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Imperfect Substitutability Between Old And Young Workers.

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Abstract

Employment rate of older workers in Italy has increased over the last decade, meanwhile youth employment rate have experienced a big decline. These divergent employment paths raise a question about the substitutability between old and young workers. In order to answer that question, we propose a novel identification strategy to estimate the elasticity of substitution in production between old and young workers. We start setting the labor demand functions for both groups within the same region-occupation-time group to estimate such elasticity. Then, we develop a theoretical model that shows towards-zero estimation bias induced by time correlations within each region-occupation-time group. To overcome this estimation problem, we use a set of instruments based on yearly employment changes by age and citizenship. Using yearly Italian administrative data for the period 1995-2004, we exploit a number of pension and labor migration reforms to create a set of exogenous instruments to time correlations within a region-occupation-time group. Finally, we find that old and young employees within the same region-occupation-time cell experience imperfect substitutability in production.

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1 Introduction

May increases in both life expectancy and retirement age affect youth employment opportunities? Most developed countries experience a decline in either youth employment rate or youth participation rate together with an increase in older participation rate. In 2018, France's and Italy's youth unemployment rates were still larger than pre 2008-crises, 20.08% and 32.2% (OECD database) respectively. While, the U.K.'s and the U.S.'s youth participation rates were 5% and 4% (OECD database) lower than pre 2008-crises, respectively. At the same time, all developed countries experience an increase in participation and employment rate for workers age over 55. These divergent patterns raise a question on the existence of a large degree of substitutability between old and young workers.

The substitutability between old and young workers is an outstanding question in labor literature. On the one hand, the *lump of labor* concept claims that old and young workers compete for a scarce good: a job. Boeri et al. (2017) show that the 2011 sudden increase in the retirement age of *baby-boomers*, the generation born between the end of the World War II and the late '50, due to a pension reform has negatively affected youth employment in Italy. Mohnen (2019), using 1980-2017 U.S. data, finds that the effect of an increase in the retirement age on the youth employment is wider the larger older worker share in low skilled jobs. Bertoni and Brunello (2017) find the same results in Italy between 2004 and 2015. Further, Bovini and Paradisi (2018) find that the effect of an increase in Italian retirement age on youth labor outcomes is wider the larger share of manufacturing workers over the period 2009-2015. On the other hand, the existence of imperfect substitutability between old and young workers should lower the competition for the same job. Brugiavini and Peracchi (2010) find that delaying retirement has a positive on the youth employment rate in Italy between 1997 and 2004. Gruber and Wise (2010) find a positive effect of an increase in older participation rate on youth employment rate by studying labor markets of several developed economies from late '70 to the beginning of the new century. Munnell and Wu (2012), using 1977-2011 U.S. data, show that an older employment increase leads to better labor outcomes for young workers, raising both wages and employment rate. Our paper fills in by offering a novel identification strategy to estimate the old-young elasticity of substitution in production.

In our paper, the elasticity of substitution between old and young workers is the ratio of the percentage change in old-young employment ratio (labor gap) to the percentage change in the old-young wage ratio (wage gap) within the same region-occupation-year cell. We estimate the inverse of such elasticity to identify the causal relation of an increase in labor gap on wage gap. The greater is the identified effect, the smaller is the substitutability between old and young workers. To put it in another way, imperfect substitutability leads to a smaller effect on the age-group wage not affected by the employment increase.

We estimate a structural model to find the elasticity of substitution between old and young workers. We choice a nested constant elasticity of substitution (CES) production function to derive the relation between labor gap and wage gap for two reasons. First, the nested CES dimensions, in our case region-occupation-age-year, allow to control for different demand shifts. Second, the linearity of log first order conditions enables to study the old-young elasticity of substitution by using linear estimators. To estimate the model, we use 1995-2004 Work Histories Italian Panel (WHIP) employee data to estimate such elasticity. We restrict the sample to 712,514 full-time male workers in the private sector as they experience larger employment spells and, hence, accumulate on-the-job human capital at a constant pace. We aggregate data on employees to build total employment and average wage per region-occupation-age-year cell.

Estimating the effect of a labor gap change on the wage gap is not trivial as long-run dynamics might bias the estimates. In the short run, age-specific labor supply shocks might lower the wage gap through a change in the labor gap, but the occurrence of general equilibrium adjustments restores the previous wage gap equilibrium in the long run. Hence, labor supply shocks might have a negative effect on wages in the short run, but a positive one through general equilibrium adjustments in the long run. The net effect might be null, showing inverse-elasticity estimates biased towards zero, since the two effects offset each other. We call the general equilibrium adjustment mechanism *offsetting mechanism*, because it offsets any wage disequilibrium in the long run. Since the *offsetting mechanism* is unobservable and positively correlated with the labor gap and wage gap, elasticity estimates are upward biased.

Our paper contributes to solve this puzzle with two main innovations. First, we develop a theoretical model to understand how the *offsetting mechanism* biases the estimates. The idea is that the *offsetting mechanism* begins to adjust the disequilibrium a year after the labor supply shock applies. Hence, we model *offsetting mechanism* as a function of past labor supply shocks. In order to reduce the bias of the past shocks, a good instrument is a shock at current year. To the best of our knowledge, this way to study the *offsetting mechanism* bias is a novelty in the elasticity of substitution estimation literature.

Second, we provide a novel set of instruments to estimate the elasticity of substitution. As mentioned above, we have to find an instrument uncorrelated with past labor supply shocks to identify such elasticity. One candidate is the labor gap in first differences, because first differences sweep away past trends. However, labor gap in first differences might be correlated with region-occupation-year unobservable heterogeneity. In order to avoid this endogeneity issue, we combine the age dimension, old and young, with the citizenship dimension, native and foreigners, to create four instruments. Each instrument is the ratio of yearly region-occupation-age-citizenship employment change to the total yearly region-occupation-age employment. We exploit a deeper dimension aiming at lowering the region-occupation-year bias. To strengthen our identification strategy, we exploit a set of age-citizenship specific reforms enacted in Italy between 1995-2004. Reforms were enacted to save the Italian social security system from default by increasing both the retirement age and the workers per retiree. The timing of the reforms is suitable to identify the elasticity of substitution since not-serial correlated employment changes lowers the bias with past region-occupation-year labor gap changes.

We find that an increase in the labor gap lowers the wage gap by around 16% within the same region-occupation-year labor market. Further, the effect corresponds to an elasticity of substitution around 6, because in our theoretical model the effect reflects the negative inverse of such elasticity. The elasticity of substitution value range starts from 0, perfect complementarity, to infinity, perfect substitutability, our findings are closer to zero than infinity showing an imperfect degree of substitutability between old and young workers. Our findings are in line with the existing literature on old-young elasticity of substitution (Borjas, 2003; Card and Lemieux, 2001; D'Amuri et al., 2010; Manarcorda et al., 2012; and Ottaviano and Peri, 2012) as scholars find very similar results for different countries in different periods.

We provide a set of robustness checks and sensitivity analyses to test our results. First, we change the weights used to estimate the elasticity, because different weights may lead to different point estimates (Borjas, et al. (2012)). We use wage gap variance as a weight in our baseline estimates, while we weight for total employment in every region-occupation-year cell to test our results. Results do not change. Second, we test our identification with the foreign employment instrument. This instrument is very common in the literature and it is widely used to estimate the old-young elasticity of substitution. We show that the instrument is weak in our specification. Third, we assume that labor supply shocks identify the effect, through our instruments, excluding region-occupation-year demand shocks. We use temporary laid-off workers as a labor demand shock instrument to check our assumption. The instrument is weak and estimates are not significant. Fourth, we evaluate whether our parameters of interest are time-varying. We interact with our instruments with a linear trend increasing the set of instruments from four to eight. The results do not change. Hence, our baseline specification is robust to time dimension.

