

R&D, Market Power and the Cyclicalities of Employment*

Uluc Aysun[†]

University of Central Florida

Melanie Guldi[‡]

University of Central Florida

Adam Honig[§]

Amherst College

Zeynep Yom[¶]

Villanova University

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Abstract

This paper provides a first look into the joint effects of research and development (R&D) and market power on the cyclicalities 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.

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[†]Corresponding author, Associate Professor, UCF College of Business Administration, 4000 Central Florida Blvd., P.O.Box 161400, Orlando, FL 32816. Email: uaysun@bus.ucf.edu

[‡]Associate Professor, UCF College of Business Administration, 4000 Central Florida Blvd., P.O.Box 161400, Orlando, FL 32816. Email: mguldi@bus.ucf.edu

[§]Professor, Amherst College, Amherst, MA 01002. Email: ahonig@amherst.edu.

[¶]Assistant Professor, Department of Economics, 1007 Bartley, Villanova School of Business, 800 E. Lancaster Avenue, Villanova, PA 19085. Email: zeynep.yom@villanova.edu

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, 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 procyclicality 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, endogenous growth model that includes firms engaging in both production and R&D activities. The model predicts that

while R&D intensity of these firms amplifies the macroeconomic sensitivity of production 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 output-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. (2019) and Aysun (2020). 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. 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 cyclicity 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/cyclicalities 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-causality. 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

¹The 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 acyclicity 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 acyclicity 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).² 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 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.^{3,4} While we do not test the predictions of the standard 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 adjust-

²Aysun and Kabukcuoglu (2019) for example finds that high R&D intensity firms and those that are more financially constrained (typically smaller firms with smaller mark-ups) retract non-R&D physical investment by more than low R&D intensity firms.

³Symeonidis (1996) provides an extensive review of the literature on the relationship between market power and innovation.

⁴There is also evidence showing that the relationship between innovation and market power could be non-linear (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).

ments cushions the blow on its production labor. With a more stable labor force, the returns to R&D are also less volatile, which in turn promotes a more steady pace 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.⁵ 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.⁶

We should note that in our analysis we assume that the delay between discovery and adaptation in the innovation process is constant over time while in reality the pace of adaptation could slow down (increase) during a recession (an expansion). We postulate that our results would be reinforced to the extent that the adaptation rate is procyclical. If there is a sharper drop in labor efficiency due to lower adaptation rates in a recession, for example, there would also be a sharper decline in the demand for production labor.

⁵We 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.

⁶Our 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.

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 :

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

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

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

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:

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

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,

$$M_{j,t} = \mu_{j,t} L_{j,t}^p. \quad (4)$$

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 stock of knowledge which in turn improve labor efficiency. 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 it is given by,

$$\mu_{j,t} = \kappa \left(\lambda^{L_{j,t}^{s,rd}} \right)^\eta (\mu_t)^{1-\eta} \quad (5)$$

where $L_{j,t}^{s,rd}$ represent stock of knowledge and it evolves as follows: $L_{j,t}^{s,rd} = L_{j,t-1}^{s,rd} + vL_{j,t}^{rd}$. v here represents the probability that R&D activity, $L_{j,t}^{rd}$, is successful in creating an innovation or the "stepping on toes" effects of R&D (as in Jones and Williams, 1998) and λ is assumed to be greater than one so that R&D activity increases the effective units of production labor. κ is a scaling parameter that is set equal to $(N-1)^{\eta-1}$. This ensures that at the symmetric equilibrium of the economy productivity of all firms are the same rate. 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,

$$\mu_t = \sum_{k=1}^N \mu_{k,t} \quad \text{for } k \neq j. \quad (6)$$

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.

Before we proceed, it is important to mention that our model is characterized by an endogenous growth mechanism and that some variables in the model have a stochastic trend growth component. This growth rate of the economy along the balanced growth path is directly related to the amount of R&D activity and it is given by $\tilde{\mu}_t^g = \tilde{\mu}_t / \tilde{\mu}_{t-1} = \lambda^{L_t^{s,rd}} / \lambda^{L_{t-1}^{s,rd}} = \lambda^{vL_t^{rd}}$. Under the symmetric equilibrium of the model $\tilde{\mu}_t = \lambda^{L_t^{s,rd}}$ represents the stochastic trend along the balanced growth path of the economy. After solving the model as described below, we detrend growing variables with this variable to ensure stationarity.

The intermediate good producer j maximizes expected life-time profits given by,

$$\Pi_{j,t} = E_0 \sum_{t=0}^{\infty} \beta^t \left[P_{j,t} Y_{j,t} - \left(1 + \frac{\phi_{rd}}{2} \left(L_{j,t}^{rd} / L_j^{rd} - 1 \right)^2 \right) SP_t W_t L_{j,t}^{rd} - W_t L_{j,t}^p - R_t^k K_{j,t} \right] \quad (7)$$

s.t.

