The Long-Run Innovation Risk Component

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Abstract

This paper provides empirical evidence that fluctuations in aggregate Research and Development (R&D) represent a significant source of risk for investors. This has been predicted by the 'long-run risk' theoretical literature, to which this work provides empirical support. The analysis pivots around a definition of R&D intensity that is grounded on few and flexible economic conditions from the endogenous growth literature, where deviations from the equilibrium level of R&D are tracked by the Error Correction Term of the cointegration between R&D, Total Factor Productivity and Labor Force. For USA, this process proves to be stationary, which allows to reliably demonstrate its high forecasting power of productivity and consumption growth as well. As it also results being highly persistent, excess R&D intensity is argued to identify the innovation long-run risk component, which is hypothesized to drive the persistent component shared by productivity and consumption growth. A key prediction would be that R&D intensity serves as a significant risk factor in the cross-section of assets, which is empirically verified, with it being associated with a significant positive risk premium in the cross-section of stocks. The empirical identification strategy of a long-run risk component in this work also constitutes a novelty, as it does not leverage new data nor improvements in statistical methodologies, but relies on economic conditions only.

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

JEL Codes: E32, E44, G12, O30

1 Introduction

Slow-moving fluctuations in macroeconomic variables can heavily impact economic agents' welfare and, consequently, the dynamics of asset prices. This is the key idea behind the 'Long-Run Risk' (LRR) framework, where consumption growth is assumed to contain a persistent process, which results being a source of risk associated to a remarkable premium in financial markets. Such a process takes the name of LRR component and grants models great power to fit the data, when coupled with preferences that exhibit aversion to uncertainty in consumption expectations, such as those in Epstein and Zin (1989). The key is that the more persistent a LRR component is, the less volatile it needs to be, to have the same

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impact on the volatility of prospects of consumption far into the future. Therefore, it is able to explain significant risk premia on a macroeconomic basis, while imperceptibly affect consumption growth dynamics. Bansal and Yaron (2004) pioneered this framework to reconcile macroeconomic theory with financial data, since under the lenses of conventional models it is well known that consumption growth is not volatile enough to explain the average difference in returns between the equity market and risk-free assets.[1] That application has been followed by the development of a substantial literature building on the LRR concept, as it has proved helpful in explaining several other macro-financial phenomena.[2] However, the latent nature of LRR is a double-edged sword when it comes to model validation because empirically identifying 'small' persistent components is challenging, which has also lead to significant criticism towards the entire framework.[3] Given the extensive literature that has developed on the LRR framework, it is essential to discuss evidence supporting it: in this paper I contribute by documenting empirically a LRR component related to innovation efforts, in the form of Research and Development (R&D) expenditure. More specifically, I form a time series to measure aggregate R&D investment intensity and I show that it fulfils all of the key theoretical assumptions and predictions of the LRR framework. Therefore, I argue that this process identifies a LRR component of the economy.

Since its inception, the relevance of the LRR framework has been advocated in different ways. On the theoretical side, the pivotal conditions have been recovered as reduced-forms of richer structural models, which provided additional conditions to test on the data.[4] On the empirical side, instead, the emphasis has been on identifying the LRR component or estimating the structural parameters, either by refining the applied statistical methodologies, as in Ortu et al. (2013), Dew-Becker and Giglio (2016), Schorfheide et al. (2018), and Gourieroux and Jasiak (2024); or by exploiting new data altogether, as in Liu and Matthies (2022). This work contributes empirically, but in a different way: the identification of the LRR component is essentially achieved by leveraging economic conditions only. These economic conditions are well established in the economic growth literature, but they have not been exploited to study the dynamic and financial aspects considered in this work. Indeed, when framed in the context of the LRR framework, these conditions highlight a close mapping between the model and reality, specifically highlighting the possibility of estimating a LRR component directly. It is only after having formed what is hypothesized to be a LRR component that is verified whether the process possesses the expected characteristics and whether it fulfills theoretical predictions.

The idea that innovation efforts can introduce a LRR in the economy has been theoretically studied in Kung and Schmid (2015), upon which this work builds. They show how persistence in R&D can endogenously arise and generate a persistent component in productivity growth, which from Croce (2014) is known to be transmitted to consumption growth, thus creating a

[1] Often referred to as the 'Equity Risk Premium Puzzle', first documented in Mehra and Prescott (1985).

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

[3] Such as Beeler and Campbell (2012), Constantinides and Ghosh (2011) and Epstein, Farhi, et al. (2014).

[4] A notable example of this approach is Kaltenbrunner and Lochstoer (2010).

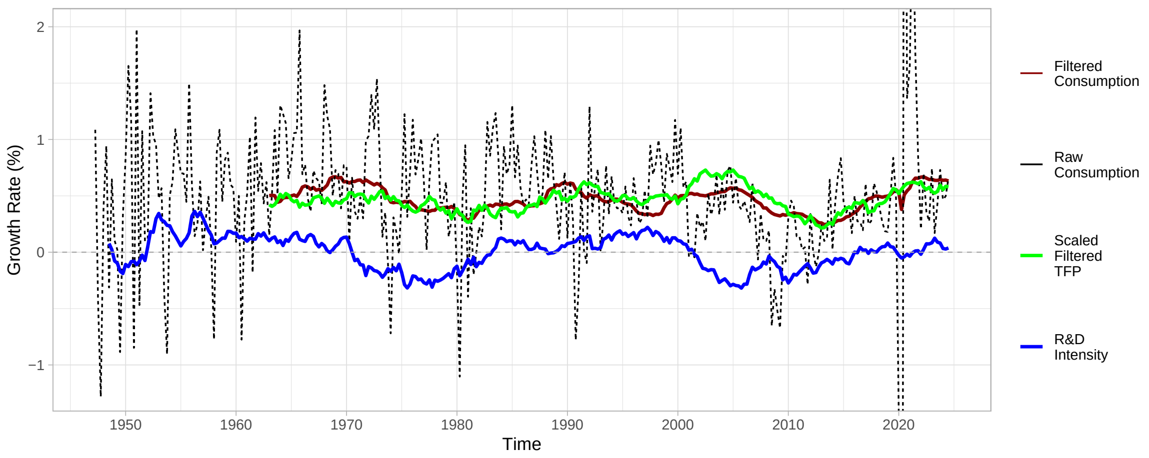

Figure 1: Consumption is US expenditures in services and non-durable from BEA; 'TFP' is the utilization-adjusted TFP from Fernald (2012). R&D intensity is in levels, not in growth rates. The filtered series are the 6$^{\text{th}}$ component of Ortu et al. (2013) decomposition. Correlation between Filtered Consumption and TFP is 0.62. Correlation between R&D (with an arbitrary lag of 1y) and the two filtered series is 0.60 and 0.53, respectively.

