UNIVERSIDAD CARLOS III DE MADRID

working papers

Working Paper 11-37
Economic Series
December, 2011

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Does dual employment protection affect TFP?. Evidence from Spanish manufacturing firms*

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December 20, 2011

Abstract

This paper analyzes the effect of having a large gap in firing costs between permanent and temporary workers in a dual labour market on TFP development at the firm level. We propose a simple model showing that, under plausible conditions, both temporary workers' effort and firms' temp-to-perm conversion rates decrease when that gap increases. We test this implication by means of a panel of Spanish manufacturing firms from 1991 to 2005, using as natural experiments some labour market reforms entailing substantial changes in this gap. Our main empirical finding is that reforms leading to a lower gap enhanced conversion rates, which in turn increased firms' TFP, and conversely for reforms that increased the gap.

JEL classification: C14, C52, D24, J24, J41.

Keywords: Firms' TFP; Workers' effort, Temporary workers; Firing Costs.

* We are grateful to César Alonso-Borrego, Manuel F. Bagües, Jesus Carro, Irma Clots, Josep Pijoan-Mas and Nawid Siassi for useful comments. This is a substantially revised version of an earlier paper circulated under the title " Do temporary contracts affect TFP?. Evidence from Spanish manufacturing firms" by Dolado and Stucchi. Financial support from the Spanish Ministry of Education (SEC2006-10827), Consolider-Ingenio 2010), Comunidad de Madrid (Consejería de Educacion and Excelecon project), MICINN (2011/00049/001) and Banco de España (Research Excellence grant) is gratefully acknowledged. The usual disclaimer applies. The views expressed in this paper are those of the authors and do not necessarily correspond to those of the Inter-American Development Bank.

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1 Introduction

From the early nineties onwards, the Spanish labour market has exhibited two salient features in cross-country comparisons: (F1) a highly segmented Employment Protection Legislation (EPL) leading to a widespread use of temporary (fixed-term) contracts, and (F2) a large slowdown in the growth rate of total factor productivity (TFP). As regards F1, it goes back to the approval in 1984 of a "two-tier" reform in Employment Protection Legislation (EPL) aiming to fight a very high unemployment rate in the early 1980s (around 18%). This reform allowed for much higher flexibility in the use of temporary contracts (entailing very low severance pay) which could be used for any type of jobs (not just for replacement or or seasonal activities), while the strict EPL regulation for regular open-ended/permanent contracts (entailing high severance pay) was left unchanged.[1] As a result, the share of temporary workers in total salaried employment surged from 10% in the mid-1980s to 35.4% in the mid-1990s, with more than 90% of new hires per year being signed under these flexible contracts. Later on, this proportion reached a plateau of 30%, about twice the European average, despite several additional countervailing reforms. Even during the recent (great) recession, where a massive destruction of temporary jobs in the real state and services sectors has taken place (see Bentolila *et al.*, 2010), the rate of temporary workers has only dropped to 26% which still remains one of the highest in the OECD.

With regard to F2, labour productivity experienced a significant slowdown during the 1990s, with average annual growth rate of GDP per hour worked falling from 2.9% in 1970-1994 to 0.3% in 1995-2005. Over the latter period, up to the onset of the current global crisis, both 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 per worker in the aftermath of rapid employment growth but rather it has been the outcome of a drastic reduction in TFP growth, from 1.5% in 1980-1994 to -0.5% in 1995-2005. Although a relevant part of this slowdown in TFP growth has been due to the strong dependence of the Spanish economy on several low value-added industries (like residential construction, tourism and personal services), there is ample evidence documenting that it has also affected tradable sectors, like manufacturing (see Escribá and Murgui, 2009). This dismal performance, over a period where the use of new ICT technologies was very intense worldwide, contrasts sharply not only with the US experience -where productivity sharply accelerated since the nineties- 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.[2]

[1] In contrast with regular open-ended contracts, the 1984 reform meant that temporary contracts entailed no severance payments and their termination could not be appealed to labour courts (for details, see Dolado *et al.*, 2002 and 2008).

[2] The data source is EUKLEMS, a harmonized data set for multifactor productivity in EU countries (see Escribá

Given that work practices are fundamental determinants of firms' productivity (see Schmitz, 2005), our goal in this paper is to analyze whether a link can be established between persistent duality/segmentation in the labour market and the TFP slowdown. In particular, we focus on evaluating the impact of having large differences between EPL for permanent and temporary workers (the *firing-cost gap*, hereafter) on TFP development in Spanish manufacturing firms. The mechanism we explore is one whereby a change in the firing-cost gap can affect firms' decisions on contract upgrading which, in turn, affects temporary workers' decisions on how much effort is exerted and how much paid-for training they receive from employers. To the extent that effort and training are important components of TFP, both of these channels can play a significant role in relating dual EPL and TPF.

In order to provide a causal interpretation of this relationship, we start by proposing a streamlined model of how firms' and workers' decisions interact in a prototypical dual labor market. Regarding firms, it is assumed that they always use a *probation* temporary contract for their initial hirings of workers.[3] Specifically, this is a non-renewable fixed-term contract, lasting for one period, after which the worker can be dismissed with low or even without termination costs. Accordingly, once this contract expires, employers must decide whether to dismiss or maintain the worker. Legal regulations imply that, if the worker remains in the job, the temporary contract should be upgraded to a open-ended (permanent) contract subject to much higher severance pay. As for workers, we simplify the model by assuming that they only choose the level of job effort when they work under a temporary contract. They do so by maximizing their expected discounted utility which is increasing in the probability of getting promoted to a preferable long-lasting job. By contrast, it is assumed that strict EPL for permanent contracts does not affect the level of effort exerted by those workers who accede to these jobs. The implicit assumption is that protection of this kind, by reducing hold-ups and opportunistic behaviour by employers and employees, implies that the latter do not shirk and provide the required level of effort to make these jobs profitable.

Hence, while temporary workers supply effort by trading off the disutility of working against a higher probability of getting promoted, firms with this type of jobs design contracts and choose conversion rates from temporary to permanent contracts (*temp-to-perm* conversion rate in short) to elicit that level of workers' effort that maximizes their expected profits, subject to workers' participation and incentive compatibility constraints. Moreover, we also extend this setup by considering firms' decisions to provide paid-for training to temporary workers as an additional way of increasing their productivity if they were to remain in the firm. Our main finding is that, insofar as effort and training are costly and severance pay is not neutral,[4] a higher firing-cost

and Murgui, 2009).

[3]We simplify the analysis by abstracting from direct hirings by firms of workers under permanent contracts since these only have represented around 10% of all annual hirings during the sample period (see Dolado *et al.*, 2008)

[4]That is, it is not perfectly transferable between employers and workers, as in Lazear (1990).

gap will reduce temp-to-perm conversion rates, effort and paid-for training. The basic insight is that an increase (decrease) in this gap reduces (increases) firm's propensity to promote temporary workers or even to train them which, in turn, induces temporary workers to exert lower (higher) effort.

To test this implication, we use longitudinal firm-level data from the *Survey on Business Strategies* (*Encuesta sobre Estrategias Empresariales*, ESEE) which provides detailed information on a representative sample of Spanish manufacturing firms from 1991 to 2005. In particular, a valuable feature of this data set is that it includes information on the different types of labour contracts held by workers in each firm. This allows us both to retrieve temp-to-perm conversion rates and TFP at the firm level in each year of the sample. .

Some preliminary motivation for our empirical approach is provided by Figure 1, where the (employment weighted) annual averages of the temp-to-perm conversion rates (left axis) and TFP growth rates (right axis) are jointly displayed for our sample of manufacturing firms.[5] As can be observed, both variables move quite closely over time. Specifically, not only they share a common declining time trend from the early 2000s, when an EPL reform ended up increasing EPL for permanent jobs, but also experience noticeable increases in 1995-1996 and 1998-1999, just after another two earlier reforms which succeeded in reducing the firing-costs gap. In view of this evidence, it is worth exploring by how much changes in dual EPL regulation are able to explain these similar time patterns in the two above-mentioned rates.

[**FIGURE 1 ABOUT HERE**]

To do so, lacking direct measures of workers' effort or paid-for training in our data set, our strategy is to assume a monotonic increasing relationship between those two variables and firms' TFP. Under this plausible assumption, we evaluate the impact of changes in the firing-cost gap on firms' TFP using as natural experiments several labour market reforms entailing changes in EPL during the available sample period (1994, 1997 and 2002) Since these reforms are nationwide, we obtain variation across firms in the "treatment" by assuming that, controlling for size and other observable characteristics, firms with higher shares of temporary workers before the reforms are bound to be more strongly affected by their subsequent implementation. Our main empirical finding is that firms which benefited the most from these reforms, because they had more candidates for promotion, exhibited higher conversion rates and, as a result, were significantly more productive than those firms which benefited the least. Hence, we interpret this result as yielding some favourable support to the main prediction of the model.[6]

[5]As will be explained in Section 3, TFP has been computed using Levinsohn and Petrin's (2003) estimation approach of production functions since the computation of standard Solow-Hall residuals would invalidate our identifying strategy of the relationship between both variables.

