Cross-Sectors Skill Intensity and Temporary Employment

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Abstract

Recent papers emphasised as the use of temporary contracts (TE) could have a detrimental effect on labour productivity, particularly because the wrong utilization of TE might induce a reduction in effort. However, there are different reasons to believe that the impact of TE might not be homogeneous across sectors and, in particular, in this paper we wonder if this negative effect differs according to sectors skill intensity. To this extent, we divide sectors between skilled and unskilled and specify a diff-in-diff strategy to identify the different impact of TE. Moreover, the industry-level panel allows us to deal with different endogeneity problems, as simultaneity and omitted variable bias. Our central result is that TE is even more damaging in skilled sectors and this would seem robust to little changes in the skill intensity index and in the sample used. Our main intuition is that the reduction in effort is more harmful in those sectors where production uses skills more intensively. Indeed, this result could have very important policy implications for labour market regulation.

JEL Classification: J41, J24, O47.

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1. Introduction

In the last decades the use of temporary employment (TE) has grown dramatically in the majority of OECD countries, raising the issue of the possible effects in labour market outcomes. Furthermore, the recent macro stylized-facts and principally the growthless job creation condition have drawn a particular attention to the impact of TE on labour productivity (see e.g. Boeri and Garibaldi, 2007 and OECD, 2007). Indeed, in the light of the predominant role of labour productivity growth in driving GDP growth in the last twenty years, this issue would appear to be really essential for macro considerations (OECD, 2003).

Hence, in recent years a growing literature is trying to answer to these questions. From a theoretical point of view it is not obvious what would be the effect of TE on labour productivity. On 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 and Stucchi, 2008). On the contrary, given the 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, which induces a reduction in effort. Moreover, TE is usually filled by younger, less educated and less experienced workers, and temporary contracts offer less access to training programmes (OECD, 2002 and Bassanini et al. 2007).

Thus, it is not surprising that there has been a proliferation of empirical studies trying to deal with this question. Still, early empirical papers studying different labour market policies did not found any significant impact of TE on labour productivity, even if they usually found a significant effect of the employment protection legislation (EPL) for PE (see e.g. Bassanini and Venn, 2007, Bassanini et al., 2009 and Cingano et al., 2009). However, in Lisi (2009) we made clear why using the EPL index for temporary contracts as in those papers might not be a good approach to identify the impact of TE. And indeed, using a different identification strategy we found a negative and significant impact on labour productivity, consistent to different robustness checks. Similar results emerge in Dolado and Stucchi (2008), where high conversion rates from temporary to permanent jobs increase firm's productivity whereas high shares of temporary contracts decrease it.

Nonetheless, there are good reasons to believe that the impact of TE might not be homogenous across sectors and, in particular, in this paper we wonder if this negative effect differs according to sectors skill intensity. From a theoretical point of view the answer to this question is far from being immediate, existing different convincing reasons for both directions. On 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). On the other hand, in skilled sectors the cost in terms of lower workers' effort induced by TE could be heavier, leading to an even greater reduction in labour productivity. Therefore, the empirical investigation turns out to be crucial to shed light on this issue.

Following this empirical literature, we estimate a Cobb-Douglas production function to identify the different impact of TE on labour productivity, according to sectors skill intensity. To make our results easily comparable with previous studies, we estimate also the impact of EPL for PE as standard in this literature. The empirical analysis is performed on an industry-level panel of EU countries, which allows us to divide sectors between skilled and unskilled and specify a diff-in-diff identification strategy. Borrowing from the Skill-Biased Technological Change (SBTC) literature, we consider (un)skilled those sectors with a ratio between skilled and unskilled workers (lower)higher than the average (see the survey Bond and Van Reenen, 2006). To test the robustness of our results, we compute different indexes of sectors skill intensity, using different definitions of skilled workers. The empirical method exploits both cross-country and time variation in TE and, in particular, the exogenous variation in the impact of TE among different industries. Among other advantages, the industry-level panel allows us to control for different specific unobserved fixed effects, which should attenuate the omitted variable bias.

The 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% of the share of TE in skilled sectors would lead to a decrease of 1.2% in labour productivity growth, whereas in unskilled ones the reduction would be only of 0.6%. To some extent, this result might support the idea that TE is currently used in the labour market more as a cheaper form of job, instead of as a least-cost way to screen new workers (see e.g. Güell and Petrongolo, 2007). Therefore, our main intuition is that the reduction in effort induced by the wrong way to use TE is more harmful in those sectors where production uses skills more intensively. Indeed, this result could have very important policy implications for labour market regulation.