LRR. Their theoretical model implied that expectations in productivity growth is mainly driven by a very specific transformation of R&D expenditure level, which they refer to as 'R&D intensity'. However, empirically, this measure proves being highly non-stationary, which is not an issue conceptually, but is problematic for all conventional tests of the theoretical predictions. Therefore, I rely on their insight but use a smaller, more flexible theoretical structure. This consists of two conditions only: a definition of Total Factor Productivity (TFP) as a function of ideas' stock and a production function of new ideas as a function of R&D. These conditions are enough to outline a meaningful definition of R&D intensity and its relation with the key macroeconomic and financial quantities. Contrary to a complete model, this structure will not impose nor make predictions about the R&D intensity dynamics, whose description is left to the empirical analysis on purpose. The most important feature of the implied R&D intensity definition is that it considers different mechanisms proposed to address scale effects, nesting the specification of Kung and Schmid (2015) as a special case. Another significant difference between this work and Kung and Schmid (2015) and Croce (2014) is the inclusion of a direct test of the R&D intensity as a risk factor in the cross-section of stocks.

The estimated R&D intensity is shown in Figure 1, together with the processes that it is called to drive, i.e. the productivity LRR component, which the literature already argued to be shared by the productivity and consumption growth rates. The flexibility in the theoretical framework pays off by returning a stationary measure of R&D intensity, which can be reliably used without the risk of spurious statistical results. Nonetheless, it also results being highly persistent, which is key in amplifying the LRR mechanism. Further, R&D intensity is shown to strongly forecast both productivity growth and consumption growth, with 2-3 years lag, validating a necessary assumption of the framework. As such, the measure fully qualifies as an innovation LRR component, and it is tested whether it acts as a significant risk factor in the cross-section of assets, as the theory predicts. This is empirically confirmed in two ways: first, by using the traditional approach of Bansal, Dittmar, et al. (2005) to facilitate comparison with previous studies and provide insights on the risk profiles of the test assets; and second, by adopting the novel method of Giglio and Xiu (2021), which addresses omitted risk bias more carefully, to provide the most reliable estimates possible. An interesting finding from the first financial analysis is that cash flows of more R&D-intensive *firms* increase more when the entire economy is investing more in R&D.

Technically, the R&D intensity definition is casted in an 'lab-equipment' ideas' production function inspired by Jones (1999),[5] with 'productivity' of R&D in creating new ideas diluted by both a flexible past ideas' returns to scale and a potentially expanding products' variety. This implies that R&D intensity can be approximated by a linear function of log-R&D, log-TFP and log-Labor. Out of the many possible ones, I mainly rely on this definition of R&D intensity because it summarizes the impact of R&D investment on future TFP growth in one variable only, tracking its conditional expectations more succinctly than other reformulations. Moreover, it does not need to explicitly model the rest of the economy, returning arguably more generalizable results. It should be noted that the framework employed here can fit both a fully- and a semi-endogenous economy, but it is not designed to advance any structural claim with respect to their distinction. Anyway, interpreting the model literally, the empirical observation of a stationary TFP growth process implies that the linear combination of the non-stationary variables constituting the R&D intensity is, in fact, stationary. This is a key result, as it implies that the deviations of R&D intensity from an unconditional value can be estimated via cointegration methods.

From a methodological point of view, cointegration models have already been employed to study the relation between R&D and technological progress in several macroeconomics studies such as Ha and Howitt (2007), Bottazzi and Peri (2007), Herzer (2022b) and Kruse-Andersen (2023). However, these papers are mostly concerned with the assessment of foreign spillovers and the distinction of fully- versus semi-endogenous economies, while this work focuses on the dynamic properties of R&D and its financial implications. Further, for technical reasons explained in the text, this work also differs from these studies in the methodology used to estimate the cointegrating relation, relying on a novel penalized version of the Dynamic OLS, as studied by Mendes (2018) and Neto (2023), which is devised to handle a conspicuous number of regressors and the related multicollinearity problem. Essentially as a consequence of this, forecasting exercises with respect to consumption and TFP growth are carried out with local projections. Anyway, this has been common practice in the empirical macro-finance literature, to which this work also contributes. Indeed, in this literature, cointegration in macroeconomic variables has been widely explored, with notable examples in Lettau and Ludvigson (2001) and Melone (2021). To my knowledge, however, this work is the first one showing a positive risk premium attached to an aggregate-R&D factor.

[5] The 'lab-equipment' 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).

The rest is structured as follows: in Section 2 I illustrate the theoretical framework, establishing the R&D intensity definition and outlining the key macroeconomic and financial predictions; in Section 3 I show the cointegration estimation results that define R&D intensity, and its properties; in Section 4 I validate the R&D intensity measure as an innovation LRR component by testing its forecasting power with respect to TFP and consumption growth rates; in Section 5 I carry out the cross-sectional pricing test; in Section 6 I conclude.

2 Theoretical framework

2.1 A flexible R&D intensity definition

Consider an economy in which the production of goods is described by a neoclassical production function. Without loss of generality, a discrete-time economy in which the aggregate productivity of rivalrous inputs at time t, 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, $\psi \in (0, 1-\xi\eta)$ 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 $\omega > 0$.

