 1991 to 1.4 million in 2010 (Castillo and Gurrieri, 2012). This increase was not monotonic along the period neither homogenous across home countries. The economic crisis in 2001 temporarily reduced the migration inflows, accelerated the number of immigrants who returned home and increased the emigration of native population. After 2003 there is an important increase in the number of immigrants from Bolivia, Brazil, Paraguay and Peru although the number of Uruguayan remains stable and the number of Chileans decreases. Overall, immigration from these six countries increased 39% between 2001 and 2010. Figure A1 in the appendix shows the distribution of immigrants by country of origin in South America according to the last Census. The figure also plots the geographical location of the 18 urban areas covered in the Argentinean sample.

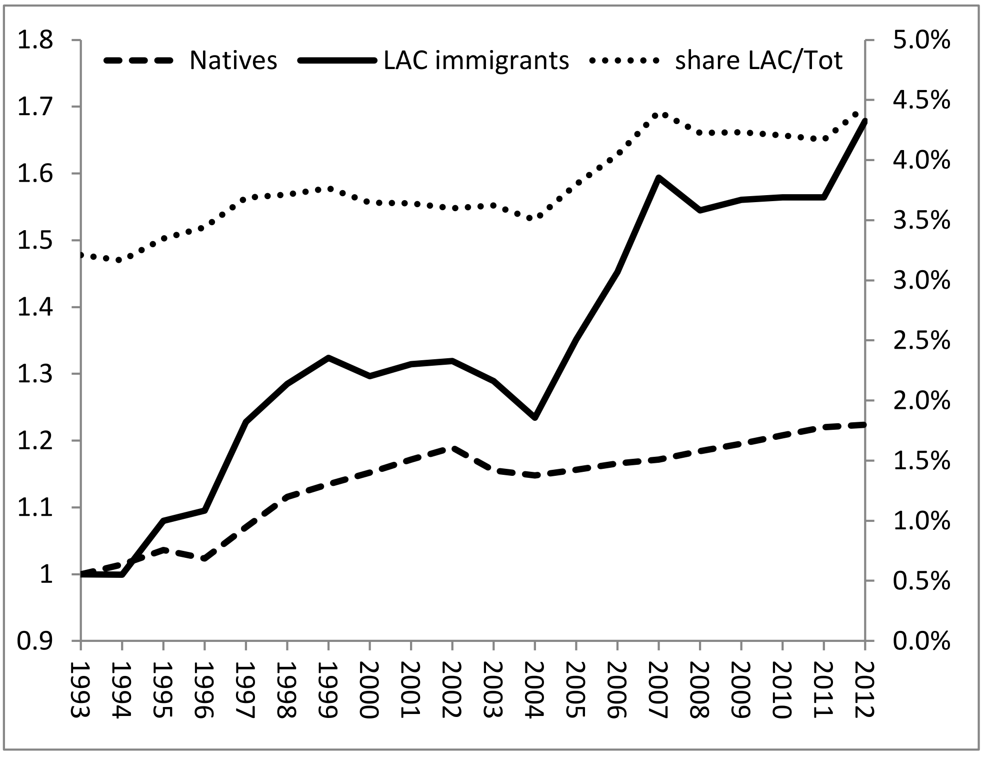
Beyond the after-crisis recovery of the Argentinean economy, the large increase in immigration during the last decade also coincided with the introduction of a new immigration law in 2004 (Law 25,871). The new law shortens the length of time required to obtain the Argentinean citizenship or the permanent residence permission, relaxes the requisites to obtain it and also legalizes the situation of thousands of immigrants who were not formally registered as workers. The previous immigration law dated from 1981 (during the military government) and was more restrictive, but in practice, the barriers to immigration were relatively low. The lack of frontier controls, the high level of informality in the labour market, regular amnesty laws (in 1974, 1984, 1992 and 1994) and the 1998 bilateral migration agreements with Bolivia and Peru, contributed to the low effectiveness of the 1981 law[8].

[7] Political instability characterized the whole region during these decades but the military coups occurred in 1973 in Uruguay and Chile were highly correlated with the sudden increase in the emigration rates from these countries (see for example Pellegrino and Vigorito, 2005)

[8] For instance, before 1994 it was possible for any immigrant to change the residence status from "temporary" (tourists for example) to "permanent" without leaving the country. After 1994 this process was more regulated although it was still feasible to remain in the country as a worker with a temporary permission. A whole analysis of the immigration laws since 1876 can be found in Pacecca and Courtis (2008).

The rest of this section uses information from the dataset described in Section 3. The panel A of Table 2 shows the population represented in the sample of 18 larger urban areas considered in this paper. Individuals are classified by country and region of birth. During the period under analysis, native population living in the 18 covered urban areas grew around 20% whereas the number of immigrants from Latin American countries increased almost 70%. These dissimilar changes boosted the share of LAC immigrants over total population from 3.4% to 4.5% (Figure 1). The figures by country/region of origin from household surveys match the Census data. Immigration from Bolivia, Peru and Paraguay increases over the period, remains stable for Chile and decreases for Uruguay. European immigration decreases considerably but this effect is driven by the aging of the stock of Europeans who arrived to the country many decades ago. The largest group of immigrants is from Paraguay, followed by Bolivia and Peru. The number of immigrants drops between 2001 and 2004 for all countries except Bolivia and Peru. After 2004, immigration from all countries increases except from Chile where this value fluctuates more.

Figure 1: Native and Immigrant index (1993=1; left axe) and share of immigrants over total population (right axe).



Source: Own calculations based on SEDLAC and EPH.

Table 2: No. of individuals (thousands) represented in the sample (1993-2012).

	Year	Native population	Immigrants by country/region of origin: LAC countries	Bolivia	Chile	Paraguay	Peru	Uruguay	Europe	Share LAC/total population
A- Whole sample	1993	16,399	563.4	103.5	103.0	187.6	21.0	119.6	559.8	3.2%
	1994	16,633	563.1	96.4	102.9	193.5	24.2	122.6	543.3	3.2%
	1995	16,988	608.4	103.3	121.6	221.3	32.5	105.6	520.6	3.3%
	1996	16,781	617.0	102.8	128.4	216.4	27.0	119.3	493.3	3.4%
	1997	17,554	691.8	134.7	151.6	208.1	26.5	148.4	487.5	3.7%
	1998	18,294	724.0	141.6	141.2	238.4	46.4	134.6	459.7	3.7%
	1999	18,609	746.0	137.5	132.9	270.0	64.7	114.2	423.5	3.8%
	2000	18,890	730.6	127.0	118.8	261.4	84.5	110.4	389.8	3.6%
	2001	19,217	740.6	138.0	114.8	282.5	77.6	95.4	353.7	3.6%
	2002	19,509	743.1	188.1	112.6	261.5	64.7	89.2	365.5	3.6%
	2003	18,941	726.4	179.9	103.6	232.6	81.9	104.9	353.4	3.6%
	2004	18,821	695.4	161.2	105.3	247.3	79.8	81.2	287.7	3.5%
	2005	18,958	761.5	195.7	103.4	263.1	76.3	99.0	283.3	3.8%
	2006	19,119	818.2	216.6	92.4	285.0	92.9	103.9	263.2	4.0%
	2007	19,209	897.9	247.0	86.5	262.7	155.3	107.7	249.7	4.4%
	2008	19,421	870.2	195.9	91.1	305.6	120.6	121.5	261.4	4.2%
	2009	19,598	879.2	209.3	107.4	312.3	116.7	91.8	253.5	4.2%
	2010	19,808	881.3	221.0	110.2	322.0	119.3	72.2	232.5	4.2%
	2011	20,009	881.4	203.5	106.4	309.1	127.3	91.2	211.4	4.2%
	2012	20,068	945.8	228.6	95.5	322.0	154.2	91.0	212.4	4.4%
B- Sub-sample of Men [18-65]	1993	3,588	171.2	27.6	35.7	53.1	11.2	41.7	100.5	4.4%
	1994	3,574	179.0	31.5	31.9	58.7	10.9	42.7	100.3	4.6%
	1995	3,470	174.4	33.1	35.3	57.3	10.6	35.4	93.7	4.6%
	1996	3,442	174.9	33.1	37.5	52.7	9.3	37.5	80.6	4.7%
	1997	3,728	210.9	40.5	44.8	58.6	8.4	54.9	84.6	5.2%
	1998	3,900	213.7	34.9	44.0	71.7	10.6	48.9	86.9	5.1%
	1999	3,903	212.3	37.7	41.9	70.6	18.9	40.2	74.2	5.1%
	2000	3,917	211.3	37.4	37.0	69.1	25.1	38.3	58.3	5.0%
	2001	3,836	199.2	37.2	33.1	69.7	17.5	33.6	41.9	4.9%
	2002	3,720	197.3	51.5	28.5	60.9	21.3	29.1	40.6	5.0%
	2003	3,907	193.6	54.4	22.5	53.8	20.0	35.8	48.3	4.7%
	2004	4,179	212.5	51.4	34.2	77.0	20.3	27.5	35.9	4.8%
	2005	4,300	235.2	61.0	34.0	75.7	21.6	37.4	37.9	5.1%
	2006	4,409	247.4	66.0	29.6	81.8	23.1	39.6	37.2	5.3%
	2007	4,531	249.9	74.7	27.7	63.9	34.4	38.4	36.8	5.2%
	2008	4,584	260.7	63.9	29.8	81.3	31.4	47.3	34.5	5.3%
	2009	4,615	244.8	61.4	31.9	81.3	30.7	30.0	35.2	5.0%
	2010	4,766	255.4	66.8	31.1	89.8	35.4	24.2	20.4	5.1%
	2011	4,898	262.5	68.5	28.8	83.3	33.3	37.9	15.6	5.1%
	2012	4,778	268.1	75.3	20.3	72.5	42.3	43.0	27.6	5.3%

Notes: 18 major cities represented in 1993 survey. Source: Own calculations using SEDLAC and EPH.

The panel B of Table 2 shows the number of male workers with 18 to 65 years old represented in the survey. This subsample constitutes the basis of the analysis in this paper. Trends are similar than those discussed for total population. For this subsample, in 2012 the largest number of immigrants is from Bolivia and Paraguay followed by immigrants from Uruguay and Peru. The percentage of Latin American immigrants in this subsample rose from 4.4% to 5.3% over the period under analysis.