The paper proceeds as follows: in Section 2 we describe the strategy we pursue to identify the different impact of TE across sectors and, in particular, the method we use to divide sectors. Then, Section 3 introduces the main features of the dataset. In Section 4 we show the results of the empirical analysis. Finally, Section 5 discusses the policy implications and concludes.

2. Identification Strategy and Skill Intensity index

In this section we show the empirical strategy used in the study to identify the different impact of TE across sectors and, in particular, we describe the method used to divide industries in our data between skilled and unskilled sectors. Indeed, this subdivision will turn out to be important to yield the exogenous source of variation to identify the different impact across sectors.

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. Indeed, from a theoretical point of view this idea of a different impact across sectors would seem well-founded. However, we do not expect ex ante a given outcome, existing different convincing reasons for both directions. On 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. On the other hand, in skilled sectors the cost in terms of lower workers' effort induced by TE could be heavier, leading to an even greater reduction in labour productivity. In addition, from an empirical point of view the inclusion of this element in the specification allows us to exploit an exogenous source of variation which, as will be more clear below, should help to reach the identification of the impact of TE.

Thus, dividing sectors between *skilled sectors* (S) and *unskilled sectors* (US), we specify the following diff-in-diff assumption, according to which the difference between the conditional expected total factor productivity growth in S and US can be modelled as some function of the share of TE:

$$\overline{\Delta \log TFP}_{it}^{S} - \overline{\Delta \log TFP}_{it}^{US} = f\left(TE\%_{ijt}\right) \quad (1)$$

where the first element indicates the conditional expected total factor productivity growth in S in country *i* at time *t*, the second one the same for US and *TE%* is the share of TE in country *i* in sector *j* at time *t*.

To divide industries between S and 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 said before, 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 assume that while the degree of regulation is equal for all industries in a given country, the impact of EPL differs in different industries, according to the physiological characteristics of each sector, such as technology, stability of tastes, incidence of aggregate shocks. The usual way to specify this different binding assumption is dividing sectors in *binding sectors* (B) and *non-binding sectors* (NB):

$$\overline{\Delta \log TFP}_{it}^{B} - \overline{\Delta \log TFP}_{it}^{NB} = f\left(EPL_{it}\right) \quad (2)$$

where the first element indicates the conditional expected total factor productivity growth in B in country *i* at time *t*, the second one the same for 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). However, this specification has not been exempt from criticisms in the literature and, accordingly, in this paper we propend for the following identification assumption (see e.g. Cingano et al., 2010):

$$\overline{\Delta \log TFP}_{ijt} - \overline{\Delta \log TFP}_{ikt} = f\left(FJR_{j} - FJR_{k}\right) * EPL_{it} \quad (3)$$

where the first element indicates the conditional expected total factor productivity 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, that is, the natural need to reallocate job in each sector, depurated from labour market regulation frictions and the effect of business cycles.

This assumption states that the difference between the conditional expected total factor productivity 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 (2), but in (3) we specify the different binding with an idiosyncratic weight *FJR* for each sector. And in fact, with weights 1 or 0 specification (3) collapses exactly to (2). To obtain our *FJR* we follow the method proposed by Ciccone and Papaioannou (2006) to obtain a measure of physiological rate of job reallocation in each industry, depurated from market frictions and aggregate shocks (see also Lisi, 2009).

Then, if we assume that *f* in (1) and (3) is linear, we could estimate the impact of TE and EPL for PE using both a specification in growth rates or in levels:

$$\Delta \log TFP_{ijt} = \alpha\left(FJR_j * EPL_{it} \right) + \beta * EPL_{it} + \lambda\left(SSII_j * TE\%_{ijt} \right) + \gamma * TE\%_{ijt} + \eta * X_{ijt} + \theta_t + \omega_{ijt} \quad (4)$$

$$\log TFP_{ijt} = \alpha\left(FJR_j * \sum_{k=1}^{t} EPL_{ik} \right) + \beta \sum_{k=1}^{t} EPL_{ik} + \lambda\left(SSII_j * \sum_{k=1}^{t} TE\%_{ijk} \right) + \gamma \sum_{k=1}^{t} TE\%_{ijk} + \eta \sum_{k=1}^{t} X_{ijk} + \mu_i + \delta_j + \varphi_t + \varepsilon_{ijt} \quad (5)$$

These two specifications are fully identical, since specification (4) is just the first-difference of specification (5), with $\theta_t = \varphi_t - \varphi_{t-1}$ and $\omega_{ijt} = \varepsilon_{ijt} - \varepsilon_{ijt-1}$. In both specifications λ is the marginal structural difference between the 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 structural difference 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, whereas μ_i, δ_j and φ_t represent respectively country, industry and time-specific fixed effects, allowed to be correlated with other covariates.