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,[6] 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:

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

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,

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

$\tilde{s}_t = s_t - \bar{s}$, 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,

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

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

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

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 $\{\mathbb{E}_{t+1} - \mathbb{E}_t\}\left(\sum_{j=0}^{\infty} \Delta \ln C_{t+1+j}\right)$ 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.[7] 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 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:[8]

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

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

[7] See, for example, Müller (2005).

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

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 $\varepsilon_{x,t+1}$:

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

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,[9] 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,[10] $\tilde{s}_t$ 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,

[9] 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 5.1.

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

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,[11] so

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

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,[12] 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 $\mathbf{f}_t$

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

[11] It is generally assumed an exponential function of the L_t^κ 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.

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

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.[13] 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 of Labor Statistics.[14] 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

[13]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.

[14]Id: LNS12000000.

(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 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;[15] 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 C.

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

[15]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.
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)

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

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

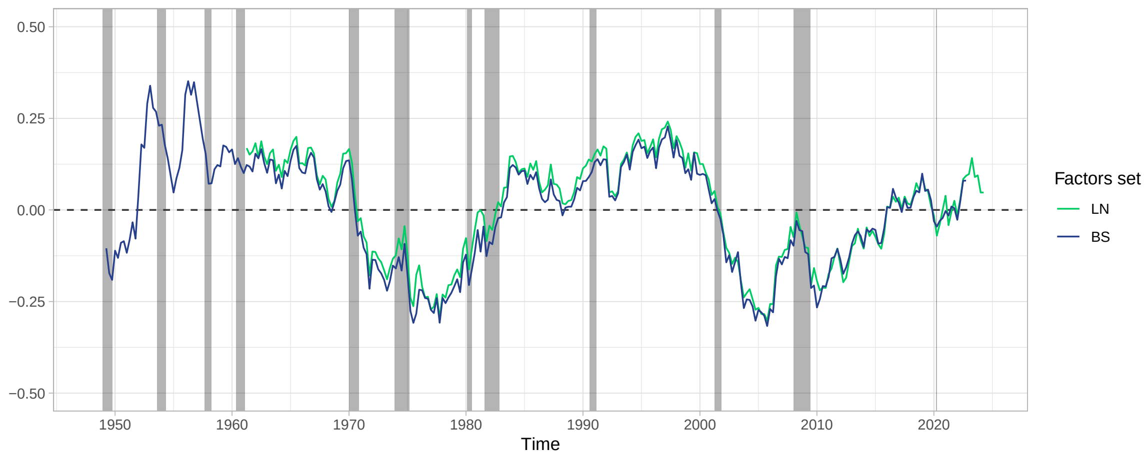

Figure 2: Shaded areas mark NBER recessions. Cross-correlation: 0.990.

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 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

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.	0.34	3.81	3.72
KPSS p.v.	0.02^{**}	$< 0.01^{***}$	$< 0.01^{***}$
AC(1)	0.993^{***}	1.000^{***}	1.000^{***}
	(0.009)	(0.000)	(0.000)
Num. obs.	57	299	299

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

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.[16]

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 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

[16]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 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

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

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

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

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.

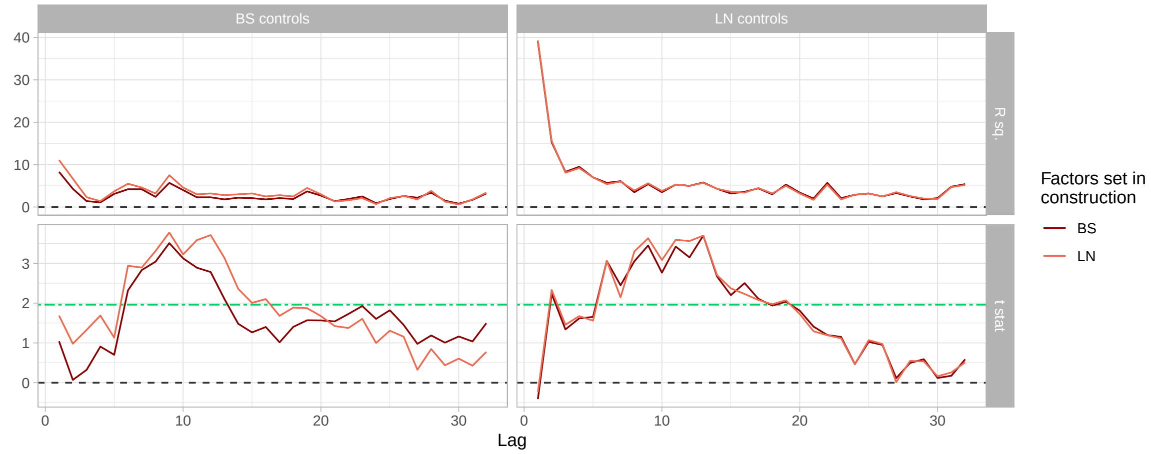

Figure 3: "BS" stands for controls used in Bansal and Shaliastovich (2013), starting in 1948 Q1; "LNG" in Ludvigson and Ng (2009), starting in 1960 Q2.

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:

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

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.

5 The cross-sectional Long-Run Risk Premia

The key implication of the Long-Run Risk framework is that assets whose values co-move more with shocks that persistently affect agents' welfare, should have higher risk premia. As R&D intensity is shown to affect long-run prospects of the economy and having a persistent behaviour, its process should also serve as a risk factor to which investors pay significant attention. In other words, assets whose returns are more sensitive to the innovation LRR component should be regarded as riskier and be held for a higher compensation, i.e. a higher expected excess return. This section shows the results of testing this prediction on the cross-section of US stocks, in two ways: first, by following Bansal, Dittmar, et al. (2005), and second, by following Giglio and Xiu (2021). The first methodology was introduced ad hoc for Long-Run Risks and is employed here to facilitate comparisons with previous results, as well as to provide descriptive yet insightful statistics that may be relevant to broader discussions on the economics of R&D. The second methodology follows a slightly less intuitive procedure but is essential for ensuring the robustness of the findings from the first method. This is necessary because the simplicity of the procedure in Bansal, Dittmar, et al. (2005) makes it more prone to biases from omitted risk factors, which is exactly the issue that is addressed in Giglio and Xiu (2021).

