Cross-Sectors Skill Intensity, Productivity and Temporary Employment

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Abstract

In this article, we study the impact of temporary employment (TE) on productivity and, in particular, we wonder if it differs according to sectors skill intensity. Our data set is an ad-hoc industry-level panel of European countries, which allows to deal with endogeneity problems. Our main result is that TE has a negative impact on productivity, but it is more damaging in skilled sectors. While an increase of 10 percentage points of the share of TE in skilled sectors decrease labour productivity growth about 1-1.5%, in unskilled sectors the decrease would be 0.5-0.8%. This result is robust to changes in the skill intensity index and in the sample composition. We also discuss policy implications of this result for labour market regulation.

JEL Classification: J41, J24, O47.

Keywords: Labour productivity, Temporary employment, Skill intensity, Differential effect.

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1. Introduction

Following the widespread diffusion of temporary contracts in the last two decades, a large concern has been growing about direct and side negative effects of increasing flexibility of labour markets. To this extent, the evaluation of the impact of temporary employment (TE) on labour productivity is especially significant because from a theoretical point of view it is not obvious what would be the effect of TE on labour productivity. On the one hand, it would seem rationale for a temporary worker to exert a greater effort in order to get the renewal of the contract and/or the passage to a more stable form of job (Engellandt and Riphahn, 2005). However, in a context where the expected probability of the renewal is low, this argument might not be valid (Dolado et al., 2012). On the contrary, given the temporary, and frequently short, duration of contracts it might be rationale for a firm to fix a lower reservation productivity under which to layoff temporary workers than permanent ones (PE), in order to avoid the direct and indirect firing costs (Lisi, 2012). Moreover, TE is disproportionally filled by younger, less educated and less experienced workers, and temporary workers often have less access to training programmes (OECD, 2002, 2007a, Bassanini et al. 2007). From an empirical perspective, early literature did not found any significant impact of TE on labour productivity (Bassanini and Venn, 2007, 2008, Bassanini et al., 2009, Cingano et al., 2010). However, more recent studies with different empirical strategies find a negative and significant impact of TE on productivity (e.g., Cappellari et al., 2012, Dolado et al., 2012, Lisi, 2013).

The main objective of this research consists of estimating the impact of the share of temporary employment on productivity, explicitly considering the differential effect in skilled and unskilled economic sectors. We go beyond the current literature arguing that there are good reasons to suspect that the impact of TE might differs significantly according to sectors skill intensity. From a theoretical perspective, this impact might be either positive or negative. On the one hand, in skilled sectors the use of TE might be more oriented towards screening new workers respect to unskilled ones, which could induce a higher effort and, in turn, a higher labour productivity (Engellandt and Riphahn, 2005, Dolado et al., 2012). On the other hand, if TE is used in the labour market as a structural cheaper form of job (Houseman, 2001), in skilled sectors the cost in terms of lower workers' effort could be heavier, leading to an even greater reduction in labour productivity (Lisi, 2012)[1].

[1] In particular, in that paper it is shown that, as long as temporary worker perceives a sufficiently low conditional probability of getting the renewal of the contract and/or the passage to a stable job, there might be a scope for exerting an effort level just in line with the firm reservation productivity, which indeed for temporary workers should not be especially high. From this perspective, the use of temporary contracts might induce a reduction in labour productivity.

The empirical analysis is performed on an industry-level panel of EU countries, which allows us to divide sectors between skilled and unskilled. Borrowing from the skill-biased technological change literature, we consider (un)skilled those sectors with a ratio between skilled and unskilled workers (lower) higher than the average (see e.g., Bond and Van Reenen, 2007). To test the robustness of our results, we compute different indexes of sectors skill intensity, using different definitions of skilled workers. Moreover, the industry-level panel allows us to control for different specific unobserved fixed effects, which should attenuate the omitted variable bias.

Differently from previous articles using the EPL index for TE, as discussed in Lisi (2013) we use directly the variation in the share of TE. The empirical specification exploits both cross-country and time variation in the share TE and, in particular, the exogenous variation in the impact of TE among different industries. Finally, to the extent that the share of TE might be endogenous in the productivity equation, we perform also an IV-strategy to test further the identification.

To the best of our knowledge, this is the first study trying to investigate the impact of TE differentiated according to sectors skill intensity. Apart from offering a more accurate description, the investigation of such differential effect should represent a valid contribution to the previous literature on TE, suggesting how temporary contracts are currently used in the labour market (that is, least-cost way of screening new workers or cheaper form of job).

Our main result is that TE is even more damaging in skilled sectors, with a negative effect significantly heavier than in unskilled sectors, and this would seem robust to little changes in the skill intensity index and in the sample used. In particular, an increase of 10 percentage points of the share of TE in skilled sectors would lead to a decrease of about 1–1.5% in labour productivity growth, whereas in unskilled ones the reduction would be only of 0.5–0.8%. In addition, statistical tests on the difference of the impact of TE between labour productivity and total factor productivity do not reject the hypothesis of equality, implying that TE affects labour productivity mainly reducing total factor productivity. Therefore, a higher share of TE is more harmful in those sectors where production uses skills more intensively. To some extent, this result might support the idea that TE is currently used more as a cheaper form of job, instead of as a least-cost way of screening new workers (see e.g., Güell and Petrongolo, 2007). Indeed, this result could have very important policy implications for labour market regulation.

The paper proceeds as follows: in Section 2 we describe the characteristics of our dataset and main variables. Then, Section 3 presents the strategy we pursue to identify the differential impact of TE across sectors and, in particular, the method we use to divide sectors. In Section 4 we show the results of the empirical analysis. Finally, Section 5 presents conclusions and discusses some policy implications.

2. Data and variables

We use an industry-level panel of EU countries. As emphasized by the previous literature, the advantage of using a panel of industry-level data is fourfold. First, not only the cross-country variation is still exploited, but also the variation on the impact of policies in different industries. Second, in contrast to the cross-country analysis, it potentially allows to control for unobserved fixed effects. Third, as the previous literature emphasised (e.g. OECD, 2007b), the within-industry "composition effect" appears to be negligible, allowing us to identify the "independent effect" of EPL for PE and TE[2]. Fourth, to the extent that events in a single industry are not so relevant alone to affect the policy in a country, the specification is less subject to the simultaneity problem between the variable of interest and policy.

To some extent, a micro-level panel with establishment or linked employer-employee data might offer a research design even more appealing to evaluate the impact of some labour market policies as temporary contracts. However, such datasets are usually bounded to a specific country[3]. Therefore, in the perspective to offer a reliable evaluation for the European context as a whole, the choice of the industry-level panel should represent a good compromise between the internal and external validity of the causal inference.

In particular, the dataset covers 10 sectors in 13 countries over the years 1992-2007, for a balanced panel of 2080 observations. Countries included are Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden and the United Kingdom. Since we make use of different data sources, we did some aggregation and

[2] In the literature the impact of a labour market policy on productivity is usually divided into "composition effect" and "independent effect". The first is the effect on productivity associated with the change in the composition of employment due to the policy variation (for instance, an increase in the share of unskilled workers). The second is the pure average effect of the policy on productivity (that is, *ceteris paribus*) and, thus, it is often the effect of interest. In this regard, different previous studies emphasize that "composition effects" are somewhat relevant in the aggregate analysis and, indeed, they cannot be easily dismissed. Therefore, any aggregate analysis of the impact of some labour market policies on productivity hardly will be able to isolate the "independent effect" of the policy and, in turn, to produce a useful contribution for policy guidance. Differently, industry-level analyses suggest that the within-industry "composition effects" are fairly negligible (OECD, 2007b) and, therefore, the use of industry-level panel data should succeed in identifying the "independent effect" of the policy.

[3] For instance, WHIP for Italy, LIAB for Germany, EPA for Spain, BHPS for the United Kingdom.

the final sectors classification is based on the standard EUROSTAT classification (see Annex 3 for details). The sectors are the following: "Agriculture, hunting and forestry", "Manufacturing", "Electricity, gas and water supply", "Construction", "Wholesale and retail trade", "Hotels and restaurants", "Transport, storage and communication", "Financial intermediation", "Real estate, renting and business activities", "Other community, social, personal service activities". With this sectors classification, we will define two aggregate groups by skill intensity consisting of five sectors with enough variability for identification.

To collect our dataset we made use of different sources. The data on labour productivity, total factor productivity and employment level at the industry-level were collected from EU KLEMS dataset (www.euklems.net). This comprehensive database contains data on economic growth, productivity, employment and other variables at the industry-level for all EU countries, providing an important data-source for policy evaluation. Moreover, productivity measures are developed with growth accounting techniques, coherently with our empirical specification.

The labour productivity measure used is the "*gross value added per hour worked, volume indices, 1995 = 100*", defined in the following way:

$$y_{ijt} = \frac{(VA/L)_{ijt}}{(VA/L)_{ij1995}} * 100 \qquad (1)$$

where *VA* is the gross value added in volumes and *L* is the total amount of hours worked (see Annex 2 for details). Looking at the behaviour of our variable over time, the mean of labour productivity in the entire sample is 110.94, whereas the mean from 1995 (base year = 100) is 114.31, telling us that labour productivity grew in EU countries, even if not so significantly.

The total factor productivity measure used is the "*TFP, 1995 = 100*" [4]. Unfortunately, no data on *TFP* at the industry-level are available for Portugal; therefore, in the estimates considering *TFP* as dependent variable data for Portugal are not included. Looking at the behaviour of our variable over time, the mean of *TFP* in the entire sample is 103.74, whereas the mean from 1995 (base year = 100) is 104.96, telling us that *TFP* growth in EU countries in the last years has been very scarce.

The data on employment level were used to construct the actual job reallocation rates, needed to obtain our measures of natural rate of job reallocation for each industry. While the estimated natural rates of job reallocation (*FJR*) are contained in a restricted range, the actual job

[4] The two productivity measures correspond respectively to the variables *LP_I* and *TFPva_I* in EU KLEMS database.

reallocation rates are much more changeable (see Annex 3), in line with the idea that actual job reallocation rates produce a short rather than a long-run measure of the need of job reallocation.

