R&D, Market Power and the Cyclicality of Employment

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August, 2020

Abstract

This paper provides a first look into the joint effects of research and development (R&D) and market power on the cyclicality of employment. It presents a theoretical model with R&D and monopolistically competitive firms which shows that firms smooth their R&D activities when they face large R&D adjustment costs. This smoothing behavior comes at the expense of higher labor volatility, and it is stronger for firms with high R&D intensity and low market power. Firm-level data support these predictions. Dynamic panel estimations reveal that employment at competitive firms engaging in a high level of R&D is more procyclical.

Keywords: R&D, employment volatility, firm-level data, COMPUSTAT.
JEL Classification: E30, E32, O30, O33.

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1 Introduction

It is well-understood that rapid innovation can cause long-term disruptions and structural shifts in labor markets (Keynes, 1931; Schumpeter, 1942). This aspect of innovation is in full force today, causing a polarization in labor markets (Michaels et al. 2014; Acemoglu and Restrepo, 2020; vom Lehn, 2020). The short-term effects of innovation on labor market dynamics, by contrast, is relatively unknown. While the number of investigations is small and most of the evidence is only at the macro level, there are some indirect signs that the innovation process could both mitigate and amplify the cyclicality of labor. On the one hand, the evidence for the procylicality of innovation-induced productivity (e.g., Fernald, J. G., 2014; Christiano et al., 2016; Anzoategui et al., 2018) and the negative relationship between productivity and labor demand (Basu et al., 2006) imply that innovation could reduce the cyclicality of labor. Empirical evidence (see, Van Reenen, 1997; Angel et al., 2004; Caballero and Hammour, 2005; Harrison et al., 2014), consistent with this hypothesis, reveals that the intensity of the job destruction mechanism associated with innovation (the liquidationist view) is smaller during economic downturns. On the other hand, the evidence showing that innovation activities can bring a substantial amount of volatility and amplification to business cycles (e.g., Comin and Gertler, 2006; Kung and Schmid, 2015) could imply that innovation amplifies the volatility of labor to the extent that labor is procyclical. It is, therefore, unclear how innovation affects short-term labor dynamics. To further complicate this relationship, there is substantial amount of micro-evidence, some of which we discuss below, showing that the relationships between innovation and business cycles mentioned above could crucially depend on the market power of firms.

Our paper provides a first look into the direct effects of research and development (R&D), constituting the input side of innovation, and market power on the cyclicality of labor. To investigate these effects, we first construct a partial equilibrium model that incorporates R&D through an endogenous growth technology, which shares some characteristics with Barlevy

(2007) and Bianchi et al. (2019). The model predicts that while R&D intensity amplifies the macroeconomic sensitivity of labor, market power mitigates it. We then use the structural constraints from our model and US firm-level data to test these predictions. The empirical results support our theoretical predictions and reveal that US firms with a high share of R&D spending and low market power shed (hire) production labor more rapidly during economic downturns (expansions). The implication of the former result is that R&D, a growth-enhancing activity that determines income per capita and the standard of living in a country can, at the same time, make labor markets more volatile. Our finding turns the standard view (see below) on the stability effects of growth upside down and implies that the negative relationship between economic growth and volatility may not hold for every driver of growth. More generally, understanding this role that R&D plays for business cycles and growth is critical going forward since advanced economies and some developing countries have been relying on technological advances to further their standard of living at an increasing rate as returns to capital and labor have been declining.

R&D is introduced in our model through a labor-augmenting technology similar to that in Bianchi et al. (2018). Firms hire skilled-labor to conduct R&D activities, and they, consistent with data (see below), incur costs when adjusting the level of these activities. Some of these R&D activities successfully create new technologies, which in turn increase the efficiency of production labor as in Barlevy (2007). In our model, firms are monopolistically competitive, and they engage in R&D activities and produce intermediate goods at the same time. This structure is informed by micro-evidence showing that R&D is mostly conducted by large firms with a substantial amount of production (Foster and Grim, 2010 and Foster et al., 2016).

Given a budget constraint, firms have to decide which type of labor to adjust more when the demand for their goods change. Although the share of R&D (and skilled-labor) is calibrated to low levels to match actual observations in the industry, R&D plays a significant role for the cyclicality of production labor by affecting the efficiency of this type of labor. Firms also choose to keep their R&D relatively smooth when they face changing demand because they face costs when adjusting the level of R&D. This smoothness comes at the expense of increased production labor volatility and this type of labor becomes the primary driver of output adjustment.[1] In our model, R&D adjustment costs and their effects on labor volatility are magnified when firms' production process is more R&D intensive. R&D intensity increases labor responsiveness even without adjustment costs. If firms' R&D intensity is low, for example, the marginal product of R&D activities is higher, and thus relatively small changes in R&D are sufficient to adjust output when matching changes in demand. Firms thus choose to hire a relatively larger amount of skilled-labor when they face higher demand, and they keep production labor relatively smooth. By contrast, if R&D intensity is high, production labor and R&D become more volatile and smooth, respectively. The effects of market power on labor responsiveness/cyclicality is relatively straightforward in our model. We observe that when a firm has high market power, shocks to demand are partially absorbed by changes in the price of the intermediate good (or mark-up), and thus production labor becomes less sensitive to changes in demand.

The optimality conditions from our model offer a unique structural identification strategy for our empirical analysis. Specifically, we combine these conditions to obtain an equation which relates firm-level production labor to only macroeconomic variables. This formulation, along with our estimation methodology, allows us to minimize the risks of reverse-casuality. To empirically test our model predictions, we collect data from three sources. Annual firm-level data on employment, R&D, and various financial variables, are obtained from the COMPUSTAT database. We combine these data with several macroeconomic variables obtained from the Federal Reserve Bank of St. Louis FRED and Bureau of Economic Analysis (BEA) databases. The choice of these variables are dictated by our theoretical equation.

The focal point of our empirical analysis is on how firms' R&D intensity and market

[1] The smoothness of R&D also generates a higher amount of volatility in capital, the third factor of production in our model. Our focus in this paper, however, is on the labor market effects of R&D.

power affect the sensitivity of their labor growth to the business cycle. Using gross domestic product (GDP) growth to approximate the stage of the business cycle and a dynamic panel estimator, we find, consistent with our theoretical predictions, that R&D intensity increases and market power decreases the responsiveness of employment. In other words, labor becomes more strongly procyclical if firms conduct more R&D and are more competitive. We find that these effects of R&D intensity and market power on the macroeconomic sensitivity of labor is economically meaningful. Further tests with different definitions of R&D intensity and market power, a different estimator, different classifications of firms based on firm-specific and sector-specific characteristics all reveal similar inferences.

The smoothness of R&D is the main reason why production labor is more responsive in our theoretical model. To more directly check whether this feature of our model is observed in the data, we use separate equations to measure the responsiveness of R&D and labor growth to macroeconomic variables. The estimations support our predictions as they show that R&D is relatively acyclical. This acyclicality is consistent with high adjustment costs associated with R&D (see below for a description of R&D adjustment costs) and it implies that the acyclicality comes at a cost: with higher R&D intensity, production labor sustains a greater impact from economic fluctuations.