Related literature.— The literature on old-young substitutability in production exploits demographic changes to understand the degree of complementary among several age groups. Freeman (1979) is one of the first to study the degree of substitution among workers belonging to different cohorts. He estimates the elasticity of substitution between *baby-boomers* and previous cohorts in the US. He finds that an increase in the young labor supply has a larger effect on younger workers' wage than on older workers' one. This result shows workers belonging to different cohorts are imperfect substitutes in production. Katz and Murphy (1992) extend the analysis by exploiting the industry level variability. They identify demand shocks with technological shifts and labor shocks with demographic cohort characteristics. They show that both have a role in setting out the degree of imperfect substitutability across different age groups. A further extension of Katz and Murphy (1992) is Card and Lemieux (2001), where they improve the accuracy of elasticity of substitution estimates by taking into account both time effects and cohort effects. The underlying intuition relies on different salary paths among cohorts over time. By exploiting "baby-boomer" shock in the U.S., Canada, and the UK in a nested constant elasticity of substitution, they are able to make cross-country comparisons of the results. They estimate an elasticity of substitution among different age groups in the range of 4 to 6 by proving that additional fixed effects play an important role to exclude any possible bias due to supply or demand shifts. Borjas (2003), D'Amuri et al. (2010), Manarcorda et al. (2012) and Ottaviano and Peri (2012) extend Card and Lemieux (2001) exploit foreign labor force as instrument to estimate old-young elasticity of substitution, but thier estimates do not show any significant difference.

All the mentioned scholars do not pay much attention to long-run effects, while Llull (2018) points out that demand for different labor inputs depend on past labor supply shocks[1]. He shows that human capital accumulation is one of the main drivers to adjust wage disequilibrium in the long run. Also Jaeger et al. (2018) show that firms anticipate the labor supply shifts by adjusting the capital level. These mechanisms happen when labor force increases are stable across years. However, they only focus on foreign labor supply shocks, while we address the long-run bias issue by taking into account native labor supply shocks as well. We provide an estimation strategy that complements the literature on old-young elasticity of substitution estimate and adds an other piece to general equilibrium adjustment puzzle. Our estimation method relies on Arellano and Bover (1995) who exploit the first differences to identify the long run parameter in a dynamic panel framework. The underlying intuition is the same, but we apply that in a static framework.

The article proceeds as follows. Section 2 describes the institutional background over the considered time span. Section 3 presents the theoretical framework. Section 4 shows the data and the descriptive statistics. Section 5 discusses the empirical strategy. Section 6 shows the results. Section 7 presents robustness checks. Section 8 concludes.

[1]People reshape their human capital accumulation after experienced labor supply shocks.

2 Institutional Background

At the turn of the 20th century, Italy has experienced a number of labor market reforms mostly tackling the supply side. Among others there were pension reforms and migration flows regulations. Depending on the type of reform, different cohorts of workers were involved.‘ What follows is a brief review of all these different policies, grouped by theme.

2.1 Pension Reforms

The age threshold defining the active population of a country clearly affects the size of labor force, and pension reforms play an important role in setting such a threshold. The idea behind reforms in the ’90s was keeping older workers in the labor market as longer as possible. This is due to an increase in life expectancy and experts were casting doubts on the sustainability of a pay as you go pension system. Two main pension reforms characterize the end of the century, Dini reform in 1995 and Prodi reform in 1997. As mentioned, the main aims were containment of public spending and curbing early retirement. The very first attempt to postpone retirement age (gradually) occurs with Amato reform, in 1992. In 1995, Dini reform, (L.335/1995), raised the age and contribution requirements for seniority pension. The change was gradual and finished in 2008. Prodi reform in 1997 further increases age and contribution requirements for seniority pensions.

2.2 Migration Reforms

Italy has long been a country of emigration. First regulations on immigration flows date back to the 80s. Up to that moment legalization of immigrant workers mainly happened through amnesties. In the ’90s, a pool of migration laws enacted and included an amnesty to legalize migrant workers who had been working (or living) in the country for a year before. In 1990, Martelli law, L. 39/1990, was the first to regulate economic immigration in the country and legalize 215,000 foreign workers.

This law imposed restrictions to incoming flows, and set a maximum number of workers to be accepted each year, based on foreseen Italian labor market needs. Dini decree, in 1995, allowed for the legalization of 244,500 immigrant workers. In 1998, the Turco-Napolitano law (L 40/1998) implemented major changes. This law represented the milestone for migration regulation in Italy. It involved inclusion of migrant workers within the labor force and made procedures and rules smoother and clearer. It allowed immigrants a temporary visa through the sponsorship channel to look for a job. Together with this reform, other 217,000 workers were regularized. Political debates spurred by increased migration flows conveyed into the Bossi Fini law (L. 189/2002). That stopped the sponsorship system and introduced stricter limitations to immigration. Few months after the enactment, the situation in black market was dramatic and, therefore, the two Ministers,Bossi and Fini, promoted the largest amnesty in Europe (634,700 immigrant workers were legalized). As such, some scholars used it to better understand the impact of amnesties on labor market outcomes. Devillanova et al. (2014) exploit it as a natural experiment and show that an increase in employment probability follows the prospect of legal status. Size of this increase is two third of the increase in employment rate illegal immigrant experience in the five years after entering the country. Di Porto et al. (2019) show the short term impact of 2002's regularization, with most of the legalized workers staying in the legal labor market for long. Amnesty regularized 62% of regular immigrants in the country in 2002 (Barbagli et al., 2004).

3 Model

3.1 Theoretical Framework

In order to study the elasticity of substitution between old and young workers we use a nested constant elasticity of substitution (CES) approach. Most of the prominent studies (e.g., Card and

Lemieux, 2001; Borjas, 2003; Ottaviano and Peri, 2012) have used an aggregate production function to estimate the elasticity of substitution between old and young workers. An aggregate model provides an overview of national labor market but loses information about differences among local labor markets. We prefer to add the regional dimension to take into account local differences in labor force. We assume an identical Cobb-Douglas production function in each region r at time t:

$$Y_{rt} = A_{rt}K_{rt}^{\alpha}L_{rt}^{1-\alpha} \tag{1}$$

where Y is the output, A is exogenous total factor productivity, K is the physical capital, L is a CES aggregate of different types of labor, and α is the income share of capital. L_{rt} includes workers who differ by occupation and age, respectively. Let

$$L_{rt} = [\theta_{rBCt}L_{rBCt}^{\frac{\sigma-1}{\sigma}} + \theta_{rWCt}L_{rWCt}^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where BC (WC) indicates blue collar workers (white collar workers) and σ is the elasticity of substitution between blue collar and white collar workers ($0 \leq \sigma < \infty$). The θs are the region-occupation-time specific productivity parameters, with $\theta_{rBCt} + \theta_{rWCt}$=1. Finally, every occupation-specific labor input is a CES aggregate of imperfect substitute age-specific labor inputs. In particular,

$$L_{rst} = [\gamma_{rsOt}L_{rsOt}^{\frac{\lambda-1}{\lambda}} + \gamma_{rsYt}L_{rsYt}^{\frac{\lambda-1}{\lambda}}]^{\frac{\lambda}{\lambda-1}} \quad s = BC, WC \tag{3}$$

where O (Y) indicates old worker (young worker) labor input and λ, our parameter of interest, is the elasticity of substitution between old and young workers, with $\lambda \geq 0$. γs are the region-occupation-age-time specific productivity parameters, with $\gamma_{rsOt}+\gamma_{rsYt}$=1. We get the old (young) labor demand within each region-occupation-year cell by assuming that marginal product of old (young) labor is equal to the old worker (young worker) wage. Using logs, the age specific labor demand within each region-occupation-year cell is equal to:

$$ln(w_{rsat}) = ln(A_{rt}K_{rt}^{\alpha}L_{rt}^{-\alpha}(1-\alpha)) + \frac{1}{\sigma}ln(L_{rt}) + ln(\theta_{rst}) - (\frac{1}{\sigma} - \frac{1}{\lambda})ln(L_{rst}) + ln(\theta_{rsat}) - \frac{1}{\lambda}ln(L_{rsat}) \quad (4)$$

Taking the difference side by side of labor demands for old and young workers, we get rid of all terms on the right-hand side, but the difference between productivity parameters and the difference between old and young labor demands:

$$ln(\frac{w_{rsOt}}{w_{rsYt}}) = ln(\frac{\theta_{rsOt}}{\theta_{rsYt}}) - \frac{1}{\lambda}ln(\frac{L_{rsOt}}{L_{rsYt}}) \quad (5)$$

Hereafter, we define the wage difference between the old and young worker as "wage gap" and the employment difference between old and young workers as "labor gap".