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

$$\mu_{j,t} = \left(\lambda L_{j,t}^{s,rd} \right)^\eta (\mu_t)^{1-\eta}$$

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

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

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

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

In this economy the cost of capital is given by,

$$R_t^k = (1 - \delta) + MPK_t \quad (8)$$

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

The optimality conditions with respect to capital and production labor are as follows:

Capital:

$$\frac{\alpha P_{j,t} Y_{j,t}}{\varphi K_{j,t}} = R_t^k \quad (9)$$

Production labor:

$$(1 - \alpha) \frac{P_{j,t} Y_{j,t}}{\varphi L_{j,t}^p} = W_t \quad (10)$$

To solve the maximization problem with respect to the R&D stock we substitute $\left(L_{j,t}^{s,rd} - L_{j,t-1}^{s,rd}\right) / \nu$ for $L_{j,t}^{rd}$. The solution to the problem yields the following optimality condition:

$$\begin{aligned} & \frac{(1-\alpha)\eta \ln(\lambda)}{\varphi} P_{j,t} Y_{j,t} - \frac{SP_t W_t}{\nu} - \frac{\phi_{rd} SP_t W_t L_{j,t}^{rd}}{\nu L_j^{rd}} \left(\frac{L_{j,t}^{rd}}{L_j^{rd}} - 1 \right) \\ & - \frac{\phi_{rd} SP_t W_t}{2\nu} \left(\frac{L_{j,t}^{rd}}{L_j^{rd}} - 1 \right)^2 + \beta E_t \left(\frac{SP_{t+1} W_{t+1}}{\nu} \right) + \beta \frac{\phi_{rd}}{\nu L_j^{rd}} E_t \left[SP_{t+1} W_{t+1} L_{j,t+1}^{rd} \left(\frac{L_{j,t+1}^{rd}}{L_j^{rd}} - 1 \right) \right] \\ & + \beta \frac{\phi_{rd}}{2\nu} E_t \left[SP_{t+1} W_{t+1} \left(\frac{L_{j,t+1}^{rd}}{L_j^{rd}} - 1 \right)^2 \right] = 0 \end{aligned} \quad (11)$$

To simplify the expression, we substitute $\frac{(1-\alpha)\eta \ln(\lambda)}{\varphi} P_{j,t} Y_{j,t}$ with $\eta \ln(\lambda) W_t L_{j,t}^p$ by using equation (10) above and we substitute $L_{j,t}^{rd}$ for $\left(L_{j,t}^{s,rd} - L_{j,t-1}^{s,rd}\right) / \nu$. We then divide the growing variables that remain, W_t and W_{t+1} , with the stochastic trend $\tilde{\mu}_t = \lambda^{L_t^{s,rd}}$ and $\tilde{\mu}_{t+1} = \lambda^{L_{t+1}^{s,rd}}$. It should be noted that L_t^{rd} and SP_t do not have a trend and they are thus stationary. Using tilde to represent the detrended variables we obtain: $\tilde{W}_t = \frac{W_t}{\tilde{\mu}_t}$ and $\tilde{W}_{t+1} = \frac{W_{t+1}}{\tilde{\mu}_{t+1}}$.

Substituting these in the equation above we get:

$$\begin{aligned} & \eta \ln(\lambda) L_{j,t}^p = \frac{SP_t}{\nu} + \frac{\phi_{rd} SP_t L_{j,t}^{rd}}{\nu L_j^{rd}} \left(\frac{L_{j,t}^{rd}}{L_j^{rd}} - 1 \right) \\ & + \frac{\phi_{rd} SP_t}{2\nu} \left(\frac{L_{j,t}^{rd}}{L_j^{rd}} - 1 \right)^2 - \beta E_t \left(\frac{SP_{t+1} \tilde{W}_{t+1} \tilde{\mu}_{t+1}}{\nu \tilde{W}_t \tilde{\mu}_t} \right) \\ & - \beta \frac{\phi_{rd}}{\nu L_j^{rd}} E_t \left[\frac{SP_{t+1} \tilde{W}_{t+1} L_{j,t+1}^{rd}}{\tilde{W}_t} \left(\frac{L_{j,t+1}^{rd}}{L_j^{rd}} - 1 \right) \frac{\tilde{\mu}_{t+1}}{\tilde{\mu}_t} \right] - \beta \frac{\phi_{rd}}{2\nu} E_t \left[\frac{SP_{t+1} \tilde{W}_{t+1}}{\tilde{W}_t} \left(\frac{L_{j,t+1}^{rd}}{L_j^{rd}} - 1 \right)^2 \frac{\tilde{\mu}_{t+1}}{\tilde{\mu}_t} \right] \end{aligned} \quad (12)$$

After substituting $\lambda^{\nu L_{t+1}^{rd}}$ for $\frac{\tilde{\mu}_{t+1}}{\tilde{\mu}_t}$ and imposing symmetry across firms to obtain the economic growth rate as $\lambda^{\nu L^{rd}}$, we linearize the condition above to obtain the following relationship between production labor and R&D labor:

$$l_{j,t}^p = \left(sp_t + \phi_{rd} l_{j,t}^{rd} \right) \psi - \beta \psi w_t - \zeta_{t+1} \quad (13)$$

where $\psi = \frac{SP}{\eta v \ln(\lambda) L_j^p}$ and $\zeta_{t+1} = \beta \psi \left[\lambda^{vL^{rd}} \{ \phi_{rd} + v \ln(\lambda) \} E_t \left(l_{j,t+1}^{rd} \right) - \{ E_t(sp_{t+1}) + E_t(w_{t+1}) \} \right]$ and lower case letters with time subscripts represent deviations from the balanced growth path.

