HIGH GROWTH FIRMS IN EMPLOYMENT AND PRODUCTIVITY: DYNAMIC INTERACTIONS AND THE ROLE OF FINANCIAL CONSTRAINTS

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Abstract

Using a panel of Spanish firms over the period 2002-2012, we investigate the interactions between high growth episodes in terms of size and productivity. We find that high growth in productivity (size) increases the likelihood of high growth in size (productivity). However, the effect from size to productivity is smaller than the effect from productivity to size. We also explore the potential role of firm-level financial constraints using information from the Central Credit Register (CIR) of Banco de España. Our results indicate that credit constraints hamper high growth episodes in terms of both size and productivity.

Keywords: high-growth firms, high-impact firms, productivity, panel firm-level data.

JEL classification: L25, L11, D24, C23.

Resumen

En este artículo se investigan las posibles interacciones entre episodios de alto crecimiento de las empresas en tamaño y en productividad, utilizando un panel de empresas españolas que comprende el período 2002-2012. Encontramos que alto crecimiento en productividad (tamaño) incrementa las posibilidades de tener alto crecimiento en tamaño (productividad). Sin embargo, el efecto de tamaño a productividad es menor que de productividad a tamaño. Además, exploramos el posible papel desempeñado por las restricciones financieras a nivel de empresa, utilizando información procedente de la Central de Información de Riesgos (CIR) del Banco de España. Nuestros resultados sugieren que las restricciones financieras dificultan los episodios de alto crecimiento tanto de empleo como de productividad.

Palabras clave: empresas de alto crecimiento, empresas de alto impacto, productividad, datos de panel a nivel empresa.

Códigos JEL: L25, L11, D24, C23.

1 Introduction

Since the seminal work of David Birch (1979, 1981, 1987), there is consensus in the literature that a few rapidly growing firms (also termed *gazelles*) are responsible for most of the employment growth in the economy. Also, it is believed that these firms might be relevant for structural change in the economy (Acs et al., 2008; Henrekson and Johansson, 2010). As a result, policymakers have focused their efforts on targeting and supporting high growth firms (HGF). This is particularly the case in Europe, where HGFs have become a central figure of the public policy agendas given the weak firm and employment dynamics in comparison with other advanced economies (Bartelsman et al., 2005). For instance, the Europe 2020 strategy explicitly mentions the support of high growth small and medium-sized enterprises (SMEs) as a public policy target (Commission, 2010) while OECD (2010) call for governmental initiatives to foster the creation of more high-growth firms.

However, while much is known about the importance of fast-growing firms for job creation, not much is known about their contribution to aggregate productivity, partly due to the lack of widely available firm-level data. On the other hand, while theoretical predictions around the relationship between firm growth and productivity are contradictory, with arguments in favor of firm growth affecting productivity (Penrose, 1959; McCombie, 1987) as well as productivity triggering firm growth ("growth of the fitter")(Alchian, 1950; Metcalfe, 1994), empirical studies analyzing the relationship between high growth episodes in productivity and high growth episodes in size are scarce (see Section 2). In this paper, we aim to fill this gap.

In studying the determinants of firm's size and productivity (high) growth[1], there is wide consensus that access to external finance, as well as the firm's financial condition, should not be absent from the analysis, specially because they can be endogenous to size and productivity growth. The availability of firm-level data on outstanding credit and loan applications in the domestic banking sector from the Central Credit Register (CIR) of Banco de España allows us to investigate the role of access to credit as a determinant of firm's size and productivity (high) growth. We believe the Spanish economy provides an ideal setting to analyze this issue, given that Spanish firms rely on bank credit more than their counterparts in most advanced economies. According to the "Survey on the Access to Finance of Enterprises(SAFE), jointly conducted by the ECB and the European Commission between September and October 2015, 30% of surveyed firms in Spain declared some sort of financial constraint, that is, either the firm's application for a bank loan was denied (9%), or the firm received less than the requested amount (20%), or the firm refused the loan offer because the rate was too high

[1]Despite their aggregate importance, focusing on HGF when analyzing growth determinants is only justified if the effects of covariates are non-linear. This is indeed our case: Our results change dramatically when high growth is replaced by continuous growth. This is particularly true in the case of employment, where almost all covariates turn non-significant.

(1%). Furthermore, 6% did not apply for a bank loan because they feared a rejection. These figures are specially significant, given that 65% of Spanish surveyed firms chose bank loans as their most preferred type of external financing when it comes to back firm's growth.[2]

The contribution of this paper is twofold. First, it extends the still scarce empirical literature on the firm growth–productivity nexus, with a focus on the so-called high growth firms (HGF). For that purpose, we define two types of fast-growing firms: *HGFs in employment* (ten percent of firms exhibiting the highest employment growth indicator[3] within the same 2-digit industry in a given year), and *HGFs in (labor) productivity* (ten percent of firms with the highest annual growth rate in labor productivity within the same 2-digit industry). We then estimate the dynamic interdependencies underlying the relationship between productivity and employment high growth episodes. Second, this paper sheds light on whether financial constraints constitute a relevant factor inhibiting firm growth and productivity increases among Spanish firms. To do so, we create a variable proxying for the extent to which a firm's access to external finance is constrained, on the basis of information on its loan applications and current credit exposures. This information is taken from the *Central Credit Register* maintained by the Banco de España.

Turning to identification, we aim to give a causal interpretation to our estimates by departing from the strict exogeneity assumption present in OLS and Within Groups estimates, whereby feedback from the dependent variable to the right-hand-side variables is not allowed (see Section 5 for more details). For that purpose, we consider panel GMM estimators advanced by Holtz-Eakin et al. (1988) and Arellano and Bond (1991), which allow for feedback effects from current high growth status to subsequent high growth episodes and financial constraints.

According to our results, high growth episodes in productivity significantly increases the likelihood of subsequent high growth episodes in terms of size. Depending on the specification, a firm experiencing a high growth episode in productivity has a probability between 1.5 and 2.2 percentage points higher of experiencing a subsequent high growth episode in size. Given our definition of high growth firms (see Section 4.2.1), the absolute probability of high growth is 10% so the magnitude of our estimated effects is sizable. In contrast, the estimated effects from high growth in size to high growth in productivity range from -0.3 to 1.0 percentage points depending on the specification. We thus conclude that feedback from productivity growth to size growth is more important than the effect from size to productivity growth.

[2] Concretely, surveyed firms were asked (question 20): "If you need external financing to realise your growth ambitions, what type of external financing would you prefer most?" The available answers were: a) bank loan, b) loan from other sources, c) equity investment, d) other.

[3] In particular, we use the Birch-Schreyer index, which is a composite measure of relative and absolute growth. See section 4.2.1 for further details.

On the other hand, our results also indicate that credit constraints hamper high growth episodes in terms of both size and productivity. Firms with all loan applications rejected in a given year are expected to have a lower probability of high growth episodes in subsequent years. For instance, these firms present a 2.3-2.7 percentage points lower probability of experiencing a high growth size episode than firms with at least one loan application approved by a new bank. This figure ranges from 1.3 to 1.9 percentage points depending on the specification in the case of high growth in productivity.

The rest of the paper is organized as follows. Section 2 briefly reviews the related literature. Section 3 develops a simple theoretical framework aimed at providing some key insights about our specification assumptions and empirical results. Section 4 goes over the details and characteristics of the two main databases used to build our final dataset. A description of the cleaning process of the data and the main features of the sample, including its representativeness, is contained in subsection 4.1. On the other hand, the set of explanatory variables are covered in subsection 4.2, with a focus on how high growth firms are defined in this paper, as well as how do we proxy for financial constraints using data on firm's credit exposure and loan requests. Section 4.3 describes the contribution of HGFs to aggregate productivity growth and job creation in Spain. The empirical specification and the econometric approach are explained in detail in section 5. Finally, section 6 contains estimation results and their discussion, and section 7 concludes.

2 Related Literature

Research on the economic importance of fast-growing firms as job creators has been vastly studied since Birch's seminal work (see Henrekson and Johansson (2010) and Moreno and Coad (2015) for a review of this literature). Although extant studies differ in the way high growth firms are defined (see section 4.2.1), and thus comparability of results is limited, they all coincide in pointing out the disproportionately large share of new net jobs attributable to a few rapidly growing firms.

In contrast to this clear-cut result regarding employment creation, the incidence of these HGFs in boosting aggregate productivity is not that clear. The few empirical studies explicitly addressing the role of productivity among HGFs yield contradicting results (see the review by Bartelsman and Doms (2000) and a discussion of the topic in Coad (2007)). On the one hand, in a research commissioned by the US Small Business Administration, Acs et al. (2008) compared the productivity level (measured as revenue per employee) between high– and low–impact firms[4]. On average, high–impact firms exhibit productivity levels 33% higher than their low–impact counterparts, and this gap seems to be increasing over time. A

[4]Acs et al. (2008, p.1) define a high-impact firm as "an enterprise with sales that doubled over the most recent four-year period and a [Birch-Schreyer Index] of two or more over the same period".

similar study conducted by the UK Department for Business Enterprise & Regulatory Reform (BERR, 2008) also finds that HGFs (Eurostat-OECD definition[5]) show above-average labor productivity levels (see also Mason et al. (2014)). On the other hand, Bottazzi et al. (2002) and Foster et al. (2001) fail to find a robust correlation between labor productivity and firms' growth. In this line, Baily et al. (1996) observe that downsizing firms contribute to aggregate labor productivity growth as much as firms increasing employment, and that the remaining unexplained growth is attributable to entry and exit processes.

From the discussion above, it follows that the joint dynamics of productivity and firm growth are not well understood. Some authors highlight the potential feedback effects that high growth in one economic dimension (such as sales or employment) may have on productivity, and vice versa. Using firm-level data from Sweden, Daunfeldt et al. (2014) define HGFs as the one percent of firms with the highest growth (over a 7-year period) in terms of labor productivity (value added per employee), employment, sales and value added. Their analysis shows very low (contemporaneous) correlations between HGFs defined in terms of labor productivity and their employment counterparts. Furthermore, HGFs in productivity contribute negatively to aggregate employment growth, whilst employment HGFs exhibit a small negative contribution to aggregate productivity growth, suggesting the existence of a short-term trade-off between both economic dimensions.

Unlike Daunfeldt et al. (2014), Du and Temouri (2015) focus on non-contemporary links between HGF status and productivity growth to conclude that the HGF experience is a "self-reinforcing process". In particular, Du and Temouri (2015) apply, to a sample of UK firms, a modified version of the Eurostat-OECD definition of HGF, using firm sales, rather than employment, as growth indicator. Controlling for firm characteristics (e.g., age, size, average wage, exporter status, etc.), their analysis yield two interesting results: first, being a HGF leads to subsequent higher TFP growth rates, and second, firms with higher TFP growth are more likely to experience fast growth in sales. Finally, Coad and Broekel (2012) focus on the dynamics underlying the firm growth – productivity nexus by means of reduced-form VARs. Their findings suggest that employment growth is associated with a subsequent decrease in total factor productivity (TFP), whereas increases in TFP growth are not followed by much employment growth.

In a recent paper, Moral-Benito (2016) considers high growth episodes in terms of employment and total factor productivity as treatment variables, and TFP growth and employment growth as outcome variables. To be more concrete, the baseline specification considers high-growth episodes as those firm-year pairs in which the growth rate is above 10%. Using

[5]The Eurostat-OECD definition identifies high growth firms as "All enterprises with average annualized growth in employees or turnover greater than 20% per annum, over a three year period, and with more than 10 employees in the beginning of the observation period" (Eurostat-OECD, 2007)

matching methods, he finds that high-productivity growth is followed by statistically significant increases in employment, while high-employment growth is not followed by subsequent gains in productivity.

Our paper also relates to studies on the role of financing constraints as obstacles for firm growth. Both theoretical and empirical evidence show that financial constraints negatively affect firm size and growth dynamics (Bottazzi et al., 2014; Cooley and Quadrini, 2001; Fagiolo and Luzzi, 2006), and that this effect is more pervasive for younger and smaller firms (Angelini and Generale, 2008; Cabral and Mata, 2003; Beck et al., 2006). This trend is grounded on two stylized facts in the corporate finance literature: first, the degree of informational opacity of small and young firms exacerbates the informational wedge between these firms and suppliers of finance, making them more prompt to be financially constrained (Stiglitz and Weiss, 1981; Berger and Udell, 1998); second, small firms face greater financial, legal, and corruption obstacles compared to large firms, and the constraining impact of these obstacles on firm growth is inversely related with firm size (Beck et al., 2005).

Additionally, our paper adds to the still scarce literature on the effect of financial constraints on employment. While there is wide consensus that financial constraints can have a significant impact on firms' decisions, such as those affecting investment (Fazzari et al., 1988; Bond et al., 2003; Campello et al., 2010), working capital (Fazzari and Petersen, 1993), R&D spending (Hall, 2002; Brown et al., 2009), and on-the-job training (Popov, 2014), little is known about their effect on firms' demand for labor. The reason for this is twofold: on the theoretical side, it is difficult to justify why labor demand would fall after a credit shock since, in principle, firms could minimize the impact of the shock on employment by reducing wages, or replacing capital with labor. On the empirical side, endogeneity concerns and data limitations have made it difficult to trace the effect of credit supply shocks to firm–level real decisions and outcomes.

Most of the empirical studies analyzing the effect of credit supply shocks on employment have exploited differences in lender health at the onset of the financial crisis of 2007–2009, as an exogenous source of variation in firms' availability of credit. Duygan-Bump et al. (2015) show that during the Great Recession small firms in sectors identified as highly dependent on external finance, in the spirit of Rajan and Zingales (1998) work, were significantly more likely to lay off workers than large firms in the same industries. By contrast, there were no significant differences in the unemployment rates of small and large firms in sectors with low external financial dependence. Greenstone et al. (2014) construct an indirect measure of credit supply shocks at the county-level, using the product of the change in banks' nationwide lending to small business and their market share at the county level. Matching this with microdata from the U.S. Census Longitudinal Business Database (LBD), they show that decreases in their proxy of credit supply are associated with reductions in county-level lending to small establishments and their employment levels over 2008-2009. However, this effect is rather small: a one standard deviation drop in the 2009 predicted credit supply shock accounts for 0.6 p.p. decrease in small business employment in the following year. Chodorow-Reich (2014) assembles a new dataset that matches loan-level data from the Dealscan syndicated loan database with the employment records from the confidential version of the U.S. Census LBD. This enables him to construct a firm-specific measure of financial constraints equal to the weighted average of the post-crisis reduction in the quantity of loans made by the firm's last pre-crisis syndicate to other borrowers[6]. Similar to Greenstone et al. (2014), he finds that firms engaged with weaker banks before the crisis faced higher financing restrictions than borrowers of healthier banks, and this translated into comparatively bigger employment losses (of about 4 - 5 pp) among the former relative to the latter. Moreover, he attributes between one-third and one-half of job losses at small and medium firms over this period to the shortage of credit. Benmelech et al. (2011) reach similar conclusions exploiting two different quasi-experiments: first, the state unemployment rate dropped by 0.7 p.p. following the introduction of state-level bank deregulation laws, that removed restrictions on both intrastate and interstate bank branching; conversely, unemployment increased by about 1 p.p. in local areas where U.S. affiliates of Japanese banks reduced lending, following the real estate price decline in Japan during the 1990s (and the subsequent erosion of Japanese bank balance sheets).

More recently, Bentolila et al. (2016) and Popov and Rocholl (2016) assess the impact of the credit crunch in Spain and Germany, respectively, on firm-level labor decisions, using again lender health variation at the onset of the crisis as an exogenous credit shock. Bentolila et al. (2016) provide evidence that firms with a relatively large pre-crisis exposure to weak banks experienced larger job cuts (of a magnitude of between 3.2 and 6.2 pp depending on the estimation method) than at non-exposed firms. This would explain around one-fourth of aggregate job losses at exposed firms. Moreover, they conclude that firm's credit history and the number and intensity of its bank relationships are key factors influencing the estimated real effects of credit constraints. In line with Bentolila et al. (2016), Popov and Rocholl (2016) also finds significant declines in employment and wages after the start of the financial crisis among firms that had a credit relationship with at least one affected bank (i.e., public German banks with large exposures to the U.S. subprime mortgage market). Interestingly, the decline in employment induced by the credit supply shock imposed by affected banks on its clients is increasing with firm size, whereas the decline in average labor compensation decreases with firm size. This suggest that smaller firms face higher firing costs, and thus are more likely to adjust to the shortage of credit by cutting on wages rather than with job cuts.

[6]His methodology relies on two assumptions: first, switching from banks that restricted lending to more healthy banks has a cost (i.e., borrower-lender relationships are sticky), and second, banks' health during the crisis is uncorrelated with pre-crisis borrowers' characteristics. The latter makes it possible to use the dispersion in lender health during the 2008-09 crisis as a source of exogenous variation in the availability of credit to borrowers.

3 Theoretical Framework

In this section, we develop a simple theoretical model in order to guide and discipline our empirical exercises as well as to rationalize our main findings.

There is ample literature rationalizing the mechanisms through which financial constraints may affect firm growth (Duygan-Bump et al., 2015; Bottazzi et al., 2014; Campello et al., 2010). However, little is known about the theoretical underpinnings of the relation between financial constraints and productivity. This is the main objective of the model. Moreover, the model also serves to illustrate a particular mechanism that rationalizes the dynamic interactions between high growth in employment and productivity. Finally, the model is also useful to better characterize gazelles as high performance firms, by identifying and excluding some specific cases that could end in high growth without good performance.

3.1 Basic setup

The model is populated by a large set of firms which take output and input prices as given and live forever. They all face a standard CES production function (Eq. 1), but can differ in the specific values of the parameters α, ρ and ν (see Table 1 for a description of these parameters). Each period, firms receive a known and exogenous productivity shock A_{it}.[7] All the realizations of the productivity shock come from a common and stable distribution, and are independent both between firms and across time.

$$f(K,L) = A_{it}\left(\alpha K_{it}^{\rho} + (1-\alpha)L_{it}^{\rho}\right)^{\frac{\nu}{\rho}}, \text{ with} \begin{cases} \nu \in (0,1) \\ \alpha \in (0,1) \\ \rho \in (-\infty,1) \end{cases} \tag{1}$$

For simplicity, we assume that the problem is solved statically.[8] Also, we model financial constraints as a limit to capital growth, which cannot exceed a certain growth rate each period. Finally, we assume capital investments are not refundable, so there is a lower bound to the

[7] The model hence incorporates some sort of total factor productivity (TFP) shock. However, we focus on labor productivity both here and in the empirical work. The reason is twofold: (i) TFP is exogenous in the model so that it cannot be affected by e.g. financial constraints in theory; (ii) TFP is difficult to measure empirically. We therefore use labor productivity in the empirical section so that we also focus here on the theoretical predictions for labor productivity.

[8] The maximization problem itself has little dynamic elements. Basically, the unique intertemporal element is the effect of K_{it} on the shadow prices of the constraints in $t+1$. We nonetheless abstract from this effect. One possible interpretation is that firms' choices are made by managers, who are mainly worried about the current profits of the firm.

amount of capital a firm can have, equal to the previous capital net of depreciation. Under these assumptions, the maximization problem can be stated as:

$$
\begin{aligned}
\max_{K_t, L_t} \quad & P_{it}A_{it}\left(\alpha K_{it}^{\rho} + (1-\alpha)L_{it}^{\rho}\right)^{\frac{\nu}{\rho}} - r_t K_{it} - w_t L_{it} \\
\text{s.t.} \quad & \delta K_{it-1} \leq K_{it} \leq \varepsilon K_{it-1} \\
& \delta \in (0,1) \\
& \varepsilon > 1
\end{aligned}
\tag{2}
$$

The interior solution to this problem is straightforward, and can be summarized in the following equations:

$$
\widehat{K}_{it} = \left(\frac{\alpha}{r_t}\right)^{\frac{1}{1-\rho}} (\nu P_{it} A_{it})^{\frac{1}{1-\nu}} \left(\left(\frac{\alpha}{r_t}\right)^{\frac{1}{1-\rho}} + \left(\frac{1-\alpha}{w_t}\right)^{\frac{1}{1-\rho}}\right)^{\frac{\nu-\rho}{\rho(1-\nu)}} \tag{3}
$$

$$
\widehat{L}_{it} = \left(\frac{1-\alpha}{w_t}\right)^{\frac{1}{1-\rho}} (\nu P_{it} A_{it})^{\frac{1}{1-\nu}} \left(\left(\frac{\alpha}{r_t}\right)^{\frac{1}{1-\rho}} + \left(\frac{1-\alpha}{w_t}\right)^{\frac{1}{1-\rho}}\right)^{\frac{\nu-\rho}{\rho(1-\nu)}} \tag{4}
$$

$$
\frac{\widehat{y}_{it}}{\widehat{L}_{it}} = \frac{1}{\nu P_{it}} \left(\left(\frac{\alpha}{r_t}\right)^{\frac{1}{1-\rho}} + \left(\frac{1-\alpha}{w_t}\right)^{\frac{1}{1-\rho}}\right) \left(\frac{w_t}{1-\alpha}\right)^{\frac{1}{1-\rho}} \tag{5}
$$

These last equations show an interesting result: labor depends positively on total factor productivity (A_{it}), but labor productivity does not. This is a direct consequence of two of our assumptions: perfect competition and decreasing returns to scale. Under them, more productive firms will increase their size until decreasing returns end up compensating for their higher productivity, because they all face the same prices.

