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Estimating the Impact of Added Jobs: A Local Multipliers Approach

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"Estimando el Impacto de Nuevos Empleos Mediante Multiplicadores Locales"

Resumen
La creación de empleo suele ser un argumento esgrimido a favor de distintas políticas. En este trabajo busco identificar que efecto tiene en el empleo no transable agregar un nuevo trabajo transable en Argentina. Encuentro que cada nuevo puesto genera 4 trabajos en el sector no transable. Para identificar este efecto utilizo un instrumento que utiliza las tendencias nacionales para aislar movimientos exógenos y dos bases de datos. La primera es una encuesta de hogares que permite medir empleo para distintas ciudades. La segunda es una muestra aleatoria de una base administrativa que permite seguir trabajadores a lo largo del tiempo. Aprovecho esto para estimar el efecto sobre contrataciones y separaciones. Encuentro que el mecanismo principal serian las contrataciones.

Palabras Clave: Empleo, Multiplicadores, Estimacion, EPH.

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Abstract
Indirect job creation is often an argument in favor of several policies. In this paper I seek to identify the impact an additional tradable job has on non tradable employment. I find that the addition of a tradable job in Argentina leads to the creation of 4 jobs in the non tradable sector in a given city. I identify this effect using a shift-share instrument and two datasets that register employment. The first is the national household survey that allows me to measure employment in different industries up to city level. The second is a random sample from an administrative dataset that allows to follow workers over time. I exploit this to estimate effects on hirings and separations. My findings suggest that the main mechanism is increased hirings.

Keywords: Employment, Multipliers, Estimation, EPH

Codigos JEL: J63, R23, R58

1 Introduction

There is a long-standing debate about the benefits of place-based industrial policies. Particular examples in Argentina include the "Regimen de Promoción Industrial" for the states of Tierra del Fuego and San Luis[1]. More recently, the possible construction of Amazon HQ2 in New York sparked a big debate that resulted in the cancelation of the development.

A common argument in favor of such plans is that the jobs generated in turn estimatulate more economic activity in the area, which leads to additional jobs and increased tax revenue. Among drawbacks, some point to increased gentrification, as high income workers displace the previous inhabitants of the area.[2]

In this paper I intend to focus on the employment spillover effects of tradable jobs, which are the ones usually created as a result of such policies. To measure the magnitude and significance of this effect I seek to identify the impact of adding a tradable job in a city in Argentina. This multiplier is not only relevant to the design of industrial policy. For instance, it allows us to have an estimate of indirect job loses or earnings as a result of changes in trade policy. It can also inform fiscal policy, helping estimate the total employment effects of certain policies.

I find that non tradable employment has an elasticity of 53 % with respect to tradable employment when measuring changes over ten years. To estimate the model I use the EPH, a national household survey that covers 70 % of the urban population of the country (CEDLAS, 2015) [3].

I then explore further in two different directions. First, I classify added tradable jobs as either high or low skilled. I consider a position to be skilled if the worker some higher education or more. I then re-estimate the multipliers for both kind of jobs. I find that the elasticity is lower for low-skilled jobs, which is consistent as these are usually lower paid.

[1] See Roman, Kataishi and Durán (2018) (Spanish)

[2] For an informal discussion see https://www.nytimes.com/2018/11/06/nyregion/amazon-long-island-city.html

[3] Equivalently, 60 % of the entire population.

Secondly, I look at the composition of this growth in net employment and estimate elasticities for hires and separations in the non tradable sector. Because estimating these require following workers, the EPH would not be useful for estimating elasticities on spans longer than a year. Instead I use a novel dataset which tracks a sample of formal private workers across 20 years. These workers are randomly selected from an administrative employer-employee matched dataset known as SIPA. While the publicly available random sample version does not allow to track firms, I can use it to compute hires and separations for different sectors in the economy.

I find that most of the increase in non-tradable employment comes from an increase in hires, although there is a drop in separations.

My estimation strategy follows closely that of Moretti (2010), who estimates job multipliers for the US. The elasticities I estimate are extremely similar to the ones he finds. An important difference is that he also estimates the multiplier of tradable jobs in other tradable sectors. I choose to focus instead on the impact on the non tradable sector.