[6]Another plausible interpretation of this effect, which is explored in our model, could be that firms invest less in

In regards to how this paper fits in the available research on the impact of reforms of EPL on the labour market, our main contribution lies in analyzing how a large firing-cost gap may affect TFP rather than employment and unemployment, which has been the main focus in most of the related literature on dual labour markets.[7] There are, however, some papers that have previously dealt with the effects of EPL on labour productivity, but from a different angle than ours. For example, Autor *et al.* (2007), Bassanini *et al.* (2008) provide empirical evidence showing that strict EPL has a depressing impact on productivity because it reduces the level of risk that firms are ready to endure in experimenting with new technologies or because there is less threat of layoff in response to poor work performance (see also Ichino and Riphan, 2005). Yet these studies do not analyze a dual EPL system, as we do, but rather focus on the effects of the overall level of EPL. Further, our focus also differs from that strand of this literature which considers dual EPL.. For example, Boeri and Garibaldi (2007) analyze the Italian two-tier labour market and find a negative relationship between the share of temporary workers and firms' labour productivity growth in Italy. They interpret this finding in terms of a transitory increase in labour demand induced by the higher flexibility of temporary jobs (i.e., the so-called "honeymoon" effect of this type of reforms) which, by, assuming decreasing marginal returns to labour, leads firms to increasingly hire less productive workers through these contracts. Likewise, estimating the reduced form of a standard efficiency-wage model for the same database we use here, albeit for a much shorter period (1991-1994), Sánchez and Toharia (2000) find a negative relationship between the share of temporary work and labour productivity in Spanish manufacturing firms. Similarly, more updated results for this country have been obtained by Alonso-Borrego (2010) using the Firms' Balance Sheets of the Bank of Spain. Yet, none of these papers explore the key mechanism linking changes in firing-costs gap to conversion rates and effort that we stress here. Finally, the closest paper to ours is Engellhandt and Riphan (2005), who find evidence 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. Yet, as will be discussed further below, the seemingly opposite results to ours that they report can be rationalized within our analytical framework. The insight is that, being the EPL gap and the share of temporary workers (12%) in Switzerland much lower than in Spain, Swiss temporary workers expect much larger conversion rates and therefore exert higher effort.

The rest of the paper is organized as follows. Section 2 lays out a simple model of the determinants

providing paid-for- training to temporary workers given their high turnover rate when the firing -costs gap is high. This result has been found elsewhere in the literature (see Alba-Ramírez, 1994 and de la Rica *et al.*, 2008) using alternative data sets that do not allow to obtain TFP estimates at the firm level. Yet, we cannot evaluate this effect since ESEE does not contain information on training.

[7] See, inter alia, Blanchard and Landier (2002), Dolado *et al.* (2002), Cahuc and Postel-Vinay (2002) and Bentolila *et al.* (2010).

of temporary workers' effort, firms' temp-to-perm conversion rates and paid-for training that provides relevant predictions for the subsequent empirical analysis. Section 3 describes the data set and presents descriptive statistics on firms' TFP, the share of temporary workers and the contract conversion rates, together with a preliminary nonparametric analysis of how the distribution of TFP differs across firms depending on their conversion rates. Section 4 presents further evidence based on panel regression about the effect of changes in the firing costs gap, via conversion rates, on firms' TFP and discusses the empirical results. Finally, Section 5 concludes. An Appendix contains detailed definitions of the variables.

2 A simple analytical framework of a two-tier labour market

It is assumed that labour-market regulations imply that the initial contract offered by firms to any job seeker is always a non-renewable fixed-term contract (T) which only lasts for one period. At its termination, the firm has to decide whether to renew the worker with a permanent contract (P) or to close the job. Workers under temporary contracts choose a level of work effort, e, and receive a wage, w_T, set by the firm. For convenience, we follow most of the literature on efficiency-wage models in assuming that workers' instantaneous utility is linear, i.e., $U(w_T, e) = w_T - e$, where effort is taken to be bounded and normalized such that $e \in [0, 1]$. Permanent contracts differ from temporary ones not only in length (they are open ended) but also in firing costs (they entail severance pay F whereas, for simplicity, temporary contracts are assumed to entail none). Hence, F can be directly interpreted as the firing- cost gap. A temporary contract is converted into a permanent one with an (endogenous) probability $p(e)R$. This signifies that the conversion probability is the product of: (i) the probability rate at which the worker becomes eligible for conversion at each level of effort, $p(e)$, which satisfies $p(0) = 0$, $p(1) = 1$ and $p'(e) > 0$, $p''(e) < 0$, and (ii) the conversion rate, R, chosen by firms among the set of eligible workers. The insight is that, if the worker chooses to exert no effort ($e = 0$) she/he will have no chances of conversion whatsoever while, even if the worker exerts maximal effort ($e = 1$), the probability of being upgraded to a permanent contract may not be unity due to the presence of other costly regulations (i.e., the firing-cost gap in our case) faced by firms in deciding whether to promote workers.

As will become clear below, our model of effort and conversion boils down to a simple problem of incentives, whereby the firm's and the worker's respective choices of the conversion rate, R, and effort, e., become interrelated. It is noteworthy that, in order to highlight this issue in the subsequent analysis, we abstract from the use of temporary contracts by firms as a screening device for workers' unobservable skills under asymmetric information, ignoring therefore the signaling role of workers' effort.[8] Also, since our focus lies on rank-and-file workers, instead of professionals, we also abstract from other arguments used in the theory of labour market tournaments (see, e.g., Lazear and Rosen, 1981) whereby temporary workers could be thought of as competing for a given number of open-ended positions. In such a setup, a low value of R could achieve higher workers' effort through competition. Yet, the alternative interpretation we stress here is that it is solely the worker's effort (plus the EPL regulations) that the firm takes into account when deciding upon contract upgrading of a particular employee, irrespectively of how other temporary workers perform.

Workers who get promoted to a permanent contract are assumed to receive a wage w_P and exert a fixed level of work effort $\overline{e}$, so that $U(w_P, \overline{e}) = w_P - \overline{e}$.[9] In contrast with temporary jobs, which are kept alive until their termination, permanent jobs are subject to an exogenous destruction rate.

The remaining notation is as follows. Let V^i and Π^i, for $i = \{T, P\}$, be the asset values of a worker with contract i and of a firm with job i, respectively. Also V^U and H denote the asset values for the workers of being unemployed and for the firm of opening a vacancy (always consisting of a temporary job), respectively.

2.1 Temporary jobs

We start by presenting the effort decision by temporary workers and then analyze firms' decisions about the wage offer and conversion rates for workers on fixed-term contracts. Workers choose the level of effort, which is not contractible, that maximizes their expected utility discounted at rate β, given by,

$$V^T = \max_e \{w_T - e + \beta[p(e)RV^P + (1 - p(e)R)\, V^U]\}. \tag{2.1}$$

The first-order condition (f.o.c) to this problem is,

$$\beta p'(e)R[V^P - V^U] \leq 1, \tag{2.2}$$

with strict inequality if $e = 0$. Notice that the concavity of $p(e)$, i.e. $p''(e) < 0$, ensures the second-order condition (s.o.c) for the maximization of V^T, namely $\beta p''(e)R[V^P - V^U] < 0$, since,

[8] See Michelacci and Pijoan-Mas (2011) for an analysis of this alternative mechanism.

[9] As mentioned earlier, one way of modelling variable effort by workers with permanent contracts could be by introducing the possibility of shirking in these jobs, as in Güell (2003) and Ichino and Riphan (2005). However, since our focus here lies on the effort exerted by temporary workers, that would unnecessarily complicate the model without qualitatively altering the main results. With shirking in permanent jobs, both types of workers would exert lower effort when F is high but, since the incentive problems are bound to be more serious for temporary workers, their effort will be lower that the one of permanent workers.

as will be shown in section 2.2, $V^P > V^U$.

Next, since the level of effort is not enforceable, the firm chooses e, R and w_T, subject to worker's participation and incentive constraints, denoted in short as PAC and INC, respectively. Thus, the firm's optimization problem becomes,

$$\begin{aligned} \Pi^T &= \max_{e,w_T,R}\{f(e) - w_T + \beta[p(e)R\Pi^P + (1-p(e)R)H]\} && (2.3) \\ s.t. & \\ & V^T \geq V^U \qquad (PAC) && (2.4) \\ & \beta p'(e)R[V^P - V^U] \leq 1 \qquad (INC), && (2.5) \end{aligned}$$

where $f(e)$ is the firm's production function, with $f' > 0$, $f'' < 0$. The PAC guarantees that a worker with a temporary contract gets at least the value of unemployment. If we restrict attention to interior solutions, the f.o.c of the above-mentioned constrained maximization problem yield,

$$w_T = e - \frac{p(e)}{p'(e)} + (1-\beta)V^U \tag{2.6}$$

$$f'(e) + \frac{d(p(e)/p'(e))}{de}\left(1 + \frac{\Pi^P - H}{V^P - V^U}\right) = 1 \tag{2.7}$$

$$\beta p'(e)R[V^P - V^U] = 1. \tag{2.8}$$

The asset value of being unemployed, V^U in (2.1), is given by,

$$V^U = b + \beta[\mu V^T + (1-\mu)V^U], \tag{2.9}$$

where b is the unemployment income flow and $\mu \in (0,1)$ is an (exogenous) hiring rate. Therefore, use of the PAC with equality implies that $V^U = b/(1-\beta)$.