It is important to mention that these figures relies on household surveys data which is subjected to some methodological issues and higher measurement error than census data.[9]

5. Empirical strategy and identification

5.1. Definitions and methodological decisions

I follow Borjas (2003) and restrict most of the analysis for the subsample of men aged 18-65 who participate in the labour force, however, some specifications use information about men not active in the labour market. I also exclude from regressions (and estimations related to earnings) those individuals who report themselves as self-employed or those working at family firms without a well-defined salary. Following Card and Lemieux (2001) and Manacorda, Manning and Wadsworth (2012), I pool different years of the survey. Conversely to those works, I define the length of each period as 4 years (instead of 5) to be consistent with the distinction between new arrived and established immigrants defined for the same length.[10] Consistently to the definition of periods, I categorize individuals in 12 age-groups of 4 years each. This decision contrasts with Borjas (2003), Bratsberg et al. (2012) and Ortega and Verdugo (2011) who use experience instead of age. As pointed by Card and Lemieux (2001) using age has the advantage of comparing individuals who attended the same education level at the same time and therefore were subjected to the same influences regarding their education decisions. On the other hand, only potential experience can be identified in the data. Since there is not an obvious way of partitioning labour force into age/experience categories, I perform some robustness exercises in order to detect if results are driven by this specific partition.

SEDLAC database define 6 levels of education which are homogeneous across years and countries. This is an important feature since questionnaires have undergone some changes in the educational module during the 20 years covered by this work. I group the 6 levels into 4 broader educational levels consistently with previous literature[11]. The categories are defined as *1) Primary education or no formal education; 2) High school dropouts; 3) High school graduates or college dropouts; 4)*

[9] For household surveys analysis, comparison between ratios and proportions is more reliable than comparison between absolute values, particularly across years.
[10] After the second semester of 2003 the survey only allows to identify whether the immigrant arrived within 4 years before the survey or not.
[11] It is also inconvenient that partition into 6 education levels implies a large number of cells with zero immigrants and low number of natives.

Professionals or university graduates. These definitions are more suitable for Argentina than definitions used in Borjas (2003) for the US since a higher share of workers are concentrated in low educational levels.

In order to relate as much as possible earnings with productivity (demand side) avoiding at the same time the indirect effect of changes in supply decisions through working hours, wages are defined as the total weekly earnings from the main occupation divided by the number of worked hours in that occupation during the week before the survey. In some specifications I also report monthly earnings from main occupation. An important caveat that should be considered is the comparison of wages across periods. The official Consumer Price Index reported by the *Instituto Nacional de Estadisticas* y Censos *(INDEC)* in Argentina has been severely criticized and widely discredited during the last few years due to a recurrently underestimation of the true inflation. This concern is particularly relevant for the last period considered in this paper (see for example Cavallo, 2013). For this reason I deflate wages in the period 2008-2012 using the average of the non-official CPIs reported by different private consultants.[12] For the rest of the years I use the official CPI.[13] I exclude from earnings estimations all the individuals with hourly incomes above $45 and below $0.2 (at 2010 prices).

Individuals are classified as immigrants based on their country of birth irrespective of the age of arrival or their parents' citizenship. Immigrants are considered as "established" if they arrived to the country at least four years before the survey. I focus on immigration from Latin American countries and ignore the reduction in the stock of Europeans. There are two reasons for this decision, first, most of the European immigrants who participate in the labour force arrived to the country as children and second, the stock decline of European immigrants is mainly due to retirement of workers who arrived during the 50s. Table A2 in the Appendix shows evidence supporting these arguments. The median age of male European immigrants participating in the labour force was already high in 1993 (53 years old) and increased over the last 20 years. The median age of arrival is below 12 in any survey and around 6 in the last 5 years with available information. The median year of arrival is 1952 in almost all the surveys[14]. These characteristics suggest that established European immigrants are highly assimilated to the local labour market

[12] Gasparini and Cruces (2010) uses a similar index to evaluate the effect of a Conditional Cash Transfers program.

[13] Note however that all the models discussed in this paper use time fixed effects and time interactions which absorb any proportional difference affecting all wages in the same period. Therefore, the under/over estimation of the true inflation does not change the results.

[14] Similar calculations for LAC immigrants show that median age is around 40 years and constant in all the period, median age at arrival over 20 years and median year of arrival rapidly increased from 1973 to 1984 during the 10 years with available information.

in the considered period. Based on these facts, I do not distinguish between natives and established Europeans in the basic specification;

Finally, following the standard assumption in the literature, the measure of labour supply is the number of individuals participating in the labour force instead of the size of the working population. This assumption ignores the non-trivial relationship between unemployment and wages but restrict the measure of labour supply to changes in labour participation and migration shocks.

Table 3 presents the share of LAC immigrants and the mean hourly wage of native men aged 18-65 for age-education cells in all periods. For presentation purposes, I group the age categories into 6 groups instead of 12 as in the rest of analysis. There are some repeated patterns like the drop in wages during the crisis period 2001-2004. Over the same period the share of immigrants seems to increase in some cells like those aged 34-41. This effect can be partly explained by selective emigration of high skilled natives during the crisis period. Beyond these figures, there is a large heterogeneity across cells and time in migration shares.

Table 3: Percentage of immigrants and mean hourly wage by education-age cell. 18 urban areas. Employed men 18-65

Education level	Age group	Share of LAC immigrants (%)					Mean hourly wage of natives				
		t=1	t=2	t=3	t=4	t=5	t=1	t=2	t=3	t=4	t=5
Primary or less	18-25	3.3	3.5	3.5	4.4	8.0	2.4	2.1	1.6	1.9	2.3
	26-33	6.0	6.6	5.3	7.2	7.6	2.8	2.6	2.0	2.3	2.9
	34-41	6.7	7.7	8.4	7.3	5.7	2.9	2.9	2.2	2.7	3.1
	42-49	7.1	8.3	6.7	6.5	7.7	3.2	3.0	2.5	2.9	3.4
	50-57	7.1	7.9	7.6	6.7	5.5	3.3	3.2	2.5	2.9	3.5
	58-65	5.0	8.1	8.6	7.8	8.4	3.4	3.3	2.5	3.1	3.6
High school droputs	18-25	2.8	2.9	2.0	2.9	3.8	2.6	2.3	1.7	2.2	2.6
	26-33	5.3	5.5	4.3	5.0	3.3	3.2	2.9	2.3	2.8	3.1
	34-41	5.4	6.3	7.4	6.8	4.5	3.9	3.3	2.6	3.1	3.6
	42-49	6.2	5.5	5.1	6.2	6.9	4.3	4.2	3.0	3.5	3.9
	50-57	6.4	7.4	7.8	7.7	6.5	4.7	4.5	3.1	3.5	3.9
	58-65	3.0	7.2	7.0	6.6	6.0	4.5	4.6	3.3	3.9	4.1
High school graduated or university dropouts	18-25	2.3	2.2	2.4	3.3	3.9	3.3	3.3	2.5	3.1	3.5
	26-33	4.9	4.7	3.7	4.0	4.6	4.5	4.2	3.2	3.6	4.2
	34-41	4.4	4.9	6.7	5.8	6.7	5.5	5.3	3.8	4.3	4.9
	42-49	4.3	6.0	5.3	6.9	5.9	6.2	6.0	4.6	4.8	5.2
	50-57	3.5	3.7	5.0	4.8	5.2	6.8	6.8	4.8	5.2	5.2
	58-65	2.7	4.7	4.9	5.3	6.1	6.8	6.8	5.0	5.3	5.3
University-professional	18-25	0.5	4.0	1.1	2.6	2.9	4.7	4.9	4.4	3.9	4.8
	26-33	2.2	1.4	2.0	2.5	2.6	8.1	7.5	5.7	5.7	6.0
	34-41	2.5	2.9	2.1	3.0	2.1	9.3	9.1	7.1	6.9	7.2
	42-49	2.4	1.2	2.0	3.4	2.3	11.3	11.4	7.9	7.8	8.0
	50-57	3.3	2.9	3.1	2.8	2.3	11.6	12.4	9.3	8.1	8.5
	58-65	3.5	2.5	3.4	1.9	2.0	11.4	13.6	8.9	8.6	8.6

Notes: **t=1**: [1993-1996]; **t=2**: [1997-2000]; **t=3**: [2001-2004]; **t=4**: [2005-2008]; **t=5**: [2009-2012]. Wages are measured in constant prices. Source: Own calculations using SEDLAC and EPH survey

5.2. Reduced form estimation under assumption of perfect substitution between natives and immigrants

Identification of the structural equations (7) and (9) relies on the validity of the CES framework. Some cautionary notes about this point have been raised in recent literature (see Aydemir and Borjas, 2011, Dustmann and Preston, 2011, Dustmann, Frattini and Preston, 2012). Alternatively, a first approach to the effect of immigration on wages without relying on further structural assumptions is the estimation of the following reduced form wage equation proposed by Borjas (2003):

$$\text{(10)} \qquad \log w_{ineat} = \varphi P_{meat} + d_e + d_a + d_t + (d_e \times d_t) + (d_a \times d_t) + (d_a \times d_e) + \beta X_{ineat} + \varepsilon_{ineat}$$

where P_{meat} is the share of immigrant labour force on the total supply of workers with education *e,* and experience *a* at time *t.* The variables d_e, d_a, d_t are education, experience and time fixed effects. Interactions capture education and experience specific time trends as well as any possible interaction between education and experience. Therefore, fixed effects and interactions absorb any effect on wages produced by a shift in the total number of workers, changes in the skill or age composition of the labour supply and any possible specific change in the age-experience cells. Since the triple interaction $d_a \times d_e \times d_t$ is omitted, identification is achieved through changes in the immigrant composition of each experience-skill cell across time. Under perfect substitution between natives and immigrants (i.e. $L_{ct} = N_{ct} + M_{ct}$ for every cell *c*), equation (10) can be easily derived as a first order approximation of the equilibrium market condition when the cell-specific labour demand takes the (generic) form: $\log w_{ct} = \alpha + \eta \log L_{ct} + \upsilon_{ct}$ and the supply of native workers at cell *c* respond to changes in wages according to $\Delta N_{ct} / N_{ct} = \beta + \sigma \Delta \log w_{ct} + \kappa_{ct}$ (see Borjas, 2003). The expression is derived as the difference in wages relative to a counterfactual scenario of no immigration.