5.1 A traditional estimation approach

Methodology

Bansal, Dittmar, et al. (2005) essentially applies the standard procedure by Fama and Macbeth (1973) to estimate (12), with a few caveats. First, they acknowledged that the risk associated to short-term fluctuations in consumption empirically explain only a small portion of the equity risk premium, whereas the LRR premium is predicted to be greater by orders of magnitude. This was the primary motivation for shifting the focus to long-run risks and suggests that the simpler cross-sectional pricing condition

$$\mathbb{E}_t\left[R^i_{t+1}\right] - R^f_t = \lambda_x \beta^i_x \tag{20}$$

serves as a reasonable approximation. Second, they strive to adhere more closely to the theoretical formulation of the LRR and other consumption-based frameworks, where the betas of returns are endogenously determined by the sensitivity of assets' cash flows to the risk factor that mirrors long-run perspectives' shocks. This is operationalized by exploiting the Campbell (1996) decomposition, where return shocks are approximated as the sum of news about cash-flow growth rates and discount rates, i.e.

$$\ln R^i_{t+1} - \mathbb{E}_t\left[\ln R^i_{t+1}\right] = \delta^i_{D,t+1} - \delta^i_{R,t+1} \tag{21}$$

with $\delta^i_{D,t} = \{\mathbb{E}_t - \mathbb{E}_{t-1}\}\left[\sum_{j=0}^{\infty} \bar{\kappa}^j \Delta \ln D^i_{t+j}\right]$ and $\delta^i_{R,t} = \{\mathbb{E}_t - \mathbb{E}_{t-1}\}\left[\sum_{j=1}^{\infty} \bar{\kappa}^j \ln R^i_{t+j}\right]$, which in turn implies that the return beta can be decomposed into a dividend-beta $\beta^i_{x,D}$ and a discount-rates-beta $\beta^i_{x,R}$:

$$\beta^i_x = \frac{\text{Cov}\left[R^i_t, x_t\right]}{\text{Var}\left[x_t\right]} \approx \frac{\text{Cov}\left[\delta^i_{D,t}, x_t\right]}{\text{Var}\left[x_t\right]} - \frac{\text{Cov}\left[\delta^i_{R,t}, x_t\right]}{\text{Var}\left[x_t\right]} = \beta^i_{x,D} - \beta^i_{x,R} \ . \tag{22}$$

When only the dividend-beta is considered, the key pricing equation can be expressed as

$$\mathbb{E}_t\left[R^i_{t+1}\right] - R^f_t = \lambda_x \beta^i_{x,D} \ . \tag{23}$$

It is worth noting that the risk premium λ_x is not affected by any of these changes. $\beta^i_{x,D}$ is estimated with a time-series regression based on the dynamic relation originally assumed in Bansal and Yaron (2004)[17]

$$\Delta \ln D^i_{t+1} = \beta^i_{x,D} \cdot x_t + v^i_{t+1} \ , \tag{24}$$

with both dependent and independent variables being demeaned before estimation. The x_t process originally considered by Bansal, Dittmar, et al. (2005) was a 'generic' persistent component of consumption growth, empirically obtained as a moving average to filter out high-frequency fluctuations, i.e. $x_t = \left(\frac{1}{L}\sum_{l=0}^{L-1} \Delta \ln C_{t-l}\right)$.[18] In this work, it is tested the hypothesis that aggregate R&D intensity directly identifies a persistent component of consumption, the one specifically related to percistence in productivity growth. This implies considering $\tilde{s}_t$ in the role of x_t from previous equations. For the sake of comparability, I will consider $\tilde{s}_t$ taking the place of $\Delta \ln C_t$ in the moving average, but directly plugging it in (24) instead of x_t does not return significantly different results since $\tilde{s}_t$ is dominated by persistent fluctuations, as illustrated in the previous section. Finally, again for comparison purposes, the analysis performed with R&D intensity are also replicated with LRR components of consumption and productivity growth as identified by Bansal, Dittmar, et al. (2005).

Test assets

Test assets are manually formed by constructing portfolios based on stocks sorts that give rise to a documented spread in average excess returns. As in Bansal, Dittmar, et al. (2005), the set of test assets considered here are all stocks portfolios, 10 of which based on size sorting, 10 on Book/Market equity sorting, and 10 on past-year return sorting. Given the nature of the LRR considered here, it is useful to consider the evidence from Jiang et al. (2016), which shows that R&D spillovers do get priced in financial markets. Therefore, it is sensible to hypothesize that fluctuations in the aggregate R&D investment leads to different cash-flows dynamics depending on the externality a firm can enjoy. In other words, portfolios

[17] The dynamic structure of the system can be more complex, but the main purpose of this exercise is to provide intuitive results. A stricter analysis is anyway conducted in the latter part of this section.

[18] This also implies that regression (24) is asymptotically equivalent to $\frac{1}{L}\sum_{l=1}^{L} \Delta \ln D^i_{t+l} = \beta^i_{x,D} x_t + {v^i_{t+1}}'$, which makes the interpretation of $\beta_{x,D}$ as the 'long-lasting impact on cash-flows growth' even clearer. The formulation in the main text, however, has an inferential advantage in small samples, as illustrated by Hodrick (1992).

formed on *firm-specific* R&D intensity have the potential to show significant heterogeneity in sensitivities to the innovation LRR. Furthermore, firm-specific R&D intensity has been known to be associated to dispersion in excess returns since Chan et al. (2001). For these reasons, among the test assets are also included 5 portfolios on firm-specific R&D intensity. This, conversely, provides descriptive statistics, in the form of sensitivities to the innovation LRR component, that may be useful to further investigations of the mechanics behind the aggregation of firms' innovation efforts. These portfolios are fewer than for other sortings in order to keep a homogeneous level of portfolios' diversification, considering the severe under-reporting of R&D expenditures which Koh and Reeb (2015) reports being 42% between 1980 and 2006.