3.2 Labor gap between old and young by citizenship

In this subsection, we show how local and foreign labor supply shocks affect the labor gap between old and young workers. We assume that the employment level for old and young workers within the same region-occupation-year cell is a function of native and foreign employment[2] :

$$L_{rsat} = f(L_{rsaNt}, L_{rsaFt})) \quad (6)$$

where N (F) indicates native (foreigner) characteristics. We assume that each age-specific labor input is continuously differentiable and the first derivative with respect to citizenship dimension

[2] A wide range of literature (e.g. D'Amuri et al., 2010, Manarcorda et al., 2012 and Ottaviano and Peri, 2012) use a CES aggregate of native and foreign labor inputs in every age-specific group. We do not assume any functional form to avoid any constraint on the age-citizenship elasticity of substitution.

is greater than zero. Looking at differential[3] in discrete form we obtain:

$$\Delta(ln(L_{rsOt}) - ln(L_{rsYt})) = \Sigma_c(\beta_{Oc}\frac{\Delta L_{rsOct}}{L_{rsOt}} - \beta_{Yc}\frac{\Delta L_{rsYct}}{L_{rsYt}}) \qquad c = N, F \tag{7}$$

where

$$\beta_{Oc} = \frac{\partial L_{rsOt}}{\partial L_{rsOct}} \qquad \beta_{Yc} = \frac{\partial L_{rsYt}}{\partial L_{rsYct}} \tag{8}$$

with c indicating if they are either natives or foreigners[4]. Each β is assumed to be fixed[5]and measures the elasticity of labor gap differential change with respect to a specific subgroup differential change, where a subgroup is the total number of workers with age a and citizenship c.

This decomposition allows us to understand how labor supply shocks affect the labor gap. By imposing β_{OF}=β_{YF}=β_F and rearranging the terms we get:

$$\frac{\Delta(ln(L_{rsOt}) - ln(L_{rsYt}))}{\frac{\Delta L_{rsOFt}}{L_{rsOFt}} - \frac{\Delta L_{rsYFt}}{L_{rsYFt}}} = \beta_F + \beta_{ON}\frac{\frac{\Delta L_{rsONt}}{L_{rsOt}}}{\frac{\Delta L_{rsOFt}}{L_{rsOFt}} - \frac{\Delta L_{rsYFt}}{L_{rsYFt}}} - \beta_{YN}\frac{\frac{\Delta L_{rsYNt}}{L_{rsYt}}}{\frac{\Delta L_{rsOFt}}{L_{rsOFt}} - \frac{\Delta L_{rsYFt}}{L_{rsYFt}}} \tag{9}$$

The left-hand side is the elasticity between a change in old-young labor gap and a change in old-young foreigner labor gap, where the denominator represents a change in foreign employment. We show that the effect of a foreign labor supply shock is not constant, but it depends on old and young native labor supply change.

This is an important result, in the literature a very common assumption is the exogeneity of foreign labor supply shock with respect to native employment. In our model, instead, the effect of a foreign labor supply shock on old-young labor gap depends also on native labor supply shocks (if any).

[3]In Appendix for the mathematical derivation.

[4]This methodology is very similar to one developed by Amiti et al. (2019) that provide a decomposition of a firm price differential.

[5]In the empirical section we allow parameters to vary over time.

In the Empirical Strategy Section we take into account this finding to estimate the elasticity of substitution.

4 Data

The empirical analysis is based on the information on the wages and employment of old and young workers drawn from the 1995-2004 Work Histories Italian Panel (WHIP) dataset. The WHIP also contains information on citizenship that we use to create our set of instruments.

The WHIP database includes information on social securities records of 2,164,829 employees from 1995 to 2004, around 140,000 observations per year. Since our aim is to provide with a new identification strategy using a standard theoretical framework, we follow the literature to create wage and employment variables.

The main sample is restricted to men aged 18-64 working in the private sector. We narrow the analysis only to male employees as old and young females do not accumulate constantly experience in their working life showing larger substitutability (Freeman, 1979). Further, foreign females in Italy are usually employed as either caregivers or domestic helper, while native females are often employed in the public sector (Venturini and Villosio, 2008). We narrow the analysis only to private sector as public sector has more rigid labor dynamics. EU15 foreign workers are excluded from the analysis to avoid confounding effects due to similarities between EU15-foreign and Italian workers. Including EU15 workers in native (foreign) group might overestimate (underestimate) the elasticity of substitution. Further, the EU15 worker exclusion allows us to focus our attention on foreigners with different skills with respect to natives. We take the gross average log daily wage as wage measure[6]. Unfortunately, we have only information on total contribution days, where one contribution day is equal to 8 hours spent at work. The lack of information on hours spent at work

[6] We get rid of the first and last percentile of the distribution in order to avoid any confounding effect due to outliers.

does not allow us to include part time jobs as they differ by hours spent at work per day. Due to this missing information we are not able to homogenize the daily wage of part-time workers. Hence, we prefer to consider only full time workers. To measure the cell-specific employment we, first, measure the days spent in each region-occupation-age-year cell to the total worked days in a year per every worker. Then, we sum these shares to obtain the total employment in each region-occupation-age-year cell. We follow this procedure to overcome the assignment of a single worker to different region-occupation-age-year cells since there are some workers that change either working region or job within a year. Following the literature (i.e. Card, 1999), we assign the 'old' label for workers age over 38[7].

Table 1 and Table 2 show the shares in each macro-region-age-citizenship[8] cell by occupation. Table shows that for every 10 young blue (white) collar workers, there are 5 old blue collar workers (7 white collar workers). This evidence shows that old employees are more likely to hold a white collar occupation than a blue collar one. Further, the age-specific ratio of the blue collar total employment to the white collar total employment is equal to 2.96 and 2.08 for the young and old employees, respectively. These ratios show that old employees compete much more for white collar occupations since there are three young blue collar workers for each young white collar worker, and only two old blue collar workers for each old white collar worker. Hence, an increase in retirement age has a larger effect on young white collar workers than young blue collar workers. Further, Table 1 and Table 2 show that foreigners are more likely to be young and blue collar workers. Hence, an increase in foreign workers affects mostly the native young blue-collar workers. Table 3 and 4 show log daily wages for blue and white collars, respectively. In each table, we have information on log daily wages in each macro region-age cell over 1995-2004 period. Wages are

[7]The explanation is that workers accumulate on-the-job human capital with a lower pace when they are age over 38.

