The Innovation Long-Run Risk Component

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Abstract

This paper provides robust empirical evidence that shocks to aggregate Research and Development (R&D) have persistent effects on macroeconomic dynamics and represent a significant risk for investors, as predicted by the 'long-run risk' literature. The analysis focuses on a single variable, 'effective R&D', which captures the entire contribution of R&D to productivity growth, flexibly accounting for knowledge spillovers and product proliferation effects. Deviations of effective R&D from its equilibrium level can be empirically identified leveraging the error correction term in the cointegration relationship among R&D, total factor productivity, and the labor force. In US data, structural effective R&D shocks affect productivity and consumption growth rates beyond business cycle horizons and are associated with a significant risk premium in a cross section of stock and bond portfolios (around 2% annually), with cash-flow sensitivities proving a key determinant.

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

JEL Codes: E32, E44, G12, O30

1 Introduction

Investments in Research and Development (R&D) have a profound and well-documented impact on the economy. At the aggregate level, R&D has been linked to slow-moving fluctuations in macroeconomic quantities such as productivity and consumption (Comin and Gertler 2006; Evans et al. 1998), and theory has shown that this nexus carries substantial implications for asset prices (Kung and Schmid 2015). The underlying mechanism is that of the 'Long-Run Risk' (LRR) framework from Bansal and Yaron (2004), who first demonstrated how persistence in consumption growth enables macroeconomic models to account for the large

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equity risk premium observed in financial markets, a premium that far exceeds predictions based on observed consumption growth volatility alone (Mehra and Prescott 1985). This framework has since become a central reference in macro-finance research,[1] but has also faced sustained criticism,[2] making rigorous empirical validation of models built on it essential.

This paper provides robust empirical evidence that shocks to US aggregate R&D have persistent effects on productivity and consumption growth, and carry substantial implications for asset prices. Specifically, I focus on a theoretical measure of aggregate R&D – 'effective R&D' – that uniquely summarizes the total impact of R&D on productivity growth, accounting for virtually any degree of spillover and product proliferation effects. I then propose an empirical framework to recover its time series and the associated structural shocks, illustrating their persistent effects on the economy. Finally, I show that structural shocks to effective R&D serve as a risk factor with significant power in pricing the cross-section of financial assets. This constitutes a twofold novelty, as it introduces the first empirically significant risk factor that is (1) based on aggregate R&D, and (2) constructed from structural shocks in a theoretically identified system.

In the long-run risk framework, agents have recursive preferences as in Epstein and Zin (1989), which are characterized by an aversion to swings in forecasts of distant future consumption growth. Persistent shocks can induce such fluctuations with very small variance, making them a powerful theoretical feature by allowing models to account for sizable risk premia with little added complexity, but also an elusive one to validate empirically, since low-frequency processes are challenging to identify in finite samples. A growing literature has tackled the empirical challenge directly, either by devising refined empirical strategies (Dew-Becker and Giglio 2016; Gourieroux and Jasiak 2024; Ortu et al. 2013; Schorfheide et al. 2018) or by exploiting new data (Liu and Matthies 2022). Another strand has derived the LRR pivotal conditions as reduced forms of richer structural models, yielding additional testable implications (e.g. Kaltenbrunner and Lochstoer 2010). Within this framework, Croce (2014) showed that the predictable component of productivity growth is persistent and does transmit to consumption growth. He termed this component the 'productivity long-run risk component', which Kung and Schmid (2015) later rationalized as originating from persistent fluctuations in R&D investment. This paper provides direct empirical evidence on the macroeconomic mechanism and financial predictions developed in this theoretical framework, while contributing a novel econometric procedure, grounded in macroeconomic theory, to identify a process that captures revisions to long-run expectations of innovation – an 'innovation long-run risk component'. The results in this study depart from the predictions in Kung and Schmid (2015) only regarding the specific mechanics behind R&D shock propagation, which empirically does not appear to arise from the persistence of effective R&D itself, but rather from its interaction with external macroeconomic factors. Figure 1 displays the estimated effective R&D, along with the processes it is expected to drive, i.e.,

[1] Applications include, among others, exchange rate dynamics (Colacito and Croce 2011), climate change asset pricing (Bansal et al. 2021), term structure models (Ai et al. 2018), and oil price dynamics (Ready 2018).

[2] Most notably Constantinides and Ghosh (2011), Beeler and Campbell (2012), and Epstein et al. (2014).

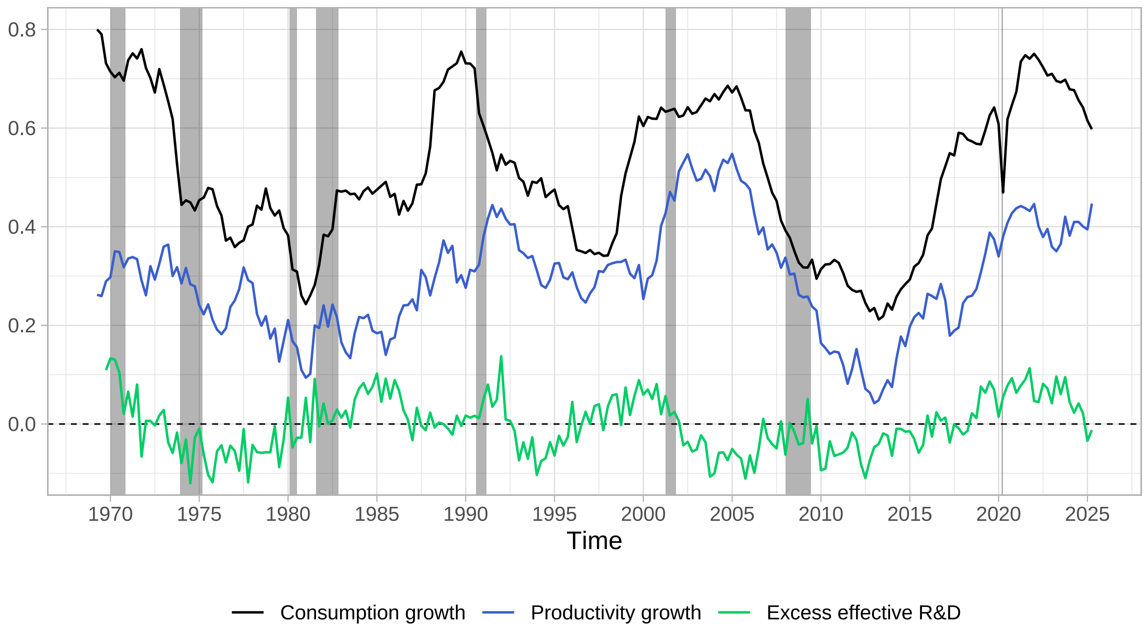

Figure 1: Consumption growth is US real total consumption per capita from BEA; 'TFP' is the utilization-adjusted, excluding R&D capital, TFP from Fernald (2012). Of both is plotted the 6$^{\text{th}}$ component of Ortu et al. (2013) decomposition, which filter the fluctuations with half-life between 8 and 16 years. Excess effective R&D is in levels, not growth rates.

the components with half-lives between 8 and 16 years of consumption and productivity growth rates, whose comovement is apparent.

Effective R&D expresses aggregate R&D in units of expected productivity growth, as prescribed by endogenous growth theory. It is a log-linear combination of aggregate R&D, the stock of ideas and a product variety measure, capturing the nonlinear impact of R&D on productivity growth. Its definition is formalized within a theoretical framework that illustrates the minimal conditions linking aggregate R&D to asset prices, while intentionally abstracting from the optimal choices driving R&D dynamics, leaving the latter to empirical analysis. This theoretical framework relies primarily on a production function of ideas that nests Kung and Schmid (2015) as a special case, while more flexibly accommodating both fully and semi-endogenous growth mechanisms. This greater flexibility, together with a closer alignment of the econometric approach and the underlying theory, allows the resulting effective R&D measure to address some undesirable statistical properties of the empirical measure in Kung and Schmid (2015).[3] In particular, I show that their effective R&D measure exhibits persistence that, while consistent with traditional calibrations of consumption LRR, is substantially higher than that of the productivity component it is intended to drive. Moreover, its proximity to a unit root raises concerns of spurious inference in standard econometric applications. By contrast, the effective R&D measure developed here generates highly persistent effects while remaining highly stationary, enabling more reliable application of established asset pricing cross-sectional tests. Another related measure is that of Kogan

[3]They refer to 'effective R&D' as 'R&D intensity'.

et al. (2017), which offers more granular information and complements effective R&D by focusing on the outcome of the innovation process – successful innovations – rather than its input.