Next, differentiating the INC with equality along the optimal contract yields,

$$\beta p'(e)[V^P - V^U]dR + \beta p''(e)R[V^P - V^U]de = 0,$$

from which we easily can solve for the relationship between e and R,

$$\frac{de}{dR} = -\frac{\beta(p'(e))^2\ [V^P - V^U]}{p''(e)} > 0 \tag{2.10}$$

Thus, under the previous assumptions, firms' temp-to-perm conversion rates and temporary workers' effort are positively related. In other words, higher conversion rates induce higher effort and vice versa. As an illustration, if we assume a hazard function of the form $p(e) = e^{\lambda}$, with $\lambda \in (0,1)$

and $e \in [0,1]$, which verifies $p(0) = 0$, $p(1)) = 1$, $p'(e) > 0$ and $p''(e) < 0$, the variation in R and e along the optimal temporary contract, given by (2.10), is given by

$$\frac{de}{dR} = \frac{\beta\lambda e^{\lambda}[V^{P}-V^{U}]}{1-\lambda} > 0. \tag{2.11}$$

2.2 Permanent jobs

The next step is to consider the decisions made by workers and firms with permanent jobs whose asset values are respectively given by,

$$V^P = w_P - \overline{e} + \beta[\delta(V^U + F) + (1-\delta)V^P]. \tag{2.12}$$

and

$$\Pi^P = zf(\overline{e}) - w_P + \beta[\delta(H - F) + (1-\delta)\Pi^P], \tag{2.13}$$

where $\delta \in (0,1)$ is an (exogenous) job destruction rate, F denotes a firing tax paid by the firm to the worker upon dismissal, and $z > 1$ is an exogenous technology parameter which captures larger productivity in these jobs. For simplicity, the level of effort exerted by permanent workers, $\overline{e}$, is assumed to be exogenously determined. Specifically, $\bar{e}$ is assumed to satisfy the following two conditions: (i) $f'(\overline{e}) = 1/z < 1$ and, (ii) $zf(\overline{e}) - \overline{e} > b$, which ensure that the expression $zf(\overline{e}) - \overline{e} - b$ is maximized. As will be later explained, this assumption, jointly with another condition on F to be discussed below, guarantees positive profits for firms with permanent jobs.

The value of a new vacancy, assumed to consist of a temporary job, is given by,

$$H = -c + \beta[\xi V^T + (1-\xi)H], \tag{2.14}$$

where $c > 0$ is the cost of opening a vacancy and ξ is the vacancy filling rate which, like the hiring rate, is assumed to be exogenous. Under free entry, we have that $H = 0$, which implies a vacancy filling rate satisfying,

$$\xi = \frac{1-\beta}{\beta}\frac{c}{b},$$

where use has also been made of $V^T = V^U$.

Contrary to TCs, where wages are set by firms, it is assumed that the wage in a PC is determined by Nash bargaining where $\gamma \in (0,1)$ denotes the worker's bargaining power. Thus,

$$\gamma[\Pi^P - (H - F)] = (1-\gamma)[V^P - (V^U + F)], \tag{2.15}$$

Notice that firms will only promote a temporary worker to a PC if $\Pi^P \geq 0$ which implies that firing costs cannot be too high since permanent workers' effort is assumed to be given. Indeed, combining (2.13) with (2.15) leads to the following upper bound for F,

$$F \leq \frac{(1-\gamma)[zf(\overline{e}) - \overline{e} - b]}{1-\beta(1-\delta)}.$$

where $zf(\bar{e}) - \bar{e} - b > 0$, given the above-mentioned properties on how $\bar{e}$ is determined. The above inequality is assumed to hold in the sequel.

Next, use of (2.12)-(2.13) and (2.15), yields the wage obtained by workers with a PC,

$$w_P = \gamma z f(\bar{e}) + (1-\gamma)(\bar{e} + b) + (1-\beta)F, \tag{2.16}$$

which leads to the following solutions for asset values in permanent jobs,

$$[V^P - V^U)] = \frac{\gamma[zf(\bar{e}) - \bar{e} - b]}{1 - \beta(1-\delta)} + F > 0,$$

$$\Pi^P = \frac{(1-\gamma)[zf(\bar{e}) - \bar{e} - b]}{1 - \beta(1-\delta)} - F > 0,$$

so that $\frac{dV^P}{dF} = 1$ and $\frac{d\Pi^P}{dF} = -1$. Notice that these two opposite results are just the outcome of a hold-up problem whereby the worker, once employed with a PC, cannot credibly refrain from exploiting an enhanced bargaining position. Consequently, the firing cost appears as negative in the employer's threat point, $H - F$, but as positive in the workers' threat point, $V^U + F$, in the surplus sharing rule (2.15).

2.3 The effect of the firing-costs gap on effort and conversion rates

Finally, replacing the wage equation into (2.12) and (2.13) and using w.l.o.g. the specific hazard function shown above to simplify the derivations, implies that (2.7) can be rewritten as,

$$f'(e) = 1 - \frac{1}{\lambda}\left[\frac{zf(\bar{e}) - \bar{e} - b}{\gamma[zf(\bar{e}) - \bar{e} - b] + [1 - \beta(1-\delta)]F}\right]. \tag{2.17}$$

Hence, since $f''(e) < 0$, it is straightforward to show that

$$\frac{de}{dF} < 0, \tag{2.18}$$

and, given that the worker's INC with equality yields $R = 1/[\beta p'(e)(V^P - V^U)]$, it must also hold that,

$$\frac{dR}{dF} < 0. \tag{2.19}$$

In other words, a higher value of F makes firms more reluctant to upgrade a TC into a PC which, in turn, reduces the level of effort exerted by temporary workers in view of their lower chances of getting promoted. This result is summarized in the following proposition.

Proposition 1 *Under our assumptions in (2.1), (2.3)-(2.5), and (2-12)-(2.15), an exogenous increase in the firing costs gap between permanent and temporary workers, F, leads to a reduction in both the optimal temp-perm conversion rate, R, decided by firms, and the optimal level of effort, e, exerted by temporary workers.*

Finally, by comparing the optimality condition in (2.17) with $f'(\overline{e}) = 1/z < 1$, it is easy to check that $e < \overline{e}$ for sufficiently large values of F relative to z, while $\overline{e} < e$ in the opposite situation. Notice that this result could be used to explain the empirical results reported by Engellhandt and Riphan (2005) on Swiss temporary workers exerting larger effort than permanent ones since, in contrast to Spain, F is fairly low relative z in Switzerland.

2.4 Adding firm-specific paid-for- training to the model

We next check whether the previous conclusions remain robust once we incorporate the possibility that firms also make decisions about how much to invest on paid–for training to their workers under TC in order to improve the profitability of permanent jobs. Whereas the z parameter was earlier taken as exogenously given in the production function for firms offering PC, it is now allowed to depend on the level of training provided by the firm to workers under the initial TC. For tractability, it is assumed that there is a one-period lag in the effect of training on worker's productivity, so that the latter only raises after the worker is renewed with a PC after the expiration of the TC. Conversely, if the worker is dismissed, then he/she loses the received training, as it is considered to be firm-specific. As a result, firms decide upon this level of training, τ, where the cost of providing training is assumed to be linear in τ, i.e., $c\tau$, with $c > 0$. Thus, while productivity in a temporary job remains $f(e)$, it becomes now $g(\tau)f(\overline{e})$ in a permanent job, instead of $zf(\overline{e})$, where $g' > 0$ and $g'' < 0$. This implies that, while V^Premains the same as in (2.12), Π^P now changes to,

$$\Pi^P(\tau) = g(\tau)f(\overline{e}) - w_P(\tau) + \beta[\delta(H - F) + (1 - \delta)\Pi^P(\tau)]. \tag{2.20}$$

Using the same Nash sharing rule as in (2.15), we get

$$\Pi^P(\tau) - H = \frac{(1 - \gamma)[g(\tau)f(\overline{e}) - \overline{e} - b]}{1 - \beta(1 - \delta)} - F, \tag{2.21}$$

$$V^P(\tau) - V^U = \frac{\gamma[g(\tau)f(\overline{e}) - \overline{e} - b]}{1 - \beta(1 - \delta)} + F. \tag{2.22}$$

Regarding the asset values of workers and firms under TC, our previous assumption about the time delay in the effect of training on productivity implies that, while workers face the same optimization problem as in (2.1), firms now have to account for the cost of training temporary workers, so that their optimization problem becomes,

$$\Pi^T = \max_{e,\tau,w_T,R} \{f(e) - w_T - c\tau + \beta[p(e)R\Pi^P(\tau) + (1 - p(e)R)H]\} \tag{2.23}$$

$s.t.$

$$V^T(\tau) \geq V^U \qquad (PAC) \tag{2.24}$$

$$\beta p'(e)R[V^P(\tau) - V^U] \leq 1 \qquad (INC), \tag{2.25}$$

where, using in the sequel for simplicity the specific hazard function discussed above, it follows from (2.11) and the PAC with equality, that $w_T = e - (e/\lambda) + b$. Moreover, before presenting the f.o.c of this problem it is convenient to use (2.15) to re-write the bracketed expression in the LHS of (2.7) as,

$$1 + \frac{\Pi^P(\tau) - H}{V^P(\tau) - V^U} = \frac{1}{\gamma}\left[1 - \frac{F}{V^P(\tau) - V^U}\right]. \tag{2.26}$$

Now, using (2.26), the three f.o.c. of the maximization problem (2.23)-(2.25) become

$$\beta p'(e)R[V^P(\tau) - V^U] = 1, \tag{2.27}$$

$$[f'(e) - 1] = -\frac{1}{\gamma\lambda}\frac{[V^P(\tau) - V^U - F]}{[V^P(\tau) - V^U]}, \tag{2.28}$$

$$\frac{eF}{\lambda}\frac{g'(\tau)f(\overline{e})}{1 - \beta(1-\delta)} = c[V^P(\tau) - V^U]^2, \tag{2.29}$$

where use has been made in (2.29) of $\partial[F/[1-\frac{F}{V^P - V^u}]/\partial\tau = [F\gamma g'(\tau)f(\overline{e})]/[1-\beta(1-\delta)][V^P - V^U]^2$ which, in turn, follows from differentiation of (2.22) w.r.t. τ and F.