The inference here is that if $\psi \phi_{rd} = 1$ and the skill-premium and wages are stable, skilled and unskilled labor are equally volatile. If adjustment costs are low and $\psi \phi_{rd} < 1$, 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 $\psi \phi_{rd} > 1$. 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 three 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. 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 causality is from macroeconomic shocks to firm-level decisions than the other way around. Finally, we reasonably assume that the expectations of future deviations from the balanced growth path is equal to zero so that $\zeta_{t+1} = 0$. In other words, the best forecast for the firm is that wages will grow at their trend growth rate in the following period and that the skill premium and R&D labor do not deviate from their steady state value.⁷

⁷We make this assumption to infer an empirically testable relationship. While this is a reasonable assumption, a more formal approach would be to use and simulate a DSGE model. This is beyond the scope of our paper and the reasonable assumption we make offers a testable empirical specification. We acknowledge though that if the shocks affecting these variables are persistent and firms, under rational expectations, are aware that a positive deviation of skill premium from its future growth path, for example, will most likely be observed in time $t + 1$ as well, this would weaken the link between theory and empirics.

We take the following steps to derive our theoretical prediction:

First we linearize equations (9), (10), (2) and (3) after detrending the growing variables to obtain:

$$p_{j,t} + y_{j,t} = r_t^k + k_{j,t} \quad (14)$$

$$p_{j,t} + y_{j,t} = w_t + l_{j,t}^p \quad (15)$$

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

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

Substituting equation (15) into equation (16) yields the condition below.^{8,9}

$$\left(\frac{\varphi - 1}{\varphi} \right) y_t + \frac{1}{\varphi} y_{j,t} = w_t + l_{j,t}^p. \quad (18)$$

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:

$$w_t + l_{j,t}^p = r_t^k + k_{j,t} \quad (19)$$

This step allows us to focus our attention on production labor as opposed to capital. Substituting equations (19) and (13) into (17) produces the following expression for firm level production:

⁸In the linearized form of the production function (equation (17)) $l_{j,t}^{rd}$ represents the deviation of the stock of knowledge from its trend value along the balanced growth path.

⁹In deriving this expression we normalize final good prices to 1 so that $P_t = 1$.

$$y_{j,t} = a_t + \alpha \left(w_t + l_{j,t}^p - r_t^k \right) + (1 - \alpha) \left(l_{j,t}^p + \frac{\eta v \ln(\lambda) L_j^{rd}}{\psi \phi_{rd}} \left(l_{j,t}^p - \psi s p_t + \beta \psi \lambda^{vL^{rd}} w_t \right) \right) \quad (20)$$

As a final step, we substitute equation (20) into equation (18), 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:

$$l_{j,t}^p = \frac{1}{1 - \chi_1 - \chi_2} \left[(1 - \chi_2) y_t + \chi_2 a_t - \chi_1 \psi s p_t - \chi_3 w_t - \alpha \chi_2 r_t^k \right] \quad (21)$$

where $\chi_1 = \frac{(1-\alpha)\eta v \ln(\lambda) L_j^{rd}}{\psi \phi_{rd}}$, $\chi_2 = \frac{1}{\phi}$ and $\chi_3 = 1 - \alpha \beta \lambda^{vL^{rd}} \chi_1$.

The broad inference from equation (21) 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:

$$\varepsilon_t + \left(\frac{1}{\phi} + \frac{(1 - \alpha) \eta v \ln(\lambda) L_j^{rd}}{\psi \phi_{rd}} \right) l_{j,t}^p - l_{j,t}^p = 0 \quad (22)$$

where ε_t denotes an exogenous change in any of the macroeconomic variables appearing on the right hand side of equation (21) that in turn affects the marginal profits of the firm. The coefficient of the second term in equation (22), $(\chi_1 + \chi_2)$ (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 (22) 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.¹⁰

If the firm is R&D intensive (with a high amount of L_j^{rd}) so that the contribution of skilled labor 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 infer-

¹⁰In equation (21), 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 .

ences 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:

$$Emp_{i,t} = \sum_{k=1}^2 \beta_k^{emp} Emp_{i,t-k} + \beta^{gdp} GDP_{t-1} + \beta^f FSV_{it-1} + \beta^i FSV_{it-1} GDP_{t-1} \quad (23)$$

$$+ \beta^{sp} SP_{t-1} + \beta^{bc} BCost_{t-1} + \beta^w W_{t-1} + u_i + \varepsilon_{i,t}$$

where subscripts i and t index firms and time, respectively and u_i is a dummy variable that represents time invariant firm fixed effects. This equation, similar to our theoretical predictions in equation (21), relates $Emp_{i,t}$ 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.¹¹ All variables mentioned above, consistent with equation (21), 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

¹¹It 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.

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.¹²

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 study whether R&D intensity and market power mitigate and amplify the cyclicalities of employment, respectively. To conduct this test, we first interact R&D intensity with GDP and include this variable in equation (23). We then repeat this step for our measure of market power.

To estimate equation (23), 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 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.

¹²We 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.

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.¹³ 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 (23). 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.¹⁴

In addition, we include sector-specific data in alternative estimations to incorporate crucial characteristics that are not available through COMPUSTAT. Specifically, we use Census

¹³The reason we use annual data is that firm-specific employment data are only available at the annual frequency.

¹⁴When 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.

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, $BCost_{t-1}$ and W_{t-1} in equation (23), 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 cyclical nature 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 negative signs of the coefficients for borrowing costs and real wages are consistent with our theoretical model. By contrast the positive coefficient of the skill premium term is

at odds with the negative coefficient in our theoretical equation. We should note, however, that when skill premium enters our empirical model without lags, we find that its coefficient is consistently positive throughout our estimations. One reason for the disparity could be that skill premiums are less sticky compared to real wages (exhibiting low or negative serial correlation).¹⁵ Labor hiring decisions as predicted by our theoretical model, therefore, are more closely related to the contemporaneous and lagged values of the skill premium and real wage variables, respectively. The coefficients of all other variables and our inferences are similar when we include skill premium contemporaneously. We, therefore, include the first lag of the skill premium throughout our estimations to maintain a consistent lag structure.