[8]I show macro regions instead of regions for the sake of table clarity. The regional summary statistics lead to the same descriptive evidences. North includes: Emilia Romagna, Friuli Venezia Giulia ,Lombardia, Liguria, Piemonte and Valle d'Aosta, Trentino Alto Adige, Veneto. Centre includes: Lazio, Marche, Toscana and Umbria. South and Islands include: Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna and Sicilia

deflated to 2001 euro by using OECD's Italian CPI series. We observe an overall sharp increase of real wages until 1999, followed by a decline and a renewal until 2004. Looking at the difference between the old and young average log daily wages, we see a declining path for blue collar wage differences, while there is no evidence of such trend for white collars. This finding suggests that old and young white collar workers are more substitute than old and young blue collar workers. Young blue collar wage does not respond to migration and pension reforms, while old blue collar wages lower over time by decreasing the gap with young blue collar workers. Instead, young white collar workers do not fill the wage gap with old white collar workers over time, showing a larger substitutability. Although these evidences are only descriptive, we might consider them as a first evidence on the degree of substitutability between old and young workers.

Finally, Figure 1 shows the trend for each instrument from 1985-2004. Each instrument is the ratio of yearly region-occupation-age-citizenship employment change to the total yearly region-occupation-age employment. We have four subgroups: old natives, young natives, old foreigners and young foreigners. Yearly changes are very noisy from 1995 to 2004, they do not follow a common path as observed for young and old natives in the previous periods. Hence, we exploit this variability to estimate old-young elasticity of substitution.

5 Empirical strategy

In this section we explain how to implement our theoretical findings in an empirical setting to estimate the elasticity of substitution between old and young workers. We estimate the equation (5) in Section 3. As shown in Section 4, we use as dependent variable the difference between average log daily wage of old workers and average log daily wage of young workers for each region-occupation-year cell (wage gap). Independent variable is the difference between the total employment of old and young workers for each region-occupation-year cell (labor gap). The old-young elasticity of substitution, $1/\lambda$, may be biased towards zero since labor gap might be positively correlated with long run *offsetting mechanism*. In the next subsection, we explain how long run adjustment may bias our estimates.

5.1 The *offsetting mechanism* function

We start estimating the equation (5) by substituting the log of old-young productivity ratio with a broad set of fixed effects and an error term. The new estimating equation is:

$$ln(\frac{w_{rsOt}}{w_{rsYt}})) = \phi_{rt} + \phi_{rs} + \phi_{st} - \frac{1}{\lambda} ln(\frac{L_{rsOt}}{L_{rsYt}}) + \varepsilon_{rst} \tag{10}$$

where ϕ_{rt} and ϕ_{st} capture every time productivity shift in each regional and occupation labor market, respectively. ϕ_{rs} captures any time invariant characteristic in each region-occupation labor market. ε_{rst} stands for whatever time variant residual components in every specific region-occupation labor market. However, we are not able to fully control for productivity shifts by using pairwise region-occupation-year fixed effects.

The unobservable region-occupation-year productivity shifts nested in the error term are very likely to be correlated with the labor gap. Indeed, the current labor gap and the current productivity shifts are both an increasing function of past age-group specific labor supply shocks. However, they have different effects on wage gap. An increase in the labor gap should have a negative effect on the wage gap, since an age-group specific labor supply has a larger negative effect on their own wages than on other age-group wages. On the other hand, an increase in productivity should have a positive effect on wage gap, since an increase in productivity might increase the wages. Hence, the positive correlation between productivity and both labor and wage gap might biases the estimates of the elasticity of substitution towards zero. We call this mechanism *offsetting mechanism* because it offsets the effect of the labor gap increase on the wage gap triggered by a labor supply shocks.

We want to shed light on this mechanism and on the correlation between labor gap and the *offsetting mechanism*. We assume that labor gap has a stable AR(1) process, we can see this process as MA(∞) process:

$$ln(\frac{L_{rsOt}}{L_{rsYt}}) = \sum_{k=1}^{t} \beta^t \epsilon_{rsk} + ln(\frac{L_{rsO0}}{L_{rsY0}}) \tag{11}$$

where $\epsilon_{rsk} = \Delta ln(\frac{L_{rsOk}}{L_{rsYk}})$, the last term is the yearly variation in the labor gap. Hence, on the right-hand side of Eq. (11) we have the sum of all labor gap yearly variations until t plus the initial condition. When $\Delta ln(\frac{L_{rsOk}}{L_{rsYk}}) \neq 0$, there is a change in the wage gap and the *offsetting mechanism* starts affecting later in time. Assuming that *offsetting mechanism* fully offsets wage shift in the following period[9], we nest the *offsetting mechanism* process in the error term:

$$\varepsilon_{rst} = \xi_{rst} + f(\epsilon_{rst-1}) \tag{12}$$

where ξrst is a random effect uncorrelated with the labor gap and $f(\epsilon_{rst-1})$ is the *offsetting mechanism* that depends on lag of yearly labor gap variation, ϵ_{rst-1}. As a result, this *offsetting mechanism* has a positive correlation with the labor gap biasing old-young elasticity of substitution estimate[10].

Offsetting mechanism function takes into account only the previous period labor gap change and not the current one. This structure allows us to exploit the current change as exogenous to the *offsetting mechanism* function.

The described mechanism is in line with papers that use new wave of migrants as an instrument to estimate the old-young elasticity of substitution (e.g. Borjas, 2003; Ottaviano and Peri, 2012), since yearly labor supply shocks are uncorrelated with previous ones[11].

[9] Adding more lags results hold.

[10] Because the $Cov(ln(\frac{L_{rsOt}}{L_{rsYt}}), f(\epsilon_{rst-1})) > 0$

[11] Jaeger et al. (2018) point out that the exogeneity of migration inflows depends on previous wave of migrants.

5.2 A short run instrument

In the previous subsection, we discussed the structure of the *offsetting mechanism* process nested in the error term and the features that an instrument must have in order to identify the elasticity parameter. In our setting, we exploit variations based on current foreign and native labor supply shocks. We exploit the elements on the right-hand side of Eq. (7) as instruments, where each of them takes into account yearly change in each region-occupation-age-citizenship cell[12]. This methodology is very common in the macro literature, especially in dynamic panel data models[13].

In order to identify the true parameter and rule out all the time correlations between the instruments and the error term, we assume that employment time series in every subgroup is a random walk:

$$\Delta L_{rsact} = \varepsilon_{rsact} \tag{13}$$

where, the first differences are equal to the error at current period. Testing this assumption we cannot reject the presence of unit root for every region-occupation-age-citizenship group[14].

The main concern is that the instruments might still depend on unobservable characteristics within region-occupation-year cell. To overcome this problem, we exploit Italian reforms enacted over the period 1995-2004. Between 1995 and 2014, Italy has enacted a series of national policies

If the flow of new migrants is stable across years, the labor demand can foresee the new inflow and adjust itself before it comes up.

[12] In the Appendix B, we compute parameter distortion when we use the first order differences as instrument and we assume that the *offsetting mechanism* function is linear. The estimated distortion is very small and equals to $-\frac{T}{(T-2)(T-1)}$, in particular it is smaller than the Nickell's one (Nickell, 1981).

[13] Arellano and Bover (1995) were the pioneers of this identification strategy that exploits the short run changes (i.e. first differences) to instrument levels. They use the lagged first differences as an instrument for the lagged value of the dependent variable that is their explanatory variable.

[14] P-values of Harris-Tzavalis unit-root test are: 1.00 for old foreign labor supply, .798 for young foreign labor supply, .1406 for old native labor supply and .9995 for young native labor supply

that have affected the labor supply of all considered categories across years. They provide us with exogenous variation to identify the effect as they are not labor market specific. This continuous treatment has allowed us to exploit short run effects as instrument.

6 Results

Table 5 shows the old-young elasticity parameter, $-\frac{1}{\lambda}$, by using different estimators. All regressions are weighted by the inverse of the wage gap variance to reduce the bias of the cells with small sample size[15]. In the first two columns we show the results by using ordinary least squares, OLS. As discussed in previous sections, the estimates are biased towards zero both without and with the time-occupation fixed effects. This finding is in line with the literature, that highlights the positive correlation between labor gap and *offsetting mechanism* in every region-occupation-year cell.

