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ABSTRACT

Do Temporary Contracts Affect TFP? Evidence from Spanish Manufacturing Firms[*]

This paper evaluates the impact of the widespread use of fixed-term contracts in Spain on firms' TFP, via its effect on workers' effort. We propose a simple analytical framework showing that, under plausible conditions, workers' effort depends positively on their perception (for given level of effort) about firms' willingness to convert fixed-term contracts into permanent ones. We test this implication using manufacturing firm level data from 1991 to 2005 by means of nonparametric tests of stochastic dominance and parametric multivariate regression approaches. Our main findings are that high conversion rates increase firm's productivity while high shares of temporary contracts decrease it. Both effects are quantitatively relevant.

JEL Classification: C14, C52, D24, J24, J41

Keywords: temporary workers, workers' effort, firms' TFP

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1 Introduction

Since the mid-1990s, the Spanish labour market has exhibited two salient features: (a) a widespread use of temporary (fixed-term) contracts, and (b) a significant labour productivity slowdown. As regards (a), aiming to fight the high level of unemployment reached in the early 1980s (20%), the Spanish government introduced in 1984 a "two tier" reform in Employment Protection Legislation (EPL). This reform allowed for much higher flexibility in the use of fixed-term contracts while the EPL regulations for permanent (open-ended) contracts were left unchanged.[1] As a result, the share of temporary jobs in total salaried employment surged from 10% in the mid-1980s to 35.4% in the mid-1990s. Afterwards, despite several additional labour market reforms providing somewhat less stringent EPL for permanent contracts and more restrictions on the use of temporary contracts, this share has stabilized around a plateau of 30% -i.e., about twice the European average nowadays - with around 90% of new hires being still signed under flexible contracts (see Dolado, Garcia Serrano, and Jimeno, 2002).

Regarding (b), labour productivity experienced a significant slowdown during the 1990s, with the average annual growth rate of GDP per hour worked falling from 2.9% in 1970-1994 to 0.3% in 1995-2005. During the last decade, employment and hours worked surged (average annual growth rates of 3.5% and 3.1%, respectively). Yet, the fall in productivity growth has not been the outcome of lower capital accumulation in the aftermath of rapid employment growth since Total Factor Productivity (TFP) growth also fell drastically from 0.6% in 1980-1994 to -0.8% in 1995-2005. This unfavourable productivity performance in the aftermath of the adoption of new IT technologies contrasts sharply not only with the US -where productivity sharply accelerated since the 1990s- but also with the rest of the EU-15, where the productivity slowdown has been less acute (labour productivity and TFP fell from 2.7% and 0.7% in 1970-1994 to 1.3% and 0.3% in 1995-2005, respectively) than in Spain.

Given that work practices are fundamental determinants of firms' productivity (see Schmitz, 2005), our goal is to analyse whether there is a link between the two above-mentioned features. In particular, we evaluate the impact of the extended use of temporary contracts on the productivity of

[1] In contrast with regular open-ended contracts, the 1984 reform meant that temporary contracts entailed much lower severance payments, could be used for regular activities, and their termination could not be appealed to labour courts; for details, see Bentolila and Dolado (1994).

Spanish manufacturing firms, measured by their TFP. In order to provide a causal interpretation to this relationship, we start by proposing a very simple model in which temporary workers choose the level of job effort that maximizes their expected utility. The main implication to be drawn is that, insofar as effort is costly, temporary workers will tend to exert higher effort the larger is their perception that firms will proceed to convert their fixed-term contracts into permanent ones (for given level of effort). When this probability is low, they will find it optimal to exert lower effort until the contract expires since they cannot influence firms' decision by working harder. In other words, if firms are reluctant to offer permanent contracts to these workers -possibly because of the much higher dismissal costs entailed by permanent contracts- workers will choose to work less hard, especially if the labour market is sufficiently tight, leading in this way to a slowdown of firms' productivity. Regarding labour market tightness conditions, the unemployment rate in Spain has fallenl from 16% in 1991 to 9% in 2005 (the period we analyse here), as a result of a drastic cut in real interest rates following Spain's access to the Euro-zone. Thus, the probability of finding another temporary job at the expiration date of the current contract has been rising throughout this period.

To test this implication of the model, we use firm-level data from the *Survey on Business Strategies* (*Encuesta de Estrategias Empresariales*, ESEE) which provides detailed information on a representative sample of Spanish manufacturing firms from 1991 to 2005. Given that our dataset lacks direct information on firms' conversion rates, our empirical strategy relies on a two-stage approach. First, the average conversion rate for each firm over the sample period is estimated using a simple procedure based on an approximation to the dynamic evolution of the stock of permanent workers in each firm. Interestingly, the average estimated conversion rate we obtain for our sample of firms is 12.7% of temporary contracts, which is in line with the evidence provided by Amuedo-Dorantes (2000, 2001) and Güell and Petrongolo (2007) on the size and determinants of aggregate conversion rates in the Spanish economy. Next, by simply assuming a monotonic increasing relationship between workers' effort and firms' productivity, we evaluate the impact of these estimated conversion rates on firms' TFP (i.e., the Solow residual). Our main finding is that, even accounting for reverse causality, firms with high conversion rates are significantly more productive than those with low conversion rates (for given shares of temporary contracts), yielding some favourable support to the main prediction of our model. Additionally, we find that firms with a large proportion of temporary workers are significatively less productive than firms with lower proportions (for given conversion rates). In spite of not dealing with this issue here, one plausible interpretation of the latter effect could be that firms invest less in training temporary workers given their high turnover rate, a result which has been found elsewhere in the literature (see Alba-Ramirez, 1994; de la Rica, Dolado, and Llorens, 2008; Güell and Petrongolo, 2007).

Since the literature studying two-tier reforms of EPL has mainly focused on their effects on employment (see Blanchard and Landier, 2002; Dolado, Garcia Serrano, and Jimeno, 2002; Cahuc and Postel-Vinay, 2002; Güell, 2003), our main contribution is to extend this analysis to study their impact of temporay contracts on firms' productivity. There is, however, a small related literature that has dealt with this issue before us, but from a different perspective. For example, Boeri and Garibaldi (2007) also find a negative relationship between the share of temporary workers and Italian firms' productivity growth. This result is interpreted in terms of a transitory increase in labour demand induced by the higher flexibility of temporary jobs (the so-called "honeymoon" effect of this type of reforms) whereby, assuming decreasing marginal returns to labour, firms increasingly hire less productive workers through these contracts. Likewise, using an efficiency wage setup, Sanchez and Toharia (2000) find a negative relationship as well for Spanish manufacturing firms, using the same database we use here but for a much shorter period (1991-1994) and without spelling out the mechanism linking conversion rates and effort. Finally, the closer paper to ours to is Engellandt and Riphahn (2005) who find that Swiss temporary workers exert a higher effort than permanent workers, using the willingness to undertake unpaid overtime work as a proxy for exerting effort. According to our interpretation, the reason for this seemingly contradictory result is that the Swiss labour market is much more unregulated than the Spanish one. In effect, given the lower EPL strictness for permanent contracts in Switzerland, the proportion of temporary workers in this country (12%) is quite below the Spanish share (30%), leading Swiss temporary workers to expect much higher conversion rates and therefore to exert higher effort.

The rest of the paper is organized as follows. Section 2 lays out a simple model of the determinants of temporary workers' effort that guides the subsequent empirical analysis. Section 3 describes the dataset and presents descriptive statistics on the share of temporary workers and firms' productivity, together with a preliminary nonparametric analysis of how the distribution of productivity levels differs among firms depending on their use of temporary contracts. Section 4 presents the two-step parametric estimation strategy. Section 5 discusses the empirical results. Finally, section 6 concludes. An

Appendix contains detailed definitions of the variables.

2 Analytical framework

The effect of temporary contracts on workers' effort is *a priori* ambiguous. It depends on workers' perception about the probability that firms will upgrade their temporary contracts into permanent ones once the former expire.[2] The basic idea is that temporary workers exert higher effort in order to maximize the probability of getting a permanent contract. However, since effort is costly, higher effort will be less profitable when they perceive that firms (for given level of effort) have a low propensity to upgrade them. In this section, we provide a simple analytical framework that incorporates these features in order to understand the mechanism at play.