It should also be noted that we do not find any evidence for second order serial correlation in the error term, and the Hansen statistic does not detect any instrument endogeneity.¹⁶

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

¹⁵When we estimate an AR(1) process for real wages and the skill premium variables we find that the persistence coefficients for real wages and skill premium are 0.51 and -0.37, respectively.

¹⁶We also infer instrument validity from the Sargan test for over-identifying restrictions.

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.¹⁷ 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 results 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.¹⁸ 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.¹⁹ 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 cyclical. In contrast to our baseline estimations, however, we observe that firms experiencing higher (lower) mark-up growth hire relatively

¹⁷We find a similar disparity when we take into account the standard deviation of the different R&D intensity variables.

¹⁸We 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.

¹⁹This 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.

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 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 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.²⁰

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.

²⁰It 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.

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 standard deviations from mean values. We do so by first subtracting the mean value of a variable, computed in a given 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 cyclicity 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 cyclicity 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. We also restrict the sample to bond-issuing firms and firms that are mature (whose ages are greater than or equal to 15 years).

In our theoretical model, firm specific characteristics are time-variant as it is their steady state values that affect the relationship between production labor and the macroeconomic variables. So far, we considered these characteristics are time-variant. While the variation of the firm specific variables is much larger across firms than they are across time, it is important test whether this disparity between our theoretical and empirical specification affects are findings. To conduct this test, we measure firm specific variables, R&D intensity and market share, as averages across time and replace the firm specific variable in equation (23) with these alter-

native variables. We should note here that since the firm specific variable is time-invariant, GDP, the firm specific variable and their interaction cannot be included simultaneously, and the firm-specific variables are dropped from the estimations. The results obtained from these estimations are reported in panel B of Table 8. The results are similar to our baseline findings. The coefficient of the market share variable, while still negative, is now insignificant.

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.

3.9 Other considerations

The theoretical framework in Section 2 assumes that the amount of labor services is only determined by demand as labor supply decisions were omitted from the model. The main

purpose of this simplifying assumption is tractability. Nevertheless it is important to determine whether this assumption alters the main inferences from the model and the empirical analysis by considering elastic labor supply. In this section, we incorporate labor supply elasticity into our model by assuming that the economy is populated by households that derive utility from consumption and leisure. The households have two types of members, skilled and unskilled agents. The skilled and unskilled agents' labor services are used in the R&D and production process, respectively. The lifetime utility function for household i is given by:

$$U_0 = E_0 \sum_{t=0}^{\infty} \beta^t \left\{ \ln(C_{i,t}) - \tau^p \frac{(L_{i,t}^p)^{1+\sigma_i^p}}{1+\sigma_i^p} - \tau^{rd} \frac{(L_{i,t}^{rd})^{1+\sigma_i^{rd}}}{1+\sigma_i^{rd}} \right\} \quad (24)$$

where the parameter σ_i^p and σ_i^{rd} are the inverse of the Frisch-elasticity of unskilled and skilled labor supply, respectively, β is the time discount parameter and τ^p and τ^{rd} are scaling parameters that determine the steady state levels of unskilled and skilled labor, respectively. For brevity, we do not include the entire budget constraint that we assume that the unskilled agents are paid the real wage rate W_t and skilled agents are paid the real wages times a skill premium, $W_t SP_t$.

The standard intra-temporal optimality condition for each agent type, can then be derived as,

$$\Lambda_{h,t} \tau^p (L_{i,t}^p)^{\sigma_i^p} = W_t \quad (25)$$

$$\Lambda_{h,t} \tau^{rd} (l_{i,t}^{rd})^{\sigma_i^{rd}} = W_t SP_t \quad (26)$$

where the variables denoted by lower case letters similarly represent deviations from steady state values and $\Lambda_{h,t}$ is the Lagrange multiplier on the households' budget constraint.

The linearized form of the two conditions can be combined to derive the following expres-

sion for the skill premium variable:

$$sp_t = \sigma_l^{rd} l_{i,t}^{rd} - \sigma_l^p l_{i,t}^p \quad (27)$$

The two types of services are hired by labor aggregators that combine them and sell them to the intermediate good producers. Assuming symmetry across both households and intermediate good producers, we combine equation (27) and equation (13) to produce the following relationship between R&D and production labor:

$$l_t^{rd} = \frac{(1 + \sigma_l^p)}{\phi_{rd} + \sigma_l^{rd}} l_t^p \quad (28)$$

We then use this equation and follow the steps in Section 2 to rederive the main relationship as,

$$l_{j,t}^p = \frac{1}{1 - \chi_1 - \chi_2} \left[(1 - \chi_2) y_t + \chi_2 a_t - \chi_1 \psi sp_t - \chi_3 w_t - \alpha \chi_2 r_t^k \right] \quad (29)$$

where χ_2 and χ_3 are the same as in Section 2 but now $\chi_1 = \frac{(1-\alpha)\eta v \ln(\lambda) L_j^{rd}}{\phi \psi \phi_{rd}} \frac{1 + \sigma_l^p}{\phi_{rd} + \sigma_l^{rd}}$. Compared to equation (13) above, skill premium does not appear on the right hand side and the sensitivity to macroeconomics variables now depends also on labor elasticities. In particular, if unskilled labor is relatively more inelastic σ_l^p is higher, the demand for this labor becomes relatively more sensitive to macroeconomic variables as the changes in macroeconomic conditions that directly or indirectly affect real wages affect the demand for intermediate good producers' output by more than they affect production labor supply. By contrast, if R&D labor's elasticity decreases (σ_l^{rd} increases), intermediate good producers react to the increase (decrease) in the demand for their goods by additional (fewer) R&D workers while keeping production labor services relatively constant. This in turn decreases the sensitivity of production labor demand to macroeconomic conditions.