Next, differentiating (2.28) w.r.t. e and τ, holding F constant, and considering again (2.22), yields,

$$f\,''(e)de = -\frac{g'(\tau)f(\overline{e})}{\lambda[1 - \beta(1-\delta)][V^P(\tau) - V^U]^2}d\tau. \tag{2.30}$$

Hence, since $f\,''(e) < 0$, (2.30) implies that,

$$\frac{de}{d\tau} = -\frac{g'(\tau)f(\overline{e})}{f\,''(e)\lambda[1 - \beta(1-\delta)][V^P(\tau) - V^U]^2} > 0, \tag{2.31}$$

leading to the result that effort and training are positively related (i.e., they are complements) in equilibrium. Further, it can be shown that differentiation of (2.28) w.r.t. e, τ and F, yields $\frac{de}{dF} < 0$, just as before.[10] Therefore $\frac{d\tau}{dF} = \frac{d\tau}{de}\frac{de}{dF} < 0$, so that an increase in F not only reduces temporary workers' effort but also decreases the amount of paid-for training they receive from

[10]This differentiation yields $[f\,'' - \frac{\gamma g'(\tau)[1-\beta(1-\delta)]}{D^2}\frac{d\tau}{de}]\frac{de}{dF} = \frac{1-\beta(1-\delta)}{\gamma D}$, where $D = \gamma[g'(\tau)f(\overline{e}) - \overline{e} - b] + [1-\beta(1-\delta)]F$.

firms. The last issue to be checked is the effect of F on R. For this, consider (2.27), where it can be easily checked that, due to (2.22), a higher value of F increases $[V^P(\tau) - V^U]$, and therefore decreases $p'(e)R$. Hence, since e is decreasing in F and $p''(e) < 0$, i$p'(e)$ must go up. Therefore, R has to go down, implying that $\frac{dR}{dF} < 0$. In sum, the signs of responses of both e and R to a change in F remain the same as in Proposition 1 whereas, in addition, τ decreases as F increases. Hence, these results can be summarized as follows

Proposition 2 *Under the assumptions in Proposition 1 and with firms being allowed to choose paid-for training for temporary workers, an increase in F leads to lower training, besides lower effort and conversion rates.*

2.5 From the model to the data

Lacking any direct proxy for effort (or paid-for training) in our data set, our indirect strategy is to relate workers' effort to firms' TFP, which can be estimated from firms' output and inputs. For that, let us assume that each firm in the economy has the following constant-returns-to- scale (CRS) Cobb-Douglas (CD) production function,[11]

$$Y = A(\bar{e}L_P)^{\alpha_P}(eL_T)^{\alpha_T}X^{1-\alpha_P-\alpha_T}$$

where Y is final output, A is an index of Harrod-neutral technical progress, e is effort of temporary workers, $\bar{e}$ is effort by permanent workers[12] (assumed to be constant as in the model), L_P and L_T are hours of work by permanent and temporary workers, respectively, and X denotes additional production inputs (i.e., capital and raw materials). Hence, using small letters to denote logs of capital ones and labeling $\alpha_0 = \alpha_P \ln \bar{e}$, we can measure logged composite TFP at the firm level as $\widetilde{a} \equiv a + \alpha_0 + \alpha_T \ln e = y - \alpha_P l_P - \alpha_T l_T - (1 - \alpha_p - \alpha_T)x$, using estimates of the different input elasticities. In this way, given a and $\bar{e}$, TFP becomes a proxy for unobservable e. Our previous results imply that, *ceteris paribus*, firms with higher conversion rates will exhibit higher TFP via higher workers' effort, i.e, $\frac{\partial \widetilde{a}}{\partial R} = \frac{\alpha_T}{e}\frac{\partial e}{\partial R} > 0$. Further, it is assumed that TFP also depends on a vector of other determinants, $\mathbf{z}$, to be described in Section 3, which affect its remaining components, i.e., a and $\bar{e}$. From these considerations, our benchmark model of firms' TFP in the empirical section can be simply summarized as follows,

$$\widetilde{a} = \widetilde{a}(R, \mathbf{z}), \tag{2.32}$$

[11]The choice of a (multiplicative) Cobb-Douglas production function is justified in our case because no firm in the data set has zero temporary or permanent contracts. Otherwise, L_P and L_T would need to be additive in a labour composite.

[12]In a broader sense, $\bar{e}$ could also be interpreted as a combined index comprising not only permanent workers' effort but also their level of paid-for training they received before being promoted. However, to simplify matters, we will only refer to effort in the sequel.

to which a disturbance term capturing unobserved components of TFP should appended (see section 3.2). Since $\widetilde{a}$ and R are endogenous variables, our strategy is to exploit natural experiments implied by three major labour market reforms in Spain implemented in 1994, 1997 and 2002, respectively, where the gap between the firing costs of permanent and temporary workers, F, was changed. As will be discussed below, once we control for other observable characteristics at the firm level (like firm's size), our implicit identification strategy of the effect of R on $\widetilde{a}$ is that an exogenous and fairly unexpected change in F will affect R in each firm differently depending on their share of temporary jobs, defined as tw $(= L_T/(L_P + L_T))$, before the reform. In other words, firms' differences in tw just before the reforms took place are bound to induce heterogeneous variation in R and, through this channel, changes in F will affect $\widetilde{a}$ across firms.

3 Data

Our microdata at the firm level come from the *Survey on Business Strategies* (*Encuesta sobre Estrategias Empresariales*, ESEE). This is an annual survey on a representative sample of Spanish manufacturing firms which has the advantage of providing the information required to compute temp-to-perm conversion rates (see below). The available sample period is 1991-2005. Firms were chosen in the base year according to a sampling scheme applied to each industry in the manufacturing sector where weights depend on their size category. While all manufacturing firms with more than 200 employees are surveyed and their participation rate in the survey reaches approximately 70%, smaller firms with 10 to 200 employees are surveyed according to a random sampling scheme with a participation rate close to 5%.

Another important feature of the survey is that the initial sampling properties have been maintained throughout all subsequent years. Newly created and exiting firms have been recorded in each year with the same sampling criteria as in the base year. As a result of this entry and exit process, the data set is an unbalanced panel where the number of firms is 3,759 while the number of firm-year observations is 22,292. Further details about the criteria used to select our specific sample are presented in the Appendix.

3.1 Temporary work

Table 1 shows the share of temporary workers by industry, size and age category. With regard to size category, small firms are defined as those with less than 50 employees, while medium-sized and large firms are those with more than 50 but less than 200 employees, and more than 200 employees, respectively. Regarding age categories, young firms are defined as those which have been operating during less than 5 years since they were opened, while mature firms are those which have been operating for a longer period.

[TABLE 1 ABOUT HERE]

As can be observed in the Table, the share of temporary workers exhibits large variability across industries, age and size categories. Within each industry, in general, small and medium-sized young firms exhibit a larger share of this type of contracts. This is traditionally rationalized by the fact that newer firms are bound to make a more widespread use of flexible temporary contracts for precautionary reasons since they are likely to face a higher probability of failure.

Next, we proceed to describe the computation of both firms' TFP and conversion rates.

3.2 TFP

As regards TFP, we construct a measure based on the generalization proposed by Levinsohn and Petrin (2003, henceforth LP) of the well-known Olley and Pakes' (1996) approach to estimate the parameters of production functions using inputs to control for unobservables.

As will become clear below, the reason for adopting this approach, rather than computing the conventional Solow residuals, is that the use of the latter invalidates our strategy to identify heterogeneity across firms in the effect of changes in F at the nationwide level on R and then on TFP (through e and τ) at the firm level. In a nutshell, the idea is that firms which have a higher proportion of temporary workers (tw) before changes in F take place will be more affected by these changes than firms with a lower proportion. Yet, this requires that tw does not directly affect TFP. It only does so indirectly through its effects on R, a condition which will not be satisfied if we were to compute Solow residuals from the available information on output and inputs in our data set. In effect, given our assumption about a CRS-CD production function, the standard Solow procedure to compute firm i's (logged) TFP level in period t, denoted by $\widetilde{a}_{it}$, would be as follows,

$$\widetilde{a}_{it} = y_{it} - \alpha_P l_{Pit} - \alpha_T l_{Tit} - \alpha_m m_{it} - \alpha_k k_{it}, \tag{3.1}$$

where y is logged final output; l_P, l_T, m and k are logged labour (hours of work) by permanent and temporary workers, respectively, materials, and capital weighted by its logged annual average capacity utilization rate reported by each firm; and α_x $(x = \{l_P, l_T, m, k\})$ are input elasticities which satisfy $\alpha_P + \alpha_T + \alpha_m + \alpha_k = 1$ under CRS.[13].

[13]Final output is measured as the value of produced goods and services deflated with each firm's output price index; capital, as as firm's value of the capital stock deflated using the price index of investment in equipment

The problem with this approach is that, lacking information on the different cost shares of permanent and temporary workers (payrolls reported in ESEE do not distinguish between wages paid by type of contract), we would end up having a measure of $\widetilde{a}$ that is contaminated by tw, invalidating the use of this variable in the construction of IVs required to estimate (2.32) consistently. To see this, let us rewrite the production function as $Y = A(\bar{e}L_P/L)^{\alpha_P}(eL_T/L)^{\alpha_T}L^{\alpha_P+\alpha_T}X^{1-\alpha_P-\alpha_T}$, with $L = L_P + L_T$. Thus, taking logs and recalling that $tw = L_T/L$, $\widetilde{a}$ would be defined as,

$$\begin{aligned} \widetilde{a} &= y - (\alpha_P + \alpha_T)l - \alpha_k k - (1 - \alpha_P - \alpha_T - \alpha_k)m = \\ &= a + \alpha_0 + \alpha_T[\ln e + \ln(tw)] + \alpha_P \ln(1 - tw), \end{aligned}$$

so that $\widetilde{a}$ depends on tw, and we cannot assume an exclusion restriction for this variable or its lagged value in a regression equation explaining $\widetilde{a}$.

