The Long-Run Innovation Risk Component

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Abstract

This paper provides empirical evidence that aggregate Research and Development (R&D) drives persistent fluctuations in productivity growth and that these embody a risk priced in financial markets. The analysis relies on a definition of R&D intensity that is cast in a semi-endogenous growth framework, where its deviations from the long-run equilibrium level are reflected in the Error Correction Term of the cointegration between R&D and Total Factor Productivity. This R&D measure results having more desirable statistical properties compared to the fully endogenous case, such as a persistence that matches previous evidence on productivity long-run risk and, more importantly, a stationary behavior. Stationarity allows to reliably document key theoretical predictions, the most notable of which is a significant cross-sectional risk premium associated to stocks' cash-flows sensitivities.

Keywords: Asset Pricing, Long-run risk, Innovation, Cointegration

JEL Codes: E32, E44, G12, O30

1 Introduction

To reconcile consumption-based asset pricing theory with the data, Bansal and Yaron (2004) focused on a 'small' but persistent component of consumption growth, named the 'long-run risk' (LRR) component. This process can add little variance to consumption growth despite heavily impacting the whole consumption path. Therefore, when coupled with preferences that are sensitive to uncertainty in future consumption expectations, as in Epstein and Zin (1989), it becomes a significant source of risk. Risks of this kind have proven useful in studying various macro-financial phenomena.[1] However, detecting LRR components empirically proves challenging, undermining the validation of mechanisms relying on them and drawing significant criticism towards the entire framework.[2] Given the extensive literature that has developed around the LRR concept, it is essential to provide evidence

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[1]For example, exchange rates dynamics as in Colacito and Croce (2011), climate change pricing as in Bansal, Ochoa, et al. (2021), term structures as in Ai et al. (2018), or oil dynamics as in Ready (2018).

[2]Most notably, Beeler and Campbell (2012) and Epstein, Farhi, et al. (2014).

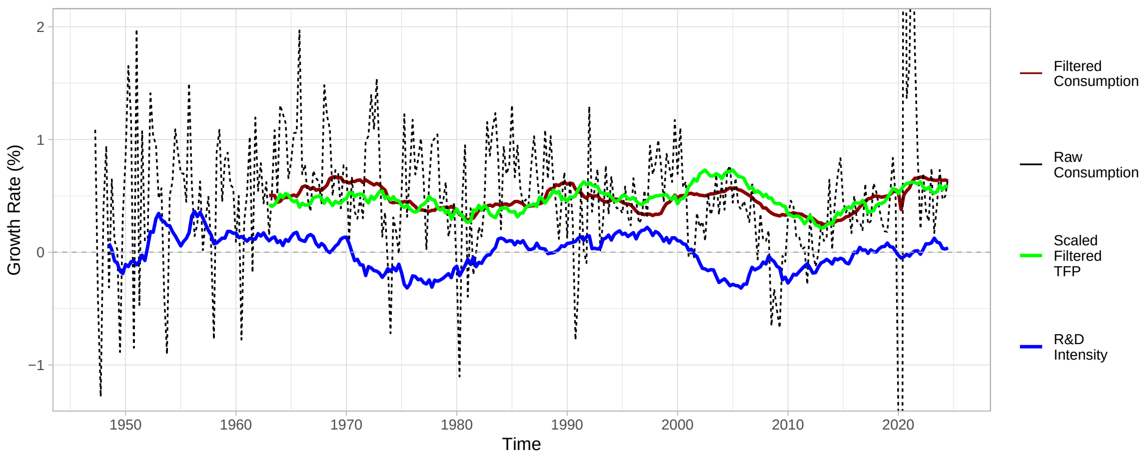

Figure 1: Consumption is US expenditures in services and non-durable from BEA; 'TFP' is the utilization-adjusted TFP from Fernald (2012). The filtered series are the 6^{th} component of Ortu et al. (2013) decomposition. Correlation between Filtered Consumption and TFP is 0.62. Correlation between R&D (arbitrarily lagged of 1y) and the two filtered series is 0.60 and 0.53, respectively.

that supports its establishment: in this paper I contribute by directly documenting a LRR component related to innovation efforts, plotted in figure **??**. More specifically, I empirically show that aggregate Research and Development (R&D) investment intensity fulfills several theoretical requirements, by being highly persistent, forecasting consumption and Total Factor Productivity (TFP) growth, and being associated to a positive risk premium in financial markets.

The significance of low-frequency macroeconomic fluctuations, long-run risks, has been previously corroborated either by directly tackling the statistical difficulties in its detection, as done for example by Ortu et al. (2013), Dew-Becker and Giglio (2016) and Schorfheide et al. (2018), or by framing their origin in richer structural models, which provide additional implications to test. Following the latter approach, Kaltenbrunner and Lochstoer (2010) first showed in general equilibrium how the long-run risk component can arise in consumption growth with standard productivity dynamics. Then, Croce (2014) went a step further, providing both theoretical arguments and empirical evidence for a long-run consumption risk component being originated in the persistence of the productivity growth process. This found additional support in Ortu et al. (2013), which empirically found high correlation between the components of consumption and TFP growth rates with half-life within eight and sixteen years. Kung and Schmid (2015) moved one further step upstream, acknowledging the well-established role of R&D in spurring productivity growth and showing how a long-run risk component in consumption could ultimately be driven by an endogenous and persistent aggregate R&D investment intensity, both theoretically and empirically. The empirical evidence they provided to support this claim, however, relied on a measure of R&D intensity that, with updated data, shows undesirable statistical properties, most importantly an apparent non-stationarity. This paper improves on this, providing empirical evidence for a long-run risk originating in R&D efforts that is based on a more reliable R&D intensity measure. The crucial difference from Kung and Schmid (2015) is the definition of R&D

intensity, which in this paper stems from a semi-endogenous growth model rather than a fully endogenous one: in semi-endogenous models R&D and TFP level are approximately cointegrated and the associated Error Correction Term (ECT) reflects the fluctuations in R&D intensity, which drive conditional expectations of productivity growth. As the estimated ECT is stationary, empirical analysis relying on this process are less likely to produce spurious results. A further novelty of this paper with respect to Kung and Schmid (2015) consists of a cross-sectional asset pricing test. This returns a positive and significant risk premium associated to assets' exposure to it, as expected. Building on theoretical arguments put forward by previous research, this paper does not provide any theoretical result concerning why R&D intensity fluctuates as persistently as it does. However, the drivers of fluctuations in R&D are investigated descriptively, with aggregate funding liquidity forecasting R&D intensity more strongly than aggregate mark-up.

The definition of R&D intensity is illustrated exploiting a semi-endogenous 'lab-equipment' R&D growth framework, specifically.[3] This provides enough structure to interpret the cointegrating relation empirically emerging between R&D and TFP, allowing to identify the long-run innovation risk component in R&D fluctuations. From a methodological point of view, as often done in the recent macro-finance literature, the cointegrating relation is estimated with the Dynamic OLS methodology studied in Phillips and Loretan (1991), Saikkonen (1991), and Stock and Watson (1993). In the macroeconomic literature, cointegration methods have already been employed to study the relation between R&D and technological progress in different studies, such as Ha and Howitt (2007), Bottazzi and Peri (2007), and more recently Herzer (2022b) and Kruse-Andersen (2023). These papers are mostly concerned with the assessment of foreign spillovers and the comparison of fully- versus semi-endogenous growth models, with more recent evidence leaning towards semi-endogenous ones, as also backed by Bloom et al. (2020). This paper does not contribute directly to the debate on the modelling comparison, rather it leverages the empirical fit of semi-endogenous growth models to perform a more effective empirical analysis of the LRR mechanism, while testing endogenous growth theory on new grounds, namely that of financial markets. In the financial economics litetarure, cointegration in macroeconomic variables has been widely exploited to price assets, with notable examples in Lettau and Ludvigson (2001) and Melone (2021), but to my knowledge this is the first application to relate aggregate R&D and asset pricing in a cross-sectional analysis. The forecasting exercise of R&D with respect to consumption and TFP growth is carried out with local projections, as standard in the literature, while descriptive investigation of the R&D fluctuations' drivers is performed estimating a VAR system with the first differences of the intermediaries' equity ratio from He et al. (2017) and of the mark-up from Nekarda and Ramey (2020).

On the financial side of the analysis, the most important contribution of the paper is providing empirical evidence that persistent swings in R&D activities is a priced risk in equity markets. This evidence comes from cross-sectional pricing tests pioneered by Bansal, Dittmar,

[3]This class of models was introduced in Romer (1987), and is characterized by the use of units of the final output good to produce ideas, instead of using labor as in more traditional cases à la Romer (1990).

and Lundblad (2005), and developed by Bansal, Dittmar, and Kiku (2009) among others. Like Bansal, Dittmar, and Lundblad (2005), in this paper I focus on the risk premium related to cash-flow growth rates' sensitivities rather than returns' sensitivities because in LRR general equilibrium models the key determinant of risk premia is exposure of dividends to long-run risks, while discount rates may be impacted by many other elements. I obviously depart from Bansal, Dittmar, and Lundblad (2005) by focusing on sensitivities to the estimated R&D intensity rather than to consumption, which ends up showing a stronger risk premium than those related to consumption. I also differ in considering a wider set of test asset portfolios: in particular, I include portfolios sorted on firm-specific R&D. This is interesting because this sorting leads to the greatest dispersion in cash-flow growth rates across portfolios and it is a dimension likely relevant for heterogeneity in sensitivities to aggregate R&D. Indeed, a clear pattern emerge: cash-flows of more R&D intensive firms prove being much more positively sensitive to aggregate R&D intensity, meaning that cash-flows of more R&D-intensive firms grow more when other firms invest more in R&D too. This is in line with both R&D-intensive firms showing higher excess returns and spillover effects being stronger than the fishing-out effect, as previously shown by Jiang et al. (2016). For the cross-sectional pricing test, a traditional Fama and Macbeth (1973) is employed.