If the share of immigrants varies exogenously within cells, φ can be interpreted as the causal (partial) effect of a shift in the supply of immigrants on the wage of native workers. In this context, exogeneity means uncorrelation between the migration inflow and any cell-specific shock. For instance, a potential violation of exogeneity is produced when individuals migrate anticipating a future productivity boom, since this confounds the change in wages produced by the increase in the labour supply with the increase in the demand. Nevertheless, this bias is positive and a negative value of φ should be interpreted as a lower bound. Similarly, identification can be undermined if immigrants enter to cells where the demand is simultaneously falling. When demand shocks are independent across countries, this behaviour is a very unlikely prediction since immigrants should be attracted to growing-demand sectors, nevertheless, if the demand in the same cell is falling faster in the country of origin, this is an important concern. Related works have not been able to solve this issue when dealing with non-experimental data[15] but something can be inferred by including (potentially endogenous) controls at demand level within each cell (Bratsberg et al, 2011).

An additional caveat is the potential selectivity bias produced by non-random dropping of native population from labour force when shifts in the supply reduce wages below the reservation wage of marginal workers. Selectivity problem is difficult to control even with panel data because Equation (10) is semi-saturated and residual variation is usually very low. In the context of Argentinean labour market, the non-random emigration of native population in reaction to falling wages is also a potential source of endogeneity since it artificially increases the share of immigrants when wages are relative low.

The Borjas' setting (Eq. 10) has the additional problem that φ also accounts for the increase in the share of immigrants due to changes in the size of native labour force. On the top of that, its interpretation is not strongly connected with the theoretical model discussed before. Indeed, it is possible that the size of some cells grow over time due for example to a secular increase in the education of the native population. If the inflow of immigrants is biased toward these growing cells, the estimations of φ will be negatively biased. An alternative equation can be derived from (7) keeping the assumption that immigrants and natives are perfect substitutes within cells in the production function ($\delta = 1$). Under this assumption, the wage equation can be written as:

$$\log w_{neat} = \tilde{\alpha} + \tilde{Y}_t + \tilde{\theta}_{et} + \tilde{v}_{ea} - \rho \log L_t + (\rho - \eta)\log L_{et} + (\eta - 1)\log(L_{neat} + b_{eat} L_{meat})$$

Defining $R_{meat} = (L_{meat} / L_{neat})$ as the ratio of immigrants to natives within each cell and using the fact that $\log(1+x) \approx x$ for small *x,* it is straightforward to show that the following approximation holds:

$$\log w_{neat} \approx \tilde{\alpha} + \tilde{Y}_t + \tilde{\theta}_{et} + \tilde{v}_{ea} - \rho \log L_t + (\rho - \eta)\log L_{et} + (\eta - 1)\log L_{neat} + (\eta - 1) b_{eat} R_{meat}$$

An estimable reduced form equivalent to the last equation is given by:

$$(11) \qquad \log w_{ineat} = \varphi R_{meat} + \zeta \log L_{neat} + d_e + d_a + d_t + (d_e \times d_t) + (d_a \times d_t) + (d_a \times d_e) + \varepsilon_{ineat}$$

[15] Card (1991) estimation of the impact of the Mariel's Boatlift event is a well-known example of quasi-experimental variation of the immigrant labour supply. Other examples using quasi-experimental variation of immigrants are Glitz (2012), De Silva et al. (2010), and Hunt (1992).

Obviously, the main concern when implementing (10) or (11) is the potential endogeneity of L_{neat}, R_{meat} and P_{meat}. In the next sub-section, I discuss alternative IV strategies to cope with the potential endogeneity of the immigrant share/ratio.

The reduced form version for the Borjas' model with imperfect substitution between immigrant groups is given by:

$$(12) \qquad \log w_{ineat} = \sum_{j=1}^{J} \varphi_j P_{jmeat} + d_e + d_a + d_t + d_j + (d_e \times d_t) + (d_a \times d_t) + (d_a \times d_e) + \varepsilon_{ineat}$$

This simply corresponds to replacing the share/ratio of immigrants by similar measures but disaggregated by country of origin. Note that the assumption that all immigrants are perfect substitutes with natives independently of the country of origin (and provide similar efficiency units) imposes the testable constraint $\varphi_1 = \varphi_2 = ... = \varphi_M$ in (12). Similarly, perfect substitution between immigrant groups would imply that $R_{meat} = \sum_j R_{jmeat}$ in equation (11) which is also a testable hypothesis. In this work, I will focus on immigrants from Bolivia, Chile, Paraguay, Peru and Uruguay since they account for most of immigration.

To see an example of why heterogeneity could be relevant, Tables A3 and A4 in the appendix shows the distribution of high and low educated workers across industries by country of origin. There are important differences in the cross-country pattern. For example in the period 1993-1996 44% of the Bolivian low skilled immigrants worked in the construction sector whereas only 12% of the low skilled Peruvian immigrants worked in this sector. The differences in Tables A3 and A4 are systematic for all countries and industries and also change over time. This suggests that the impact of immigration can be heterogeneous across countries of origin. Occupational differences could be strictly related with observed variables like education and age. In such case, this effect does not translate into heterogeneous impact within this model. However, Ortega and Verdugo (2011) find that unobservable factors can simultaneously explain wage determination and the occupational decisions of immigrants. Vela and Pattel (2007) also find that networks play an important role in explaining this heterogeneity.

5.3. Identification of the supply shock and available instruments

Identification of (10)-(12) requires that the changes in the measure of immigrant penetration along time (and within each cell) are related only with exogenous shifts of the relative labour supply. The key assumption is that all the changes within cells of education-age groups are not induced by demand changes or correlated with cell-specific shocks. As described in the previous sub-section, the most critical potential deviation from this assumption is when the immigration-native composition changes in response to rising wages due to a demand shift. Nevertheless, this bias is positive and a negative value of the estimations should be interpreted as a lower bound.. The strength of the semi-saturated specification is that it controls for any type of endogeneity related with aggregated demand shifts even at the level of education or age dimension. Naturally, there is still a chance that shocks are spread in a heterogeneous way across cells leaving some endogenous component uncontrolled.

A natural way to cope with confounding demand factors is to include some proxy control like the unemployment rate for native population. Although this proxy can uncover some bias, it is endogenous and fails to capture the whole demand variation. Consequently, a second IV strategy is proposed and discussed at the end of this subsection.

A second identification issue is the endogeneity of the participation decision among natives and already established immigrants. To control for this potential bias, I follow the strategy proposed in Borjas (2003) and instrument the measures of relative supply with similar measures but at population level, that is, including also non-participant individuals. The intuition behind this instrument is that changes in the population size only affect wages through the increase in the labour supply but the size and the age-education composition of the population is fixed in the short run for natives. Similarly, changes in the number of immigrants are connected with changes in wages only through the labour market. Thus, the total number of immigrants is assumed to be exogenous once we control for the size of the immigrant labour force. A downside of this instrument is that it ignores the changes in the population (native or immigrant) due to emigration, particularly when individuals leave the country due to falling wages in their education-age cell. Comparing results from equations (10) and (11) can uncover the potential negative bias due to native emigration. The latter equation controls for the size of the native labour force and therefore is less affected by native emigration. The return of immigrants to their home countries in response to wage drops introduce a positive bias and therefore, negative values of the coefficients in (10) or (11) should be interpreted as lower bounds.

An additional concern is the lack of coverage of rural areas and small cities in the sample. Internal migration can induce changes in the immigrant composition of the labour force if native workers move into large cities in response to changes in labour market conditions. I include the number of internal immigrants in some specifications in order control for this source of endogeneity.

In order to isolate the supply variation from demand cell-specific shocks and other confounding factors, I exploit available micro-data from other countries to build an instrument which relates changes in the supply of immigrants with variations in the economic conditions in their countries of origin.[16]

I pool different surveys from each country into 5 periods of 4 years length in the same way described for the Argentinean dataset. Unfortunately, the set of years available for each period varies from country to country as shown in Table 1. Estimations for the first period (1993-1996) are based on fewer surveys than estimations for the later periods.[17]

The first set of instruments is defined as:

$$(13) \qquad Z_{eat} = \frac{1}{J}\sum_{j=1}^{J} w^{j}_{e,(a-1),(t-1)}$$

where $w^{j}_{e,(a-1),(t-1)}$ is the hourly wage in country *j* in the period *t-1* for the education-age group *(e,a-1)*. Note that the age group is also lagged to track the same cohort over time. Wages are comparable and measured in 2005 USD-PPP prices. The relevance of the instrument comes from the fact that negative shocks in the country of origin increase the incentives to emigrate.[18] To account for a possible non-linear relationship between income in origin and migration I also include the squared instrument (see for example Chiquiar and Hanson, 2005 and Grogger and Hanson, 2002, 2011).[19]

Using lagged variables instead of contemporaneous information has two advantages. On the one hand, demand shocks can affect the wages of particular education-age cells in all the countries at the same time (including Argentina) and this could invalidate the instrument.[20] On the other hand, migration is a costly decision and do not react instantaneously to shocks in the country of origin.

As a robustness check, a second strategy uses the whole set of $w^{j}_{e,(a-1),(t-1)}$ as instruments instead of the average across countries. This specification is more flexible but in the presence of a weak first stage, the resulting bias increases with

[16] Munshi (2003) uses a related strategy by instrumenting the number of Mexican immigrants with the rainfall level in the home village. In this case, such type of instruments is not useful because is perfectly correlated with the set of fixed effects and interactions.

[17] In the case of Peru, data from the first period comes from Census without information about incomes or worked hours and therefore I only use unemployment rates from this country.

[18] I avoid using also unemployment as instrument because it is less correlated with immigration. The main reason is that unemployment is usually low for highly informal markets and do not change significantly over time.

[19] The first paper claims that propensity to migrate changes along the income distribution. The other papers test immigrant selection under different specifications of the indirect utility function.

[20] Obviously, nothing preclude that some countries are affected by contagion but observations are separated by lags of 4 years on average and this reduce the likelihood of such effect.

the number of instruments (Hahn and Hausman, 2002). In regressions with many fixed effects and interactions like Equations (10) or (11), achieving a strong first stage is commonly difficult.