To estimate this impact, OLS is not a viable strategy, as there are several elements that could give rise to biased coefficients. As an example, consider the installation of an university in a city, which in turn attracts technological start-ups. In this case it could be argued that the causality runs from non-tradable to tradable employment. To isolate exogenous changes in local tradable employment I use a shift-share instrument. The intuition behind this instrument is simple. We can decompose the growth of tradable employment into the growth of the different tradable industries. In turn, each industry growth rate can be thought of as a national component and a domestic component. If we assume the shares are exogenous and that the endogeneity is on the domestic growth component, we can build the instrument using the local industry shares and the national growth component. Thus, the validity of the instrument rests on the shares and the national industry growth being exogenous. I consider this to be a reasonable assumption, as it is unlikely that non tradable employment growth between t and $t+1$ can affect manufacturing labor shares in t. The existence of an unobserved confounder affecting both does not seem likely either. I refer to Goldsmith-Pinkham, Sorkin, Swift (2018) for a more technical description of the shift-share instrument.

Literature Review I make two contributions with respect to previous work: (i) estimation of local multipliers for Argentina and (ii) using a novel administrative dataset to build a panel of private workers in Argentina.

There is a large literature that tries to estimate local multipliers using identified shocks. Most of the literature has focused on estimating the response to demand shocks in the U.S. Autor, Dorn and Hanson (2013) estimate the response of local employment to increased China imports. They find that an increase of US $1000 in imports lead to a drop of 4 log points in tradable employment. They also find a negative effect (not significative) on non tradable employment, which is consistent with my findings. Mian and Sufi (2012) estimate the impact of an old car replacemement program in the U.S. They find that while more exposed counties bought more cars, there was a reversal after the program ended and thus, no effects on employment. Chodorow-Reich, Feiveson, Liscow and Woolston (2012) estimate the impact of increased fiscal transferences to states in the U.S. through the American Recovery and Reinvestment Act (ARRA). They find that a marginal increase of US $100,000 in transferences create almost 4 jobs. They also find evidence of an spillover effect, as 85 % of the new jobs are in sectors not directly affected by the transfer[4]. Wilson (2012) also estimates the impact of the ARRA, using a different identification strategy. He uses "exogenous formulary allocation factors" to identify the impact of increased transfers. His estimates are lower than that of Chodorow-Reich et al, finding that an extra US $1 million creates 8 jobs. All of the above estimate the employment effect of increased transfers of some sort (imports, fiscal transfers). Moretti (2010) and Moretti and Thulin (2013) estimate the impact of additional tradable jobs in Sweden and the U.S. using a specification very similar to mine. They find sizeable effects in both countries, increasing in the skill level of the created tradable job.

Among developing economies, Aragon and Rud (2013) estimate the effect of increased primary goods production on the surrounding area of a mine in Peru. They identify labor

[4]Because they exploit Medicaid reimbursements, those sectors would be Government, Health and Education.

demand shocks using a dif-in-dif approach that exploits differente distances to the mine. Estimation of multipliers in Argentina has focused on fiscal multipliers using an aggregate aproach and time series methods. Anos-Casero, Cerdeiro and Trezzi (2010) use a vector error correction model to estimate the fiscal multiplier in Argentina. They find that this multiplier is small and short lived, with a magnitude of 0.4 on private consumption. Puig (2015) uses the changes in the political representation of states to instrument federal fiscal transfers. He finds a small multiplier of magnitude 1 on the geographical GDP.

To the best of my knowledge, no papers use the publicly available random sample of the SIPA[5]. Some papers use the full dataset, which can only be accesed on site. Blanco, Drenik and Zaratiegui (2019) look at the dynamics of labor income during large devaluations. They find that real exchange rate movements lead to changes in employment in those sectors that are most exposed to it. Fajgelbaum (2019) estimates job-to-job transitions frictions and its effect on exports. Gonzalez Rozada and Ruffo (2016) explore the effect on unemployment duration of different kinds of benefits.

2 Theoretical and Empirical Framework

I follow closely the framework of Moretti (2010). Each city or commuting zone uses labor to competitively produce a finite number of tradable and non tradable goods. The former have its price set, while the latter's price is determined locally. Labor is mobile across sectors and its supply depends on preferences and mobility across cities.