Matching such a complete theoretical description of the economy is out of the scope of this paper, which instead is focused on empirically assess the dynamics of R&D and the fit of the theoretical predictions associated to it.

The rest is structured as follows: in section 2 I illustrate the theoretical framework, outlining the emergence of a long-run innovation risk component in a semi-endogenous growth models as well as its role in pricing assets; in **??** I show the first empirical results from the estimation of the R&D intensity measure, and proceed illustrating its proprieties as well as its forecasting power with respect to TFP and consumption, in addition to investigating the relation with markup and funding conditions; in **??** I carry out the cross-sectional pricing test; in section 6 I conclude.

Early contributions to the asset pricing literature, most notably Lucas (1978) and Breeden (1979), started from considering consumption as the sole determinant of investors' welfare and noted that stock markets' payouts closely track consumption too. Indeed, has established that shocks of the $\varepsilon_{x,t+1}$ kind can be originated in low-frequencies shocks to TFP growth, with Ortu et al. (2013) more precisely identifying consumption fluctuations with half-life between 8 and 16 years into TFP growth fluctuations for US.

2 Theoretical framework

2.1 A flexible R&D intensity definition

Consider, without loss of generality, a discrete-time economy in which the aggregate productivity of rivalrous inputs, Z_t, is determined by a stochastic exogenous factor a_t and the stock of ideas I_t, which embodies the technological frontier:

$$Z_t = e^{a_t} \cdot I_t^{\xi} \ , \tag{1}$$

for some positive value of ξ, capturing the degree of increasing returns to scale. a_t synthesizes every factor other than ideas to affect productivity, such as misallocation, in order to transparently keep track of their impact on productivity dynamics. What defines the intangible capital I_t as technological frontier is that it is assumed to be propelled by R&D expenditure S_t, as described by the law of motion

$$I_t = (1-\phi)I_{t-1} + \chi \cdot S_{t-1}^{\eta} I_{t-1}^{\psi} Q_{t-1}^{-\omega} \ , \tag{2}$$

where $\phi \in [0,1]$ represents the probability of ideas becoming obsolete, $\chi > 0$ is a scale parameter, $\eta \in (0,1]$ controls the extent of duplication in R&D efforts, $\psi \in (0,1)$ sets the strength of spillovers from past ideas, net of fishing-out effects, in the creation of new ones, and Q_t is a measure of goods variety, with some degree of ideas' dilution power $\omega \in [0,\eta)$.[4]

The production function of new ideas implied by the ideas' law of motion is the most pivotal assumption of this theoretical framework. It dictates and displays how R&D pushes the technological frontier forward, which is mediated both by the extent to which current research can build on previous ideas and by how widely these new ideas spread into different applications, i.e. products. These two aspects are key to removing the strong scale effects of first-generation endogenous growth models like Romer (1990), which make the models explode when introducing population growth and thus making them unsuitable for empirical applications. The fully-endogenous approach, shown for example in Aghion and Howitt (1998), focuses on the latter mechanism and implies that sustained higher growth can be obtained by increasing the share of resources devoted to R&D, while the semi-endogenous approach, reviewed in Jones (2005), pivots on the former mechanism which makes spillovers from past R&D die out in the long-run, ultimately making growth rates function of population growth only. Anyway, (2) is flexible enough to nest both specifications,[5] although the empirical analysis will not explicitly address the issue of which of the two approaches is more relevant for fitting the data. This law of motion is directly inspired by Jones (1999), but it is more conveniently reframed in a 'lab equipment' fashion, as seen in Kruse-Andersen (2023), among others. (2) represents the reduced form of equilibrium conditions from economies with different microfoundations, one of which is studied in greater depth in Sedgley and Elmslie (2013).

(1) and (2) provide enough structure to derive a meaningful description of productivity dynamics:

$$\Delta \ln Z_{t+1} \approx \gamma_0 + \gamma_1 \Big(\ln S_t - \frac{1-\psi}{\eta} \ln I_t - \frac{\omega}{\eta} \ln Q_t \Big) + \Delta a_{t+1} \ , \tag{3}$$

[4]The actual set of admissible parameters values is wider and is presented more precisely in Appendix A, where a complete model is illustrated.

[5]Kung and Schmid (2015), for example, can essentially be reproduced by setting $\psi = 1-\eta$ and $\omega = 0$.

where $\gamma_0 > 0$ and $\gamma_1 > 0$ are functions of parameters previously presented, more precisely defined in Appendix A. In other words, productivity growth is driven by changes in the external factor and by the (log-linearized) ratio of R&D to the stock of ideas weighted by products proliferation. Depending on the order of integration of a_t, its first difference might introduce white noise only (when $I(1)$), a predictable mean-reverting component (when $I(0)$), or even a unit root in the remote case a_t was $I(2)$. All these cases will be handled empirically, but this section, for the sake of exposition, will proceed by following the literature and assuming that a_t is near-$I(1)$. This assumption facilitates a more direct focus on the role of R&D, through the term consisting of R&D scaled by a measure of the technological frontier, which can be more succinctly referred to as 'R&D intensity', s_t:

$$s_t = \ln S_t - \frac{1-\psi}{\eta} \ln I_t - \frac{\omega}{\eta} \ln Q_t \ . \tag{4}$$

Intuitively, this term quantifies innovation efforts and answers the question 'how much is an economy spending in R&D relative to its size or, better, development level?' – independently of whether the economy is in a fully-endogenous or semi-endogenous growth regime. From (3), it is also clear that the R&D intensity process constitutes a part of productivity growth dynamics, specifically the part associated with innovation, which justifies its labeling as the 'innovation component'.

2.2 The 'innovation component' of productivity growth

A literal interpretation of (3), paired with the standard assumption of stationary productivity growth, which is well documented too, suggests that R&D intensity must be stationary too. A stationary R&D intensity implies the existence of an unconditional value, $\bar{s}$, which can be easily interpreted as the (very) long-run equilibrium level, around which s_t fluctuates. Then, it can be clearly seen how deviations of R&D intensity from the equilibrium level, $\tilde{s}_t = s_t - \bar{s}$, drive the dynamics of conditional expectations of future productivity growth:

$$\mathbb{E}_t \left[\Delta \ln Z_{t+1} \right] \approx \mu + \gamma_1 \cdot \tilde{s}_t \ . \tag{5}$$

In other words, R&D intensity today should inform economic agents on productivity growth tomorrow. Here, s_t plays exactly the same role in shaping the expectations of future productivity growth that the 'long-run productivity risk component' has in Croce (2014). The long-run productivity risk component is also characterized by a high persistence, which makes its current value informative about productivity growth at more distant future horizons. Indeed, any long-run risk component is defined by (1) forecasting power of significant macroeconomic variables, and (2) high persistence, as made clear from the seminal paper Bansal and Yaron (2004). In this case, to see the impact of R&D persistency, consider the innovation component having a simple AR(1) structure,

$$\tilde{s}_t = \rho_s \tilde{s}_{t-1} + \varepsilon_t^s \qquad \varepsilon_t^s \sim \mathcal{N}(0,1) \ . \tag{6}$$

Then, following a shock to R&D intensity, the infinite-horizon prospects of the economy, in terms of productivity, will jump by

$$\{\mathbb{E}_{t+1} - \mathbb{E}_t\}\Big(\sum_{j=0}^{\infty} \Delta \ln Z_{t+1+j}\Big) = \frac{\rho_s}{1-\rho_s}\varepsilon^s_{t+1} \ . \tag{7}$$

As R&D intensity drives productivity growth expectations, the longer shocks to R&D reverberate, the farther into the future productivity expectations will be affected. Kung and Schmid (2015) motivated theoretically the emergence of persistence in R&D intensity, while this work is limited to document this fact empirically. An accurate theoretical description of how this jump in productivity prospects translates into a shock of consumption prospects is also out of the scope of this work. Beyond Kung and Schmid (2015), this topic has been extensively studied in the literature, from the permanent income hypothesis in Friedman (1957) to more recent works such as Kaltenbrunner and Lochstoer (2010), Croce (2014), and L'huillier and Yoo (2019), among many others. Nonetheless, with the simplifying assumption of consumption being a constant fraction of the final goods produced, it is easy to see that $\{\mathbb{E}_{t+1} - \mathbb{E}_t\}\Big(\sum_{j=0}^{\infty} \Delta \ln C_{t+1+j}\Big)$ is always affine in $\frac{\rho_s}{1-\rho_s}\varepsilon^s_{t+1}$.

Further, the standard assumption of sustained productivity growth, in a non degenerate economy, implies that the stock of ideas, the level of R&D expenditure and products variety, all grow exponentially over time, with their logarithms being integrated of order 1 – with this observation being extensively supported by the data for the last two variables. Hence, a linear combination of non-stationary variables is predicted to be stationary; a cointegrating relationship is implied between the logarithms of R&D expenditure, stock of ideas and products variety. This feature has an important implication for empirical applications, which is that $\tilde{s}_t$ can be retrieved, since the parameters in

$$\tilde{s}_t = \alpha_0 + \ln S_t - \alpha_I \ln I_t - \alpha_Q \ln Q_t \tag{8}$$

can be estimated. It should be noted that the theoretical mapping between (8) and (4) is immediate, however (8) alone does not suffices to identify and estimate structural parameters in (4), which, anyway, is a goal out of the scope of this work.