There are two counteracting mechanisms in the literature that describe R&D spending along the business cycle. According to the first mechanism, R&D is a luxury good for firms that can be curtailed easily when firms face lower demand for their goods. Studies such as Saint-Paul (1993), Comin and Gertler (2006), Rafferty and Funk (2008), and Aghion and Saint-Paul (1998) find evidence that favors this interpretation of R&D, especially for financially constrained firms. The more long-standing liquidationist view also predicts that firms would shed skilled labor and R&D type activities more rapidly during economic downturns (Schumpeter, 1934; De Long, 1990; Beaudry and Portier, 1998)

According to the second mechanism, firms find it harder to make substantial changes to their R&D spending as they face large adjustment costs of doing so. A firm that hires engineers and scientists to conduct R&D in a research lab, for example, may be more reluctant to dismantle the lab and to release the skilled labor when it faces a temporary drop in sales. The findings of Brown et al. (2012), Hall et al. (2016) and Aysun and Kabukcuoglu (2019) support the view that R&D has high adjustment costs. International evidence showing that there are significant costs to adjusting technological infrastructure is consistent with this view (Bresnahan et al., 2002; Yeaple, 2005; Bustos, 2011). There is also evidence from macroeconomic data indicating that firms may be engaging in some R&D smoothing as R&D is less volatile compared to other types of spending (fixed investment in physical capital, for example). The fact that R&D lags the business cycle supports this view. Specifically, firms initially keep R&D steady but they reduce (increase) it when an economic downturn (expansion) is prolonged. Our results are consistent with the R&D smoothing mechanism mentioned above. This smoothness, however, does not imply that R&D intensity is trivial. We predict and find higher employment volatility with higher R&D intensity.

The standard theoretical prediction in Schumpeterian growth models (Schumpeter, 1942) is that market power is conducive to a steady pace of innovation. The reason is that firms with higher market power are less cash-strapped and have easier access to funding and can, therefore, sustain any potential large fixed cost associated with setting up R&D infrastructure due to economies of scale. There is evidence both for (e.g., Geroski, 1990) and against (Acemoglu and Lin, 2004) this prediction.[2,3] While we do not test the predictions of the standard growth theory on market power, our inferences are consistent with Schumpeterian theory. Specifically, the ability of less competitive firms to absorb macroeconomic shocks through mark-up adjustments cushions the blow on its production labor. With a more stable labor force, the

[2]Symeonidis (1996) provides an extensive review of the literature on the relationshio between market power and innovation.

[3]There is also evidence showing that the relationship between innovation and market power could be nonlinear (e.g., Aghion et al., 2005; Hashmi, 2013) and that the relationship between R&D and market power could be operating in the reverse direction (see, Peretto, 1999).

returns to R&D are also less volatile, which in turn promotes a more steady rate of innovation.

While there is no direct firm–level evidence, to the best of our knowledge, that sheds light on the relationship between R&D intensity and labor volatility, there are some macroeconomic findings that are consistent with the positive relationship between R&D intensity and volatility that we find in this paper.[4] Studies such as Kung and Schmid (2015) and Comin and Gertler (2006) find that high R&D intensity leads to more severe business cycles, and a greater volatility in output growth and asset prices. Our predictions and findings are consistent with this evidence. In a broader sense they do, however, counter the well-established negative link between growth and economic volatility in the international literature (e.g., Ramey and Ramey, 1995; Levine, 1997; Aghion and Banerjee, 2005). This disparity implies that the volatility mitigating effects of growth may not be observed for every driver of growth. R&D-driven growth in particular could amplify volatility.[5]

2 Theoretical Framework

We assume that final consumption goods in our model economy are produced by a representative, perfectly competitive firm. This firm uses the following CES technology to combine intermediate goods, $Y_{j,t}$, to produce the final good, Y_t:

$$Y_t = \left(\sum_{j=1}^{N} Y_{j,t}^{1/\varphi} \right)^{\varphi} \tag{1}$$

where N and φ denote the number of intermediate goods and the elasticity of substitution between these goods, respectively. The latter parameter regulates the degree of mark-up in the

[4]We should note that the majority of the studies in this literature take the opposite direction to our analysis and investigate the effects of the business cycle fluctuations on R&D and productivity.

[5]Our research is also related to the recently growing efforts to combine short-term dynamics with components of endogenous growth models. This literature (e.g., Bilbiie et al., 2008, 2012, 2019; Broda and Weinstein, 2010), for example, examines the economic growth and welfare implications of short-term dynamics such as firm exit/entry, monetary policy and monopolistic competition.

model. The profit maximization problem of the final goods firm yields the following demand for intermediate good j:

$$Y_{j,t} = Y_t \left(\frac{P_{j,t}}{P_t} \right)^{-\varphi/(\varphi-1)} \tag{2}$$

In our model, the intermediate goods producers play a central role. These firms, indexed by j, are monopolistically competitive and their production follows a Cobb-Douglas technology:

$$Y_{j,t} = A_t K_{j,t}^{\alpha} M_{j,t}^{1-\alpha} \tag{3}$$

where A_t is a systematic productivity shock, and α is the income share of capital. The firm rents capital from consumers. The labor input, $M_{j,t}$, is a product of two components, physical units of labor that are used in production, $L_{j,t}^{p}$, and a variable that measures the efficiency of this type of labor, $\mu_{j,t}$, so that,

$$M_{j,t} = \mu_{j,t} L_{j,t}^{p}. \tag{4}$$

Each period, the firm hires $L_{j,t}^{p}$ hours of production services at the wage rate W_t and $L_{j,t}^{rd}$ hours of services that are suitable for R&D type activities at the wage rate $SP_t W_t$, where SP_t represents a time varying skill premium. Some of the R&D effort is successful. The resulting innovations add to the firm's existing stock of knowledge that in turn improves labor efficiency. This stock variable, $L_{j,t}^{rd,s}$, evolves as follows:

$$L_{j,t}^{rd,s} = L_{j,t-1}^{rd,s} + \nu L_{j,t}^{rd} \tag{5}$$

where ν represents the probability that R&D activity is successful in creating an innovation or the "stepping on toes" effects of R&D (as in Jones and Williams, 1998). In addition, we assume that firms can adopt the innovations of others so that the efficiency of labor is positively related to both firm-specific and external R&D spending and given by,

$$\mu_{j,t} = \kappa \left(\lambda^{L^{rd,s}_{j,t}}\right)^{\eta} (\mu_t)^{1-\eta} \tag{6}$$

where the parameter λ governs the growth rate of the economy and is assumed to be greater than one. κ is a scaling parameter that is set equal to $(N-1)^{\eta-1}$. This ensures that at the symmetric equilibrium of the economy production of all firms and overall output grow at the same rate. This growth rate, along the balanced growth path, can be derived as $\mu^{g}_{t} = \lambda^{\nu L^{rd}_{j,t}}$.[6] Notice here that the second term on the right hand side of the equation above is the positive externality from the R&D activities of other firms. This externality is given by,

$$\mu_t = \sum_{k=1}^{N} \mu_{k,t} \quad for \;\; k \neq j. \tag{7}$$

Overall, labor efficiency is a Cobb-Douglas aggregate of the firm-level and industry-level effects of R&D, where $1-\eta$ captures the degree to which a firm's labor efficiency depends on new industry-level technologies/discoveries versus firm-level discoveries.

The intermediate good producer j maximizes the following profit function:

$$\Pi_{j,t} = P_{j,t} A_t \left(K_{j,t}\right)^{\alpha} M^{1-\alpha}_{j,t} - \left(1 + \frac{\phi_{rd}}{2}\left(L^{rd}_{j,t}/L^{rd}_{j} - 1\right)^2\right) SP_t W_t L^{rd}_{j,t} - W_t L^{p}_{j,t} - R^{k}_{t} K_{j,t} \tag{8}$$

The firm faces quadratic costs of adjusting R&D and production activities (ϕ_{rd} governs the level of R&D adjustment costs, and L^{rd}_{j} denotes the steady state value of R&D labor). The strength of this friction is central to the analysis in our paper as it determines how labor resources migrate from production to R&D (or vice versa) when macroeconomic conditions change.

[6] The growth rate of labor efficiency, also the source of growth in the symmetric equilibrium of the economy, at time t is given by, $\mu_t/\mu_{t-1} = \lambda^{L^{rd,s}_{t}}/\lambda^{L^{rd,s}_{t-1}} = \lambda^{\nu L^{rd}_{t}}$.

In this economy the cost of capital is given by,

$$R_t^k = (1-\delta) + MPK_t \tag{9}$$

where MPK_t is the marginal product of capital and δ is the depreciation rate.