The empirical identification of effective R&D relies on the widely supported assumption of productivity growth stationarity, which implies that the linear combination of trending variables constituting effective R&D forms a cointegration relationship that can be estimated. For technical reasons related to the timing of the variables, this relationship is estimated using a single-equation approach (Phillips and Hansen 1990). For robustness, the cointegration model is estimated using productivity levels instead of the stock of ideas, thereby introducing productivity drivers external to R&D into the error-correction term, which forms a 'gross' effective R&D measure. Identification of net effective R&D dynamics is pursued in several ways: (1) linearity of both the mapping from gross to net effective R&D and the VAR model representing system dynamics ensures structural shocks are not distorted; (2) all estimates are performed using both the gross measure and a net measure, recovered relying on a recursive formula based on a one-step productivity forecast regression with robust controls that have been shown in previous work to capture productivity growth dynamics; (3) the dynamic implications from the VAR are tested and extended to consumption growth by employing the effective R&D structural shocks from the VAR in a local projection exercise (Jordà 2005; Montiel Olea and Plagborg-Møller 2021). A crucial result is that, although effective R&D is highly stationary, its shocks consistently affect productivity and consumption growth well beyond the business cycle, likely over horizons of ten years. These are significantly longer horizons compared with the evidence in Kung and Schmid (2015), while controlling for external factors, using methods robust to small-sample bias, and allowing for richer multivariate dynamics. The persistence of effects from R&D fluctuations has also been studied by Anzoategui et al. (2019), who emphasized the role of gradual technology adoption in generating persistence, and many other studies which have leveraged it as a channel for propagating business cycle shocks.[4] Relative to these studies, this paper focuses on the financial implications while employing a novel methodology that assesses an R&D measure uniquely reflecting the time-varying efficiency of R&D to form a single risk factor.

The cross-sectional asset pricing tests rely on the effective R&D structural shocks in the macroeconomic analysis, which is orthogonalized to productivity growth shocks. This ensures that R&D shocks are isolated from the main confounding factor in these reduced-form tests. Combined with the procedure from Giglio and Xiu (2021), which exploits a wide cross-section of assets to mitigate concerns about omitted risk factor bias, this yields highly reliable estimates of the risk premia associated with effective R&D shocks. The premia are insignificant for contemporaneous shocks but highly significant and consistent for moving averages over multi-year horizons, yielding roughly 2% annually – consistent with investors' underreaction to R&D news documented in Eberhart et al. (2004). Furthermore, a key

[4]For example, Benigno and Fornaro (2018) illustrate its role in propagating negative shocks, Antolin-Diaz and Surico (2025) for military spending shocks, Beqiraj et al. (2025) for monetary shocks, Aksoy et al. (2019) for demographic changes.

feature of long-run risk models is that risk is transmitted through asset cash flows. This is tested following Bansal et al. (2005) using stock portfolios sorted by firm characteristics previously linked to R&D investment, as well as by industry portfolios. These results also provide descriptive evidence bridging the corporate finance literature on R&D investment and the asset pricing literature on firm-specific R&D risk premia. Beyond Kung and Schmid (2015), Hsu (2009) also linked aggregate R&D and financial markets. Relative to their work, this paper contributes by employing a theory-based R&D measure and providing explicit cross-sectional risk premium estimates.

From a technical perspective, the theoretical definition of effective R&D is grounded only in a definition of Total Factor Productivity (TFP) contributors and a 'lab-equipment' production function of ideas inspired by Jones (1999), making the results broadly applicable.[5] While the framework allows R&D efficiency in generating new ideas to be diluted by both decreasing returns to past ideas and an expanding variety of products, it does not explicitly assess their relative contribution to fitting the data, with product variety significance depending on which measure of R&D expenditure is employed. On the empirical side, cointegration models have been widely applied to study the relationship between R&D and technological progress in macroeconomic studies (Bottazzi and Peri 2007; Ha and Howitt 2007; Herzer 2022b; Kruse-Andersen 2023; Madsen 2008). However, these works mainly focus on foreign spillovers and the distinction between fully- and semi-endogenous economies, whereas this paper emphasizes the dynamic properties of R&D and its financial implications. Moreover, none of these studies employ a single-equation approach, which, on the other hand, is frequently used in the empirical macro-finance literature (e.g., Lettau and Ludvigson 2001; Melone 2021) and is adopted here.

The paper proceeds as follows. Section 2 outlines the theoretical framework, defining effective R&D and its key macroeconomic and financial predictions. Section 3 describes the econometric framework proposed to identify effective R&D and test the associated predictions. Section 4 presents the cointegration results and forecasting regressions that yield the effective R&D measures. Section 5 documents the impact of effective R&D on macroeconomic quantities, and Section 6 reports the cross-sectional asset pricing results. Section 7 concludes.

2 Theoretical framework

2.1 Persistent macroeconomic shocks and financial markets

In a discrete-time, arbitrage-free economy, the expected excess return of any asset i over the risk-free rate R_t^f is proportional to the covariance between its return R_t^i and the Stochastic

[5] The 'lab-equipment' class of models, introduced in Romer (1987), uses final output goods to produce ideas, in contrast to labor-based models à la Romer (1990).

Discount Factor (SDF) M_t:[6]

$$\mathbb{E}_t\left[R^i_{t+1}\right] - R^f_t = -R^f_t \cdot \mathrm{Cov}_t\left[M_{t+1}, R^i_{t+1}\right] . \tag{1}$$

To discipline and better understand the dynamics of the SDF, asset pricing theory often relates the SDF to the intertemporal marginal rate of substitution (IMRS) of a representative agent with preferences over consumption streams. Shocks to state variables that matter for investor consumption become the key drivers of asset valuations.

As illustrated by Bansal and Yaron (2004), persistent macroeconomic quantities strongly affect the IMRS and, consequently, asset valuations, when the representative agent has recursive preferences as in Epstein and Zin (1989). These preferences separate the intertemporal elasticity of substitution (IES) from risk aversion, and imply that the agent is sensitive both to contemporaneous consumption shocks

$$\varepsilon_{c,t+1} = \ln C_{t+1} - \mathbb{E}_t\left[\ln C_{t+1}\right] , \tag{2}$$

and to shocks to long-run consumption prospects

$$\varepsilon_{x,t+1} = \Big\{\mathbb{E}_{t+1} - \mathbb{E}_t\Big\} \left(\sum_{j=1}^{\infty} (\kappa_x)^j \cdot \Delta \ln C_{t+1+j}\right) , \tag{3}$$

as reflected in the log SDF,

$$\ln M_{t+1} = \mathbb{E}_t[\ln M_{t+1}] - b_c\, \varepsilon_{c,t+1} - b_x\, \varepsilon_{x,t+1} , \tag{4}$$

where $\kappa_x \in (0, 1)$ is a function of the equilibrium consumption–wealth ratio, and $b_c > 0$ and $b_x > 0$ are the loadings on contemporaneous and long-run consumption shocks, respectively. The persistence of macroeconomic shocks plays a central role in this framework because the more persistently a shock affects consumption growth, the larger the fluctuations it generates in $\varepsilon_{x,t+1}$, and hence the stronger its impact on the IMRS.[7]

Assuming that $\varepsilon_{c,t+1}$ and $\varepsilon_{x,t+1}$ are also the key stochastic determinants of asset return dynamics,[8] the following reduced-form pricing equation holds:

$$\mathbb{E}_t\left[R^i_{t+1}\right] - R^f_t = \lambda_c \beta^i_c + \lambda_x \beta^i_x , \tag{5}$$

where each asset is fully characterized by two measures of risk – its sensitivities to the shocks, β^i_j for $j \in \{c, x\}$, and the market-wide prices of risk, λ_j, which represent the compensation per unit of exposure to each shock – the 'risk premium'. The economic interpretation is that the agent dislikes fluctuations not only in realized consumption streams but also in expectations

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

[7] For instance, if consumption growth simply followed $\Delta \ln C_{t+1} = \rho_c \Delta \ln C_t + \breve{\varepsilon}_{t+1}$ with $|\rho_c| < 1$ and $\breve{\varepsilon}_{t+1}$ i.i.d., then the long-run shock would amount to $\varepsilon_{x,t+1} = \frac{1}{1-\kappa_x \rho_c} \breve{\varepsilon}_{t+1}$.

[8] One could explicitly model returns with a factor structure, e.g., $R^i_{t+1} = \bar{R}^i_t + \beta^i_c \varepsilon_{c,t+1} + \beta^i_x \varepsilon_{x,t+1} + e^i_{t+1}$, although in the LRR framework, exposure arises specifically from assets' cash-flow dynamics.

of future consumption. Consequently, to hold any asset exposed to either type of shock, the agent requires compensation in the form of higher expected returns. A significant market price of long-run risk, λ_x, has important implications for pricing the entire cross-section of financial assets, and its magnitude crucially depends on the variance of the long-run shock, which also reflects how far into the future the current shocks influence consumption growth.

Naturally, consumption expectations may shift in response to a range of macroeconomic shocks, so long-run risks can stem from multiple economic sources. Among these, productivity growth has been shown to play a central role, as agents with sufficiently high IES optimally postpone consumption in response to positive news about future productivity, generating persistent fluctuations in expected consumption growth (Croce 2014; Kaltenbrunner and Lochstoer 2010; Ortu et al. 2013). Since productivity growth is itself shaped by the long-lasting effects of innovation, Kung and Schmid (2015) predicted that R&D dynamics would be a key source of long-run risk.