Stationarity of s_t is a key feature also because it is crucial in preventing spurious statistical results when employing it in traditional tests of the theory. However, there is a well-known tension between how much a series is persistent and how difficult it is to empirically distinguish it from a non-stationary one.[6] This could represent a challenge for this framework and its empirical validation, since R&D dynamics have a greater impact on the economy, and asset prices, the more persistent R&D intensity is, as previously illustrated. Indeed, with a finite number of observations, it is possible (1) for productivity growth to appear stationary even if the data generating process of R&D intensity is non-stationary, due to considerable exogenous short-term fluctuations, and (2) for R&D intensity to appear non-stationary when its data generating process is stationary but highly persistent. Anyway, whether this specific

[6]See, for example, Müller (2005).

framework is the best representation of reality is an empirical question, but the mechanism that makes persistency so critical would be the same in the limit case of a non-stationary R&D intensity. The bottom line is that what qualifies the innovation component as a long-run risk component is that it is persistent and forecasts productivity and consumption growth. As such, the long-run risk asset pricing framework predicts it to be a relevant risk factor for investors, being priced in the cross-section of financial assets. Stationarity is only required to allow for reliable tests of these conditions.

2.3 The premium of Long-Run Risks

In perfect markets, the expected return of any asset i in excess of the risk-free return R_t^f is proportional to the extent to which the asset's return R_t^i covaries with the intertemporal marginal rate of substitution (IMRS), M_t, as the following holds:[7]

$$\mathbb{E}_t\left[R_{t+1}^i\right] - R_t^f = -R_t^f \cdot \mathrm{Cov}_t\left[M_{t+1}, R_{t+1}^i\right] \ . \tag{9}$$

The IMRS is a stochastic process that tracks marginal utility of investors in a market, thus reflecting the shocks to the state variables that affect investors' welfare. As such, it plays a key role in studying assets prices and decoding what these reveal of agents' view on the economic fundamentals. The economic interpretation of (9) is that agents dislike fluctuations in certain variables, so to hold assets that would amplify these fluctuations, such as those paying more in 'good' times and less in 'bad' times, they require a compensation in the form of higher expected returns. This spread is known as 'Risk Premium' and can also be though of as the share of the expected value of a future uncertain payout that agents are willing to forgo in order to avoid any uncertainty altogether, similar to an insurance fee. When the representative investor has recursive preferences as specified in Epstein and Zin (1989), with unitary elasticity of intertemporal sostitution (EIS) and risk aversion set by θ, log-IMRS precisely obeys

$$\ln M_{t+1} = \mathbb{E}_t\left[\ln M_{t+1}\right] - \left(\ln C_{t+1} - \mathbb{E}_t\left[\ln C_{t+1}\right]\right) - \left((\theta-1)\{\mathbb{E}_{t+1} - \mathbb{E}_t\}\sum_{j=1}^{\infty}\Delta \ln C_{t+j}\right) \ . \tag{10}$$

The key principle is that agents dislike uncertainty in consumption as well as in what they expect to consume far into the future, which is the essence of the Long-Run Risk framework. Naturally, uncertainty can originate from different sources and EIS can differ from 1, making it useful to adopt the more general formulation in which the shocks to contemporaneous consumption are captured by $\varepsilon_{c,t+1}$ and shocks to long-run prospects of the economy by $\varepsilon_{x,t+1}$:

$$\ln M_{t+1} = \mathbb{E}_t\left[\ln M_{t+1}\right] - b_c\varepsilon_{c,t+1} - b_x\varepsilon_{x,t+1} \ , \tag{11}$$

[7] A standard reference is Cochrane (2005).

with b_c and b_x expressing the weight that the representative agent places on shocks that only have a short-run impact and on those that affect expectations in the long-run, respectively. Assuming that these two shocks are also determinants of assets' returns dynamics,[8] it yields the main reduced-form pricing equation

$$\mathbb{E}_t\left[R^i_{t+1}\right] - R^f_t = \lambda_c \beta^i_c + \lambda_x \beta^i_x \ , \tag{12}$$

where every asset only needs to be characterized by two measures of risk, its sensitivities β^i_j to shocks ε_j where $j \in \{c, x\}$, and each risk is associated to a market-wide compensation of λ_j – a 'risk premium'.

The defining element of the LRR framework is a significant b_x. Its presence gives rise to a nonzero λ_x, which was initially introduced to explain the bulk of the observed equity-market risk premium $\widehat{\mathbb{E}}[R^{\text{Market}}_{t+1} - R^f_t]$ and address the empirical gap left by the Consumpion-CAPM term $\widehat{\lambda}_c \widehat{\beta}^{\text{Market}}_c$. An explicit formulation of b_x in terms of structural parameters is available in Bansal and Yaron (2004), and, as intuitively suggested by combining (10) and (7), it is greater in magnitude the longer $\varepsilon_{x,t}$ affects consumption. In the original formulation, Bansal and Yaron (2004) formalizes this mechanism by considering $\varepsilon_{x,t}$ as shocks to an autoregressive process of order 1, x_t, that contributed directly to the determination of consumption growth rates. So, the more persistent x_t, the longer it affected growth rates and the higher was b_x. In Croce (2014), instead, x_t determines TFP growth directly, but the theoretical implications are identical. In the macroeconomic framework just illustrated,[9] $\tilde{s}_t$ is predicted to affect consumption in the same way x_t does, providing an economic interpretation of this process and a method to empirically identify it. This paper is concerned with establishing empirically the identification of x_t by $\tilde{s}_t$ and the testing of the LRR predictions on the financial markets, i.e. λ_x being significantly priced.

3 The empirical R&D intensity

3.1 From the theory to the data

To bring condition (4) closer to the data, a conservative approach is followed. First, as in previous references, products variety is assumed to be a function of labor input,[10] so

$$Q_t = L_t \ . \tag{13}$$

[8] A traditional approach would be considering a factor structure in returns like $R^i_{t+1} = \bar{R}^i_t + \beta^i_c \varepsilon_{c,t+1} + \beta^i_x \varepsilon_{x,t+1} + e^i_{t+1}$, but in the LRR framework exposure specifically stems from assets' cash-flows dynamics, as illustrated in Section 5.

[9] As well as in Kung and Schmid (2015), with a different label and formulation.

[10] It is generally assumed an exponential function of the L^κ_t type with $0 < \kappa < 1$, but in this setting different values of κ make no difference, so for the sake of exposition it is fixed at 1.

Second, without introducing additional conditions, total productivity is considered instead of the ideas' stock, recalling that

$$\ln I_t = \frac{1}{\xi} \ln Z_t - \frac{1}{\xi} a_t \ . \tag{14}$$

As previously argued in the literature,[11] the stock of ideas is difficult to empirically identify. The first issue is represented by the fact that ideas are generally measured from patent data, which can be misleading regarding the innovative value. Then, for internal consistency, the ideas' stock should be formed with the same function whose parameters are being estimated. In principle, this could be done by iteratively set the parameters to obtain the time series of ideas' stock, estimate the parameters (with a system of equations) and re-start by using the newly estimated parameters, until convergence. However, there is no guarantee of convergence, it is a rather complex procedure, and heavily relies on the functional form assumed for the law of motion of ideas, making it particularly fragile to misspecification. Moreover, the production function of new ideas would have to be extended to realistically consider the contribution of foreign ideas, which, in addition to requiring additional assumptions and increasing the complexity of the estimation procedure, it would also significantly limit the timespan of the sample. On the other hand, TFP in the form of Solow residuals is a much easier variable to empirically identify, since it is a measure whose concept was born in the data and with a definition that is common to many models, thereby increasing the external validity of the analysis. As the exogenous factor a_t now enters the relation, the third, and last, refinement consists of the assumption that it is spanned by a set of pervading macroeconomic factors $\mathbf{f}_t$

$$a_t = \mathbf{b}_f' \mathbf{f}_t \ . \tag{15}$$

In the end, the theoretical relation on which the estimation is grounded is

$$\tilde{s}_t = S_t - \frac{1-\psi}{\eta\xi}(\ln Z_t - \mathbf{b}_f' \mathbf{f}_t) - \frac{\omega}{\eta} \ln L_t - \bar{s} \ . \tag{16}$$

The empirical measure of R&D that I employ here, and through out the rest of analysis, is the US quarterly private R&D expenditures series expressed in chained 2012 US Dollar prices provided by the Bureau of Economic Analysis in the National Income and Product Accounts tables.[12] This series is available from 1947 Q1 to 2024 Q3. Next, Total Factor Productivity is obtained by Fernald (2012). The baseline series will be the utilization-adjusted one, also adjusted by removing estimated changes in R&D capital for the reasons previously illustrated. Anyway, robustness checks are performed with the raw TFP series too. These series are quarterly growth rates and span from 1947 Q2 to 2024 Q3. The level series are obtained by cumulating the growth rates. Labor input is Total Employment Level from the Bureau

[11] See, for example, Reeb and Zhao (2020) and Herzer (2022a).

[12] The real series is obtained deflating the nominal R&D series Y006RC of table 5.3.5 by the deflator series Y006RG of table 5.3.4.

of Labor Statistics.[13] This is a monthly series available from 1948-01 to 2024-11, from which the values of the quarters' last month are taken. The predicting factors consist of two different sets, previously employed to forecast TFP growth in Ai et al. (2018): (1) the 5 (identified) factors from Bansal and Shaliastovich (2013), US P/D, 3m/3y/5y bond yields, and stock mkt integrated volatility, which span 1947 Q1 to 2022 Q4; and (2) 9 (non-identified) factors which Ludvigson and Ng (2009) form from a wide set of macroeconomic and financial variables, which have monthly frequency and span 1960-03 to 2024-06. The quarterly values of Ludvigson and Ng (2009) are obtained compounding the monthly values. The two sets of factors will be referred to with the shorthands 'BS' and 'LN'.