I am interested in the effect on an additional job in the tradable sector, which could come from an increase in productivity or product demand. An additional job means the city budget constraint increases. This leads to increased demand for non tradable products which translates into increased labor demand in this sector. How many jobs in the non tradable sector are created as a result depends on three factors. The first is consumer preferences, which determines how much will product demand increase as wages and employment rise. The second is the kind of jobs that are created. High-skilled positions typically pay higher wages, which should mean a bigger increase in non tradable goods'

[5]Sistema Integrado Previsional Argentino: Argentina Social Security System

demand. Lastly, general equilibrium effects may damp the multiplier as higher wages in the city reduce labor demand in all sectors. For instance, consider the toy example of a city with no geographical mobility from other locations and an inelastic labor supply. In that scenario, an increase in employment in one sector necessarily means a reduction in employment in another sector. Clearly, non tradable jobs can be skilled as well and it is likely that the skilled and non skilled jobs will be affected diferently by increased tradadable employment. In this paper I abstract from this interesting distinction, which is left for future research.

In this paper I focus solely on the impact of tradable jobs in non tradable jobs and do not explore the effects within the tradable sector. Unlike Moretti, I also look to the two components of employment growth: hires and separations. In doing this, I start to explore the mechanisms that may be behind the job multiplier. This is relevant because hires and separations are influenced by different prices: while separations may be determined by incumbents wages, hires are influenced by entrant's wages.

Because the point of this paper is to estimate multipliers for Argentina, two caveats are needed. Unlike the U.S., Argentina could be considered a small open economy. This alters the framework, as external shocks to the tradable sector should be included. I consider this to be beyond the scope of this paper and leave it to future research. The second one is the possibility that non tradable jobs could be considered tradable if the unit of observation is too small. In this paper, the geographical units of observation are either conmuting zones or states so there most jobs traditionally considered non tradables can in fact be considered non tradables.

Based on my conceptual framework, I seek to estimate the following model:

$$Y_{t,c}^{NT} = \alpha + \beta_j \Delta_{t,t-j} X_{t,c}^{T} + \gamma d_c + \ \tau d_t + \epsilon_{c,t} \tag{1}$$

Where $Y_{t,c}^{NT}$ represents net employment growth ($\Delta_{t,t-j}N$), hires (H) and separations (S) in the non tradable sector in city c at time t. X can be net employment growth (ΔN), net skilled employment growth (HN) and net skilled low employment growth (LN) in the tradable sector in city c at time t. γd_c and τd_t are city and quarter fixed effects, respectively.

In my baseline specification, I regress net non tradable employment growth on tradable employment net growth. Because both variables could be affected by an unobserved confounder I instrument tradable employment growth using a shift-share instrument commonly known as a Bartik instrument [6]. To understand the intuition of this instrument is useful to think of as total tradable employment growth in a city as the sum of tradable industries employment growth. This growth, in turn, is the sum of a national component and a domestic one. The identifying assumption here is that endogeneity is focused on the domestic component and that the shares and the national component are exogenous[7]. Thus, because the employment shares are exogenous, cities have a differential exposure to an increase in national steel production, for example. For a detailed exposition of the theoretical and empirical implications of this instrument I refer to Goldsmith-Pinkham, Sorkin and Swift (2018). In this paper the Bartik instrument is built as follows:

$$B_{c,t} = \sum_{i \in T} \omega_{t-j,c,i} \Delta_{t,t-j} N^{T,i} \tag{2}$$

Where $\omega_{t-1,c,i}$ is the lagged employment share of industry i among tradable industries in city c. $\Delta N^{T,i}$ is the national growth rate of industry i. When computing the national growth rates I omit city c to avoid finite-sample bias.

I estimate the specification in Eq. (1) for $j = 1, 2, ..., 10$. I also estimate versions of (1) that considers a quadratic trends and find that the main conclusions are not altered.

3 Data and Variables Construction

I exploit two data sources to estimate the local multipliers. For my baseline specification I use the national household survey (EPH). To look into hires and separations I exploit a novel random of an administrative employer-employee matched dataset called SIPA.

[6] Named after Bartik (1991).

[7] The important assumption is that the shares are exogenous as we could also proxy the national growth component with a different variable.

3.1 EPH

Data Description. The main source of micro-data is the Permanent Household Survey (Encuesta Permanente de Hogares), which is the main household survey in Argentina. It covers 31 large urban areas with an estimated representativeness of more than 60 % of the total population. In any given year the total sample size is around 100,000 households and the average response rate is in the order of 90 % (which is similar to the U.S. "March Current Population Survey"). The questionnaire contains extensive information of labor market participation (hours worked, labor income, tenure, industry of occupation, etc.) and demographics (level of education, age, etc.). Between 1995 and 2003 the survey was conducted twice a year and afterwards started being conducted on a quarterly basis.