Suppose that firms are characterized by an idiosyncratic parameter θ which yields information about their willingness to offer permanent contracts to their temporary workers at the expiration date of their current contracts, taking workers' effort (e) as given. For example, θ could be interpreted as that part of the average conversion rate the firm has implemented in the past which depends on labour market regulations (e.g. dismissal costs) or specific sector's features (e.g., seasonal production) which can be thought as being independent of worker's effort. We assume that workers know about θ when they join a firm. Let $p(e, \theta)$ be the *ex-ante* subjective probability that a temporary worker assigns to being offered a permanent contract. It is assumed that $p(.,.)$ is increasing in both determinants, i.e., $p_e > 0$ and $p_\theta > 0$ and concave in effort, i.e., $p_{ee} < 0$. Moreover, an additional (key) assumption is that the corresponding cross-derivative of $p(.,.)$ with respect to e and θ satisfies $p_{e\theta} > 0$. This implies that there is some sort of reciprocity between firm and worker regarding effort and contract promotion whereby the marginal effect of an extra unit of e on $p_e(.,.)$ is higher in firms with a larger value of θ, and viceversa.

It is assumed that the initial contract offered by a firm is always a non-renewable fixed-term contract which only lasts for one period. For simplicity, this contract pays an exogenous wage, w_T, which is normalized to zero. Thus, it can be interpreted as a pure probationary contract without remuneration.. At its expiration date, firms can either terminate the contract or promote the temporary worker to a permanent position (from which they cannot be

[2]The probability of finding another temporay job at the end of their current fixed-term contract would be another important factor affecting the incentive of exerting high effort.

fired) entailing an exogenous wage $w_P > 0$.[3] If dismissed, we assume that the worker can find another temporary job with probability h or become unemployed with probability $(1 - h)$. If unemployed, again for simplicity, the flow income in this state is taken to be zero. We denote the asset values (discounted utilities) of a permanent contract, a sequence of one-period temporary contract in different firms, and of unemployment by V_P, V_T and U, respectively. To further simplify the analysis, we assume no discount rate. In addition, we suppose that the level of effort exerted by permanent workers in their jobs is constant and that V_P is exogenously given. Hence, under risk neutrality, the asset value of a temporary worker satisfies:

$$V_T = -c(e) + \{p(e,\theta)V_P + (1 - p(e,\theta))\,U\}, \tag{1}$$

where $c(e)$ represents the cost of effort, which is assumed to be increasing and convex, i.e., $c_e > 0$ and $c_{ee} > 0$. Since the asset value of being unemployed satisfies $U = [hV_T + (1-h)U]$, in equilibrium we get $U = V_T$. Replacing this last condition into (1) implies that, when choosing effort, the optimization problem faced by a temporary worker is as follows:

$$\max_e V_T = \max_e \{V_P \ - \frac{c(e)}{p(e,\theta)}\}. \tag{2}$$

From (2), the following result holds:

Proposition 1. *Let $e^*(\theta, V_P)$ be the solution of (2) under the previous set of assumptions. Then $\frac{\partial e^*}{\partial \theta} > 0$ only if $p_{e\theta}(e^*,\theta) > \frac{p_e(e^*,\theta)p_\theta(e^*,\theta)}{p(e^*,\theta)}$.*

Proof. The first- and second-order conditions of t(2) are as follows

$$c(e^*)p_e(e^*,\theta) - c_e(e^*)p(e^*,\theta) = 0, \tag{3}$$

$$[c(e^*)p_{ee}(e^*,\theta) - c_{ee}(e^*)p(e^*,\theta)]p^2(e^*,\theta) < 0, \tag{4}$$

where the two remaining terms of the form $p_e(e^*,\theta)c_e(e^*,\theta)$ cancel out in (4). Notice that the second-order condition holds because $p_{ee} < 0$ and $c_{ee} > 0$.

Next, differentiating (3) with respect to θ yields

$$\frac{\partial e^*}{\partial \theta} = \frac{c_e(e^*)p_\theta(e^*,\theta) - c(e^*)p_{e\theta}(e^*,\theta)}{c(e^*)p_{ee}(e^*,\theta) - c_{ee}(e^*)p(e^*,\theta)}, \tag{5}$$

[3] For simplicity, we abstract here from efficiency wage considerations in dual labour markets as in Güell (2003).

where, given that the denominator is negative (see (4)), it holds that $\frac{\partial e^*}{\partial \theta} > 0$ only if the numerator is also negative, that is, $p_{e\theta}(e^*, \theta) > \frac{c_e(e^*)p_\theta(e^*,\theta)}{c(e^*)} > 0$. Using (3) this sufficient condition can be rewritten as $p_{e\theta}(e^*, \theta) > \frac{p_e(e^*,\theta)p_\theta(e^*,\theta)}{p(e^*,\theta)} > 0$.

This proposition simply states that, as long as $p_{e\theta}$ is positive and sufficiently large, the larger the expected conversion rate is, the higher the effort of a temporary worker will be. By contrast, if $p_{e\theta}$ is zero or small, the negative effect of the cost of effort will dominate the positive effect of getting promoted and therefore workers will exert lower effort.

Next, to relate workers' effort to firms' productivity, let us assume that each firm has a constant-returns-to- scale (CRS) Cobb-Douglas production function of the type

$$Y = B(eL)^\alpha X^{1-\alpha}$$

where Y is final output, B is an index of Harrod-neutral technical progress, e is effort (weighted by type of labour), L is aggregate labour, α is the labour share and X denotes other production inputs (i.e., capital and raw materials). Hence, we can obtain (with small letter denoting logs. of capital ones) the logged composite Solow residual at the firm level as $a = b + \alpha e = y - \alpha l - (1 - \alpha)x$, which for the sake of brevity will be labeled as TFP in the sequel. From Proposition 1, when the sufficient condition holds, it follows that firms with higher conversion rates will exhibit higher TFP, i.e, $\frac{\partial a}{\partial \theta} = \frac{\partial a}{\partial e}\frac{\partial e}{\partial \theta} = \alpha \frac{\partial e}{\partial \theta} > 0$.

From these considerations, our benchmark reduced-form model of firms' productivity in the empirical section will be as follows:

$$a = a(\theta, tw, \mathbf{z}), \tag{6}$$

where a is (logged) TFP at the firm level, tw is the share of temporary workers in the firm and $\mathbf{z}$ is a vector of other determinants of TFP, to be described below in Section 3. Allowing for tw to directly affect TFP requires some further explanation. Note that if its only role were to help temporary workers in forming expectations about the chances of being promoted, then this variable should not appear in equation (3) because all the relevant information would be summarised by θ. However, one could think of other reasons why firms with a large proportion of temporary workers could be less productive. For example, there is an ample empirical evidence showing that the share temporary workers may directly affect firms' productivity if these workers receive less firm-specific training due to their high job-turnover rate (see Alba-Ramirez, 1994; de la Rica, Dolado, and Llorens, 2008; Güell and Petrongolo, 2007). Thus, to allow for this possibility, we include both θ and tw as separate determinants of a in (5), such that we expect $\frac{\partial a}{\partial tw} < 0$ and $\frac{\partial a}{\partial \theta} > 0$.

3 Data and some preliminary analysis

3.1 Data

We use individual firm data from the *Survey on Business Strategies* (*Encuesta sobre Estrategias Empresariales*, ESEE) which is an annual survey on a representative sample of Spanish manufacturing firms. The sample period is 1991-2005. In the base year, firms were chosen according to a sampling scheme with weights depending on their size category. All firms with more than 200 employees were surveyed and their participation rate in the survey reached approximately 70% of the overall population of firms in this category. Likewise, firms with 10 to 200 employees were surveyed according to a random sampling scheme with a participation rate close to 5%. This selection scheme was applied to every industry in the manufacturing sector.

Another important feature of the survey is that the initial sample properties have been maintained in all subsequent years. Newly created firms have been added each year with the same sampling criteria as in the base year and exiting firms have been recorded in the sample of firms surveyed each year. Therefore, due to this entry and exit process, the dataset is an unbalanced panel of firms. The number of firms in our sample is 3,759 and the number of observations is 22,922. Appendix A explains the criteria we use to select our sample.

Table 1 shows the share of temporary workers by industry, size and age category. Small firms are defined as those firms with less than 50 employees, while medium-sized and large firms are those firms with more than 50 but less than 200 employees, and more than 200 employees, respectively. Regarding age, we define young firms to be those firms which have been operating during less than 5 years since their creation, while mature firms are those operating for a longer period.