The characteristics of the data employed to retrieve excess R&D intensity also dictates the method with which the cointegrating parameters are to be estimated. Indeed, there is a timing issue: R&D expenditure is a flow variable expressing the total amount of resources devoted to R&D activities through out the 3 months in t, while the TFP level is a stock variable measuring the technological frontier at a specific moment, the end of the 3 months in t. Then, one could realistically assume that either R&D is chosen at the beginning of period or it is chosen continuously through out the quarter, but for sure the TFP level at the end of the quarter is not contemporaneous to any of these decisions. Therefore, as the intermediate values of TFP are not available and interpolating them would alter the statistical and dynamic properties of the series, this means that the best approximation of the contemporaneous value of TFP should be considered to be the one at the end of period $t-1$. However, making this adjustment implies that a standard Vector Error Correction Model would be estimated with R&D forecasting TFP growth between the end of $t-1$ and t, which is essentially contemporaneous and not what (3) is designed to describe. Therefore, $\tilde{s}_t$ will be built by focusing on the long-run relation only, by employing the Dynamic Ordinary Least Squares (DOLS) method, as presented by Saikkonen (1991), Phillips and Loretan (1991) and Stock and Watson (1993).

3.2 Cointegration estimation

The DOLS procedure requires the inclusion of lagged and lead first differences of the cointegrating variables among the regressors, to remove endogeneity. So, the regression performed takes the following form:

$$\ln Z_t = \alpha_0' + \alpha_S \ln S_t + \alpha_L \ln L_t + \boldsymbol{\alpha}_f' \mathbf{f}_t + \sum_{i \in \{S, L, \mathbf{f}^{(1)}\}} \sum_{j=Lg_i}^{-Ld_i} \delta_{i,j} \Delta i_{t-j} + \epsilon_t \ . \tag{17}$$

A few notes are in order: first, because of TFP taking the place of the ideas' stock, α_0' takes the place of α_0 in (8); second, to treat agnostically the dynamic behavior of a_t, the non-stationary control factors are kept as regressors in levels, and are identified by $\mathbf{f}^{(1)}$; third, the number of lags and leads to be included is theoretically infinite, but they are empirically truncated to Lg_i and Ld_i, respectively, because it is commonly assumed that the farther

[13] Id: LNS12000000.

in time these first differences are, the less information they provide about current values, while still increasing estimation variance; fourth, TFP is kept on the left-hand side because $\max_i(Lg_i)$ turns out to always be greater than $\max_i(Ld_i)$, so this allows to perform the estimation on a sample containing the most recent values of variables in levels, although asymptotically this makes no difference;[14] fifth, the set of control factors is augmented by lags of the stationary factors themselves, lagged up to 1 year, and by both a time trend and a squared time trend, to enhance robustness.

This regression is high dimensional and has a potential problem of multicollinearity, which in principle motivates the univariate approach, but is also exacerbated by it. Indeed, the persistent component of productivity growth that is transmitted to consumption growth has been shown by Ortu et al. (2013) and Croce (2014) to have a half-life most likely between 2 and 16 years. If R&D intensity was to actually play a major role in driving the productivity LRR component, the relation between R&D and productivity is expected to play out over several years. This in turn implies that a high number of lags and leads will have to be controlled for. This issue, closely linked to the routine task of selecting the optimal number of lags and leads, is addressed by the application of AdaLASSO, as studied by Mendes (2018) and Neto (2023). This method penalizes parameters to reduce estimation variance, performing regressors selection along the way. In this application, to induce as least bias as possible, the only penalized parameters are those that are not explicitly predicted to differ from 0 by the theoretical framework, i.e. $\boldsymbol{\alpha}_f$ and $\boldsymbol{\delta}$. More details on the implemented procedure are in Appendix D.

The estimation results are shown in Table 1. The first column of the table refers to the baseline specification, from which columns on the right depart one variable at a time. First, α_S estimates are of the expected sign and always significantly different from zero. Simply put, this means that R&D expenditure level and TFP level increase together, i.e. raw R&D increases with the scale of the economy, as expected. A similarly expected coefficient is that of labor, which suggests some dilution in R&D power to advance the technological frontier and implies an adjustment in how R&D expenditure is to be related to the technological frontier to get a meaningful R&D intensity. The maximum lags selected by AdaLASSO is relatively high for R&D: always farther than 2 years, farther than 4 years for specifications employing BS factors. Nonetheless, the number of lags actually kept after the penalization is drastically lower, which highlights the relevance of the multicollinearity issue in this setting. Significant R&D leads are much fewer, with only one lead first difference retained, in just one specification. Lags and leads of labor's first differences are almost always zero, with the exception of one specification using one lag only. Time trends are never retained by the estimation procedure, as well as non-stationary control factors, which is indicative of the a_t integration order. A few stationary factors, instead, are always deemed relevant in the estimation. Finally, it can be noted that the specification feature that affects the estimates the most is the use of raw TFP levels instead of the adjusted one: this leads to slightly bigger

[14] The implied $\tilde{s}_t$ is then defined as $\ln S_t + \frac{\alpha_0'}{\alpha_S} - \frac{1}{\alpha_S}\ln Z_t + \frac{\alpha_L}{\alpha_S}\ln L_t + \boldsymbol{\alpha}_f'\mathbf{f}_t/\alpha_S$.

Table 1: Cointegration results. Standard Errors in parenthesis, computed as in Mendes (2018). AC(1) is the coefficient of an AR(1) model fit.

Z :	Adj TFP	Raw TFP	Adj TFP	
L :	Tot. emp.		Nonfarm emp.	Tot. emp.
$\mathbf{f}$:	BS			LN
α_S	0.233***	0.269***	0.217***	0.227***
	(0.022)	(0.020)	(0.021)	(0.029)
max lag	20	32	20	10
lags n.	8	19	8	6
max lead	0	4	0	0
leads n.	0	1	0	0
α_L	−0.098***	−0.261***	−0.046***	−0.085***
	(0.013)	(0.012)	(0.013)	(0.018)
max lag	0	1	0	0
lags n.	0	1	0	0
leads n.	0	0	0	0
tt	F	F	F	F
tt^2	F	F	F	F
I(1) controls	0	0	0	0
I(0) controls	3	5	3	4
Num. obs.	262	262	262	245
		$\tilde{s}_t$		
SD	0.149	0.128	0.162	0.139
ADF stat.	−2.51**	−2.66***	−2.36**	−2.23**
KPSS p.v.	> 0.1	> 0.1	0.09	> 0.1
AC(1)	0.961	0.954	0.960	0.962
	(0.015)	(0.017)	(0.015)	(0.016)

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

estimates in magnitude of the cointegrating coefficients, but with little impact, especially for the R&D coefficient.

The bottom part of Table 1 reports some key statistical properties of the implied Error Correction Term – the excess R&D intensity. The Augmented Dickey-Fuller (ADF) test, which tests the null hypothesis of a unit root in the variable, rejects the null at the 5% level in all cases. At the same time, the Kwiatkowski, Phillips, Schmidt e Shin (KPSS) test, which tests the null hypothsis of stationarity, fails to reject the null at levels lower than 10% in almost all specifications. These results provide strong support for considering the innovation component process as stationary. Nonetheless, the AC(1) statistic highlights a significant persistence in it, with a corresponding half-life between 2.5 years and 19 years at 95% confidence level – perfectly fitting previous evidence on the productivity LRR component, which R&D intensity is called to drive. Correlation among ECTs of the different specifications can be seen in Appendix E, but, as suggested by the close estimation results, it is never lower than 0.8.

Figure 2 shows the two series that will be employed in the rest of the work as innovation LRR components, which consist of the $\tilde{s}_t$ estimated by the models in the first and last

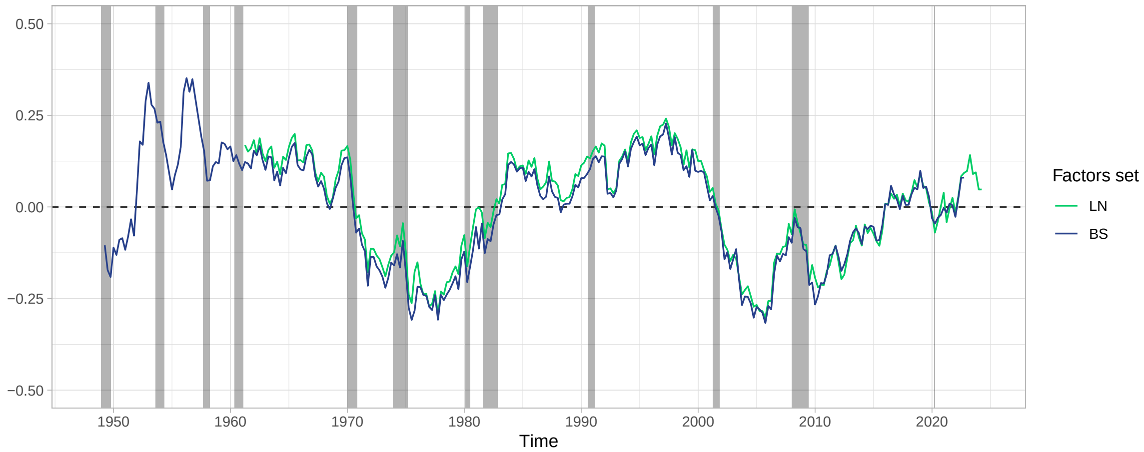

Figure 2: Shaded areas mark NBER recessions. Cross-correlation: 0.990.

column of Table 1. These qualitatively show a highly pro-cyclical behavior of innovation efforts, even to the point of suggesting some forecasting power of R&D intensity with respect to recessions. This is not formally investigated in this study, but may relate to potential inefficiencies in R&D investments that can be studied more in depth with this data. Anyway, R&D intensity dynamics appears to be in line with all the references previously mentioned, which theorized a pro-cyclical behaviour. These theories will be further exploited, and tested, in the next section, where the macroeconomic origins of R&D fluctuations are explored, in order to refine its conditional expectations and better identify R&D shocks.