Sample Selection. I restrict the sample to workers aged between 18 and 65 years. To focus on full-time jobs, I drop observations belonging to workers who worked less than 30 hours in the week before they were surveyed.

Region Definition. The EPH surveys 32 urban agglomerations or conmuting zones. I drop three agglomerations from the analysis as they were added into the survey later in time.

Sector Definition. I classify workers into the tradable or non tradable sectors. I consider an occupation to be tradable if it is within a sector belonging to manufacturing, as defined by ISIC[8]. While primary sectors such as agriculture, forestry and fishing, mining and quarrying are tradable I exclude them from the analysis. I do this mostly because the EPH is an urban survey, so it is not adequately suited to capture employment in these areas. The rest of the sectors are considered as non tradable. To build the Bartik instrument, I disagregate the tradable sector into 19 sub sectors that correspond to the 2 digit classification of the ISIC classification.

[8]International Standard Industrial Classification of All Economic Activities

High-Skill Definition. I consider a job to be high-skill if the worker has some college or more. Jobs with workers with less education are considered low-skilled.

Variable Construction. My main variable of interest is employment growth within sectors. I compute employment growth as the log difference of employment in $t, t-j$ where $j = 1, 2, ..., 10$.

3.2 SIPA

Data Description. The dataset I use is a publicly available[9] random sample of the National Social Security System ("Sistema Integrado Previsional Argentino"). By law, all employers in the formal (private and public) sector must present sworn statements providing information included in workers' paycheck to SIPA every month. This information is used for tax purposes and contributions to the social security system by employees. Readers interested in this data should see Blanco, Drenik and Zaratiegui (2019) for an extensive description of the data. The random sample has 3 % of worker-firm level monthly observations, which amounts to 1.5 million observations or half a million workers.

Sample Selection. I restrict the sample to workers aged between 18 and 65 years. The dataset does not report worked hours so excluding part-time workers is not straightforward. Instead, I drop observations belonging to jobs where workers earn less than three quarters of the current minimum wage.

Region Definition. The dataset does not report the conmmuting zone where the job is located, reporting only the state. There is one exception for the state of Buenos Aires, which is the largest in the country[10]. In this case, the dataset reports whether the job is located in what is known as "Gran Buenos Aires", a large urban aglomeration which surrounds the country's capital (itself a federal district) or the rest of the state. While this is an obvious limitation of the data, most states population is concentrated in cities so the bias is not that considerable.

[9] see http://www.trabajo.gob.ar/estadisticas/basesusuarias/mler/
[10] Buenos Aires has an area equivalent to Italy and is inhabited by 40 % of the country's population.

Sector Definition. I classify workers into the tradable or non tradable sectors. I consider an occupation to be tradable if it is within a sector belonging to manufacturing, as defined by ISIC. To keep results comparable with the EPH's results I exclude agriculture, forestry and fishing, mining and quarrying. The rest of the sectors are considered as non tradable. To build the Bartik instrument, I disagregate the tradable sector into 18 sub sectors that correspond to the 2 digit classification of the ISIC classification.

Variable Construction. I focus on 3 outcome variables: net employment growth, separations and hires in the non tradable sector between t and $t-j$. Separations is the fraction of workers who had a job in the sector in $t-j$ and now do not. Hires is the fraction of workers who did not have a job in $t-j$ and now do. In both cases the denominator is the total number of workers in the sector in $t-j$. The independent variable is again net employment growth in the tradable sector.

4 Results

Table 1 presents the results of the regressions that use the EPH data considering a time span of 10 years. The first column displays the elasticity and the second column the multiplier for net tradable employment growth. I estimate the multiplier as :

$$\begin{aligned}
\Delta^{NT}_{t,t-j} &= \beta_j \Delta^{T}_{t,t-j} \\
\frac{NT_t - NT_{t-j}}{NT_{t-j}} &= \beta_j \frac{T_t - T_{t-j}}{T_{t-j}} \\
NT_t - NT_{t-j} &= \beta_j \frac{NT_{t-j}}{T_{t-j}} (T_t - T_{t-j})
\end{aligned}$$

$$NT_t - NT_{t-j} = m^T_j (T_t - T_{t-j}) \tag{3}$$

Where $m^T_j \equiv \beta_j \frac{NT_{t-j}}{T_{t-j}}$ is the jobs multiplier.