Cash-flows growth rates of each portfolio are computed as in Bansal, Dittmar, et al. (2005), and more details are provided in Appendix D.1. 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 are deflated with the same deflator used for dividends. Key statistics of the formed portfolios' returns and cash-flow growth rates are in table 4, following the details on the construction process.

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 decrease with size, which is in line the patterns observed in the literature.

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.

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 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 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. Firms' annual R&D

Table 4: 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

expenditure is recorded by Compustat from 1975. 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.

Betas estimation

Estimates of (24) are shown in Table 5, for L fixed at 16, i.e. 4 year. Results at different horizons are qualitatively very similar. Estimates are over the period where all the portfolios

Table 5: Test assets cash-flows sensitivity to long-run risk components. Estimates shown for the horizon of 4 years. From 1975 Q1 to 2022 Q1.

Portfolio	β_C	$\beta_{Z\text{-raw}}$	$\beta_{Z\text{-adj}}$	$\beta_{\tilde{s}\text{-BS}}$	$\beta_{\tilde{s}\text{-LN}}$
size.01	1.245	4.624	8.145	16.042	18.977
size.02	0.238	7.076	9.422	12.454	13.968
size.09	1.432	7.282	1.317	-3.427	-4.200
size.10	-0.415	4.014	-2.535	-0.894	-0.934
bm.01	-2.126	12.756	6.596	2.437	2.456
bm.02	-1.861	8.248	2.371	4.085	4.683
bm.09	3.041	9.280	5.844	1.936	1.713
bm.10	-0.276	4.359	-5.128	2.698	3.078
mom.01	-5.273	-1.836	-1.620	-3.097	-3.641
mom.02	3.279	5.482	-4.846	-1.532	-1.791
mom.09	9.293	12.116	3.322	1.253	1.023
mom.10	6.509	15.769	-1.913	-2.662	-5.490
rd.01	0.794	4.354	1.465	-3.177	-2.795
rd.02	-1.902	13.573	8.317	4.332	2.802
rd.04	0.125	15.837	12.275	7.127	5.621
rd.05	-1.294	20.648	11.143	15.662	14.056

are available, i.e. from 1975 to 2022. 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. The productivity LRR components, as measured from TFP growth itself, are related to much starker patterns across all sortings, as is the *innovation* LRR component. 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 in R&D too. This is in line with the thesis empirically supported by Jiang et al. (2016) that firms gain from higher R&D investment of peers, here on a economy-wide scale. Nonetheless, changes in payout policies would have to be controlled for in a more formal setting to validate such a claim.

Risk premia estimates

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 6 4 and 32, i.e. 1 year and 8 years, respectively. The most surprising result is that the premium associated to consumption LRR is far from significant. Estimates omitted from this paper that have been performed on the sample without the R&D portfolios and ending in 2001, as in the original analysis of Bansal, Dittmar, et al. (2005), return estimates in line with them. Anyway, measurement error in consumption series is a well known phenomenon,[19] so it is not totally unexpected that focusing on specific LRR components that rely on different variables, such as the productivity LRR component,

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

Table 6: annualized 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 1975 Q1 to 2022 Q1.

	Cons.	Raw TFP	Util+R&D-adj. TFP	$\tilde{s}$ (BS)	$\tilde{s}$ (LN)
			Horizon: 1 year		
λ_0 (%)	6.06***	5.76***	7.05***	7.71***	7.59***
t-stat	[3.11]	[2.89]	[3.89]	[4.18]	[4.13]
λ_x (%)	0.08	0.12	0.24***	0.56***	0.51***
t-stat	[1.49]	[1.61]	[2.60]	[3.88]	[3.67]
MAPE (%)	0.83	0.84	0.86	0.81	0.82
R^2 (%)	1.5	2.5	4.6	31.5	27.8
			Horizon: 8 year		
λ_0 (%)	6.59***	5.70***	7.18***	4.40**	4.62**
t-stat	[3.68]	[3.17]	[4.02]	[2.41]	[2.54]
λ_x (%)	0.05	0.39***	0.46***	0.72***	0.64***
t-stat	[0.21]	[4.24]	[4.44]	[4.15]	[3.94]
MAPE (%)	0.85	0.72	0.69	0.54	0.57
R^2 (%)	−1.2	14.5	13.3	70.1	66.8

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

show a better performance. Indeed, the estimates strongly support the existence of a premium for long-run productivity risk, both measured 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. It should also be noted that the premium associated with the innovation LRR is always higher than that of the 'direct' TFP LRR and is less affected by filtering at different horizons. This is also to be expected, since the innovation LRR component relies on an Error Correction term, which is forward-looking, while the direct-TFP LRR component is formed as a moving average, which is backward-looking. Being forward-looking, it incorporates information processed by investors and encoded in asset prices earlier, leading to better statistical performance. All in all, the results presented here supports the notion that fluctuations in innovation efforts are a significant source of risk and is, as such, priced, as expected by the long-run risk framework.

5.2 A robust estimation approach

Giglio and Xiu (2021) highlights a critical issue with traditional empirical methods for estimating risk premia from a cross-section of assets: the failure to properly account for all priced sources of risk in the economy. This can lead to biased estimates and is a particularly relevant concern for the analysis performed in the previous subsection. To address this issue, the estimates of the innovation LRR premia obtained by following their procedure are also presented here.