2.2 A flexible 'innovation component' of productivity growth

To study the role of innovation in generating long-run risks, consider a neoclassical production function for goods. Without loss of generality, assume that the aggregate productivity of rivalrous inputs at time t, Z_t, is determined by the stock of ideas I_t and a stochastic factor a_t:

$$Z_t = I_t^{\xi} \cdot e^{a_t} \,, \tag{6}$$

for some positive value of ξ, capturing the degree of increasing returns to scale. Here, the intangible capital I_t embodies the technological frontier, as it is propelled by R&D expenditure S_t, according to the law of motion

$$I_t = (1-\phi)I_{t-1} + \chi \cdot S_{t-1}^{\eta} I_{t-1}^{\psi} Q_{t-1}^{-\omega} \,, \tag{7}$$

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 in the creation of new ones (net of fishing-out effects), and Q_t is a measure of goods variety, with dilution power of ideas $\omega > 0$. The process a_t, by contrast, captures all factors affecting productivity that are not direct by-products of R&D, such as misallocation, allowing their impact to be tracked transparently.

The law of motion of the stock of ideas is directly inspired by Jones (1999), but is more conveniently expressed in a 'lab equipment' form, as in Kruse-Andersen (2023), among others. This specification represents the reduced form of equilibrium conditions that can be derived from economies with different microfoundations, with their dynamic properties analyzed in depth by Sedgley and Elmslie (2013). The implied production function of new ideas is the key 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 cause the models to show explosive behaviors when introducing population growth, making them unsuitable for empirical applications. The fully-endogenous approach, shown for example in Peretto (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 a function of population growth only. (7) is flexible enough to accommodate both mechanisms,[9] even though the empirical analysis will not explicitly address the issue of which of the two mechanisms is more relevant for fitting the data.

The specification of productivity determinants in (6) and the law of motion for the stock of ideas in (7) provide enough structure to derive a meaningful characterization of productivity dynamics. Specifically, following a standard approach in the literature,[10] productivity growth can be written as

$$\Delta \ln Z_{t+1} \approx \gamma_0 + \gamma_1 \left(\ln S_t - \frac{1-\psi}{\eta} \ln I_t - \frac{\omega}{\eta} \ln Q_t \right) + \Delta a_{t+1}, \tag{8}$$

where γ_0 and $\gamma_1 > 0$ are composite parameters, with their expressions in terms of the structural parameters reported in Appendix A.1. In words, productivity growth is driven by a linear combination of R&D spending, the technological frontier, and product variety, as well as by shifts unrelated to R&D-fueled innovation, Δa_{t+1}. The term combining R&D expenditure, the technological frontier, and product variety

$$s_t \equiv \ln S_t - \frac{1-\psi}{\eta} \ln I_t - \frac{\omega}{\eta} \ln Q_t \tag{9}$$

arises from the log-linearization of the gross growth rate of ideas $S_t^\eta/(I_t^{1-\psi} Q_t^\omega)$. By capturing the contribution of R&D to the creation of new ideas while accounting for the effects of spillovers from past ideas and product proliferation, s_t is referred to as 'effective R&D' in this work. Indeed, even if absolute R&D investments are large, the economy may be so advanced that they are insufficient to keep up with the increasing difficulty of finding new ideas and offset expanding products variety, yielding relatively smaller, or even negative, productivity gains. This interpretation becomes clearer by rearranging (9) as a policy rule:

$$S_t = e^{s_t} \cdot \left(I_t^{1-\psi} Q_t^\omega \right)^{1/\eta}. \tag{10}$$

To sustain constant productivity growth, which requires constant s_t, the absolute level of R&D investments must grow with the economy as sized by its stock of ideas and product

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

[10] E.g., Ha and Howitt (2007) and Kruse-Andersen (2023). These studies use annual data, whereas this analysis relies on quarterly observations, likely improving accuracy.

variety; any lower amount, even positive ones, implies a decrease in s_t and, consequently, a decrease in productivity growth. No alternative transformation of R&D expenditure – such as its growth rate or its ratio to GDP, commonly used in the literature – fully captures its effect on expected productivity growth, which depends on the contemporaneous dynamics of the stock of ideas and product variety. Crucially, this scaling is the only one that synthesizes the effective impact of R&D in a single variable without requiring additional information and regardless of whether the economy follows a fully- or semi-endogenous growth regime. By fully and uniquely capturing the innovation-driven part of productivity growth, s_t constitutes the *innovation component* of productivity growth – the central focus of this study.

Assuming stationarity of productivity growth, as is common in the literature and supported by the data, a literal interpretation of (8) dictates that effective R&D must also be stationary, unless the external factor is integrated of order 2 (denoted $I(2)$ following econometric conventions) or higher, in levels. For the sake of exposition, this section also adopts the common assumption that a_t is near-$I(1)$, so that its first differences are close to white noise. Moreover, since in a non-degenerate economy sustained productivity growth leads to exponential growth in the stock of ideas, R&D expenditure, and product variety over time, their logarithms are predicted to be integrated of order one – a prediction strongly supported by empirical evidence for R&D expenditure and product variety proxies. Then, given that s_t is expected to be stationary and is defined as a linear combination of three $I(1)$ variables, it follows that these three variables must be cointegrated, with s_t being the associated error correction term (ECT). Intuitively, this means that, while R&D makes ideas proliferate, it is expected not to systematically increase as much as the stock of ideas and product variety jointly grow. This feature has important implications for empirical applications. A crucial one is that the series s_t can be recovered as the residual from the regression

$$\ln S_t = \alpha_I \ln I_t + \alpha_Q \ln Q_t + s_t\,, \tag{11}$$

which has a straightforward mapping with the structural equation (9) and can, in principle, be estimated. Second, the unconditional mean of effective R&D, $\bar{s}$, exists and can be interpreted as the infinite-horizon equilibrium level around which s_t fluctuates. Deviations of effective R&D from this equilibrium level, $\tilde{s}_t = s_t - \bar{s}$, will be referred to as 'excess effective R&D' and drive the dynamics of conditional expectations of future productivity growth:

$$\mathbb{E}_t\left[\Delta \ln Z_{t+1}\right] \approx \mu + \gamma_1 \cdot \tilde{s}_t\,, \tag{12}$$

where μ denotes the unconditional expectation of $\Delta \ln Z_{t+1}$.

2.3 The long-run risk from innovation

It should be noted that $\tilde{s}_t$ plays the same role in shaping expectations of future productivity growth as the 'long-run productivity risk component' in Croce (2014). To illustrate the impact of the innovation component on long-term economic dynamics, this section follows the Long-Run Risk literature and assumes it follows a simple AR(1) process:

$$\tilde{s}_t = \rho_s \tilde{s}_{t-1} + \tilde{\varepsilon} t, \qquad \tilde{\varepsilon}_t \sim \mathcal{N}(0, \sigma_s^2)\,. \tag{13}$$

In this setting, the persistence of effective R&D alone determines how long its shocks influence productivity growth, making it straightforward to characterize the response of infinite-horizon productivity prospects to R&D shocks:

$$\Big\{\mathbb{E}_{t+1} - \mathbb{E}_t\Big\}\left(\sum_{j=1}^{\infty} \Delta \ln Z_{t+1+j}\right) = \frac{\gamma_1}{1-\rho_s}\tilde{\varepsilon}_{t+1}\,. \tag{14}$$

This underscores the significance of persistence in effective R&D, which Kung and Schmid (2015) showed can emerge endogenously, making it a natural candidate for generating substantial long-run risk. With the simplifying assumption that consumption is a constant fraction of final goods produced, it is also immediately apparent that

$$\varepsilon_{x,t+1} \quad \text{is affine to} \quad \frac{\gamma_1 \kappa_x}{1-\rho_s \kappa_x}\tilde{\varepsilon}_{t+1}\,, \tag{15}$$

whose combination with (4) clearly illustrates how shocks to effective R&D can affect the IMRS. From a financial perspective, the investor is expected to require higher returns for assets whose payoffs covary positively with R&D, since higher R&D provides an early signal of elevated future productivity and, consequently, consumption, which reduces marginal utility.

It should be noted that there is a well-known tension between the degree of persistence of a series and the difficulty of empirically distinguishing it from a non-stationary one.[11] Indeed, with a finite sample, it is possible both (1) for the data-generating process of effective R&D to be non-stationary while productivity growth appears stationary, due to substantial short-term exogenous fluctuations; and (2) for effective R&D to appear non-stationary despite being stationary but highly persistent. This can pose a challenge for the framework, since the stationarity of s_t is crucial for validation, to avoid spurious statistical results in standard empirical tests, while a high persistence of s_t is essential in making the long-run risk mechanism relevant in this univariate setting, as it amplifies the impact of its shocks on the economy – with the effects being the strongest precisely when approaching the unit root behavior. Ultimately, whether a stationary effective R&D best represents reality is an empirical question, with its key characteristic for theoretically qualifying as an Innovation Long-Run Risk Component being only that its shocks can forecast growth in productivity – and, consequently, in consumption – over long horizons. Importantly, in general, the persistence of the effects of R&D shocks does not depend solely on the intrinsic persistence of the innovation component itself. Indeed, it also arises from the way in which such shocks are transmitted and amplified by the interactions with the broader economic system. Even

[11] See, for example, Müller (2005).

a transitory disturbance can generate lasting effects if its repercussions propagate across interconnected variables and feedback mechanisms.