The optimality conditions with respect to capital, production labor and R&D are as follows:

Capital:

$$\alpha \Omega_{p,t} \frac{P_{j,t} Y_{j,t}}{K_{j,t}} = R_t^k \tag{10}$$

Production labor:

$$(1-\alpha)\,\Omega_{p,t} \frac{P_{j,t} Y_{j,t}}{L_{j,t}^p} = W_t \tag{11}$$

R&D:

$$\begin{aligned}(1-\alpha)\,\kappa\eta\nu\ln(\lambda)\,\Omega_{p,t} P_{j,t} Y_{j,t} = SP_t W_t + \phi_{rd} SP_t W_t \left(\frac{L_{j,t}^{rd}}{L_j^{rd}} - 1\right)\left(\frac{L_{j,t}^{rd}}{L_j^{rd}}\right) \\ + \frac{\phi_{rd}}{2} SP_t W_t \left(\frac{L_{j,t}^{rd}}{L_j^{rd}} - 1\right)^2\end{aligned} \tag{12}$$

We use the optimality conditions with respect to production labor and R&D labor and impose symmetry to obtain a relationship between the two variables. This relationship in linearized form is given by,

$$l_t^p = sp_t + \phi_{rd} l_t^{rd} \tag{13}$$

where the variables represent deviations from steady state. The inference here is that if $\phi_{rd} = 1$ and the skill-premium is stable, skilled and unskilled labor are equally volatile. If adjustment costs are lower ($\phi_{rd} < 1$), skilled labor, consistent with the luxury good interpretation of R&D in the literature, would be more volatile than unskilled labor. The inference is reversed if adjustment costs are higher. We should also note here that while the firm does not pay quadratic costs when adjusting the level of production labor, the marginal revenue to the firm from an additional unit of labor is also smaller than the marginal revenue obtained from an additional unit of R&D. In our model, the higher marginal costs associated with R&D (adjustment costs and skill premium) offset the wedge between the marginal returns to R&D and production labor.

Hereafter, we use this theoretical framework to draw empirically testable implications. In so doing, we follow two strategies to facilitate the transition from theory to empirics. First, we begin by linearizing our model equations so that our theoretical predictions can be tested by commonly-used linear empirical models. In so doing, we normalize the variables $Y_{j,t}$ and $K_{j,t}$ by the stochastic growth rate of the economy μ_t^g to ensure stationarity. Second, when combining our model equations we relate a firm specific variable to macroeconomic variables. Doing so allows us to impose a model-determined identification into our empirical analysis and to minimize reverse causality risks. Specifically, it is more likely that the direction of casuality is from macroeconomic shocks to firm-level decisions than the other way around.

We take the following steps to derive our theoretical prediction:

First we linearize equations (10), (11), (2) and (3) to obtain:

$$\widetilde{\Omega}_{p,t} + p_{j,t} + y_{j,t} = r_t^k + k_{j,t} \tag{14}$$

$$\widetilde{\Omega}_{p,t} + p_{j,t} + y_{j,t} = w_t + l_{j,t}^p \tag{15}$$

$$p_{j,t} = p_t + \left(\frac{\varphi - 1}{\varphi}\right) y_t - \left(\frac{\varphi - 1}{\varphi}\right) y_{j,t} \tag{16}$$

$$y_{j,t} = a_t + \alpha k_{j,t} + (1 - \alpha)\left(l_{j,t}^p + L_j^{rd} \kappa \eta \nu \ln(\lambda)\, l_{j,t}^{rd}\right) \tag{17}$$

We then combine equations (14) and (15) to derive the following expression that relates the relative demand for capital and labor to their relative costs:

$$w_t + l_{j,t}^p = r_t^k + k_{j,t} \tag{18}$$

Substituting this expression into (14) yields

$$\widetilde{\Omega}_{p,t} + \left(\frac{\varphi - 1}{\varphi}\right) y_t + \frac{1}{\varphi} y_{j,t} = w_t + l_{j,t}^p. \tag{19}$$

This step allows us to focus our attention on production labor as opposed to capital.[7] The Lagrange multiplier is computed by setting output equal to 1, and expressing $L_{j,t}^p / K_{j,t}$ in terms of R_t^k / W_t by using equations (10) and (11). This multiplier, in linearized form, is derived as,

$$\widetilde{\Omega}_{p,t} = -a_t + (1-\alpha) w_t + \alpha r_t^k + \frac{\kappa \eta \nu \ln(\lambda) L_j^{rd}}{\phi_{rd}} sp_t \tag{20}$$

Substituting equations (18) and (13) into (17) produces the following expression for firm level production:

$$y_{j,t} = a_t + \alpha \left(w_t + l_{j,t}^p - r_t^k\right) + (1-\alpha)\left(l_{j,t}^p + \frac{\kappa \eta \nu \ln(\lambda) L_j^{rd}}{\phi_{rd}} \left(l_{j,t}^p - sp_t\right)\right) \tag{21}$$

where, $\kappa \eta \nu \ln(\lambda) L_j^p = SP$.

As a final step, we substitute equations (20) and (21) into equation (19), to obtain the following expression that only has firm level production labor on the left hand side and only macroeconomic variables on the right hand side:

$$l_{j,t}^p = \frac{(1-\chi_2)\chi_1}{1-\chi_1-\chi_2} sp_t + \frac{(1-\chi_2)}{1-\chi_1-\chi_2}(y_t - a_t) - \frac{\alpha(1-\chi_2)}{1-\chi_1-\chi_2} w_t + \frac{\alpha(1-\chi_2)}{1-\chi_1-\chi_2} r_t^k \tag{22}$$

[7] In deriving this expression we normalize final good prices to 1 so that $P_t = 1$.

where $\chi_1 = \frac{(1-\alpha)SP}{\varphi\phi_{rd}}\frac{L_j^{rd}}{L_j^p}$ and $\chi_2 = \frac{1}{\varphi}$.

The broad inference from equation (22) is that the sensitivity of production labor to macroeconomic variables is higher (lower) when χ_1 and χ_2 are high (low). To illustrate these relationships, it is useful to discuss the following form of our model's optimality condition for production labor:

$$\varepsilon_t + \left(\frac{1}{\varphi} + \frac{(1-\alpha)SP}{\varphi\phi_{rd}}\frac{L_j^{rd}}{L_j^p}\right) l_{j,t}^p - l_{j,t}^p = 0 \tag{23}$$

where ε_t denotes an exogenous change in any of the macroeconomic variables appearing on the right hand side of equation (22) that in turn affects the marginal profits of the firm. The coefficient of the second term in equation (23), $(\chi_1 + \chi_2)$ (less than 1 for reasonable parameter values), represents the returns from an additional unit of production labor, and the coefficient of the last term, -1, represents the change in labor costs when a unit of labor is added (given a constant wage rate). If there is a positive macroeconomic shock, $\varepsilon_t > 0$, $l_{j,t}^p$ increases until the exogenous increase in the firm's profits is offset by the difference between labor costs and the returns to labor. The coefficient of the second term then determines how production labor responds to the shock. If the coefficient is large (closer to 1) for example, returns to labor are high and thus $l_{j,t}^p$ increases (decreases) substantially in response to a positive (negative) shock. The opposite holds and $l_{j,t}^p$ is less responsive to macroeconomic shocks if the coefficient is small (closer to 0).

According to equation (23) one reason why the coefficient can be small is that the firm has a high degree of market power (φ is high). When a firm has high market power, the positive shock is mostly absorbed by changes in the price of the intermediate good instead of production (and production labor) and the firm becomes relatively insensitive to the macroeconomic shock.[8]

If the firm is R&D intensive (with a high $\frac{L_j^{rd}}{L_j^p}$ ratio) so that the contribution of skilled labor

[8] In equation (22), the coefficients of $y_t - a_t$ and w_t include χ_2 with the same sign in the denominator and the numerator. For positive values of χ_1 less than 1, nevertheless, the coefficients are monotonically decreasing functions of χ_2.

to production is high, the firm has a relatively high level of production labor efficiency. An additional unit of production labor in this firm is, therefore, much more productive and its marginal returns are higher. If this firm faces a shock that increases the demand for its goods, then it would increase its production labor more than a firm that conducts less R&D. In other words, R&D intensity increases the sensitivity to macroeconomic variables.