The data on capital stock were collected from OECD STAN database, a comprehensive tool for analyzing industrial performance across countries. In particular, the capital stock measure used is the "*CPGK – gross capital stock in volume terms*". Unfortunately, no data on capital stock at the industry-level are available for Ireland, Portugal and Sweden; therefore, in the estimates including the capital-labour ratio in the productivity equation these countries are dropped.

The shares of TE at the industry-level were constructed from EU Labour Force Survey, launched by the EUROSTAT (see Annex 2 for details)[5]. The mean and standard deviation of the share of TE in the sample are respectively 0.12 and 0.10, confirming that TE is an important feature of the labour market landscape in Europe by this time, but its importance differs significantly across countries. For instance, while in countries as Spain (0.32) and Portugal (0.16) the share of TE is far away from the mean, in the UK the mean is no more than 0.06. Interestingly, the share of TE turns out to be negatively correlated with labour productivity and total factor productivity, both cross-country (ρ_{LP_i} = – 0.2972, ρ_{TFP_i} = – 0.3224) and cross-industry (ρ_{LP_j} = – 0.4836, ρ_{TFP_j} = – 0.2481).

To construct our sector skill intensity index, we divide workers between skilled and unskilled using two main indicators. Indeed, the idea initially was to use more than two indicators, to test as much as possible our results. However, all other plausible indicators led us to the same dichotomy among sectors of those two. For both indicators the data are collected from Science, technology and innovation database (made available by the EUROSTAT), which collects data from many different publications on these themes as R&D expenditure, workers knowledge, HRST, innovations.

The first indicator concerns the level of education and we consider skilled those workers with a tertiary education (level 5 – 6 ISCED 1997). Differently, the second indicator concerns the kind of task workers make in their job. In particular, the database gives us these values as a share of total employment, for each sector from 2001 to 2007. Indeed, these two indicators lead us to a similar, but still slightly different, subdivision of sectors (see Annex 3).

[5] The EUROSTAT definition of temporary contracts is the following: "Employees with temporary contracts are those who declare themselves as having a fixed term employment contract or a job which will terminate if certain objective criteria are met, such as completion of an assignment or return of the employee who was temporarily replaced".

As measure of EPL for PE we made use of the cardinal index constructed by OECD (2004)[6]. In our sample from 1992 to 2007 the EPL index for PE ranges from 4.33 in Portugal (1992-2003) to 0.95 in the UK (1992-1999). The mean of the index follows a slightly decreasing trend, going from 2.47 to 2.33 at the end of the sample. However, the decreasing trend in the stringency of regulation of PE is far from being common to all countries, rather it seems to be driven by Spain and Portugal. On the other hand, the EPL index for TE[7] ranges from 5.38 in Italy (1992-1996) to 0.25 in the UK (1992-2001). Similarly to PE, the mean of the index for TE follows a decreasing trend, going from 2.92 to 1.86. But differently to PE, this decreasing trend seems to be a common feature in fairly all EU countries.

Data on trade union density were collected from ICTWSS database, providing information on institutional characteristics of trade unions in 34 countries between 1960 and 2007. In particular, the variable used is "*the ratio of wage and salary earners that are trade union members, divided by the total number of wage and salary earners*". The mean in the sample is 0.40, telling us how trade union are still an important subject in Europe. However, the standard deviation of 0.23 suggests how different is its importance across EU countries. Finally, product market regulation indicators used are the OECD Indicators of PMR, a comprehensive set of indicators measuring the degree to which policies promote or inhibit competition. In our sample *PMR* exhibits much variation, revealing that these policies are not homogenous in Europe.

A full description of variables and sources can be found in Annex 2, whereas the subdivisions of sectors between skilled and unskilled, along with descriptive statistics, are in Annex 3.

3. Empirical Strategy and Skill Intensity Index

In this section, we show the empirical strategy used in the study to identify the differential impact of TE across sectors and, in particular, we describe the method used to divide industries between skilled and unskilled sectors. Then, we discuss the main advantages, but also the potential drawbacks, of our empirical specification.

[6] This index is calculated by scoring different basic items concerning protection of regular workers against individual dismissal and, then, converting these scores into a cardinal index from 0 to 6, with a higher index representing a stricter regulation (see OECD, Employment Outlook 1999). Therefore, a higher index implies more protection for regular workers against individual dismissal.

[7] The procedure to compute the index for temporary workers is fairly the same described in footnote 9. However, the EPL index for TE does not measure the degree of protection of temporary workers against individual dismissal, rather it measures the restrictions on the use of temporary forms of employment (see OECD, 2004). Therefore, a higher index does not imply more protection against individual dismissal, rather it implies stricter conditions for using temporary employment.

Our starting point is that the impact of TE on labour productivity might not be homogenous across sectors and, in particular, we wonder if the effect differs according to sectors skill intensity. To divide industries between *skilled sectors* (S) and *unskilled sectors* (US) we compute the ratio between skilled and unskilled workers in each sector for different years and, then, we consider the mean across time as a general index of sector skill intensity (see e.g., Haskel and Slaughter, 2002). Finally, we take the mean of these indexes across sectors and consider (un)skilled those sectors with a skill intensity (lower) higher than the average. This procedure leads us to the binary indicator $SSII_j$, which is equal to 1 if j is a skilled sector and equal to 0 if j is an unskilled one. As showed below, this indicator $SSII_j$ will be used in the productivity equation to disentangle the effect of the share of TE among skilled and unskilled sectors. More specifically, the underlying assumption is that the difference between the *conditional expected* total factor productivity (TFP) growth in S and US is some function of the share of TE (see Annex 1 for more technical details).

To make our results easily comparable with previous studies, we estimate also the impact of EPL for PE. As standard in this literature, to identify the impact of EPL for PE we follow the method introduced in the finance literature by Rajan and Zingales (1998) to evaluate the impact of some market regulations, then extended in labour policy evaluation (e.g. Bassanini and Venn, 2007, 2008). The main assumption of this approach is that while the degree of market regulation is equal for all industries in a country, the impact of it could be different among industries, according to some "physiological" (idiosyncratic) characteristics of each sector.

In the case of labour market regulation, we expect that EPL is more binding in those industries characterized by a higher need to reallocate resources[8]. The usual way to specify this *different binding* is to divide industries between *binding sectors* (B) and *non-binding sectors* (NB), leading to the binary indicator BI_j, which is equal to 1 if j is a binding sector and equal to 0 if j is a non-binding one (see e.g., Micco and Pages, 2006 and Bassanini et al., 2009). However, this specification has not been exempt from criticisms in the literature (see e.g., Ciccone and Papaioannou, 2006, Cingano et al., 2010) and, accordingly, in this paper we propend for the different specification proposed by Ciccone and Papaioannou (2007). The underlying idea is the same as the binary indicator, but with an idiosyncratic weight FJR_j for each sector depurated from labour market frictions and aggregate shocks (see Annex 1 for details). The rationale is that some sector might have very specific characteristics requiring more or less job

[8] For instance, if firms in a sector need to lay off workers in response to changes in technologies or product demand, a stricter EPL could slow the pace of reallocation. By contrast, in industries where changes are less frequent, EPL could be expected to have little impact on reallocation and, in turn, on productivity.

reallocation than other sectors. Both specifications BI_j or FJR_j are the usual assumptions exploited in the previous literature to identify the impact of the EPL index for both PE and TE.

However, as discussed in Lisi (2013), while this approach should be appropriate for the regulation of PE, the use of the EPL index for TE does not seem to be the appropriate independent variable to identify the effect of temporary contracts on labour productivity (see also Annex 1 for a technical discussion). Therefore, in our empirical analysis we use the share of TE as the main explanatory variable of interest. Indeed, provided that we control for the potential endogeneity of TE, this should allow us to capture the effect of the use of temporary contracts without passing through the relation between the change in the EPL for TE and actual use of temporary contracts in the labour market.

Then, if we assume a linear relation with TFP growth, we could estimate the impact of TE and EPL for PE using both a specification in levels or in growth rates:

$$\log TFP_{ijt} = \alpha\left(FJR_j * \sum_{k=1}^{t} EPL_{ik}\right) + \beta \sum_{k=1}^{t} EPL_{ik} + \lambda\left(SSII_j * \sum_{k=1}^{t} TE_{ijk}\right) + \gamma \sum_{k=1}^{t} TE_{ijk} + \eta \sum_{k=1}^{t} X_{ijk} + \mu_i + \delta_j + \varphi_t + \varepsilon_{ijt} \quad (2)$$

$$\Delta \log TFP_{ijt} = \alpha\left(FJR_j * EPL_{it}\right) + \beta\, EPL_{it} + \lambda\left(SSII_j * TE_{ijt}\right) + \gamma\, TE_{ijt} + \eta\, X_{ijt} + \theta_t + \omega_{ijt} \quad (3)$$

The two specifications presume the same data generating process, in fact specification (3) is the first-difference version of specification (2), with $\theta_t = \varphi_t - \varphi_{t-1}$ and $\omega_{ijt} = \varepsilon_{ijt} - \varepsilon_{ijt-1}$. In both specifications λ is the differential impact of TE on TFP growth in skilled sectors compared to unskilled ones. On the other hand, γ represents the impact of TE in unskilled sectors and, indeed, its inclusion turns out to be important, since it allows the differential impact λ to adjust upon a non-zero impact in the control group (US). In addition, α is the marginal impact of EPL for PE in a sector with a relative high *FJR* compared to a sector with a relatively low *FJR*. Finally, X_{ijt} are other independent variables affecting TFP growth such as trade union density (*TUD*), product market regulation (*PMR*) and time trend ($T_t = t, \forall\, t = 1, 2, \ldots, 16$), whereas μ_i, δ_j and φ_t represent respectively country, industry and time-specific fixed effects. Under the exogeneity assumption both fixed-effects (2) and first-difference (3) estimating equations produce unbiased and consistent estimates of the parameters of interest.

However, for efficiency reasons we consider the fixed-effect estimates (2) as more reliable and, therefore, as the main source of our interpretation (see Annex 1).