3.3 Previous evidence

Kung and Schmid (2015) focused on a specification that returns an R&D intensity in the simple form of the ratio S_t/I_t. The empirical counterpart they formed was the raw ratio of US annual private R&D expenditure from the National Science Foundation, measuring S_t, over the R&D stock series estimated by the US Bureau of Labor Statistics, representing intangible capital I_t. They showed this measure of R&D intensity being highly persistent and co-moving at low frequencies with the price-dividend ratio as well as forecasting the growth rates of consumption, GDP and TFP. However, this approach presents a few shortcomings, which can be deduced from the statistics in first column of Table 2.[15]

Their R&D intensity measure is *extremely* persistent, with a point estimate of the yearly first autocorrelation equal to 0.993 and a standard error of 0.009. The 95% confidence interval, which goes from 0.976 to 1.010, highlights two potential issues with this measure: the upper bound reveals a significant risk of an explosive non-stationary behaviour, while the lower bound implies a half-life over 29 years. The ADF test for this series further delivers a statistic which is well above the 10% critical value of −3.15. As mentioned, sample non-stationarity is not critical to the validity of the measure and the theory it is used to support, but undermines the empirical results yielded from employing it because of the

[15] It should be noted that the R&D stock series has been updated by the Bureau of Labor Statistics with respect to the one used in their paper and now covers a slightly different time period.

Table 2: statistics of the (updated) Kung and Schmid (2015) R&D intensity measure. Data in the first column span 1963 to 2020, sources in the main text. 'AC(1)' refers to the autoregressive coefficient of an AR(1) fit.

$\tilde{s}_t$:	$(\ln S_t - \ln I_t)$	$(\ln S_t - \frac{1}{\xi}\ln Z_t)$	
$1-\xi$:	–	0.35	0.3
ADF stat.	−2.21	−2.11	−2.09
AC(1)	0.993***	1.000***	1.000***
	(0.009)	(0.000)	(0.000)
Num. obs.	57	299	299

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

high risk of these being spurious. Then, even with enough evidence of stationarity, the persistence appears to be too high to identify the productivity LRR component. It does suit the persistence of the LRR component in consumption calibrated by Bansal and Yaron (2004), so it could well identify another long-run risk source in the economy, but, as mentioned, the component of consumption that appears to be most strongly related to productivity has a high but lower persistence. All in all, the evidence for this R&D intensity specification effectively identifying the productivity LRR component is fragile.

A role could be played by the data employed, since their measure of ideas' stock is formed by simple accumulation and depreciation of R&D expenses, which is very different from the law of motion they consider in the theoretical framework. To control this, Table 2 also reports statistics for an R&D intensity modified by crudely replacing the ideas' stock with TFP, while accounting for a degree of ideas' increasing returns to scale that matches common values of the labor share. This measure is built using the quarterly data from the previous analysis in this article. However, the issues appear to be the same, if not even starker. The conclusion seems to be that the most critical aspect in defining the dynamic behavior of R&D intensity is flexibility in accommodating both the features of fully endogenous models, such as Kung and Schmid (2015), and those of semi-endogenous models, which comes down to allowing for weaker spillover effects from past ideas. Indeed, recent evidence–most notably from Bloom et al. (2020)–suggests that the latter element plays a relevant role in fitting the data, reinforcing the idea that it may be a necessary feature for a model to be empirically applicable.

4 Investigating the Macroeconomic Implications

4.1 Productivity growth forecasting

A key property of $\tilde{s}_t$ is that it is predicted to drive conditional expectations of TFP growth, therefore it should display a strong forecasting ability. Reviewing (5) to consider the Δa_t term previously disregarded, the regression model being estimated is

$$\mathbb{E}_t\left[\Delta \ln Z_{t+1}\right] = \mu + \gamma_1 \cdot \tilde{s}_t + \boldsymbol{\gamma}_g' \mathbf{g}_t \ , \tag{18}$$

Table 3: TFP growth forecast regression results. TFP growth rates are in percentage points. HAC t-statistics in square brackets.

$\ln Z$:	Adj TFP		Raw TFP	Adj TFP	
$\ln L$:	Tot. emp.			Nonfarm emp.	Tot. emp.
$\mathbf{f}$:	BS				LN
$\tilde{s}_t$	0.193***	0.171***	0.160**	0.194***	0.158***
	[4.74]	[3.91]	[2.46]	[4.80]	[3.89]
ARMA	(1,0)	(1,0)	(1,2)	(0,1)	(0,1)
Controls set	BS	LN	BS	BS	LN
Time trend	F	F	F	F	F
p.v. (F_{controls})	0.00%	0.00%	14.46%	0.21%	0.00%
p.v. (LR_{controls})	0.00%	0.00%	8.36%	0.07%	0.00%
R^2	10.6%	11.9%	5.7%	10.6%	11.6%
Num. obs.	294	251	294	294	252

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

where $\mathbf{g}_t$ will again consist of either BS or LN factors, augmented by a time trend and ARMA terms, all of which are selected by minimizing the Akaike Information Criterion (AIC). To ensure robustness, I also test the baseline innovation component $\tilde{s}_t$, which is obtained relying on BS factors, in a forecasting regression where the constrols are the LN factors. For interpretability of results, $\tilde{s}_t$ have been scaled so to have Standard Deviation (SD) equal to one; hence, γ_1 expresses the immediate response to a 1-SD shock to R&D intensity. The results are reported in Table 3.

The most relevant observation is that estimates of γ_1 are always significantly different from zero and range between 15 and 20 basis points, which, when annualized, amounts to between half and one percentage point. Time trends are never retained by AIC selection. The coefficients of retained control factors, as measured by the p-values of the F test and the Likelihood Ratio test, jointly, are mostly significant. This strongly establishes the impact of the innovation component on conditional expectations of productivity growth. Being also persistent, the innovation component fully qualifies to identify the productivity LRR component. What is left to establish before investigating the implications on financial markets, is whether the productivity LRR component is trasmitted to consumption growth as predicted.

4.2 Consumption growth forecasting

Performing the last forecasting exercise on consumption growth would provide limited evidence. For this reason, the impact of excess R&D intensity on consumption growth is studied, as previously done in the LRR literature, following a local projection method, with the regression model being:

$$\mathbb{E}_t\left[\Delta \ln C_{t+j}\right] = \pi_0 + \pi_{s,j}\tilde{s}_t + \boldsymbol{\pi}'_{g,j}\mathbf{g}_t \ , \tag{19}$$

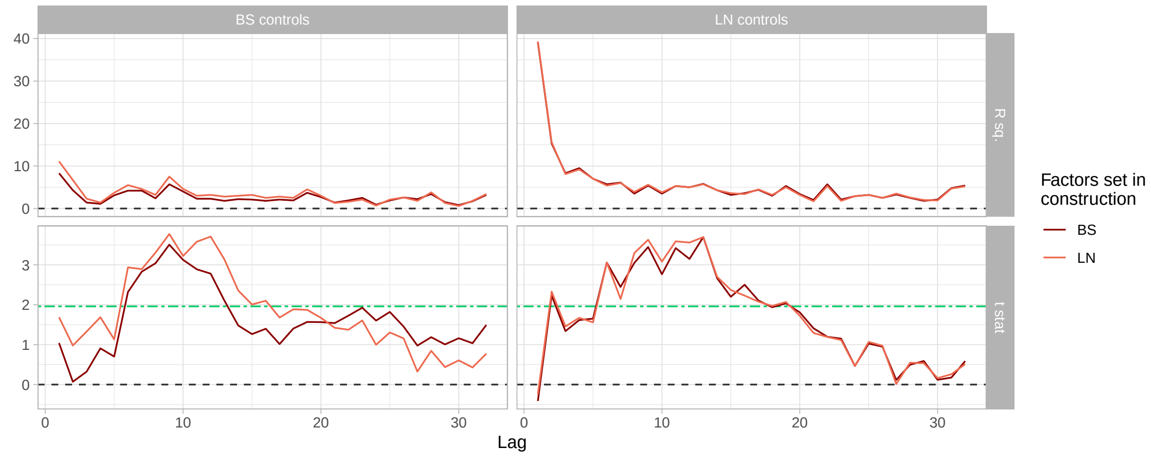

Figure 3: "BS" stands for controls used in Bansal and Shaliastovich (2013), starting in 1948 Q1; "LNG" in Ludvigson and Ng (2009), starting in 1960 Q2.

for a forecast window of 8 years, which corresponds to $\max(j) = 32$ quarters. Consumption is expenditure in nondurable goods and services. The controls, as before, consist of either the BS or the LN factors. Figure 3 reports the R^2 of the regressions and the t-statistics of $\pi_{s,j}$ estimates. Between the two- and three-year horizon, $\tilde{s}_t$ results being highly significant with both control factors sets, even when crossed. This implies that the impact on consumption is delayed, but as R&D intensity reverberates its shocks, these eventually reach consumption, affecting it for as long as innovation component is, itself, affected.

4.3 An investigation of fluctuations' determinants

While proving causal relations are beyond the scope of this paper, it is informative to outline the dynamic relation of R&D excess intensity with other macroeconomic variables. Specifically, R&D investment in Kung and Schmid (2015) is driven by markup level, but it is well known that financial constraints play a role too in the R&D investments dynamics, see for example Brown et al. (2012) and Li (2011). This might matter for both the macroeconomic 'origin' of the long-run innovation risk itself as well as for the determination of assets' sensitivities to this risk. To explore the dynamic relation between R&D intensity, mark-up and funding conditions, I estimate a VAR with endogenous variables being $\hat{s}$, the first principal component of the 5 measures of mark-up from Nekarda and Ramey (2020), which predicts 89% of the series' variance, and the intermediary capital ratio from He et al. (2017). Both the mark-up and the intermediaries funding conditions series result being non-stationary, with the ADF test unit-root statistics of -2.63 and -2.38 respectively; for this reasons I employ their first differences. The number of lags fixed for the VAR is 3, chosen by minimizing the AIC over a sample that allowed for a fair comparison up to 10 quarters. In Table 4 I report the results of the $\hat{s}$ regression.