In the following six columns we use IV methodology by exploiting different estimators. From the third to the sixth column, we show the results by using two stage least squares, 2SLS, and the limited information maximum likelihood, LIML. As pointed out by Angrist and Krueger (1991), 2SLS and LIML estimates have to be very close in an overidentified framework because asymptotically they have the same distribution. The point estimates are -0.250 and -0.259 for 2SLS and LIML without occupation-time fixed effects and -0.168 and -0.171 for 2SLS and LIML including them. The quite similar results do not show any problem in the specification. Furthermore, the specifications pass the F-statistic and the overidentification tests. The former is 45.46 and 14.69, respectively, without and with occupation-time fixed effects and the other one cannot reject the null hypothesis of good specification at a significance level of 5%. The last two columns show

[15]There is a wide debate about the weight to be used. OP (2012) use the sample size in every specific cell as weight, while Borjas et.al (2012) in a comment to their paper say that is better to use the inverse of the wage variance.

the estimates with a continuously-updated GMM estimator, that allows for heteroskedastic and autocorrelation disturbances, we add this estimation in order to take into account of a possible correlation among different shocks. Estimates confirm the previous results.

In Table 7 we show the estimates with employment cell weight to be sure that wrong weights drive our estimates. The estimates are quite similar, not showing any difference to use different weights. Results in Table 5 and 7 prove that there is not difference between the wage variance weight and employment-cell weight when the model is well specified.

In Table 8 we use a control function approach[16]. This approach used by Wooldridge (2015) is suitable for our aim, because residuals contain the endogeneity source that we cannot control in our model. In this way by adding this part in the main regression we control directly for the bias. Residuals' parameter captures the *offsetting mechanism* of shocks. Indeed, as showed in Table 8, the estimate has the opposite sign of our old-young elasticity parameter and more or less the same magnitude.

Hence, by using the control function approach we have not only the elasticity parameter but also the relative bias. In particular when we add the occupation-time fixed effects the parameter is even closer in absolute value to the elasticity estimate.

Old-young elastacity of substitution, λ, is between 4 and 6. The results are in line with Ottaviano and Peri (2012), Borjas (2003) and Card and Lemieux (2001) estimates when they use 8 level of experience and 4 level of education. Our result differ from Ottaviano and Peri (2012), when they use old and young as a proxy for experience. They find an elasticity of substitution around 3[17]. This result shed lights on time correlation bias.

[16] In the control function approach you have to run an IV first stage, then get the residuals and put them in the main regression.

[17] Their estimate is equal to -0.31

7 Robustness checks

7.1 The comparison with migration instrument

Ottaviano and Peri (2012) and Borjas (2003) exploit foreign workers as instrument to identify age-group elasticity of substitution[18]. They assume that foreign labor supply shocks in the foreign labor force in each region-occupation-year cell, once added fixed effects, identify the elasticity of substitution between old and young workers.

In subsection 4.2 we find that the effect of a change in foreign labor supply on the labor gap is not constant since it depends on native labor supply changes. In order to take that into account, we consider both native and foreign labor supply shocks in each region-occupation-age-citizenship cell aiming at having an unbiased estimate.

In this subsection, we compare our specification with the one used by Borjas (2003) and Ottaviano and Peri (2012) by using their instrument to estimate the elasticity of substitution between old and young workers.

Table 9 shows estimates close to Ottaviano and Peri (2012)[19] when we do not control occupation-time fixed effects. The results change when we add them. The parameter is not more significant with standard error quite large. Our explanation is that large standard errors are due to the correlation between instrument and error term. The missing information on native labor supply changes in other skilled categories might create a correlation between the foreign instrument and the *offsetting mechanism* process.

In our setting we add both native and foreign labor supply changes, which help us to rule out

[18] An other instrument widely used by researchers is the shift-share instrument (Altonij and Card, 1991) that exploits migrant enclaves in the previous decades to create an instrument exogenous with respect to current economic conditions. Unfortunately we cannot compare our methodology with that, because our dataset does not have information later than 1985 and because the level of inflows in decades before 1995 is almost null or is selected among high skilled workers (before 1990 in Italy there was not a labor migration policy, so for migrant was almost impossible to come in Italy with a labor VISA.)

[19] Our estimates are little bit larger because we use a regional approach as opposed to a national one. For this reason the bias is smaller than Ottaviano and Peri (2012).

any possible correlation with the long run adjustments.

7.2 Labor demand shocks

In our paper we exploit short run changes in every region-occupation-age-citizenship cell. We state that the short run changes are supply driven assuming that the possible labor demand shocks are captured by fixed effects. In this section we test this assumption by using an instrument that is based on labor demand shock.

We exploit the information on unemployment support mechanisms provided in our dataset. The Italian government helps firms to face crisis periods by paying part of employee salaries for a given period[20], when employers suspend temporary employment relationships. During the suspension firms cannot hire other workers in order to hold the benefit and, at the same time, employees cannot engage in another job. This tool has been created mainly to help the manufacturing sector, where most of the workers are engaged. We, thus, use the information whether a worker is in this program to capture a labor demand shock due to a firm's temporary crisis.

Our first stage is the labor gap on the log of the number of temporary suspended workers. The sample is reduced to 322 observations from 1996-2004 since we have some cells that do not experience any temporary suspension. Table 10 shows the results. The estimates are not significant and F-stat of the instrument is very low. The F stat is very low showing how a labor demand-driven instrument is not suitable to provide an exogenous variation to identify labor gap.

7.3 Relaxing time invariant assumption on the first-stage parameters

In subsection 4.2 we have assumed that the derivatives of each specific region-occupation-age labor input with respect to a change in both native and foreign employment is constant over time.

[20] The so called "Cassa Integrazione"

In this subsection we show the results when derivatives vary over time.

In order to add a time dimension to parameters, we multiply the instruments by a linear time trend[21]. Rearranging Eq. (7) we get:

$$\Delta(ln(L_{rsOt}) - ln(L_{rsYt})) = \Sigma_c(\beta_{Oc}(1+trend)\frac{\Delta L_{rsOct}}{L_{rsOt}} - \beta_{Yc}(1+trend)\frac{\Delta L_{rsYct}}{L_{rsYt}}) \qquad c = N, F \tag{14}$$

Table 11 shows the results using this broader set of instruments that takes into account of time dimension. The results are quite similar to the time constant ones. Hence, without loss of generality, we can assume time invariant parameters.

8 Conclusions

How much old and young workers are substitutes in production is of great interest worldwide. Demographic changes have affected the composition of the labor force. This paper tries to shed light on the degree of substitutability between old and young workers in production.

In line with the tradition on this topic, we use a nested-CES framework at regional level to derive the elasticity of substitution between old and young workers. The choice of a local approach allows us to rule out any possible misleading effect due to huge differences across Italian regions. We can get a more precise estimate of the overall elasticity of substitution controlling for different local growth patterns.

In the literature, adding specific skill fixed effects is generally used to control for different demand shifts. Still, possible biases might remain due to log-run factors. In particular, skill-specific unobservable long-run adjustments offset any variation suited to study the effect of a skill-specific labor force change on the skill-specific wages biasing the elasticity estimates towards zero. Studying the dynamics of the *offsetting mechanism*, we identify the bias and create an instrument

[21] We try also to interact time dummies with every instrument. The results are not different from adding a linear trend.

to overcome the omitted variable problem. We exploit the variation triggered by Italian reforms to create a set of instruments exogenous to skill-specific . The estimated elasticity of substitution is between 4 and 6, in line with previous findings.