When the interior solution for capital ($\widehat{K}_{it}$) lies between the two constraints, then equations (3), (4) and (5) are the solution to the problem stated in (2). On the contrary, when the financial constraint is binding ($\widehat{K}_{it} > \varepsilon K_{it-1}$), the solution to (2) is to choose $K_t^* = \varepsilon K_{it-1}$ and obtain L_{it} from:

$$
\max_{L_t} \quad P_{it}A_{it}\Big(\alpha(\varepsilon K_{it-1})^{\rho} + (1-\alpha)L_{it}^{\rho}\Big)^{\frac{\nu}{\rho}} - r_t \varepsilon K_{it-1} - w_t L_{it} \tag{6}
$$

First order conditions for this problem are:

$$
\frac{\nu}{\rho} P_{it}A_{it}\Big(\alpha(\varepsilon K_{it-1})^{\rho} + (1-\alpha)L_{it}^{\rho}\Big)^{\frac{\nu-\rho}{\rho}} (1-\alpha)\rho L_{it}^{\rho-1} = w_t \tag{7}
$$

Similarly, if the non-revertible capital constraint is binding, then the solution is $K_t = \delta K_{it-1}$ and obtain L_{it} from:

$$\underset{L_t}{\text{Max}} \quad P_{it}A_{it}\left(\alpha(\delta K_{it-1})^{\rho} + (1-\alpha)L_{it}^{\rho}\right)^{\frac{\nu}{\rho}} - r_t\delta K_{it-1} - w_t L_{it} \tag{8}$$

With similar FOC:

$$\frac{\nu}{\rho}P_{it}A_{it}\left(\alpha(\delta K_{it-1})^{\rho} + (1-\alpha)L_{it}^{\rho}\right)^{\frac{\nu-\rho}{\rho}}(1-\alpha)\rho L_{it}^{\rho-1} = w_t \tag{9}$$

In both cases, the corner solution cannot be obtained analytically. We present below a simulation solving the problem numerically[9] for a large set of firms.

In any event, one can get some insights about the problem by looking at FOC of the corner solution under extreme parameter values. In particular, if $\rho \longrightarrow 1$, equation (7) tends to:

$$\nu P_{it}A_{it}\left(\alpha\,\varepsilon\,K_{it-1} + (1-\alpha)L_{it}\right)^{\nu-1}(1-\alpha) = w_t \tag{10}$$

And therefore labor productivity tends to:

$$\frac{y_{it}^*}{L_{it}^*} \longrightarrow \frac{(1-\alpha)A_{it}\left(\dfrac{\nu P_{it}A_{it}(1-\alpha)}{w_t}\right)^{\frac{\nu}{1-\nu}}}{\left(\dfrac{\nu P_{it}A_{it}(1-\alpha)}{w_t}\right)^{\frac{1}{1-\nu}} - \alpha\varepsilon K_{it-1}} \tag{11}$$

This last equation illustrates an important result: labor productivity is increasing in ε (the financial constraint parameter), which means that, if capital and labor are close to substitutes ($\rho \longrightarrow 1$), then labor productivity is higher if financial constraints are eased. The intuition is simple: imagine a firm that receives a large positive shock in A_{it}; the firm finds optimal to increase its capital stock but since the financial constraint is binding the firm reacts by using labor to grow instead; as a result, labor productivity decreases. Had this firm faced looser financial constraints, then the firm would have used a capital-labor mix more intensive in capital, and hence its productivity would have been higher.

Turning to the simulation for different parameter values, we populate the model with $200,000$ firms, and simulate them through 35 periods. Each firm gets an independent random draw of each parameter ρ, α, ε and ν, which is invariant for the whole life of the firm. Also, they receive a shock A_{it} in each period. These shocks are independent both across firms and along time. All the distributions used to pick the random draws are summarized in Table 1. We also assume that all prices P_{it}, w_{it} and r_{it} to be constant and equal to 1. Initial capital is fixed as the interior solution for period $t = 1$. We nevertheless run the model for another 34 periods just to ensure that all firms had the opportunity to converge to a desired steady state capital stock. Then we use only the last period to analyze the results of the simulation.

[9] In particular, we use Newton–Raphson algorithm to solve for L_{it}^* in equations (7) and (9), using the interior solution ($\widehat{L}_{it}$) as the initial guess.

Table 1: Parameters Distributions

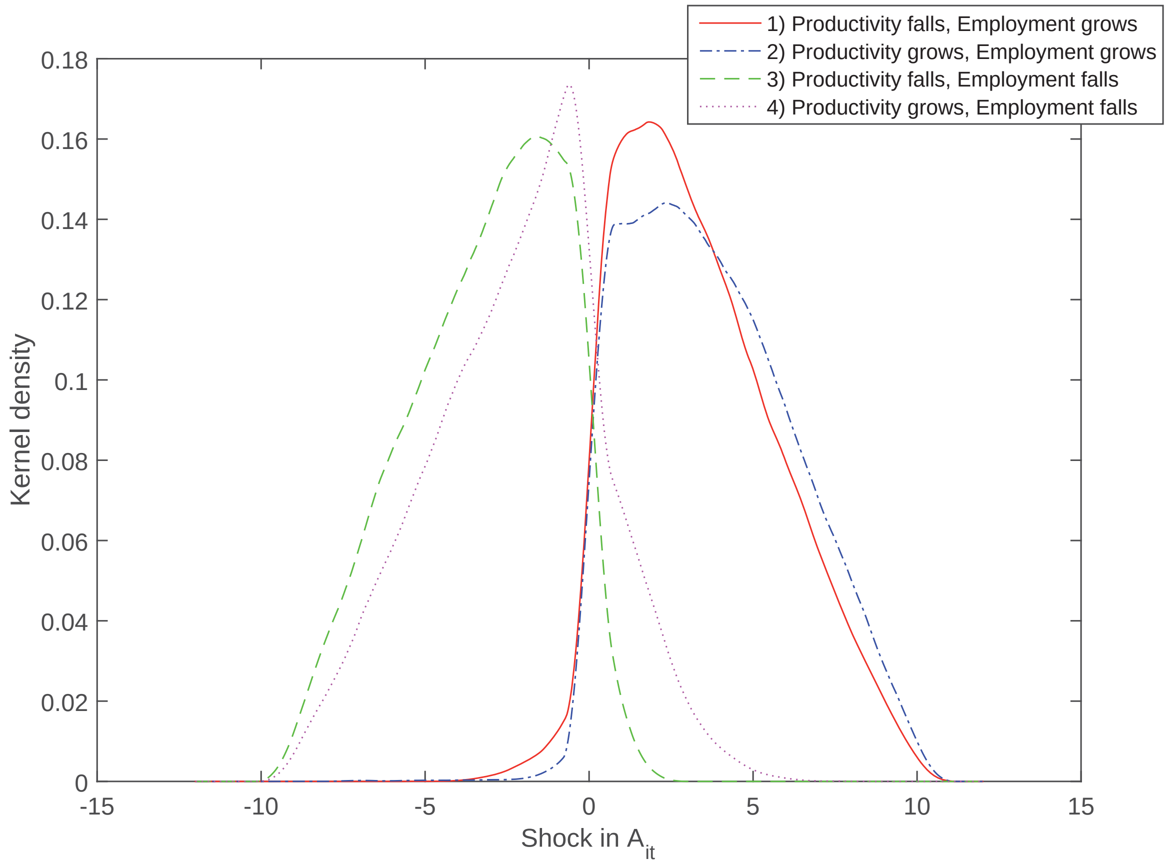
Parameter	Description	Distribution
ν_i	Returns to scale parameter	Uniform (0.7, 0.9)
α_i	Capital intensity in production	Uniform (0.2, 0.6)
ε_i	Limit on capital growth	Uniform (1.05, 1.35)
ρ_i	Elasticity of substitution	Normal $(1, 1.4815)$, folded to the left[1]
A_{it}	Efficiency in production	Uniform (0.95, 1.05)
δ	Capital depreciation	0.95 (constant)
r_{it}	Price of one unit of capital	Normalized to 1
w_{it}	Price of one unit of labor	Normalized to 1
P_{it}	Price of selling goods	Normalized to 1

[1] Domain: $(-\infty, 1]$. The standard deviation chosen for the distribution of ρ is such that half of the population of firms will have a $\rho > 0$ (substitutability) and the other half will have a $\rho < 0$ (complementarity).

3.2 Implications for gazelles definition

The first result we want to illustrate is plotted in Figure 1. The graph includes a density function of actual shocks A_i faced by firms, dividing them into four groups, depending on positive or negative labor productivity and employment growth. Two of these four densities have a clear mass on positive values, while the opposite is true for the other two. One of the positive densities (not surprisingly) is the set of firms with positive growth in both variables. These are firms reacting to a positive shock by increasing employment, but not very fast, so at the end labor productivity is still increasing. The other set of firms receiving mostly positive shocks also react by increasing employment, but much faster than the other group, so for this set labor productivity even falls as a result of the positive TFP shock. On the other side of the graph, firms facing negative shocks always react by reducing employment. But some of them reduce it so fast that labor productivity even increases after the bad shock. To get this result, the assumption of non-reversibility of capital investments is crucial: after a very bad shock, a firm wants to react by reducing size, but with some optimal capital-labor mix. For firms hitting the non-reversibility constraint, this is not feasible, so they react by further reducing labor, hence increasing the capital labor ratio, and with it, labor productivity. We found this feature also in the data, and that's the reason we impose an additional non-negative employment growth constraint to our productivity gazelles definition (see section 4.2.1).

Figure 1



3.3 Implications for the role of financial constraints

Another goal of the model is to better understand the role of financial constraints on employment, and especially, labor productivity growth. For this purpose, we take our simulation and construct a new, alternative period 35, which is the same as the previous period 35, but now with an additional easing of the financial constraint parameter ε.[10] We then compare this new period 35 with the previous period 35. The difference can be interpreted as the differential behavior of firms had the financial constraints been looser.

Starting with employment growth, Figure 2 plots the difference,[11] conditional on two key parameters: the share of capital in production function (α), and the degree of substitutability (ρ). The result is that all firms increase employment as a result of less intense financial constraints, but the increase is higher for firms with low ρ (i.e, high degree of complementarity). This indicates that these firms have now the opportunity to increase their capital stock, and the higher is the complementarity, the more employment they need to complement the capital increase.

[10] In particular, ε is increased by 0,10. Only firms already constrained in $t = 35$ are included.

[11] Note that in this and subsequent figures, the position of axis and scale are changed for expositional purposes, given the 3D nature of the graph.

Figure 2

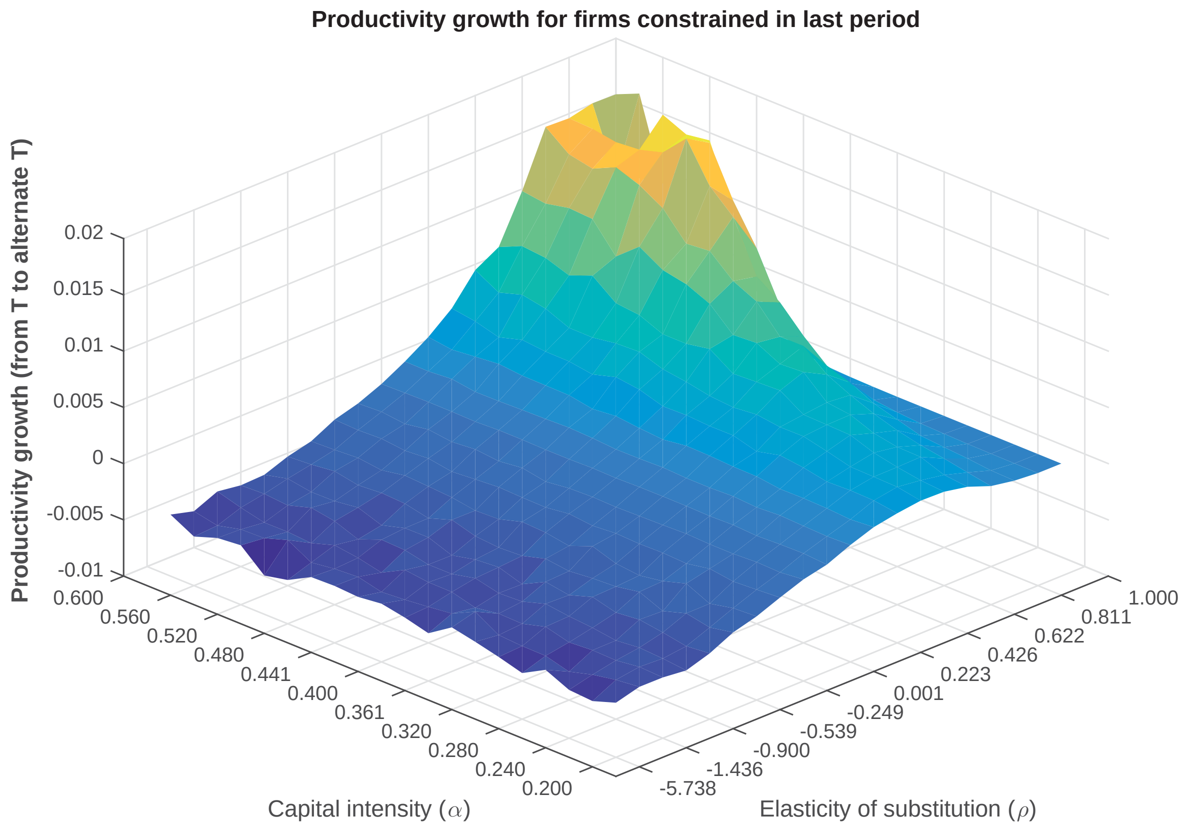
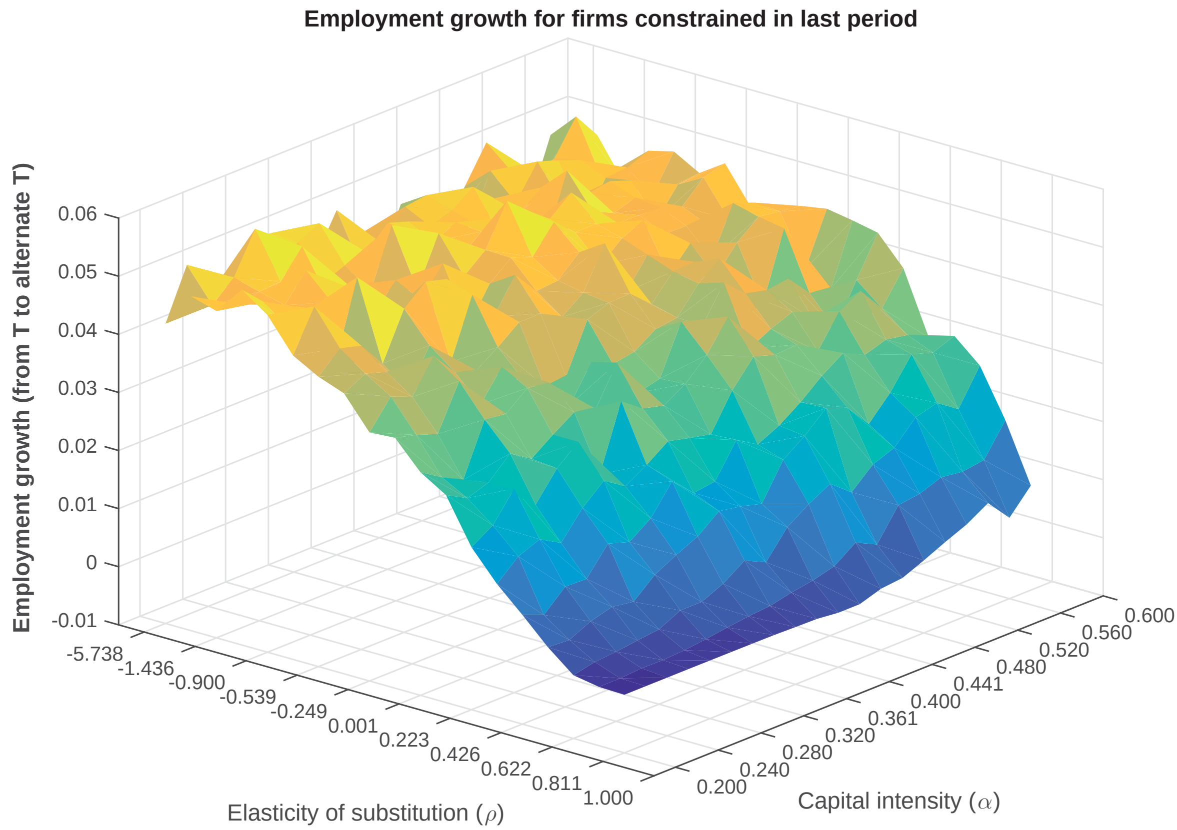


Figure 3



Regarding productivity (Figure 3), these same firms actually decrease labour productivity after the easing of financial constraints. Since they increase capital and labour in an almost fixed mix, the predominant effect is the decreasing returns to scale produced by ν.

However, as ρ increases, this effect is eventually reversed, so that for firms with high enough capital-labour substitution, productivity increases after reducing financial constraints. And among those firms, the share of capital α is crucial in determining the size of the labour productivity increase, with much higher increases for firms with a large α.

To sum up, after an easing of constraints, the model clearly predicts a positive effect on employment. The sign of the effect is not so clear in terms of labour productivity, being negative when capital and labour are complements, and positive otherwise. Finally, the size of this last positive effect depends positively on the share of capital in the production function. The overall effect on productivity thus remains to be an empirical question, given the lack of general agreement on how to best quantify the elasticity of substitution between labor and capital. In this regard, many papers provide point estimates of this elasticity at the country and sector level (Arrow et al. (1961); Behrman (1972); Balistreri et al. (2003), among others). Taken together, their results suggest that this elasticity of substitution moves within a wide range of values. Furthermore, it varies greatly for different sectors within the same economy. Consequently, we should rather let the data speak and answer this question empirically.

3.4 Implications for the joint dynamics of employment and productivity growth

So far, we have used the model to better define gazzelles in productivity, and to illustrate the possible effects of financial restrictions on employment and labour productivity. However, in order to tackle the last goal of the model (dynamic interactions between high growth in employment and productivity), we need to further expand the model. Without any momentum, a firm receiving a good shock in $t-1$ will on average decrease its TFP in t, by an instant mean reversion of A_{it}. Therefore, high growth will be usually followed by negative growth. Hence, the model as it is so far described cannot generate any dynamics other than negative correlation in performance caused by mean reversion. Hence, we extend A_{it} to a dynamic process including an autoregressive component, to introduce the needed momentum:

$$A_{it} = \mu + \phi A_{it-1} + a_{it} \quad \text{with} \begin{cases} \phi \in [0,1) \\ a_{it} \sim U(-0.05, 0.05) \end{cases} \tag{12}$$

The inclusion of the autoregressive component can introduce different dynamics. Moreover, its interaction with the two capital constraints already defined could further enrich dynamics.

For example, a firm with a very good shock, financially constrained, could also exhibit high growth in next period, even if the new shock is negative, only because it did not manage to reach a large enough size due to the financial constraint.

In order to analyze these different dynamics, we repeat the simulation described, but for different values of ϕ. For each simulation, we define HGF in employment and productivity as in section 4.2.1. That is, the top 10% of firms with the highest "Birch-Schreyer index"[12] (HGF in employment), and respectively, the top 10% of fastest growing firms in labor productivity on a given year, conditional on its employment having not decreased in the same period (HGF in productivity). We then plot autocorrelations and cross–correlations between employment and labor productivity high growth. The result is in figures (4)—(7). We see that, for low ϕ, autocorrelations in employment are close to zero, and increase smoothly up to significant values as ϕ increases. On top of that, tighter financial constraints imply slightly higher autocorrelations, but the effect is small compared to ϕ. Regarding labour productivity, autocorrelations start negative for low ϕ, but soon turn to positive as ϕ increases beyond some point. Again, there is a small but positive effect of tighter financial constraints on these autocorrelations.

Regarding cross–correlations, the effect from employment to productivity is slightly negative but very close to zero for the whole domain of parameters ϕ and ε[13]. On the other hand, the effect from productivity to employment is also slightly negative, but for high values of ε and ϕ (looser constraints) it vanishes (and indeed become slightly positive).

So, in summary, the model, augmented with an autoregressive component in TFP, can generate diverse dynamics in employment and productivity growth, depending on the degree of inertia in TFP, and on the tightness of financial constraints. Again, it remains to be an empirical problem to assess where actual firms lie on.

4 Data

Firm-level data are taken from the Central Balance Sheet Database (*Central de Balances Integrada* (CBI) in Spanish) provided by the Banco de España. In particular, for each firm, we observe the main entries of the firm's balance sheet and income statement, such as total revenues, value of intermediate consumption, labor expenses, and book value of assets and liabilities. In addition, the CBI database provides information on the year of foundation, sector of activity (4-digit level), and average employment (distinguishing between permanent and non-permanent employees).

[12]The Birch-Schreyer index is defined as absolute growth times relative growth in employment.
[13]Note the change in the vertical scale.