The inverse root value indicates that the VAR is not too far from an explosive behaviour, but it is still stationary. What is most impressive from these results is that while mark-up does not show any predictive power with respect to R&D excess intensity, intermediaries'

Table 4: estimates of the $\hat{s}$ regression from the VAR. In parenthesis, estimates' standard errors; 'max |roots|' is the maximum eigenvalue of the companion matrix estimated. Sample from 1970 Q2 to 2017 Q4.

	$\hat{s}$	ΔMark-Up	ΔI.C.R.
Lag: 1	1.520^{***}	-0.058	0.146
	(0.072)	(0.131)	(0.259)
Lag: 2	-0.756^{***}	0.008	0.341
	(0.121)	(0.137)	(0.258)
Lag: 3	0.213^{***}	-0.183	0.654^{**}
	(0.071)	(0.131)	(0.258)
T	R^2	$p(F)$	max |roots|
188	0.978	0	0.976

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

capital ratio does, with a highly significant coefficient when lagged thrice. While this is not conclusive, it is suggestive of a role for aggregate funding conditions on R&D and the long-run risk, which calls for deeper research.

5 Cross-sectional risk premium

The key asset pricing implication of swings in R&D intensity generating persistent fluctuations in expected growth rates of the economy, is that asset returns covarying more with R&D intensity should be regarded as riskier and be held for a higher compensation, i.e. a higher expected excess return. Following Bansal, Dittmar, and Lundblad (2005), this hypothesis is tested in the cross-section of US stocks, by forming portfolios based on stocks sorts that give rise to a documented spread in average excess returns and testing whether the differences in sensitivities of these portfolios' cash flows to aggregate R&D intensity are related to the differences in excess returns in a manner consistent with theory.

5.1 A traditional test of Long-Run Risk Premia

Answering to the classical failure of short-term fluctuations in consumption to justify the stock market risk premium, the main take-away of the long-run risk models is that the heavy lifter in explaining stocks risk premium is, by orders of magnitude, the risk of exposure to the LRR factor, i.e. β_x^i. So, as Bansal, Dittmar, and Lundblad (2005), I will proceed focusing on the cross-sectional pricing equation

$$\mathbb{E}_t\left[R_{t+1}^i\right] - R_t^f = \lambda_x \beta_x^i \tag{20}$$

instead. Next, consider the decomposition shown in Campbell (1996), where returns innovations can be approximated as the sum of news to cash-flow growth rates and to discount rates:

$$\ln R_{t+1}^{i} - \mathbb{E}_t\left[\ln R_{t+1}^{i}\right] = \delta_{D,t+1}^{i} - \delta_{R,t+1}^{i} \qquad \text{where}$$

$$\delta_{D,t+1}^{i} = \{\mathbb{E}_{t+1} - \mathbb{E}_t\}\left[\sum_{j=0}^{\infty} \kappa^j \Delta \ln D_{i,t+j}\right] \quad \text{and} \quad \delta_{R,t+1}^{i} = \{\mathbb{E}_{t+1} - \mathbb{E}_t\}\left[\sum_{j=1}^{\infty} \kappa^j \ln R_{t+j}^{i}\right]. \tag{21}$$

Then, as

$$\beta_r^i = \frac{\text{Cov}\left[R_t^i, \tilde{s}_t\right]}{\text{Var}\left[\tilde{s}_t\right]} \approx \frac{\text{Cov}\left[\delta_{D,t}^i, \tilde{s}_t\right]}{\text{Var}\left[\tilde{s}_t\right]} - \frac{\text{Cov}\left[\delta_{R,t}^i, \tilde{s}_t\right]}{\text{Var}\left[\tilde{s}_t\right]} = \beta_{s,D}^i - \beta_{s,R}^i, \tag{22}$$

the cross-sectional pricing equation can be expressed as

$$\mathbb{E}_t\left[R_{t+1}^i\right] - R_t^f = \lambda_s \beta_{s,D}^i - \lambda_s \beta_{s,R}^i. \tag{23}$$

In the theoretical models that are under scrutiny here, assets' exposure to LRRs is grounded in fundamentals' sensitivities to LRRs, therefore, following Bansal, Dittmar, and Lundblad (2005), I focus on the cash-flows' exposure $\beta_{r,D}$ to aggregate R&D intensity, as key dimension of risk to explain excess returns, rather than conditional discount rates. The key pricing relation that I will test is then

$$\mathbb{E}_t\left[R_{t+1}^i\right] - R_t^f = \lambda_s \beta_{s,D}^i. \tag{24}$$

Test assets Following Bansal, Dittmar, and Lundblad (2005), the set of test assets considered here are all stocks portfolios, 10 based on size sorting, 10 on Book/Market equity sorting, 10 on past-year return sorting and 5 on firm-specific R&D intensity. The R&D-sorted portfolios are less than the other sortings to keep a level of diversification inside the portfolio that is homogeneous with the others, considering the severe under-reporting of R&D expenditures which Koh and Reeb (2015) reports being 42% between 1980 and 2006.

A potential driver of heterogeneity in sensitivities to the long-run innovation risk is represented by the firm-specific R&D intensity: evidence from Jiang et al. (2016) shows that R&D spillovers do get priced in financial markets, so it is sensible to hypothesize that fluctuations in the aggregate R&D investment leads to different return dynamics depending on the externality a firm can enjoy. This will be explored in the empirical analysis by looking at the sensitivity distribution over firm-specific-R&D-sorted stocks portfolios, but, as more mechanisms could play a role, there is ground for further investigation.

Cash-flows growth rates of each portfolio is computed as in Bansal, Dittmar, and Lundblad (2005). A measure h_t of capital gain is built for each stock and then summed up with those of the other stocks proportionally to the respective portfolio weight, obtaining a portfolio capital gain series $h_{p,t}$. From this series the current value of a dollar invested at the beginning of the series is computed as $V_{p,t+1} = h_{p,t+1} V_t$, where V_t is naturally initialized setting $V_{p,0} = 1$.

The measure of cash-flows obtained with such strategy is then $D_{p,t+1} = y_{p,t+1}V_{p,t}$ where $y_{p,t+1}$ is the portfolio dividend-yield, obtained exploiting $R_{p,t} = h_{p,t} + y_{p,t}$. h_t is computed adjusting CRSP ex-dividend returns RETX for share repurchases as follows:

$$h_t = \left(\frac{P_{t+1}}{P_t}\right) \cdot \min\left[\left(\frac{n_{t+1}}{n_t}\right), 1\right]. \tag{25}$$

Essentially, capital gains are less than proportional to price appreciation when there is a reduction in (equivalent) shares outstanding, which is likely related to share repurchases, a form of payout not accounted for in dividends records. Then, quarterly dividends series are obtained by simply summing monthly values up and deflating them by the implicit price deflator of nondurable and services consumption shown in Hansen et al. (2005). As the quarterly series still show strong seasonalities, quarterly values are de-seasoned by applying a 4-quarter rolling mean. The series of cash-flows growth rates are then obtained taking the first difference of the log-series of de-seasoned real quarterly dividends.

Monthly stock data is from CRSP, starting at the beginning of 1926 and stopping and the end of 2021. Yearly accounting data is from Compustat Fundamentals dataset, starting in 1950 and ending in 2021. All the monthly returns are compounded to obtain a quarterly figure and then deflated with the same deflator used for dividends. The construction of the portfolios closely follows Bansal, Dittmar, and Lundblad (2005) for comparison purposes; detailed procedure descriptions follow while the main statistics of the formed portfolios' returns and cash-flow growth rates are in table 5.

Size-sorted portfolios All firms covered by CRSP are assigned to deciles based on their market capitalization at the end of June of each year relative to NYSE breakpoints. Weights are assigned based on the market capitalization relative to the total capitalization of the portfolio and are re-assigned at the end of every June. Both returns and cash-flows growth display a remarkable reduction for greater-size portfolios, which is in line the usual Small-minus-Big returns spread and cash-flows patterns observed in Bansal, Dittmar, and Lundblad (2005).

B/M-sorted portfolios All firms covered by both CRSP and Compustat are assigned to deciles based on their book to market ratio and NYSE breakpoints. Portfolios are value-weighted and formed at the end of every June, where for year t the book-to-market ratio is based on book equity of fiscal year $t-1$ and market capitalization at the end of calendar year $t-1$. Both portfolio returns and cash-flows growth rates show an increasing pattern with the B/M ratio, in line with previous evidence on the value premium and Bansal, Dittmar, and Lundblad (2005)

Momentum portfolios This set of portfolios employs stocks traded on NYSE or AMEX markets only. The assignment of a stock to a decile portfolio is determined at each end-of-quarter month t and is based the rank of the respective stock compound return from the beginning of month $t-12$ to the end of month $t-1$. These portfolios too are

Table 5: Test asset portfolios returns and cash-flows growth: quarterly summary statistics. All series are from 1947 Q2 to 2022 Q1, a part from the R&D portfolios, which start from 1975 Q1.