To overcome this problem, we follow instead LP's (2003) approach, where it is assumed that $\widetilde{a}_{it}$ can be expressed as the sum of two unobserved components,

$$\widetilde{a}_{it} = \omega_{it} + \upsilon_{it}, \tag{3.2}$$

such that ω_{it} represents a firm-specific component which is known to the firm, while υ_{it} is an idiosyncratic component unknown to the firm but with no impact on firm's decisions. The endogeneity problem in estimating the production function by OLS arises from the correlation of ω_{it} with the input choices. LP (2003) follow Olley and Pakes (1996) in considering k as a quasi-fixed input and l_P, l_T and m as freely adjustable inputs. Olley and Pakes' (1996) original approach relied upon the assumption that investment, i, installed in period t only becomes productive at $t+1$, so that $i_{it} = i(\omega_{it}, k_{it})$ can be inverted to yield $\omega_{it} = \omega_t(i_{it}, k_{it})$ under the assumption of increasing monotonicity of i_{it} in ω_{it}. Yet, instead of using the investment demand function, LP (2003) advocate to invert the materials' demand function $m_{it} = m(\omega_{it}, k_{it})$ to obtain $\omega_{it} = \omega_t(m_{it}, k_{it})$, also under monotonicity plus some additional assumptions.[14]. The justification for this alternative choice is that, while most firms (99.3% in our case) report positive expenditure on materials every year, a much lower proportion (about 52% in our sample) undertake investment every year, implying a severe efficiency loss when about half of the sample of firms needs to be truncated.

In what follows we briefly describe the details of LP's (2003) procedure to estimate our (logged) production function,

$$y_{it} = \alpha_P l_{Pit} + \alpha_T l_{Tit} + \phi_t(m_{it}, k_{it}) + \upsilon_{it}, \tag{3.3}$$

such that $\phi_t(m_{it}, k_{it}) = \alpha_0 + \alpha_k k_{it} + \alpha_m m_{it} + \omega_t(m_{it}, k_{it})$. Equation (3.3) is estimated by OLS in the first stage using a third-order polynomial in m_{it} and k_{it} with constant slopes over time. However,

goods; materials, as the value of intermediate consumption deflated by a firm's price index of materials. Finally, following Hall (1990), the input elasticities would correspond to.firms' average cost shares over our sample period, which are available in ESEE.

[14]For example, input prices are assumed to be common across firms.

we allow for time-variant intercepts (by means of binary time dummies) to get time variation in $\bar{e}$ which, for simplicity, was earlier assumed to be constant. The estimates $\widehat{\alpha}_P$ and $\widehat{\alpha}_T$ will consistently identify the two labour elasticities α_P and α_T. Next, following Olley and Pakes (1996), it is assumed that ω_{it} follows a first-order Markov process, leading to $\omega_{it} = g(\omega_{it-1})$. Although $g(.)$ has been specifically chosen to be a fourth-order polynomial in our empirical implementation, we will consider a simple AR(1) process $\omega_{it} = \rho\omega_{it-1} + \varepsilon_{it}$, where ε_{it} is i.i.d., to briefly illustrate the second stage of the procedure which yields the remaining input elasticities. By defining $\widetilde{y}_{it} = y_{it} - \widehat{\alpha}_P l_{Pit} - \widehat{\alpha}_T l_{Tit}$, and taking into account that $\omega_{it-1} = \omega_{t-1}(m_{it-1}, k_{it-1})$, it holds that,

$$\begin{aligned}\widetilde{y}_{it} &= \alpha_0^* + \alpha_k k_{it} + \alpha_m m_{it} + \\ &+\rho[\phi_{t-1}(m_{it-1}, k_{it-1}) - \alpha_k k_{it-1} - \alpha_m m_{it-1}] + \upsilon_{it} + \varepsilon_{it}. \qquad (3.4)\end{aligned}$$

This is the equation estimated by NLS in the second stage, using the predicted values for $\widetilde{y}_{it}$ and $\phi_{t-1}(m_{it-1}, k_{it-1})$ obtained from the first-stage estimation. As LP (2003) have shown, this second stage leads to consistent estimates of α_k and α_m. Notice that, since the predicted values have been used for $\widetilde{y}_{it}$ and $\phi_{t-1}(.,.)$, the standard errors of the estimated coefficients in (3.4) should be corrected by bootstrap. We implement this procedure separately for each of the 18 manufacturing industries included in our data set. In Table 2 we report the estimates of the parameters, where CRS is imposed in all instances since the null hypothesis that the sum of the four input elasticities is equal to unity cannot be rejected at typical significance levels in all cases. Overall, the coefficients on labour, capital and materials are in line with those available in the literature using data on Spanish firms (see, e.g, Aguirregabiria and Alonso-Borrego, 2010, and González and Miles, 2011) though a novelty in this paper is that we distinguish between the elasticities of permanent and temporary labour in the production function. Our estimates point out that the former tends to be about 4 to 5 times larger than the latter in most industries.

[TABLE 2 ABOUT HERE]

3.2.1 Conversion rates

Our data set provides direct information on the types of contracts used by firms in each year of the sample, from which conversion rates at the firm level can be retrieved. In effect, we have data on the number of permanent and temporary workers in firm i at period t ($L_{P,it}$ and $L_{T,it}$, respectively), as well as on the number of permanent contracts which have been signed in each year by workers who previously held temporary contracts in the firm. This is denoted as $L_{TP,it}$ where the subscript "TP" signifies conversion from "T" to "P". Using this information, we compute annual conversion rates as $R_{it} = L_{TP,it} / L_{T,it-1}$. On average, it yields an estimate of R equal to 0.118, that is, about 12% of temporary workers get permanent contracts when their contracts expire. Interestingly, this value is quite close to the conversion rates reported in other available studies in Spain about this topic which use information from aggregate labour surveys (see Alba-Ramírez, 1994, Amuedo-Dorantes, 2000, 2001, and Güell and Petrongolo, 2007) whose estimates range between 10% and 15%.

Figure 2 displays the histogram of the estimated conversion rates. About 85% of firms exhibit conversion rates between 0% and 20%, and only 3% of firms exhibit rates above 50%. Industries like "Vehicles and motors", "Textiles and apparels" and "Paper and printing products" are the ones exhibiting the higher conversion rates whilst other industries, like "Food and tobacco", exhibit very low rates. In sum, this evidence points out that, in general, Spanish manufacturing firms have been rather reluctant to offer contract conversions, most plausibly due to the large EPL gap between permanent and temporary workers.

[FIGURE 2 ABOUT HERE]

3.3 Conversion rates and TFP: A descriptive (nonparametric) bivariate analysis

To motivate the econometric analysis undertaken later in Section 4.1, we start by evaluating whether there are significant differences in the distribution of TFP across firms with different conversion rates. To do so, we follow the nonparametric approach proposed by Delgado *et al.* (2002) in their analysis of productivity differences between exporting and non-exporting manufacturing firms in Spain. In our slightly different setup, we test the null hypothesis that the c.d.f.'s of TFP in firms with low and high conversion rates 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 shown in Delgado *et al.* (2002), this index allows to pool observations across different industries, facilitating comparison on a homogeneous basis of TFP in different firms. 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 input elasticities equal to the arithmetic mean of the elasticities obtained by the LP's (2003) approach 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:

$$\begin{aligned}\tilde{a}_{it} &= y_{it} - \overline{y}_{\tau j} - \frac{1}{2} \sum_{x=\{l_P, l_T, m, k\}} \left(\alpha_{it}^x + \bar{\alpha}_{\tau j}^x\right)\left(x_{it} - \overline{x}_{\tau j}\right) \\ &+ \overline{y}_{\tau j} - \overline{y}_j - \frac{1}{2} \sum_{x=\{l_P, l_T, m, k\}} \left(\bar{\alpha}_{\tau j}^x + \bar{\alpha}_j^x\right)\left(\overline{x}_{\tau j} - \overline{x}_j\right), \end{aligned} \tag{3.5}$$

where $x = \{l_P, l_T, m, k\}$; $j = 1, 2, \ldots, 18$; τ={small & medium-sized, large}; [15] 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.

As shown earlier in Table 1, young manufacturing firms tend to hire a larger proportion of temporary workers that more mature firms. Given that the former may be less productive than the latter, a potential concern is that TFP gaps may just reflect differences in firms' age and not in their fraction of temporary workers (see Fariñas and Ruano, 2004). For this reason, Figure 3 displays the empirical c.d.f's of the estimated TFP index $\tilde{a}$ in the four categories of firms which result from combining the two age (young and mature) and the two size (small & medium sized, and large) groups. In each of the four panels, the dashed line corresponds to firms with conversion rates below a preset threshold, whereas the solid line represents those firms with conversion rates above that threshold value. This threshold value is set to be equal to 8% (approximately the average level of the conversion rate in all sectors of the Spanish economy throughout the sample period). Admittedly, this choice is somewhat arbitrary, but we have experimented with other choices ranging from 5% to 15% obtaining very similar results. As can be observed, the c.d.f. of the TFP index for firms with conversion rates above 8% lies to the right of the c.d.f. of the TFP index for those with less than 8% in three out of the four cases, implying that the former are seemingly more productive than the latter. The only exception holds for the group of young, large firms, which might be due to the low proportion of such firms in our sample (only 276 out of 22,292 observations).