Figure 4

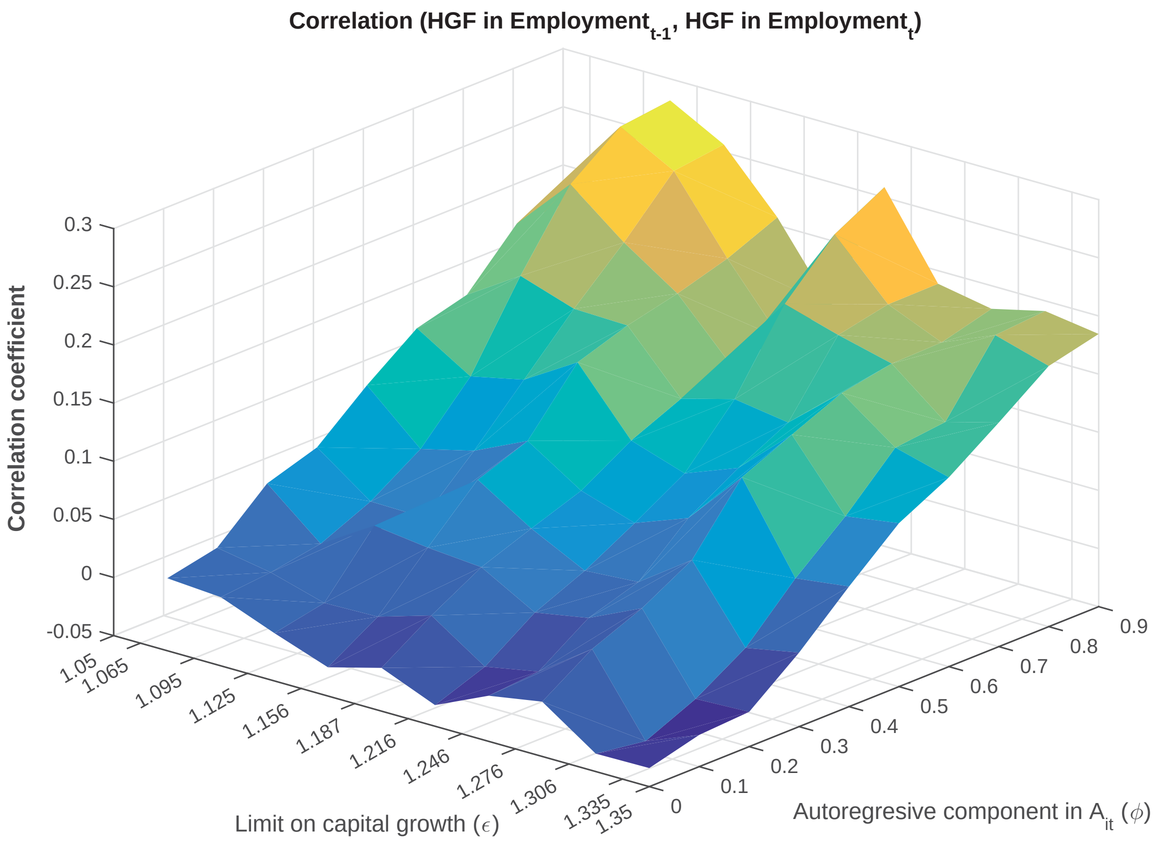


Figure 5

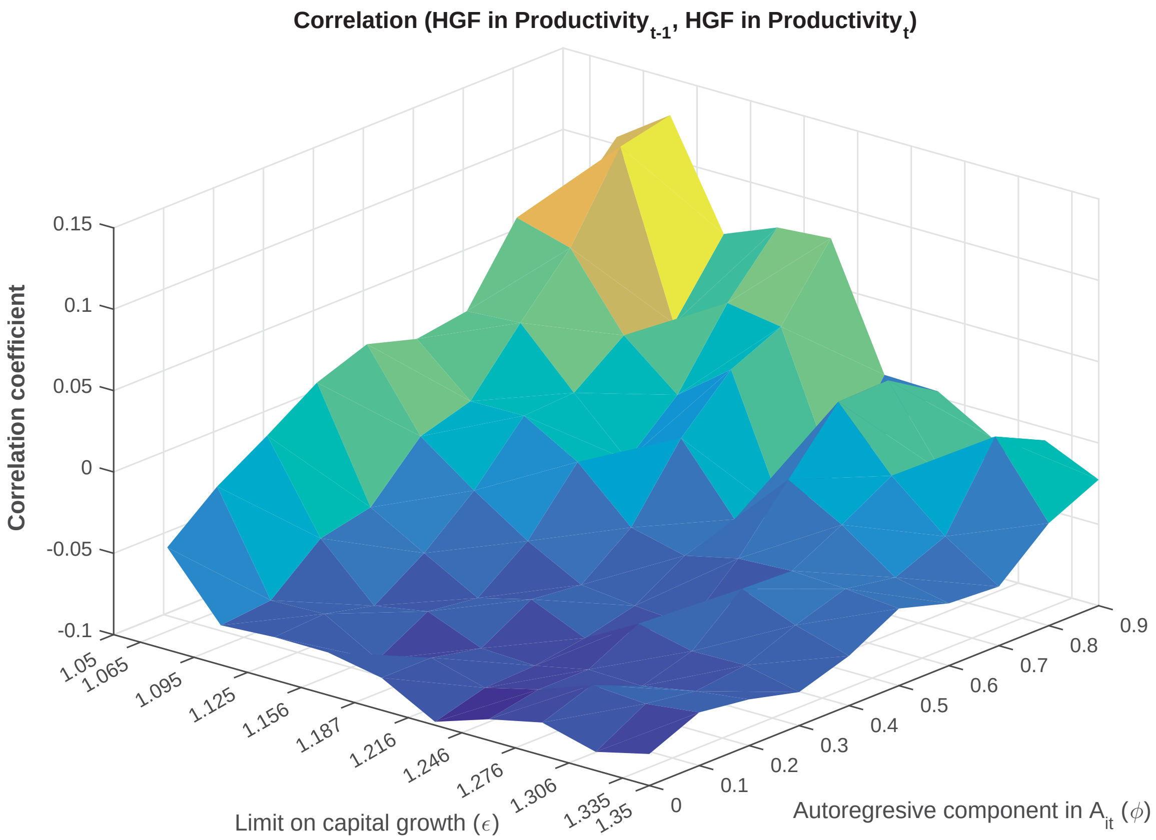


Figure 6

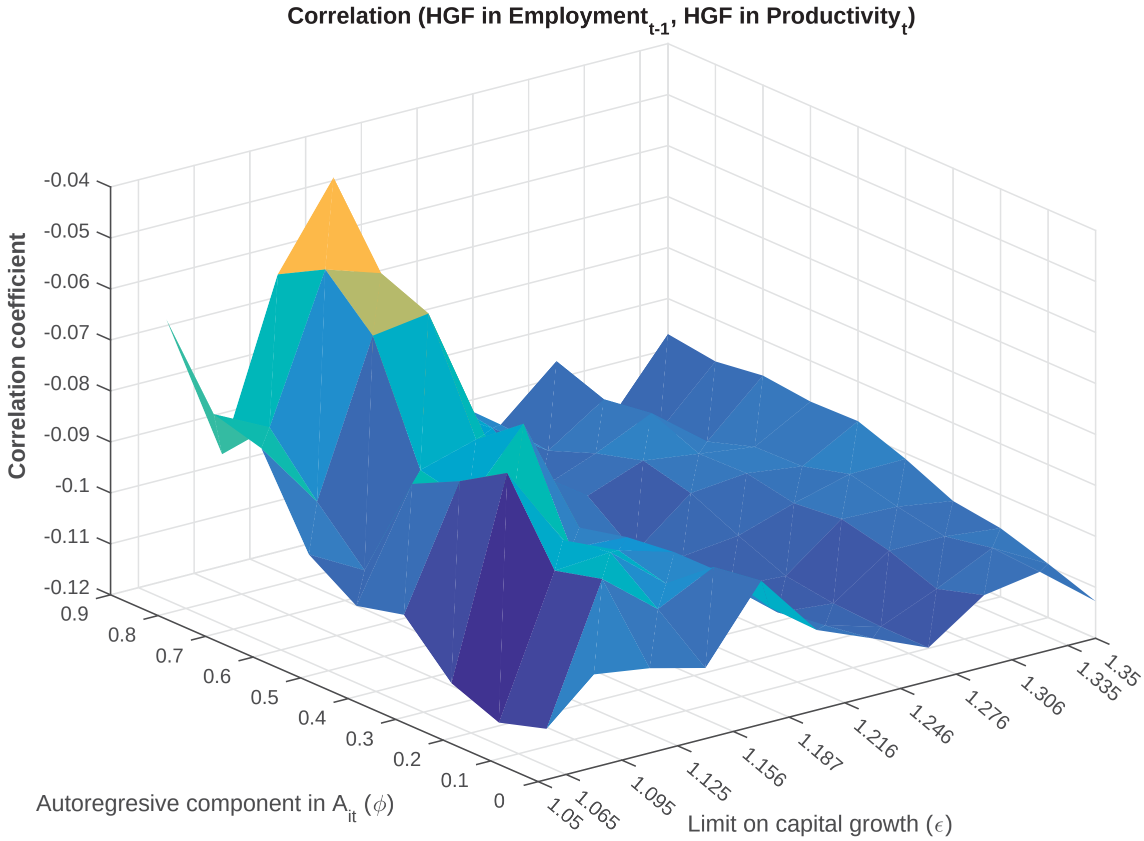
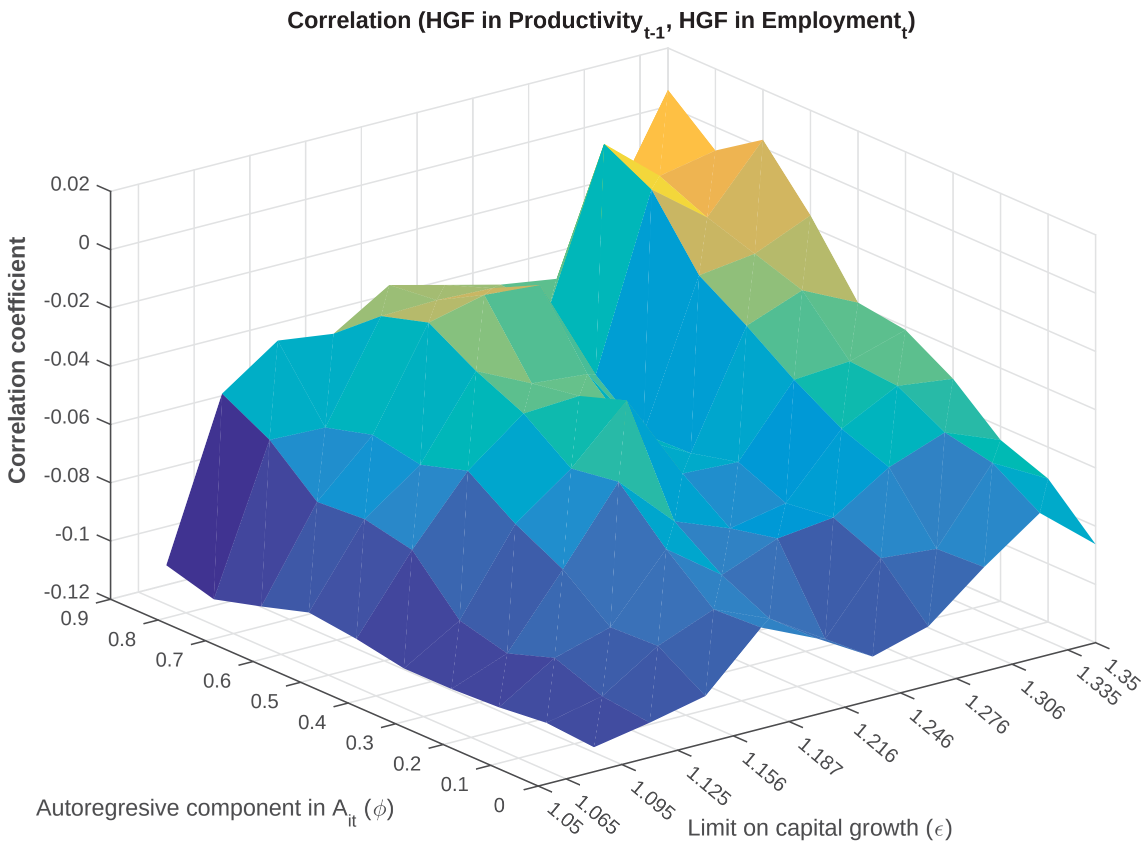


Figure 7



The CBI is the result of integrating and aggregating two complementary datasets. The first one is the CBA database (*Central de Balances Anual* in Spanish), whose input is a standardized questionnaire that gathers information on the legal form, employment and balance sheet of the firms collaborating on a voluntary basis with the Banco de España. While the data collected is highly detailed and reliable, the sample size is reduced, with an average of 9,000 companies submitting the survey each year, and most of them being large firms. The second one is the CBB database, which is created in collaboration with the Mercantile Registries where firms deposit their annual accounts. In Spain, since 1990 trading companies (*sociedades mercantiles* in Spanish) have the legal obligation to deposit their annual financial statements on the Mercantile Registry of the province in which their registered office is located. This results in a wide coverage of all active firms each year, with the caveat that the compilation and cleaning of the dataset implies keeping only the readable and quality-printed statements, and those with coherent figures (e.g., total assets equal to total liabilities, labor expenses in line with the employment data reported, etc.). Nevertheless, advances in information technologies have allowed consistent data collection of between 400,000 and 600,000 firms in the last years, which represent more than 50% of the population of active firms in Spain. Despite this, it is common to find firms with coherent statements that "disappear" one year from the CBB database, and appear again some year(s) after. Benefiting from the fact that firms must report comparable figures of the previous year when filing the annual accounts of a given year, the Banco de España Central Balance Sheet Office (in charge of maintaining the CBI database) fills (if possible) the missing data generated when firms "disappear", thus increasing the availability of *consecutive* firm observations.

In order to analyze the role of financial constraints in productivity and employment growth, we cross the firm-level data provided by the CBI with information on loan applications and current credit exposures from the Central Credit Register[14] of the Banco de España (*Central de Información de Riesgos* (CIR) in Spanish), using firms' unique fiscal identification number. This dataset is maintained by the Banco de España in its role as primary banking supervisory agency, and contains detailed monthly information on all outstanding loans over 6,000 euros to non-financial firms granted by all banks operating in Spain since 1984. Given the low reporting threshold, virtually all firms with outstanding bank debt will appear in the CIR.

In its role of assisting banks in controlling their credit risk, the CIR provides banks with two types of reports. On the one hand, all banks receive, on a monthly and automated basis, updated information on the total current debts of their own current borrowers vis-à-vis all credit entities in Spain (face value, default risk, maturity, guarantees, etc.). On the other hand, any bank can request (at zero cost) this information on firms that may become new borrowers, though the law stipulates that the prospective borrower must give its consent, thus

[14]Further details on the contents and maintenance of the CIR can be found in http://www.bde.es/bde/en/secciones/informes/

signaling the firm's real intent to obtain credit. This in turn implies that banks will lodge requests only following loan applications and in one of the following situations: either the bank has never granted any type of lending to the firm, or the lending relationship between the firm and the bank ended before the request was made.

Since 2002 the CIR compiles monthly information on these requests, uniquely identifying firm-bank pairs. We extract information on the total number of requests made on a given firm each year, as well as the total number of those requests that ended in the granting of credit. We assume the credit application was accepted if the bank declares some credit exposure with the firm at most three months after the request was made. Furthermore, we also retrieve firm-year information on the average drawable and drawn down credit, as well as on the average number of outstanding credits.

4.1 Sample

Using the Central Balance Sheet Database, we extract data on a representative sample of non-financial non-agricultural firms, covering the period 2001 – 2013. This leaves us with an unbalanced panel of 1,416,518 firms that we observe for an average of 5.3 years, amounting to 7,538,516 firm-year observations. Next we match this data, on a yearly basis, with the information from the Credit Register, using firm's fiscal ID number.

In spite of the fact that the CBI data is available since 1995, we set the starting point of our sample at 2001. The reason for this is twofold. On the one hand, the information on banks' requests on prospective borrowers – central to our analysis of financial constraints – is only observable since 2002. On the other hand, we start collecting balance sheet data from 2001 (instead of 2002), since 2001 annual accounts are needed to compute our measures of employment and productivity growth for the fiscal year 2002.

As it was mentioned earlier, our balance sheet data draws mainly on the annual accounts filed by firms in their corresponding Mercantile Registries. Although this provides us with a wide coverage of financial and accounting information at the firm level, a major concern arises when it comes to employment data. Specifically, firms are not compelled to report average employment when depositing their annual accounts. This in turn implies that we lose 1,589,349 observations for having missing values for the number of employees. We also exclude firms with a reported average employment of less than one, since these firms are likely to exhibit a very erratic behavior and the overall reliability of their financial statements tends to be rather small. Furthermore, we drop firms for which the year of constitution is missing (we need this to compute firm's age), observations with non-positive values for age, and those in which negative net equity amounted to more than half the value of total assets. Moreover, to avoid the influence of outliers, we drop observations at the top and bottom 1% of labor

Table 2: Sequential data cleansing process

Data cleansing stage	**Nº obs.**	**Nº firms**
Raw data	7,538,516	1,416,518
Missing employment data	-1,589,349	
Average nº employees < 1	-322,086	
Missing year of foundation	-2,196	
Non-positive age	-2,369	
Negative net equity > 50% Total Assets	-367,985	
Top and bottom 1% of labor expenses per employee and GVA	-191,036	
Cleaned data	5,063,495	955,690
Obs. not belonging to spell of at least 3 consecutive data points	-2,244,937	
Missing values in regressors	-41,192	
Estimation sample	2,777,366	623,072

expenses per employee and deflated gross value added per employee[15] by year and 2-digit sector. Table 2 summarizes the data cleansing process here described.

At this point, we are left with 955,690 firms, and 5,063,495 observations. However, as it will become clear in subsequent sections, the computation of growth rates and the inclusion of a lagged dependent variable among the regressors, implies that spells of firm observations with less than 3 consecutive data points will be automatically excluded from our estimation sample. It is at this stage where the sample size is dramatically reduced by over 40%, leaving us with 2,777,366 observations. Despite these data limitations, our sample remains remarkably large and thorough, with around 252,000 active firms per year and an average of 4.5 observations per firm.

In order to extend inferences drawn from our data to the universe of Spanish firms, we first verify that the distribution of firms in our final sample is representative of the reference population. Table 3 breaks down firms by size category and compares the distribution of sample firms to that of the population of Spanish firms for the period 2002 – 2012, as provided by the Central Directory of Firms (DIRCE in Spanish). In general, although medium firms (10 – 49 employees) are a bit overrepresented in detriment of small ones, the representativeness of our final sample is substantially good, specially in the last years of study. Unfortunately, we don't have population distributions for variables such as gross valued added or labor productivity, thus we cannot readily check whether our sample of firms is representative in this respect.

[15]Given that financial statements are reported in nominal terms, we employ the value added deflator from the Spanish National Accounts, constructed at the 2-digit sector level with 2010 as the base year.

Table 3: Size distribution of firms (Business census vs Final sample)

Firm size cateogory	Panel A: Central Business Register (number of firms and share by employment size)										
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	Total
1-9 employees	521,945	555,442	592,875	624,678	651,899	689,095	719,884	705,950	685,023	666,620	658,036	7,071,447
10-19 employees	74,900	77,776	81,561	84,464	89,009	92,398	94,092	87,285	75,394	72,210	67,271	896,360
20-49 employees	44,663	45,405	46,930	49,705	51,910	53,764	54,764	49,089	42,448	39,956	37,013	515,647
+50 employees	21,343	21,790	21,871	23,043	24,138	25,470	26,417	23,700	21,402	20,373	19,552	249,099
Total	662,851	700,413	743,237	781,890	816,956	860,727	895,157	866,024	824,267	799,159	781,872	8,732,553
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	Total
1-9 employees	78.7%	79.3%	79.8%	79.9%	79.8%	80.1%	80.4%	81.5%	83.1%	83.4%	84.2%	81.0%
10-19 employees	11.3%	11.1%	11.0%	10.8%	10.9%	10.7%	10.5%	10.1%	9.1%	9.0%	8.6%	10.3%
20-49 employees	6.7%	6.5%	6.3%	6.4%	6.4%	6.2%	6.1%	5.7%	5.1%	5.0%	4.7%	5.9%
+50 employees	3.2%	3.1%	2.9%	2.9%	3.0%	3.0%	3.0%	2.7%	2.6%	2.5%	2.5%	2.9%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Firm size cateogory	Panel B: Final Sample (number of firms and share by employment size)										
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	Total
1-9 employees	131,553	153,723	173,534	188,300	189,791	183,550	192,037	231,926	233,304	229,980	206,467	2,114,165
10-19 employees	28,151	31,809	34,748	36,945	36,655	34,834	34,721	37,815	36,806	35,323	29,958	377,765
20-49 employees	16,542	18,720	20,318	21,757	21,179	19,857	19,386	20,767	20,479	19,851	16,587	215,443
+50 employees	5,202	5,847	6,443	7,028	6,804	6,091	5,962	6,669	6,831	6,979	6,137	69,993
Total	181,448	210,099	235,043	254,030	254,429	244,332	252,106	297,177	297,420	292,133	259,149	2,777,366
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	Total
1-9 employees	72.5%	73.2%	73.8%	74.1%	74.6%	75.1%	76.2%	78.0%	78.4%	78.7%	79.7%	76.1%
10-19 employees	15.5%	15.1%	14.8%	14.5%	14.4%	14.3%	13.8%	12.7%	12.4%	12.1%	11.6%	13.6%
20-49 employees	9.1%	8.9%	8.6%	8.6%	8.3%	8.1%	7.7%	7.0%	6.9%	6.8%	6.4%	7.8%
+50 employees	2.9%	2.8%	2.7%	2.8%	2.7%	2.5%	2.4%	2.2%	2.3%	2.4%	2.4%	2.5%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Notes: Only public limited company and limited liability companies are included.