Table 1: Effect on Non Tradable Employment

	Elasticity	Multiplier	N
Tradable Jobs	0.54 (0.07)	4.06	897
High-Skill Tradable Jobs	0.26 (0.08)	13.35	834
Low-Skill Tradable Jobs	0.17 (0.01)	1.67	897

Note: Results from estimating Equation (1) using EPH

The first row shows the results for total tradable employment growth. The elasticity is 0.53 which is similar to the US elasticity estimated by Moretti (2010). It translates into a multiplier of 4. These estimates change if we focus on whether the added jobs are high-skill or low-skill.

The second row shows that each high-skill tradable job adds on average 13 jobs in the non tradable sector. On the other hand, the multiplier for low-skill jobs shown in the third row is a bit less than 2. This result is expected, as higher-paying jobs are usually asociated with higher wages, which would lead to higher spending in the city.

Having estimated net employment growth multipliers, I move on to the mechanisms behind employment growth: hires and separations. Table 2 shows the employment, hires and separations elasticities using the random sample from SIPA.

Table 2: Effect on Non Tradable Employment, Hires and Separations

	Emp. Growth (%)	Hires (p.p)	Separations (p.p)
Coefficients	0.72 (0.02)	1.18(0.04)	-0.24 (0.09)
N	2975	2975	2975

Note: Results from SIPA

As the first column shows, there is a positive effect of tradable employment on non tradable employment. There is both a significant effect on hires and separations. The fraction of hired workers increases by 1.18 percentage points (2nd column) for each 1 % increase in employment. In turn, the fraction of separations is reduced by 0.24 percentage points (3rd column).

Davis, Faberman and Haltiwanger (2012) show that the behavior of hires and separations is not lineal in firms. When expanding, firms increase the number of hires while separations remain constant. When contracting, separations increase and hires remain constant. Thus, the effect of employment changes is not lineal.

To account for this possibility, I re-estimate the model allowing for different effects for positive and negative shocks:

$$T_{t,c}^{NT} = \alpha + \beta_j^p D_{t,t-j}^p \Delta_{t,t-j} X_{t,c}^T + \beta_j^n D_{t,t-j}^n \Delta_{t,t-j} X_{t,c}^T \gamma d_c + \epsilon_{c,t} \tag{4}$$

Where I estimate the effects on transitions T of positive (β^p) and negative (β^n) employment shocks.

Table 3 shows the results of this regression. A positive employment shock (1st row) increases hires and reduces separations, as expected. The effects are consistent with the previous results and with Davis, Faberman and Haltiwanger (2012), as the increase in hires is larger and the reduction in separations is smaller. The effects of a negative shock (first row) are different. There is a strong negative effect on hires and a small increase in separations which is not statistically significant. These somewhat puzzling effects could be due to the fact that there are few observations where employment growth is negative. There is, however, evidence of assymetric results.

Table 3: Effect on Hires and Separations of Positive and Negative Shocks

	Hires (p.p)	Separations (p.p)
Positive Shock	1.30(0.05)	-0.16 (0.006)
Negative Shock	-1.79 (0.40)	0.05 (0.05)
N	2975	2975

Note: Results from estimating Equation (4) using SIPA

5 Discussion

This paper makes two important contributions. The first is estimating local multipliers for Argentina. A new tradable job adds in average 4 jobs in the non tradable sector in a given city. This effect is bigger when the new job is high-skill and lower when its not. A preliminary exploration using a novel dataset shows that there is an effect on both hires and separations. The former increases while there is a reduction in the latter. The main driver seems to be the increase in hires. Because there is evidence that hires and separations are not linear on employment growth, I allow for assymetric effects. I find that consistent with previous work, the effect on hires is stronger when only positive shocks are considered. When considering only negative shocks, results are less precise, in part due to a reduced sample. There seems to be a strong effect on hires as well. Negative employment growth is uncommon in the sample and in most cases it is close to zero, so this result should be considered with caution.

The second, and perhaps most important, contribution is establishing the framework for the estimation of multipliers. This includes using a new, publicly available dataset that complements the household survey. To the best of my knowledge, no published papers use this dataset. The framework is extremely flexible and allows to estimate multipliers for a variety of shocks.