Following the previous literature, we assume a Cobb-Douglas production function with constant returns to scale at the industry level:

$$Y_{ijt} = A_{ijt} K_{ijt}^{\rho} L_{ijt}^{1-\rho} \tag{4}$$

where Y_{ijt} is total output, A_{ijt} is total factor productivity, K_{ijt} is capital and L_{ijt} is labour. To obtain the estimating equation, we divide by L_{ijt}, take the logs and substitute (2) in (4):

$$\begin{aligned}\log y_{ijt} = {} & \rho \log k_{ijt} + \alpha \left(FJR_j * \sum_{k=1}^{t} EPL_{ik} \right) + \beta \sum_{k=1}^{t} EPL_{ik} + \lambda \left(SSII_j * \sum_{k=1}^{t} TE_{ijk} \right) \\ & + \gamma \sum_{k=1}^{t} TE_{ijk} + \eta \sum_{k=1}^{t} X_{ijk} + \mu_i + \delta_j + \varphi_t + \varepsilon_{ijt} \end{aligned} \tag{5}$$

where y_{ijt} is labour productivity, k_{ijt} is the capital-labour ratio and the remainder is as in (2). Finally, to the extent that the level of EPL for regular contracts and the level of temporary contracts affect firms decision on investment and, in turn, the level of capital affects labour productivity growth, we omit the capital-labour ratio and estimate a reduced form model to capture the overall effect on labour productivity growth:

$$\begin{aligned}\log y_{ijt} = {} & \alpha \left(FJR_j * \sum_{k=1}^{t} EPL_{ik} \right) + \beta \sum_{k=1}^{t} EPL_{ik} + \lambda \left(SSII_j * \sum_{k=1}^{t} TE_{ijk} \right) + \gamma \sum_{k=1}^{t} TE_{ijk} \\ & + \eta \sum_{k=1}^{t} X_{ijk} + \mu_i + \delta_j + \varphi_t + \varepsilon_{ijt} \end{aligned} \tag{6}$$

In what follows, even if we report some estimates with the capital-labour ratio as in (5), equation (6) represents our baseline specification.

However, a potential drawback of specification (6) is that it produces consistent estimates under the strictly exogeneity of all covariates, which might not be the case in our empirical analysis. In particular, to the extent that hiring a temporary worker is a firm's decision, the share of TE might be endogenous in the productivity equation. Therefore, we perform also an IV–strategy, using the EPL index for TE as an instrumental variable for the share of TE. In particular, the main idea here is that the country legislation concerning the use of temporary contracts certainly affect the share of TE in a country, like so the variation of the legislation affects the share over time. In this regard, the EPL index for TE turns out to be significantly correlated (p-value = 0.000) with the share of TE in our sample (see also Table A3.4). Differently, the legislation about TE should not have any impact on labour productivity but for the actual use of temporary contracts; in fact, as long as temporary contracts are not used in the labour market, a change in the legislation would be expected to have no impact on labour productivity[9]. Moreover, in the following section we provide the results of different statistical tests supporting further the use of our instrument.

Hence, in the first stage we estimate the reduced form equation for the share of TE (7) including the EPL index for TE; then, in the second stage we estimate the model for labour productivity (8) using the fitted value $\widehat{TE}_{ijt}$ as the explanatory variable:

$$TE_{ijt} = \zeta\left(FJR_j * \sum_{k=1}^{t} EPL_{ik}^{PE}\right) + \phi \sum_{k=1}^{t} EPL_{ik}^{PE} + \eta \sum\nolimits_{k=1}^{t} EPL_{ijk}^{TE} + \psi \sum_{k=1}^{t} X_{ijk} + \mu_i + \delta_j + \varphi_t + \varepsilon_{ijt} \quad (7)$$

$$\log y_{ijt} = \alpha\left(FJR_j * \sum_{k=1}^{t} EPL_{ik}\right) + \beta \sum_{k=1}^{t} EPL_{ik} + \lambda\left(SSII_j * \sum_{k=1}^{t} \widehat{TE}_{ijk}\right) + \gamma \sum_{k=1}^{t} \widehat{TE}_{ijk} + \eta \sum_{k=1}^{t} X_{ijk} + \mu_i + \delta_j + \varphi_t + \varepsilon_{ijt} \quad (8)$$

Our empirical specifications follow previous literature on the topic. However, we introduce a crucial difference: instead of identifying an average impact of TE across sectors, here we introduce an ulterior assumption with the aim of identifying the differential impact of TE according to sectors skill intensity. On the one hand, this should offer a more accurate description of the impact of TE; on the other hand, the investigation of this differential impact of TE might suggest how temporary contracts are currently used in the labour market (that is, least-cost way of screening new workers or cheaper form of job).

Moreover, while previous papers in this literature use the same identification strategy for the two EPL indexes, in this paper we distinguish between EPL for PE and TE. In particular, our IV–approach would seem fairly consistent, considering that the EPL index for TE can be

[9] As standard in the IV–procedure, while we can easily test for the correlation between instrument and instrumented variable, we cannot test for the exogeneity condition of our instrument. Nonetheless, on the one hand, our reasoning on the inappropriateness of the direct use of the EPL index for TE as explanatory variable in the labour productivity equation leads us to consider fairly reliable also the exogeneity condition of our instrument; on the other hand, in the literature this kind of instrument (index measuring the strictness of a national legislation) tend to be considered strictly exogenous because of the same reason. For example, OECD (2004) and Bassanini et al. (2009) use as IV exactly the EPL index for TE, and Amable and Ledesma (2013) use the product market regulation index as an exogenous instrumental variable. In a previous general article on temporary work and labour productivity, we have also used the EPL indicator for TE in IV estimations (Lisi, 2013).

considered exogenous in (6) and certainly it is correlated with the share of TE once the other exogenous variables have been netted out. In this regard, we will show below different tests confirming the goodness of our IV strategy. In our view, this different identification strategy for TE, along with our investigation of the differential effect according to sectors skill intensity, should allow us to describe more consistently the impact of TE on labour productivity.

Potential drawbacks of our empirical specification are related to the exogeneity of our assumption concerning the differential effect of TE across sectors. In particular, if the use of TE changes extensively the skill composition of our sectors and, in turn, the selection of them in S and US sectors, then our assumption would not be useful anymore. In fact, in that case we are not exploiting the exogenous variation on the impact of the treatment (TE) between control group (US) and treatment group (S), because groups themselves are endogenously determined by the treatment. Differently, if sectors skill composition and, in turn, control group and treatment group are exogenously set by sectors production functions, then our assumption should allow us to exploit the exogenous variation on the impact of TE across sectors.

Indeed, the clear picture emerging from our data is that the correlation between the share of TE and sectors skill composition is almost null. In particular, in Figure 1 we report the scatter plot between TE and SSI and, as we can see, the cloud would seem to suggest that there is no correlation. Moreover, the small and insignificant correlation coefficient ($\rho = -0.037$), as well as the insignificant coefficient of SSI in the reduced form equation for TE, also confirm that there is no correlation between TE and SSI. Therefore, the different skill composition across sectors would seem more driven by the technology underpinning the production function in each sector, which leads us to pursue our identification assumption for the differential impact of TE on labour productivity.

Fig. 1 ***Correlation between TE and SSI***

4. Estimations Results

In this section, we present and discuss the results of the empirical analysis. First, we present a battery of estimates for the productivity equation, from the simple POLS to the 2SLS with a full set of fixed-effects. Then, we present a similar battery for total factor productivity. Finally, we provide some sensitive analysis to check if our findings are robust to little changes in the sample used.

4.1. Labour Productivity

In Table 1 we report different estimates of the productivity equation, using the first sector skill intensity index, that is, the index concerning the level of workers education (see Annex 2 and 3). In the first column we run a simple POLS regression, including among the explanatory variables also the capital–labour ratio. Both point estimates of TE and TE*SSII1 are negative and significant at 1%, indicating that TE is even more damaging in skilled sectors, with a negative effect significantly heavier than in unskilled sectors. Similarly, the point estimate of EPL*FJR is negative and significant, confirming the evidence of previous literature (e.g., Cingano et al., 2010). While these estimates are useful to get an insight on the direction of the effect, they cannot be interpreted as causal impact, given the omitted variable bias and the potential endogeneity of both TE and *k* in the productivity equation.

Table 1. LABOUR PRODUCTIVITY (SSII1)

Differently, from the second column on we introduce a large set of fixed-effects (controlling for institutional, technological and time differentials in productivity), allowed to be correlated with the other explanatory variables. In particular, in the second column are the coefficients from equation (5) including *k*, whereas in the third column we omit *k* and estimate the reduced form model (6) to capture the overall effect on labour productivity. Still, in both specifications the coefficients of TE and TE*SSII1 are negative and significant at 1%, so is the coefficient of EPL*FRJ. As long as strictly exogeneity holds in (6), the estimated coefficients in column three could be interpreted as causal impact of TE on labour productivity growth, differentiated according to sectors skill intensity. Notice also that the R-squared values in FE regressions are significantly higher than POLS[10]. However, we had already underlined valid reasons for which TE might be endogenous in the productivity equation. Therefore, in the next columns we report the estimates of our IV-strategy described above. As additional check, we compare also the

[10] The extremely high values of R-squared in FE are probably due to the inclusion of the large set of dummies (country, sector and time fixed effects) in our FE regressions. Therefore, such high explanatory power should be largely ascribed to fixed effects, which indeed we can interpret just as general institutional, technological and time factors driving productivity differentials. Nonetheless, their inclusion should help us to alleviate significantly the omitted variable bias and, consequently, to isolate the impact of our variables of interest.

results for the two standard identification assumptions BI_j and FJR_j for the EPL index of PE, without any sizeable differences in the coefficients of TE and TE*SSII1.