We assume a Cobb-Douglas production function with constant returns to scale at sector level:

$$Y_{ijt} = A_{ijt} K_{ijt}^{\rho} L_{ijt}^{1-\rho} \tag{6}$$

where Y_{ijt} is total output, A_{ijt} is total factor productivity, K_{ijt} is capital and L_{ijt} is labour. Then, we divide for L_{ijt}, take the logs and plug equation (5) in (6), to get the following:

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

where y_{ijt} is labour productivity and k_{ijt} is the capital-labour ratio. Finally, to the extent that the level of capital is affected by the labour market regulation, we omit the capital-labour ratio and estimate a reduced form model to capture the overall effect on labour productivity growth:

$$\begin{aligned} \log y_{ijt} = {} & \alpha\left(FJR_j * \sum_{k=1}^{t} EPL_{ik} \right) + \beta \sum_{k=1}^{t} EPL_{ik} + \lambda\left(SSII_j * \sum_{k=1}^{t} TE\%_{ijk} \right) + \gamma \sum_{k=1}^{t} TE\%_{ijk} \\ & + \eta \sum_{k=1}^{t} X_{ijk} + \mu_i + \delta_j + \varphi_t + \varepsilon_{ijt} \end{aligned} \tag{7}$$

In the following empirical analysis equation (7) represents our baseline specification. Indeed, this specification is similar to Lisi (2009), with the difference that while there we identify an average impact of TE across sectors, in this paper we introduce a diff-in-diff assumption for the impact of TE in different sectors, according to sectors skill intensity. On one hand, this should offer a more accurate description of the impact of TE; on the other hand, since we exploit the exogenous source of variation on the different impact across sectors, this should increase the identification power of the empirical analysis.

Furthermore, as emphasized by the previous literature, the advantage of using industry-level panel data, instead of cross-country, is manifold. First, not only the variation of TE and EPL is exploited, but also the exogenous variation on their impact in different industries. And considering that the use of the share of TE as covariate might be at least questionable for an endogeneity consideration, the inclusion of this exogenous variation to identify the impact of TE should give more consistency to our result. Still, the industry-level panel allows us to control for unobserved fixed effects, allowed to be correlated with other covariates, which should help to alleviate both omitted variable bias and misspecification. Moreover, as the previous literature emphasised (OECD, 2007), the within-industry "composition effect" appears to be negligible, allowing us to identify the "independent effect" of TE on labour productivity.

Possible drawbacks of the specification are basically about the exogeneity of our diff-in-diff assumption (1). In particular, if the use of TE changes extensively the skill composition of our sectors and, in turn, the subdivision of them in S and US, then assumption (1) 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 diff-in-diff 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, along with the results of a simple, but still informing, OLS regression. As we can see, both the cloud and the OLS estimation suggest 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 this identification assumption in the following empirical analysis.

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

3. Data-set

The empirical specification is performed on an industry-level panel of EU countries. In particular, the sample covers 10 sectors in 13 countries over the years 1992-2005, for a balanced panel of 1820 observations. Countries included in the sample are Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden and the United Kingdom. Since we make use of data sources with different levels of sectors classification, we did some aggregation and the final sectors segmentation reflects the EUROSTAT classification (see Annex 2). As usual in this literature (see e.g. Bassanini et al., 2009), we excluded some important industries as public sector, where labour productivity is not easily measured. With this sectors classification, our diff-in-diff strategy produces two groups of five sectors and it is evident from the data analysis that the final sample exhibits a sufficient amount of variation to reach the identification of the different impact of TE.

The data on labour productivity and employment level at the industry-level are collected from EU KLEMS dataset. 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 mean of labour productivity in the entire sample is 108,57, whereas the mean omitting 1992-1993-1994 is 111,91, telling us that labour productivity grew from 1995 (base year = 100) to 2005 in EU countries, even if not so significantly. The data on employment level are 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 *FJR* are contained in a restricted range, the actual job reallocation rates are much more changeable, which confirms the idea that actual rates are significantly influenced by aggregate shocks, producing a short rather than a long-run measure of the natural need of job reallocation.

The shares of TE at the industry-level are constructed from EU – Labour Force Survey (EUROSTAT), a labour market survey providing annually and quarterly information about trends on the labour market in EU countries. The mean and the standard deviation in the sample are respectively 0,09 and 0,075, confirming the idea that TE is by now an important feature of the labour market landscape in Europe, but its importance differs significantly across countries. For instance, while in countries as Spain and Portugal the share of TE is far away from the mean, in the UK the mean is no more than 0,05.