This opens up the door for future research. One possible direction is understanding the role of the country's macroeconomic context and labor institutions in these multipliers. Appendix D shows some time series for macroeconomic aggregates of interest for the period of estimation: 2006-2018. Because this is a relatively stable for the country's standards, it doesn't allow to identify how this multiplier varies over recessions and expansions. Labor institutions also matter, as they affect how wages respond to shocks and how easy it is for firms to change employment. A recent paper by Boeri, Ichino, Moretti and Posch (2019) suggests that nationwide bargaining bargaining, as it is the case in Argentina, may have detrimental effects on the job market. Another question is does inflation buffer negative shocks by lowering real wages? The other possible direction is looking into the non-linearity of hires and separations.

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A Data: Additional Information

A.1 Data Description

A.1.1 EPH

Variables description. Table A.1 describes the variables used from the EPH in the paper. Worker's variables include: Identification code, gender, age and education level. The latter details whether the worker has (some) primary, secondary, college or graduate education. The EPH also lets us know whether the person is working or not and whether she is employed or self-employed. Lastly, we can identify in which conmmuting zone the worker lives.

Regarding the occupation, the EPH reports the industry, using a 4-digit ISIC Rev. 3 classification.

Table A.1: Variables in EPH

Variable	**Years in data**	**Short description**
Worker's variables		
Worker identification	1996-2018	Household ID + HH Component ID
Gender	1996-2018	
Age	1996-2018	
Education	1996-2018	(Partial) Primary, Secondary, College, Graduate.
Activity Status	1996-2018	Employed, Unemployed, Inactive
Kind of Occupation	1996-2018	Self-Employed, Employee
Ocuppation Variables		
Conmuting Zone	1996-2018	CZ where the employee works
Industry	1996-2018	4-digits CIIU

Notes: The table describes the variables in the EPH, together with the years of coverage in the sample.

Sample construction. Table A.2 describes how I built the sample used for the analysis. I start by appending two different EPH datasets. The first (EPH Puntual), that spans 1995-2003 was conducted twice a year (May and October). The second (EPH Continua) spans 2003-2018 and is conducted during the entire year, with results being representative of each quarter.

In total, there are $4,772,032$ individuals-data observations in the dataset. In average, there are $70,217$ people in each period surveyed. When using the population weights, this amounts to an average of $24,035,476$ people.

I first removed observations belonging to 1995, as not all cities were covered in that year. There are also some conmmuting zones that were included in the survey later in time. To keep a balanced panel, I drop these as well. Observations dropped in the last two steps account to almost 9 % of the sample. Because I am interested in changes in employment, I will consider only employed workers who are between 18 and 65 years old. I also drop those workers who report working less than 30 hours a week. Observations excluded in this two steps are approximately 67 % of the sample. Finally, I drop those observations that do not report an industry. These are 0.18 % of the sample. The resulting dataset has $1,155,393$ observations, which is equivalent to 24 % of the original dataset.

Table A.2: Data Description: Cleaning Statistics

Description	EPH	
Start Year	1995-Q2	
End Year	2018-Q2	
Avg. Number of Individuals per Period (Weighted)	70, 217 (24,305,476)	
Total Number of Date-Individuals Observations	4,772,032	
Cleaning	Number of Removed Observations	
	Total	%
Observations in 1995	205,563	4.30%
CZs that started being surveyed later	203,949	4.29%
Age <18 or >65	1,774,758	37.19%
Works less than 30 hours a week	1,423,441	29.82%
No defined Industry	8,928	0.18%
Remaining observations	1,155,393	24.21%

Notes: The table describes the size of the original sample, the different groups of workers (i.e., private vs. public sector workers, non-prime age workers, etc.), and the size of the dropped sample after applying the filters discussed in the main text. Percentages are estimated over the original number of observations so they sum up to 100%.

A.1.2 SIPA

Variables description. Table A.3 describes the variables used from the random sample of the SIPA dataset. Regarding the workers, we have three important variables: Worker ID, age and gender. The former is an anonymized version of the social security number and allows us to track workers over the entire sample.

When the worker is employed, we can know the industry of the occupation, which follows the same 4-digit ISIC Rev. 3 classification as the EPH. There is also a firm ID. The purpose of this ID is not to identify firms across workers but rather to distinguish different employment spells within workers. That is, a given firm ID only tells us whether this current firm the worker is employed at is different from his previous occupation. Lastly, this dataset also informs the state where the worker is currently employed.

Table A.3: Variables in SIPA

Variable	Years in data	Short description
Worker's variables		
Worker identification	1996-2015	
Gender	1996-2015	
Age	1996-2015	
Ocuppation Variables		
State	1996-2015	State where employed works
Industry	1996-2018	4-digits CIIU
Firm ID	1996-2015	Relative to Worker, Allows to distinguish work spells.