[FIGURE 3 ABOUT HERE]

The next step is to test formally whether these gaps in the c.d.f.'s are statistically significant. We apply the nonparametric test of (first-order) stochastic dominance (SD) proposed by Delgado *et al* (2002) which works as follows. Let F_t and G_t denote the c.d.f. of the TFP index in period t of

[15] Due the selective sampling scheme in our data set, in what follows we 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).

firms with conversion rates in period t below and above preset thresholds, respectively.[16] We test for SD in each size category, τ, by conditioning the distributions F_t and G_t on a given size group τ_0 with $\tau_0 = \{$small & medium-sized, large$\}$, and a given age group κ_0 with $\kappa_0 = \{$young and mature$\}$.[17] Then, the distribution $F_t(\cdot|\tau = \tau_0, \kappa = \kappa_0)$ stochastically dominates the distribution $G_t(\cdot|\tau = \tau_0, \kappa = \kappa_0)$ if the null hypothesis $H_0^a : F_t(\cdot|\tau = \tau_0, \kappa = \kappa_0) = G_t(\cdot|\tau = \tau_0, \kappa = \kappa_0)$ (two-sided test) is rejected and $H_0^b : F_t(\cdot|\tau = \tau_0, \kappa = \kappa_0) > G_t(\cdot|\tau = \tau_0, \kappa = \kappa_0)$ (one-sided test) is not rejected. In each period, the Kolmogorov-Smirnov test statistics for these one- and two-sided tests are as follows:

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

and

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

where n and m denote, respectively, the sample size of firms with conversion rates below and above the threshold values, $N = n+m$, 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 comparison always takes place in each period). The limiting distributions of these statistics are known under independence (see Delgado *et al.*, 2002).[18]

For brevity, we discuss here the results of the SD test conditioning on size, namely $F_t(\cdot|\tau = \tau_0)$ against $G_t(\cdot|\tau = \tau_0)$, which are reported in Table 3. For the group of small & medium- sized firms, we find that H_0^a can be rejected at the 5% significance level in every year between 1992 and 2005, while the hypothesis that the sign of the difference is favourable to firms with a higher conversion rate (H_0^b) can always be rejected at any reasonable significance level. In the case of large firms, H_0^a can be rejected except in 1992 and 1993. Further, in all the remaining years H_0^b cannot be rejected. Similar results hold when conditioning on firms' age.[19]

[TABLE 3 ABOUT HERE]

Overall, these preliminary findings point out that the TFP distribution of firms with higher conversion rates (above our threshold of 8%) stochastically dominates the corresponding distribution of firms with lower conversion rates. Yet, there are two shortcomings when interpreting this evidence as fully supportive for our model. First, it ignores other factors, captured by $\mathbf{z}$ in (2.32), that may also affect the link between conversion rates and firms' TFP, like e.g., R&D expenditure, workers'

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

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

[18] Under this assumption, 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).

[19] These results are available upon request.

educational attaintment, etc. Secondly, and foremost, it just captures a relationship between a pair of variables without identifying a causal link. After all, it may well be that less productive firms offer lower conversion rates rather than the other way around.[20] Given these caveats, the next step is to use a parametric panel regression approach to estimate equation (2.32) in order to check whether a causal interpretation holds once we are able to identify valid instruments for the effect of conversion rates on TFP.

4 Panel regression

To evaluate the impact of the firing-cost gap on manufacturing firms' TFP, via its effect on conversion rates, we regress our estimate of TFP, $\widetilde{a}$, on R plus a set of additional controls in the following dynamic panel data model at the firm level,

$$\widetilde{a}_{it} = \eta_i + \eta_t + \rho\widetilde{a}_{i,t-1} + \beta R_{it} + \gamma' \mathbf{z}_{it} + v_{it}, \tag{4.1}$$

where η_i and η_t are firm fixed effects and time effects, respectively, while v_{it} is an i.i.d. error term. As discussed earlier, the vector $\mathbf{z}_{it}$ contains a set of controls which are likely to affect the a and $\overline{e}$ components of $\widetilde{a}$.[21] It includes an index of skilled human capital available at the firm level (i.e., the proportion of employees with a college degree), size, age and its square, a dummy variable for incorporated companies, the proportion of foreign capital, the proportion of public capital, two indicators on whether the firm perceives it operates in an expansive or recessive market, R&D expenditure by the firm, industry dummies, firm' s entry, exit, merger and scission dummies.[22] Detailed definitions of these variables can be found in the Appendix. Lastly, since TFP levels are highly persistent over time, we also include a lagged dependent variable.

Table 4 contains descriptive statistics of the variables in (4.1). As can be seen, there is a large and persistent slowdown in firms' TFP growth since 2000 leading to even a negative growth rate in 2005. This path 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 become negative since the mid-nineties (see Escribá and Murgui, 2009). It is also noteworthy that the average share of temporary workers in our sample is about 23%, namely, around 10 pp. lower than the aggregate share for

[20] Yet, very similar results hold when we use an average of R_{it-1} and R_{it} as a predetermined variable since most reforms took place in the middle of the year.

[21] Notice that, to the extent that some of these covariates capture changes in effort of permanent workers, our identification strategy will capture variations in the relative effort exerted by temporary workers vis-á-vis permanent ones.

[22] These variables take value 1 in all the periods in which the firm appears in our sample.

the Spanish economy during the whole sample period, given that seasonal activities associated to the manufacturing industry are much less prevalent than in the services and construction sectors.

[TABLE 4 ABOUT HERE]

According to our model, the main driving force behind the positive correlation between temporary workers' effort and firms' conversion rates is a change in the gap of firing costs between permanent and temporary workers. During the available sample period, there have been three major EPL reforms following the introduction of widespread temporary contracts in 1984.

The first one took place in May 1994 (Law 10/94), which relaxed the conditions for "fair" dismissals of permanent workers, and restricted conditions for the use of temporary contracts. Regarding the former, fair dismissals —involving redundancy pay of 20 days' wages per year of seniority (*dpys*) with a maximum of 12 months, against a pay of 45 *dpys* with a maximum of 42 months of wages for "unfair" dismissals— that could only be used for economic reasons, also qualified for organizational and technological reasons. As regards conditions for the use of temporary contracts, the most popular temporary contract, i.e., the so-called *contrato de fomento* (with a maximum duration of 3 years) was abolished, except for some disadvantaged groups of workers. Overall, we interpret this reform as lowering F. The next reform was implemented in May 1997 (Law Decrees 8 and 9/97) reducing the above-mentioned mandatory redundancy pay in case of "unfair" dismissals to 33 *dpys* with a maximum of 24 months of wages for most new hires, with the exception of workers aged 30-44 years old whose unemployment spells were below one year. In parallel, a new severance payment of 8 *dpys*, instead of no firing cost, was implemented for temporary workers whose fixed-term contracts were not renewed and significant rebates of social security contributions were also introduced for conversions or direct hires under the new permanent contract (see Dolado *et al.*, 2002).[23] All in all, we interpret again this reform as one where F was significantly reduced.

Finally, in December 2002 (Law 45/02), the use of the new 33 *dpys* contracts was extended to the hiring of new workers aged 16-30 years old (instead of 18-29) as well as of the unemployed with more than 6 months. However, the most important change in this reform was the abolition of the firm's obligation to pay interim wages when dismissed workers appealed to labour courts, as long as the the firm acknowledged the dismissal to be unfair and deposited the highest severance pay (45 *dpys*) in court two days before the dismissal. It is arguable whether this reform meant a reduction in F since, although the extension of the new contract aimed to do so, many excessively risk-averse employers may have ended up paying much higher firing costs than the statutory ones (under "fair" dismissals) to avoid the uncertainty of going to court.

[23] The rebates ranged from 40% to 60% during the first two years of the new contracts used to hire workers in some targeted groups (youth, long-term unemployed, and women under-represented in some industries).

In line with the previous discussion, the idea is to use these three reforms separately as natural experiments to generate exogenous changes in F which subsequently would affect R without having a direct effect on $\widetilde{a}$, i.e., fulfilling the required exclusion properties for a valid instrument. In principle, we would construct three dummy variables denoted $F1$, $F2$ and $F3$ which take the value 1 from the year after the implementation of the reforms (1995, 1998 and 2003, respectively) onwards, and zero before those dates. However, one important problem with these indicators is that, capturing nationwide reforms, they would hardly correlate well with the situation of each particular firm. For example, a firm with very few temporary workers and another with plenty of them will benefit very differently from the reforms. To address this problem, we use the interactions of the three reform dummies with the value of the rate of temporary workers in the year before the reform took place, denoted as tw_{it-1}. This leads to the choice of three interacted indicators, denoted respectively as $F1_{it-1}$,$F2_{it-1}$ and $F3_{it-1}$, as the corresponding IVs with variation both across firms and over time. Notice that, since we also control for firm's size, our comparison focuses on firms with equal size but with a rather different number of temporary workers.

4.1 Estimation method

Since the dependent variable in (4.1), $\widetilde{a}_{it}$, is usually very persistent, our estimation method relies on Blundell and Bond's (1998) System-GMM which consists of the estimation of a system of two simultaneous equations, one in levels (with lagged levels as instruments) and the other in first differences (with lagged first differences as instruments). We use as IVs the three reform dummies interacted with tw_{it-1}, plus the remaining variables in (4.1) lagged twice (except size, age and its square). As shown in the first column of Table 5, the choice of FS_{it-1}, $(S = 1, 2, 3)$ as our key IVs is seemingly validated by the relatively high partial R^2's in the first-stage OLS regressions of R_{it} on these three dummies, where the remaining lagged IVs in (4.1) have also been included. We find that the three FS_{it-1} turn out to be strongly significant and that, while $F1_{it-1}$ and $F2_{it-1}$ have large positive estimated coefficients (in line with their attempt to reduce that firing cost gap), $F3_{it-1}$ exhibits a smaller negative one, pointing out that, in net terms, the EPL reform in 2002 increased F. These results are supported by the scatter plots displayed in Figure 4 which depict conversion rates the year before and after each of the three reforms, together with the 45 degree line, for each of the 72 cells of firms which result from combining industry (18), size (2) and age (2) categories.

Finally, as a robustness check on our identification strategy, we depict a similar scatter plot in Figure 5 for a placebo reform taking place in 1999, namely, a year when there was no change in EPL regulations. As can be observed, the observations are neither above the 45^o line (as in the 1994 and 1997 reforms) nor below it (as in 2002). Further, when adding a similar reform dummy variable interacted with tw_{it-1} at that year (denoted by $F4_{t-1}$) in the second column of Table 5, its coefficient turns out to be highly insignificant.