Finally, I consider an instrument that exploits all the information available for each country of birth. Card (2001) uses the lagged regional distribution of immigrants to predict the actual distribution at cell level and uses this prediction as a valid instrument. I follow a related strategy and predict the cell-distribution of immigrants from each country using all the available information one period lagged (excluding Argentina).[21] For example, I predict the number of immigrants from Bolivia, with primary education aged 30-33 in period t=2, using information on wages and unemployment from the 6 countries of origin in t=1 for individuals with the same education but aged 26-29.[22] The variables I use to build this set of instruments are the unemployment rate, the log hourly wage, the log monthly wage and the average number of worked hours.[23]

An important point is that, as previously discussed for the baseline specification, validity of the instruments is not affected by aggregated shocks, education-specific shocks, age-specific shocks or any persistent process involving them because the set of fixed effect and interactions is also included in the first stage. As I show in the results section, this convenient feature also creates some concerns about the power of the first stage because after controlling for all the set of interactions, the residual variation of the instrument can be weakly correlated with the immigration explanatory variable.[24]

5.4. Identification from geographical variation

Borjas, Freeman and Katz (1997) and Borjas (2003) raised an important question about the validity of previous studies that used geographical variation in immigration flows as identification strategy.[25] According to this critique, if cities within a country operate as open economies, supply shocks will be spread across them and wages will tend to be equalized. If this hypothesis is true, the magnitude of the impact estimated using cities or regions as unit of comparison across time, should be biased toward zero. Additionally, if immigrants can decide the settlement

[21] Using the whole set of lagged measures directly as instruments would account for 21 instruments, leading to a large small-sample bias as discussed in Hahn and Hausman (2002).
[22] I include information from all countries to account for cross-country effects of shocks. For example, a positive shock in Peru can reduce immigration from Bolivia to Argentina.
[23] I use worked hours since informal work is extremely high in some countries and unemployment is not an accurate measure of economic conditions. In most cases, unemployment rate is very low since many workers perform low remunerated tasks during a few hours a week.
[24] This trade-off between exogeneity of the instrument and power of the first stage is one of the points discussed in Stock, Wright and Yogo (2002).
[25] For example Altonji and Card (1991), Card (1990), LaLonde and Topel (1991).

place, it is likely that cities or regions with booming wages will attract a higher share of immigrants inducing a positive correlation between wages and immigration.[26] I explore this setting by replicating some of the previous results at the level of city-education-age cell. The stratification is based on the 18 urban areas described in Table A1 in the appendix.

5.5. A note on the structural parameters of the model

Reduced forms (10) and (11) cannot be interpreted as the total impact of immigration on wages. For instance, the interaction terms capture the indirect effect of immigration on wages trough the change in cell's total employment. Complementarities among education groups or age/experience groups could even change the sign of the impact if we also consider cross-cell effects. Therefore, φ should be interpreted as a partial direct derivative which only captures the average impact of immigration among similar workers. Moreover, this effect is assumed to be homogenous across cells, which is a strong assumption. Additionally, both specifications assume that immigrants and natives are perfect substitutes within each cell. The structural parameters of the model can reveal more information about the total effect of immigration and potential imperfect substitution across groups. For the model with imperfect substitution by country of origin, the structural parameters can be estimated extending the procedure proposed in Manacorda, Manning and Wadsworth (2012) for the case of imperfect substitution between immigrants. This extension is straightforward but beyond the scope of this paper.

6. Results

6.1. Baseline estimations

Table 4 reports OLS and 2SLS estimates for the reduced form proposed by Borjas (Equation 10 - Panel A) and the first order approximation of the CES model (Equation 11 - Panel B). 2SLS uses population measures as instruments for labour force variables. Following the discussion in Section 5, all the results presented throughout this paper are estimated using both equations.

Dependant variables are the *average log hourly wages* and the *average log monthly earnings* calculated at each education-age-time cell for men aged 18-65. standard errors are clustered at education-age level to allow for autocorrelation within cells over time. Additionally, all the regressions are weighted by the sample size of each cell at every period.

[26] However, Card and DiNardo (2000) find little evidence of such effect.

OLS results indicate that immigration has a significant (partial) negative effect on wages under any specification. The point estimates are close to -1 for the first specification and around -0.8 for the second specification. The magnitude of this effect is higher than the effects find by Borjas (2003) for the US.[27] The elasticity of wage to immigration can be calculated as $\partial \log w_{eat} / \partial R_{eat} = \varphi / (1 + R_{eat})^2$ in the first model and simply φ in the second model. Over the whole period, the average ratio of LAC immigrants to native population is 0.053. This implies that elasticity in the first specification is close to -0.9 and around -0.8 in the second model. It is not surprising that the first specification results in a higher impact because it fails to control for changes in the share of immigrants induced by changes in the absolute number of natives. This is a particular concern for the case of Argentina because native's emigration rate is high for periods of low economic activity.

Table 4: Impact of immigration on wages. Reduced form specifications

	OLS				**2SLS**			
	Baseline controls		Include demand control		Baseline controls		Include demand control	
A. Baseline model (eq. 10)	Log hrly wage	Log mthly wage	Log hrly wage	Log mthly wage	Log hrly wage	Log mthly wage	Log hrly wage	Log mthly wage
Share of LAC immigrants	-1.084**	-1.070**	-1.106**	-1.091**	-0.865**	-0.808**	-0.882**	-0.824**
	(0.436)	(0.496)	(0.442)	(0.508)	(0.331)	(0.368)	(0.334)	(0.375)
Native's unemployment rate			-0.126	-0.122			-0.111	-0.104
			(0.227)	(0.288)			(0.167)	(0.211)
B. Model 2 (eq. 11)								
Ratio LAC immigrants/Natives	-0.780**	-0.786**	-0.797**	-0.803**	-0.631**	-0.609**	-0.646**	-0.623**
	(0.325)	(0.385)	(0.330)	(0.392)	(0.256)	(0.293)	(0.259)	(0.297)
Log size of native labour force	0.115***	0.100**	0.115***	0.099**	0.094***	0.070*	0.092***	0.069*
	(0.038)	(0.047)	(0.038)	(0.046)	(0.028)	(0.036)	(0.028)	(0.035)
Native's unemployment rate			-0.107	-0.104			-0.096	-0.092
			(0.207)	(0.271)			(0.153)	(0.200)

Additional controls: *time fixed effects, education fixed effects, age fixed effects, education-age interactions, education-time interactions, age-time interactions*

Notes: Robust standard errors are adjusted for clustering within education-age cell. All the calculations are based on 240 observations. Regressions are weighted by the sample size of each education-age-time cell. The 2SLS estimations instrument the share of immigrants participating in the labour force with the share of immigrants in the population in the same education-age-time cell, lagged by period and cohort (see section 5 for details). Similarly, the ratio of immigrants and the Log size of native labour force are instrumented with the corresponding population measures (see text for details). The sample consists of men aged 18-65. Source: Own calculations using SEDLAC and EPH survey.

The second OLS specification in Table 4 includes the native's unemployment rate as a proxy control for demand side shocks. This is an endogenous variable but coefficients remain very stable after its inclusion. The sign of the unemployment coefficient is negative as expected although non-significant.

[27] Borjas (2003) finds coefficients between -0.54 and -0.63 for Log weekly earnings and between -0.72 and -1.23 for annual earnings. Estimated elasticities of earnings to immigration are between -0.4 and -0.9.

The second group of columns in Table 4 presents the Two Stage Least Squares estimations using population measures as instruments for labour force variables.[28] As extensively discussed in section 5, this intends to control for the potential endogeneity in the decision of participating into the labour force. Point estimates are slightly smaller in absolute value, indicating that there is some positive correlation between wages and the participation decision of native population.[29] This hypothesis is also consistent with the reduction in the coefficient estimated for the *log size of native labour force* in Panel A. A positive value of this coefficient (after instrumenting with population size) can be explained by different effects, first, a strong emigration response of natives to wage drops, second, higher wages can attract internal migrants from rural areas or small cities and finally, in terms of the theoretical model discussed in Section 2, a low elasticity of substitution across ages or education groups.

In order to explore the potential bias due to internal mobility, Table 5 shows OLS and 2SLS results when the number of internal immigrants in the cell is included as regressor. Internal immigrants are defined as those individuals who do not live in their birth province.[30] This variable is highly correlated with immigration from rural areas or small cities not covered in the survey. The evidence suggests that internal mobility could explain the positive estimated coefficient of the *log size of native labour force*. Indeed, the estimates for this variable become close to zero or negative after controlling for internal migration. Moreover, the coefficient of the number of internal migrants is positive. Since it is very unlikely that internal migrants are not perfect substitutes with other natives, this positive sign can be caused by the endogenous effect of wages on internal mobility. Under both models, the coefficients of the LAC immigration variable remain significant. In the first specification point estimates drop around 20% in absolute value and in the second specification they remain almost unchanged. The implied wage elasticities are around -0.7 for OLS and in the range of -0.5 to -0.6 for 2SLS estimations. These values are in line with Borjas' estimations for the US.

[28] First stage is not reported since by construction instruments are highly correlated with explanatory variables and F statistics above 200.

[29] Higher wages would increase the participation rate of natives (relative to immigrants) and this would artificially reduce the share of immigrants introducing a negative bias in the estimation.

[30] I do not use migration at municipal level since some urban areas like Great Buenos Aires are comprised by many municipalities.

Table 5: Impact of immigration on wages. Additional controls for internal migration.

	OLS		2SLS	
A. Baseline model (eq. 10)	Log hrly wage	Log mthly wage	Log hrly wage	Log mthly wage
Share of LAC immigrants	-0.834**	-0.778*	-0.640**	-0.545*
	(0.361)	(0.403)	(0.279)	(0.295)
Log internal migrants	0.086***	0.100***	0.089***	0.104***
	(0.024)	(0.027)	(0.018)	(0.019)
B. Model 2 (eq. 11)				
Ratio LAC immigrants/Natives	-0.748**	-0.736**	-0.593**	-0.552**
	(0.312)	(0.353)	(0.243)	(0.260)
Log size of native labour force	0.021	-0.047	-0.011	-0.088
	(0.066)	(0.080)	(0.045)	(0.058)
Log internal migrants	0.076*	0.119**	0.093***	0.139***
	(0.039)	(0.045)	(0.027)	(0.033)

Additional controls: *time fixed effects, education fixed effects, age fixed effects, education-age interactions, education-time interactions, age-time interactions*

Notes: Robust standard errors are adjusted for clustering within education-age cell. All the calculations are based on 240 observations. Regressions are weighted by the sample size of each education-age-time cell. The 2SLS estimations instrument the share of immigrants participating in the labour force with the share of immigrants in the population in the same education-age-time cell. Similarly, the ratio of immigrants and the Log size of native labour force are instrumented with the corresponding population measures (see text for details). The sample consists of men aged 18-65. Source: Own calculations using SEDLAC and EPH survey.