In columns four and five we show the IV estimates using the EPL index of TE as an instrument for TE, without considering the differential effect of TE, along with the result of different tests. Interestingly, the results of the endogeneity test tend to confirm that the share of TE is, indeed, endogenous in the productivity equation, implying that the estimates of the FE regressions are bias and inconsistent (e.g., Lisi, 2013). Likewise, the Kleibergen-Paap weak identification tests report significantly high values of F-statistic[11], implying that the EPL index for TE is, indeed, a strong instrument for the share of TE in our IV identification strategy. Nonetheless, even if different in magnitude respect to FE, the estimated coefficients of TE are still negative and significant. Finally, in the last two columns we include explicitly the differential effect of TE in the 2SLS equation (8), using the linear projection of TE. Both point estimates of TE and TE*SSII1 are negative and significant, confirming the result that TE is even more damaging in skilled sectors respect to unskilled sectors.

Since we are able to control for several unobserved factors, as well as for the endogeneity of the share of TE, we interpret these estimates as causal impact on labour productivity growth and, in particular, the coefficient of TE*SSII1 as the differential effect of temporary employment on labour productivity between skilled and unskilled sectors. Our central result is that TE is even more damaging in skilled sectors, with a negative effect significantly heavier than in unskilled sectors. In particular, an increase of 10 percentage points of the share of TE in skilled sectors would lead to a decrease of about 1–1.5% in labour productivity growth, whereas in unskilled ones the reduction would be only of 0.5–0.8%. Interestingly, the coefficient of TE in column six (or seven) is somewhat lower than the corresponding one in the estimation without SSII (column four and/or five); furthermore, notice that the sum of TE and TE*SSII1 in column six (or seven) tends to be bigger than the coefficient of TE in the estimation without SSII (column four and/or five). Indeed, this suggests that in the estimation without SSII we identify the average impact of TE across sectors, whereas with the inclusion of the differential effect according to sectors skill intensity we are able to capture a more accurate description of the impact of TE.

[11] In the case of one endogenous regressor, as in our case, the Kleibergen-Paap rk Wald test reduces to the standard F-statistic on the exclusion of the instrument from the first stage. Baum et al. (2007) suggest applying the critical values for the F-statistic reported in Stata provided by Stock and Yogo (2005). In particular, if we are willing to accept an actual rejection rate of 10% (the lowest tabulated in Stata), the critical value for the F-statistic is 16.38. Therefore, the Kleibergen-Paap F-statistics of 59.971 and 59.029 in Table 1 indicate that there is not a problem of weak identification in our IV strategy.

To the extent that a subdivision between skilled and unskilled sectors has to be necessarily based on a discretional criteria, in Table 2 we repeat the same estimations using our second sector skill intensity index, that is, the index concerning the kind of task workers make in their job. As said before, this second index leads to a similar, but slightly different, subdivision of sectors and, therefore, represents a perfect candidate to test the stability of our findings (see Annex 2 and 3).

Table 2. LABOUR PRODUCTIVITY (SSII2)

Nonetheless, as can be clearly seen from Table 2, this change in the SSII used in the estimation does not change at all our conclusions. Still, the coefficients of TE and TE*SSII2 are negative and significant at 1%, even with a magnitude very close to the SSII1 estimation.

4.2. Total Factor Productivity

The estimated coefficients in Table 1 and 2 represent the overall impacts on labour productivity, which is exactly what we aimed to identify. Nonetheless, they do not allow to disentangle the overall effect in the production function between total factor productivity and capital–labour ratio. Neither the specifications including k allow us to distinguish consistently these two effects, since we cannot consider k exogenous in the productivity equation and, in turn, the estimated parameters as the true causal impact. However, as long as we are able to estimate consistently the impact of our variables of interest on *TFP*, simple statistical tests on the difference of the estimated impact of TE between labour productivity and total factor productivity should be able to shed more light on this.

Therefore, in Table 3 we present different estimates of *TFP* equation (2), using the first sector skill intensity index. In particular, the first column shows the estimates from a simple POLS regression, whereas from the second column on we introduce our large set of fixed-effects. In both specifications the point estimates of TE and TE*SSII1 are negative and significant, confirming also for *TFP* that TE is even more damaging in skilled sectors, with a negative effect heavier than in unskilled sectors. Similarly, the point estimates of EPL*FJR are negative and significant. As long as strictly exogeneity holds in (2), the FE estimated coefficients could be interpreted as causal impact of TE on total factor productivity growth, differentiated according to sectors skill intensity. However, following the same argument discussed for labour productivity, these estimates cannot be interpreted as causal impact, given the potential endogeneity of TE also in the *TFP* equation. Therefore, in the next columns we perform our IV-strategy also for total factor productivity.

Table 3. TOTAL FACTOR PRODUCTIVITY (SSII1)

In columns 3 and 4 we show the IV estimates using the EPL index of TE as an instrument for TE, without considering the differential effect of TE, along with the result of different tests. Notice that also for *TFP* the endogeneity and weak identification tests tend to confirm the goodness of our IV identification strategy. Finally, in the last two columns we include explicitly the differential effect of TE in the 2SLS equation, using the linear projection of TE. We can see that both point estimates of TE and TE*SSII1 are negative and significant, confirming the result that TE is even more damaging in skilled sectors respect to unskilled sectors. Since we are able to control for several unobserved factors, as well as for the endogeneity of the share of TE, we interpret these estimates as causal impact on total factor productivity growth and, in particular, the coefficient of TE*SSII1 as the differential effect of temporary employment between skilled and unskilled sectors.

Table 4. TOTAL FACTOR PRODUCTIVITY (SSII2)

As we did for labour productivity, in Table 4 we re-estimate all specifications using our second sector skill intensity index. Similar to labour productivity, we can see from Table 4 that this change in the SSII does not change the results on the impact of our variables of interest on *TFP*. Still, the coefficients of TE and TE*SSII2 are negative and significant, even with a magnitude very close to the estimated coefficients using the first skill intensity index.

As we said above, as long as the impact of our variables of interest are consistently estimated, simple statistical tests on the difference of the estimated impact of TE between labour productivity and total factor productivity should be able to disentangle the overall effect in the production function between total factor productivity and capital–labour ratio. In particular, if there is a significant difference between the two estimated impacts, this would imply that TE affects labour productivity not only reducing *TFP* but also through the impact on capital–labour ratio. Differently, if there is no significant difference, then TE would affect labour productivity mainly through the impact on *TFP*. In order to test the null hypothesis $H_0 = \beta_{LP} - \beta_{TFP} = 0$, we perform the following standard z-test on the difference of both regression coefficients of TE and TE*SSII (see e.g., Clogg et al., 1995, Brame et al., 1998):

$$Z = \frac{\widehat{\beta}_{LP} - \widehat{\beta}_{TFP}}{\sqrt{s.e.(\widehat{\beta}_{LP})^2 - s.e.(\widehat{\beta}_{TFP})^2}} \tag{9}$$

where the numerator is the estimated difference between the coefficients and the denominator is the estimated standard deviation of the difference. Under the null H_0 this statistic is distributed as a standard normal. Therefore, we compute the value of this *Z*-statistic for both the coefficients of TE and TE*SSII and, then, compare them with the value of the standard normal at the 95th quantile, implying a significance level of α = 0.05 for our test.

Table 5. Z-test on the difference of regression coefficients

From Table 5, we can see that fairly all *Z*-statistics tend to be smaller (in absolute value) than the standard normal at the 95th quantile (z = 1.645) and, thus, z-tests do not reject the null hypothesis of equality between the coefficients[12]. Indeed, for the coefficient of TE*SSII1 the statistic (Z = – 1.671) is barely higher than the standard normal; however, with just a significance level of α = 0.047, even for this coefficient the *Z*-statistic became smaller (in absolute value) than the standard normal at the 95.3th quantile (z = 1.675). Therefore, the statistical tests performed on the estimated coefficients of TE and TE*SSII reveal that there is no significance difference between the impact of our variables of interest on labour productivity and total factor productivity. Interestingly, this imply that TE affects labour productivity mainly reducing total factor productivity.

4.3. Sensitivity Analysis

Finally, to check whether our results depend crucially on the inclusion of some countries in the sample or not, we re-estimate the model excluding all countries one-by-one. Therefore, we run many FE and 2SLS regressions, where in each regression we exclude one different country.

[12] We decided to report the z-test only for the coefficients of 2SLS regressions, since in the paper they are the main source of interpretation of our results. Nonetheless, Z-statistics for the coefficients of FE regressions produce exactly the same results.

Indeed, this further robustness check should be especially relevant for the issue of temporary contracts, since we have already seen in section 2 that the extent of TE is not homogeneous across EU countries. In particular, the inclusion of Spain and Portugal in the sample might potentially be important in driving our results, as both countries not only have had the highest share of temporary contracts for many years, but also they have implemented reforms reducing considerably the protection of permanent workers. In Fig. 2 are the coefficients of TE and TE*SSII, arranged from the greatest to the smallest, for both FE and 2SLS[13].

Fig. 2 ***Coefficients of TE and TE*SSII from the Reduced Sample***

As Fig. 2 clearly shows, the results of the estimation do not depend on the sample of countries included in the sample. Indeed, both the coefficients of TE and TE*SSII are fairly always negative and significant, even omitting Spain and Portugal. Furthermore, the magnitude of the coefficients would seem to validate sufficiently our result that an increase of 10 percentage points of the share of temporary contracts would lead to a decrease of about 1–1.5% in labour productivity growth, whereas in unskilled ones the reduction would be only of 0.5–0.8%.

4.4. General discussion

Our results appear to be fairly robust and rather stable to the sector skill intensity index and the sample of countries used in the analysis. Even omitting Spain and Portugal –the two countries with TE shares much above the mean– does not seem particularly crucial for driving our results. Provided that we control for several unobserved factors, as well as for the endogeneity of the share of TE, we interpret our estimates as causal impact on labour productivity growth and, thus, the coefficient of TE*SSII as the differential effect of temporary employment on labour productivity between skilled and unskilled sectors. Our main finding is that TE is even more damaging in skilled sectors, with a negative effect significantly heavier than in unskilled sectors. In particular, an increase of 10 percentage points of the share of TE in skilled sectors would lead to a decrease of about 1–1.5% in labour productivity growth, whereas in unskilled ones the reduction would be only of 0.5–0.8%.