To construct our sector skill intensity index, we divide workers between skilled and unskilled using two main indicators. Indeed, at the beginning the idea was to use more than two indicators of workers skill, to test as much as possible our results. However, all other plausible indicators led us to the same dichotomy between sectors of those two, therefore in the paper we show the results only for these. For both indicators the data are collected form Science, technology and innovation database (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 between skilled and unskilled.

As measure of EPL for PE we make use of the cardinal index constructed by OECD (2004), varying in theory from 6 for the most stringent to 0 for the least stringent regulation. The time-series for the EPL index are currently available until 2003, except for some country where there has been some significant change in the regulation after 2003 (e.g. in Portugal 2004). To the extent that from 2003 to 2005 there not seem to have been significant changes in the regulation of PE (and, if any, they are included in the time-series), for the values after 2003 we consider the least value available. In our sample the EPL index 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 2,46 at the beginning of the sample 1992, to 2,31 at the end 2005. Indeed, the decreasing trend in the stringency of regulation of PE is far away from being common to all countries, rather it seems to be driven by changes in Spain and Portugal.

Even if the EPL index for TE is not used in the regression analysis, it is useful to see what happen to the index in our sample. The EPL index for TE 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 in 1992 to 1,92 in 2005. But differently to PE, the decreasing trend seems to be a common feature in fairly all EU countries.

Unfortunately, no data on trade union density at industry-level are available, therefore they are collected at country-level from OECD – Labour Force Statistics. The mean in the sample is 0,41, telling us how trade union are still an important subject in Europe. In our data trade union density ranges from 0,84 in Sweden (1993) to 0,08 in France (2005).

A description of variables and sources can be found in Annex 1, whereas the subdivisions of sectors between skilled and unskilled produced by the two indicators, along with descriptive statistics, are in Annex 2.

4. Results

In this section we show the results of the empirical analysis. First, we discuss the outcomes of the baseline equation (7), then we provide some sensitive analysis to check if our findings are robust to little changes in the skill intensity index and in the sample used in the estimation.

In Table 1 we estimate different specifications of the baseline equation, using the first sector skill intensity index, that is, the index concerning the level of workers education (see Annex 1 and 2). In the first two columns we run a POLS regression, with a technology trend and trade union density in (2). In both specifications the point estimates of TE% and TE%*SSII1 are negative and significant at 1%. Moreover, both the R-squared are greater than the corresponding ones in the estimation without SSII (see Lisi 2009). However, these coefficients cannot be interpreted as causal impact but just as a simple correlation, given the evident omitted variable bias in this POLS estimation.

Differently, from (3) on we implement a FE regression, where we allow specific factors to be correlated with EPL, TE and SSII. In columns (3)-(4) we include country and sector dummies in the estimation, to control for institutional and technological specific effects. Still, in both specifications the coefficients of TE% and TE%*SSII1 are negative and significant at 1%. Interestingly, the coefficient of TE% is significantly lower than the corresponding one in the estimation without SSII; on the other hand, the sum of TE% and TE%*SSII1 is bigger than the coefficient of TE in the estimation without SSII (see Lisi 2009). Indeed, this suggests that in the estimation without SSII we identify the average impact of TE across sectors, whereas with the inclusion of SSII we are able to capture a more accurate description of the impact of TE.

In columns (5)-(6) we include also time dummies to control for differential trends without any sizable difference. Since we are able to control for all unobserved factors, we interpret these results as the causal impact of these labour market policies and, in particular, the coefficient of TE%*SSII1 as the structural difference of the impact of TE on labour productivity between skilled and unskilled sectors. The main result is that TE is even more damaging in skilled sectors, with a negative effect significantly heavier than in unskilled ones. In particular, an increase of 10% of the share of TE in skilled sectors would lead to a decrease of 1.2% in labour productivity growth, whereas in unskilled ones the reduction would be only of 0.6%.

Table 1. LABOUR PRODUCTIVITY (SSII1)

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 (see Annex 1 and 2). 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.

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.

Furthermore, to check if our results depend crucially on the inclusion of some country in the sample, we re-estimate the model excluding all countries one-by-one. Therefore, we run as many FE regressions as countries in our sample, where in each regression we exclude one different country. Then, in Fig. 2 we show the coefficients of TE% and TE%*SSII, using respectively SSII1 and SSII2, arranged from the greatest to the smallest. In particular, the value associated with a country (e.g. *ITA*) is the estimated coefficient from the reduced sample excluding that country. Finally, in Table 3 and 4 we report the complete results of the 13 regressions, using respectively SSII1 and SSII2.