4.2 Variable definitions

4.2.1 Definition of HGFs

A controversial issue in this field of research is the considerable heterogeneity in terms of how HGFs are selected. In their taxonomy of the literature on high growth firms, Delmar et al. (2003) point out four important factors that shape this heterogeneity when it comes to identifying HGF: the indicator variable (i.e., the variable over which we measure growth), the measurement of growth (relative vs. absolute change), the time window studied, and the criteria for screening out HGF.

The most commonly used indicators in the literature are sales and employment, partly due to the relative easiness to access data on them, but also because empirical evidence suggests they are moderately correlated (Coad, 2010), and hence results do not change much upon deciding between the two. However, the results in Daunfeldt et al. (2014) suggests there exists a trade-off between employment growth and productivity growth, meaning that HGF in terms of employment are not the same as HGF in terms of productivity.

Taken this into account, we define two types of HGF: HGF in terms of employment, using the average number of employees as indicator, and HGF in terms of productivity, using labor productivity (defined as deflated gross value added (GVA) per employee) as indicator.

On the other hand, measuring growth in relative, as opposed to absolute terms (and viceversa) can considerably change the group of firms selected as HGF (Almus, 2002; Daunfeldt et al., 2014). Relative changes in growth may be considerably higher for small firms than for larger ones (for instance, a one-employee firm that hires an additional staff member would exhibit a 100% rate of growth), resulting in smaller HGF. Conversely, measures of absolute growth would introduce a bias towards larger firms, in detriment of smaller ones. Many studies alleviate this concern by requiring sample firms to have a minimum employment size (usually more than 10 or 20 employees). However, in the case of Spain, that would imply ignoring more than 90% of firms, and thus not taking into consideration a large part of the business dynamics. This is why, in the case of HGF in employment we opt for the so-called "Birch-Schreyer Index" as our measure of growth, which combines both absolute and relative growth and is defined as:

$$BS = (L_{i,t} - L_{i,t-k})\frac{L_{i,t}}{L_{i,t-k}} \tag{13}$$

with $L_{i,t}$ and $L_{i,t-k}$ representing the average number of employees reported by a given firm i at time t and $t-k$, respectively.

This composite measure of employment growth, jointly put forward by the work of Schreyer (2000) and Birch (1987), is certainly less sensitive to biases favoring any particular firm size category, since it gives emphasis to larger (smaller) firms whose relative growth rates correspond to larger (smaller) absolute growth increments. In the case of HGF in terms of productivity, these type of biases are less pervasive, since our indicator variable, total GVA over firm employment, is already correcting for differences in firm size, and it further controls for the intermediate input usage (Gal, 2013). As a result, we employ the relative change in labor productivity as our measure of productivity growth[16]:

$$\text{Labor productivity growth (\%)} = \left(\frac{\frac{GVA_{i,t}}{L_{i,t}}}{\frac{GVA_{i,t-k}}{L_{i,t-k}}} - 1 \right) \times 100 \tag{14}$$

where $GVA_{i,t}$ and $GVA_{i,t-k}$ are the deflated gross value added (in K euros) reported by firm i at time t and $t-k$, respectively, and $L_{i,t}$ and $L_{i,t-k}$ are defined as previously.

As for the time horizon considered, most studies compute growth rates over long periods (usually between 3 and 5 years), in order to smooth the distribution of growth rates and correct for one-time growth peaks. However, there are HGF studies that use shorter time horizons (1 or 2 years) (see Lopez-Garcia and Puente (2012); Lee (2014)). In our case, data limitations hinder our ability to measure growth over long time periods. Given that we have an unbalanced panel with an average of 5.3 observations per firm, we measure growth over a one-year period, that is, we set k equal to one.

Next we need to set the criteria for screening out HGF. Studies in the literature has mainly used two distinct definitions. One the one hand, some definitions are based on a certain cutoff or threshold (usually 10%, 5% or 1%) that identifies the top $x\%$ fastest growing firms during a particular period. On the other hand, other definitions, require firms to grow at a particular pace. This is the case for the Eurostat-OECD definition, which identifies HGF as firms with at least 10 employees in the starting period, and an annualized employment growth exceeding 20% during a 3-year period (Eurostat-OECD, 2007). One important advantage of the latter type of (absolute) definitions over the former (relative) ones is that they are time-invariant, so that the definition of HGF is always identifying the same patterns of growth. The drawback is that the number of HGF is highly sensitive to changes in the business cycle and the sector composition. Given that our sample spans periods of both economic expansion and financial turmoil, we decided for a relative measure.

Consequently, a firm is identified as a HGF in employment in a given year if it belongs to the top 10% of firms with the highest “Birch-Schreyer index” in the same 2-digit sector[17]. Similarly, for a firm to be classified as a HGF in productivity, it must be among the 10%[18]

[16] In any case, selecting HGF in productivity with an indicator analogous to 13 yields almost the same set of firms.

[17] To define HGF, the year-sector cell must have at least 25 observations.

[18] In Appendix C we repeat our analysis using two different cutoffs to select HGF, namely the top 1% and 5% of fastest growing firms in labor productivity, and the top 1% and 5% of firms with the highest “Birch-Schreyer index”. Tables C.3–C.7 use HGF selected under top 1% cutoff, and are analogous to tables 6–10.

of firms with the fastest growth in labor productivity in the same 2-digit sector, under the condition that its employment has not decreased in the same period. This last requirement avoids classifying as a HGF those firms that are in distress or going through a rough patch, and that are thus boosting their labor productivity through massive dismissals[19]. This caveat is specially relevant in our analysis since we focus on yearly growth rates (likely, if we used wider time windows to compute growth rates, this would be less of a problem).

4.2.2 Financial constraints

We use the information on credit requests from the CIR to construct a categorical variable that measures firm's financial constraints. Firms are classified into four distinct groups:

1. The first group is comprised of firms that apply for credit to one or more *new* banks (i.e., any bank with which the firm has no lending relationship at the time of the loan application) and obtain credit from at least one of them.

2. In the second group fall firms that have covered their need of additional funds with their *current* banks. To be precise, these are firms that are not in group 1, and that fulfill at least one of the following conditions: (a) the stock of credit vis-à-vis all its current lenders has increased with respect to the previous year, (b) the average number of outstanding credits vis-à-vis its current lenders has increased w.r.t the previous year, (c) firm has unused credit facilities amounting to more than half of the total credit exposure vis-à-vis its current lenders (meaning it still has plenty of room for drawing down credit).

3. In the third group appear firms that make credit requests to one or more *new* banks but all of them get rejected. Moreover, we require firms in this group to not having increased their debt with *current* lenders. That is, a firm that is denied credit by all *new* banks but that, in spite of that, obtains more funds from current lenders (as defined in 2) would be included in group 2.

4. The last category works as a "catch-all" solution, where one can find either firms that haven't approached new banks and that satisfy none of the conditions listed in 2, or firms that don't appear in the CIR database (i.e., they have no credit exposures with any banking institution reporting to the Credit Register). This group of firms act as the base category in all regressions.

In a nutshell, firms may be granted new loans from a *new* bank(s) (category 1), or they may borrow more credit from their *current* lenders (category 2), after (or not) having been

Similarly, tables C.8–C.12 use HGF selected under top 5% cutoff, and are equivalent to tables 6–10. Results are barely unchanged when we use 5% as the cutoff point, and are weaker (though the sign and direction of the coefficients is the same) in the 1% case.

[19] Our theoretical model lends further support to this requirement for HGF in productivity (see section 3).

rejected by all *new* banks to which they applied for credit. On the other hand, firms may be denied credit by all *new* banks, as well as by their *current* lenders[20] (category 3). The remaining firms (i.e., firms with no declared bank debt or no increases in credit with current nor new banks) would fall in category 4.

Consequently, firms in groups 1 and 2 are regarded as the least financially constrained of all, since they are able to obtain more funds either through current or new lenders. By contrast, firms in category 3 are the most financially constrained, due to their inability to raise new funds either through new or current lenders.

To lend further support to the validity of our methodology, we compared our measure of financial constraints to the responses of a subset of sample firms to the Wage Dynamic Network (WDN) survey, in which, firms were explicitly asked, among other things, about the pervasiveness of the financial constraints they might have faced during 2010-2013[21]. We find a positive and statistically significant correlation between our measure of financial constraints and the degree of financial constraints declared by the same firms in the WDN survey[22].

An important factor affecting firm's ability to access new credit, and hence, finance growth, is its capital structure. On the one hand, sufficiently high leverage may make it more difficult to get additional funds to finance growth due to the debt overhang created by prior debt financing, and the increased probability of financial distress (Myers, 1977; Titman, 1984). These agency problems are especially severe for small firms since they are more *informationally* opaque than larger firms. On the other hand, high debt ratios may send a signal about the firms ability to face fixed debt-related payments, and thus could result in lower financing constraints if the firm has built a good credit history. To control for the correlation between leverage and financial constraints, we include the share of long term debt over total liabilities as a regressor. We further include a quadratic term for long term debt ratio to capture potential non-monotonic effects of leverage.

[20]Note that we are unable to explicitly observe whether a firm that approaches new banks for funding, has first resorted to its current lenders and the latter have denied this additional credit (since the firm's current lenders would not need to lodge a request to the Credit Register, given that they already receive this information on an automated monthly fashion). However, the fact that the firm doesn't increase funds vis-à-vis its current lenders, while having applied for credit to other banks, implicitly signals that the firm may be somehow constrained by its current lenders.

[21]For more information on the survey and the Wage Dynamics research Network, visit http://www.ecb.europa.eu/pub/economic-research/research-networks/html/researcher_wdn.en.html

[22]In particular, we use data coming from the third wave of the WDN survey, which aims to assess recent labor market adjustments and how firms have reacted to the labor market reforms that took place between 2010 and 2013. At present, 25 EU National Central Banks participate in this research network, including Banco de España. We match this survey data with our database and identify 1,688 firms that completed the WDN survey. At some point in the questionnaire, firms are asked about how badly the shortage of credit and the tightening of financial conditions have affected them in terms of higher difficulties to cover basic financial needs, make new investments or refinance outstanding debt. Firms answering that (any of) these factors have affected them in a "relevant" or "very relevant" way are thought of as being financially constrained. We then compare this synthetic variable of financial constraints to ours, and find a positive and statistically significant correlation between them.

4.2.3 Control variables

The empirical literature on firm dynamics has recurrently emphasized the large impact that firm demographics, such as **firm size** and **firm age**, have on firm growth and job creation (Haltiwanger et al., 2013), and therefore they need to be considered. Thus we include firm size and firm age fixed effects in all of our regressions. On the one hand, firms are classified, according to their average employment, into micro (1-9 employees), small (10-19 employees), medium (20-49 employees) or large (more than 50 employees) enterprises. Given the nature of our data, it is not surprising that micro and small firms are overrepresented, covering 90 percent of the sample, whereas large firms comprise less than 3 percent of the sample. On the other hand, we define six groups of age ranging from newborn firms (0-2 years old), representing only 7 percent of the sample, to old firms (21 years or older) which constitute over 12 percent of the firms in the sample (see Tables 4 and 5 for further details).

The literature on the role of international trade in promoting growth in general, and productivity in particular, has for long emphasized firm's participation in international markets as a relevant factor affecting firm and productivity growth (see Wagner (2007) and Greenaway and Kneller (2007)). In particular, the majority of studies in this field find a positive link between participation in international markets and firm's productivity, documenting a productivity premium vis-à-vis firms that do not trade internationally. Given that being an exporter and/or importer is often regarded as an indicator of internationalization, we match information on **importer/exporter status** from the microdata used to construct the Spanish Balance of Payments. We include these two dummy variables as regressors to correct for the impact of international trade on the probability of becoming a HGF in productivity and employment growth. The final sample contains an average number of 12,605 (16,933) exporters (importers) per year, of which an average of 6,846 are two-way traders (that both export and import).

Being one of the key firm inputs, **human capital** has also been put forward as a source of firm-level heterogeneity in productivity, growth, and value (Abowd et al., 2005). We therefore introduce human capital controls in all specifications. In particular, we include as a regressor the firm's wage premium (in logarithmic terms), that we compute as the average wage paid in the firm[23] over the average wage paid by other firms in its 2-digit sector. On the other hand, one needs to control for the composition of firms' staff in order to correctly interpret the heterogeneity in average wages across firms. Ideally, we would control for characteristics such as level of education or tenure, however, this information is unobservable for us. Nevertheless, we do have information on the fraction of permanent employees working at the firm and include this as an additional regressor. The strong duality of the Spanish labor market lowers skill-

[23]We use personnel expenses per worker as a proxy for wages.

building incentives in the temporary work segment, which in turn may affect negatively the productivity of these workers. Thus, controlling for the mix between permanent and temporary contracts is crucial, especially when analyzing Spanish firms, given the high incidence of temporary contracts in Spain. We expect both these variables to measure firm's ability to accumulate human capital, thereby affecting its growth prospects.

4.3 A characterization of Spanish HGF

Contribution to employment and productivity growth

Graphs 8 and 9 present the contribution of HGF to aggregate employment growth and aggregate labor productivity growth, respectively. By aggregate, we refer to the totals for studied firms. For comparison purposes, non-HGF are further broken down into two groups: slow growth firms (with non-negative changes in labor productivity/employment, but not large enough to be considered a HGF) and shrinking firms (with negative changes in labor productivity/employment).

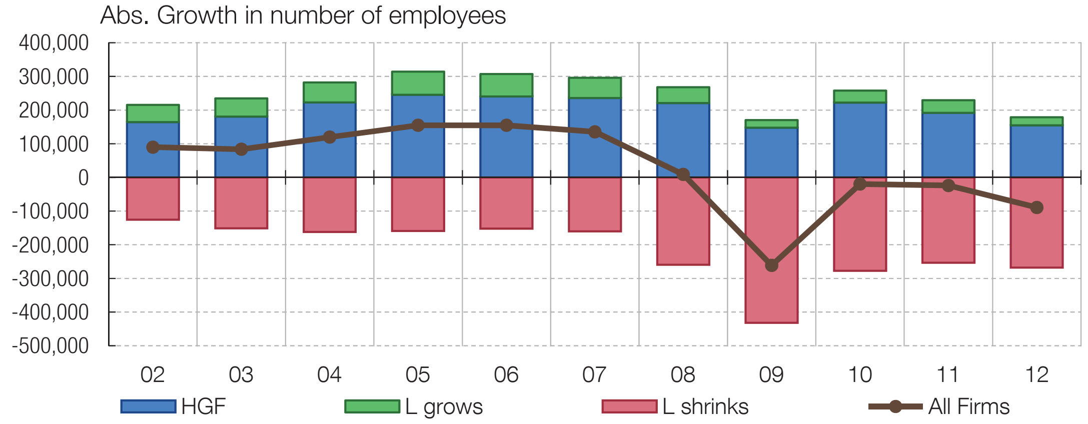
In the years preceding the financial crisis, the overall creation of jobs attributable to HGF was of such a scale that it more than made up for the job destruction induced by shrinking firms in the sample. Taking the period 2006–2007 as example, we observe that HGF accounting for 10% of the studied firms in 2007, created 235,965 jobs, almost two times the figure of net employment of that year (135,501 jobs), and more than offsetting the whole of the jobs destroyed by shrinking firms (-160,435 jobs) (see Table A.1).

The contribution of HGF to job creation is non-negligible either in the post-crisis, when these firms offset on average a 67% of the jobs destroyed during the 2007 – 2012 period. Moreover, they added about 85% of the total new jobs, or in other words, they provided almost six times more jobs than slow growth firms (before 2007, the gap between HGF and slow growth firms was smaller, with HGF creating around 3.5 times more jobs than slow growth firms).

Regardless of the criteria used to identify HGF in employment, most of the empirical evidence coincides with this result. In recent work, Lopez-Garcia and Puente (2012) find that 7.7% of HGF account for roughly 80% of the total net employment creation among firms with less than 20 employees in Spain. In Finland, Deschryvere (2008) finds that the top 5% of rapid growth firms generate 90% of all net jobs in the economy. In UK, the 7% of firms selected as HGF according to the Eurostat-OECD definition, created around half of all gross new employment between 2007 and 2010 (NESTA, 2011).

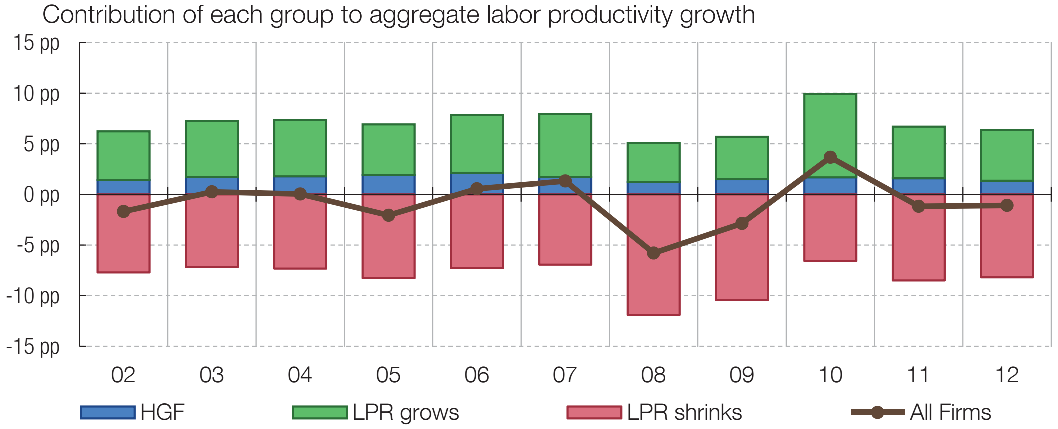
The impact of productivity HGF on aggregate labor productivity is much smaller than that made by employment HGF on aggregate net employment (see Graph 9 and Table A.2).

Graph 8 Contribution to employment growth[a]



[a]Figures represented in the chart are computed as follows. Each year (t) firms are classified into one of the following groups: HGF in employment (top 10% of firms with the highest "Birch-Schreyer index" in the same 2-digit sector), slow growth firms (firms that don't qualify as HGF but that either kept their employment constant or increased it), and shrinking firms (firms that don't qualify as HGF but that decreased their employment). We then compute firms' absolute change in the number of employees from $t-1$ to t, and sum it all up across firms within the same group. See Table A.1 for further details.

Graph 9 Contribution to labor productivity growht[b,c]



[b]The contribution of the different reference groups (i.e., HGF, slow growth firms and shrinking firms) to overall labor productivity growth is computed as follows. First we calculate the growth in productivity for all studied firms had the reference group not grown. We do this by setting the labor productivity growth of the reference group to zero; in particular, we set the deflated GVA to a level such that GVA *per employee* from $t-1$ to t remains unchanged. Then we compute the growth rate in labor productivity from $t-1$ to t as:

$$Labor\ productivity\ growth_{\,t}\ (\%) = \left(\frac{\sum_{i=1}^{n} GVA_{i,t}}{\sum_{i=1}^{n} L_{i,t}} \Bigg/ \frac{\sum_{i=1}^{n} GVA_{i,t-1}}{\sum_{i=1}^{n} L_{i,t-1}} - 1 \right) \times 100$$

Secondly, we define the contribution of each group to overall growth as the difference between overall (actual) growth for all studied firms and the rate of growth for all studied firms had the reference firms' not grown. See Table A.2 for further details.

[c]The thick brown line represents the annual rate of growth of labor productivity for the whole estimation sample, regardless of the HGF status (i.e., whether high-growth, slow growth or shrinking firm). Note that this aggregate statistic that we compute is not readily comparable with the evolution of labor productivity in Spain for the same time period coming from National Accounts. Two factors that may explain this discrepancy is, first, that we compute productivity growth in a given year t for surviving firms between at least $t-1$ and t, and secondly, that we work with an unbalanced panel of firms, likely affected by attrition.

In particular, while HGF in employment added significantly more jobs than slow growing firms, the same is not true for productivity gazelles. That is, the contribution of productivity HGF to aggregate productivity is roughly a third of that made by slow growing firms. On the other hand, unlike employment HGF, the contribution of productivity HGF is rather stable over time, moving around the 1.5 p.p threshold throughout the studied period, though there are marked differences across sectors.

A potential explanation for the lower contribution of productivity HGF to aggregate productivity growth, in comparison with the employment counterparts, could be related to the way in which the two types of HGF are selected. That is, while HGF in employment are selected based on a growth index that combines relative and absolute growth in employment, HGF in productivity are selected based on relative growth rates of labor productivity. However, applying the spirit of the Birch-Schreyer Index (absolute growth times relative growth) to our measure of labor productivity, and selecting as HGF the top 10% of firms with the highest score in this index (in the same 2-digit sector) leads us to select practically the same group of firms as productivity gazelles. All in all, while figures are not as impressive as for employment, the impact of these rapid growing firms on labor productivity is non-trivial, taking into account that they only represent a 10% of studied firms.

Age and size distribution of HGF

Overall, these numbers show that productivity growth and most of all, job creation, are very much concentrated in a few rapidly-growing firms, suggesting that firm growth rates resemble a Laplace "tent-shape" distribution, as Bottazzi and Secchi (2006) claim. As a result, researchers and policy makers have focused their attention on the characteristics of these HGF. Overall, there is much consensus on that HGF tend to be younger than the average firm in the industry. Accordingly, among both the productivity and employment HGF of our sample, young firms (less than 5 years old) are overrepresented in comparison with the distribution of non-HGF (see Table 4).