The specification in equation (29) is different from that in equation (13) as skill premium drops out of the right hand side. To test whether our main conclusions are altered, we estimate equation (23) without the skill premium variable. The results from this exercise are reported in the first two columns of Table 10. Notice here that the main inferences remain the same as the signs and the significance of the coefficients are quite similar.

Another simplifying assumption we made in our theoretical framework was that the markup rate was time invariant as it was represented by a parameter. In the data, however, markup rates vary across time, and they depend on macroeconomic conditions and market structure. Studies such as Jaimovich and Floetotto (2008) and Corhay et al. (2020), for example, use an oligopolistic structure to show that markup rates depend on entry risks and can alter macroeconomic volatility.

Relaxing the assumption that markup rates are time invariant in equation (2) and following the steps in Section 2, we rederive our main theoretical equation as,

$$l_{j,t}^p = \frac{1}{1 - \chi_1 - \chi_2} \left[(1 - \chi_2) y_t + \chi_2 a_t - \chi_1 \psi sp_t - \chi_3 w_t - \alpha \chi_2 r_t^k - \frac{\ln(Y/N^\varphi)}{\varphi} \varphi_t \right] \quad (30)$$

where φ_t is the markup variable and φ is its steady state value.

To determine whether time-varying markups alter our results, we include the average markup rate, computed across all firms in a given year, on the right hand side of equation (23). The results from the estimation of this equation are reported in columns 3 and 4 of Table 10. The sign and significance of all coefficients are similar to those in our baseline estimations. We find no evidence, however, that the industry markup rate is significantly related to firm-level employment growth.

As a final exercise, we respecify equation (23) so that production labor is contemporaneously related to the independent variables. The reason we use this alternative exercise is to form a closer link between the theoretical relationship in Section 2 with our empirical specification. The results from this alternative estimation are reported in columns 5 and 6 of Table

10. While the signs of the coefficients are similar, the coefficients of the interactive variables and the market share variable are now insignificant. We should note that while it is not critical to use lagged values to minimize risks of reverse causality as the right hand side variables are mostly aggregate variables, the lag structure allows us to capture any impact lags between macroeconomic developments and firm-level behavior, possibly due to price/wage rigidities, and labor and capital adjustment costs. This is why we use this structure in our baseline configuration.

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 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.

Finally, we should acknowledge that we have assumed that the lag between discovery and adaptation is constant over time and that it does not depend on the business cycle. It would be interesting and more realistic to extend the framework to investigate the trade-off between

production and R&D labor along the business cycle when delays are countercyclical.

References

- [1] Acemoglu, D., J. Linn, 2004. "Market size in innovation: theory and evidence from the pharmaceutical industry," *The Quarterly Journal of Economics*, 119(3), 1049-1090.
- [2] Acemoglu D., P. Restrepo, 2020. "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy* 128, 6.
- [3] Aghion, P., P. Askenazy, N. Berman, G. Clette, L. Eymard, 2012. "Credit constraints and the cyclicity of R&D investment: Evidence from France," *Journal of the European Economic Association*, 10(5), 1001-1024.
- [4] Aghion, P., A. Banerjee, 2005. "Volatility and growth," Oxford University Press.
- [5] Aghion, P., N. Bloom, R. Blundell, R. Griffith and P. Howitt, 2005. "Competition and innovation: An inverted-U relationship," *The Quarterly Journal of Economics*, 120(2), 01-728.
- [6] Aghion, P., G. Saint-Paul, 1998. "Virtues of bad times interaction between productivity growth and economic fluctuations," *Macroeconomic Dynamics*, 2(3), 322-344.
- [7] Aghion, P., P. Howitt, 2009. "The Economics of Growth," MIT Press.
- [8] Almus, M., 2000. "Testing 'Gibrat's Law' for young firms—empirical results for West Germany," *Small Business Economics*, 15(1), 1-12.
- [9] Anzoategui, D., D. Comin, M. Gertler, J. Martinez, 2019. "Endogenous technology adoption and R&D as sources of business cycle persistence," *American Economic Journal: Macroeconomics*, 11(3), 67-110.

- [10] Aysun, U., 2020. "Volatility costs of R&D," *European Economic Review*, 122(C).
- [11] Aysun, U., Z. Kabukcuoglu, 2019. "Interest rates, R&D investment and the distortionary effects of R&D incentives," *European Economic Review*, 111, 191-210.
- [12] Basu, S., J.G. Fernald, M.S. Kimball, 2006. "Are technology improvements contractionary?" *American Economic Review*, 96(5), 1418-1448.
- [13] Bianchi, F., H. Kung, G. Morales, 2019. "Growth, slowdowns, and recoveries," *Journal of Monetary Economics*, 101, 47-63.
- [14] Bilbiie, F.O., F. Ghironi, M.J. Melitz, 2008. "Monopoly power and endogenous product variety: Distortions and remedies" (No. w14383). National Bureau of Economic Research.
- [15] Bilbiie, F.O., F. Ghironi, M.J. Melitz, 2012. "Endogenous entry, product variety, and business cycles," *Journal of Political Economy*, 120(2), 304-345.
- [16] Bilbiie, F.O., F. Ghironi, M.J. Melitz, 2019. "Monopoly power and endogenous product variety: Distortions and remedies," *American Economic Journal: Macroeconomics*, 11(4), 140-74.
- [17] Blundell, R., S. Bond, 1998. "Initial conditions and moment restrictions in dynamic panel data models," *Journal of Econometrics*, 87(1), 115-143.
- [18] Bresnahan, T. F., 1989. "Empirical Studies of Industries with Market Power," *Handbook of Industrial Organization*, 2, 1011-1057.
- [19] Bresnahan, T.F., E. Brynjolfsson, L.M. Hitt, 2002. "Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence," *The Quarterly Journal of Economics*, 117(1), 339-376.