[TABLE 1 ABOUT HERE]

As can be seen, the share of temporary workers exhibits large variability across industries, age and size categories. Within each industry, small and medium-sized young firms have in general a larger share. This is quite reasonable since newer firms are likely to face a higher probability of failure, and therefore are bound to make a more widespread use of flexible contracts for precautionary reasons.

As discussed above, to compute firms' productivity, we consider a standard TFP measure derived from a standard constant returns to scale (CRS) Cobb-Douglas production function, such that, firm i's (logged) TFP level in period t, a_{it}, is given by

$$a_{it} = y_{it} - \alpha_l l_{it} - \alpha_m m_{it} - \alpha_k \left(k_{it} + \kappa_{it}\right), \tag{7}$$

where y is logged final output; l, m, and k are logged labour, materials, and capital, respectively; κ is logged annual average capacity utilization rate reported by each firm; and α_x ($x = \{l, m, k\}$) are input elasticities such that $\alpha_l + \alpha_m + \alpha_k = 1$. Final output is measured by the value of produced goods and services deflated with each firm's output price index. Labour by both temporary and permanent employees is measured in hours worked , capital as firm's value of the capital stock deflated using the price index of investment in equipment goods, and materials as the value of intermediate consumption deflated by a firm's price index of materials. Further details on these variables can be found in Appendix A. To measure the input elasticities, α_x, we use firms' average cost shares over our sample.[4]

3.2 Temporary workers and firms' TFP: Some preliminary (nonparametric) analysis

In this section, we start by evaluating whether there are significant differences in the distribution of productivity across firms with different shares of temporary contracts. To do so, we adopt the nonparametric approach proposed by Delgado, Fariñas, and Ruano (2002) in their analysis of productivity differences between exporting and non-exporting Spanish manufacturing firms. Following their approach, the procedure in our slightly different setup consists of testing the null hypothesis that the c.d.f.'s of the productivity levels

[4]The advantage of using cost shares is that it is not necessary to assume perfect competition in the product market (see Hall, 1988). Additionally, this accounting procedure does not require to deal with the endogeneity of the inputs as in the case where production functions are estimated; see Ackerberg, Caves, and Frazer (2005) and the references therein.

in firms with low and high shares of temporary workers are identical against the alternative of stochastic dominance.

The initial stage in this procedure is to construct a TFP index at the firm level that measures the proportional difference of TFP in firm i at time t relative to a given (artificial) reference firm in each industry. As Delgado, Fariñas, and Ruano (2002) show, this index allows one to pool observations across different industries, facilitating comparison of TFP in different firms on a homogeneous basis. The reference firm in a given industry j is defined as the firm which satisfies the following properties over the entire sample period: (i) its output is equal to the geometric mean of firms' output quantities in industry j; (ii) its input quantities are equal to the geometric means of firms' input quantities in industry j; and (iii) its cost shares of inputs are equal to the arithmetic mean of firms cost shares in industry j. Hence, if firm i belongs to the size group τ and to industry j, its logged TFP index at time t is given by:

$$\begin{aligned} \tilde{a}_{it} &= y_{it} - \overline{y}_{\tau j} - \frac{1}{2} \sum_{x=\{l,m,k\}} \left(\alpha_{it}^{x} + \bar{\alpha}_{\tau j}^{x}\right)\left(x_{it} - \overline{x}_{\tau j}\right) \\ &+ \overline{y}_{\tau j} - \overline{y}_{j} - \frac{1}{2} \sum_{x=\{l,m,k\}} \left(\bar{\alpha}_{\tau j}^{x} + \bar{\alpha}_{j}^{x}\right)\left(\overline{x}_{\tau j} - \overline{x}_{j}\right), \end{aligned} \tag{8}$$

where $x = \{l, m, k\}$; $j = 1, 2, \ldots, 18$; τ={small & medium-sized, large}; and, for a generic variable z_{it} ($= y_{it}$, α_{it}^{x} or x_{it}), $\bar{z}_{\tau j} = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} z_{it}\mathbf{1}[i \in \text{size group } \tau]\mathbf{1}[i \in \text{ industry } j]$; and $\bar{z}_{j} = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} z_{it}\mathbf{1}[i \in \text{ industry } j]$ where $\mathbf{1}[\cdot]$ is an indicator function.
Note that the selective sampling scheme in our dataset forces us to restrict the three firm-size categories discussed above to two broader groups: small & medium-sized (less than 200 employees), and large firms (more than 200 employees).[5]

Figure 1 depicts the empirical c.d.f.'s of the TFP index, $\tilde{a}$, defined in (8) in two groups of firms:[6] those with a proportion of temporary workers above

[5]The c.d.f for the whole population of firms with a proportion of temporary workers below the threshold can be obtained weighting by the probabilities of having less and more than 200 employees in the group of firms with low shares. The same procedure is applied to obtain the c.d.f. for those firms having high shares.

[6]Note that in this section we use firms' productivity defined in equation (8) instead of the definition in equation (7) because we want to control for the differences in productivity of firms belonging to different industries. In the rest of the paper we will apply a parametric procedure that allow to control for many relevant variables (including industries) and therefore we will use the standard TFP measure defined according to (7).

and below a preset threshold value. This value is chosen to be 10% (approximately the average level of the proportion of temporary workers in the EU-15). Admittedly, this value is somewhat arbitrary, but we have experimented with other choices ranging from 8% to 15% obtaining very similar results.

[FIGURE 1 ABOUT HERE]

Inspection of Figure 1 shows that, after controlling for industry and size, the c.d.f. of the TFP index for firms with less than 10% of temporary workers lies to the right of the c.d.f. of the TFP index of firms with shares above 10%, implying that the former are seemingly more productive than the latter.

The next step is to test formally whether this gap in the c.d.f.'s is statistically significant. To do so, we apply the nonparametric test of stochastic dominance proposed by Delgado, Fariñas, and Ruano (2002) which works as follows. Let F_t and G_t denote the c.d.f. of the TFP index in period t of firms with a proportion of temporary workers below and above the preset threshold, respectively.[7] We test for stochastic dominance in each size category, τ, by conditioning the distributions F_t and G_t on a given size group τ_0 with $\tau_0 = \{\text{small \& medium-sized, large}\}$.[8] We then state that the distribution $F_t(\cdot|\tau = \tau_0)$ stochastically dominates the distribution $G_t(\cdot|\tau = \tau_0)$ if the null hypothesis $H_0^a : F_t(\cdot|\tau = \tau_0) = G_t(\cdot|\tau = \tau_0)$ (two-sided test) is rejected and $H_0^b : F_t(\cdot|\tau = \tau_0) > G_t(\cdot|\tau = \tau_0)$ (one-sided test) is not rejected. In each period, the Kolmogorov-Smirnov test statistics for these one- and two-sided tests are as follows:

$$\delta_N = \sqrt{\frac{n.m}{N}} \max_{1 \le i \le N} |T_N(\tilde{a}_i)| \tag{9}$$

and

$$\eta_N = \sqrt{\frac{n.m}{N}} \max_{1 \le i \le N} \{T_N(\tilde{a}_i)\}, \tag{10}$$

where n and m denote, respectively, the sample size of firms with a proportion of temporary workers below and above the threshold value, $N = n + m$, and $T_N(\tilde{a}_i) = F_n(\tilde{a}_i) - G_m(\tilde{a}_i)$ with F_n and G_m being the empirical counterparts of F and G (although the time subindex is omitted to simplify notation, the

[7] We use the distributions in each period of time because observations have to be independent and this condition is not satisfied if we pool observations of the same firm in different years.

[8] Notice that, given that the TFP index removes the difference in productivity between firms' in different industries, we are in fact not only controlling for size but also for industry.

comparison always takes place in each period). The limiting distributions of these statistics are known under independence (see Delgado, Fariñas, and Ruano (2002)).[9]

For the group of small & medium- sized firms, Table 2, shows that H_0^a can be rejected at the 5% significance level after 1992. Further, in all these years, the hypothesis that the sign of the difference is favourable to firms with lower share of temporary workers (H_0^b) cannot be rejected at any reasonable significance level. In the case of large firms, H_0^a can be rejected only in 1995, 1996, 2000, 2001, and 2005. However, it is again not possible to reject the H_0^b in these five years.