Another factor that affects the response of production labor is R&D adjustment costs, ϕ_{rd}. If the value of this parameter is high, the firm insulates its R&D from business cycles. The complementarity between R&D and production labor discussed above then implies that there are smaller output gains from increasing production labor without a commensurate increase in the level of R&D when there is a positive shock. Higher R&D adjustment costs therefore mitigate the response of production labor to macroeconomic shocks.

It should be noted that these mechanisms operate in reverse when the macroeconomic shock is negative and that the mechanisms are stronger if labor's share in production $(1-\alpha)$ is higher compared to capital.

In the next section, we test whether R&D intensity and market power, increase and decrease, respectively, the macroeconomic sensitivity of production labor, and we draw inferences about the size of R&D adjustment costs ϕ_{rd} by comparing the responsiveness of R&D and production labor to macroeconomic fluctuations.

3 Empirical Analysis

In this section we describe the methodology and the data that we use to test our hypotheses above. We then discuss our baseline results and those obtained by conducting various sensitivity tests.

3.1 Methodology

We measure the sensitivity of firm-specific employment growth, $Emp_{i,t}$, to macroeconomic variables with the following equation:

$$Emp_{i,t} = \sum_{k=1}^{2} \beta_k^{emp} Emp_{i,t-k} + \beta^{gdp} GDP_{t-1} + \beta^{f} FSV_{it-1} + \beta^{i} FSV_{it-1} GDP_{t-1} \qquad (24)$$
$$+\beta^{sp} SP_{t-1} + \beta^{bc} BCost_{t-1} + \beta^{w} W_{t-1} + \varepsilon_{i,t}$$

where subscripts i and t index firms and time, respectively. This equation, similar to our theoretical predictions in equation (22), relates $Emp_{i,t-k}$ to output, GDP_{t-1}, the skill premium in wages, SP_{t-1}, the cost of capital, $BCost_{t-1}$, and real wages, W_{t-1}. Below we describe the data that we use to approximate these variables.[9] All variables mentioned above, consistent with equation (22), are measured as log differences and thus reflect growth rates. We also use the lags of the independent variables, which is a procedure in macro-econometric modeling commonly-used to account for the impact and recognition lags in shock transmission. We choose to use the first lag of each variable with the exception of the dependent variable. We include two lags of the dependent variable on the right hand side to account for the persistence in employment.[10]

The focal point of our analysis is the firm specific variable, FSV_{it-1}. In this section, we use the two firm specific variables, R&D intensity and market power, that we predicted would be related to employment's macroeconomic sensitivity. The main goal here is to test our theoretical prediction that R&D intensity and market power are positively and negatively related to

[9] It should be noted that while in our theoretical equation we relate employment to total factor productivity (tfp) adjusted GDP, here we only use GDP. The reason we do so is that the growth rates of the two variables were very similar (producing similar results) due to the relatively low volatility of tfp and the interpretation of GDP coefficients was much simpler.

[10] We use two lags of the dependent variable since this allows us to avoid second order serial correlation throughout our estimations. In these estimations we apply the Windmeijer's finite-sample correction since the standard errors become downward biased in two-step estimations. We should also note that in some of our sensitivity analyses (see below), we use an alternative lag structure.

macroeconomic sensitivity, respectively. To conduct this test, we first interact R&D intensity with *GDP* and include this variable in equation (24). We then repeat this step for our measure of market power.

To estimate equation (24), we use the Blundell and Bond (1998) two-step general method of moments (GMM) dynamic panel estimator. The main reason we follow this strategy is that it allows us to control for any firm fixed effects while avoiding the dynamic panel bias that standard estimators with time and firm fixed effects are prone to having. We do, however, check whether we obtain similar results by using a standard fixed effects estimator. This alternative estimator also proves useful when we estimate our model by splitting firms into groups since instruments become less valid with fewer cross-sectional observations. That said, the dynamic panel estimator that we use is a good fit for our full dataset since it is designed for panels with a relatively bigger cross-section and a short time period; in our panel there are over 1,900 firms but only 17 years. In addition, the estimator accounts for potential heteroscedasticity and serial correlation in errors and fixed and random effects at the panel level. As mentioned above, our identification strategy relies on the fact that it is more likely for macroeconomic variables to affect a firm's employment decision than the other way around. Nevertheless, we follow standard practice and instrument the endogenous variables in our model with the lags of their first differences.

3.2 Data

To estimate our empirical model we use annual data for the period 2000 to 2018. In the default specification, we omit the crisis periods 2008 and 2009 because the reduced-form models that we use cannot capture the nonlinear dynamics that govern crisis episodes. Most of the variables used in our analysis are obtained from two data sources. The firm level variables are from the COMPUSTAT (North America) database, and the majority of the macroeconomic variables are from the Federal Reserve Bank of St. Louis, FRED database.

From COMPUSTAT we only include US headquartered firms with R&D spending, and we convert all firm level financial variables into real values using the GDP deflator. The dependent variable throughout our estimations is the firm-specific employment growth rate, measured as the annual growth in the number of employees of firms.[11] The two firm-specific variables that are the focal point of our estimations are R&D intensity and market power. These two variables are included, in separate estimations, as the firm-specific regressor, FSV_{it}, in equation (24). In our baseline estimations we use the R&D expenditures to total cost ratio and the share of a firm's total sales in their respective industries to approximate R&D intensity and market power, respectively. In our sensitivity analyses, we also use other firm-specific characteristics such as financial constraints, size, liquidity, profitability, bond ratings, age and size. These variables, as well as all other variables used in our analysis, are described in more detail in Table A.1 of Appendix A.[12]

In addition, we include sector-specific data in alternative estimations to incorporate crucial characteristics that are not available through COMPUSTAT. Specifically, we use Census BRDIS data to infer the amount of external funding for R&D, the amount of R&D conducted domestically and overseas and the amount of external versus internal R&D at the sector level. We then combine these data with our firm-level dataset by using firms' 3 digit SIC codes. We also classify sectors and thus firms as high-tech versus low-tech by using the classification in Brown et al. (2009).

The key macroeconomic variable in our estimations is the real GDP growth rate. We use this variable as the primary indicator of macroeconomic conditions in the US and the key macroeconomic driver of firms' employment decisions. Borrowing costs and real wages,

[11] The reason we use annual data is that firm-specific employment data are only available at the annual frequency.

[12] When we construct the sample, we winsorize the number of employees, total assets, cash and short-term investments, sales and R&D expenses at 1 percent and 99 percent. When we create the KZ index, in order to prevent too many firms from dropping from the sample, we replace missing observations of cash flow, debt, dividend or cash equal to zero. Finally, we drop observations if R&D-to-total cost ratio is not between 0 and 1 or employment growth does not fall between -100% and 100% to eliminate unrealistically high positive and negative values.

$BCost_{t-1}$ and W_{t-1} in equation (24), are measured as the annual growth in the spread between AAA and BBB rated corporate bond indices (ICE BofA US Corporate index values) and the annual growth in the average weekly real earning index of full time workers.

As indicated in Table 1, there are 1,983 firms in our dataset. Although these firms are large for the most part (the mean asset size is \$3.1 billion), they do exhibit a large degree of heterogeneity with the standard deviation of firm-specific variables exceeding their corresponding mean values. While the mean share of a firm's sales in the total sales of a given sector is roughly 6%, for example, the standard deviation of this ratio in our panel dataset is 15.8%. The R&D expenditures on average are a small share of total costs. We do, however, show evidence below that R&D, despite its small share, plays a critical role for the macroeconomic sensitivity of employment. We should also note that R&D expenditures are positive for each time-firm pair in our panel.