3 Econometric framework

3.1 Measuring effective R&D

An operational definition

To estimate (11), measures of R&D expenditure, the stock of ideas, and product variety are required. The first has straightforward counterparts in reality, while the latter two are mapped into observable data following approaches previously adopted in the literature. Product variety is simply assumed to be proportional to labor input L_t.[12] The stock of ideas, instead, is replaced by the productivity level exploiting the definition of TFP in (6). This substitution allows one to bypass the challenging task of measuring the stock of ideas, which is significantly harder to identify than TFP in the data. A first issue concerns the data underlying most measures of ideas, namely patents, which numerous studies have argued do not well represent successful innovation.[13] Then, even with a reliable proxy for new ideas, the stock of ideas must be manually constructed. This requires specifying depreciation rates and aggregating foreign ideas, which would severely limit the sample's timespan and expose the measure to a significant risk of misspecification. On the other hand, TFP, measured as Solow residuals, is much easier to identify empirically. Its concept originates directly from the data, and its definition is common to many models, thereby enhancing the external validity of the analysis. Importantly, these benefits come at the cost of introducing the external component a_t into the definition of effective R&D. Indeed, rewriting effective R&D as

$$\tilde{s}_t = \ln S_t - \frac{1-\psi}{\eta\xi}(\ln Z_t - a_t) - \frac{\omega}{\eta}\ln L_t - \bar{s} \tag{16}$$

prescribes a regression that depends only on observable data:

$$\ln S_t = \alpha_0 + \alpha_Z \ln Z_t + \alpha_L \ln L_t + \hat{s}_t \,, \tag{17}$$

but the residuals of this regression no longer identify $\tilde{s}_t$, but rather a 'gross effective R&D'

$$\hat{s}_t = \tilde{s}_t - \alpha_Z a_t \,, \tag{18}$$

so additional steps are required to recover $\tilde{s}_t$ from the error correction term of (17).

[12] Product variety is generally assumed to be an exponential function of the L_t^κ type with $0 < \kappa < 1$, but κ has no impact on this analysis and would not be identified anyway, so for the sake of exposition it is fixed at 1.

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

Single-equation cointegration estimation

The timing of the data involved in retrieving effective R&D informs the choice of method for estimating the cointegrating parameters in (17). Indeed, R&D expenditure is a flow variable, with its measure capturing the amount of resources devoted to R&D activities throughout the period, whereas TFP and employment levels, being stock variables, are only measured at the end of the period. One could realistically assume, as most models do, that R&D is either decided at the beginning of the period or chosen continuously throughout it, but the end-of-period stock levels are clearly not part of the information set underlying these decisions. Since intermediate values of stock variables are unavailable, and interpolating them would alter the statistical and dynamic properties of the series, the best approximation of the contemporaneous stock values is taken to be their value at the beginning of the period, i.e. the end of the period before. This adjustment implies that a standard Vector Error Correction Model would effectively use R&D from time $t-1$ to t to forecast TFP growth over the same interval, which is not the predictive relation described by discrete-time endogenous growth theory. Therefore, $\hat{s}_t$ is estimated by focusing solely on the long-run relation (17).

This relation is estimated using the Fully Modified Ordinary Least Squares (FM-OLS) method (Phillips and Hansen 1990), which corrects for endogeneity in cointegration regressions by adjusting the dependent variable to account for the long-run covariance with endogenous variables. FM-OLS is particularly suitable here because the error correction term is expected to be highly persistent. Therefore, by contrast, addressing endogeneity as in Dynamic OLS (Stock and Watson 1993), i.e., by including leads and lags of the differenced regressors, would consume many degrees of freedom and substantially reduce the effective sample size. For robustness, the Integrated Modified (IM) OLS of Vogelsang and Wagner (2014) is also considered, although it is expected to perform less efficiently than FM-OLS on a dataset of over 300 observations, as used in this work.

Recovery of the innovation component

Endowed by γ_1, one can explicitly recover the time series of $\tilde{s}_t$ from $\Delta\hat{s}_t$ and $\Delta \ln Z_t$, through a simple recursive relation derived from (8) and (18):

$$\tilde{s}_t = \alpha_Z \left(\sum_{j=0}^{t-1} \kappa_s^j (\Delta \ln Z_{t-j} - \mu) \right) + \sum_{j=0}^{t-1} \kappa_s^j \Delta\hat{s}_{t-j} + \kappa_s^t \tilde{s}_0 \,, \tag{19}$$

where $\kappa_s \equiv 1-\alpha_Z\gamma_1$. Since the initial value $\tilde{s}_0$ cannot be observed, the feasible recovery – that is, the estimates obtained by omitting the term involving $\tilde{s}_0$ – constitutes an approximation. Nevertheless, the influence of the initial condition decays exponentially through the weights κ_s^t, which decline rapidly over time under the baseline specification. Furthermore, as illustrated below, the main analysis can be conducted equivalently using either $\hat{s}_t$ or $\tilde{s}_t$, and both measures are employed to ensure robustness of the findings. Section A.3 provides a detailed discussion of the recovery's accuracy and precision, deriving analytical expressions for the standard errors of the recovered series that account for both the unobservability of the initial condition and sampling variability.

To obtain a reliable estimate of γ_1, two assumptions are made. First, it is assumed that a set of pervasive macroeconomic factors $\mathbf{f}_t$ spans the non-innovation component of TFP growth, so that $a_t = \mathbf{c}'\mathbf{f}_t$ for some vector $\mathbf{c}$. This assumption is supported by the extensive literature on the predictable part of TFP growth (Ai et al. 2018; Croce 2014), of which a_t represents the non-idea component; accordingly, it should already be captured by the information set of the predictors previously used. Second, the effects of the first lag of effective R&D on the external component a_t are negligible in magnitude. This assumption is conceptually motivated by the external component's likely dependence on numerous aggregate economic factors, and is strongly corroborated by the empirical findings presented in subsequent analysis. Therefore, while feedback mechanisms may eventually amplify the contribution of effective R&D to the fluctuations of a_t, the immediate impact is expected to be negligible. Under these assumptions, γ_1 is identified by b_s in the estimation of (8) as

$$\Delta \ln Z_{t+1} = b_0 + b_s \hat{s}_t + \mathbf{b}_f'\mathbf{f}_t + u_{t+1}\,. \tag{20}$$

Since this estimation focuses solely on the parameter b_s rather than the full dynamics of the R&D impact, this forecasting regression is also estimated as a single equation rather than within a system. Relative to a multivariate approach, this method trades a modest increase in estimation variance for a substantial reduction in bias, incorporating numerous control variables in $\mathbf{f}_t$, including lagged values of the dependent variables, with lag lengths selected using standard information criteria.

An alternative approach to recover $\tilde{s}$ is to estimate the cointegration between $\ln S_t$, $\ln Z_t$, $\ln L_t$, and the factors $\mathbf{f}_t$ directly. However, this approach requires estimating a long-run covariance matrix with 144 elements using fewer than 280 observations, which is challenging and may lead to imprecise and unstable cointegrating parameter estimates.

3.2 Innovation shocks and long-run dynamics

Following the estimation of effective R&D, the dynamics of a_t, $\Delta \ln Z_t$, and $\tilde{s}_t$ (or $\hat{s}_t$) are studied jointly, as a system, to achieve two objectives. First, this approach enables an integrated assessment of the long-run impact of effective R&D, accounting for dynamic feedbacks and contemporaneous correlations that univariate models would overlook. Second, it allows identification of structural shocks to the innovation component. The identification strategy, detailed below, isolates shocks to innovation efforts that are orthogonal to fluctuations in other macroeconomic variables of the system, most importantly productivity growth. This separation is crucial to minimize contamination from other sources of risk in estimates of the risk premium from reduced-form asset pricing tests using effective R&D as a risk factor.

The stochastic processes from Section 2 are then extended to incorporate arbitrary persistence in a_t (controlled by ρ_a) and feedback effects between a_t and $\tilde{s}_t$ (governed by θ_s and θ_a). Importantly, the shocks to effective R&D that are not determined by external factors, $\varepsilon_{s,t}$, are assumed to have no effect on the contemporaneous level of the non-idea component. This is a common assumption in the literature (see, for instance, Moran and Queralto (2018)), since the innovation process rarely has outcomes within such a short time frame to be considered contemporaneous.[14]

The resulting structural system is

$$a_{t+1} = \theta_s \tilde{s}_t + \rho_a a_t + b_{aa}\varepsilon_{a,t+1} \tag{21a}$$

$$\Delta \ln Z_{t+1} = (\gamma_1 + \theta_s)\tilde{s}_t + (\rho_a - 1)a_t + b_{aa}\varepsilon_{a,t+1} \tag{21b}$$

$$\tilde{s}_{t+1} = \rho_s \tilde{s}_t + \theta_a a_t + b_{as}\varepsilon_{a,t+1} + b_{ss}\varepsilon_{s,t+1}\,, \tag{21c}$$

where $\varepsilon_{a,t+1}$ and $\varepsilon_{s,t+1}$ are i.i.d. shocks from a standardized normal distribution, and b_{aa}, b_{as}, and b_{ss} are free parameters controlling the volatility of the shocks and their cross-effects. A similar system can be written for $\hat{s}_t$ by substituting $\tilde{s}_t = \hat{s}_t + \alpha_Z a_t$ into the above equations. Notably, each variable continues to be driven by the same underlying structural shocks whether $\tilde{s}$ or $\hat{s}$ is used; only the reduced-form coefficients differ, allowing the same identification scheme to recover the same structural shocks. More details of the system are provided in Appendix A.2.