In a global scenario, young workers concern about the longer working life of some old workers. Our results show old and young workers are imperfect substitution in production. Hence, policies aiming at reducing the youth unemployment should not consider the early retirement as a solution. Instead, they should look at specific characteristics of young workers to increase the match between firms needs and young worker skills.

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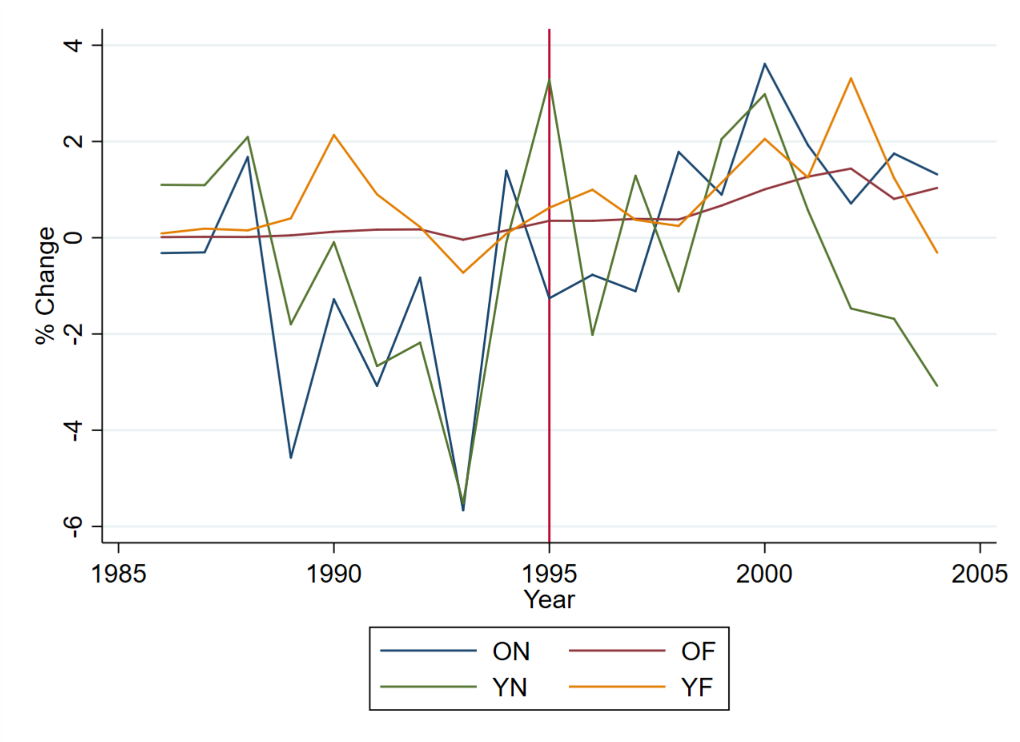
Tables and Figures

Figure 1: Ratios of age-citizenship yearly employment changes to the relative yearly age employment between 1985 and 2004



ON: old natives. OF: old foreigners. YN:young native. YF: young foreigners.

Table 1: Blue collar subgroup shares within all sample, within the subgroup sample and within the sector sample

		Old			Young		
Macro Region	Place of birth	(1)	(2)	(3)	(1)	(2)	(3)
North	Foreign-born	1.695	5.122	19.616	6.947	10.384	80.384
	Native-born	15.880	47.982	32.917	32.362	48.371	67.083
Centre	Foreign-born	0.434	1.312	21.110	1.623	2.426	78.890
	Native-born	5.674	17.144	36.439	9.897	14.793	63.561
South and Islands	Foreign-born	0.177	0.534	22.971	0.593	0.886	77.029
	Native-born	9.235	27.905	37.365	15.481	23.140	62.635
Subgroup Obs			168,968			341,571	

Notes: (1) subgroup share in the row sector with respect to all sample;(2) subgroup share in the row sector with respect to subgroup sample; (3) subgroup share in the row sector with respect to row-sector sample. Sample from 1995 to 2004.

Table 2: White collar subgroup shares within all sample, within the subgroup sample and within the sector sample

		Old			Young		
Macro Region	Broad Experience	(1)	(2)	(3)	(1)	(2)	(3)
North	Foreign-born	0.289	0.709	35.850	0.517	0.873	64.150
	Native-born	23.499	57.635	38.952	36.830	62.185	61.048
Centre	Foreign-born	0.172	0.422	46.964	0.195	0.328	53.036
	Native-born	8.667	21.256	42.406	11.771	19.874	57.594
South and Islands	Foreign-born	0.088	0.215	39.955	0.132	0.222	60.045
	Native-born	8.058	19.762	45.164	9.783	16.518	54.836
Subgroup Obs			82,375			119,660	

Notes: (1) subgroup share in the row sector with respect to all sample;(2) subgroup share in the row sector with respect to subgroup sample; (3) subgroup share in the row sector with respect to row-sector sample. Sample from 1995 to 2004.

Table 3: Average log daily wage for male blue collar workers, 1995-2004

Macro Region	Broad Experience	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
North	Old	4.4465	4.4394	4.4551	4.4504	4.4455	4.4258	4.4259	4.4154	4.4040	4.4255
	Young	4.2900	4.2879	4.3038	4.3111	4.3045	4.2988	4.2974	4.2924	4.2915	4.3116
Centre	Old	4.4341	4.4239	4.4318	4.4214	4.4174	4.4127	4.3780	4.3712	4.3611	4.3762
	Young	4.2591	4.2570	4.2639	4.2703	4.2615	4.2619	4.2587	4.2425	4.2473	4.2639
South and Islands	Old	4.4278	4.4087	4.4175	4.3898	4.3941	4.3781	4.3700	4.3526	4.3514	4.3596
	Young	4.2612	4.2430	4.2471	4.2269	4.2184	4.2410	4.2381	4.2430	4.2397	4.2609

Notes: The table reports the mean of the log daily wage of workers in each region-age group. All wages are deflated to 2001 euro using the Italian CPI index from OECD database.

Table 4: Average log daily wage for male white collar workers, 1995-2004

Macro Region	Broad Experience	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
North	Old	4.9591	4.9633	4.9865	4.9917	5.0035	5.0045	4.9935	4.9927	4.9949	5.0029
	Young	4.6578	4.6478	4.6752	4.6835	4.6943	4.6969	4.6991	4.7036	4.6916	4.7041
Centre	Old	4.9576	4.9545	4.9712	4.9756	4.9598	4.9522	4.9507	4.9392	4.9479	4.9503
	Young	4.6336	4.6288	4.6339	4.6441	4.6497	4.6499	4.6426	4.6455	4.6350	4.6320
South and Islands	Old	4.8804	4.8644	4.8806	4.8623	4.8648	4.8614	4.8413	4.8333	4.8241	4.8364
	Young	4.5260	4.5136	4.5329	4.5257	4.5026	4.4920	4.4916	4.4737	4.4747	4.4880

Notes: The table reports the mean of the log daily wage of workers in each region-age group. All wages are deflated to 2001 euro using the Italian CPI index from OECD database.