As Fig. 2 clearly shows, the estimated coefficients of TE% and TE%*SSII do not appear to depend on countries included in the estimation. Indeed, the coefficients are always negative and significant at 1%, and even the magnitudes appear to be rather stable across the sample and the sector skill intensity index used in the empirical analysis.

In conclusion, our result of a negative and double effect of TE in skilled sectors would seem to be fairly robust to the sector skill intensity index and the sample of countries used in the analysis. Moreover, the stability of our estimates despite the robustness checks, along with the fact we control for many different confounding factors, lead us to interpret our estimates as the causal impacts on labour productivity and, in particular, the coefficient of TE%*SSII as the structural difference of the impact of TE between skilled and unskilled sectors.

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

Table 3. LABOUR PRODUCTIVITY (Reduced sample SSII1)

Table 4. LABOUR PRODUCTIVITY (Reduced sample SSII2)

5. Conclusions

In this study we have implemented a well-known method in policy evaluation to identify the different 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 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 attenuate significantly the omitted variable and other endogeneity problems. 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% of the share of TE in skilled sectors would lead to a decrease of 1.2% in labour productivity growth, whereas in unskilled ones the reduction would be only of 0.6%. Indeed, this result could have very important policy implications and, certainly, leads us to question if the actual European regulation corresponds exactly to the lines of the best practice. In particular, it might support the growing feeling that TE is currently used in the labour market more as a cheaper form of job, instead of as a least-cost way to screen new workers and, to some extent, this wrong use might incentive workers to reduce the effort, instead of growing it in order to get the passage to a more stable job. Consequently, this undesirable practice in the labour market could damage more exactly the skilled sectors, where production uses skills more intensively.

The main implication raising from this picture is that TE does not harm labour market outcomes per se, rather is the actual use done in the labour market that distorts the incentives and damages labour productivity. Therefore, 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 job. 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. Even if we leave the answer to this issue for future research, a first starting point might be to make the renewal of a temporary contract less cheaper than the first one and/or less than a permanent contract. On the other hand, a reduction on the consistent level of firing costs in Europe might help to make a labour market with many temporary contracts less attractive for firms. Therefore, a regime with a gradual path towards more stable forms of job, with increasing firing costs, would apparently be a good compromise between short-term flexibility and long-term stability.

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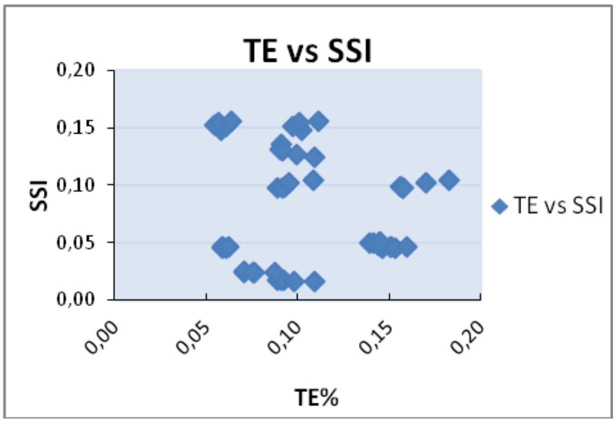
Fig. 1 ***Correlation between TE% and SSI***