In this work, the estimation of (21) is approached by focusing on parsimonious 2-variable Vector Autoregression (VAR) models that approximate the VAR–moving-average representation obtained from substituting the external factor out of the 3-variable systems:

$$\Delta \ln Z_{t+1} = (\gamma_1 + \theta_s)\tilde{s}_t + \rho_a \Delta \ln Z_t - (\theta_s + \rho_a\gamma_1)\tilde{s}_{t-1} + b_{aa}\varepsilon_{a,t+1} - b_{aa}\varepsilon_{a,t} \tag{22a}$$

$$\begin{aligned}\tilde{s}_{t+1} = \rho_s \tilde{s}_t - \frac{\theta_a\rho_a}{1-\rho_a}\Delta \ln Z_t + \left(\theta_a\theta_s + \frac{\theta_a\rho_a(\gamma_1+\theta_s)}{1-\rho_a}\right)\tilde{s}_{t-1} + \\ b_{as}\varepsilon_{a,t+1} + b_{ss}\varepsilon_{s,t+1} + \frac{\theta_a b_{aa}}{1-\rho_a}\varepsilon_{a,t}\,,\end{aligned} \tag{22b}$$

where the number of lags is chosen based on standard information criteria. A Cholesky decomposition of the reduced-form residuals' covariance matrix, with $\tilde{s}_t$ ordered last, identifies the structural shocks to effective R&D, $\varepsilon_{s,t}$, from the estimates of (22). As anticipated, the same holds if the system is expressed in terms of $\hat{s}_t$ instead of $\tilde{s}_t$, since only the coefficients change. Crucially, this approach leaves the external component unobserved, which may introduce serial correlation in the reduced-form residuals if its dynamics are poorly reflected in the two-variable system, potentially invalidating structural identification. However, the adequacy of this specification can be assessed ex post through standard diagnostic tests.

A natural way to incorporate a wider information set in the system could be approaching the system (21) with a Factor-Augmented VAR in which the pervasive macroeconomic factors $\mathbf{f}_t$ that have been previosuly argued to span the productivity external component were to be included among the endogenous variables in place of a_t. However, as with the cointegration problem, the rapidly increasing number of parameters in this approach leads to substantial costs in terms of estimation noise (11 endogenous variables imply 121 coefficients per lag in

[14] The implausibility of contemporaneous outcomes is further supported by the significant lag in the diffusion of new technologies, as argued in Rotemberg (2003) and Anzoategui et al. (2019).

the VAR) and a high risk of overfitting.

Robustness of the impulse response functions (IRFs) is ensured by the use of recursive residual bootstrap standard errors of VAR estimates (Lütkepohl 2005), complemented with local projection (LP) estimates following Jordà (2005) and Montiel Olea and Plagborg-Møller (2021). LPs exploit lags of both the macroeconomic factors and the dependent variable, providing results that are generally more robust to misspecification though more volatile than those from the VAR. Following the standard approach, to analyze the dynamic responses of productivity and consumption growth rates to effective R&D shocks with local projections, cumulative responses are estimated using the following specification:

$$\sum_{j=1}^{h} \Delta y_{t+j} = b_{y,h,0} + b_{y,h,s} \cdot \varepsilon_{s,t} + \sum_{l=0}^{k} (\mathbf{b}'_{y,h,f,l} \mathbf{f}_{t-l} + b_{yy,h,l} \cdot y_{t-l}) \,. \tag{23}$$

Conveniently, the coefficients $b_{y,h,s}$ precisely reflect the impact of R&D shocks on the dynamics of long-run expectations, truncated at horizon h; that is, they indicate how strongly these shocks affect the long-run risk factor $\varepsilon_{x,t}$, as defined in (3).

3.3 Asset pricing tests

The key prediction from the theoretical framework in Section 2 is that if shocks to effective R&D influence the long-run dynamics of consumption growth (and agents have recursive preferences), then λ_x in (5) should be positive and significant. Although the covariance-based nature of asset pricing would, in principle, allow effective R&D to serve as the long-run risk factor in levels – as is common in the macro-finance literature, since estimation procedures net out predictable components – this analysis focuses on structural shocks to effective R&D as the risk factor, while also reporting results based on the levels. This choice provides a more stringent test of the theory and ensures consistency with the tests of the macroeconomic predictions.

The key concern in estimating factor models such as (5) is omitted variable bias, which arises when the estimation model fails to capture all priced sources of risk in the economy. This concern is particularly relevant here because the theoretical framework underlying this work, like most asset-pricing models, is deliberately stylized and does not explicitly account for all systematic risks. Recent work by Giglio and Xiu (2021) addresses this issue by proposing a methodology that improves the robustness of risk premia estimates through explicit control for omitted variables.

To further investigate the sources of innovation long-run risk premia, this study replicates the analysis of Bansal et al. (2005). Their methodology, specifically designed for the Long-Run Risks framework, focuses on stocks' cash-flow risks rather than total return variation, isolating the channel through which long-run risk factors theoretically generate equity risk premia. While this approach is less stringent than the Giglio and Xiu (2021) methodology, it provides complementary evidence that facilitates comparison with existing studies and contributes to broader discussions on the economics of R&D. The remainder of this section presents the two methodological approaches in greater detail, while details on the test assets are provided in the next sub-section.

A robust approach to risk premia estimation

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

$$\mathbf{R}_t - R^f_{t-1} = \boldsymbol{\beta}\boldsymbol{\lambda} + \boldsymbol{\beta}\mathbf{v}_t + \mathbf{u}_t \,, \tag{24}$$

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 x_t of interest that is affine in the 'true' factors, with measurement error w_t,

$$x_t = \zeta_0 + \boldsymbol{\zeta}_v \mathbf{v}_t + w_t \,, \tag{25}$$

and show that the risk premia associated with it can be effectively estimated without bias. In this framework, the risk premium associated with x_t amounts to $\boldsymbol{\zeta}_v\boldsymbol{\lambda}$, which corresponds to the expected excess return of an asset with a beta of one with respect to x_t and zero with respect to any other independent factor.

The key to its estimation is that $\boldsymbol{\zeta}_v H^{-1}$ can be obtained by regressing x_t on $\hat{\mathbf{v}}_t$, while $H\boldsymbol{\lambda}$ can be obtained by regressing $\mathbf{R}_t$ on $\boldsymbol{\beta}H^{-1}$, the latter being estimated by regressing returns on the 'true' factors. This delivers all the necessary elements to recover $\boldsymbol{\zeta}_v\boldsymbol{\lambda}$, since

$$\boldsymbol{\zeta}_v H^{-1} H\boldsymbol{\lambda} = \boldsymbol{\zeta}_v\boldsymbol{\lambda} \,. \tag{26}$$

In this setting, a crucial modeling choice concerns the number of principal components treated as the 'true' risk factors of the economy. This analysis considers multiple specifications for the number of factors, guided by the standard approach of Bai and Ng (2002) and the criteria proposed in Alessi et al. (2010).[15] Equally important is the breadth of the test assets: the wider the span of economic states they represent, the more robust the control for omitted risk factors will be. Moreover, to allow the information contained in the shocks to be incorporated into prices gradually (Eberhart et al. 2004), the innovation long-run risk factor is examined both as contemporaneous shocks to effective R&D $\varepsilon_{s,t}$ and as rolling sums of these shocks. Specifically, results are reported for rolling sums with horizons of 1 quarter (i.e., contemporaneous shocks), two years (matching the analysis on cash flows), and four years (corresponding to the typical length of a business cycle).

A traditional estimation approach

Bansal et al. (2005) applies the standard procedure of Fama and Macbeth (1973) with two modification. First, they ignore the risk associated with short-term fluctuations in

[15] The latter consists of two criteria and is implemented by taking the median across 300 repetitions.

consumption growth, based on the empirical finding that such fluctuations account for a negligible portion of the equity risk premium (Mehra and Prescott 1985). This observation is precisely what motivates the focus on long-run risks, whose premia are predicted to be larger by orders of magnitude. Second, they measure asset risk by the sensitivity of cash-flow growth to the risk factors rather than by return sensitivities. This choice aligns more closely with the theoretical formulation of Long-Run Risk and other consumption-based models, in which return betas are endogenously determined by the sensitivity of cash flows to the risk factors.