Methodology

In the context of a standard factor structure for returns such as

$$\mathbf{R}_t - R^f_{t-1} = \boldsymbol{\beta}\boldsymbol{\lambda} + \boldsymbol{\beta}\mathbf{v}_t + \mathbf{u}_t \ , \tag{25}$$

when the number of observations and test assets go to infinity, the 'true' risk factors in the economy $\mathbf{v}_t$ can be recovered by the Principal Component Analysis up to an arbitrary rotation $\hat{\mathbf{v}}_t = H\mathbf{v}_t$, where H is a full-rank matrix. Then, Giglio and Xiu (2021) focus on an observable factor g_t that is affine in the 'true' factors, with measurement error w_t,

$$g_t = \zeta_0 + \boldsymbol{\zeta}_v \mathbf{v}_t + w_t \ , \tag{26}$$

and show that the risk premia associated to it can be effectively estimated without biases. In this framework, the risk premium associated with g_t amounts to $\boldsymbol{\zeta}_v\boldsymbol{\lambda}$, which is the expected excess return of an asset with a beta of 1 with respect to g_t, and 0 with respect to all other factors. The key to its estimation is that $\boldsymbol{\zeta}_v H^{-1}$ can be obtained by regressing g_t on $\hat{\mathbf{v}}_t$ and $H\boldsymbol{\lambda}$ can be obtained by regressing $\mathbf{R}_t$ on $\boldsymbol{\beta}H^{-1}$. This provides all the necessary elements to recover $\boldsymbol{\zeta}_v\boldsymbol{\lambda}$, since

$$\boldsymbol{\zeta}_v H^{-1} H \boldsymbol{\lambda} = \boldsymbol{\zeta}_v \boldsymbol{\lambda} \ . \tag{27}$$

Test assets

This procedure addresses the issue of omitted risk factors, but the test assets that the factor model fits have to span as many risks as possible from the outset to obtain the most generalizable results. The more of the state space is covered, the more representative and robust will be the estimates. To this end, 153 anomaly portfolios from Jensen et al. (2021) are considered here. As portfolios have different lengths, two different 'pools' of portfolios will be used to perform estimations: the 'wide pool' one, maximizing the cross-sectional numerosity, returning a sample starting in 1971 and ending in 2023; and the 'long pool', retaining the 118 portfolios that start being available from 1951 and also end in 2023.

The 'true' un-identified risk factors

Clearly, the choice of the number of principal components to consider as the 'true' risk factors in the economy is critical. Here, the procedure suggested in Alessi et al. (2010) is followed, returing 9 factors for the long pool, and 10 for the wide pool. Screeplots of the principal component analysis are in Figure 4, in Appendix E. Notice however, that what matters is the cross-sectional fit of the factors with respect to the test assets, which depends on the estimates of the market-wide risk premia. These will also be reported. In addition to the specification of the factor structure chosen 'optimally', estimates with a fixed number of factors—both higher and lower—are also reported for comparison. These estimates rely on 6 and 14 factors, respectively.

Table 7: risk premia estimation. Optimal number of components $p*$ estimated as in Alessi et al. (2010). The long pool consists of 118 portfolios ranging between 1951 Q4 and 2023 Q4, the wide pool are 153 portfolios between 1971 Q4 to 2023 Q4. In square brackets, the t statistics.

$\ln Z$:	Adj TFP	Raw TFP	Adj TFP	
$\ln L$:	Tot. emp.		Nonfarm emp.	Tot. emp.
$\mathbf{f}$:	BS			LN
	Long pool (N=118)			
$p_0 = 6$	2.11	1.83*	2.08	3.81**
(R^2:41.5%)	[1.43]	[1.74]	[1.31]	[2.22]
$p_l* = 9$	3.63	3.65*	3.76	7.22***
(R^2: 62.0%)	[1.48]	[1.86]	[1.34]	[2.94]
$p_1 = 14$	6.19*	7.05***	6.88*	10.11***
(R^2: 83.4%)	[1.90]	[2.69]	[1.92]	[3.18]
T	285	285	285	251
	Wide pool (N=153)			
$p_0 = 6$	3.32*	2.65**	3.49*	3.84*
(R^2: 46.2%)	[1.68]	[2.00]	[1.66]	[1.89]
$p_w* = 10$	7.40**	4.85*	8.36**	8.13***
(R^2: 71.1%)	[2.37]	[1.86]	[2.50]	[2.79]
$p_1 = 14$	9.18***	6.55**	10.50***	11.20***
(R^2: 84.3%)	[2.58]	[2.42]	[2.75]	[3.22]
T	205	205	205	209

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

Risk premia estimates

Table 7 shows the estimated risk premia for different R&D intensity specifications and test assets pools. Despite a weaker significance for lower numbers of 'true' risk factors and fewer test assets, the overall results are in line with those of the previous subsection. The risk associated to fluctuations in R&D intensity consistently appears to be positively priced by investors.

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 proves to identify the 'long-run *innovation* risk component', by being persistent and predicting relevant macroeconomic quantities, in addition to being associated to a significant risk premium in the cross section of US stocks. This provides further support to the relevance of the long-run risk framework as well as of the endogenous growth framework, proving a novel measure of R&D intensity that can be reliably exploited for further studies.

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A Balanced Growth Path in a simple full model

A.1 A full model

To characterize a Balanced Growth Path (BGP) in an economy featuring conditions (1) and (2) from Section 2, first assume the production function

$$Y_t = e^{a_t} I_t^{\xi} L_t \ , \tag{28}$$

where output only depends on the labor employed L_t and some elements scaling its productivity, $e^{a_t} I_t^{\xi}$, which constitute the so-called Total Factor Productivity (TFP) level. Next, consider the resource constraint of the economy

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

where C_t is consumption. Next, in the spirit of Jones (2005), assume a stochastic rule of thumb as a policy rule for resources allocation:

$$S_t = \hat{s}_t Y_t \ . \tag{30}$$

Lastly, assume an exogenous non-degenerate growth rate for the labor force, $\Delta \ln L_t$.