Turning to macroeconomic variables, we observe a smaller amount of variation compared to firm-specific variables. Real R&D expenditures (obtained from the FRED database) have the largest growth rate and also the highest standard deviation amongst the macroeconomic variables in our dataset. This variable is also relatively less cyclical compared to employment. Below we test whether this relative smoothness of R&D across the business cycle comes at the expense of higher fluctuations in employment. Also note that the growth rate of total employment in the US is much less volatile compared to firm-level employment growth rate due to aggregation. A similar observation can be made from sector-level data. The sector-level statistics, displayed in the bottom of Table 1, are computed using the Bureau of Economic Analysis KLEMS data (1997-2017). They show that production labor (labor not allocated to R&D activities) is more volatile in sectors with high R&D intensity, sectors that are listed in the last five rows of the table.

3.3 Baseline results

Our baseline estimation results are reported in Table 2. The results displayed in columns 1 and 2 are obtained by using the R&D-to-total-costs and sales-to-total-sector-sales ratios as the firms-specific variables, respectively. The main inference from these results is that while R&D intensity increases the cyclicality of employment, market share makes employment acyclical. In other words, if a firm has a high level of R&D spending, and if this firm has a low sales share in its sector, its employment decisions are more strongly related to GDP growth. By contrast, a firm with low R&D spending and a higher market share is less sensitive to macroeconomic conditions.

GDP's coefficient value in the first column implies that if real GDP growth increases by 1 percentage point, firms' employment growth increases by 0.86 percentage points. To visualize the economic importance of the interactive term coefficient, assume that there is a 1 percentage point increase in the GDP growth rate and there are two firms, x and y. Firm x only has a ratio of R&D spending to total costs nearly equal to 1, and firm y does not conduct R&D so that its corresponding ratio is 0. The interactive variable coefficient value in the first column then implies that firm x's employment growth is roughly 6.7 percentage points higher than firm y's employment growth. These inferences, of course, are reversed if there is a 1 percentage point decrease in the GDP growth rate. A more realistic interpretation of the coefficient value can be made if we assume that a firm has a R&D-to-total-costs ratio one standard deviation (7.99%) more than the mean value across all firms. This firm would then expand its labor force 0.53 percentage points more than the average firm when real GDP growth increases by 1 percentage point. This is approximately one-fifth of the mean employment growth in our sample (2.45%). Below, we investigate the economic significance of coefficient values in more detail, but the inference that we draw here is that R&D has a meaningful impact on the macroeconomic sensitivity of hiring decisions.

We draw opposite conclusions for the interaction between GDP and market share. As a firm increases its share of sales in its sector, it becomes less sensitive to GDP. A similar thought experiment shows that this interaction is also economically significant. Specifically, a one standard deviation (15.76%) increase in market share decreases the sensitivity to GDP by roughly 25%. This drop in sensitivity corresponds to roughly 15% of mean growth in employment. In other words, the employment growth rate of a firm whose sales share is one-standard-deviation higher than the average sales share in its sector is 15 percentage points lower than that of an average firm when there is a 1 percentage point increase in the real GDP growth rate.

The coefficients of the firm specific factors indicate that firms with high R&D intensity and market share have expanded their labor force less rapidly compared to firms with opposite characteristics. The negative link between R&D intensity and employment is consistent with the trade-off between R&D and production labor in our model. Given a fixed demand for its goods, a firm that uses more R&D to meet this demand would use less production labor. The negative link between market share and employment growth implies that smaller firms grow faster. This is a common finding in the empirical literature (e.g., Evans, 1987; Wagner, 1992; Reid, 1995; Weiss, 1998; Almus, 2000; Santarelli et al., 2006; Nassar et al., 2014) showing that Gibrat's law (Gibrat, 1931) is not supported by more recent data.

The signs of the remaining coefficients are consistent with our theoretical predictions. The results in both columns indicate that employment growth is positively related to the skill premium and negatively related to borrowing costs and real wages. We also do not find any evidence for second order serial correlation in the error term, and the Hansen statistic does not detect any instrument endogeneity.[13]

[13] We also infer instrument validity from the Sargan test for over-identifying restrictions.

3.4 Alternative measures of R&D intensity and market power

In this section we use alternative indicators of R&D intensity and market power to test the sensitivity of our baseline results.

For R&D intensity we first use sales in the denominator instead of costs. The reason is that most of the firms have high markups, and R&D as a share of total revenue could be a better indicator of R&D's effects on a firm's budget constraint. Table 3 presents our findings. The results displayed in column 2 are similar to our baseline results (reproduced in column 1 of Table 3). The interactive coefficient, however, is smaller in magnitude indicating that R&D's share in total revenue has a smaller impact on firms' macroeconomic sensitivity. Second, we use the R&D-to-total-assets ratio. Unlike the first two ratios, the denominator, total assets, is a stock variable that is a reasonable proxy for firms' total wealth. Using this ratio allows us to consider a more realistic financial model in which R&D spending and hiring decisions of firms are more closely related to their total wealth instead of their flows of revenues or costs. The results from this alternative measure of R&D intensity, displayed in the third column of the table, are similar. The smaller coefficient of GDP and the larger interactive variable coefficient suggest that this measure of R&D intensity is a stronger determinant of employment growth's macroeconomic sensitivity.[14] The last column presents results when measuring R&D relative to the market. In doing so, we compute the mean R&D-to-total-costs ratio for every year and measure the deviation of firm specific ratios from these mean values. The results again indicate that R&D intensity increases macroeconomic sensitivity. The interactive term coefficient value of 14.3 implies that if a firm's R&D intensity is 1 percentage point higher than the mean value in a given year, the firm's hiring growth would be 0.14 percentage points higher than the average firm if GDP growth rate increases by 1 percentage point.

Next, we replace our baseline proxy for market power with alternative measures. The re-

[14] We find a similar disparity when we take into account the standard deviation of the different R&D intensity variables.

sults from this exercise are reported in Table 4. We first recompute market share as the share of a firm's assets and number of employees in the total amount of assets and employees in their sectors. The coefficient values, reported in columns 2 and 3, are very similar both in significance and magnitude. We then use a more dynamic indicator of market power to observe how employment decisions are affected when market power changes. We capture this dynamic by measuring the annual change in firm-level mark-ups.[15] In doing so, we follow the formulation in Loecker et al. (2020) and measure mark-up as marginal revenue over marginal cost of goods sold.[16] The interactive variable and GDP coefficients displayed in the last column of the table, similar to our baseline estimations, suggest that employment is procyclical and that higher market power reduces the strength of this cyclicality. In contrast to our baseline estimations, however, we observe that firms experiencing higher (lower) mark-up growth hire relatively more (fewer) workers. This shows that static and dynamic features of market power could produce different inferences. A reasonable postulation here is that while growth in mark-up could prompt more hiring due to short-term profit opportunities, firms with generally higher mark-up are already on their balanced growth path without these incentives to deviate from their steady state pace of hiring.

3.5 Fixed effects estimator

An advantage of the difference GMM estimator is that it allows us to control for firm and time fixed effects while avoiding dynamic panel bias. The methodology does however use a large number of instruments and lags of first differences, which decreases the degrees of freedom and shrinks the panel substantially. In this section, we follow a more standard approach and estimate the model with firm and time fixed effects. Given the large number of firms, we choose to use a fixed effects estimator (areg with robust standard errors in STATA) that is

[15]We prefer markup over the Herfindahl-Hirschman concentration measure because studies such as Bresnahan (1989) and De Loecker et al. (2020) show that this measure is not necessarily related to market power.

[16]This definition implies that output elasticity is fixed. Loecker et al. (2020) show that they find the same pattern of markups with time-invariant values for output elasticity.

designed for panels with a long cross-sectional dimension. We still use the first lags of the independent variables to minimize the risk of reverse causality and to accommodate impact lags of macroeconomic shocks.[17]

The results from this alternative estimator are reported in Table 5. These results are obtained by using our baseline definitions of R&D intensity and market power. The coefficient values and their significance are consistent with our earlier inferences, i.e., R&D intensity decreases and market power increases the macroeconomic sensitivity of employment. Comparing with our baseline results, we observe that although coefficient values are different in magnitude, these differences are not too large when we consider the standard errors of the coefficients. Note that we are incorporating a larger number of observations when we use the fixed effects estimator and therefore our results are robust to using both an alternative estimator and a larger sample.