The model they test is:

$$\mathbb{E}_t\left[R^i_{t+1}\right] - R^f_t = \lambda_x \beta^i_{x,D}\,, \tag{27}$$

where the dividend-beta, $\beta^i_{x,D}$, is estimated from the univariate time-series regression

$$\Delta \ln D^i_t = \beta^i_{0,D} + \beta^i_{x,D} \cdot \frac{1}{H}\sum_{l=1}^{H} \varepsilon_{s,t-l} + u^i_t\,. \tag{28}$$

Bansal et al. (2005) uses the raw series of consumption growth as regressor, so the moving average primarily serves to filter out high-frequency fluctuations and identify shifts in long-run consumption prospects. In contrast, since shocks to effective R&D are shown in the macroeconometric analysis to have persistent effects on consumption growth, they capture changes in long-run consumption prospects directly, without the need for filtering. To assess this, the sensitivity of the results to the aggregation horizon is examined, reporting outcomes both for the traditional horizon in Bansal et al. (2005) ($H = 8$ quarters) and for $H = 1$ quarter. Further details on this framework are provided in Appendix A.4.

3.4 Data

Macroeconomic data

The baseline measure of R&D in this study is the real US quarterly private R&D expenditures (chained 2017 dollars), consistent with closely related studies (Beqiraj et al. 2025; Kung and Schmid 2015; Moran and Queralto 2018). Private R&D reflects the profit-maximizing innovation decisions at the core of most endogenous growth models more directly than total R&D, since government expenditures operate through distinct institutional mechanisms, likely materializing in a fundamentally different knowledge production function. The total R&D series is used as a robustness check. Both series are provided by the Bureau of Economic Analysis (BEA) via the Federal Reserve Economic Data (FRED) online database and span 1947 Q1 to 2025 Q2.[16]

Total Factor Productivity is obtained following Fernald (2012). The baseline series is the quarterly TFP growth adjusted for utilization and excluding R&D from capital,

[16]The real series is obtained by deflating the nominal R&D series `Y006RC1Q027SBEA` with the deflator `Y006RG3Q086SBEA`. The total series has ID `Y694RX1Q020SBEA`.

while robustness checks use the raw TFP series. The utilization adjustment is preferred because removing cyclical utilization dynamics – like any non-idea-related factor – enhances the signal-to-noise ratio of the underlying technological component of productivity, thereby improving the precision of the estimates; the R&D capital is excluded because its construction through simple cumulation and depreciation of R&D flows is inconsistent with the knowledge production function studied in this work. Differences between the series mainly arise from the utilization adjustment, with minimal impact from the exclusion of R&D from capital. The series span 1947 Q2 to 2025 Q1, and levels are obtained by cumulating the growth rates.[17]

The labor force is measured by the total employment level, with non-farm employment used as a robustness check. Both series are provided monthly by the Bureau of Labor Statistics via FRED. The quarterly series is constructed by taking the last value of each quarter, spanning 1948 Q1 to 2025 Q2.[18]

The predicting factors consist of two distinct sets, previously employed to forecast TFP growth in Ai et al. (2018): (1) nine identified factors, extending those used in Bansal and Shaliastovich (2013); and (2) nine non-identified factors directly from Ludvigson and Ng (2009). These are referred to with the shorthands 'BS' and 'LN', respectively. The BS factors set originally comprised the US Cycle Adjusted Price Earnings (CAPE) ratio, the 3-month Treasury-bill yield, and the 3- and 5-year Treasury bond yields. Ai et al. (2018) later expanded this set to include the US stock market integrated daily volatility. This work additionally incorporates the 10-year Treasury bond yield, real US corporate profits, real US nonfinancial corporate liquid assets, and labor input growth, in order to better capture macroeconomic dynamics at longer horizons, as well as aspects related to financing conditions, profitability, and product proliferation — all known to influence productivity and R&D decisions. These controls span 1951 Q4 to 2025 Q1.[19] The LN factors set instead is formed by the principal components of a wide array of macroeconomic and financial variables. These series have monthly frequency and are aggregated as quarterly averages, yielding a time span from 1960 Q1 to 2025 Q2.[20] As illustrated in Appendix C, all BS variables appear to exhibit unit-root behaviour, whereas there is only weak evidence of non-stationarity among the LN factors. Therefore, while the LN factors are used in levels, the BS factors are included in first differences to mitigate the risk of spurious regression.

Finally, consumption is measured as real total personal consumption expenditures per capita, in chained 2017 US dollars. The series is provided by the BEA via FRED and span 1947 Q1 to 2025 Q2.[21]

More details on the data can be found in Appendix B.1.

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[17] The data are provided online by the author and also include the utilization adjustment and changes in capital excluding R&D.

[18] IDs: `CE16OV` and `LNS12035019`.

[19] CAPE is from R. Shiller's website; bill and bond yields are from Finaeon until the first availability of `DGS3MO`, `DGS3`, `DGS5`, and `DGS10` on FRED; daily stock market data is from CRSP. US corporate profits and liquid assets are the series `CPROFIT` and `BOGZ1FL104001005Q` on FRED, deflated by `GDPDEF` from FRED.

[20] Publicly available on S. Ludvigson's website.

[21] ID: `A794RX0Q048SBEA`.

Test assets data

The selection of test assets for the robust risk premia estimation is guided by the need to cover as broad a portion of the economic state space as possible, ensuring that the resulting estimates are generalizable and robust. Expanding on the approach of Bryzgalova et al. (2025), this work employs 153 anomaly stock portfolios from Jensen et al. (2021), 17 industry-sorted stock portfolios from K. French's database, and 13 bond portfolios. The bond portfolios are constructed from the zero-coupon yield data of Gürkaynak et al. (2007) by fitting Nelson-Siegel-Svensson curves and subtracting the return on a three-month Treasury bill. These portfolios span maturities of 6 months and 1, 2, 3, 4, 5, 6, 7, 10, 15, 20, 25, and 30 years. The final dataset covers the period from 1971 Q4 to 2024 Q4.

The test assets employed for the Bansal et al. (2005) exercise include only stock portfolios, as in the original study: 10 sorted by size, 10 by book-to-market equity, and 10 by past-year returns. This set is referred to as the 'legacy pool'. It is expanded with 2-by-3 portfolios jointly sorted by size (big vs. small) and various firm characteristics related to R&D investment to form the 'extended pool', and further complemented by 17 industry portfolios to form the 'wide pool'. The firm characteristics considered in the extended pool capture (i) the intensity of innovative efforts (*firm-specific* R&D ratio to market capitalization), (ii) financing capacity (leverage, turnover, and profitability), and (iii) growth opportunities (assets growth and Tobin's q). These dimensions have been associated with dispersion in cross-sectional risk premium and different forms of sensitivity to innovation dynamics, therefore are likely to generate heterogeneity in exposure to the long-run risk carried by aggregate R&D. Specifically, variation in firms' R&D intensity affects the spillovers and 'fishing out' effects experienced by a firm, which Jiang et al. (2016) showed to be priced in financial markets, while financing capacity and growth opportunities interact with aggregate R&D investment by affecting firms' ability to react to innovation shocks (Aghion et al. 2012; Brown et al. 2009; Hall 2002; Hall et al. 2010; Li 2011; Maletic 2018; Zhang 2014). Their inclusion further provides descriptive statistics that contribute to the discussion on the cross-sectional variation in returns with firm-specific R&D intensity, which, since its first documentation in Chan et al. (2001), remains debated (Ahmed et al. 2025; Leung et al. 2020). The payout series is constructed following Bansal et al. (2005) and Hansen et al. (2005), with details provided in Appendix B.2. Monthly stock data come from CRSP, and annual accounting data from the Compustat Fundamentals dataset. Monthly returns are compounded to obtain quarterly figures and then deflated using the consumption deflator. The portfolio return and cash-flow growth rate series begin at different dates: the long-pool and industry-sorted portfolios start in 1967 Q1, while the others begin in 1975 Q1; all series end in 2022 Q4. Key statistics of the formed series are reported in Appendix B.2.

4 The empirical innovation component

4.1 The gross effective R&D

The estimation results for the long-run relation in (17) are shown in Table 1. The first column of the table shows the baseline specification, with the columns to the right substituting one variable at a time with the alternative robustness measure. The last column uses the baseline data but employs the IM-OLS method instead.

First, the α_Z estimates have the expected sign and are always significantly different from zero. Simply put, this means that R&D expenditure and TFP levels increase together; raw R&D rises with the scale of the economy, as expected. A similarly expected coefficient is that of labor, α_L, which suggests some dilution in R&D's power to advance the technological frontier and implies a mediating effect on how R&D expenditure relates to the technological frontier to obtain a meaningful measure of effective R&D. The only exception occurs when total R&D is used, highlighting the possibility that public R&D may operate through a different production function than private R&D.[22] Further, the use of nonfarm employment does not result in discernible changes, while the use of raw TFP, although it does not materially affect the estimates, alters the short-term fluctuations in the resulting error correction term, as can be seen from the plots of all ECT time series in Appendix C (Figure 10). Visual inspection of the time series also reveals the considerable instability of the IM-OLS estimates, as reflected by the large condition number of the coefficients' covariance matrix κ, even though the estimates essentialy confirm the baseline results.