SSI	OLS	s.e.	p-value
TE%	-0,154	0,197	(0,438)_
CONSTANT	0,098	0,022	(0,000)***

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

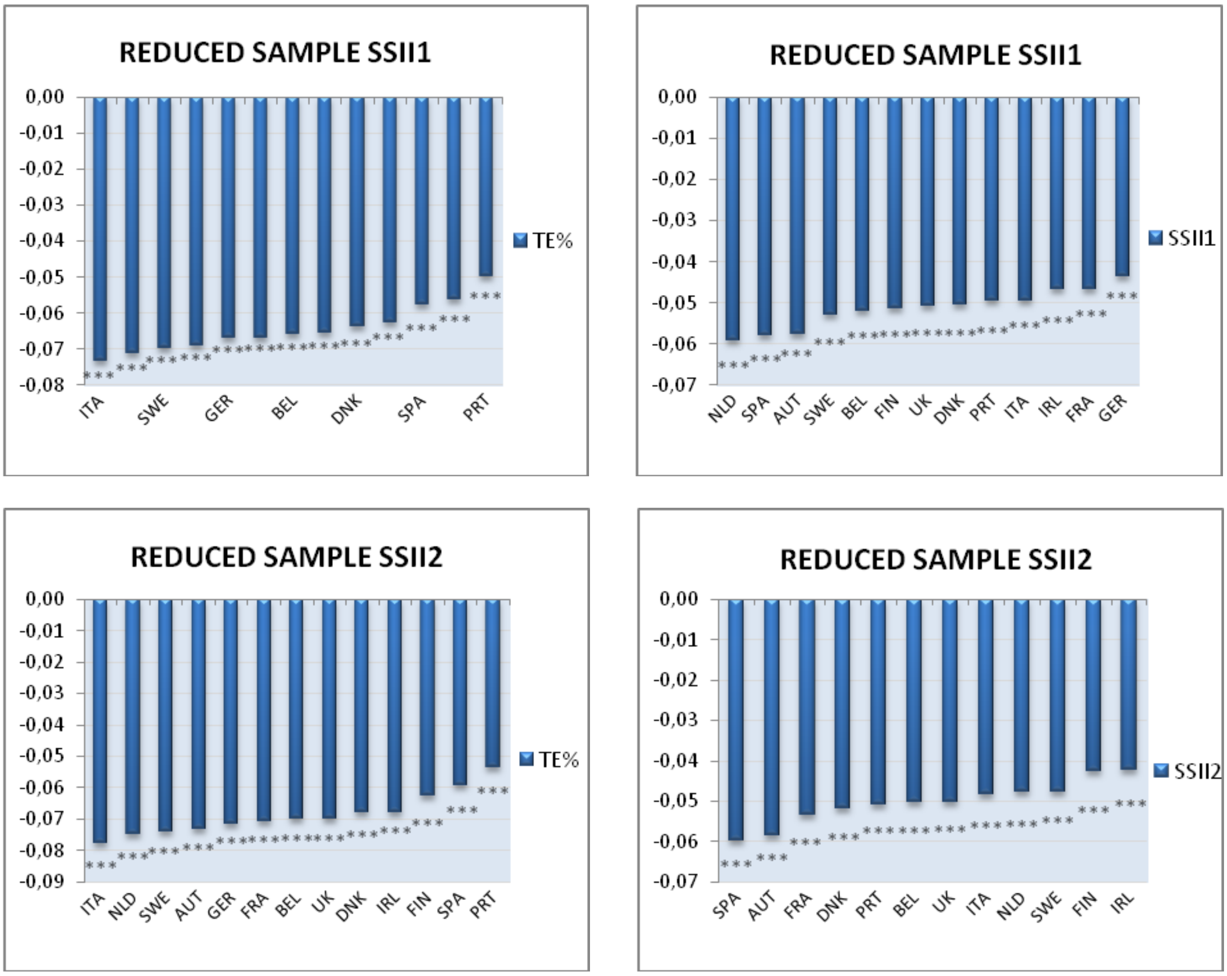


Table 1. LABOUR PRODUCTIVITY (SSII1)

	(1)_	(2)_	(3)_	(4)_	(5)_	(6)_
	POLS	POLS	FE	FE	FE	FE
EPL	0,010 (0,001)***	0,004 (0,001)***	0,014 (0,002)***	0,006 (0,002)***	0,006 (0,002)***	0,006 (0,002)**
EPL*FJR	-0,054 (0,026)**	-0,061 (0,025)**	-0,090 (0,039)**	-0,093 (0,039)**	-0,094 (0,039)**	-0,093 (0,040)**
TE%	-0,061 (0,007)***	-0,084 (0,007)***	-0,056 (0,009)***	-0,065 (0,009)***	-0,066 (0,009)***	-0,065 (0,009)***
TE%*SSII1	-0,039 (0,008)***	-0,040 (0,007)***	-0,051 (0,008)***	-0,051 (0,008)***	-0,051 (0,008)***	-0,051 (0,008)***
TUD		-0,001 (0,000)***		-0,002 (0,002)		-0,002 (0,002)
TREND		0,024 (0,002)***		0,022 (0,003)***		0,355 (0,012)***
CONSTANT	4,582 (0,006)***	4,554 (0,008)***				
SECTOR DUMMIES	NO	NO	YES	YES	YES	YES
COUNTRY DUMMIES	NO	NO	YES	YES	YES	YES
YEAR DUMMIES	NO	NO	NO	NO	YES	YES
Observations	1820	1820	1820	1820	1820	1820
R-squared	0,2025	0,3193	0,9992	0,9993	0,9993	0,9993

POLS: pooled ordinary least squares; FE: fixed effects (dummy variable regression); 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.