[**TABLE 2 ABOUT HERE**]

It was shown in Table 1 that young firms tend to hire a larger proportion of temporary workers the older ones. Given that the former may be less productive that more mature firms (see Fariñas and Ruano, 2004), a potential concern is that the documented productivity gaps may just reflect differences in firms' age and not differences in their fraction of temporary workers. To check this, Figure 2 displays the same graphs as in Figure 1 but this time for each age category. In the group of small & medium-sized firms, the previous conclusion remains unaltered, i.e., firms with lower share of temporary workers are less productive irrespectively of their age. In the case of large firms, the results are robust for mature firms and not so clear cut for young firms. This ambiguous finding may be due to the low proportion of large firms with less than five years in the market in our sample (only 176 out of 5,738 observations).

[**FIGURE 2 ABOUT HERE**]

Summing up, the previous evidence yields two preliminary conclusions. First, the productivity distribution of small & medium-sized firms with a proportion of temporary workers below 10% stochastically dominates the productivity distribution of small and medium sized firms with a higher proportion of temporary workers. Secondly, despite not such a clear-cut evidence

[9] Under the assumption that all the observations are independent, the limiting distributions of δ_N and η_N under H_0 are given by $\lim_{N\to\infty} P(\delta_N > v) = -2\sum_{k=1}^{\infty}(-1)^k exp(-2k^2v^2)$ and $\lim_{N\to\infty} P(\eta_N > v) = exp(-2v^2)$, respectively. For more details, see Darling (1957).

for large firms, there are significant productivity gaps in favour of firms with a low proportion of temporary workers when the first null hypothesis is rejected.

In spite the rather neat evidence presented above, one should be aware that this nonparametric test suffers at least from two important caveats. First, it does not control for other factors that may also affect the link between firms' productivity and the proportion of temporary workers; in particular, it does not disentangle the direct impact of perceived conversion rates on workers' effort from other effects stemming from temporary contracts, as discussed in Section 2. Secondly, it just points out to a relationship between the two variables without identifying a causality link. After all, it may well be the case that less productive firms make a higher use of flexible contracts rather than the other way around. Thus, given these shortcomings, the next two sections are devoted to study in more detail whether a causal interpretation holds by means of a parametric regression approach to estimating equation (6).

4 Empirical strategy

4.1 Regression model

To evaluate the impact of the conversion rate on firms' productivity we regress (logged) TFP on this rate and on a set of control variables using the following pooled regression model at the firm level

$$a_{it} = \beta_1 c_i + \beta_2 c_i^2 + \beta_3 \; tw_{it} + \beta_4 \; shc_{it} + \gamma' \mathbf{z}_{it} + \rho(L) \; a_{i,t-1} + v_{it}, \tag{11}$$

where a_{it} is the (logged) productivity level of firm i in period t, as defined in equation (7), v_{it} is an i.i.d. error term, c_i is the historical conversion rate at firm i (see below for the construction of this variable), tw_{it} is the proportion of temporary workers and shc_{it} is an index skilled human capital at the firm (i.e., the proportion of engineers and employees with a college degree). The vector $\mathbf{z}_{it}$ contains an additional set of control variables that includes size, logged age and its square, a dummy variable for incorporated companies, the proportion of public and foreign capital, R&D investment by the firm, year and industry dummies, dummy variables for firm's perception of whether they face an expansive or recessive market, firm' s entry, exit, merger and scission dummies.[10] Lastly, given that TFP levels are highly persistent over time we also include some lag polynomial, $\rho(L)$, of the dependent variable. Detailed definitions of these variables can be found in Appendix A.

Table 3 contains descriptive statistics of the variables in (11), except for c_i whose measurement will be discussed in the next sub-section. As can be seen, there is a large slowdown in firms' TFP growth rate since the mid-1990s, including a negative growth rate in the first half of the 2000s. This evolution is somewhat similar to the one discussed in the Introduction for the overall market economy, although much less dramatic than in other sectors - like construction, distribution, personal and social services- where TFP growth has been negative since the early 1990s. The average share of temporary workers in our sample is about 23%, that is, around ten percentage points (p.p.) lower than the aggregate share for the whole Spanish economy.

[TABLE 3 ABOVE HERE]

According to the main implication of our model in Section 2, firms with higher conversion rates will be more productive because temporary workers in these firms have a stronger incentive to exert higher effort. However, there is empirical evidence (see Bassanini, Nunziata, and Venn (2008) and the references therein) showing that strict EPL (e.g., high firing costs or long advance notice periods) has a depressing impact on productivity. This is so either because EPL reduces the level of risk that firms are ready to endure in experimenting with new technologies or because it reduces workers' effort since there is less threat of layoff in response to poor work performance or absenteeism (see Ichino and Riphan, 2005). As a result, it may be the case that, if a sufficiently high probability of conversion is perceived, the worker may exert lower effort since he/she feels almost sure about receiving a permanent contract. To allow for this possibility we use a quadratic function in c_i which we expect to be increasing if the sufficient condition on $p_{e\theta}$ holds ($\beta_1 > 0$) and concave ($\beta_2 < 0$) giving rise to an optimal conversion rate , c_i^* ($= -c_1/2c_2$), beyond which there is a slack in effort. By contrast, as discussed earlier, a higher share of temporary workers could lower TFP if firms invest less in (specific) training of these workers given their high turnover rate (i.e., $\beta_3 < 0$). Additionally, an index of the quality of human capital is

[10] These variables take value 1 in all the periods in which the firm appears in our sample. The proportion of public capital is used because a small fraction of the firms in our sample (2%) are participated by the public sector.

also included in the set of controls because firms with higher human capital are likely to achieve higher productivity (i.e., $\beta_4 > 0$) (see Wasmer, 1999).

4.2 Estimating conversion rates

Unfortunately, our dataset does not contain direct information on conversion rates at the firm level However, given that we have a panel of firms, it is possible to partially circumvent this problem by estimating an average of the missing conversion rates through the following simple procedure.

Denoting the number of permanent workers in firm i at period t by $L_{P,it}$, this stock equals the number of permanent workers in the previous period, $L_{P,i,t-1}$, minus a fraction b of those workers who quit the firm, plus a fraction c of the temporary workers in the previous period that are converted into permanent workers, $L_{T,i,t-1}$,[11] Using an stochastic approximation of this accumulation equation, we can estimate an approximate conversion rate as the slope coefficient on $L_{T,i,t-1}$ in the following regression model:

$$L_{P,it} = (1 - b_i)L_{P,i,t-1} + c_i L_{T,i,t-1} + \alpha' \mathbf{x}_{it} + \varepsilon_{it}, \tag{12}$$

where the vector $\mathbf{x}_{it}$ is a set of control variables that includes year, size, and industry dummies, and ε_{it} is an *i.i.d.* error term . Since some heterogeneity of conversion rates across firms is required to evaluate their effect on firms' productivity, we estimate an industry-size-age specific coefficient c_i by including interactions between industry-size-age dummies and $L_{T,i,t-1}$. Likewise, we also allow for firm specific coefficients b_i in each industry-size-age cell using a similar procedure. Notice that a drawback of this procedure is that the estimated conversion rates are time invariant. However, lack of time variation would be consistent with our interpretation of this variable as a signal that new temporary workers perceive about their firms' *average* propensity to offer them a contract conversion (for given level of effort). It seems rather plausible that temporary workers, in choosing their optimal level of effort, learn about this sort of aggregate information when they join the firms.

Estimating this equation (12) by pooled OLS (without the interaction terms) yields an average (across firms) estimate of c equal to 0.127. In other

[11] As mentioned in section 3.2, we are assuming that all the workers start with a temporary contract and that, when they expire, some of them get promoted to permanent contracts. This assumption is not restrictive since, as Dolado, Garcia Serrano, and Jimeno (2002) pointed out, more than 90% of the new hires are temporary workers since the 1984 reform.

words, on average, 12.7% of the temporary workers get permanent contracts. The coefficient is statistically significant at 10% level (t-ratio= 1.87) and the fit is quite good ($R^2 = 0.98$). Interestingly, this value of the estimated conversion rate is quite close to those reported in other available studies about this topic in Spain, using aggregate information from aggregate labour surveys (see Alba-Ramirez, 1994; Amuedo-Dorantes, 2000, 2001; Güell and Petrongolo, 2007).