The lower part of Table 1 reports descriptive statistics of the error correction term resulting from the estimation, i.e., the time series of $\hat{s}_t$. All estimated gross effective R&D series are found to be stationary according to both the ADF and KPSS tests, with none exhibiting a time trend or a squared time trend. The persistency of the series, as measured by an AR(1) fit, is in line with the persistent component of productivity growth that is transmitted to consumption growth, which Ortu et al. (2013) and Croce (2014) has shown having a half-life between 2 and 16 years. As shown in Appendix C (Table 10), correlations among ECTs from different specifications never drop below 86%, consistent with the close estimation results, except for the IM estimation.

4.2 The effective R&D

The estimated $\hat{s}_t$ series allows for the estimation of equation (20), which yields γ_1, the missing parameter required to recover the effective R&D series. Information criteria (Appendix C, Figure 8) select one lag for specifications based on the adjusted TFP measure and two lags for those based on the raw TFP measure. The corresponding results are reported in Table 2.

The estimated R&D coefficient is consistently positive and statistically significant, confirming a strong empirical relationship between innovation intensity and productivity growth. Its magnitude closely matches the empirical estimates in Kung and Schmid (2015) and implies

[22] Unreported estimates are in fact significantly negative when only public R&D is used

Table 1: Cointegration results. Standard errors in parentheses. T is the number of observations; κ is the condition number of the coefficients' covariance matrix. Statistics in the bottom part of the table refer to the error correction term $\hat{s}$: $\sigma_{\hat{s}}$ is its standard deviation; tt and tt^2 are the time trend and squared time trend coefficients (with HAC standard errors); *ADF* and *KPSS* are stationarity tests in levels; *AR(1)* is the coefficient from an AR(1) fit; *HL* are the lower and upper bounds, at 95% confidence, of the half-life implied by the AR(1) estimate, in years.

	Baseline	S**: Tot. R&D**	Z**: Raw TFP**	Q**: N.F. Empl.**	**Est. Meth.: IM**
α_Z	3.526***	4.197***	3.655***	3.349***	2.821***
	(0.439)	(0.516)	(0.490)	(0.464)	(0.552)
α_L	0.909***	−0.354	0.956***	0.953***	1.387***
	(0.336)	(0.395)	(0.356)	(0.325)	(0.398)
T	309	309	309	309	309
κ	3.4×10^6	3.4×10^6	3.3×10^6	3.5×10^6	1.1×10^8
			$\hat{s}_t$		
$\sigma_{\hat{s}}$	0.130	0.144	0.128	0.129	0.253
tt	0.00	0.00	0.00	0.00	0.00
tt^2	0.00	0.00	0.00	0.00	0.00
ADF	−2.57**	−2.45**	−2.92***	−2.45**	−9.18***
KPSS	0.09	0.09	0.09	0.10	0.29
AR(1)	0.96	0.96	0.95	0.97	0.15
HL low	2.6	2.7	2.1	2.7	0.1
HL high	21.0	23.6	12.0	25.1	0.1

* p <0.1, ** p <0.05, *** p <0.01

an annualized increase of about 0.8% in TFP growth following a one-standard-deviation increase in $\hat{s}_t$. Control variables are always jointly significant, and specifications using LN-based controls consistently achieve higher explanatory power, as reflected in higher R^2 values and lower information criteria.

Table 2 also reports the estimated implied κ_s and the recovered $\tilde{s}_t$ series. Specifically, $\tilde{s}_t$ is obtained by applying equation (19) for each t in the sample, using parameter estimates of α_Z from Table 1 and b_s from Table 2. The series are trimmed at the beginning of the sample, up to the first t such that $\kappa_s^t < 0.01$, ensuring that the influence of the unobserved initial condition is negligible, as the omitted portion corresponds to only one-hundredth of $\tilde{s}_0$. Appendix A.3 provides a detailed discussion of the uncertainty in this recovery, arising both from the initial condition approximation and the estimation noise, and it also includes details on the computation of the reported standard errors. Figure 11 in Appendix C shows all recovered series with confidence intervals, illustrating that precision greatly varies across specifications. The series from the baseline specification, in particular, exhibit the smallest uncertainty, primarily reflecting the lower uncertainty in the estimates of b_s. Descriptive statistics reported in the lower panel of Table 2 indicate broadly consistent time series volatility across specifications. The recovered series display no trend, are stationary as confirmed by ADF and KPSS tests, and exhibit substantially lower persistence than the $\hat{s}_t$

Table 2: One-step productivity growth forecast results. HAC standard errors in parentheses. T is the number of observations; R^2 is the goodness-of-fit; k is the number of control variables among the regressors; $W(k)$ is the Wald statistic for their joint significance. Details on κ_s and its standard errors are in Section A.3. The lower panel reports statistics for the recovered time series $\tilde{s}$ (see Section 3.1): $\sigma_{\tilde{s}}$ is its standard deviation; tt and tt^2 are the coefficients of the linear and quadratic time trends (with HAC significance levels); *ADF* and *KPSS* are stationarity tests in levels; *AR(1)* is the autoregressive coefficient from a first-order fit; *HL* are the 95% confidence bounds of the implied AR(1) half-life, in years.

	Baseline		**S: Tot. R&D**		**Z: Raw TFP**		**Q: N.F. Empl.**	
	BS	*LN*	*BS*	*LN*	*BS*	*LN*	*BS*	*LN*
b_s (%)	1.558***	1.549***	1.066***	1.223***	0.997***	0.794**	1.507***	1.520***
	(0.429)	(0.285)	(0.318)	(0.254)	(0.355)	(0.337)	(0.418)	(0.289)
T	292	261	292	261	291	260	292	261
R^2 (%)	9.5	12.4	7.4	11.8	21.8	41.7	9.1	12.2
k	10	10	10	10	20	20	10	10
$W(k)$	79.97***	61.00***	64.56***	50.27***	287.53***	2775.10***	73.09***	61.99***
κ_a	0.964	0.971	0.950	0.949	0.945	0.945	0.955	0.949
	(0.014)	(0.013)	(0.016)	(0.012)	(0.017)	(0.012)	(0.014)	(0.012)
				$\tilde{s}_t$ $(\kappa_a^t < 0.01)$				
$T_{\tilde{s}}$	226	225	207	220	183	151	219	219
$\sigma_{\tilde{s}}$	0.058	0.057	0.068	0.065	0.060	0.062	0.055	0.055
tt	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
tt^2	0.00	0.00	0.00	0.00	0.00***	0.00***	0.00	0.00
ADF	−3.91***	−3.95***	−3.17***	−3.49***	−3.95***	−3.50***	−3.56***	−3.56***
KPSS	0.09	0.09	0.18	0.13	0.22	0.19	0.14	0.14
AR(1)	0.71	0.70	0.72	0.68	0.68	0.70	0.70	0.70
HL low	0.4	0.3	0.4	0.3	0.3	0.3	0.3	0.3
HL high	0.8	0.8	0.8	0.7	0.7	0.8	0.7	0.7

* p <0.1, ** p <0.05, *** p <0.01

series. Notably, both the persistence of $\tilde{s}$ and the magnitude of b_s are significantly lower than those assumed in the theoretical model of Kung and Schmid (2015). This discrepancy is not problematic, as the econometric framework developed in this work accounts for feedback effects between innovation and external components – a feature absent in that model but useful for capturing the complex propagation of R&D shocks through the economy.

Figure 2 plots the baseline $\hat{s}_t$ series alongside the $\tilde{s}_t$ series corresponding to the baseline specification using controls based on LN factors, chosen for their superior explanatory power, though the series obtained from BS factors is virtually identical. This $\tilde{s}_t$ series will serve as the baseline for subsequent analysis. Since the difference between $\hat{s}_t$ and $\tilde{s}_t$ is proportional to the external component a_t, the figure already highlights a strongly pro-cyclical behavior of innovation efforts, consistent with the predictions of Kung and Schmid (2015) and related contributions.