It is also interesting to note that while the distribution of studied firms across age categories is very similar between HGF in employment and HGF in productivity, the same is not true when we observe the size class distribution of HGF. In particular, firms with fewer than 10 employees are overrepresented among HGF in productivity, but largely underrepresented across HGF in employment; the reverse happens when we focus on larger firms (more than 20 employees) (compare Panels A and B of Table 5). One possible explanation might be that new firms entering the market are uncertain about their productivity, their costs structures or their capacity; as this uncertainty disappears, firms invest in growth or exit (Jovanovic, 1982). This means that achieving a certain size might be a necessary (yet not sufficient) condition to start being a productive firm.

Table 4: Age distribution of HGF

Panel A: HGF in productivity by firm age category						
Firm age category	non-HGF		HGF		Total	
0-2 years old	140,857	5.6%	49,231	17.9%	190,088	6.8%
3-5 years old	402,988	16.1%	56,052	20.4%	459,040	16.5%
6-10 years old	706,363	28.2%	70,035	25.5%	776,398	28.0%
11-15 years old	589,579	23.6%	50,323	18.3%	639,902	23.0%
16-20 years old	360,577	14.4%	28,597	10.4%	389,174	14.0%
21 or more years old	301,914	12.1%	20,850	7.6%	322,764	11.6%
Total observations	2,502,278	100.0%	275,088	100.0%	2,777,366	100.0%

Panel B: HGF in employment by firm age category						
Firm age category	non-HGF		HGF		Total	
0-2 years old	149,208	6.0%	40,880	14.5%	190,088	6.8%
3-5 years old	407,894	16.4%	51,146	18.1%	459,040	16.5%
6-10 years old	706,288	28.3%	70,110	24.8%	776,398	28.0%
11-15 years old	585,842	23.5%	54,060	19.1%	639,902	23.0%
16-20 years old	355,535	14.3%	33,639	11.9%	389,174	14.0%
21 or more years old	289,874	11.6%	32,890	11.6%	322,764	11.6%
Total observations	2,494,641	100.0%	282,725	100.0%	2,777,366	100.0%

Table 5: Size distribution of HGF

Panel A: HGF in productivity by firm size category						
Firm size category	non-HGF		HGF		Total	
1-9 employees	1,876,073	75.0%	238,092	86.6%	2,114,165	76.1%
10-19 employees	355,177	14.2%	22,588	8.2%	377,765	13.6%
20-49 employees	204,254	8.2%	11,189	4.1%	215,443	7.8%
+50 employees	66,774	2.7%	3,219	1.2%	69,993	2.5%
Total observations	2,502,278	100.0%	275,088	100.0%	2,777,366	100.0%

Panel B: HGF in employment by firm size category						
Firm size category	non-HGF		HGF		Total	
1-9 employees	1,975,526	79.2%	138,639	49.0%	2,114,165	76.1%
10-19 employees	315,931	12.7%	61,834	21.9%	377,765	13.6%
20-49 employees	161,771	6.5%	53,672	19.0%	215,443	7.8%
+50 employees	41,413	1.7%	28,580	10.1%	69,993	2.5%
Total observations	2,494,641	100.0%	282,725	100.0%	2,777,366	100.0%

5 Empirical specification

Our empirical model is based on the following specification:[24]

$$HGF_{i,t} = \gamma HGF_{i,t-1} + \beta x_{i,t-1} + \delta_t + \eta_i + v_{i,t} \tag{15}$$

where $HGF_{i,t}$ is a dummy that takes the value one if firm i $(i = 1, ..., N)$ in year t $(t = 1, ..., T)$ is a high-growth firm, and zero otherwise. The HGF labeling may refer to either employment or productivity as dicussed above. $x_{i,t-1}$ is a vector of covariates such as firm's age, size, wage premium, share of permanent workers, and importer/exporter status. Crucially, the vector $x_{i,t-1}$ also contains the financial constraints indicators described above. Moreover, persistence and mean-reverting dynamics of the high-growth status are captured by the coefficient of the lagged dependent variable on the right-hand side. η_i captures firm-specific fixed heterogeneity potentially correlated with the rest of variables on the right-hand side, and δ_t represents a set of time-specific shocks common to all firms in our sample. Finally, transitory shocks to firm's growth and other omitted factors in the model are represented in the term $v_{i,t}$.

Equation (15) can be estimated under different correlation structures between the the error term $\delta_t + \eta_i + v_{it}$ and the regressors $x_{i,t-1}$, $HGF_{i,t-1}$. Despite we are aware of the limitations of certain exogeneity assumptions when estimating dynamic panel models, we still consider these strategies in order to ensure comparability with previous papers in the literature and also to explore the direction of the expected biases from OLS-based estimators in this setting. To be more concrete, we first consider pooled OLS, which assumes that the firm-specific effects are uncorrelated with the variables on the right hand-side. Second, we allow for correlation between the firm-specific effects (η_i) and the variables on the right hand-side. Fixed effects estimates accommodate this correlation and are consistent as $N \to \infty$ and $T \to \infty$.

With respect to the correlation between the transitory shock $v_{i,t}$ and the regressors, we consider two different working hypothesis in this paper. We first estimate the model under the strict exogeneity assumption presented in equation (16) which implies that both lagged HGF $(HGF_{i,t-1})$ and lagged covariates $(x_{i,t-1})$ are uncorrelated with the full path of shocks $v_i = (v_{i,1}, ..., v_{i,t}, ..., v_{i,T})'$:

$$E(v_{i,t} \mid HGF_i, x_i, \delta_t, \eta_i) = 0 \tag{16}$$

where HGF_i and x_i are the $T \times 1$ vectors $(HGF_{i1}, ..., HGF_{iT})'$ and $(x_{i1}, ..., x_{iT})'$. Standard fixed effects estimators are based on this assumption, which does not hold by definition because HGF_{it-1} is correlated with $v_{i,s}$ for $s < t$, when T is small (Nickell, 1981). Moreover, under

[24]Since we are mainly interested in average marginal effects, throughout our regressions we focus on a linear specification, treating our dummy of HGF as continuous. However, we also considered the non-linear case in separate regressions. In appendix C, we perform random effects probit regressions à la Wooldridge, and compare the average marginal effects with those of the fixed effects estimations described in the main text (see tables C.1 and C.2). As expected, the results remain virtually the same.

the strict exogeneity assumption, feedback from HGF to the covariates is not allowed (i.e. covariates such as firm size or credit constraints are not affected by changes in the HGF status).

In order to alleviate these two limitations of the strict exogeneity assumption in (16), we also consider the following working hypothesis:

$$E(v_{i,t} \mid HGF_i^{t-1}, x_i^{t-1}, \delta_t, \eta_i) = 0 \tag{17}$$

where HGF_i^{t-1} and x_i^{t-1} are the $(t-1)\times 1$ vectors $(HGF_{i,1}, ..., HGF_{i,t-1})'$ and $(x_{i,1}, ..., x_{i,t-1})'$. We label this assumption as predeterminedness because all past shocks up to the current period (t) $(v_{i,1}, ..., v_{i,t})$ affect not only HGF $(HGF_{i,t})$ but also other firm characteristics included in the vector of covariates $x_{i,t}$. However, future shocks $(v_{i,t+1}, ..., v_{i,T})$ are uncorrelated with both current HGF and current firm characteristics.

Therefore, we allow for feedback effects from changes in HGF status to changes in firm characteristics which seems to us a desirable property.[25] In order to accommodate the predeterminedness assumption in (17), and given the dimensions of our panel dataset,[26] we resort to panel GMM estimators advanced by Holtz-Eakin et al. (1988) and Arellano and Bond (1991). The intuition behind these panel GMM estimators is that lagged levels of the right-hand-side variables are used as instruments for the same variables in first differences.[27]

The most important reason, but also the most controversial one, that justifies our preference for the Arellano-Bond estimator over within-groups, is the aim to give a causal interpretation to our estimates. To be more concrete, our estimates are robust to feedback from high-growth episodes to other firm characteristics. However, this type of estimators is also interesting in this context because firms characteristics used in this study are likely to have measurement error. The within-group transformation may exacerbate the attenuation bias due to measurement error while, under some conditions, panel GMM estimators are robust to measurement error in regressors.[28]

[25] In addition to strict exogeneity and predeterminedness, there is also a third possible configuration labeled as strict endogeneity in which HGF and firm characteristics are correlated with the full path of shocks from $t = 1$ to T. Estimating the model under this assumption would require the availability of additional firm-specific time-varying variables uncorrelated with past, present and future shocks to firms' growth but correlated with other firm characteristics. Given the difficulty and controversy of this task we prefer to work with the somehow less ambitious predeterminedness assumption.

[26] The panel dataset we consider has $T = 10$ and $N \approx 600,000$, so small T oriented estimators seem to be more appropriate than other time-series oriented estimators such as Anderson and Hsiao (1982)

[27] Note also that the first stage coefficients in this GMM framework proliferate as T increases and this might cause a problem of overfitting. In order to alleviate this concern, we only exploit one instrument —the first available lag— for each regressor and time period instead of the full path of available instruments. This strategy precludes the consideration of Sargan-type tests of overidentifying restrictions, which, in any case, would present extremely low power in our setting (see e.g. Bowsher (2002)).

[28] Whenever measurement error is free of serial correlation, the panel dimension of the data is helpful for dealing with attenuation bias because it provides internal instruments. See Griliches and Hausman (1986) for further discussion.

Finally, we do not consider the so-called system-GMM estimator because it requires an additional identifying assumption for consistency (Blundell and Bond, 1998). In particular, it relies on the mean stationarity assumption that has been proved to be controversial in most empirical settings. Intuitively, this assumption requires that the variables observed in the data set come from dynamic processes that started in the distant past so that the have already reached their steady state distribution, which is hard to motivate in panels with many young firms.

The univariate AR specification in (15) does not allow for interactions between high-growth episodes in employment and productivity. In order to explore how HGF in employment affects HGF in productivity and vice versa, our preferred specification is given by a bivariate VAR that captures these potential interactions:

$$HGF^E_{i,t} = \gamma_{EE} HGF^E_{i,t-1} + \gamma_{EP} HGF^P_{i,t-1} + \beta_E x_{i,t-1} + \delta^E_t + \eta^E_i + v^E_{i,t} \tag{18}$$

$$HGF^P_{i,t} = \gamma_{PE} HGF^E_{i,t-1} + \gamma_{PP} HGF^P_{i,t-1} + \beta_P x_{i,t-1} + \delta^P_t + \eta^P_i + v^P_{i,t} \tag{19}$$

where $HGF^E_{i,t}$ refers to high-growth in terms of employment while $HGF^P_{i,t}$ corresponds to high-growth in terms of productivity. As discussed above, we consider two identification assumptions based on (16) and (17) but including the additional regressors $HGF^E_{i,t-1}$ and $HGF^P_{i,t-1}$ in the conditioning set. Therefore, high-growth in terms of employment is allowed to affect high-growth in terms of productivity, and vice versa. Finally, we separately estimate both equations despite it might possible to improve the efficiency by jointly estimating the two equations given that joint GMM estimates would use a weight matrix that takes into account the correlation between the moment conditions of the HGF^E and HGF^P equations. However, note that consistency properties are not affected by joint estimation of the two equations (see Arellano (2003)).

6 Results

We first present in Table 6 the results of univariate models. For each dependent variable (HGF in employment, HGF in productivity), we present three estimations. The first one is a simple OLS estimation. The second one controls for unobserved heterogeneity, by adding fixed effects. Finally, the third one uses the Arellano and Bond (1991) estimator, as described above, to control for possible feedback of high growth episodes on other firms' characteristics.

Focusing now on first column of Table 6, we see that high growth in employment has significant persistence, as evidenced by the positive coefficient of the lagged high growth variable. Indeed, the effect is large (0.072 for a dependent variable with mean .1, by definition).

Financial conditions are estimated by using two different set of variables: one is simple long-term leverage ratio (and square, to capture non-linearity), and the other one measures access to new credit, as explained before. The results for the leverage ratio yield an inverted U-shape pattern, with additional increments of long term debt having a positive effect on probability of high growth in employment practically on the entire domain of the long term debt ratio. This means that the vast majority of studied firms would benefit from raising new long-term debt. Regarding access to new credit, firms getting an approval for a new loan with a new bank have highest probability, followed by firms that obtain new credit from their current lenders. Firms asking for a new one, but getting none have a smaller probability of becoming a HGF, though this probability is higher than that of firms without bank debt (i.e., they don't appear in the Central Credit Register) or increases in debt vis-à-vis current lenders. One interpretation for this is that expanding firms are more prone to ask for additional financing than stable ones. Results for other controls suggest that older firms have monotonically decreasing probability of presenting high growth in employment, with the oldest firms being five times less prone to reach high growth than the youngest firms. The effect of size is even more intense, with large firms having 0.20 more probability of experiencing high growth than smallest ones. This result overturns Gibrat's Law of Proportionate Effect, which states that firm growth rates are independent of initial firm size (see Sutton (1997)).

Some of the previous results could be affected by unobserved heterogeneity, in such a way that good firms have some values of some covariates, and also higher probability of growing. To control for that, the second column in Table 6 reports the same equation, but controlling for fixed firm effects. The most important change with respect to the first column is the auto-regressive effect, which turns into negative values. The interpretation is that the OLS estimator indeed captures the fact that some firms are more prone to have high growth, but this effect vanishes once we control for firm-specific fixed effects. Concerning financial conditions, the main change is that leverage ratio becomes negative, though its magnitude is reduced. Also, firms with no constraints with their current bank now exhibit a coefficient very close to the one estimated for firms getting an approval in a new bank. This is more intuitive than in column one, as now firms not constrained have the highest probability of high growth, no matter where they find the funds. We thus surmise that asking for additional finance may be regarded as a good proxy for high growth. Furthermore, it is no longer true that firms with all new loans rejected have higher probability of high growth than the reference group.

Regarding other covariates, the effect of size is now reversed, with smaller firms having more probability of high growth. Although these estimates are apparently at odds with the coefficients on firm size produced by OLS (and Arellano-Bond estimator), both results mutually reinforce each other in explaining employment growth dynamics. That is, conditional on survival and controlling for firm age, as firms become bigger they find it more difficult to grow both in absolute and relative terms (focus on within firm variation). However, small

Table 6

HGF in employment (year-sec)(t+1)	OLS	Within estimator (FE)	Arellano-Bond estimator (GMM)
HGF in employment (year-sec)	0.0720***	−0.1018***	0.0379***
	(0.0008)	(0.0008)	(0.0013)
3-5 years old[a]	−0.0116***	−0.0204***	−0.0182***
	(0.0008)	(0.0011)	(0.0014)
6-10 years old	−0.0247***	−0.0210***	−0.0406***
	(0.0008)	(0.0014)	(0.0017)
11-15 years old	−0.0345***	−0.0149***	−0.0590***
	(0.0008)	(0.0018)	(0.0021)
16-20 years old	−0.0416***	−0.0085***	−0.0709***
	(0.0009)	(0.0023)	(0.0026)
21 or more years old	−0.0553***	−0.0080***	−0.0885***
	(0.0009)	(0.0029)	(0.0037)
10-19 employees[b]	0.0323***	−0.0787***	0.0458***
	(0.0006)	(0.0012)	(0.0034)
20-49 employees	0.0845***	−0.1676***	0.1201***
	(0.0009)	(0.0024)	(0.0076)
+50 employees	0.1996***	−0.2911***	0.2813***
	(0.0022)	(0.0053)	(0.0195)
Credit approved by a new bank[c]	0.0349***	0.0164***	0.0267***
	(0.0006)	(0.0007)	(0.0012)
Not constrained by current bank	0.0217***	0.0167***	0.0242***
	(0.0004)	(0.0005)	(0.0009)
All rejected	0.0071***	−0.0067***	0.0033**
	(0.0009)	(0.0010)	(0.0016)
LT debt ratio[d]	0.0151***	−0.0040**	−0.0034
	(0.0017)	(0.0019)	(0.0073)
LT debt ratio^2	−0.0056***	0.0012	−0.0031
	(0.0022)	(0.0011)	(0.0053)
Time fixed effects	Yes	Yes	Yes
Firm-year obs.	2 777 366	2 777 366	2 777 366
Number of firms		623 072	623 072
Avg. number of observations per firm		4.458	4.458
R-squared	0.055	0.047	
Number of instruments			191
AR(1) test (z)			−260.263
p-value			0.000
AR(2) test (z)			1.462
p-value			0.144

Notes: HGFs in employment are defined as top 10% of firms with the highest "Birch-Schreyer index" in the same 2-digit sector. GMM regressions have been estimated using twostep robust estimation (Windmeijer, 2005). All estimations contain controls for: firm's wage premium w.r.t firms in the same 2-digit sector, importer/exporter status, and share of permanent workers.Significance: *p < 0.1, **p < 0.05, ***p < 0.01. Robust standard errors in parentheses.

[a] The base category are firms with 2 or less years old.

[b] The reference category are firms with 1 – 9 employees.

[c] The base category are firms of which we have no credit-related information (that is, either they haven't made credit requests to new banks or they are not in the CIR database).

[d] Expressed on a per unit basis.

Table 7

HGF in productivity (year-sec)(t+1)	OLS	Within estimator (FE)	Arellano-Bond estimator (GMM)
HGF in productivity (year-sec)	0.0009	-0.1839***	-0.0286***
	(0.0006)	(0.0007)	(0.0010)
3-5 years old[a]	-0.0254***	-0.0532***	-0.0426***
	(0.0009)	(0.0011)	(0.0015)
6-10 years old	-0.0398***	-0.0647***	-0.0678***
	(0.0008)	(0.0014)	(0.0018)
11-15 years old	-0.0458***	-0.0600***	-0.0825***
	(0.0008)	(0.0018)	(0.0022)
16-20 years old	-0.0482***	-0.0531***	-0.0868***
	(0.0009)	(0.0022)	(0.0028)
21 or more years old	-0.0466***	-0.0453***	-0.0902***
	(0.0009)	(0.0028)	(0.0040)
10-19 employees[b]	-0.0394***	-0.0411***	-0.0155***
	(0.0004)	(0.0009)	(0.0026)
20-49 employees	-0.0433***	-0.0707***	-0.0244***
	(0.0005)	(0.0014)	(0.0049)
+50 employees	-0.0506***	-0.0990***	-0.0338***
	(0.0009)	(0.0027)	(0.0095)
Credit approved by a new bank[c]	0.0100***	0.0131***	0.0222***
	(0.0006)	(0.0007)	(0.0011)
Not constrained by current bank	0.0087***	0.0113***	0.0188***
	(0.0004)	(0.0005)	(0.0009)
All rejected	-0.0033***	-0.0021**	0.0026*
	(0.0008)	(0.0010)	(0.0015)
LT debt ratio[d]	0.0052	0.0437***	0.1425***
	(0.0032)	(0.0029)	(0.0064)
LT debt ratio^2	0.0081*	0.0010	-0.0075***
	(0.0044)	(0.0030)	(0.0023)
Time fixed effects	Yes	Yes	Yes
Firm-year obs.	2 777 366	2 777 366	2 777 366
Number of firms		623 072	623 072
Avg. number of observations per firm		4.458	4.458
R-squared	0.016	0.047	
Number of instruments			191
AR(1) test (z)			-285.043
p-value			0.000
AR(2) test (z)			0.771
p-value			0.441

Notes: HGF in productivity are defined as top 10% of fastest growing firms in labor productivity in the same 2-digit sector on a given year, conditional on its employment having not decreased in the same period. GMM regressions have been estimated using twostep robust estimation (Windmeijer, 2005). All estimations contain controls for: firm's wage premium w.r.t firms in the same 2-digit sector, importer/exporter status, and share of permanent workers. Significance: *p $<$ 0.1, **p $<$ 0.05, ***p $<$ 0.01. Robust standard errors in parentheses.

[a] The base category are firms with 2 or less years old.

[b] The reference category are firms with 1 – 9 employees.

[c] The base category are firms of which we have no credit-related information (that is, either they haven't made credit requests to new banks or they are not in the CIR database).

[d] Expressed on a per unit basis.

firms have a much lower likelihood of surviving and are more volatile. Accordingly, small firms are underrepresented among HGF in terms of employment (see Panel B of Table 5), and we observe that larger firms are more likely to experience high growth when the focus is on cross-sectional variation (i.e., OLS and Arellano-Bond estimator).

Fixed effects estimators can be biased if present or past high growth affects future covariates. This seems to be the case, as the third column in Table 6 shows. Size and the auto-regressive component now return to positive (albeit the second one is still one half lower than in OLS), suggesting that for these two variables, the biases corrected by fixed effects and Arellano-Bond estimators are opposite, and partially cancel out with each other. On the other hand, leverage becomes non-significant and the variables related to access to new credit are not qualitatively affected, with the exception of the coefficient on firms with all new loans rejected, which becomes positive. The fact that firms with all new loans rejected have higher probability than the reference groups implicitly implies that some of those firms, despite having asked for new loans and got all rejected, managed to grow at the end, so they didn't really need the extra financing, and found other ways of funding their growth.

Overall, the comparison between columns two and three reveals the well-known negative bias introduced by FE in dynamic panel models (Flannery and Hankins, 2013). In summary, using then our preferred estimation (Arellano-Bond), high growth in employment has some degree of persistence, is negatively affected by age, and positively affected by size and access to new finance. Leverage structure seems to be unrelated to high growth, and firms asking for new finance still have a positive effect on high employment growth, even if they get only rejections.