Notes: The table describes the variables in SIPA, together with the years of coverage in the sample.

Sample Construction Table A.4 describes how the SIPA random sample was cleaned. The dataset, that spans 1996-2015 has a total number of 35,438,482 observations. In each period there are in average 119,347 workers.

When possible, I followed the same procedure as with the EPH dataset. I dropped workers aged less than 18 or 65 years old, who represented 1.67 % of the sample. Because I do not observe worked hours, I can't exclude observations with less than 30 hours a week as I did with the EPH. To substitute for this, I dropped observations that corresponded to jobs earning less than three quarters of the current minimum wage. They represent almost 10 % of the sample. I also dropped observations where either the state or the industry is not defined. Together, they account for almost 7 % of the sample. Lastly, I onlyfocus on the main job held by a worker in each month. I define the main job as the one who pays the more. In the EPH this is done automatically as the survey asks about main and secondary job. The resulting sample is approximately 81 % of the original dataset.

B Panel Construction

Table B.1 describes the panel used in the regressions in Section 4. There are a number of differences. In a geographical dimension, the EPH surveys conmuting zones. The random sample of SIPA only allows to determine the state where the job is located. Because the EPH is in quarterly frequency, there are fewer periods than in the SIPA panel. This leads to the SIPA panel having three times as many observations. Another difference is that the EPH has weights that allow us to obtain population estimates. Hence there are in average 179,381 people employed in a given city in a given quarter. On the other hand, there are in average 4,463 people employed in a given state in a given month in the SIPA panel.

Table A.4: Data Description: Cleaning Statistics

Description	SIPA	
Start Year	1996-M1	
End Year	2015-M12	
Avg. Number of Individuals per Period	119,347	
Total Number of Date-Individuals Observations	35,438,482	
Cleaning	Number of Removed Observations	
	Total	%
Age <18 or >65	593,424	1.67%
Works less than 30 hours a week	3,387,050	9.55%
No defined state	2,390,456	6.74%
No defined industry	4257	0.012%
Second job	419,968	1.18 %
Remaining observations	28,643,328	80.82%

Notes: The table describes the size of the original sample, the different groups of workers (i.e., private vs. public sector workers, non-prime age workers, etc.), and the size of the dropped sample after applying the filters discussed in the main text. Percentages are estimated over the original number of observations so they sum up to 100%.

Table B.1: Data Description: Panels

	Dataset	
	EPH	SIPA
Geographical Unit	CZ	State
Number of geographical units	29	25
Time frequency	Quarterly	Monthly
Number of periods	71	240
Total number of observations	2057	6000
Avg. total employment in each observation	179,381 (weighted)	4,463

Notes: The table describes the panels used in the regressions used in Section 4.

C Instrument Construction

The Bartik instrument is built as follows:

$$B_{c,t} = \sum_{i \in T} \omega_{t-j,c,i} \Delta_{t,t-j} N^{T,i} \tag{5}$$

Where $\omega_{t-1,c,i}$ is the lagged employment share of industry i among tradable industries in city c. $\Delta N^{T,i}$ is the national growth rate of industry i. When computing the national growth rates I omit city c to avoid finite-sample bias.

Figure C.1 plots the histogram of both the employment growth and its instrument for the EPH dataset.