A.2 The approximately linear law of motion of ideas

From (1) it follows that

$$\ln Z_t = a_t + \xi \ln I_t \ , \tag{31}$$

while from (2) it follows that

$$\Delta \ln I_{t+1} = \ln \left\{ 1 - \phi + \chi \cdot S_{t-1}^{\eta} I_{t-1}^{-(1-\psi)} Q_{t-1}^{-\omega} \right\} \ , \tag{32}$$

which for small values can be well approximated by

$$\Delta \ln I_{t+1} \approxeq -\phi + \chi \cdot S_{t-1}^{\eta} I_{t-1}^{-(1-\psi)} Q_{t-1}^{-\omega} \ . \tag{33}$$

The shorter the time steps, the more accurate the approximation is. For small values of $S_{t-1}^{\eta} I_{t-1}^{-(1-\psi)} Q_{t-1}^{-\omega}$, this can be further approximated as

$$\begin{aligned} \exp \left\{ \ln \left[S_{t-1}^{\eta} I_{t-1}^{-(1-\psi)} Q_{t-1}^{-\omega} \right] \right\} &= \exp \left\{ \eta \ln S_{t-1} - (1-\psi) \ln I_{t-1} - \omega \ln Q_{t-1} \right\} && (34) \\ &\approxeq 1 + \eta \ln S_{t-1} - (1-\psi) \ln I_{t-1} - \omega \ln Q_{t-1} \ , && (35) \end{aligned}$$

which leads to

$$\Delta \ln I_{t+1} \approxeq -\phi + \chi \left(1 + \eta \ln S_{t-1} - (1-\psi) \ln I_{t-1} - \omega \ln Q_{t-1} \right) \ . \tag{36}$$

This can be more succintly written as

$$\Delta \ln I_{t+1} \approxeq (\chi - \phi) + \chi\eta \left(\ln S_{t-1} - \left(\frac{1-\psi}{\eta} \right) \ln I_{t-1} - \left(\frac{\omega}{\eta} \right) \ln Q_{t-1} \right) \ . \tag{37}$$

Plugging $\ln I_t$, and the implied $\Delta \ln I_t$, from (31), one gets

$$\frac{1}{\xi}(\Delta \ln Z_{t+1} - \Delta a_{t+1}) \approxeq (\chi - \phi) + \chi\eta \left(\ln S_{t-1} - \left(\frac{1-\psi}{\eta} \right) \frac{1}{\xi}(\ln Z_{t+1} - a_{t+1}) - \left(\frac{\omega}{\eta} \right) \ln Q_{t-1} \right) \ . \tag{38}$$

Rearranging:

$$\Delta \ln Z_{t+1} \approxeq \xi(\chi - \phi) + \xi\chi\eta \left(\ln S_{t-1} - \left(\frac{1-\psi}{\eta\xi} \right) (\ln Z_{t+1} - a_{t+1}) - \left(\frac{\omega}{\eta} \right) \ln Q_{t-1} \right) + \Delta a_{t+1} \ . \tag{39}$$

It is clear that bringing (39) to the data as illustrated in the main text does not allow to identify the structural parameters. Thus, assuming $\kappa \neq 1$ in $Q_t = L_t^{\kappa}$ does not affect the theoretical interpretation of empirical results. Therefore, I will maintain this assumption in the theoretical analysis of this appendix.

A.3 The Balanced Growth Path

Assuming a stationary consumption share of output implies that $1 - \hat{s}_t$ has an unconditional expected value and

$$\mathbb{E}\left[\Delta \hat{s}_t\right] = 0 \ . \tag{40}$$

Then,

$$\begin{aligned} \mathbb{E}\left[\Delta \ln S_t\right] &= \mathbb{E}\left[\Delta \ln Y_t\right] & (41)\\ &= \mathbb{E}\left[\Delta a_t + \xi \Delta \ln I_t + \Delta \ln L_t\right] \ . & (42) \end{aligned}$$

Similarly, assuming $\Delta \ln I_t$ is stationary too, its unconditional expectation also has a finite value. Thus, taking expectations of both sides of (32) and differencing them returns

$$\mathbb{E}\left[\Delta \ln S_t - \frac{1-\psi}{\eta} \Delta \ln I_t - \frac{\omega}{\eta} \Delta \ln Q_t\right] = 0 \ . \tag{43}$$

Subtracting (43) from (42), one gets an expression for the unconditional expectation of the growth rate of ideas' stock that is only function of structural variables:

$$\mathbb{E}\left[\Delta \ln I_t\right] = \frac{\eta + \omega}{\eta(1-\psi-\xi\eta)} \mathbb{E}\left[\Delta \ln L_t\right] + \frac{\mathbb{E}\left[a_t\right]}{1-\psi-\xi\eta} \ . \tag{44}$$

Clearly, the order of integration of a_t does not need to be 0, but cannot exceed 2 either, in this framework. (44) shows the basis for the domain restriction on ψ stated in the main text, while the positivity of η, ψ, ξ, and ω is taken as given, since R&D increasing productive input' productivity and past ideas increasing R&D impact are the conceptual foundations of the endogenous growth theory. It should be noted that products' variety can impact final goods productivity, but this channel is not explicitly considered here, although in principle it is captured by a_t. Finally, leveraging the definition of excess R&D intensity and rewriting (32) as $\mathbb{E}\left[\Delta \ln I_t\right] = \gamma_0' + \gamma_1'(\bar{s} + \tilde{s}_t)$, an expression determining the BGP value of $\bar{s}$ can be derived:

$$\bar{s} = \frac{\mathbb{E}\left[\Delta \ln I_t\right] - \gamma_0'}{\gamma_1'} \ . \tag{45}$$