Now, going into high growth in productivity, first column in Table 7 shows that, according to OLS estimates, there is no persistence. Access to new finance has the same ranking as before (first firms asking and getting new loans from new banks, followed by firms not constrained in their current bank, then firms in the reference category, and finally firms asking for new finance, but getting only rejections), however the effects are smaller. Leverage effect, on the other hand, turns non-significant, though the picture changes when we introduce firm fixed effects and control for feedback effects with Arellano-Bond estimator. Finally, for high productivity growth, both age and size have negative effects.

Adding fixed effects does not introduce many changes, with the exception of the auto-regressive component, which becomes strongly negative, and the coefficient on the long term debt ratio, which turns positive and significant. Taking into account possible feedback from high productivity growth in covariates, as the third column in Table 7 shows, poses some more changes. First, the auto-regressive coefficient is also negative, but its size is substantially reduced in comparison with the fixed effects estimator. Consistent with Coad and Broekel (2012), this finding implies that firms that experienced high growth in productivity one year are unlikely to repeat such behavior the next year. Second, access to new finance is not

Table 8

HGF in employment (year-sec)(t+1)	OLS	Within estimator (FE)	Arellano-Bond estimator (GMM)
HGF in employment (year-sec)	0.0720***	−0.1018***	0.0376***
	(0.0008)	(0.0008)	(0.0013)
HGF in productivity (year-sec)	0.0217***	0.0176***	0.0151***
	(0.0006)	(0.0006)	(0.0009)
3-5 years old[a]	−0.0087***	−0.0183***	−0.0154***
	(0.0008)	(0.0011)	(0.0014)
6-10 years old	−0.0211***	−0.0186***	−0.0370***
	(0.0008)	(0.0014)	(0.0017)
11-15 years old	−0.0306***	−0.0126***	−0.0553***
	(0.0008)	(0.0018)	(0.0021)
16-20 years old	−0.0377***	−0.0065***	−0.0672***
	(0.0009)	(0.0023)	(0.0026)
21 or more years old	−0.0513***	−0.0062**	−0.0850***
	(0.0009)	(0.0029)	(0.0037)
10-19 employees[b]	0.0332***	−0.0787***	0.0447***
	(0.0006)	(0.0012)	(0.0034)
20-49 employees	0.0855***	−0.1677***	0.1180***
	(0.0009)	(0.0024)	(0.0076)
+50 employees	0.2008***	−0.2914***	0.2780***
	(0.0022)	(0.0053)	(0.0195)
Credit approved by a new bank[c]	0.0347***	0.0163***	0.0266***
	(0.0006)	(0.0007)	(0.0012)
Not constrained by current bank	0.0217***	0.0166***	0.0243***
	(0.0004)	(0.0005)	(0.0009)
All rejected	0.0072***	−0.0067***	0.0032**
	(0.0009)	(0.0010)	(0.0016)
LT debt ratio[d]	0.0148***	−0.0043**	−0.0037
	(0.0018)	(0.0019)	(0.0071)
LT debt ratio^2	−0.0057***	0.0012	−0.0027
	(0.0022)	(0.0011)	(0.0050)
Time fixed effects	Yes	Yes	Yes
Firm-year obs.	2 777 366	2 777 366	2 777 366
Number of firms		623 072	623 072
Avg. number of observations per firm		4.458	4.458
R-squared	0.056	0.047	
Number of instruments			201
AR(1) test (z)			−260.291
p-value			0.000
AR(2) test (z)			1.349
p-value			0.177

Notes: HGFs in employment are defined as top 10% of firms with the highest "Birch-Schreyer index" in the same 2-digit sector. HGF in productivity are defined as top 10% of fastest growing firms in labor productivity in the same 2-digit sector on a given year, conditional on its employment having not decreased in the same period. GMM regressions have been estimated using twostep robust estimation (Windmeijer, 2005). All estimations contain controls for: firm's wage premium w.r.t firms in the same 2-digit sector, importer/exporter status, and share of permanent workers. Significance: *p $<$ 0.1, **p $<$ 0.05, ***p $<$ 0.01. Robust standard errors in parentheses.

[a] The base category are firms with 2 or less years old.

[b] The reference category are firms with 1 – 9 employees.

[c] The base category are firms of which we have no credit-related information (that is, either they haven't made credit requests to new banks or they are not in the CIR database).

[d] Expressed on a per unit basis.

Table 9

HGF in productivity (year-sec)(t+1)	OLS	Within estimator (FE)	Arellano-Bond estimator (GMM)
HGF in productivity (year-sec)	0.0009	−0.1839***	−0.0285***
	(0.0006)	(0.0007)	(0.0010)
HGF in employment (year-sec)	−0.0018***	−0.0030***	0.0105***
	(0.0006)	(0.0006)	(0.0009)
3-5 years old[a]	−0.0256***	−0.0535***	−0.0410***
	(0.0009)	(0.0011)	(0.0016)
6-10 years old	−0.0401***	−0.0650***	−0.0657***
	(0.0008)	(0.0014)	(0.0019)
11-15 years old	−0.0461***	−0.0603***	−0.0804***
	(0.0008)	(0.0018)	(0.0022)
16-20 years old	−0.0485***	−0.0534***	−0.0847***
	(0.0009)	(0.0022)	(0.0028)
21 or more years old	−0.0469***	−0.0455***	−0.0886***
	(0.0009)	(0.0028)	(0.0040)
10-19 employees[b]	−0.0392***	−0.0407***	−0.0200***
	(0.0004)	(0.0009)	(0.0025)
20-49 employees	−0.0429***	−0.0698***	−0.0351***
	(0.0005)	(0.0015)	(0.0048)
+50 employees	−0.0500***	−0.0974***	−0.0535***
	(0.0009)	(0.0028)	(0.0094)
Credit approved by a new bank[c]	0.0101***	0.0132***	0.0220***
	(0.0006)	(0.0007)	(0.0011)
Not constrained by current bank	0.0088***	0.0114***	0.0187***
	(0.0004)	(0.0005)	(0.0009)
All rejected	−0.0033***	−0.0021**	0.0026*
	(0.0008)	(0.0010)	(0.0015)
LT debt ratio[d]	0.0052	0.0437***	0.1418***
	(0.0032)	(0.0029)	(0.0065)
LT debt ratio^2	0.0081*	0.0010	−0.0074***
	(0.0043)	(0.0030)	(0.0026)
Time fixed effects	Yes	Yes	Yes
Firm-year obs.	2 777 366	2 777 366	2 777 366
Number of firms		623 072	623 072
Avg. number of observations per firm		4.458	4.458
R-squared	0.016	0.047	
Number of instruments			201
AR(1) test (z)			−285.004
p-value			0.000
AR(2) test (z)			0.682
p-value			0.495

Notes: HGFs in employment are defined as top 10% of firms with the highest "Birch-Schreyer index" in the same 2-digit sector. HGF in productivity are defined as top 10% of fastest growing firms in labor productivity in the same 2-digit sector on a given year, conditional on its employment having not decreased in the same period. GMM regressions have been estimated using twostep robust estimation (Windmeijer, 2005). All estimations contain controls for: firm's wage premium w.r.t firms in the same 2-digit sector, importer/exporter status, and share of permanent workers. Significance: *p < 0.1, **p < 0.05, ***p < 0.01. Robust standard errors in parentheses.

[a] The base category are firms with 2 or less years old.

[b] The reference category are firms with 1 – 9 employees.

[c] The base category are firms of which we have no credit-related information (that is, either they haven't made credit requests to new banks or they are not in the CIR database).

[d] Expressed on a per unit basis.

Table 10

	HGF in employment year-sec(t+1)		HGF in productivity year-sec(t+1)	
HGF in employment (year-sec)	0.0386***	0.0382***		0.0110***
	(0.0013)	(0.0013)		(0.0009)
HGF in productivity (year-sec)		0.0152***	−0.0284***	−0.0283***
		(0.0009)	(0.0010)	(0.0010)
3-5 years old[a]	−0.0191***	−0.0163***	−0.0434***	−0.0417***
	(0.0014)	(0.0014)	(0.0015)	(0.0016)
6-10 years old	−0.0427***	−0.0391***	−0.0695***	−0.0674***
	(0.0017)	(0.0017)	(0.0018)	(0.0019)
11-15 years old	−0.0628***	−0.0590***	−0.0857***	−0.0835***
	(0.0021)	(0.0021)	(0.0022)	(0.0022)
16-20 years old	−0.0763***	−0.0727***	−0.0916***	−0.0894***
	(0.0026)	(0.0026)	(0.0028)	(0.0028)
21 or more years old	−0.0967***	−0.0932***	−0.0972***	−0.0955***
	(0.0038)	(0.0037)	(0.0040)	(0.0040)
10-19 employees[b]	0.0466***	0.0456***	−0.0145***	−0.0193***
	(0.0034)	(0.0034)	(0.0026)	(0.0025)
20-49 employees	0.1215***	0.1195***	−0.0227***	−0.0340***
	(0.0076)	(0.0076)	(0.0049)	(0.0048)
+50 employees	0.2830***	0.2797***	−0.0314***	−0.0521***
	(0.0195)	(0.0195)	(0.0096)	(0.0094)
LT debt ratio[c]	0.0290***	0.0286***	0.1663***	0.1654***
	(0.0093)	(0.0092)	(0.0064)	(0.0064)
LT debt ratio^2	−0.0119	−0.0114	−0.0091***	−0.0091***
	(0.0083)	(0.0081)	(0.0009)	(0.0010)
Time fixed effects	Yes	Yes	Yes	Yes
Firm-year obs.	2 777 366	2 777 366	2 777 366	2 777 366
Number of firms	623 072	623 072	623 072	623 072
Avg. number of observations per firm	4.458	4.458	4.458	4.458
Number of instruments	161	171	161	171
AR(1) test (z)	−260.081	−260.112	−285.024	−284.983
p-value	0.000	0.000	0.000	0.000
AR(2) test (z)	1.544	1.431	0.777	0.685
p-value	0.123	0.152	0.437	0.493

Notes: HGFs in employment are defined as top 10% of firms with the highest "Birch-Schreyer index" in the same 2-digit sector. HGF in productivity are defined as top 10% of fastest growing firms in labor productivity in the same 2-digit sector on a given year, conditional on its employment having not decreased in the same period. GMM regressions have been estimated using twostep robust estimation (Windmeijer, 2005). All estimations contain controls for: firm's wage premium w.r.t firms in the same 2-digit sector, importer/exporter status, and share of permanent workers. Significance: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors in parentheses.

[a] The base category are firms with 2 or less years old.
[b] The reference category are firms with 1 – 9 employees.
[c] The base category are firms of which we have no credit-related information (that is, either they haven't made credit requests to new banks or they are not in the CIR database).
[d] Expressed on a per unit basis.

qualitatively affected, but the coefficients are around twice as large as in the cases of OLS or fixed effects. And third, the leverage ratio becomes strongly positive, with a virtually nonexistent U-shape pattern. In conclusion, as opposed to employment, high productivity growth is negatively auto-correlated, depends negatively on age and size, and positively on leverage and access to new credit.

So far, we have studied each type of high growth separately. Tables 8 and 9 extend the previous models to allow cross auto-correlation between high growth in employment and productivity. The first thing to notice is that all other coefficients are hardly affected; hence the omission of crossed effects did not affect their estimation. Focusing now on cross correlation coefficients, it's clear that high productivity growth has a positive effect on the probability of future high employment growth. We find this positive effect on all the three estimation methods considered. On the contrary, crossed effect from high growth in employment on productivity is less clear. It is negative for the OLS and FE estimators, but positive for the Arellano-Bond one. Even in this latter case, the magnitude is 0.01, which is around one third lower than the effect of productivity on employment for the same method. These results are in line with those in Moral-Benito (2016).

Finally, we want to stress the importance of omitted variables bias in the estimation of financial factors. Some papers (e.g. Lopez-Garcia and Puente, 2012) have estimated the effect of leverage on high growth. However, this estimation could be biased if the important issue for high growth is to have access to new credit, not leverage by itself. If access facilitates an increase in leverage (a sensible possibility), then omitting access to credit could substantially bias up the estimated effect of leverage. Table 10 presents Arellano-Bond estimators for both types of high growth, but excluding variables related to access to new credit. The result is that all coefficients are more or less unaffected, except the leverage ones. In the case of high employment growth, leverage estimators turn positive and significant, moreover they are 7-8 times larger in absolute value. For high productivity growth, changes are not that intense: the relation is still positive and quadratic, though coefficients on both the linear and quadratic terms are larger. These results point to a warning when estimating effects of financial structure, as estimators could suffer from an important bias if variables related to access to new credit are not taken into account.

7 Conclusions

This paper adds to a wide range of recent research in entrepreneurship, innovation, and firm demography devoted to understanding what characterizes high growth firms (Almus, 2002; Lopez-Garcia and Puente, 2012; Segarra and Teruel, 2014). Our analysis extends this literature by providing evidence on the role of financial constraints as a growth barrier,[29] and by exploring the potential feedback effects from productivity growth to size growth, and vice versa.

According to our results, being a HGF in productivity significantly increases the probability of experiencing subsequent high growth in employment. Similarly, employment HGF status leads to higher probability of becoming a HGF in productivity in the following period, however, the magnitude of this crossed effect is around one third of that of productivity on employment high growth. Our interpretation of this finding is that while barriers to firm growth might be important (e.g. size-dependent regulations) the key determinant of firm growth is productivity, as predicted by standard models of firm dynamics (Jovanovic, 1982).

As for the role of financial constraints, our findings indicate that, regardless of whom provides the funds (whether current lenders or new ones), firms getting a loan approval have significantly more probability of experiencing high growth of any kind than firms without bank debt increases or with no bank debt at all. We thus conclude that credit constraints hamper high growth episodes in terms of size and productivity.

While we acknowledge there are other potential factors affecting firm's growth and productivity prospects that are absent in our analysis (e.g., innovation and R&D intensity, managerial talent, market competition), the purpose of this paper is to emphasize the role of financial constraints as determinants of size and productivity high growth, as well as to open the door to future research on the firm size–productivity nexus. One potential avenue for future research could be to explore the importance of the high growth phenomenon at the aggregate level, by taking into account firm entry and exit rates together with the underlying resource reallocation process.

[29] In this regard, our paper also contributes to the literature on the effects of financial constraints on firms' real outcomes (Campello et al., 2010; Chodorow-Reich, 2014; Popov and Rocholl, 2016).

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A Other Tables and figures

Table A.1: Contribution to employment (L) growth*

	Number of firms in each group				*Absolute growth in number of employees*			
All sectors	HGF in L	L grows	L shrinks	All Firms	HGF in L	L grows	L shrinks	All Firms
2001 - 2002	18,452	119,074	43,922	181,448	164,374.9	51,006.4	- 125,583.6	89,797.7
2002 - 2003	21,313	135,723	53,063	210,099	180,736.1	54,107.3	- 151,215.9	83,627.6
2003 - 2004	23,811	149,694	61,538	235,043	222,810.2	59,086.8	- 162,090.2	119,806.8
2004 - 2005	25,388	162,664	65,978	254,030	245,697.5	68,289.1	- 159,184.1	154,802.6
2005 - 2006	25,180	159,890	69,359	254,429	240,449.4	66,660.5	- 152,351.0	154,758.8
2006 - 2007	24,628	149,930	69,774	244,332	235,965.5	59,971.0	- 160,435.4	135,501.2
2007 - 2008	26,067	133,708	92,331	252,106	221,039.0	47,066.0	- 259,281.9	8,823.1
2008 - 2009	30,673	135,531	130,973	297,177	147,898.7	22,489.5	- 431,820.9	- 261,432.7
2009 - 2010	30,575	149,977	116,868	297,420	222,359.0	35,536.4	- 277,475.4	- 19,580.0
2010 - 2011	30,096	156,041	105,996	292,133	191,958.9	37,517.6	- 253,372.1	- 23,895.6
2011 - 2012	26,542	128,878	103,729	259,149	154,882.5	24,112.8	- 268,096.2	- 89,100.9
Total	282,725	1,581,110	913,531	2,777,366	2,228,171.7	525,843.5	- 2,400,906.7	353,108.6

* Figures in the table are computed as follows. Each year (t) firms are classified into one of the following groups: HGF in employment (top 10% of firms with the highest "Birch-Schreyer index" in the same 2-digit sector), slow growth firms (firms that don't qualify as HGF but that either kept their employment constant or increased it), and shrinking firms (firms that don't qualify as HGF but that decreased their employment). We then compute firms' absolute change in the number of employees from $t-1$ to t, and sum it all up across firms within the same group.

Table A.2: Contribution to labor productivity (LPR)

All sectors	*Number of firms in each group* HGF in LPR	LPR grows	LPR shrinks	All Firms	*How much aggregate productivity would have grown, had the reference group not grown* HGF	LPR grows	LPR shrinks	All Firms	*Contribution of each group to aggregate growth*[a] HGF	LPR grows	LPR shrinks	All Firms
2001 - 2002	17,739	70,084	93,625	181,448	−3.1%	−6.5%	6.0%	−1.7%	1.4*pp*	4.8*pp*	−7.7*pp*	−1.7%
2002 - 2003	20,801	86,807	102,491	210,099	−1.5%	−5.3%	7.4%	0.3%	1.7*pp*	5.5*pp*	−7.2*pp*	0.3%
2003 - 2004	23,182	93,391	118,470	235,043	−1.7%	−5.5%	7.4%	0.0%	1.8*pp*	5.6*pp*	−7.3*pp*	0.0%
2004 - 2005	24,971	102,298	126,761	254,030	−4.0%	−7.1%	6.2%	−2.1%	1.9*pp*	5.0*pp*	−8.3*pp*	−2.1%
2005 - 2006	24,992	109,992	119,445	254,429	−1.6%	−5.1%	7.8%	0.6%	2.1*pp*	5.7*pp*	−7.3*pp*	0.6%
2006 - 2007	24,001	109,175	111,156	244,332	−0.4%	−4.9%	8.3%	1.3%	1.7*pp*	6.2*pp*	−6.9*pp*	1.3%
2007 - 2008	25,225	82,781	144,100	252,106	−7.0%	−9.6%	6.1%	−5.8%	1.2*pp*	3.9*pp*	−11.9*pp*	−5.8%
2008 - 2009	29,280	99,006	168,891	297,177	−4.4%	−7.1%	7.6%	−2.9%	1.5*pp*	4.2*pp*	−10.4*pp*	−2.9%
2009 - 2010	29,734	123,466	144,220	297,420	2.0%	−4.5%	10.2%	3.7%	1.7*pp*	8.2*pp*	−6.6*pp*	3.7%
2010 - 2011	28,942	105,544	157,647	292,133	−2.8%	−6.3%	7.3%	−1.2%	1.6*pp*	5.1*pp*	−8.5*pp*	−1.2%
2011 - 2012	25,889	91,569	141,691	259,149	−2.4%	−6.1%	7.1%	−1.1%	1.4*pp*	5.0*pp*	−8.2*pp*	−1.1%
Total	274,756	1,074,113	1,428,497	2,777,366	−2.4%	−6.2%	7.5%	−0.8%				

[a] The contribution of the different reference groups (i.e., HGF, slow growth firms and shrinking firms) to overall labor productivity growth is computed as follows. First we calculate the growth in productivity for all studied firms had the reference group not grown. We do this by setting the labor productivity growth of the reference group to zero; in particular, we set the deflated GVA to a level such that GVA *per employee* from $t-1$ to t remains unchanged. Then we compute the growth rate in labor productivity from $t-1$ to t as:

$$\textit{Labor productivity growth}_{\,t}\ (\%) = \left(\frac{\sum_{i=1}^{n} GVA_{i,t}}{\sum_{i=1}^{n} L_{i,t}} \Big/ \frac{\sum_{i=1}^{n} GVA_{i,t-1}}{\sum_{i=1}^{n} L_{i,t-1}} - 1 \right) \times 100$$

Secondly, we define the contribution of each group to overall growth as the difference between overall (actual) growth for all studied firms and the rate of growth for all studied firms had the reference firms' not grown.