Portfolio	Returns Mean	Returns SD	CF growth Mean	CF growth SD
size.01	0.06569	0.18418	0.02767	0.17561
size.02	0.03768	0.15135	0.01470	0.15258
size.03	0.03366	0.14015	0.01166	0.15642
size.04	0.03014	0.13445	0.00962	0.16473
size.05	0.02812	0.13136	0.00491	0.14426
size.06	0.02720	0.11971	0.01022	0.14199
size.07	0.02575	0.11947	0.01026	0.12372
size.08	0.02432	0.11418	0.00699	0.14256
size.09	0.02213	0.10717	0.00659	0.15094
size.10	0.01758	0.09801	0.00241	0.09691
bm.01	0.02476	0.10114	0.02050	0.28804
bm.02	0.02337	0.09135	0.01872	0.25541
bm.03	0.02499	0.08891	0.01845	0.23877
bm.04	0.02297	0.08454	0.01540	0.26606
bm.05	0.02271	0.10876	0.00682	0.14774
bm.06	0.02234	0.10538	0.00496	0.13942
bm.07	0.02118	0.10769	0.00411	0.14106
bm.08	0.02991	0.09674	0.01757	0.22745
bm.09	0.02741	0.11662	0.00933	0.20893
bm.10	0.03312	0.12231	0.01144	0.19516
mom.01	0.01498	0.21583	-0.01330	0.22345
mom.02	0.01176	0.12973	-0.00812	0.16180
mom.03	0.01468	0.11705	-0.00452	0.15323
mom.04	0.01739	0.10650	-0.00042	0.20205
mom.05	0.01824	0.09819	0.00122	0.15589
mom.06	0.01622	0.09966	0.00043	0.15794
mom.07	0.01882	0.09758	0.00126	0.16452
mom.08	0.02378	0.09693	0.00536	0.17665
mom.09	0.02605	0.10352	0.00245	0.26211
mom.10	0.03639	0.12087	-0.00819	0.29443
rd.01	0.02895	0.10367	0.00954	0.15829
rd.02	0.02464	0.08621	0.00528	0.12731
rd.03	0.02935	0.09370	0.01006	0.17154
rd.04	0.03991	0.11387	0.01552	0.16616
rd.05	0.06591	0.19221	0.03406	0.20777

value-weighted. In line with previous evidence both returns and cash-flows increase with momentum, with the exception of the cash-flows growth of the most positive momentum portfolio.

R&D-sorted portfolios Firm-specific R&D intensity has been known to be associated to dispersion in excess returns since Chan et al. (2001). I specifically include these portfolios to provide further evidence that can be relevant in the study of the effects of R&D efforts aggregation. If spillover effects are stronger than fishing-out effects, then one would expect more R&D intensive firms to gain more when the whole economy invests more in R&D and the innovation LRR is higher, which leads to sensitivity

Table 6: Test assets cash-flows sensitivity to long-run risk components. From 1975 Q1 to 2022 Q1.

Portfolio	β_C	β_Z	$\beta_{\hat{s}}$	$\beta_{\tilde{s}}$
size.01	1.865	6.873	12.360	9.570
size.02	0.773	7.586	8.042	8.557
size.03	-0.072	1.919	1.013	-7.730
size.04	0.655	3.010	2.808	-3.880
size.05	1.231	2.638	2.087	7.114
size.06	1.104	0.541	0.025	0.411
size.07	1.087	3.675	2.443	-9.770
size.08	1.443	-0.924	1.416	-6.097
size.09	1.011	1.257	-3.608	-16.928
size.10	0.190	-0.688	-0.348	-7.804
bm.01	0.631	7.751	-3.374	-8.638
bm.02	0.902	6.230	-0.130	-4.021
bm.03	1.677	7.184	0.152	-2.351
bm.04	1.105	7.258	-2.307	-3.631
bm.05	0.954	2.592	2.052	-1.085
bm.06	0.144	0.354	-1.179	-4.207
bm.07	-0.166	2.900	-0.417	-12.966
bm.08	0.226	6.503	-2.226	-1.546
bm.09	0.129	0.334	0.536	-11.556
bm.10	0.437	-0.834	1.842	-0.085
mom.01	-0.770	-4.243	-0.953	2.946
mom.02	1.496	-2.634	-0.821	-8.086
mom.03	1.305	-2.806	-3.117	-0.962
mom.04	-0.418	-2.404	0.893	-8.338
mom.05	1.971	-2.639	-2.557	-6.691
mom.06	0.488	-3.783	1.353	-6.335
mom.07	-0.125	0.069	3.677	-8.790
mom.08	-0.204	-4.465	1.471	2.005
mom.09	2.283	-3.785	1.352	2.935
mom.10	1.099	-2.887	-2.676	-20.877
rd.01	0.366	-0.605	-1.988	2.864
rd.02	-1.151	3.810	-1.506	-8.603
rd.03	-1.452	2.862	-2.036	-16.581
rd.04	-0.307	7.867	-0.220	-6.877
rd.05	-0.779	4.454	7.927	11.295

heterogeneity along the R&D dimension. To enter these portfolios a stock has to be: of ordinary or common type; traded on either NYSE, AMEX, or NASDAQ; not being of a firm working in the utility or financial sectors; have at least one record of R&D expenditure. Similarly to book-market-ratio sorting, at the end of each June each firm is ranked depending on its own R&D intensity, measured by the ratio of R&D expenditure in the previous fiscal year over market capitalization at the end of the previous calendar year. Then, stocks are value weighted. The data highlights higher returns and higher cash-flows growth for higher firm-specific R&D intensity.

Time-series sensitivities As in Bansal, Dittmar, and Lundblad (2005), $\theta_{p,x}$, the sensitivity of portfolio p to a risk factor – the long-run risk component in variable x, is estimated with the following regression:

$$\Delta \ln D_{p,t} = \theta_{p,x} \left(\frac{1}{L} \sum_{l=1}^{L} x_{t-l} \right) + v_{p,t}. \tag{26}$$

Both dependent and independent variables are demeaned before estimation. Estimating the coefficient over the rolling mean of the process x_t has the purpose of filtering persistent components of the regressor that should have a long-lasting impact on cash-flows growth. Indeed, the coefficient is asymptotically equivalent to the one estimated in the regression

$$\frac{1}{L} \sum_{l=1}^{L} \Delta \ln D_{p,t+l} = \theta_{p,x} x_t + v'_{p,t}. \tag{27}$$

with an inferential advantage in small samples, as illustrated by Hodrick (1992). The long-run risk components studied here are those contained in consumption growth, productivity growth and R&D intensity, i.e. $x \in \{\Delta \ln C,\ \Delta \ln Z,\ \hat{s},\ \tilde{s}\}$, where I also include $\tilde{s}$, the series based on ideas proxied by patents, for robustness. K is fixed to 12, i.e. 3 years, in the main analysis, but results are not significantly different for reasonable changes. Results over the period where all the portfolios are available, i.e. from 1975 to 2022, are shown in table 6.

It can be noted that sensitivities to persistent movements in consumption show a pattern for size and BM portfolios, but not quite as much for momentum and R&D portfolios. Long-run *productivity* risk component produce much starker patterns across all sortings and the long-run *innovation* risk component too. Even more interestingly, the sensitivities to R&D intensity increases with firm-specific R&D intensity, meaning that cash-flows of firms investing more in R&D grow more when the whole economy is investing relatively more too. This could support the thesis empirically studied by Jiang et al. (2016) that firms gain from higher R&D investment of peers, here on a economy-wide scale, but changes in payout policies would have to be controlled for in a more formal setting to validate such claim.

Cross-sectional risk premium Following Fama and Macbeth (1973), risk premia are estimated with a second-step where each period the returns are regressed on a constant and the risk measure – the cash-flows sensitivities. Estimates are shown in table 7.

The most surprising result is that the premium associated to long-run consumption risk is far from significant. This could be related to known measurement error in consumption series,[16] as well as the predominance of other factors in pricing R&D portfolios. Indeed, in estimations over different time periods not shown here, exploiting the series from the beginning of its availability in 1947 and ignoring R&D portfolios, it becomes stronger. The other results, on the other hand, strongly support the existence of a premium for long-run productivity risk, both directly and through the innovation channel, i.e. related to sensitivities of cash-flows to R&D excess intensity. In both cases the premium is significantly different from 0 and the cross-sectional R^2 is remarkable for a single non-traded factor. This is further

[16] See, for example, Savov (2011).

Table 7: cross-sectional risk premia estimated following Fama and Macbeth (1973). t-statistics are HAC, computed as advised by Lazarus et al. (2018), and corrected for error-in-variable following Shanken (1992). From 1947 Q2 to 2022 Q1.

	C	Z	$\hat{s}$	$\tilde{s}$
λ_0 (%)	1.920***	1.621***	1.730***	2.329***
t-stat	(3.899)	(3.225)	(3.625)	(4.450)
λ_x (%)	0.015	0.196***	0.315***	0.096***
t-stat	(0.083)	(3.100)	(3.619)	(3.619)
R^2 (%)	0.01	29.12	55.71	24.93

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

supported by the premium associated to sensitivity to the R&D intensity measure based on patents being significant too. These results suggest that persistent innovation originated in R&D is indeed priced, as expected by the long-run risk framework.

5.2 An omitted-factors robust test

6 Conclusion

Persistent fluctuations in consumption are theorized to heavily impact investors welfare and how they price financial assets. These swings have also been shown to be originated in persistent swings in productivity, which has, itself, proven to be strictly related to R&D investments in the economy. This paper defines a relevant and empirically-feasible measure of R&D investment intensity and its estimates adhere to theoretical predictions. Specifically, deviations of R&D investment from an equilibrium proportion of TFP level, labelled 'long-run *innovation* risk component', prove being persistent, predict productivity growth rates and are associated to a significant risk premium in the cross section for assets whose cash-flows are more sensitive to them. This provides further support to the existence of a long-run risk component and the relevance of the long-run risk framework.

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A A simple complete economy

An full economy providing a full example for the conditions discussed in the main body, can be one where the production of goods can be represented by a function of the labor at time t, L_t, by a neo-classical production function, such as, without loss of generality,

$$Y_t = Z_t L_t \ , \tag{28}$$

where L_t is the labor employed in production and Z_t is the level of Total Factor Productivity (TFP). Then, following the 'lab-equipment' literature, further assume that such goods can be employed in consumption C_t and R&D expenditures S_t, i.e.

$$Y_t = C_t + S_t \ . \tag{29}$$

The model could be closed with laws of motion for L_t and S_t, and it would be able to describe an economy that endogenously grows on a Balanced Growth Path.