[TABLE 5 & FIGUREs 4 & 5 ABOUT HERE]

4.2 Empirical results

Table 6 reports the estimated coefficients of the controls in equation (4.1). For comparison, columns [1] and [2] present specifications including and excluding tw_{it-1}, respectively, in the list of regressors as to check the validity as IV of this key component of our three interacted reform dummies.[24] Finally, in column [3], estimates are shown for a specification where the placebo interacted dummy variable $F4_{it-1}$ is also included as an IV. Notice that, in all specifications, the Sargan $m1$ and $m2$ tests for MA(1) and MA(2) in the first-differenced disturbances point out that the choice of the second lags as IVs is not rejected.

The main findings are as follows. First, tw_{it-1} does not appear significantly in column [1] confirming our identification strategy. Secondly, and foremost, the effect of R_{it} on $\widetilde{a}_{it}$ is positive and highly significant in both columns [1] and [3] when the whole set of controls is considered. The estimated coefficient on R_{it} in column [2] is 0.119 (t-ratio: 4.90). Finally, the estimates in columns [2] and [3] are very similar, pointing out the the placebo dummy does not provide any additional explanatory power.

If we were to take this point estimate at face value, we could compute the fraction of the slowdown in TFP growth during 1992-2005 (from 1.52% in 1992 to -0.17% in 2005, that is, a decrease of 1.67 pp.) which is due, *ceteris paribus,* to the fall in the conversion rate (from 12.2% in 1992 to 10.3 in 2005, that is, a decrease of 1.9 pp.). Once the dynamic effects of the AR(1) in (4.1) are considered, our simulation results imply that the observed decline in conversion rates explains 0.32 pp. of the 1.67 pp. reduction in TFP growth, namely about 20 percent. Alternatively, if a future (after 2005) labour market reform entailing reduction in the firing-cost gap were to increase temp-to-perm conversion rates, say from 10.3% to 15%, TFP growth rates for manufacturing firms would raise from -0.17% to 0.55% in five years. These are admittedly not very large effects, since we keep constant all the other determinants of TFP, but they are unambiguously relevant.

[TABLE 5 ABOUT HERE]

[24] In column [1], only second lags of the regressors are used as IVs, whereas in column [2] the three reform dummies interacted with tw_{it-1} are also added to the set of IVs.

5 Conclusions

Since the early nineties, Spain has been the EU country with the highest proportion of temporary workers, with more than twice the average share in the EU-15. In parallel, it has suffered from a drastic productivity slowdown since the mid-1990s. In this paper we document the relationship between these two stylized features using an unbalanced panel of Spanish manufacturing firms from 1991 to 2005. To interpret the empirical evidence, we build a simple model of a two-tier labour market in which temporary workers choose their level of effort in order to maximize expected utility while firms choose their temp-to-perm conversion rates to maximize profits, facing a sizeable firing-cost gap between permanent and temporary workers. The main implication is that both temporary workers' effort and firms' conversion rates decrease as the firing- cost gap increases. Further, we also show that the higher is the firing-cost gap, firms have less incentive to provide paid-for training to temporary workers. Since workers' effort and training can be thought of as components of TFP, it is through this mechanism that dual EPL affects TFP developments.

Our empirical findings imply that, all else equal, up to 20% of the the slowdown of TFP growth in Spanish manufacturing firms could be explained by the reduction in conversion rates and that if a future labour market reform were to increase the conversion rate by around 5 pp. per year, TFP growth would pick up from current (as of 2005) -0.17% to about 0.55 pp. in five years.

One shortcoming of our empirical approach is the lack of direct information on workers' effort or firms' paid-for training which are embedded in a measure of TFP. Yet, even in the absence of direct information on these variables, the results obtained in this paper shed some light on how dual EPL in two-tier labour markets may have sizeable detrimental effects on firms' productivity.

Part I

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Part II

Appendix: Data and definition of variables

5.1 Sample selection rules

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

5.2 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*: Workers hired under an indefinite contract until December 31st of each year.
- *Temporary workers*: Workers hired under a fixed-term contract until December 31st.
- *Conversions from temporary to permanent contracts:* Number of workers promoted to an indefinite contract who had a temporary contract at the same firm before December 31st. of the previous year.
- *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.
- *Index of human capital*: Proportion of workers with an enginnering or other college degrees.
- *Age*: The age of the firm is the difference between the current year and the year of birth declared by the firm.
- *Size*: Three 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 2.
- *R&D investment*: Value of current investment in R&D.
- *Expansive/ Recessive Market*: Dummy variables that take value 1 when the firm reports that its market is in expansion/recession and 0 otherwise.

Table 1. Proportion of temporary workers by firm's age and size

Small and Medium-sized firms (less than 200 employees)

	Mean	SD	Obs
Less than 5 years in the market	41.5	31.0	2641
More than 5 years in the market	20.4	22.1	12, 833

Large firms (more than 200 employees)

	Mean	SD	Obs
Less than 5 years in the market	18.5	22.7	276
More than 5 years in the market	15.4	16.5	6, 542

Source: ESEE (1991-205)

Table 2. Estimates of input elasticities with Levinsohn and Petrin's (2003) approach

INDUSTRY	α_p	α_T	α_k	α_m	N	N_a
Ferric and Non Ferric Metals	0.252***	0.065***	0.098***	0.585***	739	716
Non Metallic Mineral Products	0.168***	0.056***	0.094***	0.682***	1675	1541
Chemical Products	0.288***	0.046**	0.187***	0.479***	1616	1503
Metallic Products	0.320***	0.094***	0.202***	0.384***	2050	1886
Agricultural and Industrial Machinery	0.289***	0.126***	0.057***	0.528***	1473	1399
Office Machinery, Data Processing Machinery, etc.	0.325***	0.094**	0.083**	0.498***	364	345
Electrical Material and Electrical Accessories	0.282***	0.100***	0.105***	0.513***	1586	1475
Vehicles and Motors	0.292***	0.073**	0.102***	0.533***	1117	1050
Other Transport Material	0.214***	0.085**	0.121***	0.580***	463	444
Meat and Meat Products	0.254***	0.072***	0.089**	0.585***	680	646
Food and Tobacco	0.204***	0.076***	0.159***	0.561***	2322	2136
Beverages	0.202***	0.071**	0.087***	0.640***	511	475
Textiles and Apparels	0.286***	0.114***	0.073***	0.527***	2421	2251
Leather products and shoes	0.185***	0.088**	0.138***	0.589***	772	710
Wood and Furniture	0.289***	0.099***	0.183***	0.429***	1829	1683
Paper, Paper Products and Printing Products	0.238***	0.053***	0.093***	0.616***	1949	1813
Plastic Products and Rubber	0.308***	0.086***	0.113***	0.493***	1004	943
Other Manufactured Products	0.307***	0.085***	0.072**	0.464***	551	523

Notes: * * significant at 10%, ** at 5%, *** at 1%. CRS are not rejected in all cases with p-values always exceeding 0.20; N is the number of firms in each industry; N_a denotes the number of available observations satisfying the assumptions of Levinsohn and Petrin (2003).

Table 3. TFP differences between firms with low and high temp-to-perm conversion rates

	No. of firms		Equality of Dns.		Diff. favourable to firms with $R > 8\%$	
	$\%R \leq 8\%$	$\%R\, 8\%$	Statistic	p-value	Statistic	p-value
			Small & Medium Sized Firms			
1992	346	705	0,098	0,038	0.008	0,946
1993	357	652	0,093	0,044	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			
1992	224	274	0,051	0,914	-	-
1993	224	197	0,058	0,888	-	-
1994	194	205	0,094	0,041	0,127	0,924
1995	180	198	0,169	0,000	0,011	0,980
1996	176	174	0,144	0,000	0,033	0,840
1997	180	202	0,097	0,037	0,037	0,793
1998	175	192	0,098	0,038	0,042	0,704
1999	176	168	0,092	0,047	0,049	0,667
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	0,004	0,008	0,987
2003	175	139	0,118	0,006	0,002	0,998
2004	157	154	0,110	0,005	0,008	0,967
2005	192	209	0,135	0,004	0,009	0,985

Notes: Firms' TFP measured using the TFP index, $\tilde{a}$, defined in equation (3.5).

Table 4. Descriptive statistics of the sample

	Mean	S.D.
Average TFP growth 1992-1995 (in percent)	1.60	—
Average TFP growth 1996-2000 (in percent)	1.56	—
Average TFP growth 2001-2005 (in percent)	0.40	—
Average change in share of temp workers 1992-1995	1.53	—
Average change in share of temp workers 1996-2000	−1.12	—
Average change in share of temp workers 2001-2005	−1.08	—
Average conversion rate 1992-1995	12.55	—
Average conversion rate 1996-2000	12.78	—
Average conversion rate 2001-2005	10.30	—
Percentage of temporary workers	22.99	22.85
Percentage of foreign capital	16.87	35.73
Percentage of workers with a college degree	4.05	6.78
$R\&D$ Expenditure / Sales (in percentage)	0.69	2.2
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	11.4
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

Source: ESEE (1991-2005)

Table 5. First-stage estimates

	[1]	[2]
$F_1 * t_{w-1}$	0.133^{***}	0.141^{***}
	[0.036]	[0.034]
$F_2 * t_{w-1}$	0.109^{***}	0.115^{***}
	[0.031]	[0.030]
$F_3 * t_{w-1}$	-0.053	-0.051^{**}
	[0.025]	[0.024]
$F_4 * t_{w-1}$	—	0.007
		[0.015]
No. obs.	15792	15792
Partial R-squared	0.46	0.45

Notes: S.e's in brackets. Estimation method: OLS. Additional regressors: IVs in Table 6; * significant at 10%, ** at 5%, *** at 1%.