Finally, the above specifications rely on a rather arbitrary pre-allocation of workers into homogeneous age intervals. However, an alternative approach discussed in Appendix A.2 shows than the sign of the impact of immigration is robust to different specifications and assumptions about intra-cell substitution of workers with same education but different age.

6.2. Evidence from instrumental variables estimation

Tables 6 and 7 present the estimated impact of immigration using information in country of birth as instrument. The main purpose of these sets of instruments is to control for endogeneity induced by demand side changes and other confounding factors. Table 6 uses the average wage for Bolivia, Chile, Brazil, Paraguay and Uruguay lagged by time and cohort (see section 5 for more details). The specification also includes the squared instrument to account for a possible non-linear relationship. Figure 2, plots the relationship between the share of immigrants and the instrument.

The impact estimated by 2SLS is more negative than OLS results.[31] Elasticities are in the range of -1.2 to -1.9 in both models. This finding suggests, as hypothesized before, that demand shocks are positively correlated with immigration and that OLS

[31] Differences are statistically significant despite of the higher standard errors.

results are positively biased. Estimations are not significant after including the internal migration control but the coefficients are still negative and high.

Table 6: Impact of immigration on wages. Instruments based on the average wage in immigrants' country of origin lagged by period and cohort.

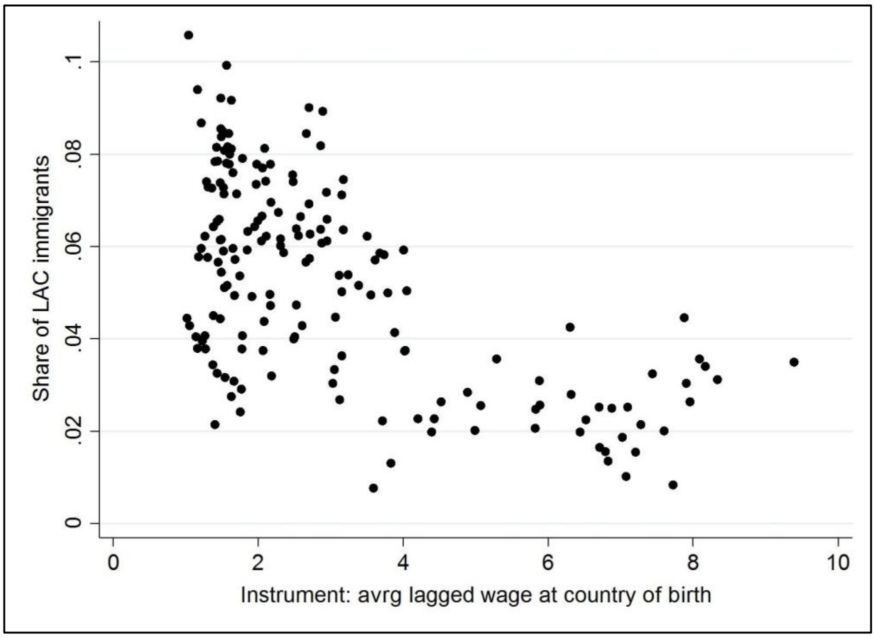
	2SLS					
	Baseline controls		Include demand control		Include internal migration control	
A. Baseline model (eq. 10)	Log hrly wage	Log mthly wage	Log hrly wage	Log mthly wage	Log hrly wage	Log mthly wage
Share of LAC immigrants	-2.157**	-1.942*	-2.177**	-1.845*	-1.371	-1.324
	(0.856)	(1.081)	(0.890)	(1.116)	(0.963)	(1.441)
Native's unemployment rate			-0.027	0.136		
			(0.199)	(0.265)		
Log internal migrants					0.052	0.064
					(0.035)	(0.049)
F excluded instruments 1	3.755	3.755	3.998	3.998	4.058	4.058
B. Model 2 (eq. 11)						
Ratio LAC immigrants/Natives	-1.631*	-1.584	-1.648*	-1.447	-1.364	-1.268
	(0.865)	(1.181)	(0.946)	(1.279)	(0.869)	(1.275)
Log size of native labour force	0.013	-0.002	0.012	0.011	-0.047	-0.095
	(0.058)	(0.075)	(0.063)	(0.080)	(0.062)	(0.078)
Native's unemployment rate			-0.009	0.150		
			(0.210)	(0.282)		
Log internal migrants					0.067*	0.101**
					(0.039)	(0.051)
F excluded instruments 1	3.755	3.755	3.908	3.908	3.002	3.002
F excluded instruments 2	318.4	318.4	251.0	251.0	196.8	196.8

Additional controls: *time fixed effects, education fixed effects, age fixed effects, education-age interactions, education-time interactions, age-time interactions*

Notes: Robust standard errors are adjusted for clustering within education-age cell. All the calculations are based on 173 observations. Regressions are weighted by the sample size of each education-age-time cell. **2SLS :** Instrument for the share/ratio of immigrants is the average lagged hourly-wage and its square fo each education-age cell among the five most popular countries of origin among immigrants (see Section 5 in text for details). Log size of native labour force instrumented with the population size of the corresponding cell. The sample consists of men aged 18-65. Source: Own calculations using SEDLAC and EPH survey.

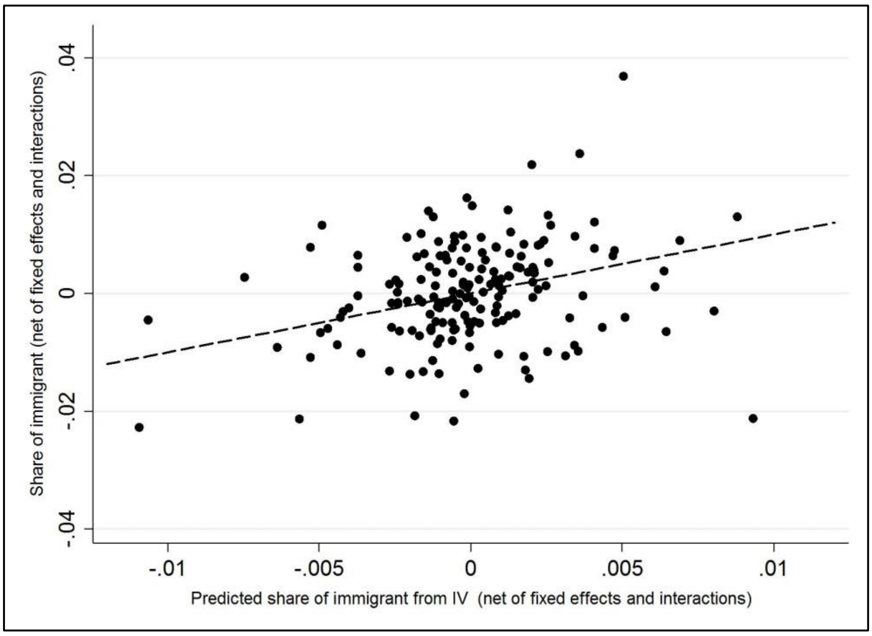
The 2SLS results also imply either a very high substitution across education and age groups or a high degree of substitution between natives and immigrants. An interesting result is that the coefficient of the log size of the native labour force becomes negative in contrast with the baseline regressions. A drawback of these estimations is that the first stage is not very strong with F-statistics between 3 and 4 (significant in all cases). This is not surprising because the first stage includes a huge number of fixed effects and interactions that remove most of the variation in the instruments. As a result, residual variation is only weakly correlated with the immigration measures for each specific cell. Additionally, regressions exclude the first period (because of lagging) and therefore precision decreases considerably. Figure 3 plots the relationship between the share of immigrants and the first stage prediction after removing the effect of other regressors like fixed effects and interactions.

Figure 2: Share of immigrants and excluded instrument



Note: Each observation corresponds to a different education-age cell at a particular period.

Figure 3: First Stage



Note: Both variables are residuals from a regression on the set of fixed effects and interactions by age, education and time.

Table 7 shows the 2SLS results when the instruments are included in the first stage disaggregated by country of origin. Estimations become even more negative than before and remain significant in all cases. Implied elasticities are clustered around -1.7 and -2.1. The power of the first stage does not improve relative to Table 6 and F statistics are between 2.8 and 3.4.

Table 7: Impact of immigration on wages. Alternative set of Instruments disaggregated by country of origin.

	2SLS					
	Baseline controls		Include demand control		Include internal migration control	
A. Baseline model (eq. 10)	Log hrly wage	Log mthly wage	Log hrly wage	Log mthly wage	Log hrly wage	Log mthly wage
Share of LAC immigrants	-2.449***	-2.450***	-2.438***	-2.411***	-2.031**	-1.994*
	(0.805)	(0.803)	(0.834)	(0.822)	(1.020)	(1.098)
Native's unemployment rate			-0.037	0.114		
			(0.212)	(0.280)		
Log internal migrants					0.035	0.046
					(0.036)	(0.044)
F excluded instruments 1	2.827	2.827	2.774	2.774	2.092	2.092
B. Model 2 (eq. 11)						
Ratio LAC immigrants/Natives	-2.064**	-2.247**	-2.032**	-2.162**	-1.871**	-1.911*
	(0.873)	(0.972)	(0.957)	(1.027)	(0.893)	(1.011)
Log size of native labour force	-0.004	-0.034	-0.004	-0.026	-0.058	-0.117*
	(0.057)	(0.062)	(0.064)	(0.066)	(0.062)	(0.067)
Native's unemployment rate			-0.038	0.090		
			(0.234)	(0.300)		
Log internal migrants					0.056	0.091*
					(0.039)	(0.051)
F excluded instruments 1	3.559	3.559	3.439	3.439	2.764	2.764
F excluded instruments 2	178.3	178.3	122.3	122.3	112.5	112.5

Additional controls: *time fixed effects, education fixed effects, age fixed effects, education-age interactions, education-time interactions, age-time interactions*

Notes: Robust standard errors are adjusted for clustering within education-age cell. All the calculations are based on 173 observations. Regressions are weighted by the sample size of each education-age-time cell. **2SLS :** Instrument for the share/ratio of immigrants is the lagged hourly-wage and its square fo each education-age cell in the five most popular countries of origin among LAC immigrants. The first stage includes instruments dissagregated by country of origin of the immigrants (see Section 5 for details). Log size of native labour force instrumented with the population size of the corresponding cell. The sample consists of men aged 18-65. Source: Own calculations using SEDLAC and EPH survey.