3.6 Economic significance

So far, we have estimated the response of employment growth, expressed as a percent change, to a one percentage point change in real GDP growth and its interaction with firm-specific variables. While this analysis shows that both R&D intensity and market power have a meaningful effect on firms' macroeconomic sensitivity, it is confounded by the fact that employment growth and the firm specific variables have different mean values and volatility. Employment growth, for example, is much more volatile compared to the R&D-to-total-costs ratio in our dataset. Observations made based on percent changes, therefore, could be misleading as these changes could be more important for some variables than others. In this section, we transform our variables to better understand the economic significance of these effects. Specifically, we rescale each variable, both dependent and independent, so that they represent deviations from mean values. We do so by first subtracting the mean value of a variable, computed in a given

[17] It should be noted that our analysis here is a robustness check and including lagged dependent variables in fixed effects models can introduce a dynamic panel bias.

year, and dividing by its standard deviation, also computed in the same year.

The results from the estimations with these transformed variables are displayed in Table 6. The coefficient of *GDP* in the first column now implies that a one-standard-deviation increase in GDP growth generates a 0.43 standard deviation increase in employment growth. This effect of GDP growth is approximately 40% higher if a firm's R&D-to-total cost ratio is 1 standard deviation higher than the average value across firms. These findings imply that the firm's employment growth response to a one percentage point increase in the GDP growth rate would be 1.42 percentage points higher than that of the average firm. The economic significance of the R&D-GDP interaction that we find here is comparable, if not higher, than in our baseline estimations. The results displayed in the second column also reveal that market power has an economically meaningful effect on macroeconomic sensitivity. The response of employment growth to a one-standard deviation increase in GDP is 24% lower for a firm with a market share one-standard deviation higher than the average share.

3.7 Comparing the cyclicality of R&D and employment

Our theoretical analysis identifies a complementarity between R&D and production labor. The marginal returns to each factor of production are higher when there is more of the other factor. The same framework, however, introduced a trade-off between the two factors due to budgetary constraints. In other words, firms deciding to expand or downsize production in our model have to decide which factor to cut more. Our baseline estimation results provide some evidence for both the trade-off and complementarity mechanisms. While we find that firms with higher R&D intensity experience slower labor growth, providing evidence for the trade-off mechanism, this labor growth is also more procyclical, indicating a positive link between production labor and R&D. It is, therefore, unclear which mechanism prevails.

Our theoretical model also predicts that the trade-off between the two factors crucially depend on R&D adjustment costs. As predicted by equation (13), higher adjustment costs amplify the trade-off between R&D and labor, and weakens the link between the two factors. With high adjustment costs, R&D becomes less volatile and less cyclical. In this section, we investigate the relative cyclicality of the two factors separately to infer the strength of the trade-off between them.

The results from this investigation are reported in Table 7. The dependent variables listed in column headings are all in log-difference form, and R&D represents the growth of real R&D expenditures. The main result is that employment is procyclical and R&D, whether measured as the growth of R&D expenditures or as a share of total costs, is acyclical. These results support the trade-off mechanism over complementarity. With high R&D adjustment costs, employment absorbs the impact of macroeconomic shocks, while R&D is kept insulated. This does not imply that R&D is unimportant for employment. Quite the contrary, our earlier results show that R&D intensity actually amplifies the response of employment.

3.8 Firm and sector characteristics

In this section, we classify firms based on their financial and structural characteristics and those of their respective sectors. We then estimate our model with these restricted samples to determine if the importance of R&D intensity and market power for employment is more pronounced in specific types of firms and industries.

The first column of Table 8 lists the seven different characteristics that we use to group the firms. As a first test we identify firms that are in high-technology industries. We follow the classification of Brown et al. (2009) and designate chemical and allied products (SIC=28), industrial machinery and equipment (SIC=35), electronic and other electric equipment (SIC=36), transportation equipment (SIC=37), instruments and related products (SIC=38) and business services (SIC=73) as high-tech industries. Second, we reconstruct the Kaplan-Zingales (KZ) index for the set of firms in our sample. This index measures how cash-strapped firms are and the degree of financial constraints that they face (see Appendix A for a more detailed description). We then restrict our sample to firms that are in the top half of the KZ index distribution in a given year. We use the same methodology to restrict the sample to only large and high mark-up firms. Here, mark-ups are measured as profits (sales minus cost of goods sold) divided by sales and size is measured by total assets. Finally, we also restrict the sample to bond-issuing firms and firms that are mature (whose ages are greater than or equal to 15 years).

The main result in Table 8 is that the signs and the significance for a majority of the coefficients are similar to those in our baseline estimations. Moreover, the difference between these coefficients and those from our baseline estimations do not appear to be statistically significant.

Next, we use the Census BRDIS data to obtain sector-level data on the amount of external funding for R&D, the amount of R&D conducted domestically (versus abroad) and the amount of internal R&D. Next, we combine these sector level data with our firm-level data by using the 3-digit NAICS codes. Similar to the methodology above, we then identify firms that are in sectors receiving a large amount of external funding (external funding/total amount of funds for R&D), conducting R&D mostly domestically (domestic funds / worldwide funds) or conducting R&D mostly internally (R&D paid for and conducted by the company / total funds to R&D). Specifically, for each year we restrict our sample to firms in industries that are in the top half of the distribution of the respective variable. The results displayed in Table 9 show that the interaction between R&D intensity and macroeconomic sensitivity of employment growth is higher for firms that receive higher amounts of external funding and mostly conduct R&D activities internally in the US. We should again note, however, that these departures from baseline results are not statistically significant.

4 Concluding remarks

This paper predicted and demonstrated that the labor force of firms with a high level of R&D and market power is more sensitive to macroeconomic shocks. If firms conduct more R&D and they are more competitive, labor shedding is more severe during economic downturns and hiring is more pronounced during upswings. For firms with less R&D and higher market power, these effects are reversed and the labor force of these firms is more stable. Using a theoretical framework, we identified R&D adjustment costs as a key determinant of the stronger procyclicality of labor. Given these costs, firms keep their R&D spending relatively smooth and instead adjust the level of their production labor when they face changes in the demand for their goods. If the firms have high market power, by contrast, their mark-up absorbs some of the impact of macroeconomic shocks, which in turn stabilizes their labor force and makes it relatively acyclical.

We derived a relationship between firm-level labor growth and macroeconomic variables from the optimality conditions of our model. We then used this relationship as a structural identification strategy to empirically test our main theoretical predictions. We obtained the data for the firm-level and macroeconomic variables in our theoretical model and we combined these data to form a panel dataset. The estimation results showed that employment for more R&D intense and low market power firms is more sensitive to business cycles. Consistent with our theoretical predictions, these firms hire (shed) labor more substantially when GDP grows (contracts). A variety of robustness tests produced similar inferences. Also consistent with our theoretical predictions, we found evidence for an R&D smoothing behavior as this variable was found to be relatively acyclical. These results were important as they demonstrated that structural and long-term characteristics of an economy such as innovativeness and competitiveness can have substantial short-term effects.

There are a number of possible extensions to this work. One key message of our paper is that R&D, a known growth-enhancing activity, can also have negative effects on an economy that manifest itself through labor volatility. It would be interesting to quantify these negative effects by using a computational welfare analysis. Specifically, one could incorporate the R&D processes and the corresponding endogenous growth mechanisms in this paper into standard medium scale New Keynesian DSGE frameworks with numerous macroeconomic shocks to investigate the trade-off between the R&D driven growth and labor market volatility.