B Extended Summary Statistics

Table B.1: Summary statistics by HGF status

		HGF in productivity		HGF in employment		**Total**
		0	1	0	1	
Avg. nº employees	Mean	16.70	7.67	11.29	55.58	15.80
	10th percentile	1.00	1.00	1.00	3.00	1.00
	Median	4.83	3.00	4.00	10.00	4.47
	90th percentile	21.00	12.00	17.00	50.00	20.00
	Standard deviation	283.25	92.45	181.64	652.37	270.44
Firm age	Mean	12.01	9.41	11.85	10.93	11.75
	10th percentile	3.00	2.00	3.00	2.00	3.00
	Median	11.00	8.00	10.00	9.00	10.00
	90th percentile	22.00	19.00	21.00	22.00	21.00
	Standard deviation	8.66	8.15	8.52	9.66	8.64
Total assets	Mean	3,061.27	1,609.76	2,220.54	9,067.15	2,917.50
	10th percentile	57.66	45.18	53.66	94.04	56.07
	Median	336.39	244.74	306.42	584.96	325.94
	90th percentile	2,425.20	1,905.48	2,160.67	5,347.89	2,376.20
	Standard deviation	104,405.30	36,640.55	88,810.84	167,770.20	99,769.62
Total sales	Mean	2,741.36	1,418.48	1,929.83	8,614.74	2,610.33
	10th percentile	65.73	54.94	60.66	139.61	64.31
	Median	364.28	265.76	324.68	791.24	352.60
	90th percentile	2,497.85	1,747.57	2,114.90	5,696.13	2,427.78
	Standard deviation	80,081.52	33,747.74	66,977.54	135,078.80	76,751.68
LT debt ratio	Mean	0.17	0.18	0.17	0.18	0.17
	10th percentile	0.00	0.00	0.00	0.00	0.00
	Median	0.06	0.06	0.06	0.09	0.06
	90th percentile	0.51	0.57	0.52	0.51	0.52
	Standard deviation	0.23	0.25	0.23	0.22	0.23

(continuation Table B.1)

		HGF in productivity		HGF in employment		**Total**
		0	1	0	1	
Wage premium (within sector)	Mean	1.02	0.99	1.02	0.96	1.01
	10th percentile	0.56	0.51	0.56	0.54	0.55
	Median	0.95	0.91	0.95	0.91	0.94
	90th percentile	1.55	1.58	1.57	1.43	1.56
	Standard deviation	0.42	0.45	0.43	0.37	0.42
Share of permanent workers	Mean	0.81	0.81	0.83	0.69	0.81
	10th percentile	0.43	0.38	0.47	0.25	0.43
	Median	0.94	1.00	0.98	0.75	0.95
	90th percentile	1.00	1.00	1.00	1.00	1.00
	Standard deviation	0.25	0.28	0.25	0.28	0.26
Firm exports	Nº of cases	114,499	11,546	102,080	23,965	126,045
	Relative Frequency	90.8%	9.2%	81.0%	19.0%	100.0%
Firm imports	Nº of cases	153,830	15,498	138,628	30,700	169,328
	Relative Frequency	90.8%	9.2%	81.9%	18.1%	100.0%
Firm-year observations in sample		2,502,278	275,088	2,494,641	282,725	2,777,366
		90.10%	9.90%	89.82%	10.18%	100.00%

Table B.2: Summary statistics by degree of financial constraints

		No info	Credit approved by a new bank	Not constrained by current bank	All rejected	Total
Avg. nº employees	Mean	9.10	24.33	20.78	24.57	15.80
	10th percentile	1.00	2.00	1.68	1.25	1.00
	Median	3.34	6.95	5.66	5.42	4.47
	90th percentile	13.39	31.75	24.00	26.85	20.00
	Standard deviation	163.84	308.66	341.58	388.52	270.44
Firm age	Mean	11.43	11.83	12.04	12.74	11.75
	10th percentile	3.00	3.00	3.00	3.00	3.00
	Median	10.00	10.00	10.00	11.00	10.00
	90th percentile	21.00	22.00	22.00	23.00	21.00
	Standard deviation	8.23	9.08	8.95	9.15	8.64
Total assets (K euros)	Mean	1,716.98	3,883.78	3,957.60	4,684.87	2,917.50
	10th percentile	38.65	105.55	86.25	78.86	56.07
	Median	216.84	601.02	422.75	533.15	325.94
	90th percentile	1,573.79	3,987.22	2,773.50	3,838.18	2,376.20
	Standard deviation	87,547.02	87,085.62	114,973.60	115,053.30	99,769.62
Total sales (K euros)	Mean	1,269.06	3,760.66	3,823.53	3,910.12	2,610.33
	10th percentile	45.66	118.10	102.52	79.63	64.31
	Median	225.77	684.07	503.40	485.72	352.60
	90th percentile	1,341.78	4,337.50	3,051.98	3,426.94	2,427.78
	Standard deviation	51,722.31	79,230.16	96,317.04	105,836.90	76,751.68
LT debt ratio	Mean	0.15	0.21	0.18	0.20	0.17
	10th percentile	0.00	0.00	0.00	0.00	0.00
	Median	0.02	0.14	0.08	0.10	0.06
	90th percentile	0.50	0.54	0.51	0.55	0.52
	Standard deviation	0.23	0.22	0.22	0.24	0.23

(continuation Table B.2)

		No info	Credit approved by a new bank	Not constrained by current bank	All rejected	Total
Wage premium (within sector)	Mean	0.97	1.05	1.05	1.03	1.01
	10th percentile	0.51	0.61	0.60	0.58	0.55
	Median	0.90	0.98	0.98	0.97	0.94
	90th percentile	1.52	1.56	1.60	1.56	1.56
	Standard deviation	0.43	0.40	0.42	0.41	0.42
Share of permanent workers	Mean	0.83	0.78	0.80	0.81	0.81
	10th percentile	0.47	0.36	0.40	0.43	0.43
	Median	1.00	0.88	0.92	0.93	0.95
	90th percentile	1.00	1.00	1.00	1.00	1.00
	Standard deviation	0.25	0.27	0.26	0.25	0.26
Firm exports goods	Nº of cases	28,665	25,620	65,330	6,430	126,045
	Relative Frequency	22.7%	20.3%	51.8%	5.1%	100.0%
Firm imports goods	Nº of cases	38,550	34,704	88,265	7,809	169,328
	Relative Frequency	22.8%	20.5%	52.1%	4.6%	100.0%
HGF in productivity = 1	Nº of cases	134,247	32,436	98,277	10,128	275,088
	Relative Frequency	48.8%	11.8%	35.7%	3.7%	100.0%
HGF in employment = 1	Nº of cases	97,533	51,498	121,311	12,383	282,725
	Relative Frequency	34.5%	18.2%	42.9%	4.4%	100.0%
Firm-year observations in sample		1,315,116	313,911	1,036,805	111,534	2,777,366
		47.4%	11.3%	37.3%	4.0%	100.0%

C Robustness Checks

Table C.1: Marginal effects: RE probit vs FE

	HGF in employment (year-sec) (t+1)			
	RE probit model	Fixed effects	RE probit model	Fixed effects
HGF in employment (year-sec)	0.0666***	−0.1018***	0.0662***	−0.1018***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
HGF in productivity (year-sec)			0.0164***	0.0176***
			(0.0007)	(0.0006)
3-5 years old[a]	−0.0145***	−0.0204***	−0.0126***	−0.0183***
	(0.0008)	(0.0011)	(0.0008)	(0.0011)
6-10 years old	−0.0310***	−0.0210***	−0.0287***	−0.0186***
	(0.0009)	(0.0014)	(0.0009)	(0.0014)
11-15 years old	−0.0462***	−0.0149***	−0.0440***	−0.0126***
	(0.0010)	(0.0018)	(0.0010)	(0.0018)
16-20 years old	−0.0580***	−0.0085***	−0.0562***	−0.0065***
	(0.0010)	(0.0023)	(0.0011)	(0.0023)
21 or more years old	−0.0719***	−0.0080***	−0.0705***	−0.0062**
	(0.0011)	(0.0029)	(0.0011)	(0.0029)
10-19 employees[b]	−0.0681***	−0.0787***	−0.0681***	−0.0787***
	(0.0005)	(0.0012)	(0.0005)	(0.0012)
20-49 employees	−0.0939***	−0.1676***	−0.0940***	−0.1677***
	(0.0005)	(0.0024)	(0.0005)	(0.0024)
+50 employees	−0.0923***	−0.2911***	−0.0923***	−0.2914***
	(0.0003)	(0.0053)	(0.0003)	(0.0053)
Credit approved by a new bank[c]	0.0130***	0.0164***	0.0129***	0.0163***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Not constrained by current bank	0.0170***	0.0167***	0.0170***	0.0166***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
All rejected	−0.0061***	−0.0067***	−0.0061***	−0.0067***
	(0.0009)	(0.0010)	(0.0009)	(0.0010)
LT debt ratio[d]	−0.0003	−0.0036**	−0.0004	−0.0039**
	(0.0016)	(0.0017)	(0.0016)	(0.0017)
Time fixed effects	Yes	Yes	Yes	Yes
Firm-year obs.	2,777,366	2,777,366	2,777,366	2,777,366
Number of firms	623,072	623,072	623,072	623,072
Avg. nº observations per firm	4.458	4.458	4.458	4.458
R-squared		0.047		0.047
Rho	0.021		0.022	
Sigma u	0.148		0.149	

Notes: We apply Wooldridge (2005) solution to the initial conditions problem for dynamic nonlinear unobserved-effects models. In doing so, we include the within-means of time-varying regressors as additional explanatory variables. Several authors have forewarned that this methodology performs poorly for short panels if the within-means are based on all periods, including the initial period. However, following Rabe-Hesketh and Skrondal (2013), we overcome this problem by including the initial-period explanatory variables as additional regressors. HGF in employment are defined as top 5% of firms with the highest "Birch-Schreyer index" in the same 2-digit sector. All estimations contain controls for: firm's wage premium w.r.t other firms in the same 2-digit sector (in logs), importer/exporter status, and share of permanent workers.

[a] The base category are firms with 2 or less years old.

[b] The reference category are firms with 1 – 9 employees.

[c] The base category are firms of which we have no credit-related information (that is, either they haven't made credit requests to new banks or they are not in the CIR database).

[d] Expressed on a per unit basis.

Table C.2: Marginal effects: RE probit vs FE

	HGF in productivity (year-sec) (t+1)			
	RE probit model	Fixed effects	RE probit model	Fixed effects
HGF in productivity (year-sec)	−0.0182***	−0.1839***	−0.0182***	−0.1839***
	(0.0005)	(0.0007)	(0.0005)	(0.0007)
HGF in employment (year-sec)			−0.0030***	−0.0030***
			(0.0007)	(0.0006)
3-5 years old[a]	−0.0271***	−0.0532***	−0.0275***	−0.0535***
	(0.0007)	(0.0011)	(0.0007)	(0.0011)
6-10 years old	−0.0408***	−0.0647***	−0.0416***	−0.0650***
	(0.0009)	(0.0014)	(0.0009)	(0.0014)
11-15 years old	−0.0447***	−0.0600***	−0.0456***	−0.0603***
	(0.0010)	(0.0018)	(0.0010)	(0.0018)
16-20 years old	−0.0456***	−0.0531***	−0.0467***	−0.0534***
	(0.0011)	(0.0022)	(0.0011)	(0.0022)
21 or more years old	−0.0475***	−0.0453***	−0.0486***	−0.0455***
	(0.0014)	(0.0028)	(0.0014)	(0.0028)
10-19 employees[b]	−0.0431***	−0.0411***	−0.0426***	−0.0407***
	(0.0008)	(0.0009)	(0.0008)	(0.0009)
20-49 employees	−0.0671***	−0.0707***	−0.0664***	−0.0698***
	(0.0009)	(0.0014)	(0.0009)	(0.0015)
+50 employees	−0.0784***	−0.0990***	−0.0779***	−0.0974***
	(0.0009)	(0.0027)	(0.0009)	(0.0028)
Credit approved by a new bank[c]	0.0134***	0.0131***	0.0136***	0.0132***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Not constrained by current bank	0.0130***	0.0113***	0.0131***	0.0114***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
All rejected	−0.0041***	−0.0021**	−0.0041***	−0.0021**
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
LT debt ratio[d]	0.0407***	0.0441***	0.0407***	0.0441***
	(0.0015)	(0.0022)	(0.0015)	(0.0022)
Time fixed effects	Yes	Yes	Yes	Yes
Firm-year obs.	2,777,366	2,777,366	2,777,366	2,777,366
Number of firms	623,072	623,072	623,072	623,072
Avg. nº observations per firm	4.458	4.458	4.458	4.458
R-squared		0.047		0.047
Rho	0.087		0.086	
Sigma u	0.309		0.307	

Notes: We apply Wooldridge (2005) solution to the initial conditions problem for dynamic nonlinear unobserved-effects models. In doing so, we include the within-means of time-varying regressors as additional explanatory variables. Several authors have forewarned that this methodology performs poorly for short panels if the within-means are based on all periods, including the initial period. However, following Rabe-Hesketh and Skrondal (2013), we overcome this problem by including the initial-period explanatory variables as additional regressors. HGF in employment are defined as top 5% of firms with the highest “Birch-Schreyer index” in the same 2-digit sector. All estimations contain controls for: firm’s wage premium w.r.t other firms in the same 2-digit sector (in logs), importer/exporter status, and share of permanent workers.
[a] The base category are firms with 2 or less years old.
[b] The reference category are firms with 1 – 9 employees.
[c] The base category are firms of which we have no credit-related information (that is, either they haven’t made credit requests to new banks or they are not in the CIR database).
[d] Expressed on a per unit basis.

Table C.3: Top 1% HGF (equivalent to Table 6)

HGF in employment (year-sec) (t+1)	OLS	Within estimator (FE)	Arellano-Bond estimator (GMM)
HGF in employment (year-sec)	0.1010∗∗∗	−0.1107∗∗∗	0.0337∗∗∗
	(0.0026)	(0.0023)	(0.0028)
3-5 years old[a]	0.0006∗∗	−0.0025∗∗∗	−0.0015∗∗∗
	(0.0003)	(0.0003)	(0.0004)
6-10 years old	−0.0008∗∗∗	−0.0014∗∗∗	−0.0034∗∗∗
	(0.0002)	(0.0004)	(0.0005)
11-15 years old	−0.0018∗∗∗	0.0005	−0.0054∗∗∗
	(0.0002)	(0.0006)	(0.0006)
16-20 years old	−0.0022∗∗∗	0.0023∗∗∗	−0.0067∗∗∗
	(0.0003)	(0.0007)	(0.0007)
21 or more years old	−0.0039∗∗∗	0.0026∗∗∗	−0.0098∗∗∗
	(0.0003)	(0.0010)	(0.0010)
10-19 employees[b]	0.0014∗∗∗	−0.0106∗∗∗	0.0082∗∗∗
	(0.0002)	(0.0004)	(0.0011)
20-49 employees	0.0103∗∗∗	−0.0287∗∗∗	0.0213∗∗∗
	(0.0003)	(0.0009)	(0.0029)
+50 employees	0.0857∗∗∗	−0.0696∗∗∗	0.0755∗∗∗
	(0.0014)	(0.0029)	(0.0103)
Credit approved by a new bank[c]	0.0041∗∗∗	0.0019∗∗∗	0.0036∗∗∗
	(0.0002)	(0.0002)	(0.0004)
Not constrained by current bank	0.0020∗∗∗	0.0017∗∗∗	0.0030∗∗∗
	(0.0001)	(0.0001)	(0.0002)
All rejected	0.0001	−0.0011∗∗∗	0.0003
	(0.0003)	(0.0003)	(0.0005)
LT debt ratio[d]	0.0010∗∗∗	−0.0004	−0.0002
	(0.0003)	(0.0005)	(0.0015)
LT debt ratio^2	−0.0001	0.0003	−0.0001
	(0.0003)	(0.0003)	(0.0001)
Time fixed effects	Yes	Yes	Yes
Firm-year obs.	2,777,366	2,777,366	2,777,366
Number of firms	623,072	623,072	623,072
Avg. nº observations per firm		4.458	4.458
R-squared	0.051	0.022	
Number of instruments			191
AB test for autocorrelation of order 1 (z)			−82.113
Prob > z			0.000
AB test for autocorrelation of order 2 (z)			0.351
Prob > z			0.726

Notes: HGF in employment are defined as top 5% of firms with the highest "Birch-Schreyer index" in the same 2-digit sector. GMM regressions have been estimated using twostep robust estimator (Windmeijer, 2005). All estimations contain controls for: firm's wage premium w.r.t other firms in the same 2-digit sector (in logs), importer/exporter status, and share of permanent workers.

[a] The base category are firms with 2 or less years old.

[b] The reference category are firms with 1 – 9 employees.

[c] The base category are firms of which we have no credit-related information (that is, either they haven't made credit requests to new banks or they are not in the CIR database).

[d] Expressed on a per unit basis.

Table C.4: Top 1% HGF (equivalent to Table 7)

HGF in productivity (year-sec) (t+1)	OLS	Within estimator (FE)	Arellano-Bond estimator (GMM)
HGF in productivity (year-sec)	−0.0009	−0.1614∗∗∗	−0.0127∗∗∗
	(0.0006)	(0.0014)	(0.0013)
3-5 years old[a]	−0.0022∗∗∗	−0.0068∗∗∗	−0.0037∗∗∗
	(0.0003)	(0.0003)	(0.0005)
6-10 years old	−0.0035∗∗∗	−0.0073∗∗∗	−0.0047∗∗∗
	(0.0003)	(0.0004)	(0.0006)
11-15 years old	−0.0039∗∗∗	−0.0061∗∗∗	−0.0040∗∗∗
	(0.0003)	(0.0005)	(0.0007)
16-20 years old	−0.0037∗∗∗	−0.0050∗∗∗	−0.0018∗∗
	(0.0003)	(0.0006)	(0.0008)
21 or more years old	−0.0033∗∗∗	−0.0046∗∗∗	−0.0007
	(0.0003)	(0.0008)	(0.0012)
10-19 employees[b]	−0.0051∗∗∗	−0.0043∗∗∗	−0.0017∗∗∗
	(0.0001)	(0.0002)	(0.0006)
20-49 employees	−0.0055∗∗∗	−0.0069∗∗∗	−0.0022∗
	(0.0001)	(0.0004)	(0.0012)
+50 employees	−0.0053∗∗∗	−0.0091∗∗∗	−0.0030
	(0.0002)	(0.0005)	(0.0021)
Credit approved by new bank[c]	0.0004∗∗	0.0003∗	0.0018∗∗∗
	(0.0002)	(0.0002)	(0.0003)
Not constrained by current bank	0.0005∗∗∗	0.0002∗	0.0014∗∗∗
	(0.0001)	(0.0001)	(0.0003)
All rejected	−0.0001	−0.0010∗∗∗	−0.0007∗
	(0.0002)	(0.0003)	(0.0005)
LT debt ratio[d]	0.0014∗	0.0059∗∗∗	0.0185∗∗∗
	(0.0007)	(0.0008)	(0.0023)
LT debt ratio^2	0.0018∗	0.0008	−0.0004
	(0.0010)	(0.0007)	(0.0017)
Time fixed effects	Yes	Yes	Yes
Firm-year obs.	2,777,366	2,777,366	2,777,366
Number of firms	623,072	623,072	623,072
Avg. n observations per firm		4.458	4.458
R-squared	0.003	0.035	
N of instruments used			191
AR(1) (p-value)			−87.311
Prob > z			0.000
AR(2) (p-value)			1.926
Prob > z			0.054

Notes: HGF in productivity are the top 5% of fastest growing firms in labor productivity in the same 2-digit sector on a given year, conditional on its employment having not decreased in the same period. GMM regressions have been estimated using twostep robust estimator (Windmeijer, 2005). All estimations contain controls for: firm's wage premium w.r.t other firms in the same 2-digit sector (in logs), importer/exporter status, and share of permanent workers.
[a] The base category are firms with 2 or less years old.
[b] The reference category are firms with 1 – 9 employees.
[c] The base category are firms of which we have no credit-related information (that is, either they haven't made credit requests to new banks or they are not in the CIR database).
[d] Expressed on a per unit basis.

Table C.5: Top 1% HGF (equivalent to Table 8)

HGF in employment (year-sec)(t+1)	OLS	Within estimator (FE)	Arellano-Bond estimator (GMM)
HGF in employment (year-sec)	0.1009***	−0.1107***	0.0336***
	(0.0026)	(0.0023)	(0.0028)
HGF in productivity (year-sec)	0.0035***	0.0035***	0.0028***
	(0.0006)	(0.0007)	(0.0009)
3-5 years old[a]	0.0007***	−0.0024***	−0.0013***
	(0.0003)	(0.0003)	(0.0004)
6-10 years old	−0.0006***	−0.0013***	−0.0033***
	(0.0002)	(0.0004)	(0.0005)
11-15 years old	−0.0016***	0.0006	−0.0052***
	(0.0002)	(0.0006)	(0.0006)
16-20 years old	−0.0021***	0.0024***	−0.0065***
	(0.0003)	(0.0007)	(0.0007)
21 or more years old	−0.0038***	0.0027***	−0.0096***
	(0.0003)	(0.0010)	(0.0010)
10-19 employees[b]	0.0014***	−0.0106***	0.0082***
	(0.0002)	(0.0004)	(0.0011)
20-49 employees	0.0103***	−0.0287***	0.0212***
	(0.0003)	(0.0009)	(0.0029)
+50 employees	0.0857***	−0.0696***	0.0753***
	(0.0014)	(0.0029)	(0.0103)
Credit approved by new bank[c]	0.0041***	0.0019***	0.0036***
	(0.0002)	(0.0002)	(0.0004)
Not constrained by current bank	0.0020***	0.0017***	0.0029***
	(0.0001)	(0.0001)	(0.0002)
All rejected	0.0001	−0.0011***	0.0003
	(0.0003)	(0.0003)	(0.0005)
LT debt ratio[d]	0.0010***	−0.0004	−0.0002
	(0.0003)	(0.0005)	(0.0015)
LT debt ratio^2	−0.0001	0.0003	−0.0001
	(0.0003)	(0.0003)	(0.0001)
Time fixed effects	Yes	Yes	Yes
Firm-year obs.	2,777,366	2,777,366	2,777,366
Number of firms	623,072	623,072	623,072
Avg. n observations per firm		4.458	4.458
R-squared	0.051	0.022	
N of instruments used			201
AR(1) (p-value)			−82.100
Prob > z			0.000
AR(2) (p-value)			0.340
Prob > z			0.734

Notes: HGF in employment are defined as top 5% of firms with the highest “Birch-Schreyer index” in the same 2-digit sector. GMM regressions have been estimated using twostep robust estimator (Windmeijer, 2005). All estimations contain controls for: firm’s wage premium w.r.t other firms in the same 2-digit sector (in logs), importer/exporter status, and share of permanent workers.
[a] The base category are firms with 2 or less years old.
[b] The reference category are firms with 1 – 9 employees.
[c] The base category are firms of which we have no credit-related information (that is, either they haven’t made credit requests to new banks or they are not in the CIR database).
[d] Expressed on a per unit basis.