Moreover, we have seen that statistical tests on the difference of the impact of TE between labour productivity and total factor productivity do not reject the hypothesis of equality,

[13] Full regressions are available upon request from the authors.

implying that TE affects labour productivity mainly reducing total factor productivity. Apart from offering a more accurate description of the impact of TE, our results should represent a valid contribution to the previous literature on TE, suggesting how temporary contracts are currently used in the labour market. In particular, this evidence should support the idea that TE is currently used more as a cheaper form of job, instead of as a least-cost way of screening new workers (see e.g., Güell and Petrongolo, 2007).

Our interpretation is that the reduction in workers' effort and accumulation of human capital induced by the actual way to use TE is more harmful in those sectors where production uses skills more intensively. Therefore, rather than considering TE as harmful per se, the main issue is how they are used by firms organizing production and how we can preserve an easy entry into the labour market improving screening by firms but also retiring incentives to use temporary contracts as a mere cheaper way to hire workers.

5. Conclusions

In this study we have implemented a well-known method in policy evaluation to identify the differential impact of TE on labour productivity, according to sectors skill intensity. In particular, making use of an industry-level panel of EU countries, we divided industries between skilled and unskilled and, then, specified a diff-in-diff style assumption to exploit the exogenous source of variation in the impact of TE among different sectors. Moreover, the industry-level panel allowed us to control for different unobserved confounding factors, which should mitigate significantly the omitted variable and other endogeneity problems. Finally, to the extent that the share of TE might be endogenous in the productivity equation, we performed also an IV-strategy to test further the identification. Indeed, the empirical analysis on this question turns out to be crucial, given that from a theoretical point of view is ambiguous what sectors might be more affected by TE.

The main finding of the paper is that TE is even more damaging in skilled sectors, with a negative effect significantly heavier than in unskilled sectors, robust to little changes in the skill intensity index and in the sample used. In particular, an increase of 10 percentage points of the share of TE in skilled sectors would lead to a decrease of about 1–1.5% in labour productivity growth, whereas in unskilled ones the reduction would be only of 0.5–0.8%. Finally, statistical tests performed on the estimated coefficients revealed that there is no significance difference between the impact of TE on labour productivity and total factor productivity, implying that TE affects labour productivity mainly reducing total factor productivity.

Apart from offering a more accurate description of the impact of TE, these results could have very important policy implications and, certainly, lead us to question if the actual European regulation corresponds exactly to the lines of the best practice. In particular, this evidence might support the growing feeling that TE is currently used in fairly all industries more as a permanent feature much beyond the role as screening device. Consequently, temporary contracts seem to be related with permanently high levels of workers' rotation, damaging all sectors but especially skilled sectors, where production uses skills more intensively.

The main regulatory implication raising from this picture is that the real challenge for labour regulation is to find a design to address the use of temporary contracts as a flexible way to enter in the market allowing firms to screen new workers towards more stable form of jobs, instead of as a structural cheaper form of work. Probably, only in those conditions labour market outcomes could be able to benefit from all the advantages in terms of flexibility induced by TE, without suffering the secondary consequences on labour productivity. Hence, the future agenda of labour market research should certainly include the identification of such kind of regulation.

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Fig. 1 ***Correlation between TE and SSI***

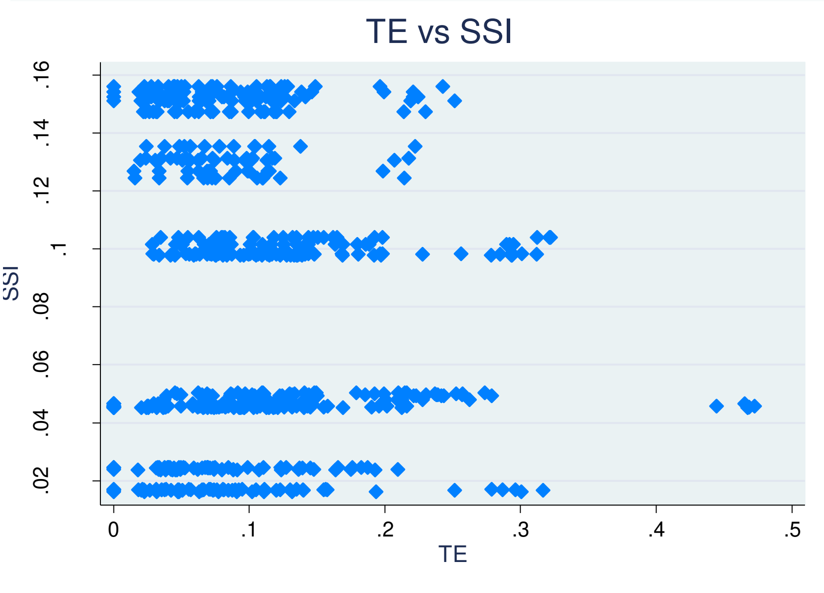

Fig. 2 ***Coefficients of TE and TE*SSII from the Reduced Sample***

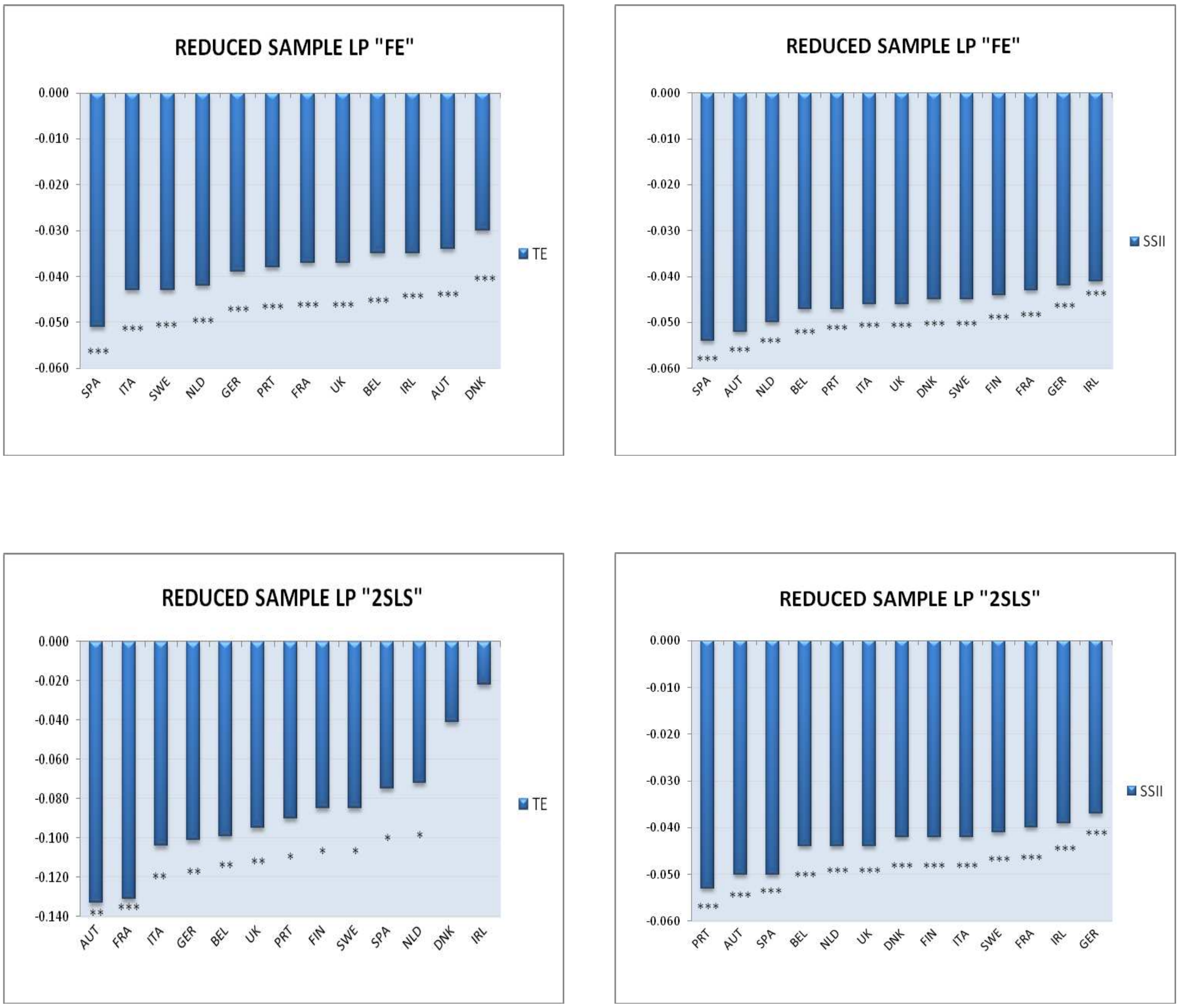

Table 1. LABOUR PRODUCTIVITY (SSII1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	POLS	FE	FE	IV [b]	IV [b]	2SLS [d]	2SLS [d]
K/L [c]	0.011 (0.003)***	0.032 (0.010)***					
EPL	0.008 (0.001)***	0.006 (0.002)***	0.007 (0.002)***	0.007 (0.002)***	0.005 (0.002)***	0.009 (0.002)***	0.005 (0.002)***
EPL*FJR	-0.096 (0.029)***	-0.056 (0.035)*	-0.092 (0.039)***	-0.083 (0.042)**		-0.110 (0.040)***	
EPL*BI					-0.002 (0.000)***		-0.002 (0.000)***
TE	-0.051 (0.008)***	-0.049 (0.008)***	-0.035 (0.009)***	-0.109 (0.050)**	-0.109 (0.051)**	-0.087 (0.052)*	-0.085 (0.052)*
TE*SSII1	-0.056 (0.008)***	-0.039 (0.007)***	-0.046 (0.008)***			-0.044 (0.011)***	-0.048 (0.012)***
TUD	-0.006 (0.002)***	-0.006 (0.004)*	-0.003 (0.004)	-0.005 (0.004)	-0.005 (0.004)	-0.005 (0.004)	-0.005 (0.004)
PMR	-0.002 (0.001)*	-0.008 (0.002)***	-0.009 (0.002)***	-0.008 (0.002)***	-0.008 (0.002)***	-0.008 (0.002)***	-0.008 (0.002)***
TREND	0.002 (0.000)***	0.034 (0.001)***	0.037 (0.001)***	0.001 (0.002)	0.001 (0.002)	0.037 (0.001)***	0.037 (0.001)***
CONSTANT	4.461 (0.036)***						
SECTOR DUMMIES	NO	YES	YES	YES	YES	YES	YES
COUNTRY DUMMIES	NO	YES	YES	YES	YES	YES	YES
YEAR DUMMIES	NO	YES	YES	YES	YES	YES	YES
Endogeneity Test [a]				p-val = 0.02	p-val = 0.02		
F-statistic [e]				59.971	59.029		
Observations	1600	1600	2080	2080	2080	2080	2080
R-squared	0.2635	0.9993	0.9991	0.9990	0.9990	0.9991	0.9991

POLS: pooled ordinary least squares; FE: fixed effects (dummy variable regression); IV: instrumental variable; 2SLS: two stage least square (second stage); K/L: capital-labour ratio; EPL: employment protection legislation; FJR: frictionless job reallocation; BI: binding indicator for EPL; TE: the share of temporary employment; SSII1: sector skill intensity index concerning the level of workers education; TUD: trade union density; PMR: product market regulation.