Table 5: Estimated old-young elasticity of substitution, $-\frac{1}{\lambda}$, weighted by the inverse of dependent variable variance

$ln(\frac{w_{rsOt}}{w_{rsYt}})$	OLS (1)	OLS (2)	LIML (3)	LIML (4)	2SLS (5)	2SLS (6)	GMM-CUE (7)	GMM-CUE (8)
$ln(\frac{L_{rsOt}}{L_{rsYt}})$	-0.0893***	-0.0157	-0.259***	-0.171***	-0.250***	-0.168***	-0.215***	-0.164***
	(0.0322)	(0.0366)	(0.0518)	(0.0510)	(0.0494)	(0.0499)	(0.0461)	(0.0484)
Skill x Time FE	NO	YES	NO	YES	NO	YES	NO	YES
P-value Lm-stat			0.000298	0.000745	0.000298	0.000745	0.000298	0.000745
F-stat			45.46	14.69	45.46	14.69	45.46	14.69
P-value J-stat			0.0773	0.389	0.0742	0.386	0.0742	0.386
Observations	342	342	342	342	342	342	342	342

Notes: All regressions include region-year fixed effects and region-occupation fixed effects. The reported standard errors are clustered by region-occupation. The regressions are weighted by the inverse of the wage ratio variance. The dependent variable is the log ratio of average old and young worker wages in a region-occupation-age-time-specific cell and the explanatory variable is the log of the ratio between old and young employment inside the same cell. LM test is for underidentification test, F statistic is for weak identification test (Cragg-Donald or Kleibergen-Paap) and J test is for overidentification test. Time span covers from 1996-2004. * p<0.10, ** p<0.05, *** p<0.01

Table 6: First stage and Reduced Form weighted by the inverse of dependent variable variance

	First stage		Reduced Form	
$\frac{\Delta L_{rsOFt}}{L_{rsOt-1}}$	1.399	-0.0254	-0.659***	-0.138
	(0.907)	(0.716)	(0.213)	(0.253)
$\frac{\Delta L_{rsYFt}}{L_{rsYt-1}}$	-0.448*	-0.160	0.102	0.0300
	(0.246)	(0.521)	(0.105)	(0.183)
$\frac{\Delta L_{rsONt}}{L_{rsOt-1}}$	0.433***	0.508***	-0.0850**	-0.0658*
	(0.119)	(0.0918)	(0.0391)	(0.0393)
$\frac{\Delta L_{rsYNt}}{L_{rsYt-1}}$	-0.743***	-0.569***	0.166***	0.115**
	(0.107)	(0.105)	(0.0520)	(0.0538)
Skill x Time FE	NO	YES	NO	YES
Observations	342	342	342	342

Notes: All regressions include region-year fixed effects and region-occupation fixed effects. The reported standard errors are clustered by region-occupation. The regressions are weighted by the inverse of wage ratio variance. The explanatory variables are measured as the yearly change in the old (young) native (foreign) group over the total old (young) employment. Time span covers from 1996-2004. * p<0.10, ** p<0.05, *** p<0.01

Table 7: Estimated old-young elasticity of substitution, $-\frac{1}{\lambda}$, weighted by the size of independent variable

$ln(\frac{w_{rsOt}}{w_{rsYt}})$	OLS (1)	OLS (2)	LIML (3)	LIML (4)	2SLS (5)	2SLS (6)	GMM-CUE (7)	GMM-CUE (8)
$ln(\frac{L_{rsOt}}{L_{rsYt}})$	-0.0897***	-0.0168	-0.258***	-0.167***	-0.249***	-0.164***	-0.210***	-0.158***
	(0.0306)	(0.0343)	(0.0499)	(0.0492)	(0.0472)	(0.0480)	(0.0436)	(0.0470)
Skill x Time FE	NO	YES	NO	YES	NO	YES	NO	YES
P-value Lm-stat			0.000108	0.000190	0.000108	0.000190	0.000108	0.000190
F-stat			51.22	18.00	51.22	18.00	51.22	18.00
P-value J-stat			0.0525	0.402	0.0490	0.400	0.0490	0.400
Observations	342	342	342	342	342	342	342	342

Notes: All regressions include region-year fixed effects and region-occupation fixed effects. The reported standard errors are clustered by region-occupation. The regressions are weighted by the size of every region-occupation-time cell. The dependent variable is the log ratio of average old and young worker wages in a region-occupation-age-time-specific cell and the explanatory variable is the log of the ratio between old and young employment inside the same cell. LM test is for underidentification test, F statistic is for weak identification test (Cragg-Donald or Kleibergen-Paap) and J test is for overidentification test. Time span covers from 1996-2004. * p<0.10, ** p<0.05, *** p<0.01

Table 8: Control function estimates of elasticity of substitution $\frac{1}{\lambda}$

$ln(\frac{w_{rsOt}}{w_{rsYt}})$	Control Function (1)	Control Function (2)
$ln(\frac{L_{rsOt}}{L_{rsYt}})$	-0.250***	-0.168***
	(0.0435)	(0.0509)
Residuals	0.209***	0.180***
	(0.0559)	(0.0568)
Skill x Time FE	NO	YES
Observations	342	342

Notes: All regressions include region-year fixed effects and region-skill fixed effects. The reported standard errors are clustered by region-skill. The regressions are weighted by the inverse of the wage ratio variance. Time span covers from 1996-2004. * p<0.10, ** p<0.05, *** p<0.01

Table 9: Estimated old-young elasticity of substitution, $-\frac{1}{\lambda}$ by exploiting foreign employment as instrument

$ln(\frac{w_{rsOt}}{w_{rsYt}})$	OLS (1)	OLS (2)	2SLS (3)	2SLS (4)
$ln(\frac{L_{rsOt}}{L_{rsYt}})$	-0.0893*** (0.0322)	-0.0157 (0.0366)	-0.298*** (0.104)	-0.0167 (0.338)
Skill x Time FE	NO	YES	NO	YES
P-value Lm-stat			0.00981	0.415
F-stat			5.285	0.336
Observations	342	342	334	334

Notes: All regressions include region-year fixed effects and region-occupation fixed effects. The reported standard errors are clustered by region-occupation. The dependent variable is the log ratio of average old and young worker wages in a region-occupation-age-time-specific cell and the explanatory variable is the log of the ratio between old and young employment inside the same cell. The instrument is the log oh the total region-occupation-time specific foreign employment. LM test is for underidentification test and F statistic is for weak identification test (Cragg-Donald or Kleibergen-Paap). Time span covers from 1996-2004. * p<0.10, ** p<0.05, *** p<0.01

Table 10: Estimated old-young elasticity of substitution, $-\frac{1}{\lambda}$, by exploiting temporary laid-off workers as instrument

$ln(\frac{w_{rsOt}}{w_{rsYt}})$	OLS (1)	OLS (2)	2SLS (3)	2SLS (4)
$ln(\frac{L_{rsOt}}{L_{rsYt}})$	-0.0915*** (0.0310)	-0.0264 (0.0535)	-0.268 (0.220)	0.0263 (0.796)
Skill x Time FE	NO	YES	NO	YES
P-value Lm-stat			0.100	0.619
F-stat			1.055	0.106
Observations	342	342	322	322

Notes: All regressions include region-year fixed effects and region-occupation fixed effects. The reported standard errors are clustered by region-occupation. The regressions are weighted by the inverse of the wage ratio variance. The regression are run only on the manufacturing sector. The dependent variable is the log ratio of average old and young worker wages in a region-occupation-age-time-specific cell and the explanatory variable is the log of the ratio between old and young employment inside the same cell. The instrument is the log of the total number of temporary laid-off workers. LM test is for underidentification test and F statistic is for weak identification test (Cragg-Donald or Kleibergen-Paap). Time span covers from 1995-2004. * p<0.10, ** p<0.05, *** p<0.01

Table 11: Estimated old-young elasticity of substitution, $-\frac{1}{\lambda}$, by adding a linear trend to instruments