Another direction that one could follow with this line of work is the relationship between R&D intensity and market power. In our model, we assumed that there is no dynamic interaction between these two characteristics. It could be insightful to investigate these potential dynamic relationships. If, for example, firms become more competitive as they do more R&D (or if firms do more R&D as they become more competitive), this would reinforce the main mechanism in our analysis. Conversely, a negative relationship between R&D intensity and the degree of competition would imply that the two main forces acting on labor volatility offset each other. It would be interesting to determine the quantitative importance of this dynamic relationship between R&D intensity and market power.

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Appendix A. Data sources and definitions

Table A.1. Firm-specific data

Variable	Definition	Source
Emp	Number of employees	COMPUSTAT, EMP (#29)
R&D intensity		
1st measure	R&D expense/Total cost	
R&D expense	Research and development expense	COMPUSTAT, XRD (#46)
Total cost	Cost of goods sold + Admin. expense	COMPUSTAT, COGS (#41)
	+ Operating expense	+ XSGA (#132)+ XPOR
2nd measure	R&D expense/Total revenue	COMPUSTAT, XRD (#46)/SALE (#12)
3rd measure	R&D expense/Total assets	COMPUSTAT, XRD (#46)/AT (#6)
4th measure	Relative R&D intensity: Deviation of firm specific R&D-to-total cost (defined as the 1st measure) from annual mean R&D-to-total cost	
Market Share		
1st measure	Sales	
	Firm sales/Total sales in industry	COMPUSTAT, SALE (#12)
2nd measure	Assets	
	Firm assets/Total assets in industry	COMPUSTAT, AT (#6)
3rd measure	# of employee	
	Firm employee/Total employee in industry	COMPUSTAT, EMP (#29)
4th measure	Change in markup	
Markup	Revenue share of variable input cost × Output elasticity of variable input	(De Loecker, et al (2020))
Revenue share of input cost	Sales/Cost of goods sold	SALE (#12) / COGS (#41)
Output elasticity of input	0.85	(De Loecker, et al (2020))

Table A.2. Data descriptions for sample classifications and control variables

Variable	Definition	Source
Profitability	Market Value/Sales	COMPUSTAT, MKVALT
Cost of capital	The difference between ICE BofA BBB rated index and AAA rated indices	St. Louis FED, FRED
Skill premium	Ratio of the median earning of workers with advanced degree divided by median earning of workers with college degree or higher	BLS
KZ index	-1.002xCashFlow + 3.319xDebt -39.368xDividend - 1.315xCash	
Cash flow	Income before ext. items and depreciation amortization divided by total assets	COMPUSTAT, (IB (#18)+DP (#14))/AT (#6)
Debt	Long term debt and debt in current liabilities divided by total assets	COMPUSTAT, (DLTT (#9)+DLC (#34))/AT (#6)
Dividend	Preferred dividends divided by total property, plant and equipment	COMPUSTAT, DVP (#19)/PPENT (#141)
Cash	Cash and short term investments divided by total assets	COMPUSTAT, CHE (#1)/AT (#6)
Sector level R&D	Domestic R&D	BRDIS
	Internal R&D	BRDIS
	External R&D	BRDIS

Table 1. Descriptive statistics

Number of firms	1,983	

Firm-specific variables

	Mean	Standard deviation
Assets	3,149	8,948
R&D/Total Costs	7.07	7.99
Market share	5.93	15.76
Employment growth	2.45	21.71

Macroeconomic variables

	Mean	Standard deviation
Skill premium	2.06	0.04
Borrowing spreads	1.35	0.63
GDP growth	2.04	1.47
Real Wages	0.41	1.13

	Mean	Standard deviation	Correlation with GDP
GDP growth	2.04	1.47	
Employment growth, US	0.84	1.38	0.51
R&D growth	4.81	2.66	0.28

	non-R&D labor volatility
All industries	1.57
Low-R&D industries	1.40
High-RD industries	2.62
Chemical products	1.99
Computers	4.36
Information	2.30
Professional services	2.65
Transportation	2.06

Notes: This table reports statistics for various firm-specific and macroeconomic variables.

Table 2. Baseline estimation results

	R&D / Total Costs	Market Share
GDP	0.8564	1.3436
	(0.3706)***	(0.3603)***
Firm specific factor * GDP	7.0642	-1.9720
	(3.7062)***	(1.0791)*
Firm specific factor	-0.3753	-0.1291
	(0.1529)***	(0.0564)**
Skill premium	0.0049	0.0045
	(0.0019)***	(0.0019)**
Cost of capital	-0.0273	-0.0276
	(0.007)***	(0.0069)***
Real wages	-0.0210	-0.0199
	(0.0088)***	(0.0089)***
Dependent variable lags	0.1643	0.1487
	(28.35)***	(26.19)**
# of observations	10,145	10,145
Hansen test	0.869	0.861
AR2 test	0.661	0.635

Notes: This table reports the results obtained from the estimation of equation (22). For each estimation, firm-level employment growth is the dependent variable. The results are obtained separately for each of the firm specific factors displayed in the column headers. *, **, *** significant at 10%, 5%, 1%, respectively. The numbers reported in parentheses for the dependent variable lags is the chi-square statistic. The statistics reported for the Hansen and AR2 tests are the p-values and z-values, respectively.

Table 3. Alternative measures of R&D intensity

	R&D / Total Costs	R&D / Sales	R&D / Assets	Relative R&D intensity
GDP	0.8564	0.8106	0.5874	1.2412
	(0.3706)***	(0.3465)**	(0.3509)*	(0.4071)***
Firm specific factor * GDP	7.0642	4.4387	8.4525	14.2993
	(3.7062)*	(2.2337)**	(3.2588)***	(4.5354)***
Firm specific factor	-0.3753	-0.2120	-0.3059	-0.8267
	(0.1529)***	(0.0729)***	(0.0942)***	(0.2408)***
Skill premium	0.0049	0.0049	0.0048	0.0058
	(0.0019)***	(0.0019)**	(0.0019)**	(0.0029)**
Cost of capital	-0.0273	-0.0272	-0.0275	0.0097
	(0.007)***	(0.0069)**	(0.0069)***	(0.0065)
Real wages	-0.0210	-0.0209	-0.0207	-0.0474
	(0.0088)***	(0.0088)***	(0.0089)**	(0.0167)***
Dependent variable lags	0.1643	0.1557	0.1546	0.1661
	(28.35)***	(27.39)***	(27.67)***	(21.04)***
# of observations	10,145	10,145	10,145	10,145
Hansen test	0.869	0.837	0.877	0.874
AR2 test	0.661	0.621	0.640	0.953

Notes: This table reports the results obtained from the estimation of equation (22). For each estimation, firm-level employment growth is the dependent variable. The results are obtained separately for each of the firm specific factors displayed in the column headers. *, **, *** significant at 10%, 5%, 1%, respectively. The numbers reported in parentheses for the dependent variable lags is the chi-square statistic. The statistics reported for the Hansen and AR2 tests are the p-values and z-values, respectively.

Table 4. Alternative measures of market share

	Market Share, Sales	Market Share, Assets	Market Share, # of employee	Change in mark-up
GDP	1.3436	1.3424	1.3400	1.1711
	(0.3603)***	(0.3598)***	(0.3594)***	(0.3247)***
Firm specific factor * GDP	-1.9720	-1.7814	-2.2862	-0.0814
	(1.0791)*	(1.080)*	(1.072)**	(0.0411)**
Firm specific factor	-0.1291	-0.1406	-0.1677	0.0032
	(0.0564)**	(0.0554)**	(0.0513)***	(0.0015)**
Skill premium	0.0045	0.0045	0.0043	0.0040
	(0.0019)**	(0.0019)**	(0.0019)**	(0.0019)**
Cost of capital	-0.0276	-0.0275	-0.0278	-0.0289
	(0.0069)***	(0.0069)***	(0.0069)***	(0.007)***
Real wages	-0.0199	-0.0201	-0.0195	-0.0169
	(0.0089)***	(0.0089)**	(0.0089)**	(0.0086)**
Dependent variable lags	0.1487	0.1474	0.1479	0.1720
	(26.19)**	(26.36)**	(26.33)**	(30.21)**
# of observations	10,145	10,145	10,145	10,145
Hansen test	0.861	0.857	0.860	0.860
AR2 test	0.635	0.627	0.636	0.675

Notes: This table reports the results obtained from the estimation of equation (22). For each estimation, firm-level employment growth is the dependent variable. The results are obtained separately for each of the firm specific factors displayed in the column headers. *, **, *** significant at 10%, 5%, 1%, respectively. The numbers reported in parentheses for the dependent variable lags is the chi-square statistic. The statistics reported for the Hansen and AR2 tests are the p-values and z-values, respectively.