Robust standard errors in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

[a] The endogeneity test is the difference of two Sargan-Hansen statistics: one for the equation with the smaller set of instruments and one for the equation with the larger set of instruments. Unlike the Hausman tests, this statistic is robust to heteroskedasticity and serial correlation. [b] First-stage estimates reported in Table A3.4. [c] Data not available for Ireland, Portugal and Sweden. [d] Second-stage estimates considering the linear projection of the share of temporary employment. [e] F-statistic of the Kleibergen-Paap *rk* Wald test for weak identification.

Table 2. LABOUR PRODUCTIVITY (SSII2)

	(1)	(2)	(3)	(4)	(5)
	POLS	FE	FE	2SLS [d]	2SLS [d]
K/L [c]	0.015 (0.003)***	0.035 (0.010)***			
EPL	0.009 (0.001)***	0.006 (0.002)***	0.006 (0.002)***	0.008 (0.002)***	0.005 (0.002)***
EPL*FJR	-0.105 (0.029)***	-0.049 (0.030)*	-0.089 (0.039)***	-0.095 (0.028)***	
EPL*BI					-0.002 (0.000)***
TE	-0.052 (0.008)***	-0.052 (0.008)***	-0.039 (0.008)***	-0.099 (0.043)***	-0.103 (0.043)***
TE*SSII2	-0.051 (0.008)***	-0.031 (0.008)***	-0.041 (0.008)***	-0.021 (0.011)**	-0.016 (0.010)*
TUD	-0.007 (0.003)***	-0.006 (0.004)*	-0.003 (0.003)	-0.005 (0.003)	-0.005 (0.003)
PMR	-0.002 (0.001)*	-0.008 (0.002)***	-0.009 (0.002)***	-0.008 (0.002)***	-0.008 (0.002)***
TREND	0.002 (0.000)***	0.034 (0.001)***	0.037 (0.001)***	0.038 (0.001)***	0.038 (0.001)***
CONSTANT	4.412 (0.036)***				
SECTOR DUMMIES	NO	YES	YES	YES	YES
COUNTRY DUMMIES	NO	YES	YES	YES	YES
YEAR DUMMIES	NO	YES	YES	YES	YES
Observations	1600	1600	2080	2080	2080
R-squared	0.2581	0.9993	0.9991	0.9991	0.9991

POLS: pooled ordinary least squares; FE: fixed effects (dummy variable regression); 2SLS: two stage least square (second stage); K/L: capital-labour ratio; EPL: employment protection legislation; FJR: frictionless job reallocation; BI: binding indicator for EPL; TE: the share of temporary employment; SSII2: sector skill intensity index concerning the kind of task workers make in their job; TUD: trade union density; PMR: product market regulation.

Robust standard errors in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

[c] Data not available for Ireland, Portugal and Sweden. [d] Second-stage estimates considering the linear projection of the share of temporary employment.

Table 3. TOTAL FACTOR PRODUCTIVITY [c] (SSII1)

	(1)	(2)	(3)	(4)	(5)	(6)
	POLS	FE	IV	IV	2SLS [d]	2SLS [d]
EPL	0.006 (0.001)***	0.009 (0.002)***	0.012 (0.002)***	0.008 (0.002)***	0.010 (0.002)***	0.007 (0.002)***
EPL*FJR	-0.043 (0.019)***	-0.097 (0.031)***	-0.108 (0.033)***		-0.111 (0.032)***	
EPL*BI				-0.002 (0.001)***		-0.002 (0.001)***
TE	-0.056 (0.006)***	-0.035 (0.008)***	-0.099 (0.038)***	-0.099 (0.037)***	-0.112 (0.047)***	-0.141 (0.046)***
TE*SSII1	-0.021 (0.007)***	-0.016 (0.008)**			-0.018 (0.011)*	-0.013 (0.010)
TUD	-0.003 (0.002)*	-0.001 (0.003)	-0.002 (0.003)	-0.002 (0.004)	-0.002 (0.004)	-0.003 (0.004)
PMR	-0.002 (0.001)*	-0.004 (0.002)**	-0.003 (0.002)*	-0.003 (0.002)*	-0.001 (0.002)	-0.001 (0.002)
TREND	0.001 (0.000)***	0.034 (0.001)***	0.001 (0.001)	0.001 (0.001)	0.035 (0.001)***	0.034 (0.001)***
CONSTANT	4.595 (0.006)***					
SECTOR DUMMIES	NO	YES	YES	YES	YES	YES
COUNTRY DUMMIES	NO	YES	YES	YES	YES	YES
YEAR DUMMIES	NO	YES	YES	YES	YES	YES
Endogeneity Test [a]			p-val = 0.10	p-val = 0.09		
F-statistic [e]			71.132	70.005		
Observations	1920	1920	1920	1920	1920	1920
R-squared	0.1171	0.9993	0.9993	0.9993	0.9993	0.9993

POLS: pooled ordinary least squares; FE: fixed effects (dummy variable regression); IV: instrumental variable; 2SLS: two stage least square (second stage); EPL: employment protection legislation; FJR: frictionless job reallocation; TE: the share of temporary employment; SSII1: sector skill intensity index concerning the level of workers education; TUD: trade union density; PMR: product market regulation.

Robust standard errors in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

[a] The endogeneity test is the difference of two Sargan-Hansen statistics: one for the equation with the smaller set of instruments and one for the equation with the larger set of instruments. Unlike the Hausman tests, this statistic is robust to heteroskedasticity and serial correlation. [c] Data not available for Portugal. [d] Second-stage estimates considering the linear projection of the share of temporary employment. [e] F-statistic of the Kleibergen-Paap *rk* Wald test for weak identification.

Table 4. TOTAL FACTOR PRODUCTIVITY [c] (SSII2)

	(1)	(2)	(3)	(4)
	POLS	FE	2SLS [d]	2SLS [d]
EPL	0.007	0.010	0.010	0.007
	(0.001)***	(0.002)***	(0.002)***	(0.001)***
EPL*FJR	-0.051	-0.105	-0.109	
	(0.019)***	(0.031)***	(0.028)***	
EPL*BI				-0.002
				(0.001)***
TE	-0.053	-0.034	-0.113	-0.150
	(0.006)***	(0.007)***	(0.038)***	(0.038)***
TE*SSII2	-0.034	-0.030	-0.014	-0.013
	(0.007)***	(0.008)***	(0.009)*	(0.010)
TUD	-0.003	-0.001	-0.002	-0.003
	(0.002)**	(0.003)	(0.003)	(0.003)
PMR	-0.001	-0.004	-0.001	-0.001
	(0.001)*	(0.002)**	(0.002)	(0.002)
TREND	0.001	0.034	0.034	0.036
	(0.000)***	(0.001)***	(0.001)***	(0.001)***
CONSTANT	4.595			
	(0.006)***			
SECTOR DUMMIES	NO	YES	YES	YES
COUNTRY DUMMIES	NO	YES	YES	YES
YEAR DUMMIES	NO	YES	YES	YES
Observations	1920	1920	1920	1920
R-squared	0.1260	0.9993	0.9993	0.9993

POLS: pooled ordinary least squares; FE: fixed effects (dummy variable regression); 2SLS: two stage least square (second stage); EPL: employment protection legislation; FJR: frictionless job reallocation; TE: the share of temporary employment; SSII2: sector skill intensity index concerning the kind of task workers make in their job ; TUD: trade union density; PMR: product market regulation.

Robust standard errors in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

[c] Data not available for Portugal. [d] Second-stage estimates considering the linear projection of the share of temporary employment.

Table 5. Z-test on the difference of regression coefficients

Estimate 2SLS	LP (SSII1)	TFP (SSII1)	*Z*-statistic	Standard normal
TE	-0.087	-0.112	0.356	1.645
s.e. ($\hat{\beta}$)	0.052	0.047		
TE*SSII1	-0.044	-0.018	-1.671	1.645
s.e. ($\hat{\beta}$)	0.011	0.011		
	LP (SSII2)	**TFP (SSII2)**		
TE	-0.099	-0.113	0.243	1.645
s.e. ($\hat{\beta}$)	0.043	0.038		
TE*SSII2	-0.021	-0.014	-0.492	1.645
s.e. ($\hat{\beta}$)	0.011	0.009		

ANNEX 1: TECHNICAL APPENDIX

Identification assumption on the differential effect of TE

The main inspiration of the paper is that the impact of TE on labour productivity might not be homogenous across sectors and, in particular, we wonder if this effect differs according to sectors skill intensity. More specifically, dividing industries between *skilled sectors* (S) and *unskilled sectors* (US), we specify the following diff-in-diff style assumption with continuous treatment, according to which the difference between the *conditional expected* total factor productivity growth in the control group US and in the treatment group S is some function of the share of TE:

$$\overline{\Delta \log TFP}_{it}^{S} - \overline{\Delta\, log\, TFP}_{it}^{US} = f\left(TE_{ijt}\right) \qquad \text{(A1.1)}$$

where the first element indicates the *conditional expected* TFP growth in the treatment group S in country *i* at time *t*, the second one the same for the control group US and *TE* is the share of TE in country *i* in sector *j* at time *t*. In particular, the TFP growth in (A1.1) are *conditional* in the sense that our assumption is valid after that all the other explanatory variables affecting TFP growth have been netted out; on the other hand, TFP growth are *expected* in the sense that in (A1.1) they are the average across all sectors within the two groups. Finally, notice that with respect to the standard diff-in-diff assumption where only observations in the treatment group are treated, in our case we assume that is the impact of the treatment to be different between the two groups. To this extent, our assumption is very close to the spirit of the method introduced by Rajan and Zingales (1998) to evaluate the impact of some market regulations.