Table A5 in the Appendix presents the estimations for the alternative set of instruments discussed in section 5. The first group of columns uses the predicted distribution of immigrants from lagged cell-specific information from Bolivia, Chile, Brazil, Paraguay, Peru and Uruguay (See Section 5 for more details). The F statistics of the first stage rise above 4 after including the demand controls. Point estimates and standard errors are also higher. The weak instrument problem is neither rejected in this case.

The results of the following sub-section indicates that instrumental variables estimations should be interpreted with caution, but overall, the evidence from different IV strategies suggests that demand shocks are positively correlated with immigration flows and in this sense, the negative impact identified by OLS is a lower bound for the true impact. For instance, Ortega and Verdugo (2011) estimate a bias in the same direction.

6.3. Weak instruments and alternative IV estimation

As mentioned before, the weakness of the first stage is also the price of a stronger exclusion restriction. The presence of a large list of fixed effects and interactions in the first stage eliminates from the instrument the influence of any simultaneous shock affecting all countries in the region, contagion processes and common trends in wages. This is true even for shocks occurring within education or age groups.

In order to provide additional evidence about the relevance of the proposed instruments, Table 8 summarizes alternative IV estimators. This strategy to cope with potential weak instruments follows the discussion in Stock, Wright and Yogo (2002), and Stock and Yogo (2002). The alternative estimators are the Limited Information Maximum Likelihood estimator (LIML) and Jackknife IV estimation (JIVE) proposed in Angrist, Imbens and Krueger (1999).[32] The sets of instruments presented are the same than those in Tables 2a and 2b. Differences between 2SLS and LIML estimations usually indicate the presence of a bias due to weak instruments since LIML is approximately median unbiased (Angrist and Pischke, 2008).[33] In this case, LIML estimations are close to 2SLS results for the first set of instruments (based on the average lagged wage in other countries) but not close for the second set of instruments (which includes lagged wages disaggregated also at country level). This result could be driven by the fact that 2SLS bias increases with the number of excluded (weak) instruments and the second set of instruments is large.

JIVE is usually described as an estimator with superior small sample properties than 2SLS in the presence of weak instruments[34]. One of the sources of 2SLS bias is the correlation between the error terms of the two stages for the same observation ith. The JIVE procedure eliminates this correlation by excluding the observation ith when predicting the fitted value of the endogenous regressor from the first stage. In

[32] An alternative JIVE estimator is discussed in Blomquist and Dahlberg (1999).
[33] 2SLS is biased toward OLS in the presence of weak instruments.
[34] Nevertheless, there is recent debate about this point that can be followed in Davidson and MacKinnon (2006) and Ackerberg and Devereux (2006).

this case, JIVE estimations are lower than 2SLS and close to OLS results for both set of instruments.[35]

Evidence from the alternative estimators do not allow to safely conclude that the estimated impact of immigration is as high as 2SLS and LIML suggests, but in all cases the point estimates remains significant and negative. Naturally, the exclusion restriction relies on the assumption that fixed effects and interactions remove any source of simultaneity in wage determination across countries. Without a randomized variation in the amount of immigrants it cannot be ensured that this assumption holds, but as discussed in previous sections, the direction of the bias seems to operate toward zero. The results from different IV strategies do not contradict this hypothesis.

Table 8: Alternative IV estimators. Limited Information Maximum Likelihood (LIML) and Jackknife IV estimation (JIVE)

	IV 1				**IV 2**			
	Baseline model		Model 2		Baseline model		Model 2	
	LIML	**JIVE**	**LIML**	**JIVE**	**LIML**	**JIVE**	**LIML**	**JIVE**
Share (Ratio) of LAC immigrants	-2.516**	-0.765**	-2.211**	-0.692**	-4.521**	-1.069**	-3.595**	-0.954**
	(1.137)	(0.340)	(0.948)	(0.299)	(2.180)	(0.537)	(1.697)	(0.463)

Additional controls: *time fixed effects, education fixed effects, age fixed effects, education-age interactions, education-time interactions, age-time interactions*

Notes: Robust standard errors are adjusted for clustering within education-age cell in the LIML and adjusted for heteroskedasticity in the JIVE. All the calculations are based on 173 observations. The sample consists of men aged 18-65. **IV 1:** Instrument for the share/ratio of immigrants is the average lagged hourly-wage and its square fo each education-age cell among the five most popular countries of origin among immigrants (see text for details). **IV 2:** Instrument for the share/ratio of immigrants is the lagged hourly-wage and its square for each education-age cell in the five most popular countries of origin among immigrants (see text for details). **Baseline model** uses the share of immigrants from LAC countries to measure the impact of immigration. **Model 2** is based on equation 11 in text and uses the Ratio of imigrants to natives along with the size of the native labour supply. Source: Own calculations using SEDLAC and EPH survey.

6.4. Impact by country of origin

Table 9 shows the impact of immigration when the total share of immigrants is disaggregated by country of origin (Equation 12). In all cases other than Uruguay, the estimated impact is negative but significant only for Bolivia and Peru.[36] In most cases, the hypothesis of homogenous impact by origin is rejected by the Wald test. Further research is needed to understand this pattern. Particularly, the positive impact of immigrants from Uruguay could be explained by two different effects. First,

[35] A note of caution should be made since the JIVE procedure does not allow for clustering standard errors and only heteroskedastic-robust standard errors are reported.

[36] The OLS estimated coefficient for Chile is also significant when the hourly wage is the dependant variable.

strong complementarities in the production function or self-selection of immigrants (immigration concentrated in cells with low elasticity of substitution). Second, the distance between Buenos Aires and Montevideo is short enough to allow for a high mobility in response to demand-side shocks which will upward bias the estimations. None of the instruments used in Tables 6 and 7 achieve a significant first stage when immigration variables are disaggregated by country of origin and those results are not presented.

Table 9: Impact of immigration on wages by country of origin. OLS estimations

	A. Baseline model				B. Model 2			
	OLS		2SLS		OLS		2SLS	
Share (Ratio) of immigrants from:	Log hrly wage	Log mthly wage	Log hrly wage	Log mthly wage	Log hrly wage	Log mthly wage	Log hrly wage	Log mthly wage
Bolivia	-1.749***	-1.741**	-1.656***	-2.017***	-1.597***	-1.591**	-1.515***	-1.890***
	(0.515)	(0.680)	(0.551)	(0.747)	(0.459)	(0.625)	(0.504)	(0.694)
Chile	-1.743*	-1.448	-1.391	-0.860	-1.611*	-1.375	-1.266	-0.802
	(1.015)	(1.105)	(1.001)	(1.071)	(0.937)	(1.026)	(0.931)	(1.011)
Paraguay	-0.426	-0.209	-0.260	0.133	-0.347	-0.222	-0.224	0.028
	(0.470)	(0.510)	(0.471)	(0.474)	(0.417)	(0.447)	(0.417)	(0.407)
Peru	-2.050**	-1.999*	-2.320**	-2.211*	-1.889**	-1.896*	-2.174**	-2.096*
	(0.889)	(1.180)	(0.923)	(1.251)	(0.840)	(1.096)	(0.861)	(1.144)
Uruguay	0.622	0.372	1.028	0.932	0.597	0.357	0.989	0.917
	(0.630)	(0.676)	(0.664)	(0.739)	(0.591)	(0.628)	(0.620)	(0.684)
Log size of native LF					0.021	-0.044	-0.015	-0.085
					(0.045)	(0.057)	(0.043)	(0.057)
Log internal migrants	0.080***	0.098***	0.083***	0.100***	0.071**	0.115***	0.088***	0.134***
	(0.016)	(0.019)	(0.016)	(0.018)	(0.028)	(0.033)	(0.028)	(0.033)
Wald test equality shares/ratios								
p-value	0.0520	0.160	0.0206	0.0468	0.0500	0.171	0.0204	0.0492

Additional controls: *time fixed effects, education fixed effects, age fixed effects, education-age interactions, education-time interactions, age-time interactions*

Notes: Robust standard errors are adjusted for clustering within education-age cell. All the calculations are based on 240 observations. The sample consists of men aged 18-65. **2SLS:** immigration shares/ratios in the labour force are instrumented with the corresponding measure at population level. Source: Own calculations using SEDLAC and EPH survey.

6.5. Geographical stratification

This section presents the estimated impact of immigration when the source of variation is the change in the distribution of immigrants across different urban areas. According to Borjas (2003) this approach likely underestimates the true impact for the reasons discussed in Section 5. Table 10 shows results in line with this hypothesis.[37] The first column includes city, education, age and period fixed effects. It also includes interactions between city, education and age with the time variable and the interaction between city and education. The effect of immigration is identified from changes along time in a particular education group in a particular city. The estimated coefficients are negative and significant but closer to zero

[37] Table 9 is similar to Table V in Borjas (2003).

compared with previous results. Borjas (2003) and Ortega and Verdugo (2011) also find lower effects from regional stratification.

The second column adds to the previous specification the three-way interaction between city, education and age. In this case, identification comes from comparing the same education-age-city cell in different periods. The coefficient from Borjas' model is still negative and significant but in the second specification it is not.