Table 6. System-GMM estimates of determinants of firms' TFP

Variables	[1]	[2]	[3]
Conversion rate in t	0.123***	0.119***	0.120***
	[0.026]	[0.024]	[0.024]
Proportion of temporary workers in $t-1$	−0.028	—	—
	[0.022]	—	—
(logged) TFP in $t-1$	0.340***	0.315***	0.321***
	[0.059]	[0.057]	[0.050]
Proportion of workers with college degree in $t-1$	0.027*	0.050**	0.051**
	[0.016]	[0.023]	[0.025]
R&D Expenditure (logged) in $t-1$	0.003***	0.003***	0.003***
	[0.001]	[0.001]	[0.001]
Proportion of public capital in $t-1$	0.005	0.004	0.04
	[0.005]	[0.004]	[0.004]
Proportion of foreign capital in $t-1$	0.012***	0.012***	0.012***
	[0.004]	[0.004]	[0.004]
Incorporated company in $t-1$	−0.014	−0.022	−0.023
	[0.027]	[0.017]	[0.021]
Age	0.026	0.031**	0.032**
	[0.019]	[0.015]	[0.015]
Age Sq.	−0.001	−0.001	−0.004
	[0.003]	[0.002]	[0.003]
No. obs.	15792	15792	15792
Partial R-squared	0.93	0.92	0.94
Sargant Test			
$m1$ Test (p-value)	0.023	0.031	0.017
$m2$ Test (p-value)	0.392	0.315	0.517

Notes: S.e's in brackets. Estimation method: System GMM: Dependent variable, (logged) TFP. Additional regressors: Industry, Size, Year, Entry, Exit, Merger and Scission dummies; IVs are second lags (except for size, age and its square) in column [1] plus reform dumies interacted with $tw_{i,t-1}$ in columns [2] and [3]; * significant at 10%, ** at 5%, ****

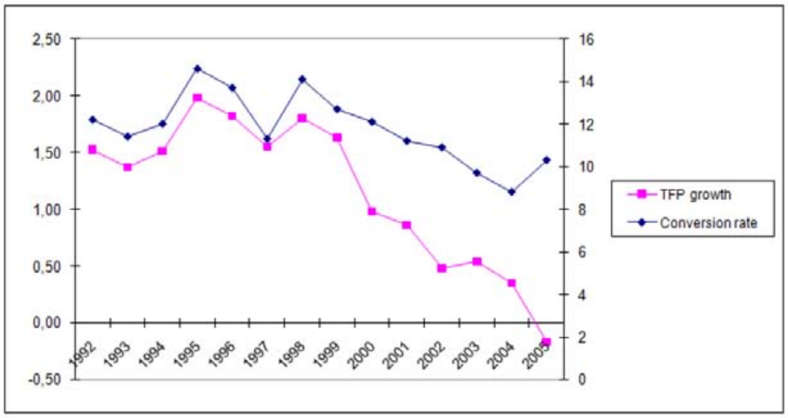

Figure 1: Weighted averages of conversion rates and firms' TFP growth rates (ESEE, 1992-2005).

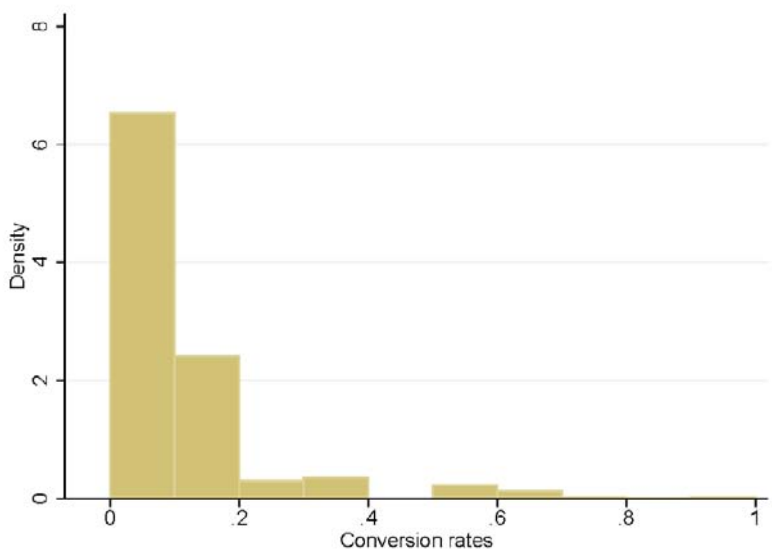

Figure 2: Weighted averages of conversion rates and firms' TFP growth rates (ESEE, 1992-2005).

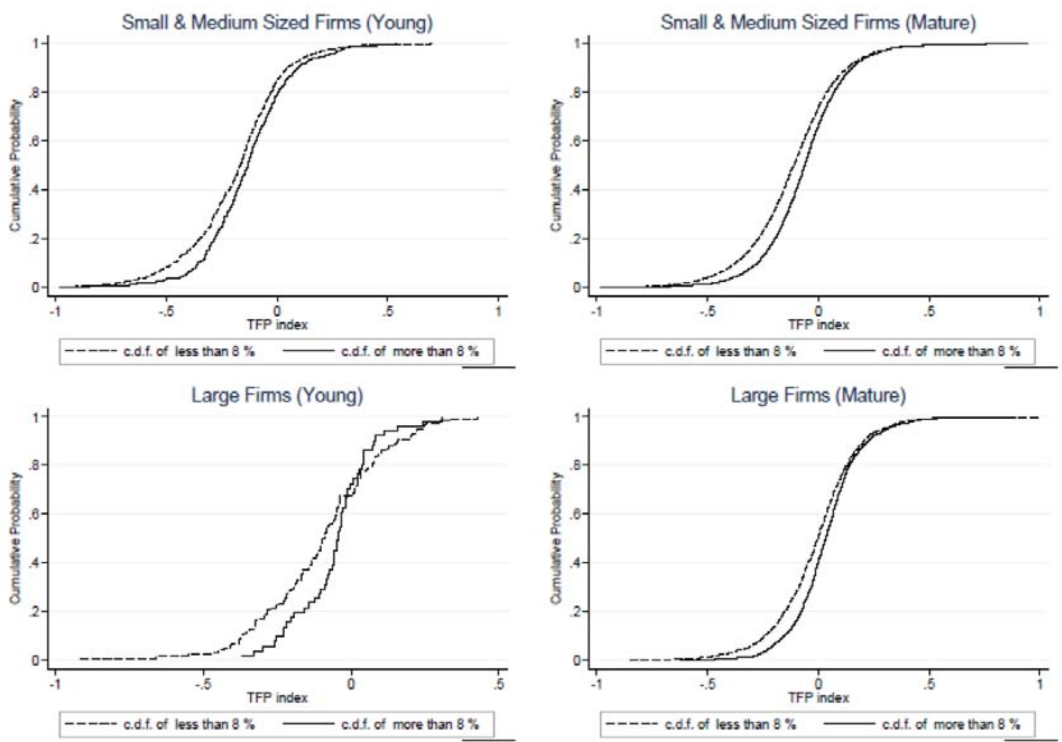

Figure 3: C.d.fs of conversion rates and firms' TFP by size and age. Firms' TFP measured using the TFP index, $\tilde{a}$, estimated by Levisohn and Petrin's (2003) approach; conversion rates are obtained from ESEE.

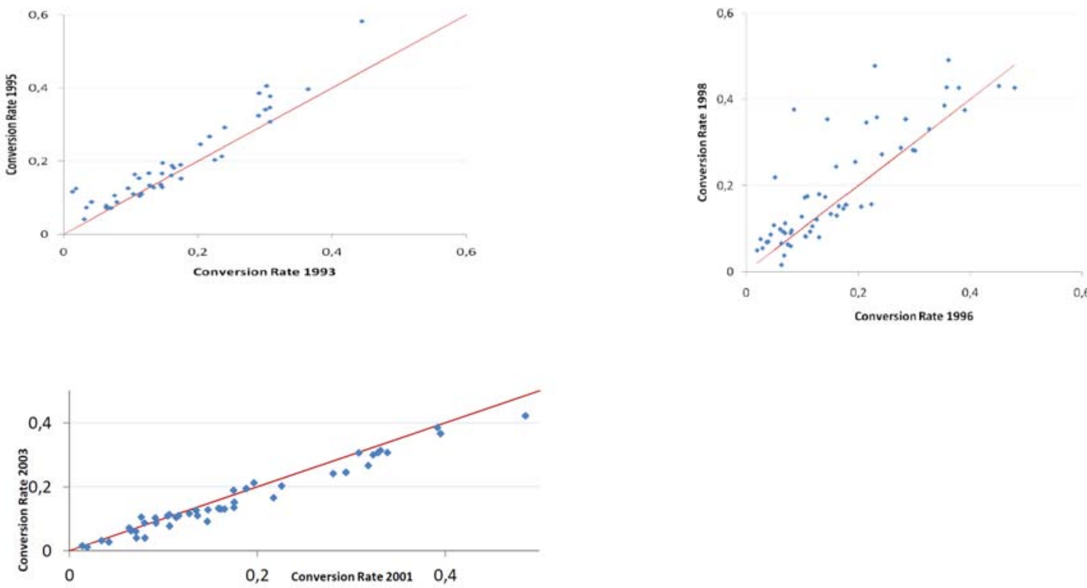

Figure 4: Conversion rates before and after 1994, 1997 and 2002 EPL reforms.

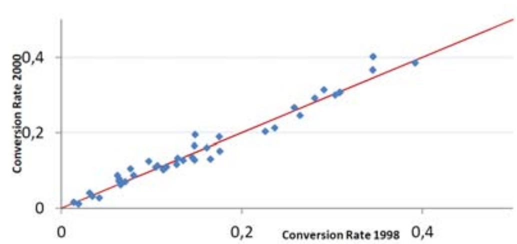

Figure 5: Conversion rates before and after 1999 when there was no reform.