Sector Skill Intensity Index

To divide industries between *skilled sectors* (S) and *unskilled sectors* (US) we compute the ratio between skilled (SW) and unskilled workers (USW) in each sector for different years and, then, we consider the mean across time as a general index of sector skill intensity (see e.g., Haskel and Slaughter, 2002):

$$SSI_j = \frac{1}{T}\sum_{t=1}^{\mathrm{T}}\left(\frac{\mathrm{SW}}{\mathrm{USW}}\right)_{\mathrm{jt}} \qquad \text{for each } j = 1, 2, \dots, J \qquad \text{(A1.2)}$$

Finally, we take the mean of these indexes across sectors and consider (un)skilled those sectors with a skill intensity (lower)higher than the average. This procedure leads us to the binary indicator $SSII_j$, which is equal to 1 if j is a skilled sector and equal to 0 if j is an unskilled one:

$$SSII_j = \begin{cases} 1 & if \quad SSI_j > \frac{1}{J} \sum_{j=1}^{J} SSI_j \\ 0 & if \quad SSI_j < \frac{1}{J} \sum_{j=1}^{J} SSI_j \end{cases} \qquad \text{for each } j = 1, 2, \dots, J \tag{A1.3}$$

Identification assumption on the impact of EPL for PE

As standard in this literature, the empirical strategy to identify the impact of EPL for PE follows the method introduced in the finance literature by Rajan and Zingales (1998) to evaluate the impact of some market regulations, then extended in labour policy evaluation (e.g. Bassanini and Venn, 2007, 2008). The main assumption of this approach is that while the degree of market regulation is equal for all industries in a given country, the impact of it could be different among industries, according to some "physiological" characteristics of each sector.

The usual way to specify this different binding assumption is dividing industries in *binding sectors* (B) and *non-binding sectors* (NB) and specifying the following diff-in-diff style assumption with continuous treatment, according to which the difference between the *conditional expected* TPF growth in the control group NB and in the treatment group B is some function of the degree of market regulation EPL:

$$\overline{\Delta \log TFP}_{it}^{B} - \overline{\Delta \log TFP}_{it}^{NB} = f\,(EPL_{it}) \tag{A1.4}$$

where the first element indicates the *conditional expected* TFP growth in the treatment group B in country i at time t, the second one the same for the control group NB and *EPL* is the degree of regulation in country i at time t (see e.g., Micco and Pages, 2006 and Bassanini et al., 2009). Again, the TFP growth in (A1.4) are *conditional* in the sense that the assumption is valid after that all the other explanatory variables affecting TFP growth have been netted out; on the other hand, TFP growth are *expected* in the sense that in (A1.4) they are the average across all sectors within the two groups. Finally, with respect to the standard diff-in-diff assumption where only observations in the treatment group are treated, in this case is the impact of the treatment assumed to be different between the two groups.

As far as EPL studies are concerned, the main problem is to recover an appropriate measure of the natural need of job reallocation in each industry to divide sectors. In fact, since the actual turnover rates are themselves affected by EPL, they should not be used as a reliable index for the natural need of job reallocation. The method proposed by Rajan and Zingales (1998) to deal with this problem is to use data from a frictionless country as a proxy for the physiological characteristics of each industry. Following this idea, a standard approach to classify industries in EPL studies is to use turnover rates in the US, usually considered the quintessential frictionless country (Micco and Pagés, 2006, Bassanini et al., 2009).

However, this specification has not been exempt from criticisms in the literature and, accordingly, in the paper we propend for the following identification assumption (see e.g. Cingano et al., 2010):

$$\overline{\Delta logTFP}_{ijt} - \overline{\Delta logTFP}_{ikt} = f\left(FJR_j - FJR_k\right) * EPL_{it} \tag{A1.5}$$

where the first element indicates the *conditional expected* TFP growth in sector *j* in country *i* at time *t*, the second one the same in sector k and *FJR* represent the frictionless job reallocation rate. More specifically, this assumption states that the difference between the conditional expected TFP growth in two sectors *j* and *k*, in country *i* at time *t*, is a function of the degree of regulation weighted with the natural need of job reallocation of those sectors. Therefore, the underlying idea is the same as (A1.4), but in (A1.5) we specify the different binding with an idiosyncratic weight *FJR* for each sector.

Frictionless Job Reallocation

To obtain our *FJR* we follow the method proposed by Ciccone and Papaioannou (2006, 2007) to obtain a measure of "physiological" rate of job reallocation in each industry, depurated from the frictions introduced by labour market regulation and the effect of aggregate shocks. In particular, we regress the actual job reallocation rate at industry level on industry dummies π_j, industry dummies interacted with the EPL index $\tau_j * EPL_{it}$ and country-time dummies ϑ_{it}:

$$JR_{ijt} = \pi_j + \tau_j * EPL_{it} + \vartheta_{it} + v_{ijt} \tag{A1.6}$$

The presence of country-time dummies ϑ_{it} should control for any time-varying differences across countries, whereas the interaction term $\tau_j * EPL_{it}$ should absorb the effect of market regulation on job reallocation rate, allowing us to obtain an appropriate estimate $FJR_j = \hat{\pi}_j$ of natural rate of job reallocation in each industry. Specifically, the job reallocation rate in (A1.6) are defined following Davis and Haltiwanger (1992) and Cingano et al. (2010), that is:

$$JR_{ijt} = \frac{|E_{ijt} - E_{ijt-1}|}{(E_{ijt} + E_{ijt-1})/2} \tag{A1.7}$$

where E_{ijt} is the level of employment in industry j, in country i, at time t.

Empirical strategy for TE (EPL for TE vs. the share of TE)

The different binding assumption is the usual empirical strategy implemented in the previous literature to identify the impact of the EPL index for both PE and TE. However, as discussed in Lisi (2013), while this approach should be appropriate for the regulation of PE, the use of the EPL index for TE does not seem to be the appropriate independent variable to identify the effect of temporary contracts on labour productivity. The EPL index for regular contracts expresses the degree of layoff protection for permanent workers. Thus, it certainly influences firms and workers behaviour on investment and effort, affecting directly labour productivity. Differently, the EPL index for temporary contracts does not express the degree of layoff protection, rather the permissiveness to use temporary contracts. Therefore, the legislation on TE influences labour productivity only to the extent firms actually use temporary contracts. Evidently, the EPL index affects the use of TE by firms, but it is certainly difficult to establish what is the relation between the timing of a reform introducing (or facilitating) the use of temporary contracts and their actual use and expansion in the labour market. Thus, provided that we check for the potential endogeneity of TE, it would seem more appropriate to use directly the variation in the share of TE, rather than the EPL index for temporary contracts. In this way we should be able to isolate the impact of TE on labour productivity growth, without passing through the relation between the change in the EPL for TE and actual use of temporary contracts in the labour market. Moreover, using the share of TE as covariate instead of the EPL index for TE, we do not need to rely on some assumption concerning how much the EPL index is binding in different industries.

Fixed-effects vs. First-difference

Under the exogeneity assumption $E(\varepsilon_{ijt} | EPL_{it}, TE_{ijt}, X_{ijt}, \mu_i, \delta_j, \varphi_t) = 0$ both fixed-effects (2) and first-difference (3) estimating equations produce unbiased and consistent estimates of the parameters of interest, therefore the choice between them concerns exclusively the efficiency of the estimation. In particular, it is well-known that the fixed-effects estimator is the most efficient estimator under the assumption of idiosyncratic errors ε_{ijt} serially uncorrelated; on the other hand, the first-difference estimator is more efficient when ε_{ijt} follows a random walk, which means that there is very substantial serial correlation. In this regard, with T large and *N* not so large and especially if one is dealing with unit root processes, first-difference estimator has the advantage of ruling out the unit root, implying that one can still appeal to the central limit theorem even with *T* larger than *N*. Differently, when *N* is consistently larger than T, the serial correlation of the error term should not represent a big problem. Moreover, if the strict exogeneity assumption is somehow violated, event we investigate below in the paper, fixed-effects estimator is likely to exhibit substantially less bias than first-difference (Wooldridge, 2010). Hence, in our case with $N = 130$ and $T = 16$, there might be a scope for choosing fixed-effects for the greater efficiency, provided that one includes in the estimation the time trend and the variance estimator robust to heteroskedasticity and serial correlation. In addition, regardless of the theoretical assumption on the idiosyncratic error term, in cases where the explanatory variables do not exhibit a sufficient amount of variation in both dimensions (time and cross-section) the first-difference transformation might further reduce their variation and, thus, the first-difference estimator might in practice produce estimates with very little precision. For all these reasons, in this paper we consider the fixed-effect estimates as more reliable and, therefore, as the main source of our interpretation.

ANNEX 2: DATA DESCRIPTION

Labour Productivity

Definition: gross value added in volume terms (base 1995 = 100) divided by total hours worked (variable *LP_I* in EU KLEMS database).

$$y_{ijt} = \frac{(VA/L)_{ijt}}{(VA/L)_{ij1995}} * 100$$

Source: EU KLEMS database.