- [20] Broda, C., D.E. Weinstein, 2010. "Product creation and destruction: Evidence and price implications," *American Economic Review*, 100(3), 691-723.
- [21] Brown, J. R., S. M. Fazzari, B. C. Petersen, 2009. "Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom," *The Journal of Finance*, 64(1), 151-185.
- [22] Brown, J.R., G. Martinson, B.C. Petersen, 2012. "Do financing constraints matter for R&D?," *European Economic Review*, 56(8), 1512-1529.
- [23] Bustos, P., 2011. "Trade liberalization, exports, and technology upgrading: Evidence on the impact of MERCOSUR on Argentinian firms," *American Economic Review*, 101(1), 304-40.
- [24] Caballero, R.J., M.L. Hammour, 2005. "The cost of recessions revisited: A reverse liquidationist view," *The Review of Economic Studies*, 72(2), 313-341.
- [25] Christiano, L. J., M. S. Eichenbaum, M. Trabandt, 2016. "Unemployment and Business Cycles," *Econometrica*, 84(4), 1523-1569.
- [26] Comin, D., M. Gertler, 2006. "Medium-term business cycles," *American Economic Review*, 96(3), 523-551.
- [27] Corhay, A. H. Kung, L. Schmid, 2020. "Competition, Markups, and Predictable Returns," *Review of Financial Studies*, 33 (12). 5906-5939.
- [28] De Loecker, J., J. Eeckhout, G. Unger, 2020. "The rise of market power and the macroeconomic implications," *The Quarterly Journal of Economics*, 135(2), 561-644.
- [29] De Long, J.B., 1990. "'Liquidation' Cycles: Old-Fashioned Real Business Cycle Theory and the Great Depression," (No. w3546). National Bureau of Economic Research.

- [30] Evans, D. S., 1987. "Tests of alternative theories of firm growth," *Journal of Political Economy*, 95(4), 657-674.
- [31] Fernald, J. G., C. I. Jones, 2014. "The Future of US Economic Growth," *American Economic Review*, 104(5), 44-49.
- [32] Foster, L., C. Grim, 2010. "Characteristics of the Top R&D Performing Firms in the US: Evidence from the Survey of Industrial R&D," US Census Bureau Center for Economic Studies Paper No. CES-WP-10-33.
- [33] Foster, L., J. Haltiwanger, C. Syverson, 2016. "The slow growth of new plants: Learning about demand?" *Economica*, 83(329), 91-129.
- [34] Gibrat, R., 1931. "Les inegalites economiques," Librairie du Recueil Sirey.
- [35] Geroski, P.A., 1990. "Innovation, technological opportunity, and market structure," *Oxford Economic Papers*, 42(3), 586-602.
- [36] Hall, B.H., P. Moncada-Paternò-Castello, S. Montresor, A. Vezzani, 2016. "Financing constraints, R&D investments and innovative performances: new empirical evidence at the firm level for Europe," *Economics of Innovation and New Technology*, 25(3), 183-196.
- [37] Harrison, R., J. Jaumandreu, J. Mairesse, B. Peters, 2014. "Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries," *International Journal of Industrial Organization*, 35, 29-43.
- [38] Hashmi, A.R., 2013. "Competition and innovation: The inverted-U relationship revisited," *Review of Economics and Statistics*, 95(5), 1653-1668.
- [39] Jaimovich, N., M. Floetotto, 2008. "Firm dynamics, markup variations, and the business cycle," *Journal of Monetary Economics*, 55(7), 1238-1252.

- [40] Jones, C.I., J.C. Williams, 1998. "Measuring the social return to R&D," *The Quarterly Journal of Economics*, 113(4), 1119-1135.
- [41] Keynes, J.M., 1931. "Economic Possibilities for Our Grandchildren," In *Essays in Persuasion*, 358-74. London: Macmillan.
- [42] Kung, H., L. Schmid, 2015. "Innovation, growth, and asset prices," *The Journal of Finance*, 70(3), 1001-1037.
- [43] Levine, R., 1999. *Financial development and economic growth: views and agenda*. The World Bank.
- [44] Michaels, G., A. Natraj, J. Van Reenen, 2014. "Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years." *Review of Economics and Statistics*, 96(1), 60-77.
- [45] Nassar, I. A., M. K. Almsafir, M. H. Al-Mahrouq, 2014. "The validity of Gibrat's Law in developed and developing countries (2008–2013): comparison based assessment," *Procedia-Social and Behavioral Sciences*, 129, 266-273.
- [46] Peretto, P.F., 1999. "Cost reduction, entry, and the interdependence of market structure and economic growth," *Journal of Monetary Economics*, 43(1), 173-195.
- [47] Rafferty, M., M. Funk, 2008. "Asymmetric effects of the business cycle on firm-financed R&D," *Econ. Innov. New Techn.*, 17(5), 497-510.
- [48] Ramey, G., V.A. Ramey. 1995. "Cross-Country Evidence on the Link Between Volatility and Growth," *American Economic Review*, 85(5), 1138-51.
- [49] Reid, G. C., 1995. "Early life-cycle behaviour of micro-firms in Scotland," *Small Business Economics*, 7(2), 89-95.