Figure C.1: Comparison of Tradable Employment Growth and its Instrument:SIPA

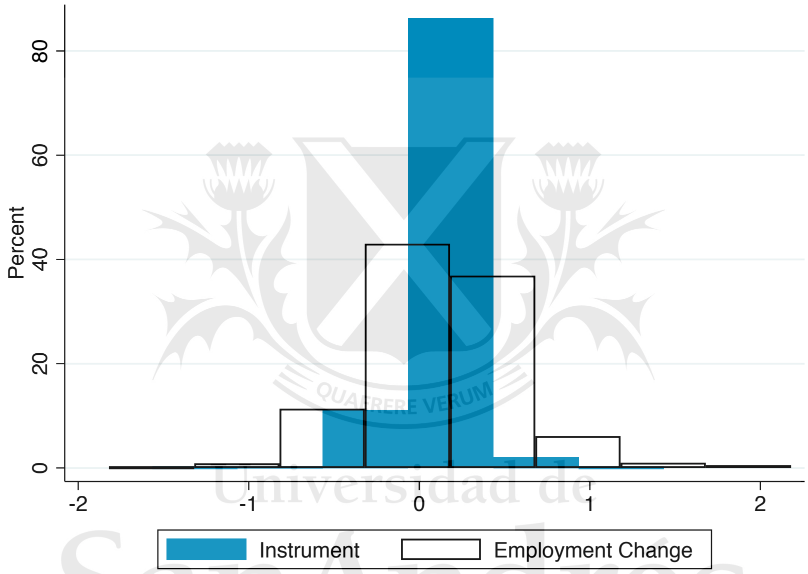
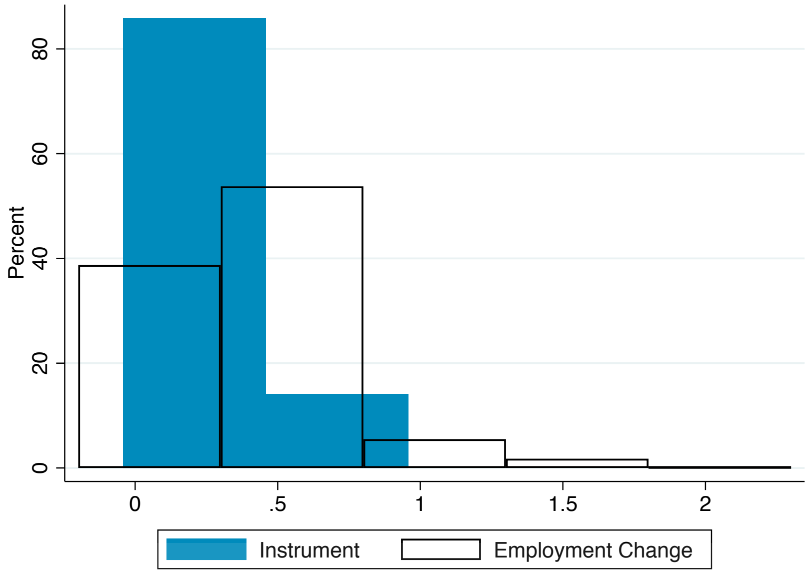


Figure C.2 plots the histogram of both the employment growth and its instrument for the SIPA dataset.

Figure C.2: Comparison of Tradable Employment Growth and its Instrument:SIPA



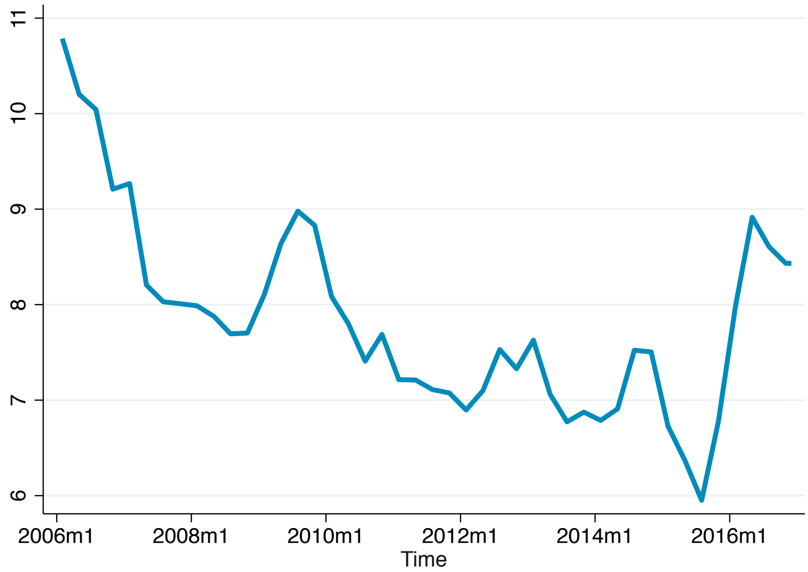
D Macroeconomic Time Series

In this section I plot the GDP and Unemployment of Argentina for the estimation period 2006-2018.

Figure D.1: Argentina's GDP 2006-2018

Notes: The figure shows the time series of log gdp at a quarterly frequency. To remove the cyclical component I used a moving average with a window of three periods. Source:INDEC

Figure D.2: Argentina's Unemployment 2006-2016



Notes: The figure shows the time series of unemployment at a monthly frequency. To remove the cyclical component I used a moving average with a window of three periods. Source:INDEC