When we allow for heterogeneity in the coefficients c and b, we can obtain in principle estimates of the conversion rate for each industry-size-age cell (108 values). However, as Table 1 shows, some industry-size-age cells lack enough number of observations to to yield precise estimates of the coefficients. To solve this problem we redefine the cells in such a way that each one contains at least 25 observations. This aggregation procedure yields 77 conversion rates distributed among 17 industries which are reported in Table 4 together with the number of observations and the proportion of temporary workers in each category. Notice that, although the estimation procedure does not guarantee the conversion rate to lie in the [0,1] interval, it turned out that almost all estimated values lied inside above range once nonsignificant estimated coefficients in regression (3.8) were restricted to be zero.[12]

[**TABLE 4 ABOVE HERE**]

Figure 3 displays the histogram of the estimated conversion rates once the highly insignificant ones are restricted to be zero. Its average is 11.2%, quite close to the above-mentioned 12.7% without inteaction terms. About 85% of firms have conversion rates between 0% and 20%, with and only 3% of firms exhibit rates above 50%. Industries like “Vehicles and motors” (8), “Textiles and apparels” (13) and “Paper and printing products” (16) exhibit the higher conversion rates whilst others like “Food and tobacco” (11) exhibit very low rates. In sum, our evidence point out that Spanish manufacturing firms have been rather reluctant to offer contract conversions. This reluctance is most likely due to the large existing gap between severance payments associated to unfair dismissals (the most frequent ones) of workers holding open-ended contracts (45 days’ wages per year of service with a maximum of 42 months) and to fixed-term contracts (8 days’ wages per year of service).

[12]The only exception is the estimated conversion rate in the group of young small & medium sized firms in the “Other manufactured products” industry. In this case, the estimate is -0.07 and statistically significant at 5%. Like with the highly non-significant coefficients, we set it equal to zero.

[FIGURE 3 ABOVE HERE]

4.3 Some econometric issues

A first issue to raise is that, although regression model (11) could be in principle interpreted a panel data model, we cannot account for firm's individual effects in the estimation (say, by means of a *within* least squares approach) since the conversion rates only vary at the industry-size-age level and hence they lack time variation. This shortcoming, however, has the advantage that, in an econometric sense, the average (over time) conversion rates can be considered as predetermined variables when estimating equation (11).

Secondly, there is the problem that the estimated conversion rates are generated regressors in equation (11). This would not affect the consistency of the estimation procedure but it does affect the estimation of the standard errors and therefore inference (see Pagan, 1986). To estimate correct standard errors in equation (11) it is necessary to consider the sampling variation in the estimation of c_i. To address this problem, we apply block bootstrap, namely, we resample over i but not over t. In each bootstrap iteration, a different conversion rate is estimated, so that the standard errors in (11) account for the sampling error of equation (12).

5 Empirical results

Table 5 reports the estimated coefficients of equation (11). Below each coefficient we present the standard error clustered by firm (squared brackets) and the bootstrap standard errors (brackets). In general, they are remarkably similar. As a benchmark, column [1] presents the OLS results in a specification with the whole set of controls. The contemporaneous share of temporary workers is used as a regressor, whereas the other explanatory variables (except firm's age) are treated as predetermined by dating them at $t-1$. After trying with several lag lengths of the dependent variable, we found that only the first two lags were significant and that an LM test for autocorrelated disturbances could not reject the null of no autocorrelation (p-value=0.125). The estimated coefficients on the linear a squared conversion rates are positive and negative, respectively, and statistically significant, although the latter only at 10% level. The estimated coefficients imply that productivity is maximised at $c^* = 0.321$ $[= 0.059/(2 \times 0.092)]$, a value which is much higher than the average estimated conversion rate (12.7 %) and that it is also above the rates for a large majority of firms (around 90%) in our sample. By contrast, the estimated coefficient on the share of temporary workers turns out to be negative and highly significant leading to a short-run impact on productivity of -0.032 and a long-run one of -0.13 $[= -0.032/(1 - 0.535 - 0.225)]$, in line with the evidence presented by Sanchez and Toharia (2000) for the Spanish manufacturing sector during the early 1990s.

[TABLE 5 ABOUT HERE]

Nonetheless, as discussed earlier, an endogeneity bias may be present since firms' TFP and workers' type of contract are likely to be jointly determined. To avoid reverse causality, in Column [2] we replace the contemporaneous value of tw_{it} by its first lag, tw_{it-1}. We again tried several lags of this variable, but only tw_{it-1} turned out to be significant. The results are rather similar to those discussed before, although the short and long run impacts of the (lagged) share of temporary contracts fall slightly to -0.024 and -0.10, respectively.

Finally, in Column [3] we go back to the first specification but this time instrumenting the contemporaneous value of tw using two lags of this variable and of the proportion of public capital as IVs. All of these variables turned out to be highly insignificant when included as additional explanatory variables in Column [1] so that, in principle, they qualify as valid IVs. Moreover, the share of public capital is bound to be correlated with the share of temporary contracts since, according to Dolado, Garcia Serrano, and Jimeno (2002), workers in firms with a large fraction of public capital have lower probability of being hired with temporary contracts. This is confirmed in our dataset where the average proportion of temporary workers in firms with positive participation of public capital (about 1.2% in the sample, see Table 3) is 10% against 23% in fully private firms. An overidentification J-test of these IVs yields a p-value of 0.65 and a partial R^2 in the first stage regression of 0.70, thereby providing favourable support to our choice of IVs. Whereas the estimated impact of the conversion rate on TFP is identical to that reported in Column [1] ($c^* = 0.321$), the estimated effects of tw lies in between those reported in the first two columns. These findings therefore support the main prediction of our model about the detrimental effects of low conversion rates on firms' productivity, via lower workers' effort, as well as confirm our preliminary analysis in Section 3.2 on the negative impact of temporary contracts on firm's TFP levels. As mentioned earlier, one plausible conjecture is that workers with fixed-term contracts receive less specific training by firms given their very high job turnover rates.

Summing up, if we take the IV estimates in Column [3] to be the more appropriate ones, the previous results imply that, *ceteris paribus*, an increase of five p.p.in the average conversion rate (i.e., from 12.7% to 17.7%) would lead to a rise in TFP of about 0.15 and 0.65 p.p. in the short and long run, respectively. Likewise, a reduction of five p.p in the average share of temporary contracts (i.e., from 20.8% to 15.8%) would lead to an increase in TFP of 0.14 p.p. in the short run and of 0.58 p.p. in the long run. Since, according to Table 3, the average annual TFP growth rate has been 0.94% in our sample of manufacturing firms over the period 1991-2005, the joint contribution of both effects could be unambiguously large.

6 Conclusions

Since the early 1990s, Spain is the European country with the highest proportion of temporary workers, with more than twice the average proprtion in the EU-15. At the same time it has suffered from a drastic productivity slowdown since the mid-1990s. In this paper we study the relationship between these these two features using an unbalanced panel of Spanish manufacturing firms from 1991 to 2005. To interpret the empirical evidence, we present a very simple model in which temporary workers choose their level of effort in order to maximize expected utility. The main implication of this analysis is that temporary workers provide higher effort when they perceive a sufficiently large probability of getting their fixed-term contracts converted into a permanent ones, for given effort. In this fashion, we assume that temporary workers use some average of the previous conversion rates in their current firms as a signal of the probability of getting upgraded. Therefore, the model implies that, other things equal, workers exert higher effort in firms with larger conversion rates. We find suppoting evidence about this prediction. Moreover, using both bivariate nonparametric tests of stochastic dominance and multivariate regression techniques, we also find that, even after controlling for expected conversion rates, firms with a high share of temporary workers are less productive than those with lower shares. Our empirical findings imply that if a future EPL reform were to reduce the share of temporary contracts by five p.p. as well as increase the conversion rate by the same amount, firms' TPF levels would raise by 0.29 p.p. in the short run and by 1.23 p.p. in the long run these are large effects since the average annual TFP growth in our sample of firms has been 0.94%.

A limitation of our empirical approach is the lack of direct information on conversion rates at the firm level. Thus, by having to estimate these rates at the industry-size-age level, this key variable in our analysis lacks time variation which prevents us from controlling for individual firm effects. Nonetheless, this procedure is in line with our interpretation of workers extracting a signal about their future prospects of promotion based upon the firms ´ average historical conversion rates.