Table 10: Impact of immigration on wages using geographical stratification. OLS estimations

	A. Baseline model				B. Model 2			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Share of LAC immigrants	-0.110**	-0.169**	-0.139*	0.029				
	(0.054)	(0.080)	(0.079)	(0.100)				
Ratio LAC immigrants/Natives					-0.046**	-0.032	-0.013	0.010
					(0.023)	(0.040)	(0.039)	(0.056)
Time, Age, Education, City	YES	YES	YES	YES	YES	YES	YES	YES
Time × Age , Time × Education, Time × City, Education × City	YES	YES	YES	YES	YES	YES	YES	YES
Education × Age × City	NO	YES	YES	YES	NO	YES	YES	YES
Education × Age × Time	NO	NO	YES	YES	NO	NO	YES	YES
Education × City × Time, Age × City × Time	NO	NO	NO	YES	NO	NO	NO	YES

Notes: Dependant variable: Log hourly wage. Robust standard errors are adjusted for clustering within education-age cell. All the calculations are based on 4013 observations. The sample consists of men aged 18-65. Additional controls: Log-size of internal immigration in both models and Log size of native labour force in the second model. Regressions are weighted by the population size of the cell. Source: Own calculations using SEDLAC and EPH survey.

The third and fourth columns add the others three-way interactions allowing for time effects to vary across education-age, city-age, and city-education cells. Only the first specification remains significant in the third column and the last column's results are close to zero for both models. Naturally, these findings do not imply that immigration effect dilutes as it is spread across cities. Indeed, this pattern can be driven by a large attenuation bias resulting from the high level of data disaggregation and the small residual variability after controlling for a larger set of interactions and fixed effects (see the discussion in Borjas, 2003).

7. Conclusions

This paper evaluates the effects of cross-border immigration on the wages of Argentinean native workers over the period 1993-2012. As discussed in Section 1, this is an important South-South corridor that has not received much attention in the literature.

The main source of data for this paper is the Socioeconomic Database for Latin America and the Caribbean (SEDLAC). Other sources of information include the first semester round of the Argentinean EPH and the 1993 IPUMS Census Data for Peru. All the variables are harmonized following the SEDLAC methodology.

The empirical setting follows a recent literature based on the "national approach" proposed in Borjas (2003) which identify the labour supply variation with changes in the size of predetermined skill groups, usually experience-age categories. Alternatively to Borjas' setting, I also estimate reduced form that can be obtained as a log-linear approximation of the demand equation from the nested CES framework proposed in Ottaviano and Peri (2012) or Manacorda, Manning and Wadsworth (2012) under the assumption of perfect substitution between immigrants and natives. Results from this methodology should be interpreted as a partial equilibrium effect of immigration since cross-skills effects are captured by a large set of fixed effects and interactions.

The paper also contrasts the baseline results with IV estimations from a set of instruments based on labour market conditions in immigrants' countries. An alternative specification also explores the hypothesis of heterogeneous impact by country of origin of immigrants.

OLS results show a significant negative impact of immigration with wage elasticities in a range slightly above the estimated by Borjas (2003) for the US, although controlling for internal migration results in similar wage elasticities. These results are robust to different specifications and do not change when proxy-demand controls are included. Although the literature agrees that OLS can be biased toward zero, there are two potential confounders that need to be considered in this case. The first one is emigration of native population in response to lower wages and the second is internal migration from rural areas toward large cities. Estimations remain significative after controlling for internal immigration rates although there is evidence of some negative bias. Controlling for proxies of these factors reduces the estimated impact but do not eliminate its significance.

IV estimations suggest that OLS results are a lower bound for the (partial) causal effect of immigration as assumed by Borjas (2003). This implies that if there are some confounder demand factors, they bias the results toward zero. IV results should be interpreted with caution, the main drawback is a significant first stage but not strong enough to reject a bias driven by a weak instrument problem. However, under alternative estimators like LIML and JIVE, the sign of the estimated impact remains negative.

The hypothesis of heterogeneous effect of immigration by country of origin cannot be rejected in a reduced form. Nevertheless, results are rather imprecise due to high measurement error and further research is needed to make additional inference about the size of the impact. Particularly, estimation of the structural parameters of the model would reveal more information about this effect.

Finally, when the supply shock is also identified from variations of immigration at geographical level, the estimated impact is lower.

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Appendix

A.1 Tables and figures

Figure A1: Immigration from South American countries.

Note: Urban areas covered in the Argentinean sample are listed in Table A1. Source: Census 2010, Argentina

Table A1: Geographic stratification

Urban Area
Ciudad de Buenos Aires *
Partidos del GBA *
Gran La Plata
Gran Rosario
Gran Santa Fé
Gran Paraná
Gran Córdoba
Santa Rosa - Toay
Gran Mendoza
San Luis - El Chorrillo
Jujuy - Palpalá
Gran Catamarca
Salta
Gran Tucumán - T. Viejo
Neuquén – Plottier
Río Gallegos
Ushuaia - Río Grande
Cdro. Rivadavia – Rada Tilly

Notes: NEA region exluded because immigration data is N/A for 1993. (*) grouped into the same urban area.

Table A2: Median values for European immigrants. Males 18-65 in the LF

Year	age	age at arrival	year of arrival
1993	53	12	1952
1994	50	11	1952
1995	49	9	1952
1996	51	9	1952
1997	53	10	1952
1998	53	8	1952
1999	53	7	1952
2000	54	6	1951
2001	54	5	1952
2002	55	5	1953
2003	56	6	1953
2004	56	N/A	N/A
2005	57	N/A	N/A
2006	58	N/A	N/A
2007	59	N/A	N/A
2008	59	N/A	N/A
2009	60	N/A	N/A
2010	60	N/A	N/A
2011	61	N/A	N/A
2012	59	N/A	N/A

Source: Own calculations using SEDLAC and EPH survey

Table A3: Distribution of workers by economic/industry sector and country/region of birth.
Low educated workers. Men 18-65

	Natives					Bolivia					Chile					Paraguay					Peru					Uruguay				
Industry Sector	**t=1**	**t=2**	**t=3**	**t=4**	**t=5**	**t=1**	**t=2**	**t=3**	**t=4**	**t=5**	**t=1**	**t=2**	**t=3**	**t=4**	**t=5**	**t=1**	**t=2**	**t=3**	**t=4**	**t=5**	**t=1**	**t=2**	**t=3**	**t=4**	**t=5**	**t=1**	**t=2**	**t=3**	**t=4**	**t=5**
Primary activities	1.2	1.3	1.8	1.9	2.8	3.1	2.3	3.5	4.3	0.2	5.5	3.6	5.4	5.9	5.2	1.8	0.0	1.1	0.9	1.3	0.0	0.0	1.1	0.9	1.0	0.0	0.4	0.0	0.9	3.8
Industry low tech	9.0	7.4	8.0	9.4	9.3	10.1	7.8	19.5	16.6	16.8	6.2	5.6	4.8	9.3	8.8	9.6	12.3	9.6	13.0	12.5	36.2	22.0	6.2	6.5	12.8	6.7	6.2	6.5	8.5	9.9
Industry high tech	16.0	13.7	10.8	10.3	10.3	6.0	7.4	6.0	4.8	5.3	10.0	9.5	7.4	7.3	10.8	13.3	11.4	7.1	8.5	8.0	3.0	8.0	10.0	5.8	2.2	13.8	20.8	9.7	9.1	4.9
Construction	14.5	17.4	16.2	20.5	21.4	44.4	56.3	40.4	53.9	44.0	35.4	27.8	30.5	38.0	35.2	43.0	50.6	43.0	48.9	47.5	12.4	18.1	28.5	10.6	19.9	15.8	24.9	12.5	18.3	23.3
Commerce	26.3	25.0	25.9	25.1	24.7	23.3	14.6	18.2	13.9	23.8	22.2	23.5	24.4	17.2	17.2	15.6	14.9	22.9	14.1	14.2	22.4	35.1	54.1	52.3	55.0	28.8	16.6	30.5	28.0	23.4
Utilities & trnsprt	14.4	14.9	13.9	13.1	13.5	7.7	3.8	5.0	3.8	7.0	7.3	14.1	12.9	11.7	9.0	4.5	2.3	5.9	4.7	3.5	0.0	6.7	0.0	2.9	0.0	14.7	10.5	14.6	15.2	10.9
Skilled services	3.8	4.8	4.6	6.2	5.3	0.9	0.7	0.7	0.4	0.1	1.7	3.9	1.9	1.2	2.7	2.4	1.5	1.6	2.0	2.7	2.1	8.7	0.0	5.6	6.5	2.8	4.6	3.1	10.2	6.2
Public admin	6.4	6.2	7.5	5.0	4.6	2.2	3.4	2.6	0.7	0.5	5.3	5.3	5.8	3.1	6.1	1.4	0.2	1.4	0.6	2.4	0.0	1.1	0.0	0.0	0.0	1.1	0.0	1.0	0.7	1.3
Education & Health	6.8	8.1	9.6	7.7	7.6	1.7	2.8	2.0	0.9	2.2	5.4	4.7	6.3	6.0	4.9	7.2	6.3	5.1	6.6	7.0	8.7	0.4	0.0	10.2	2.5	12.4	14.2	21.1	9.2	14.9
Domestic servants	1.4	1.3	1.5	0.7	0.5	0.6	0.7	2.1	0.7	0.2	0.9	1.9	0.6	0.4	0.0	1.2	0.4	2.3	0.5	0.9	15.3	0.0	0.0	5.2	0.0	3.8	1.8	1.1	0.0	1.4

Notes: **t=1**: [1993-1996]; **t=2**: [1997-2000]; **t=3**: [2001-2004]; **t=4**: [2005-2008]; **t=5**: [2009-2012]. Low educated=HS dropout or less. Source: Own calculations using SEDLAC and EPH survey

Table A4: Distribution of workers by economic/industry sector and country/region of birth.
High educated workers. Men 18-65