Table C.6: Top 1% HGF (equivalent to Table 9)

HGF in productivity (year-sec)	OLS	Within estimator (FE)	Arellano-Bond estimator (GMM)
HGF in productivity (year-sec)	−0.0008	−0.1614***	−0.0127***
	(0.0006)	(0.0014)	(0.0013)
HGF in employment (year-sec)	−0.0012***	−0.0005	0.0004
	(0.0003)	(0.0004)	(0.0005)
3-5 years old[a]	−0.0022***	−0.0068***	−0.0036***
	(0.0003)	(0.0003)	(0.0005)
6-10 years old	−0.0035***	−0.0073***	−0.0047***
	(0.0003)	(0.0004)	(0.0006)
11-15 years old	−0.0039***	−0.0061***	−0.0040***
	(0.0003)	(0.0005)	(0.0007)
16-20 years old	−0.0037***	−0.0050***	−0.0018**
	(0.0003)	(0.0006)	(0.0008)
21 or more years old	−0.0034***	−0.0046***	−0.0007
	(0.0003)	(0.0008)	(0.0012)
10-19 employees[b]	−0.0051***	−0.0043***	−0.0017***
	(0.0001)	(0.0002)	(0.0006)
20-49 employees	−0.0055***	−0.0069***	−0.0023**
	(0.0001)	(0.0004)	(0.0012)
+50 employees	−0.0051***	−0.0090***	−0.0031
	(0.0002)	(0.0005)	(0.0020)
Credit approved by new bank[c]	0.0004**	0.0003*	0.0018***
	(0.0002)	(0.0002)	(0.0003)
Not constrained by current bank	0.0005***	0.0002*	0.0014***
	(0.0001)	(0.0001)	(0.0003)
All rejected	−0.0001	−0.0010***	−0.0007*
	(0.0002)	(0.0003)	(0.0005)
LT debt ratio[d]	0.0014*	0.0059***	0.0186***
	(0.0007)	(0.0008)	(0.0023)
LT debt ratio^2	0.0018*	0.0008	−0.0004
	(0.0010)	(0.0007)	(0.0017)
Time fixed effects	Yes	Yes	Yes
Firm-year obs.	2,777,366	2,777,366	2,777,366
Number of firms	623,072	623,072	623,072
Avg. n observations per firm		4.458	4.458
R-squared	0.003	0.035	
N of instruments used			201
AR(1) (p-value)			−87.309
Prob > z			0.000
AR(2) (p-value)			1.924
Prob > z			0.054

Notes: HGF in productivity are the top 5% of fastest growing firms in labor productivity in the same 2-digit sector on a given year, conditional on its employment having not decreased in the same period. GMM regressions have been estimated using twostep robust estimator (Windmeijer, 2005). All estimations contain controls for: firm's wage premium w.r.t other firms in the same 2-digit sector (in logs), importer/exporter status, and share of permanent workers.
[a] The base category are firms with 2 or less years old.
[b] The reference category are firms with 1 – 9 employees.
[c] The base category are firms of which we have no credit-related information (that is, either they haven't made credit requests to new banks or they are not in the CIR database).
[d] Expressed on a per unit basis.

Table C.7: Top 1% HGF (equivalent to Table 10)

	HGF in employment (year-sec) (t+1)		HGF in productivity (year-sec) (t+1)	
HGF in employment (year-sec)	0.0339***	0.0338***		0.0004
	(0.0028)	(0.0028)		(0.0005)
HGF in productivity (year-sec)		0.0029***	−0.0127***	−0.0127***
		(0.0009)	(0.0013)	(0.0013)
3-5 years old[a]	−0.0016***	−0.0015***	−0.0037***	−0.0037***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)
6-10 years old	−0.0037***	−0.0036***	−0.0049***	−0.0049***
	(0.0005)	(0.0005)	(0.0006)	(0.0006)
11-15 years old	−0.0058***	−0.0057***	−0.0043***	−0.0043***
	(0.0006)	(0.0006)	(0.0007)	(0.0007)
16-20 years old	−0.0074***	−0.0073***	−0.0023***	−0.0023***
	(0.0007)	(0.0007)	(0.0008)	(0.0008)
21 or more years old[b]	−0.0108***	−0.0107***	−0.0014	−0.0014
	(0.0010)	(0.0010)	(0.0012)	(0.0012)
10-19 employees	0.0083***	0.0083***	−0.0016**	−0.0016**
	(0.0011)	(0.0011)	(0.0007)	(0.0006)
20-49 employees	0.0216***	0.0215***	−0.0020*	−0.0021*
	(0.0029)	(0.0029)	(0.0012)	(0.0012)
+50 employees	0.0761***	0.0759***	−0.0028	−0.0029
	(0.0103)	(0.0103)	(0.0021)	(0.0020)
LT debt ratio[c]	0.0032	0.0032	0.0210***	0.0211***
	(0.0021)	(0.0021)	(0.0023)	(0.0023)
LT debt ratio^2	−0.0006	−0.0006	−0.0008	−0.0008
	(0.0008)	(0.0008)	(0.0014)	(0.0014)
Time fixed effects	Yes	Yes	Yes	Yes
Firm-year obs.	2,777,366	2,777,366	2,777,366	2,777,366
Number of firms	623,072	623,072	623,072	623,072
Avg. n observations per firm	4.458	4.458	4.458	4.458
N of instruments used	161	171	161	171
AR(1) (p-value)	−82.131	−82.119	−87.317	−87.315
Prob > z	0.000	0.000	0.000	0.000
AR(2) (p-value)	0.363	0.354	1.928	1.926
Prob > z	0.717	0.723	0.054	0.054

Notes: HGF in employment are defined as top 10% of firms with the highest “Birch-Schreyer index” in the same 2-digit sector. HGF in productivity are defined as top 10% of fastest growing firms in labor productivity in the same 2-digit sector on a given year, conditional on its employment having not decreased in the same period. GMM regressions have been estimated using twostep robust estimator (Windmeijer, 2005). All estimations contain controls for: firm’s wage premium w.r.t other firms in the same 2-digit sector (in logs), importer/exporter status, and share of permanent workers.
[a] The base category are firms with 2 or less years old.
[b] The reference category are firms with 1 – 9 employees.
[c] Expressed on a per unit basis.

Table C.8: Top 5% HGF (equivalent to Table 6)

HGF in employment (year-sec) (t+1)	OLS	Within estimator (FE)	Arellano-Bond estimator (GMM)
HGF in employment (year-sec)	0.0804***	−0.1036***	0.0362***
	(0.0010)	(0.0011)	(0.0015)
3-5 years old[a]	−0.0050***	−0.0127***	−0.0107***
	(0.0006)	(0.0008)	(0.0010)
6-10 years old	−0.0119***	−0.0117***	−0.0212***
	(0.0006)	(0.0010)	(0.0012)
11-15 years old	−0.0175***	−0.0074***	−0.0302***
	(0.0006)	(0.0013)	(0.0014)
16-20 years old	−0.0212***	−0.0031*	−0.0353***
	(0.0006)	(0.0016)	(0.0018)
21 or more years old	−0.0296***	−0.0027	−0.0411***
	(0.0007)	(0.0021)	(0.0025)
10-19 employees[b]	0.0157***	−0.0454***	0.0296***
	(0.0004)	(0.0009)	(0.0025)
20-49 employees	0.0560***	−0.1034***	0.0745***
	(0.0007)	(0.0019)	(0.0059)
+50 employees	0.1790***	−0.2013***	0.2132***
	(0.0020)	(0.0047)	(0.0167)
Credit approved by a new bank[c]	0.0199***	0.0096***	0.0151***
	(0.0005)	(0.0005)	(0.0008)
Not constrained by current bank	0.0110***	0.0092***	0.0131***
	(0.0003)	(0.0003)	(0.0006)
All rejected	0.0024***	−0.0045***	−0.0002
	(0.0006)	(0.0007)	(0.0012)
LT debt ratio[d]	0.0073***	−0.0023*	−0.0028
	(0.0009)	(0.0013)	(0.0045)
LT debt ratio^2	−0.0028***	0.0008	−0.0014
	(0.0011)	(0.0006)	(0.0027)
Time fixed effects	Yes	Yes	Yes
Firm-year obs.	2,777,366	2,777,366	2,777,366
Number of firms	623,072	623,072	623,072
Avg. nº observations per firm		4.458	4.458
R-squared	0.056	0.036	
Number of instruments			191
AB test for autocorrelation of order 1 (z)			−189.270
Prob > z			0.000
AB test for autocorrelation of order 2 (z)			1.465
Prob > z			0.143

Notes: HGF in employment are defined as top 5% of firms with the highest "Birch-Schreyer index" in the same 2-digit sector. GMM regressions have been estimated using twostep robust estimator (Windmeijer, 2005). All estimations contain controls for: firm's wage premium w.r.t other firms in the same 2-digit sector (in logs), importer/exporter status, and share of permanent workers.

[a] The base category are firms with 2 or less years old.

[b] The reference category are firms with 1 – 9 employees.

[c] The base category are firms of which we have no credit-related information (that is, either they haven't made credit requests to new banks or they are not in the CIR database).

[d] Expressed on a per unit basis.

Table C.9: Top 5% HGF (equivalent to Table 7)

HGF in productivity (year-sec) (t+1)	OLS	Within estimator (FE)	Arellano-Bond estimator (GMM)
HGF in productivity (year-sec)	0.0027***	−0.1791***	−0.0245***
	(0.0006)	(0.0008)	(0.0011)
3-5 years old[a]	−0.0137***	−0.0332***	−0.0228***
	(0.0006)	(0.0008)	(0.0011)
6-10 years old	−0.0216***	−0.0392***	−0.0347***
	(0.0006)	(0.0010)	(0.0013)
11-15 years old	−0.0246***	−0.0362***	−0.0389***
	(0.0006)	(0.0012)	(0.0016)
16-20 years old	−0.0248***	−0.0322***	−0.0367***
	(0.0006)	(0.0015)	(0.0020)
21 or more years old	−0.0233***	−0.0290***	−0.0344***
	(0.0007)	(0.0019)	(0.0028)
10-19 employees[b]	−0.0245***	−0.0237***	−0.0140***
	(0.0003)	(0.0006)	(0.0017)
20-49 employees	−0.0263***	−0.0379***	−0.0212***
	(0.0003)	(0.0009)	(0.0031)
+50 employees	−0.0289***	−0.0525***	−0.0219***
	(0.0005)	(0.0016)	(0.0058)
Credit approved by a new bank[c]	0.0043***	0.0054***	0.0110***
	(0.0004)	(0.0005)	(0.0007)
Not constrained by current bank	0.0040***	0.0043***	0.0090***
	(0.0003)	(0.0003)	(0.0006)
All rejected	−0.0005	−0.0014**	0.0006
	(0.0006)	(0.0007)	(0.0010)
LT debt ratio[d]	0.0047**	0.0267***	0.0849***
	(0.0023)	(0.0020)	(0.0069)
LT debt ratio^2	0.0059*	0.0016	−0.0012
	(0.0032)	(0.0020)	(0.0073)
Time fixed effects	Yes	Yes	Yes
Firm-year obs.	2,777,366	2,777,366	2,777,366
Number of firms	623,072	623,072	623,072
Avg. nº observations per firm		4.458	4.458
R-squared	0.012	0.044	
Number of instruments			191
AB test for autocorrelation of order 1 (z)			−203.673
Prob > z			0.000
AB test for autocorrelation of order 2 (z)			2.363
Prob > z			0.018

Notes: HGF in productivity are the top 5% of fastest growing firms in labor productivity in the same 2-digit sector on a given year, conditional on its employment having not decreased in the same period. GMM regressions have been estimated using twostep robust estimator (Windmeijer, 2005). All estimations contain controls for: firm's wage premium w.r.t other firms in the same 2-digit sector (in logs), importer/exporter status, and share of permanent workers.
[a] The base category are firms with 2 or less years old.
[b] The reference category are firms with 1 – 9 employees.
[c] The base category are firms of which we have no credit-related information (that is, either they haven't made credit requests to new banks or they are not in the CIR database).
[d] Expressed on a per unit basis.

Table C.10: Top 5% HGF (equivalent to Table 8)

HGF in employment (year-sec)(t+1)	OLS	Within estimator (FE)	Arellano-Bond estimator (GMM)
HGF in employment (year-sec)	0.0804***	−0.1036***	0.0360***
	(0.0010)	(0.0011)	(0.0015)
HGF in productivity (year-sec)	0.0160***	0.0120***	0.0109***
	(0.0006)	(0.0007)	(0.0009)
3-5 years old[a]	−0.0033***	−0.0116***	−0.0091***
	(0.0006)	(0.0008)	(0.0010)
6-10 years old	−0.0099***	−0.0105***	−0.0193***
	(0.0006)	(0.0010)	(0.0012)
11-15 years old	−0.0155***	−0.0063***	−0.0283***
	(0.0006)	(0.0013)	(0.0014)
16-20 years old	−0.0192***	−0.0021	−0.0334***
	(0.0006)	(0.0016)	(0.0018)
21 or more years old	−0.0275***	−0.0018	−0.0393***
	(0.0007)	(0.0021)	(0.0025)
10-19 employees[b]	0.0161***	−0.0453***	0.0293***
	(0.0004)	(0.0009)	(0.0025)
20-49 employees	0.0565***	−0.1033***	0.0739***
	(0.0007)	(0.0019)	(0.0059)
+50 employees	0.1795***	−0.2012***	0.2122***
	(0.0020)	(0.0047)	(0.0167)
Credit approved by a new bank[c]	0.0198***	0.0096***	0.0151***
	(0.0005)	(0.0005)	(0.0008)
Not constrained by current bank	0.0110***	0.0092***	0.0131***
	(0.0003)	(0.0003)	(0.0006)
All rejected	0.0024***	−0.0045***	−0.0002
	(0.0006)	(0.0007)	(0.0012)
LT debt ratio[d]	0.0071***	−0.0024*	−0.0029
	(0.0009)	(0.0013)	(0.0045)
LT debt ratio^2	−0.0029***	0.0008	−0.0013
	(0.0011)	(0.0006)	(0.0026)
Time fixed effects	Yes	Yes	Yes
Firm-year obs.	2,777,366	2,777,366	2,777,366
Number of firms	623,072	623,072	623,072
Avg. nº observations per firm		4.458	4.458
R-squared	0.056	0.036	
Number of instruments			201
AB test for autocorrelation of order 1 (z)			−189.269
Prob > z			0.000
AB test for autocorrelation of order 2 (z)			1.403
Prob > z			0.161

Notes: HGF in employment are defined as top 5% of firms with the highest "Birch-Schreyer index" in the same 2-digit sector. GMM regressions have been estimated using twostep robust estimator (Windmeijer, 2005). All estimations contain controls for: firm's wage premium w.r.t other firms in the same 2-digit sector (in logs), importer/exporter status, and share of permanent workers.
[a] The base category are firms with 2 or less years old.
[b] The reference category are firms with 1 – 9 employees.
[c] The base category are firms of which we have no credit-related information (that is, either they haven't made credit requests to new banks or they are not in the CIR database).
[d] Expressed on a per unit basis.

Table C.11: Top 5% HGF (equivalent to Table 9)

HGF in productivity (year-sec)	OLS	Within estimator (FE)	Arellano-Bond estimator (GMM)
HGF in productivity (year-sec)	0.0027***	−0.1791***	−0.0245***
	(0.0006)	(0.0008)	(0.0011)
HGF in employment (year-sec)	−0.0035***	−0.0036***	0.0045***
	(0.0005)	(0.0006)	(0.0008)
3-5 years old[a]	−0.0140***	−0.0334***	−0.0223***
	(0.0006)	(0.0008)	(0.0011)
6-10 years old	−0.0219***	−0.0394***	−0.0340***
	(0.0006)	(0.0010)	(0.0013)
11-15 years old	−0.0250***	−0.0364***	−0.0383***
	(0.0006)	(0.0012)	(0.0016)
16-20 years old	−0.0251***	−0.0324***	−0.0361***
	(0.0006)	(0.0015)	(0.0020)
21 or more years old	−0.0237***	−0.0292***	−0.0339***
	(0.0007)	(0.0019)	(0.0028)
10-19 employees[b]	−0.0243***	−0.0234***	−0.0152***
	(0.0003)	(0.0006)	(0.0016)
20-49 employees	−0.0259***	−0.0371***	−0.0242***
	(0.0003)	(0.0009)	(0.0031)
+50 employees	−0.0278***	−0.0509***	−0.0281***
	(0.0005)	(0.0016)	(0.0057)
Credit approved by a new bank[c]	0.0044***	0.0055***	0.0109***
	(0.0004)	(0.0005)	(0.0007)
Not constrained by current bank	0.0041***	0.0043***	0.0089***
	(0.0003)	(0.0003)	(0.0006)
All rejected	−0.0005	−0.0014**	0.0006
	(0.0006)	(0.0007)	(0.0010)
LT debt ratio[d]	0.0047**	0.0267***	0.0845***
	(0.0023)	(0.0020)	(0.0070)
LT debt ratio^2	0.0059*	0.0016	−0.0010
	(0.0031)	(0.0020)	(0.0075)
Time fixed effects	Yes	Yes	Yes
Firm-year obs.	2,777,366	2,777,366	2,777,366
Number of firms	623,072	623,072	623,072
Avg. nº observations per firm		4.458	4.458
R-squared	0.013	0.044	
Number of instruments			201
AB test for autocorrelation of order 1 (z)			−203.668
Prob > z			0.000
AB test for autocorrelation of order 2 (z)			2.332
Prob > z			0.020

Notes: HGF in productivity are the top 5% of fastest growing firms in labor productivity in the same 2-digit sector on a given year, conditional on its employment having not decreased in the same period. GMM regressions have been estimated using twostep robust estimator (Windmeijer, 2005). All estimations contain controls for: firm's wage premium w.r.t other firms in the same 2-digit sector (in logs), importer/exporter status, and share of permanent workers.
[a] The base category are firms with 2 or less years old.
[b] The reference category are firms with 1 – 9 employees.
[c] The base category are firms of which we have no credit-related information (that is, either they haven't made credit requests to new banks or they are not in the CIR database).
[d] Expressed on a per unit basis.

Table C.12: Top 5% HGF (equivalent to Table 10)

	HGF in employment (year-sec) (t+1)		HGF in productivity (year-sec) (t+1)	
HGF in employment (year-sec)	0.0366***	0.0364***		0.0048***
	(0.0015)	(0.0015)		(0.0008)
HGF in productivity (year-sec)		0.0110***	−0.0245***	−0.0245***
		(0.0009)	(0.0011)	(0.0011)
3-5 years old[a]	−0.0112***	−0.0097***	−0.0232***	−0.0227***
	(0.0010)	(0.0010)	(0.0011)	(0.0011)
6-10 years old	−0.0224***	−0.0205***	−0.0356***	−0.0349***
	(0.0012)	(0.0012)	(0.0013)	(0.0013)
11-15 years old	−0.0323***	−0.0304***	−0.0405***	−0.0398***
	(0.0014)	(0.0014)	(0.0016)	(0.0016)
16-20 years old	−0.0385***	−0.0366***	−0.0391***	−0.0384***
	(0.0018)	(0.0018)	(0.0019)	(0.0020)
21 or more years old	−0.0459***	−0.0441***	−0.0378***	−0.0372***
	(0.0026)	(0.0026)	(0.0028)	(0.0028)
10-19 employees[b]	0.0301***	0.0298***	−0.0135***	−0.0148***
	(0.0025)	(0.0025)	(0.0017)	(0.0016)
20-49 employees	0.0753***	0.0748***	−0.0203***	−0.0236***
	(0.0059)	(0.0059)	(0.0031)	(0.0031)
+50 employees	0.2141***	0.2131***	−0.0204***	−0.0271***
	(0.0167)	(0.0167)	(0.0058)	(0.0057)
LT debt ratio[c]	0.0150**	0.0149**	0.0988***	0.0983***
	(0.0064)	(0.0063)	(0.0059)	(0.0060)
LT debt ratio^2	−0.0059	−0.0058	−0.0040	−0.0039
	(0.0055)	(0.0054)	(0.0049)	(0.0051)
Time fixed effects	Yes	Yes	Yes	Yes
Firm-year obs.	2,777,366	2,777,366	2,777,366	2,777,366
Number of firms	623,072	623,072	623,072	623,072
Avg. nº observations per firm	4.458	4.458	4.458	4.458
Number of instruments	161	171	161	171
AB test for autocorrelation of order 1 (z)	−189.135	−189.134	−203.673	−203.667
Prob > z	0.000	0.000	0.000	0.000
AB test for autocorrelation of order 2 (z)	1.495	1.433	2.358	2.325
Prob > z	0.135	0.152	0.018	0.020

Notes: HGF in employment are defined as top 10% of firms with the highest "Birch-Schreyer index" in the same 2-digit sector. HGF in productivity are defined as top 10% of fastest growing firms in labor productivity in the same 2-digit sector on a given year, conditional on its employment having not decreased in the same period. GMM regressions have been estimated using twostep robust estimator (Windmeijer, 2005). All estimations contain controls for: firm's wage premium w.r.t other firms in the same 2-digit sector (in logs), importer/exporter status, and share of permanent workers.
[a] The base category are firms with 2 or less years old.
[b] The reference category are firms with 1 – 9 employees.
[c] Expressed on a per unit basis.

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