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A Appendix: Data and variable definitions

A.1 Sample selection rules

We follow five rules for dropping firms or observations: (i), we exclude those firms that change from one industry to another because their TFP in different moments of time is not comparable; (ii) we exclude observations with negative value added or negative intermediate consumption; (iii) with ratios of labour cost to sales or material cost to sales larger than unity; (iv) when the firm reports an incomplete exercise in a year different than the one in which it leaves the market; and finally (v) fwhen the firm does not report all the information needed to compute productivity or only provides that information for one year.

A.2 Variable definitions

- *Output*: Value of the produced goods and services computed as sales plus the variation of inventories deflated by the firm's price index of output.

- *Permanent workers*: Full time plus half of part time permanent workers at December 31st.

- *Temporary workers*: Workers hired under fixed term contract at December 31st. When firms report that the proportion of fixed term contract varies during the year, this variable is the mean of each quarter.

- *Total effective worked hours*: Computed as the number of workers times the average hours per worker. The average hours per worker is computed as the normal hours plus average overtime minus average working time lost at the workplace.

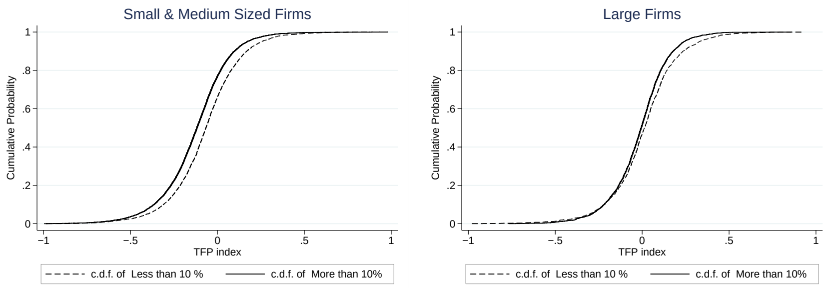
- *Materials*: Value of intermediate consumption deflated by the firm's price index of materials.

- *Capital*: Capital at current replacement values is computed recursively from an initial estimate and the data on current investments in equipment goods (but not buildings or financial assets) applying the recursive formula, $K_{it} = (1-d)\frac{P_{It}}{P_{I,t-1}}K_{i,t-1} + I_{i,t}$, where d is an industry-specific rate of depreciation and P_{It} a price index of investment in equipment goods. Real capital is obtained by deflating capital at current replacement values with the price index of investment in equipment goods.

For more details and descriptive statistics on this variable see Escribano and Stucchi (2008).

- *Investment*: Value of current investment in equipment goods.
- *Wages*: Firm's hourly wage rate (total labour cost divided by effective total hours of work) deflated by the firm's price index of output.
- *Capital usage cost*: Weighted sum of long term interest rate with banks and other long term debt plus the industry-specific depreciation rate minus the investment inflation rate.
- *Age*: The age of the firm is the difference between the current year and the year of birth declared by the firm.
- *Size*: There categories. Firms with more than 200 employees (Large firms) and firms with less than 200 but more that 50 employees (Medium size firms) and firms with less than 50 employees (Small firms).
- *Industry*: Firms are classified in 18 industries. See Table 5.
- *R& D investment*: Value of current investment in R& D.
- *Expansive Market*: Dummy variable that takes value 1 when the firm reports that its market is in expansion.
- *Recessive Market*: Dummy variable that takes value 1 when the firm reports that its market is in recession.

Figure 1: Temporary Workers and Firms' TFP by Size.

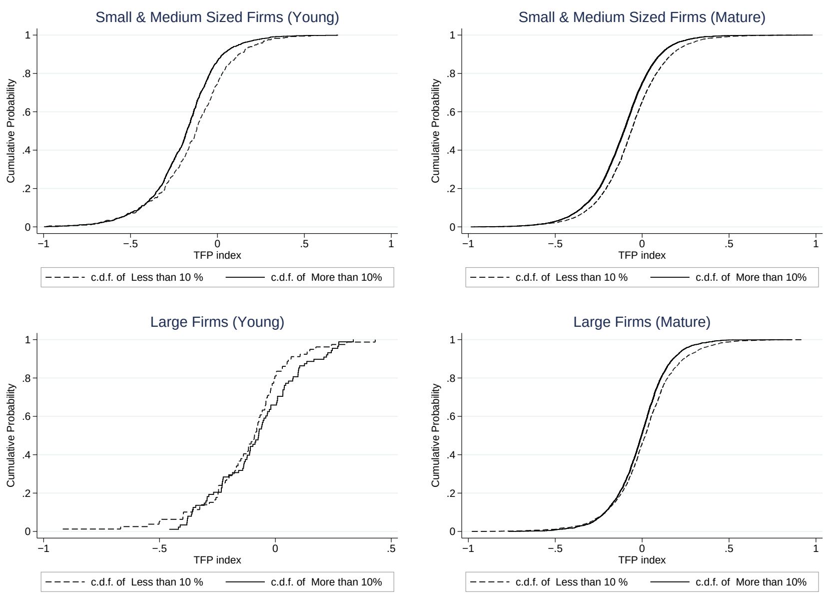


Notes: Firms' TFP measured using the TFP index, $\tilde{a}$, defined in equation (8) therefore productivity differences across firms in different industries are removed.

Table 1: Descriptive Statistics: Percentage of Temporary Workers by Industry, Size and Age

	Small			Medium			Large		
INDUSTRY	**Mean**	**S.D**	**Obs.**	**Mean**	**S.D**	**Obs.**	**Mean**	**S.D**	**Obs.**
				Young Firms (Less than five years old)					
1.- Ferric and Non Ferric Metals	45.2	31.6	36	30.3	38.5	9	0.1	0.2	6
2.- Non Metallic Mineral Products	41.0	32.4	108	29.2	28.3	29	10.0	8.4	12
3.- Chemical Products	19.6	25.9	28	7.7	11.5	19	5.7	6.4	37
4.- Metallic Products	38.0	29.7	268	33.1	32.1	33	11.1	13.4	5
5.- Agricultural and Industrial Machinery	29.8	27.9	127	32.1	29.4	22	13.4	12.8	16
6.- Office Machinery, Data Processing Machinery, etc.	42.8	32.2	8	20.4	25.1	7	18.0	16.6	7
7.- Electrical Material and Electrical Accessories	45.9	31.2	82	30.6	34.0	30	16.6	21.2	42
8.- Vehicles and Motors	33.9	24.3	49	30.4	29.8	33	9.6	14.0	41
9.- Other Transport Material	51.5	28.8	18	34.2	29.0	7	4.4	8.2	8
10.- Meat and Meat Products	47.0	23.2	59	19.5	20.2	11	2.7	3.3	4
11.- Food and Tobacco	47.3	30.2	147	33.0	28.6	36	30.3	30.4	27
12.- Beverages	28.9	32.5	7	2.2	3.1	2	11.8	0.0	1
13.- Textiles and Apparels	43.0	33.6	277	42.0	33.0	23	17.4	19.3	21
14.- Leather products and shoes	62.4	32.3	153	30.0	30.3	4	-	-	0
15.- Wood and Furniture	46.2	26.2	271	29.2	26.0	25	39.1	28.3	17
16.- Paper, Paper Products and Printing Products	26.9	25.4	195	23.0	14.7	17	13.5	10.4	17
17.- Plastic Products and Rubber	36.6	31.8	129	35.2	34.1	33	35.6	20.1	15
18.- Other Manufactured Products	42.4	30.6	26	5.5	7.8	5	-	-	0
				Mature Firms (More than five years old)					
1.- Ferric and Non Ferric Metals	21.5	24.0	156	18.9	19.1	111	9.8	12.9	381
2.- Non Metallic Mineral Products	25.0	23.4	667	14.0	16.7	290	12.9	13.0	529
3.- Chemical Products	12.4	15.6	457	11.2	12.8	249	8.0	7.6	786
4.- Metallic Products	20.9	21.2	1054	22.5	19.9	336	20.1	20.1	405
5.- Agricultural and Industrial Machinery	15.2	18.4	612	13.9	15.5	264	13.4	11.6	483
6.- Office Machinery, Data Processing Machinery, etc.	12.2	16.3	106	23.2	17.0	69	17.1	13.1	127
7.- Electrical Material and Electrical Accessories	25.2	23.0	532	21.1	20.4	321	15.9	15.4	539
8.- Vehicles and Motors	15.8	18.3	172	21.4	20.4	185	12.8	11.7	596
9.- Other Transport Material	28.2	31.4	98	23.8	24.9	101	10.2	13.4	191
10.- Meat and Meat Products	27.2	22.1	294	14.7	17.0	73	28.3	20.4	197
11.- Food and Tobacco	26.2	25.3	1134	30.8	28.4	315	29.1	27.1	623
12.- Beverages	15.3	16.7	143	13.5	9.8	76	13.9	10.7	245
13.- Textiles and Apparels	21.8	25.5	1124	13.6	18.2	400	12.9	13.6	536
14.- Leather products and shoes	32.2	28.9	464	19.7	21.8	80	11.2	16.8	31
15.- Wood and Furniture	24.8	23.9	1064	25.0	22.2	178	22.1	17.2	234
16.- Paper, Paper Products and Printing Products	12.9	15.9	882	12.8	13.4	287	10.3	9.3	511
17.- Plastic Products and Rubber	18.2	17.3	428	24.3	25.2	238	19.0	15.6	321
18.- Other Manufactured Products	18.4	22.2	318	21.3	19.0	64	21.3	18.1	98