- [50] Saint-Paul, G., 1993. "Productivity growth and the structure of the business cycle," *European Economic Review*, 37(4), 861-883.
- [51] Santarelli, E., L. Klomp, A. R. Thurik, 2006. "Gibrat's law: An overview of the empirical literature," *Entrepreneurship, growth, and innovation*, 41-73.
- [52] Schumpeter, J.A., 1934. "The theory of economic development", translated by Redvers Opie. Harvard: Economic Studies, 46, 1600-404.
- [53] Schumpeter, J.A., 1942. "Capitalism, Socialism, and Democracy," New York: Harper & Bros.
- [54] Symeonidis, G., 1996. "Innovation, Firm Size and Market Structure: Schumpeterian Hypotheses and Some New Themes," OECD Economics Dept. Working Paper 16.
- [55] Van Reenen, J., 1997. "Employment and technological innovation: evidence from UK manufacturing firms," *Journal of Labor Economics*, 15(2), 255-284.
- [56] Vom Lehn, C., 2020. "Labor market polarization, the decline of routine work, and technological change: A quantitative analysis," *Journal of Monetary Economics*, 110, 62-80.
- [57] Wagner, J., 1992. "Firm size, firm growth, and persistence of chance: Testing GIBRAT's law with establishment data from Lower Saxony, 1978-1989," *Small Business Economics*, 4(2), 125-131.
- [58] Yeaple, S.R., 2005. "A simple model of firm heterogeneity, international trade, and wages," *Journal of International Economics*, 65(1), 1-20.

Appendix A. Data sources and definitions

Table A.1. Firm-specific data

Variable	Definition	Source
<i>Emp</i>	Number of employees	COMPUSTAT, EMP (#29)
<i>R&D intensity</i>		
<i>1st measure</i>	R&D expense/Total cost	
	R&D expense	Research and development expense COMPUSTAT, XRD (#46)
	Total cost	Cost of goods sold + Admin. expense + Operating expense COMPUSTAT, COGS (#41) + XSGA (#132)+ XPOR
<i>2nd measure</i>	R&D expense/Total revenue	COMPUSTAT, XRD (#46)/SALE (#12)
<i>3rd measure</i>	R&D expense/Total assets	COMPUSTAT, XRD (#46)/AT (#6)
<i>4th measure</i>	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	
<i>Market Share</i>		
<i>1st measure</i>	Sales	
	Firm sales/Total sales in industry	COMPUSTAT, SALE (#12)
<i>2nd measure</i>	Assets	
	Firm assets/Total assets in industry	COMPUSTAT, AT (#6)
<i>3rd measure</i>	# of employee	
	Firm employee/Total employee in industry	COMPUSTAT, EMP (#29)
<i>4th measure</i>	Change in markup	
<i>Markup</i>	Revenue share of variable input cost \times Output elasticity of variable input	(De Loecker, et al (2020))
<i>Revenue share of input cost</i>	Sales/Cost of goods sold	SALE (#12) / COGS (#41)
<i>Output elasticity of input</i>	0.85	(De Loecker, et al (2020))