A potential disadvantage of using an index measure with value added in volumes is that it limits the comparability *in productivity levels* among countries and industries. Nonetheless, in our econometric analysis we are interested in exploiting the variation *in productivity growth*, which indeed is entirely exploited using our measure (1). In fact, the index measure (1) leads to a labour productivity growth as that produced by the unit measure of value added

$$\frac{y_{ijk+1} - y_{ijk}}{y_{ijk}} = \frac{\frac{(VA/L)_{ijk+1}}{(VA/L)_{ij1995}}*100 - \frac{(VA/L)_{ijk}}{(VA/L)_{ij1995}}*100}{\frac{(VA/L)_{ijk}}{(VA/L)_{ij1995}}*100} = \frac{\frac{100}{(VA/L)_{ij1995}}\left((VA/L)_{ijk+1} - (VA/L)_{ijk}\right)}{\frac{(VA/L)_{ijk}}{(VA/L)_{ij1995}}*100} = \frac{(VA/L)_{ijk+1} - (VA/L)_{ijk}}{(VA/L)_{ijk}}$$

which is entirely comparable among countries and industries. Furthermore, the productivity measure (1) has the advantage of being neutral to any difference in price dynamics between countries and industries. Finally, this index measure is the productivity measure largely most used in the literature (e.g. OECD, 2007, Bassanini et al., 2009), with the considerable advantage of making our study more comparable to previous results in the literature.

Total Hours Worked

Definition: product of average hours worked and total person engaged.

Source: EU KLEMS database.

Total Factor Productivity

Definition: total factor productivity (base 1995 = 100)
(variable *TFPva_I* in EU KLEMS database).

Source: EU KLEMS database.

Employment Level

Definition: total persons engaged.

Source: EU KLEMS database.

Job Reallocation Rate

Definition: Davis and Haltiwanger measure of job reallocation rate $JR_{ijt} = \frac{|E_{ijt} - E_{ijt-1}|}{(E_{ijt} + E_{ijt-1})/2}$.

Source: own calculation from the employment level data from EU KLEMS database.

Frictionless Job Reallocation Rate ($\boldsymbol{FJR_j}$)

Definition: job reallocation rate depurated from the frictions introduced by labour market regulation and the effect of aggregate shocks.

Source: own estimation.

Capital Stock

Definition: gross capital stock in volume terms
(variable *CPGK* in OECD STAN database).

Source: OECD STAN database.

Share of Temporary Employment

Definition: the share of persons engaged with temporary contracts over total person engaged. A job may be considered temporary if employer and employee agree that its end is determined by objective conditions such as a specific date, the completion of a task or the return of another employee who has been temporarily replaced. The following belong to these categories:

- Persons with fixed-term contracts (FTC);
- Persons engaged by an agency (TWA) and hired to a third party to perform a specific task (unless there is a written work contract of unlimited duration with the agency);

- Persons with seasonal employment;
- Persons with specific training contracts (if there are no objective criteria for the end of a job or work contract, this should be considered permanent or of unlimited duration);
- Persons on probationary period.

Source: EUROSTAT Labour Force Survey.

For an object so heterogeneous like TE perfect comparability among countries is difficult to achieve, even by means of a single survey carried out at the same time, using the same questionnaire and a single method of recording. Nonetheless, the degree of comparability of the LFS is considerably higher than that of any other existing set of statistics on employment available for countries in our sample. Given these institutional discrepancies, the LFS concept of TE describes situations which, in different institutional contexts, can be considered similar.

SSII1 – 2

Definition: binary indicators equal to 1 for skilled sectors and equal to 0 for unskilled ones. Indicator 1 concerns the workers' level of education, 2 the task workers made in their job.

Source: own calculation.

Share of skilled workers in SSII1

Definition: share of workers with a tertiary education (level 5 – 6 ISCED 1997).

Source: EUROSTAT Science, technology and innovation database.

Share of skilled workers in SSII2

Definition: share of workers occupied in science and technology tasks (HRST).

Source: EUROSTAT Science, technology and innovation database.

EPL for Permanent Employment

Definition: OECD index of employment protection legislation on regular contracts.

Source: OECD *Employment Outlook* (2004).

EPL for Temporary Employment

Definition: OECD index of the permissiveness on the use of temporary contracts.

Source: OECD *Employment Outlook* (2004).

Trade Union Density

Definition: employees trade union members divided by total number of employees.

Source: ICTWSS database.

Product Market Regulation

Definition: OECD Indicators of Product Market Regulation, a comprehensive set of indicators measuring the degree to which policies promote or inhibit competition in areas of the product market where competition is viable. The indicators cover formal regulations in the following areas: state control of business enterprises; legal and administrative barriers to entrepreneurship; barriers to international trade and investment.

Source: OECD database.

ANNEX 3: DESCRIPTIVE STATISTICS

TABLE A3.1 DESCRIPTIVE STATISTICS

Variable	Obs	Mean	Std. Dev.	Min	Max
Labour Productivity	2080	110.936	24.237	63.486	286.575
Log Labour Productivity	2080	4.689	0.192	4.151	5.658
Total Factor Productivity	1920	103.742	15.522	61.629	199.388
Log Total Factor Productivity	1920	4.632	0.141	4.121	5.295
Capital-Labour ratio	1600	754330.1	2222605	11961.45	23719022
Log Capital-Labour ratio	1600	12.324	1.376	9.389	16.982
Job Reallocation	1950	0.027	0.026	0.000	0.239
Frictionless Job Reallocation	2080	0.043	0.009	0.028	0.059
Share of TE	2080	0.118	0.103	0.000	0.694
EPL for Regular Contracts	2080	2.376	0.826	0.948	4.333
EPL for Temporary Contracts	2080	2.189	1.255	0.250	5.375
Trade Union Density	2080	0.402	0.229	0.076	0.839
Product Market Regulation	2080	1.696	0.481	0.771	2.528
Sector Skill Intensity 1	910	0.082	0.049	0.016	0.156
Sector Skill Intensity 2	520	0.217	0.152	0.034	0.518

TABLE A3.2 INDUSTRY DESCRIPTIVE STATISTICS

Industry	$\overline{TE}_j$	$\overline{LP}_j$	$\overline{TFP}_j$	FJR_j
Agriculture, Hunting and Forestry	0.2048	117.1452	113.3016	0.049
Total Manufacturing	0.0891	119.5393	107.4631	0.038
Electricity, Gas and Water Supply	0.0631	126.7167	110.3447	0.059
Construction	0.1400	100.1263	97.8735	0.045
Wholesale and Retail Trade	0.1046	110.8905	104.1041	0.028
Hotels and Resturants	0.1761	100.0441	97.1390	0.040
Transport, Storage and Communication	0.0827	117.4543	108.4009	0.036
Financial Intermediation	0.0633	120.8515	106.3441	0.039
Real Estate, Renting and Business Activities	0.0932	96.2325	97.1183	0.057
Other Community, Social and Personal Services	0.1679	100.3553	95.3268	0.040

		$\overline{TE}$	$\overline{LP}$	$\overline{TFP}$	
ρ_j	$\overline{TE}$	1	-0.4836	-0.2481	
	$\overline{LP}$	-0.4836	1	0.9130	
	$\overline{TFP}$	-0.2481	0.9130	1	

TABLE A3.3 COUNTRY DESCRIPTIVE STATISTICS

Country		$\overline{TE}_i$	$\overline{LP}_i$	$\overline{TFP}_i$
Austria		0.0631	109.6844	106.0690
Belgium		0.0545	108.1211	101.0587
Denmark		0.0936	105.5621	98.1947
Finland		0.1289	112.1675	108.3581
France		0.1245	112.1939	106.8663
Germany		0.1164	110.7430	107.3981
Ireland		0.0626	119.8140	106.7250
Italy		0.1079	102.9484	98.2979
Netherlands		0.1374	111.0894	103.6141
Portugal		0.1624	116.6231	103.7416
Spain		0.3241	105.3882	98.8157
Sweden		0.1061	112.1912	104.4574
United Kingdom		0.0588	115.6359	105.0443
		$\overline{TE}$	$\overline{LP}$	$\overline{TFP}$
ρ_i	$\overline{TE}$	1	-0.2972	-0.3224
	$\overline{LP}$	-0.2972	1	0.7256
	$\overline{TFP}$	-0.3224	0.7256	1

Table A3.4 SHARE OF TEMPORARY EMPLOYMENT (FIRST-STAGE IV)

	(1)	(2)
	FS	FS
EPL for TE	-0.026 (0.003)***	-0.026 (0.004)***
EPL for PE	0.035 (0.004)***	0.026 (0.003)***
EPL*FJR	-0.245 (0.065)***	
EPL*BI		-0.003 (0.001)**
TUD	-0.018 (0.010)*	-0.018 (0.010)*
PMR	-0.045 (0.009)***	-0.045 (0.010)***
TREND	0.007 (0.001)***	0.008 (0.002)***
SECTOR DUMMIES	YES	YES
COUNTRY DUMMIES	YES	YES
YEAR DUMMIES	YES	YES
Observations	2080	2080
R-squared	0.8584	0.8579

FS: first-stage estimates of the IV regression; EPL for TE: employment protection legislation for temporary employment; EPL for PE: employment protection legislation for permanent employment; FJR: frictionless job reallocation; BI: binding indicator for EPL for PE; TUD: trade union density; PMR: product market regulation.

Robust standard errors in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

SKILLED AND UNSKILLED SECTORS PRODUCED BY "SSII1"

SKILLED SECTORS	UNSKILLED SECTORS
Manufacturing	Agriculture, hunting and forestry
Wholesale and retail trade	Electricity, gas and water supply
Hotels and restaurants	Construction
Financial intermediation	Transport, storage and communication
Real estate, renting and business activities	Other community, social and personal services

SKILLED AND UNSKILLED SECTORS PRODUCED BY "SSII2"

SKILLED SECTORS	UNSKILLED SECTORS
Manufacturing	Agriculture, hunting and forestry
Wholesale and retail trade	Electricity, gas and water supply
Financial intermediation	Construction
Real estate, renting and business activities	Hotels and restaurants
Other community, social and personal services	Transport, storage and communication

EPL BINDING AND NON-BINDING SECTORS PRODUCED BY "BI"

BINDING SECTORS	NON-BINDING SECTORS
Agriculture, hunting and forestry	Electricity, gas and water supply
Manufacturing	Construction
Transport, storage and communication	Wholesale and retail trade
Real estate, renting and business activities	Hotels and restaurants
Other community, social and personal services	Financial intermediation