Figure 2: Temporary Workers and Firms' TFP by Size and Age.



Notes: Firms' TFP measured using the TFP index, $\tilde{a}$, defined in equation (8) therefore productivity differences across firms in different industries are removed. Young are those firms that have been operating 5 or less than 5 years and mature firms those that have operated for a longer period.

Figure 3: Estimated conversion rates

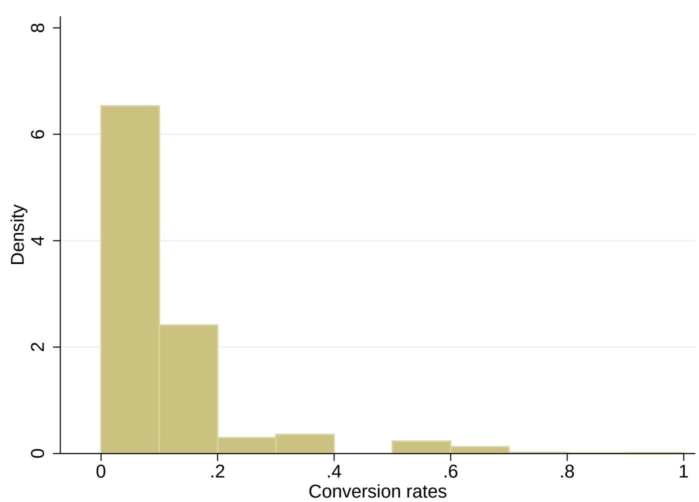


Table 2: Productivity differences between firms with more and less than 10% of temporary workers

	Number of firms		Equality of Distributions		Difference favourable to firms with TC in [0, 10%]	
	% of TC in [0,10%]	% of TC in (10%,100%]	Statistic	p-value	Statistic	p-value
			Small firms & Medium Sized Firms			
1991	273	647	0.061	0.477	-	-
1992	346	705	0.058	0.420	-	-
1993	357	652	0.087	0.064	0.003	0.996
1994	313	613	0.120	0.006	0.000	1.000
1995	274	577	0.157	0.000	0.011	0.954
1996	305	582	0.122	0.006	0.005	0.991
1997	427	684	0.133	0.000	0.009	0.958
1998	401	611	0.116	0.004	0.002	0.997
1999	433	591	0.153	0.000	0.004	0.994
2000	440	547	0.150	0.000	0.003	0.996
2001	417	504	0.117	0.005	0.002	0.998
2002	436	447	0.144	0.000	0.002	0.998
2003	374	313	0.139	0.003	0.007	0.983
2004	374	307	0.103	0.060	0.007	0.985
2005	545	470	0.093	0.028	0.006	0.985
			Large Firms			
1991	219	311	0.063	0.709	-	-
1992	224	274	0.051	0.914	-	-
1993	224	197	0.058	0.888	-	-
1994	194	205	0.064	0.839	-	-
1995	180	198	0.169	0.011	0.011	0.980
1996	176	174	0.134	0.116	0.033	0.840
1997	180	202	0.097	0.367	-	-
1998	175	192	0.088	0.529	-	-
1999	176	168	0.088	0.569	-	-
2000	201	255	0.148	0.027	0.019	0.935
2001	187	205	0.187	0.005	0.015	0.962
2002	193	178	0.111	0.254	-	-
2003	175	139	0.118	0.282	-	-
2004	157	154	0.110	0.345	-	-
2005	192	209	0.135	0.072	0.009	0.985

Notes: Firms' TFP measured using the TFP index, $\tilde{a}$, defined in equation (8) therefore productivity differences across firms in different industries are removed.

Table 3: Descriptive Statistics: TFP Growth of the Spanish manufacturing sector and variables in equation (11)

	Mean	S. D.
Average TFP growth in the period 1992-1995 (in percentage)	2.58	-
Average TFP growth in the period 1996-2000 (in percentage)	1.21	-
Average TFP growth in the period 2001-2005 (in percentage)	-0.74	-
TFP (in logs)	3.63	0.55
Percentage of temporary workers	22.99	22.85
Percentage of foreign capital	16.87	35.73
Percentage of public capital	1.15	9.59
Percentage of the workers with a college degree	4.05	6.78
R&D Expenditures / Sales (in percentage)	0.69	2.20
Age (in years)	24.11	20.48
Percentage of incorporated companies	64.94	47.72
Percentage of entrants	7.03	25.57
Percentage of exiting firms	1.32	11.40
Percentage of firms with scission	0.66	8.09
Percentage of firms involved in a merger process	1.42	11.85
Percentage of firms reporting expansive market	29.03	45.39
Percentage of firms reporting recessive market	20.56	40.42

Notes: "Average TFP growth" refers to the average growth rate of the aggregate level of productivity obtained by weighting the productivity of each firm by its market share.

Table 4: Estimated conversion rates

Industry	**Group**	**Num.** of Obs.	**Temporary Workers (%) Mean (S.D.)**	**Conversion Rate Coeff. (S.D.)**
1.- Ferric and Non Ferric Metals	Small & Medium (Young)	45	42.23(33.19)	0.706 (0.228)***
	Small & Medium (Old)	267	20.41 (22.11)	0.098 (0.048)**
	Large (Young & Old)	387	9.65 (12.81)	0.163 (0.293)
2.- Non Metallic Mineral Products	Small (Young)	108	40.96 (32.44)	0.168 (0.080)**
	Small (Old)	667	24.97 (23.39)	0.053 (0.019)***
	Medium (Young)	29	29.23 (28.27)	0.980 (0.259)***
	Medium (Old)	290	14.03 (16.71)	-0.066 (0.081)
	Large (Young & Old)	541	12.88 (12.91)	0.121 (0.060)**
3.- Chemical Products	Small (Young)	28	19.55 (25.94)	0.135 (0.018)***
	Small (Old)	457	12.45 (15.56)	0.125 (0.057)**
	Medium (Young & Old)	269	10.95 (12.76)	0.001 (0.116)
	Large (Young)	37	5.68 (6.40)	-0.009 (0.247)
	Large (Old)	786	7.97 (7.65)	0.327 (0.080)***
4.- Metallic Products	Small (Young)	268	37.98 (29.65)	0.142 (0.049)***
	Small (Old)	1,054	20.86 (21.18)	0.109 (0.037)***
	Medium (Young)	33	33.10 (32.07)	0.065 (0.037)*
	Medium (Old)	336	22.54 (19.87)	0.103 (0.059)*
	Large (Young & Old)	410	19.99 (20.00)	0.140 (0.031)***
5.- Agricultural and Industrial Machinery	Small & Medium (Young)	149	30.12 (28.02)	0.09 (0.051)*
	Small & Medium (Old)	876	14.77 (17.59)	0.131 (0.046)***
	Large	499	13.40 (11.66)	0.155 (0.029)***
6.- Office Machinery, Data Processing Machinery, etc.	Small & Medium (Young)	15	32.37 (30.39)	0.284 (0.174)
	Small & Medium (Old)	175	16.54 (17.39)	0.115 (0.144)
	Large (Young & Old)	134	17.11 (13.20)	0.298 (0.235)
7.- Electrical Material and Electrical Accessories	Small (Young)	82	45.93 (31.16)	0.196 (0.101)*
	Small (Old)	532	25.15 (22.97)	0.046 (0.116)
	Medium (Young)	30	30.55 (33.99)	0.027 (0.269)
	Medium (Old)	321	21.07 (20.37)	-0.061 (0.070)
	Large (Young)	42	16.63 (21.23)	0.263 (0.026)***
	Large (Old)	539	15.87 (15.44)	0.011 (0.038)
8.- Vehicles and Motors	Small (Young)	49	33.85 (24.27)	0.216 (0.066)***
	Small (Old)	172	15.78 (18.34)	0.144 (0.120)
	Medium (Young)	33	30.40 (29.84)	0.114 (0.289)
	Medium (Old)	185	21.37 (20.37)	0.142 (0.066)**
	Large (Young)	41	9.63 (14.00)	0.652 (0.065)***
	Large (Old)	596	12.76 (11.72)	0.202 (0.142)
9.- Other Transport Material	Small & Medium (Young)	25	46.66 (29.30)	-0.159 (0.119)
	Small & Medium (Old)	199	25.96 (28.28)	0.03 (0.030)
	Large (Young & Old)	199	9.97 (13.28)	0.113 (0.086)