$ln(\frac{w_{rsOt}}{w_{rsYt}})$	OLS (1)	OLS (2)	LIML (3)	LIML (4)	2SLS (5)	2SLS (6)	GMM-CUE (7)	GMM-CUE (8)
$ln(\frac{L_{rsOt}}{L_{rsYt}})$	-0.0893*** (0.0322)	-0.0157 (0.0366)	-0.268*** (0.0532)	-0.168*** (0.0556)	-0.249*** (0.0476)	-0.164*** (0.0541)	-0.189*** (0.0353)	-0.144*** (0.0406)
Skill x Time FE	NO	YES	NO	YES	NO	YES	NO	YES
P-value Lm-stat			0.00321	0.00808	0.00321	0.00808	0.00321	0.00808
F-stat			46.73	12.09	46.73	12.09	46.73	12.09
P-value J-stat			0.208	0.802	0.192	0.798	0.192	0.798
Observations	342	342	342	342	342	342	342	342

Notes: All regressions include region-year fixed effects and region-occupation fixed effects. The reported standard errors are clustered by region-occupation. The dependent variable is the log ratio of average old and young worker wages in a region-occupation-age-time-specific cell and the explanatory variable is the log of the ratio between old and young employment inside the same cell. LM test is for underidentification test, F statistic is for weak identification test (Cragg-Donald or Kleibergen-Paap) and J test is for overidentification test. Time span covers from 1995-2004. * p<0.10, ** p<0.05, *** p<0.01

Appendix A

By defining labor gap for old and young workers as function of native and foreigners, we get

$$ln(L_{rsOt}) - ln(L_{rsYt}) = ln(f(L_{rsONt}, L_{rsOFt})) - ln(f(L_{rsYNt}, L_{rsYFt})) \tag{15}$$

Computing the differential, we get:

$$d(ln(L_{rsOt}) - ln(L_{rsYt})) = d(ln(f(L_{rsONt}, L_{rsOFt})) - ln(f(L_{rsYNt}, L_{rsYFt}))) =$$

$$= \frac{1}{L_{rsOt}} \frac{\partial L_{rsOt}}{\partial L_{rsONt}} dL_{rsONt} + \frac{1}{L_{rsOt}} \frac{\partial L_{rsOt}}{\partial L_{rsOFt}} dL_{rsOFt} - (\frac{1}{L_{rsYt}} \frac{\partial L_{rsYt}}{\partial L_{rsYNt}} dL_{rsYNt} +$$

$$+ \frac{1}{L_{rsYt}} \frac{\partial L_{rsYt}}{\partial L_{rsYFt}} dL_{rsYFt}) \tag{16}$$

Labor ratio differential in discrete is:

$$\Delta(ln(L_{rsOt}) - ln(L_{rsYt})) = \Sigma_c(\beta_{Oc} \frac{\Delta L_{rsOct}}{L_{rsOt}} - \beta_{Yc} \frac{\Delta L_{rsYct}}{L_{rsYt}}) \qquad c = N, F \tag{17}$$

where

$$\beta_{Oc} = \frac{\partial L_{rsOt}}{\partial L_{rsOct}} \qquad \beta_{Yc} = \frac{\partial L_{rsYt}}{\partial L_{rsYct}} \tag{18}$$

with c indicating if they are natives or foreigners.

Appendix B

By assuming that the residuals, x, obtained by applying Frisch–Waugh–Lovell theorem to labor gap first difference, follow an AR(1) process:

$$x_{rst} = \rho x_{rst-1} + \varepsilon_{rst} \tag{19}$$

By subtracting x_{rst-1} on both sides we obtain:

$$\Delta x_{rst} = (\rho - 1)x_{rst-1} + \varepsilon_{rst} \tag{20}$$

By substituting the first difference in the labor demand we have:

$$ln(\frac{w_{rsOt}}{w_{rsYt}}) = \beta \Delta x_{rst} + u_{rst} \tag{21}$$

Where y_{rst} is the residuals from wages by using the Frisch–Waugh–Lovell theorem and t goes from 2 to T. We omit to multiply the parameter from the first stage regression.

$$\operatorname*{plim}_{N\to\infty} \widehat{\beta} = \beta + \frac{\text{plim}_{N\to\infty} \frac{1}{N}\Sigma_{i=1}^{N}(x_{rst} - x_{rs.})(u_{rst} - u_{rs.})}{\text{plim}_{N\to\infty} \frac{1}{N}\Sigma_{i=1}^{N}(x_{rst} - x_{rs.})^2} \tag{22}$$

$$\operatorname*{plim}_{N\to\infty} \widehat{\beta} - \beta = \frac{\text{plim}_{N\to\infty} \frac{1}{N}\Sigma_{i=1}^{N}(x_{rst} - x_{rs.})(u_{rst} - u_{rs.})}{\text{plim}_{N\to\infty} \frac{1}{N}\Sigma_{i=1}^{N}(x_{rst} - x_{rs.})^2} = \frac{A}{B} \tag{23}$$

$$A = \underbrace{E[x_{rst}u_{rst}]}_{\text{endogeneity bias}} \underbrace{-E[x_{rst}u_{rs.}] - E[x_{rs.}u_{rst}] + E[x_{rs.}u_{rs.}]}_{\text{Nickell bias}} \tag{24}$$

$$B = E[x_{rst}^2] - 2E[x_{rst}x_{rs.}] + E[x_{rs.}^2] \tag{25}$$

Let u_{rst} equals to the sum of a random effect and a *offsetting mechanism*:

$$u_{rst} = \xi_{rst} + f(\varepsilon_{rst-1}) \tag{26}$$

Let $f(\epsilon_{rst-1})$ linear and function of labor supply shock at t-1:

$$f(\epsilon_{rst-1}) = \varepsilon_{rst-1} \tag{27}$$

Let ρ is equal to one:

$$\Delta x_{rst} = \varepsilon_{rst} \tag{28}$$

Then A turns into:

$$A = E[\varepsilon_{rst}\varepsilon_{rst-1}] - E[\varepsilon_{rst}\varepsilon_{rs.-1}] - E[\varepsilon_{rs.}\varepsilon_{rst-1}] + E[\varepsilon_{rs.}\varepsilon_{rs.-1}] \tag{29}$$

Showing the time means of A:

$$A = E[\varepsilon_{rst}\varepsilon_{rst-1}] - \tfrac{1}{T-1}E[\varepsilon_{rst}\textstyle\sum_{j=2}^{T}\varepsilon_{rsj-1}] - \tfrac{1}{T-1}E[\textstyle\sum_{j=2}^{T}\varepsilon_{rsj}\varepsilon_{rst-1}] + \frac{1}{(T-1)^2}E[\sum_{j=2}^{T}\varepsilon_{rsj}\sum_{j=2}^{T}\varepsilon_{rsj-1}] \tag{30}$$

Solving covariates:

$$A = 0 - \frac{1}{T-1}\sigma_{\varepsilon}^2 - \frac{1}{T-1}\sigma_{\varepsilon}^2 + \frac{1}{(T-1)^2}(T-2)\sigma_{\varepsilon}^2 \tag{31}$$

$$A = -\frac{T}{(T-1)^2}\sigma_\varepsilon^2 \tag{32}$$

Doing the same for B:

$$B = E[\varepsilon_{rst}^2] - 2E[\varepsilon_{rst}\varepsilon_{rs.}] + E[\varepsilon_{rs.}^2] \tag{33}$$

$$B = E[\varepsilon_{rst}^2] - \frac{2}{(T-1)}E[\varepsilon_{rst}\sum_{j=2}^{T}\varepsilon_{rsj}] + \frac{1}{(T-1)^2}E[\sum_{j=2}^{T}\varepsilon_{rsj}^2] \tag{34}$$

$$B = \sigma_\varepsilon^2 - \frac{2}{T-1}\sigma_\varepsilon^2 + \frac{1}{(T-1)^2}(T-1)\sigma_\varepsilon^2 \tag{35}$$

$$B = \sigma_\varepsilon^2\frac{T-2}{T-1} \tag{36}$$

Computing the ratio between A and B:

$$\frac{A}{B} = -\frac{T}{(T-2)(T-1)} \tag{37}$$