	Natives					Bolivia					Chile					Paraguay					Peru					Uruguay				
Industry Sector	**t=1**	**t=2**	**t=3**	**t=4**	**t=5**	**t=1**	**t=2**	**t=3**	**t=4**	**t=5**	**t=1**	**t=2**	**t=3**	**t=4**	**t=5**	**t=1**	**t=2**	**t=3**	**t=4**	**t=5**	**t=1**	**t=2**	**t=3**	**t=4**	**t=5**	**t=1**	**t=2**	**t=3**	**t=4**	**t=5**
Primary activities	1.3	1.0	1.6	1.6	1.7	0.1	0.4	0.2	0.1	0.6	2.3	3.9	6.4	2.9	2.8	0.0	0.4	1.6	0.2	0.5	0.4	0.4	0.2	0.2	1.7	0.2	1.1	0.1	0.5	0.2
Industry low tech	4.6	3.7	4.9	5.6	5.6	24.0	24.9	20.1	25.2	31.8	2.3	3.9	6.0	4.3	3.9	7.2	9.6	13.1	19.3	17.4	3.5	8.4	5.1	7.8	9.3	6.8	5.7	3.4	11.9	15.3
Industry high tech	14.0	13.4	10.8	11.5	10.7	5.8	3.7	10.5	6.6	4.2	13.3	6.6	11.9	11.3	6.7	19.9	9.8	14.0	9.4	11.1	5.4	13.0	16.7	6.7	8.4	15.0	25.5	11.8	10.0	14.5
Construction	4.5	4.6	5.2	6.1	7.0	17.5	21.5	21.3	29.6	28.5	10.6	16.8	14.1	15.5	24.7	13.1	24.1	21.3	28.5	28.7	10.2	18.4	18.0	17.5	18.8	14.2	14.6	10.5	6.2	16.6
Commerce	22.6	21.7	22.1	22.5	22.3	24.9	19.8	18.3	22.7	14.3	31.3	24.5	26.2	25.7	22.5	26.0	19.9	20.5	17.4	22.6	25.1	28.6	25.7	33.7	37.5	27.1	24.5	19.9	31.3	13.6
Utilities & trnsprt	10.5	11.0	10.7	10.1	10.2	7.7	4.7	11.2	4.4	5.5	12.4	10.2	8.9	16.3	12.0	10.5	1.5	3.1	5.2	4.0	5.9	6.9	11.9	4.6	6.3	13.9	6.1	11.9	14.3	10.0
Skilled services	17.5	18.7	17.5	16.6	16.4	1.0	7.5	3.9	6.2	6.4	11.2	15.6	3.0	7.1	10.3	12.3	14.1	7.2	4.3	4.7	8.8	4.1	8.1	6.0	8.8	12.6	11.3	11.8	7.9	7.2
Public admin	9.7	10.3	10.2	10.2	10.5	3.3	3.3	1.4	0.4	1.1	2.4	2.1	5.5	3.7	4.2	0.0	0.0	1.0	0.2	1.3	2.6	2.0	1.3	0.9	1.4	0.9	0.9	2.9	4.1	2.4
Education & Health	15.3	15.5	16.6	15.7	15.3	15.5	9.4	13.0	5.0	7.2	13.9	15.7	16.4	13.2	12.8	11.1	20.5	18.2	14.9	8.6	33.9	16.8	12.0	20.9	7.0	8.2	9.5	26.1	13.3	20.1
Domestic servants	0.1	0.2	0.4	0.1	0.1	0.0	4.8	0.0	0.0	0.4	0.2	0.7	1.6	0.2	0.2	0.0	0.0	0.0	0.6	0.9	4.1	1.3	1.2	1.9	0.7	1.0	0.7	1.6	0.5	0.1

Notes: **t=1**: [1993-1996]; **t=2**: [1997-2000]; **t=3**: [2001-2004]; **t=4**: [2005-2008]; **t=5**: [2009-2012]. High educated=HS graduated or more. Source: Own calculations using SEDLAC and EPH survey

Table A5: Impact of immigration on wages. Alternative set of instruments

	2SLS			
	Baseline controls		Include demand control	
	Log hourly wage	Log monthly wage	Log hourly wage	Log monthly wage
A. Baseline model (eq. 10)				
Share of LAC immigrants	-2.357*	-2.908*	-2.360*	-2.900*
	(1.416)	(1.586)	(1.417)	(1.601)
Native's unemployment rate			-0.034	0.094
			(0.206)	(0.295)
F excluded instruments 1	5.538	5.538	5.404	5.404
B. Model 2 (eq. 11)				
Ratio LAC immigrants/Natives	-2.687	-2.935	-2.221	-2.930
	(1.738)	(1.830)	(1.654)	(1.890)
Log size of native labour force	-0.109	-0.170	-0.025	-0.082
	(0.111)	(0.120)	(0.105)	(0.111)
Native's unemployment rate				
F excluded instruments 1	2.403	2.403	4.375	4.375
F excluded instruments 2	112.5	112.5	205.6	205.6

Additional controls: *time fixed effects, education fixed effects, age fixed effects, education-age interactions, education-time interactions, age-time interactions*

Notes: Robust standard errors are adjusted for clustering within education-age cell. All the calculations are based on 173 observations. Regressions are weighted by the sample size of each education-age-time cell. **2SLS** Instrument for the share (ratio) of immigrants is the predicted cell distribution of immigrants using lagged information from the six most popular countries of origin among LAC immigrants in Argentina. Log size of native labour force instrumented with the population size of the corresponding cell. The sample consists of men aged 18-65. Source: Own calculations using SEDLAC and EPH survey.

A.2 Robustness to age-substitution assumption

The "national approach" proposed by Borjas (2003) and the nested CES framework (Card and Lemieux, 2001) assume an arbitrary partition of the labour force into homogenous categories. This partition is based on observable characteristics and workers are perfect substitutes within each cell. Although it seems natural to group workers according to education levels, it is not clear in the case of age. Different age grouping could lead to different conclusions. To test the robustness of results to this assumption, I allow a more flexible specification with a fuzzier definition of labour input categories. For an individual with age a and education e, define the "relevant share of immigration" $P_{et}(a)$ as a function of the shares of immigrants with education e at every possible age x:

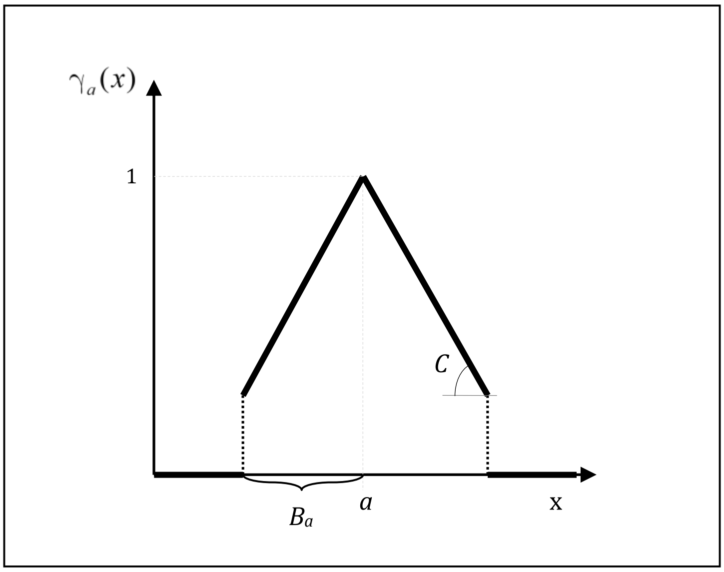
$$P_{et}(a) = \sum_{x=a_{\min}}^{a_{\max}} \gamma_a(x) P_{tex}$$

The function $\gamma_a(x)$ summarizes de degree of substitution between workers of age *a* and workers of age *x*, within a given level of education. For simplicity, I assume the following triangular weighting function:

$$\gamma_a(x) = \begin{cases} \max\{0, 1 - C|a-x|\} & \text{if } |a-x| \leq B_a \\ 0 & \text{otherwise} \end{cases}$$

A lower value of $C \in 0,1$ implies higher homogeneity of workers with different ages and similar education. $B_a \geq 0$ trims the range of relevant ages to be consider as potential substitutes in the production function. Figure A2 presents an example of this weighting scheme. Only workers with the same age are considered as perfect substitutes. Substitution decreases for individuals either older or younger than *a*.

Figure A2: Weighting function $\gamma_a(x)$



The standard approach in the literature of defining homogenous inputs within arbitrary age ranges, correspond to the case when $C = 0$ and B_a is defined to match a fixed interval of ages.

Table A6 summarizes the findings for different configurations of the parameters B and C. Each value corresponds to the estimated coefficient of the variable $P_{et}(a)$ in the wage equation. For comparison purposes, the weights has been rescaled to sum up to one and the estimated model corresponds to equation (11) since the coefficients of the Ratio of immigrants are directly interpreted as partial elasticities. The estimated impact is negative and significant in all cases and this is robust to different configurations of the weighting function $\gamma_a(x)$. The point estimates change with the parameters B, C, varying in the range from -0.36 to -1.3. Standard errors are smaller than previous results.

Table A6: Impact of immigration on wages. Robustness to age-substitution assumption. Different configuration of the weighting function $\gamma_a(x)$

Parameter C	**Parameter B**							
	0	1	2	3	4	5	6	7
0.01	-0.361**	-0.593***	-0.686**	-0.867***	-1.134***	-1.277***	-1.380***	-1.304***
	(0.145)	(0.215)	(0.279)	(0.301)	(0.361)	(0.419)	(0.448)	(0.478)
0.1	-0.361**	-0.595***	-0.702**	-0.887***	-1.134***	-1.273***	-1.378***	-1.399***
	(0.145)	(0.215)	(0.276)	(0.300)	(0.348)	(0.394)	(0.417)	(0.434)
0.2	-0.361**	-0.596***	-0.713***	-0.876***	-1.008***	-1.008***	-1.008***	-1.008***
	(0.145)	(0.215)	(0.271)	(0.294)	(0.315)	(0.315)	(0.315)	(0.315)
0.4	-0.361**	-0.590***	-0.672***	-0.672***	-0.672***	-0.672***	-0.672***	-0.672***
	(0.145)	(0.212)	(0.241)	(0.241)	(0.241)	(0.241)	(0.241)	(0.241)
0.6	-0.361**	-0.562***	-0.562***	-0.562***	-0.562***	-0.562***	-0.562***	-0.562***
	(0.145)	(0.203)	(0.203)	(0.203)	(0.203)	(0.203)	(0.203)	(0.203)

Notes: Table shows the estimated coefficient of the relevant ratio of immigrants to natives for different parameter configuration of the weighting function. Weights are rescaled to sum to one. Dependant variable: Log hourly wage. Robust standard errors are adjusted for clustering within education-age cell. All the calculations are based on 952 observations. The sample consists of men aged 18-65. Additional controls: log size of native labour force, time fixed effects, education fixed effects, age fixed effects, education-age interactions, education-time interactions, age-time interactions, log-size of internal immigration and unemployment rate of natives. Regressions are weighted by the population size of the cell. Source: Own calculations using SEDLAC and EPH survey.