B R&D-TFP cointegration

B.1 In Kung and Schmid (2015)

Using their notation, the starting conditions are:

$$Z_t = \bar{A}(e^{a_t} N_t)^{1-\alpha} \tag{30}$$

$$\frac{N_{t+1}}{N_t} = 1 - \phi + \chi \left(\frac{S_t}{N_t} \right)^{\eta} . \tag{31}$$

Then, the intangible capital growth rate is

$$\Delta \ln N_{t+1} \approx \chi \left(\frac{S_t}{N_t} \right)^{\eta} - \phi \tag{32}$$

$$\approx \chi e^{\eta \bar{r}} \left\{ 1 + \eta \left(\ln S_t - \ln N_t \right) - \eta \bar{r} \right\} - \phi \tag{33}$$

$$= a_N + b_N \left(\ln S_t - \ln N_t \right) , \tag{34}$$

and the TFP growth rate, in terms of intangible capital is[17]

$$
\begin{aligned}
\frac{Z_{t+1}}{Z_t} &= e^{(1-\alpha)(a_{t+1}-a_t)} \left(\frac{N_{t+1}}{N_t}\right)^{(1-\alpha)} && (35)\\
\Delta \ln Z_{t+1} &= (1-\alpha)((\rho-1)a_t + \varepsilon_{t+1}) + (1-\alpha)\ln\left[1-\phi+\chi\left(\frac{S_t}{N_t}\right)^{\eta}\right] && (36)\\
&\approx (1-\alpha)((\rho-1)a_t + \varepsilon_{t+1}) + (1-\alpha)\left[\chi\left(\frac{S_t}{N_t}\right)^{\eta} - \phi\right] && (37)\\
&= (1-\alpha)((\rho-1)a_t + \varepsilon_{t+1}) + (1-\alpha)\left[\chi e^{\eta(\ln S_t - \ln N_t)-\eta\bar{r}} e^{\eta\bar{r}} - \phi\right] && (38)\\
&\approx (1-\alpha)((\rho-1)a_t + \varepsilon_{t+1}) + (1-\alpha)\left[\chi\left(1+\eta\left(\ln S_t - \ln N_t\right)-\eta\bar{r}\right) e^{\eta\bar{r}} - \phi\right] && (39)\\
&= (1-\alpha)((\rho-1)a_t + \varepsilon_{t+1}) + (1-\alpha)\left[\chi e^{\eta\bar{r}}(1-\eta\bar{r}) - \phi + \chi\eta e^{\eta\bar{r}}\left(\ln S_t - \ln N_t\right)\right]. && (40)
\end{aligned}
$$

Expressing this in terms of TFP level, from Equation 36,

$$
\begin{aligned}
\Delta \ln Z_{t+1} &= (1-\alpha)((\rho-1)a_t + \varepsilon_{t+1}) + (1-\alpha)\ln\left[1-\phi+\chi\left(\frac{S_t}{Z_t^{\frac{1}{1-\alpha}}\bar{A}^{\frac{1}{\alpha-1}}e^{-a_t}}\right)^{\eta}\right] && (41)\\
&= (1-\alpha)((\rho-1)a_t + \varepsilon_{t+1}) + (1-\alpha)\ln\left[1-\phi+\chi\left(\frac{S_t}{Z_t^{\frac{1}{1-\alpha}}}\bar{A}^{\frac{1}{1-\alpha}}e^{a_t}\right)^{\eta}\right] && (42)\\
&\approx (1-\alpha)((\rho-1)a_t + \varepsilon_{t+1}) + (1-\alpha)\left[\chi\left(\frac{S_t}{Z_t^{\frac{1}{1-\alpha}}}\bar{A}^{\frac{1}{1-\alpha}}e^{a_t}\right)^{\eta} - \phi\right] && (43)\\
&= (1-\alpha)((\rho-1)a_t + \varepsilon_{t+1}) + && (44)\\
&\quad + (1-\alpha)\left[\chi\cdot\exp\left(\eta(\ln S_t - \frac{1}{1-\alpha}\ln Z_t + \frac{\ln\bar{A}}{1-\alpha} + a_t) - \eta\bar{r}\right)e^{\eta\bar{r}} - \phi\right]\\
&\approx (1-\alpha)((\rho-1)a_t + \varepsilon_{t+1}) + && (45)\\
&\quad + (1-\alpha)\left[\chi\left(1+\eta(\ln S_t - \frac{1}{1-\alpha}\ln Z_t + \frac{\ln\bar{A}}{1-\alpha} + a_t) - \eta\bar{r}\right)e^{\eta\bar{r}} - \phi\right]\\
&= a_Z + b_Z a_t + c_Z\varepsilon_{t+1} + d_Z\left(\ln S_t - \frac{1}{1-\alpha}\ln Z_t\right). && (46)
\end{aligned}
$$

B.2 In my model

The conditions needed for derivation of (**??**):

$$
\begin{aligned}
Z_T &\equiv e^{a_t} I_t^{\xi} && (47)\\
I_{t+1} &= (1-\phi)I_t + S_t^{\eta} {I_t}^{\Psi}. && (48)
\end{aligned}
$$

[17]In this simple formulation the presence of a deterministic trend would surely deteriorate the accuracy of the last approximation but would not necessarily invalidate it, depending on its magnitude. Anyway, as shown in the following analysis, the presence of a time trend is statistically rejected.

Consider the following basic manipulations,

$$\frac{I_{t+1}}{I_t} = 1 - \phi + \left(\frac{S_t}{I_t{}^{\psi}}\right)^{\eta} \tag{49}$$

$$\Delta \ln I_{t+1} \approx \left(\frac{S_t}{I_t{}^{\psi}}\right)^{\eta} - \phi \tag{50}$$

$$\ln Z_{t+1} = a_t + \xi \ln I_t \tag{51}$$

$$\begin{aligned}
\Delta \ln Z_{t+1} &= (\rho^a - 1)a_t + \varepsilon^a_{t+1} + \xi \Delta \ln I_{t+1} &(52)\\
&\approx (\rho^a - 1)a_t + \varepsilon^a_{t+1} + \xi \left[\left(\frac{S_t}{I_t{}^{\psi}}\right)^{\eta} - \phi\right] &(53)\\
&= (\rho^a - 1)a_t + \varepsilon^a_{t+1} + \xi \left[\exp\left\{\eta(\ln S_t - \psi \ln I_t)\right\} - \phi\right] &(54)\\
&\approx (\rho^a - 1)a_t + \varepsilon^a_{t+1} + \xi \left[1 + \eta(\ln S_t - \psi \ln I_t) - \phi\right] &(55)\\
&= (\rho^a - 1)a_t + \varepsilon^a_{t+1} + \xi \left[1 - \phi\right] + \xi\eta(\ln S_t - \psi \ln I_t). &(56)
\end{aligned}$$

Then, assuming $\rho^a \approx 1$,

$$\Delta \ln Z_{t+1} = \gamma_0 + \gamma_1(\ln S_t - \psi \ln I_t) + \varepsilon^a_{t+1}. \tag{57}$$

C Half-lives

The half-life of the AR(1) process of interest is between 8 and 16 years,

$$\rho_Y^{N_Y} = 0.5 \quad \Rightarrow \quad \frac{\ln(0.5)}{\ln \rho_Y} = N_Y \in [8, 16]. \tag{58}$$

The coefficient ρ_Y such that this is true can range between

$$0.5^{1/8} = 0.9170 < \rho_Y < 0.9576 = 0.5^{1/16}. \tag{59}$$

Quarterly,

$$\rho_Q^{N_Q} = 0.5 \quad \Rightarrow \quad \frac{\ln(0.5)}{\ln \rho_Q} = N_Q \in [32, 64]. \tag{60}$$

So, the AR(1) coefficient can take values

$$0.5^{1/32} = 0.9786 < \rho_Q < 0.9892 = 0.5^{1/64}. \tag{61}$$

D AdaDOLS

1. Start by setting standard maximum number of lags and leads (see Choi and Kurozumi (2012)):

$$Lg = Ld = 12 \times (T/100)^{1/4}$$

2. Perform 10-fold cross-validation to select optimal regularization parameter λ in

$$\min_{\begin{pmatrix}\boldsymbol{\alpha}\\ \boldsymbol{\alpha}_f\\ \boldsymbol{\delta}\end{pmatrix}} \sum_{t=1}^{T} \left\{ \ln Z_t - \begin{bmatrix}\boldsymbol{\alpha}\\ \boldsymbol{\alpha}_f\end{bmatrix}' \begin{bmatrix}1\\ \ln S_t\\ \ln L_t\\ \mathbf{f}_t\end{bmatrix} + \boldsymbol{\delta}' \begin{bmatrix}\Delta S_{t-Lg}\\ \dots\\ \Delta S_{t+Ld}\\ \Delta L_{t-Lg}\\ \dots\\ \Delta L_{t+Ld}\\ \Delta(\mathbf{f}^{(1)})_{t-Lg}\\ \dots\\ \Delta(\mathbf{f}^{(1)})_{t+Ld}\end{bmatrix} \right\}^2 + \lambda \left(\sum_i w_i \cdot |\delta_i| + \sum_j w_j \cdot |(\alpha_f)_i| \right)$$

3. Set $w_i = |\delta_i|^{-0.9}$ and $w_j = |(\alpha_f)_j|^{-0.9}$ (initial values set by a preliminary OLS or Ridge Regression)

4. Repeat steps 2 and 3 until convergence

5. Replicate steps 2, 3 and 4, 999 times; select median model (i.e. the one associated to the median value of λ)

6. Repeat steps 2, 3, 4 and 5 by increasing/decreasing lags/leads by 4 (a year) if boundaries are hit/slack

E Additional tables and graphs

Correlations among the R&D intensity measures are in Table 8.

Table 8: correlation among specifications of the ECTs. Naming format: Z-variable, S-variable, Q-variable, factors set.

	nord_util.tot.bs	raw.tot.bs	nord_util.nonfarm.bs	nord_util.tot.ln
raw.tot.bs	0.829	-	-	-
nord_util.nonfarm.bs	0.993	0.798	-	-
nord_util.tot.ln	0.990	0.876	0.99	-