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

Table 2. LABOUR PRODUCTIVITY (SSII2)

	(1)_	(2)_	(3)_	(4)_	(5)_	(6)_
	POLS	POLS	FE	FE	FE	FE
EPL	0,010 (0,001)***	0,004 (0,001)***	0,014 (0,002)***	0,006 (0,002)***	0,006 (0,002)***	0,006 (0,002)***
EPL*FJR	-0,051 (0,026)**	-0,061 (0,025)**	-0,088 (0,039)**	-0,092 (0,039)**	-0,093 (0,040)**	-0,092 (0,040)**
TE%	-0,065 (0,007)***	-0,087 (0,007)***	-0,060 (0,009)***	-0,069 (0,009)***	-0,070 (0,009)***	-0,069 (0,009)***
TE%*SSII2	-0,034 (0,008)***	-0,040 (0,007)***	-0,048 (0,009)***	-0,051 (0,008)***	-0,051 (0,008)***	-0,051 (0,008)***
TUD		-0,001 (0,000)***		-0,002 (0,002)		-0,002 (0,002)
TREND		0,025 (0,002)***		0,022 (0,003)***		0,354 (0,012)***
CONSTANT	4,583 (0,007)***	4,555 (0,008)***				
SECTOR DUMMIES	NO	NO	YES	YES	YES	YES
COUNTRY DUMMIES	NO	NO	YES	YES	YES	YES
YEAR DUMMIES	NO	NO	NO	NO	YES	YES
Observations	1820	1820	1820	1820	1820	1820
R-squared	0,1994	0,3188	0,9992	0,9993	0,9993	0,9993

POLS: pooled ordinary least squares; FE: fixed effects (dummy variable regression); 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.

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

Table 3. LABOUR PRODUCTIVITY (Reduced Sample SSII1)

	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE
	AUT	BEL	DNK	FIN	FRA	GER	IRL	ITA	NLD	PRT	SPA	SWE	UK
EPL	0,007 (0,002)***	0,005 (0,002)**	0,005 (0,002)**	0,005 (0,002)**	0,006 (0,002)***	0,007 (0,002)***	0,005 (0,002)**	0,005 (0,002)**	0,005 (0,002)**	0,007 (0,002)***	0,007 (0,002)***	0,004 (0,002)*	0,007 (0,002)***
EPL*FJR	-0,107 (0,040)***	-0,093 (0,040)**	-0,097 (0,041)**	-0,088 (0,041)**	-0,097 (0,041)**	-0,116 (0,042)***	-0,088 (0,040)**	-0,098 (0,040)**	-0,076 (0,042)*	-0,130 (0,039)***	-0,117 (0,043)***	-0,044 (0,039)	-0,089 (0,041)**
TE%	-0,069 (0,009)***	-0,066 (0,009)***	-0,064 (0,009)***	-0,056 (0,009)***	-0,067 (0,009)***	-0,067 (0,009)***	-0,063 (0,009)***	-0,073 (0,009)***	-0,071 (0,009)***	-0,050 (0,009)***	-0,058 (0,017)***	-0,070 (0,009)***	-0,066 (0,009)***
TE%*SSII1	-0,057 (0,008)***	-0,052 (0,008)***	-0,051 (0,008)***	-0,051 (0,008)***	-0,047 (0,008)***	-0,044 (0,008)***	-0,047 (0,008)***	-0,049 (0,008)***	-0,059 (0,008)***	-0,050 (0,008)***	-0,058 (0,015)***	-0,053 (0,008)***	-0,051 (0,008)***
TUD	-0,003 (0,002)	-0,001 (0,002)	-0,001 (0,002)	-0,003 (0,002)	-0,003 (0,002)	-0,002 (0,002)	-0,001 (0,003)	-0,001 (0,002)	-0,001 (0,002)	-0,002 (0,002)	-0,003 (0,002)	-0,002 (0,002)	-0,002 (0,002)
TREND	0,630 (0,007)***	0,630 (0,007)***	0,633 (0,007)***	0,632 (0,007)***	0,632 (0,008)***	0,630 (0,007)***	0,620 (0,009)***	0,630 (0,007)***	0,635 (0,023)***	0,649 (0,022)***	0,652 (0,024)***	0,638 (0,022)***	0,639 (0,021)***
SECTOR DUMMIES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
COUNTRY DUMMIES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
YEAR DUMMIES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1680	1680	1680	1680	1680	1680	1680	1680	1680	1680	1680	1680	1680
R-squared	0,9993	0,9993	0,9993	0,9993	0,9992	0,9993	0,9993	0,9993	0,9993	0,9993	0,9992	0,9993	0,9992

FE: fixed effects (dummy variable regression); 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.