Table 5. Fixed effects estimator

	R&D / Total Costs	Market Share
GDP	1.0999	2.0131
	(0.2855)***	(0.2514)***
Firm specific factor * GDP	8.9893	-4.9327
	(2.8016)***	(0.9068)***
Firm specific factor	-0.2565	-0.0635
	(0.0962)***	(0.0386)***
Skill premium	0.0015	0.0015
	(0.0012)	(0.0012)***
Cost of capital	-0.0344	-0.0348
	(0.0059)***	(0.0059)***
Real wages	-0.0080	-0.0082
	(0.0017)***	(0.0017)***
# of observations	16,284	16,284
Adj-R2	0.208	0.210

Notes: This table reports the results obtained from a fixed effects estimation of equation (22). For each estimation, firm-level employment growth is the dependent variable. The results are obtained separately for each of the firm specific factors displayed in the column headers. *, **, *** significant at 10%, 5%, 1%, respectively. The numbers reported in parentheses for the dependent variable lags is the chi-square statistic. The statistics reported for the Hansen and AR2 tests are the p-values and z-values, respectively.

Table 6. Economic Significance

	R&D / Total Costs	Market Share
GDP	0.4313	0.3858
	(0.1078)***	(0.1114)***
Firm specific factor * GDP	0.1679	-0.0935
	(0.0917)*	(0.0528)***
Firm specific factor	-0.6902	-1.1209
	(0.3231)**	(0.2905)*
Skill premium	0.2574	0.2316
	(0.1252)**	(0.1258)*
Cost of capital	-0.3410	-0.3484
	(0.0943)***	(0.0944)***
Real wages	-0.9457	-0.8724
	(0.5604)*	(0.5606)
Dependent variable lags	0.1632	0.1536
	(26.95)***	(24.83)***
# of observations	10,145	10,145
Hansen test	0.704	0.720
AR2 test	0.704	0.710

Notes: This table reports the results obtained from the estimation of equation (22). The right hand side variables are in mean-deviation form. The dependent variable is measured as the percent deviation of employment growth from its mean value. The results are obtained separately for each of the firm specific factors displayed in the column headers. *, **, *** significant at 10%, 5%, 1%, respectively. The numbers reported in parentheses for the dependent variable lags is the chi-square statistic. The statistics reported for the Hansen and AR2 tests are the p-values and z-values, respectively.

Table 7. Macroeconomic sensitivity of R&D and employment

	Employment	R&D	R&D / Total Costs
GDP	0.3903	-2.3139	1.5880
	(0.1096)***	(2.2101)	(1.2919)
Skill premium	0.2403	-2.2163	1.0946
	(0.1256)*	(1.9204)	(1.3033)
Cost of capital	-0.3509	2.2671	-1.0546
	(0.0942)***	(1.8647)	(1.3476)
Real wages	-0.8863	-8.7551	3.7755
	(0.5600)	(6.1384)	(4.2162)
Dependent variable lags	0.1572	0.0785	-0.5138
	(26.07)***	(0.77)	(28.01)***
# of observations	10,145	10,145	10,145
Hansen test	0.712	0.695	0.644
AR2 test	0.684	0.456	0.823

Notes: This table reports the results obtained from the estimation of equation (22). The results are obtained by using the firm specific factors displayed in the column headers as the dependent variable. *, **, *** significant at 10%, 5%, 1%, respectively. The numbers reported in parentheses for the dependent variable lags is the chi-square statistic. The statistics reported for the Hansen and AR2 tests are the p-values and z-values, respectively.

Table 8. Firm characteristics

		GDP		Firm specific factor * GDP		Firm specific factor	
Baseline	R&D / Total Costs	1.0999	(0.2855)***	8.9893	(2.8016)***	-0.2565	(0.0962)***
	Market Share	2.0131	(0.2514)***	-4.9327	(0.9068)***	-0.0635	(0.0386)***
Technology	R&D / Total Costs	1.3386	(0.3484)**	7.1060	(3.1392)**	-0.2287	(0.1042)***
	Market Share	2.0960	(0.2805)***	-6.0480	(1.2802)***	-0.0328	(0.0580)
KZ index	R&D / Total Costs	1.0813	(0.2965)***	8.4546	(2.8629)***	-0.2465	(0.0954)***
	Market Share	1.9382	(0.2583)***	-4.5409	(0.9888)***	-0.0707	(0.0429)*
Mark-up	R&D / Total Costs	1.1448	(0.4066)***	6.8984	(3.3637)***	-0.2011	(0.1064)***
	Market Share	1.9118	(0.3087)***	-3.9508	(1.1905)***	-0.1305	(0.0649)***
Maturity	R&D / Total Costs	0.6886	(0.3771)**	12.5576	(5.1795)**	-0.4294	(0.1894)**
	Market Share	1.6601	(0.3681)***	-4.1430	(1.0223)***	-0.0147	(0.0411)
Bond finance	R&D / Total Costs	1.0563	(0.2893)***	10.2046	(2.9429)***	-0.2796	(0.1016)***
	Market Share	2.0572	(0.2545)***	-5.0555	(0.9078)***	-0.0710	(0.0388)*
Size	R&D / Total Costs	0.8819	(0.3255)***	9.3265	(3.4128)***	-0.2923	(0.1268)**
	Market Share	1.8723	(0.3053)***	-4.1086	(0.9684)***	-0.0673	(0.0402)*

Notes: This table reports the results obtained from a fixed effects estimation of equation (22). The results are obtained separately for the firm specific factors displayed in column 2. *, **, *** significant at 10%, 5%, 1%, respectively. The numbers reported in parentheses for the dependent variable lags is the chi-square statistic. The statistics reported for the Hansen and AR2 tests are the p-values and z-values, respectively.

Table 9. Sector characteristics

		GDP		Firm specific factor * GDP		Firm specific factor	
Baseline	R&D / Total Costs	1.0999	(0.2855)***	8.9893	(2.8016)***	-0.2565	(0.0962)***
	Market Share	2.0131	(0.2514)***	-4.9327	(0.9068)***	-0.0635	(0.0386)***
Domestic R&D	R&D / Total Costs	1.6017	(0.5176)***	19.3884	(4.7538)***	-0.6253	(0.1585)***
	Market Share	3.4902	(0.4771)***	-6.9078	(1.6846)***	0.0000	(0.0764)
Internal R&D	R&D / Total Costs	1.3764	(0.5542)**	14.9087	(4.8594)***	-0.4677	(0.1479)***
	Market Share	2.7045	(0.4942)***	-4.9162	(1.8005)***	-0.0945	(0.0789)
External Funding	R&D / Total Costs	1.4622	(0.5078)***	12.2301	(4.0983)***	-0.5894	(0.1412)***
	Market Share	2.6077	(0.4241)***	-4.5204	(2.0882)**	-0.1676	(0.0977)*

Notes: This table reports the results obtained from a fixed effects estimation of equation (22). For each estimation, firm-level employment growth is the dependent variable. The results are obtained separately for each of the firm specific factors displayed in column 2. *, **, *** significant at 10%, 5%, 1%, respectively. The numbers reported in parentheses for the dependent variable lags is the chi-square statistic. The statistics reported for the Hansen and AR2 tests are the p-values and z-values, respectively.