B Returns' cash-flow component

$$\begin{aligned} \Delta \ln D_{i,t+1} &= \beta^i_{x,D} x_t + \varepsilon^i_{D,t+1} & (46)\\ \mathbb{E}_t[\Delta \ln D_{i,t+j}] &= \beta^i_{x,D} (\rho_x)^{j-1} \cdot x_t & (47)\\ \mathbb{E}_t[\Delta \ln D_{i,t+j}] - \mathbb{E}_{t-1}[\Delta \ln D_{i,t+j}] &= \beta^i_{x,D} \left[(\rho_x)^{j-1} \cdot x_t - (\rho_x)^j \cdot x_{t-1}\right] & (48)\\ &= \beta^i_{x,D} (\rho_x)^{j-1} \cdot \varepsilon^x_t & (49) \end{aligned}$$

$$\{\mathbb{E}_t - \mathbb{E}_{t-1}\}\left[\sum_{j=0}^{\infty}\bar{\kappa}^j \Delta \ln D_{i,t+j}\right] = \beta^i_{x,D}\rho_x \left[\sum_{j=0}^{\infty}(\rho_x\bar{\kappa})^j \varepsilon^x_{t+j}\right] \tag{50}$$

$$\{\mathbb{E}_t - \mathbb{E}_{t-1}\}\left[\sum_{j=0}^{\infty}\bar{\kappa}^j \Delta \ln D_{i,t+j}\right] = \beta^i_{x,D}\frac{\rho_x}{1-\rho_x\bar{\kappa}}\varepsilon^x_{t+j} \tag{51}$$

$$\delta^i_{D,t} = \beta^i_{x,D}\frac{\rho_x}{1-\rho_x\bar{\kappa}}\varepsilon^x_{t+j} \tag{52}$$

C 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

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

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

D Data

D.1 Cash-flow series

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:

$$h_t = \left(\frac{P_{t+1}}{P_t}\right) \cdot \min\left[\left(\frac{n_{t+1}}{n_t}\right), 1\right]. \tag{53}$$

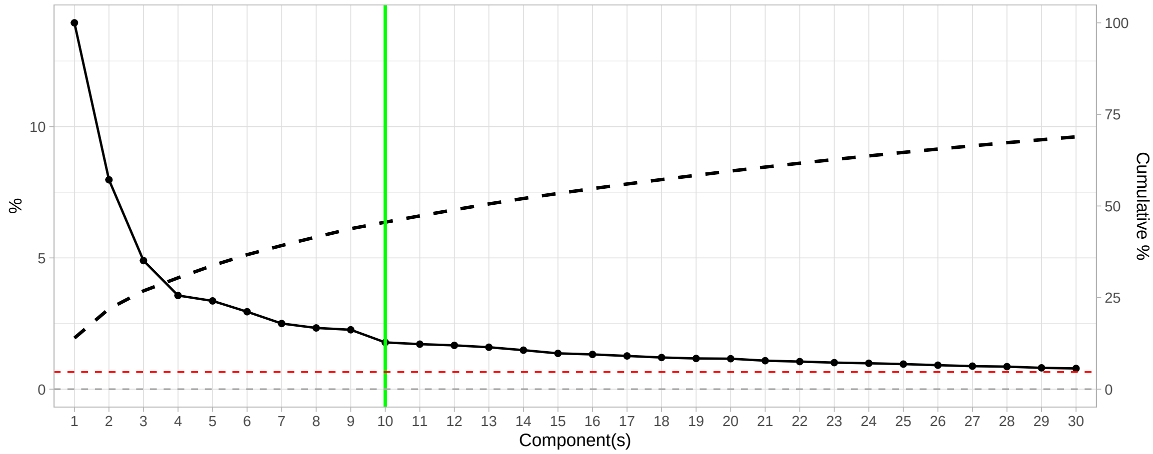
Essentially, capital gains are less than proportional to price appreciation when there is a reduction in (equivalent) shares outstanding, which is likely related to share repurchases, a form of payout not accounted for in dividends records. Then, quarterly dividends series are obtained by simply summing 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.

E Additional tables and figures

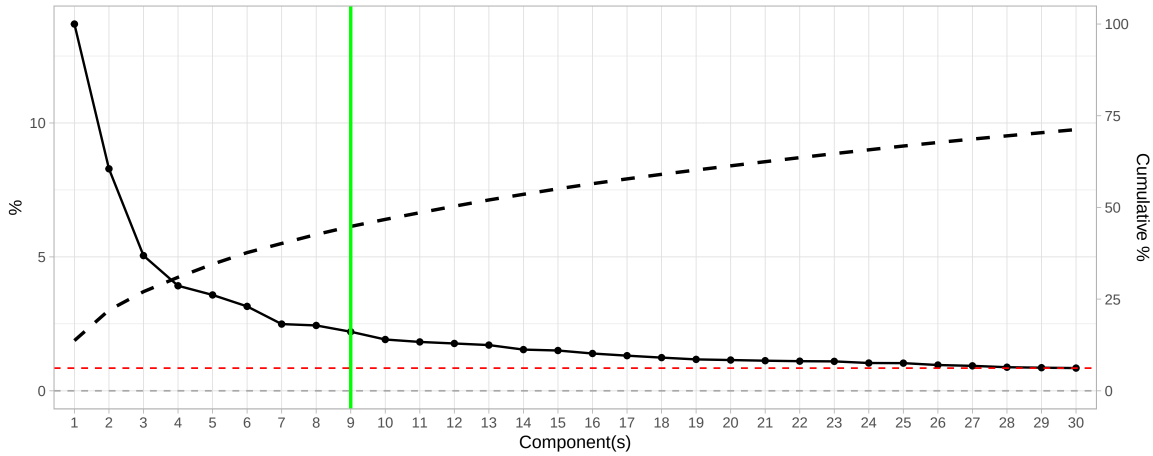
Correlations among the R&D intensity measures are in Table 8. The screeplots of the PCAs performed in 5.2 are in Figure 4.

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	-



(a) Wide pool



(b) Long pool

Figure 4: Screeplots of PCAs of test assets in 5.2. On the y axis on the left, the variance explained by each factor (continuos line); on the right y axis, the cumulative variance explained. The green vertical line highlights the chosen number of factors, while the red horizontal line marks the reciprocal of test assets number.