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

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

Table 1. Descriptive statistics

Firm-specific variables			Macroeconomic variables		
	Mean	Standard deviation		Mean	Standard deviation
Number of firms	1,983				
Assets	3,149	8,948	Skill premium	2.06	0.04
R&D/Total Costs	7.07	7.99	Borrowing spreads	1.35	0.63
Market share	5.93	15.76	GDP growth	2.04	1.47
Employment growth	2.45	21.71	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 (0.3706)***	1.3436 (0.3603)***
Firm specific factor * GDP	7.0642 (3.7062)***	-1.9720 (1.0791)*
Firm specific factor	-0.3753 (0.1529)***	-0.1291 (0.0564)**
Skill premium	0.0049 (0.0019)***	0.0045 (0.0019)**
Cost of capital	-0.0273 (0.007)***	-0.0276 (0.0069)***
Real wages	-0.0210 (0.0088)***	-0.0199 (0.0089)***
Dependent variable lags	0.1643 (28.35)***	0.1487 (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 (21). 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 (0.3706)***	0.8106 (0.3465)**	0.5874 (0.3509)*	1.2412 (0.4071)***
Firm specific factor * GDP	7.0642 (3.7062)*	4.4387 (2.2337)**	8.4525 (3.2588)***	14.2993 (4.5354)***
Firm specific factor	-0.3753 (0.1529)***	-0.2120 (0.0729)***	-0.3059 (0.0942)***	-0.8267 (0.2408)***
Skill premium	0.0049 (0.0019)***	0.0049 (0.0019)**	0.0048 (0.0019)**	0.0058 (0.0029)**
Cost of capital	-0.0273 (0.007)***	-0.0272 (0.0069)**	-0.0275 (0.0069)***	0.0097 (0.0065)
Real wages	-0.0210 (0.0088)***	-0.0209 (0.0088)***	-0.0207 (0.0089)**	-0.0474 (0.0167)***
Dependent variable lags	0.1643 (28.35)***	0.1557 (27.39)***	0.1546 (27.67)***	0.1661 (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 (21). 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 (0.3603)***	1.3424 (0.3598)***	1.3400 (0.3594)***	1.1711 (0.3247)***
Firm specific factor * GDP	-1.9720 (1.0791)*	-1.7814 (1.080)*	-2.2862 (1.072)**	-0.0814 (0.0411)**
Firm specific factor	-0.1291 (0.0564)**	-0.1406 (0.0554)**	-0.1677 (0.0513)***	0.0032 (0.0015)**
Skill premium	0.0045 (0.0019)**	0.0045 (0.0019)**	0.0043 (0.0019)**	0.0040 (0.0019)**
Cost of capital	-0.0276 (0.0069)***	-0.0275 (0.0069)***	-0.0278 (0.0069)***	-0.0289 (0.007)***
Real wages	-0.0199 (0.0089)***	-0.0201 (0.0089)**	-0.0195 (0.0089)**	-0.0169 (0.0086)**
Dependent variable lags	0.1487 (26.19)**	0.1474 (26.36)**	0.1479 (26.33)**	0.1720 (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 (21). 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 (0.2855)***	2.0131 (0.2514)***
Firm specific factor * GDP	8.9893 (2.8016)***	-4.9327 (0.9068)***
Firm specific factor	-0.2565 (0.0962)***	-0.0635 (0.0386)***
Skill premium	0.0015 (0.0012)	0.0015 (0.0012)***
Cost of capital	-0.0344 (0.0059)***	-0.0348 (0.0059)***
Real wages	-0.0080 (0.0017)***	-0.0082 (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 (21). 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 (0.1078)***	0.3858 (0.1114)***
Firm specific factor * GDP	0.1679 (0.0917)*	-0.0935 (0.0528)***
Firm specific factor	-0.6902 (0.3231)**	-1.1209 (0.2905)*
Skill premium	0.2574 (0.1252)**	0.2316 (0.1258)*
Cost of capital	-0.3410 (0.0943)***	-0.3484 (0.0944)***
Real wages	-0.9457 (0.5604)*	-0.8724 (0.5606)
Dependent variable lags	0.1632 (26.95)***	0.1536 (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 (21). 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 (0.1096)***	-2.3139 (2.2101)	1.5880 (1.2919)
Skill premium	0.2403 (0.1256)*	-2.2163 (1.9204)	1.0946 (1.3033)
Cost of capital	-0.3509 (0.0942)***	2.2671 (1.8647)	-1.0546 (1.3476)
Real wages	-0.8863 (0.5600)	-8.7551 (6.1384)	3.7755 (4.2162)
Dependent variable lags	0.1572 (26.07)***	0.0785 (0.77)	-0.5138 (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 (21). 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	
<i>Panel A: Other firm characteristics</i>							
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)*
<i>Panel B: Time invariant characteristics</i>							
		GDP		Firm specific factor * GDP			
Sample averages	R&D / Total Costs	0.6144	(0.3598)*	10.0518	(3.9759)**		
	Market Share	1.3407	(.3622)***	-1.3527	(1.1212)		

Notes: This table reports the results obtained from a fixed effects estimation of equation (21). 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 (21). 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.

Table 10. Other considerations

	Labor supply elasticity		Endogenous markup rate		Specification without lags	
	R&D / Total Costs	Market Share	R&D / Total Costs	Market Share	R&D / Total Costs	Market Share
GDP	0.7351 (0.3581)**	1.2185 (0.344)***	0.7126 (0.3776)*	1.2682 (0.3576)***	4.5390 (1.9132)**	4.2795 (1.2294)***
Firm specific factor * GDP	6.8075 (3.724)*	-1.9867 (1.0857)*	7.8652 (4.0446)*	-2.0499 (1.0961)*	8.6389 (20.2416)	-6.0341 (4.4091)
Firm specific factor	-0.3509 (0.1547)**	-0.1315 (0.0559)**	-0.4173 (0.1639)**	-0.1402 (0.0589)**	-1.6090 (0.6978)**	-0.1055 (0.1326)
Skill premium			0.0042 (0.0019)**	0.0039 (0.0019)**	0.0070 (0.0044)	0.0029 (0.0039)
Cost of capital	-0.0237 (0.0074)***	-0.0244 (0.0074)***	-0.0293 (0.0072)***	-0.0288 (0.0071)***	-0.0645 (0.0348)*	-0.0321 (0.0282)
Real wages	-0.0183 (0.0083)**	-0.0174 (0.0084)**	-0.0157 (0.0087)*	-0.0151 (0.0087)*	-0.0101 (0.0117)	-0.0103 (0.0107)
Markup			0.0032 (0.0089)	0.0056 (0.0089)		
Dependent variable lags	0.1551 (29.19)***	0.1432 (27.27)***	0.1787 (31.06)***	0.1579 (28.35)***	0.3972 (54.68)***	0.3221 (54.15)**
# of observations	10,145	10,145	9,845	9,846	10,145	10,145
Hansen test	0.677	0.829	0.555	0.494	0.756	0.861
AR2 test	0.572	0.570	0.656	0.588	0.258	0.635

Notes: Notes: This table reports the results obtained from the estimation of the different forms of equation (21). 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. To obtain the results in the first two columns, we omit skill premium from the right hand side. To obtain the results in columns three and four, we add average the growth rate of average markups on the right hand side. The results in the last two columns correspond to the model where the dependent variables are contemporaneously related to the independent variables. *, **, *** 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.