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

Table 4. LABOUR PRODUCTIVITY (Reduced Sample SSII2)

	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE
	AUT	BEL	DNK	FIN	FRA	GER	IRL	ITA	NLD	PRT	SPA	SWE	UK
EPL	0,007 (0,002)***	0,005 (0,002)**	0,005 (0,002)**	0,005 (0,002)**	0,006 (0,002)***	0,007 (0,002)***	0,005 (0,002)**	0,005 (0,002)**	0,005 (0,002)**	0,007 (0,002)***	0,007 (0,002)***	0,004 (0,002)*	0,007 (0,002)***
EPL*FJR	-0,106 (0,040)***	-0,092 (0,040)**	-0,097 (0,041)**	-0,086 (0,041)**	-0,100 (0,041)**	-0,114 (0,042)***	-0,072 (0,040)**	-0,097 (0,040)**	-0,071 (0,042)*	-0,130 (0,040)***	-0,119 (0,043)***	-0,041 (0,039)	-0,088 (0,041)**
TE%	-0,073 (0,009)***	-0,070 (0,009)***	-0,068 (0,009)***	-0,062 (0,009)***	-0,071 (0,009)***	-0,071 (0,009)***	-0,068 (0,009)***	-0,077 (0,009)***	-0,075 (0,009)***	-0,054 (0,008)***	-0,059 (0,016)***	-0,074 (0,009)***	-0,070 (0,009)***
TE%*SSII2	-0,060 (0,008)***	-0,051 (0,008)***	-0,053 (0,008)***	-0,048 (0,008)***	-0,058 (0,008)***	-0,042 (0,008)***	-0,043 (0,008)***	-0,050 (0,008)***	-0,048 (0,008)***	-0,052 (0,008)***	-0,069 (0,015)***	-0,048 (0,008)***	-0,050 (0,008)***
TUD	-0,002 (0,002)	-0,001 (0,002)	-0,001 (0,002)	-0,002 (0,002)	-0,003 (0,002)	-0,002 (0,002)	-0,001 (0,003)	-0,001 (0,002)	-0,001 (0,002)	-0,002 (0,002)	-0,002 (0,002)	-0,001 (0,002)	-0,002 (0,002)
TREND	0,649 (0,022)***	0,630 (0,007)***	0,632 (0,007)***	0,646 (0,023)***	0,652 (0,024)***	0,629 (0,007)***	0,621 (0,009)***	0,630 (0,007)***	0,635 (0,023)***	0,646 (0,022)***	0,632 (0,008)***	0,638 (0,022)***	0,637 (0,021)***
SECTOR DUMMIES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
COUNTRY DUMMIES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
YEAR DUMMIES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1680	1680	1680	1680	1680	1680	1680	1680	1680	1680	1680	1680	1680
R-squared	0,9993	0,9992	0,9993	0,9993	0,9992	0,9993	0,9993	0,9993	0,9993	0,9993	0,9992	0,9993	0,9992

FE: fixed effects (dummy variable regression); 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.

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

ANNEX 1: DATA DESCRIPTION

Labour Productivity

Definition: gross value added in volume terms (base 1995 = 100) divided by total hours worked.

Source: EU KLEMS database.

Total Hours Worked

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

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 $JR_{ijt} = \frac{\left|E_{ijt} - E_{ijt-1}\right|}{\left(E_{ijt} + E_{ijt-1}\right)/2}$.

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

Frictionless Job Reallocation Rate

Definition: job reallocation rate depurated from the frictions introduced by labour market regulation and the effect of aggregate shocks ($FJR_j = \hat{\pi}_j$).

Source: own estimation.

Temporary Employment

Definition: total persons engaged with temporary contracts.

Source: EUROSTAT Labour Force Survey.

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 the stringency 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: OECD Labour Force Statistics.

ANNEX 2: SUBDIVISION OF SECTORS AND DESCRIPTIVE STATISTICS

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 comunication
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 comunication

DESCRIPTIVE STATISTICS

Variable	Obs	Mean	Std. Dev.	Min	Max
Labour Productivity	1820	108,565	20,757	63,486	268,792
Log Labour Productivity	1820	4,672	0,170	4,151	5,594
Job Reallocation	1820	0,028	0,027	0,000	0,239
Frictionless Job Reallocation	1820	0,043	0,009	0,028	0,059
Share of TE	1820	0,089	0,075	0,000	0,488
EPL for Regular Contracts	1820	2,372	0,846	0,948	4,333
Trade Union Density	1820	0,408	0,232	0,080	0,839