Table 4: Estimated conversion rates (cont.)

Industry	**Group**	**Num.** of Obs.	**Temporary Workers (%) Mean (S.D.)**	**Conversion Rate Coeff. (S.D.)**
10.- Meat and Meat Products	Small (Young)	59	47.03 (23.16)	0.082 (0.078)
	Small (Old)	294	27.22 (22.11)	0.077 (0.030)**
	Medium (Young & Old)	84	15.34 (17.43)	-0.041 (0.087)
	Large (Young & Old)	201	27.76 (20.50)	0.11 (0.045)**
11.- Food and Tobacco	Small (Young)	147	47.30 (30.15)	0.03 (0.080)
	Small (Old)	1,134	26.24 (25.25)	0.031 (0.031)
	Medium (Young)	36	33.10 (28.58)	-0.061 (0.058)
	Medium (Old)	315	30.79 (28.38)	0.001 (0.021)
	Large (Young)	27	30.27 (30.42)	-0.054 (0.113)
	Large (Old)	623	29.09 (27.09)	0.069 (0.027)**
12.- Beverages	Small (Young & Old)	151	15.80 (17.74)	0.054 (0.111)
	Medium (Young & Old)	78	13.22 (9.88)	0.334 (0.118)***
	Large (Old) (a)	246	13.85 (10.68)	0.673 (0.446)
13.- Textiles and Apparels	Small (Young)	277	42.95 (33.56)	0.087 (0.044)**
	Small (Old)	1,124	21.79 (25.50)	-0.08 (0.070)
	Medium (Young)	23	41.98 (33.01)	0.237 (0.165)
	Medium (Old)	400	13.56 (18.19)	0.096 (0.090)
	Large (Young)	21	17.39 (19.33)	0.875 (0.618)
	Large (Old)	536	12.90 (13.65)	0.145 (0.026)***
14.- Leather products and shoes	Small & Medium (Young)	157	61.60 (32.59)	0.119 (0.063)*
	Small & Medium (Old)	544	30.38 (28.32)	0.12 (0.036)***
	Large (Old) (a)	31	11.20 (16.78)	0.054 (0.414)
15.- Wood and Furniture	Small (Young)	271	46.17 (26.19)	0.135 (0.061)**
	Small (Old)	1,064	24.76 (23.92)	0.097 (0.025)***
	Medium (Young)	25	29.19 (26.04)	0.329 (0.087)***
	Medium (Old)	178	25.05 (22.25)	0.125 (0.042)***
	Large (Young & Old)	251	23.26 (18.60)	0.275 (0.087)***
16.- Paper, Paper Products and Printing Products	Small & Medium (Young)	212	26.61 (24.68)	0.267 (0.068)***
	Small & Medium (Old)	1,169	12.85 (15.29)	0.146 (0.049)***
	Large (Young & Old)	528	10.43 (9.31)	0.566 (0.134)***
17.- Plastic Products and Rubber	Small (Young)	129	36.58 (31.83)	0.038 (0.082)
	Small (Old)	428	18.20 (17.34)	0.196 (0.040)***
	Medium (Young)	33	35.16 (34.11)	-0.037 (0.246)
	Medium (Old)	238	24.25 (25.23)	-0.002 (0.030)
	Large (Young & Old)	336	19.69 (16.14)	0.14 (0.034)***
18.- Other Manufactured Products	Small & Medium (Young)	31	36.45 (31.28)	-0.071 (0.027)***
	Small & Medium (Old)	382	18.85 (21.66)	0.124 (0.042)***
	Large (Old) (a)	98	21.32 (18.05)	0.237 (0.131)*

Notes: (a) No young firms.

Significance levels: $*$: 10%, $**$: 5%, and $***$: 1%.

Table 5: The determinants of firms' TFP

	Model 1	**Model 2**	**Model 3**
Conversion Rate	0.059	0.06	0.059
	[0.029]**	[0.029]**	[0.029]**
	(0.037)*	(0.037)*	(0.037)*
Conversion Rate Squared	-0.092	-0.095	-0.092
	[0.050]*	[0.050]*	[0.050]*
	(0.059)	(0.058)	(0.058)
Proportion of Temporary Workers in t	-0.032	-	-0.028
	[0.008]***		[0.009]***
	(0.007)***		(0.009)***
Proportion of Temporary Workers in t-1	-	-0.024	
		[0.008]***	
		(0.008)***	
Human Capital in t-1	0.100	0.101	0.101
	[0.032]***	[0.032]***	[0.032]***
	(0.032)***	(0.032)***	(0.032)***
R&D Expenditures in t-1 (in logs)	0.001	0.001	0.001
	[0.000]	[0.000]	[0.000]
	(0.000)	(0.000)	(0.000)
Incorporated company in t-1	0.011	0.011	0.011
	[0.003]***	[0.003]***	[0.003]***
	(0.003)***	(0.003)***	(0.003)***
Proportion of Foreign Capital in t-1	0.014	0.014	0.014
	[0.004]***	[0.004]***	[0.004]***
	(0.004)***	(0.004)***	(0.004)***
Age in logs	-0.027	-0.026	-0.026
	[0.014]*	[0.014]*	[0.014]*
	(0.014)*	(0.014)*	(0.014)*
Age Squared (Square of logs)	0.004	0.004	0.004
	[0.002]*	[0.002]*	[0.002]*
	(0.002)*	(0.002)*	(0.002)*
Expansion	0.004	0.004	0.004
	[0.003]	[0.003]	[0.003]
	(0.003)	(0.003)	(0.003)
Recession	-0.014	-0.014	-0.014
	[0.004]***	[0.004]***	[0.004]***
	(0.004)***	(0.004)***	(0.004)***
TFP t-1 (in logs)	0.535	0.535	0.535
	[0.018]***	[0.018]***	[0.018]***
	(0.018)***	(0.018)***	(0.018)***
TFP t-2 (in logs)	0.225	0.225	0.225
	[0.013]***	[0.013]***	[0.013]***
	(0.013)***	(0.013)***	(0.013)***
N Obs.	13139	13139	13138
R-squared	0.94	0.94	0.94
Hansen J (p-value)			1.637(0.651)
First Stage Regression:			
Partial R-squared			0.70
F-pvalue			2953.9(0.000)

Notes: (i) Dependent Variable: TFP, a_{it}, defined in eq. (7). (ii) All equations include a constant term and industry, size, year, entry, exit, merger and scission dummies. They also include dummies for expansive and recessive markets. (iii) Cluster by firm standard errors in squared brackets. (iv) Bootstrap standard errors in brackets, 1000 replications. To consider the sampling error of equation (12) in the estimation of the conversion rate, the bootstrap procedure is applied to equations (12) and (11). (iv) (a) Endogenous variable: Proportion of Temporary Workers. Additional instruments: Proportion of temporary workers in t-1 and t-2 and Proportion of Public Capital in t-1 and t-2. (v) Significance levels: (b):12%, $*$: 10%, $**$: 5%, and $***$: 1%.