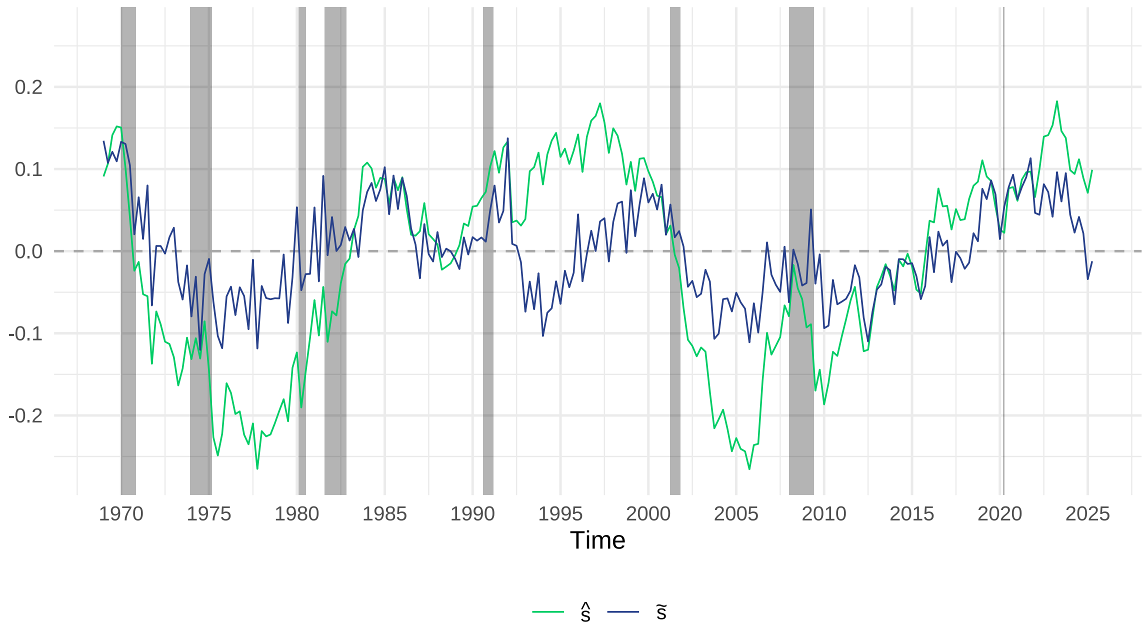


Figure 2: Baseline effective R&D measures. Shaded areas mark NBER recessions.

4.3 Previous evidence

By construction and purpose of use, the closest measure in the literature is Kung and Schmid (2015). They focused on a specification of effective R&D defined as the simple ratio S_t/I_t. The empirical counterpart was constructed as the ratio of U.S. annual private R&D expenditures reported by the National Science Foundation (measuring S_t) to the R&D stock series estimated by the U.S. Bureau of Labor Statistics (representing intangible capital I_t). They showed that this measure of effective R&D fulfilled several theoretical predictions: it was highly persistent, co-moved at low frequencies with the price-dividend ratio, and univariately forecasted the growth rates of consumption, GDP, and TFP up to 5 years.

Their measure, however, presents a few shortcomings, documented in greater detail in Appendix C (Table 13).[23] Most notably, it exhibits extreme persistence, with a first-order annual autocorrelation of 0.995, with standard error 0.063. This estimate raises two potential concerns: the upper confidence bound indicates a significant risk of non-stationary behavior, while the lower bound implies persistence that may be excessively high for the productivity component it is intended to capture. Formal stationarity tests yield conflicting results: the ADF test rejects non-stationarity at the 10% level, while the KPSS test rejects stationarity at 1%, with visual inspection of the series more consistent with the latter result. While non-stationarity would not undermine the theoretical validity of the measure and the underlying theory, it would pose serious challenges for empirical applications due to the heightened risk of spurious regression results. Even disregarding stationarity concerns, an implied half-life exceeding 40 years raises questions about its economic interpretation. This

[23]It should be noted that the R&D stock series has been updated by the provider and now covers a slightly different time period.

persistence far exceeds that of the productivity LRR component documented in Croce (2014) and Ortu et al. (2013), which, as noted earlier, never exceeds 20 years. Although this level of persistence aligns with the consumption-based LRR calibration in Bansal and Yaron (2004), it appears too long-lived to accurately reflect the productivity channel of long-run risk. These findings cast doubt on the suitability of this effective R&D specification for identifying the productivity LRR component within this empirical framework.

The problematic dynamics of the effective R&D used by Kung and Schmid (2015) may stem from the data employed, as the measure of the stock of ideas they use is constructed through simple accumulation and depreciation of R&D expenditures, deviating from the law of motion assumed in the model. To address this inconsistency, one could construct an alternative effective R&D measure by substituting TFP for the stock of ideas (as previously argued), maintaining the assumption of labor-augmenting technology, and calibrating it using standard labor share values from the literature, as well as employing the longer datasets used in this work. However, the results exhibit similar, if not more pronounced, issues (see Table 13). The root cause likely lies in the lack of flexibility in the strength of knowledge spillovers from past innovations in the Kung and Schmid (2015) framework, a limitation that recent work, such as Bloom et al. (2020), has highlighted as crucial for achieving a good empirical fit to the data.

Another closely related measure is proposed by Kogan et al. (2017), who link changes in market valuations to patent announcements to assess the private value of successful innovations. Whereas their measure captures the outcome of the innovation process, effective R&D reflects its input side. The two measures thus offer complementary perspectives on innovation. For the purposes of this paper, however – namely, constructing a process that forecasts future innovation and productivity growth – effective R&D is particularly suitable. This is further supported by the results in Appendix C (Table 14), which show that effective R&D Granger-causes the innovation measure of Kogan et al. (2017), but not vice versa.

5 The long-run impact of effective R&D shocks

Table 3 reports the key statistics from the estimation of (22), for different specifications of $\hat{s}$ and, in the last column, for the baseline estimate of $\tilde{s}$. The maximum number of lags considered is 10, with the Akaike, Hannan–Quinn, and Bayesian information criteria generally agreeing on the optimal lag length, except for the specification using raw TFP, for which the most parsimonious lag order indicated by the criteria is applied. The predictability of TFP growth, as measured by the equation R^2, is comparable to those estimates in Croce (2014) that are based on samples of similar length. The system and its estimates appear reliable: the moduli of the companion matrix roots lie well within the unit circle, and the condition number of the residual covariance matrix is moderate.

Tests on the VAR residuals, reported in the middle panel of Table 3, indicate significant heteroskedasticity in the effective R&D residuals for all specifications except that using $\tilde{s}$, and no significant autocorrelation at any horizon up to 10 years (based on heteroskedasticity-robust

Table 3: VAR estimation diagnostics. *N. Obs.* and *N. Lags* denote the number of observations and VAR lags; $R^2_{\Delta Z}$ is the fit of the TFP growth equation; max |roots| is the largest root of the companion matrix; κ is the condition number of the residual covariance matrix. *H-LM* are 1-year horizon heteroskedasticity tests for TFP growth and effective R&D; *AC-LM* are heteroskedasticity-robust autocorrelation tests at different lags; *F-GC(s)* is the F-test for Granger causality with respect to effective R&D.

	Baseline	S**: Tot. R&D**	Z**: Raw TFP**	Q**: N.F. Empl.**	$\tilde{s}$
N. Obs.	305	305	306	305	223
N. Lags	3	3	2	3	2
$\mathrm{R}^2_{\Delta Z}$ (%)	5.3	4.4	4.8	5.3	2.8
max |roots|	0.92	0.90	0.93	0.92	0.93
κ	2.2×10^3	5.7×10^3	2.7×10^3	2.2×10^3	2.8×10^3
H-LM(ΔZ, 4)	3.2	2.3	22.6***	3.3	4.9
H-LM(s, 4)	30.2***	27.0***	33.2***	29.4***	6.4
AC-LM(1)	5.8	6.3	6.2	5.1	7.2
AC-LM(8)	29.4	37.9	41.9	26.7	37.5
AC-LM(16)	69.6	68.6	69.3	69.6	69.1
AC-LM(40)	169.4	155.7	166.9	165.9	154.7
GC-F(s)	5.3***	6.5***	6.1***	5.5***	1.7

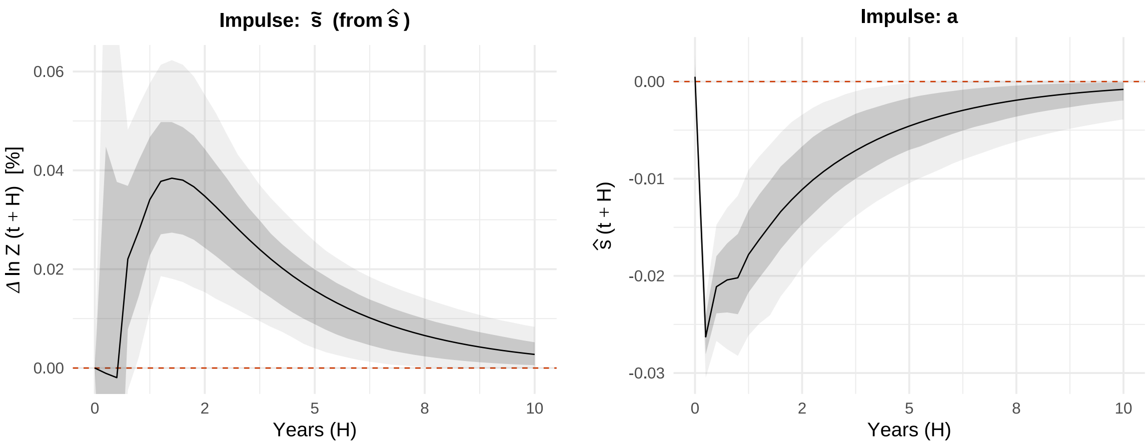
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

wild-bootstrap tests as in Ahlgren and Catani (2017)).

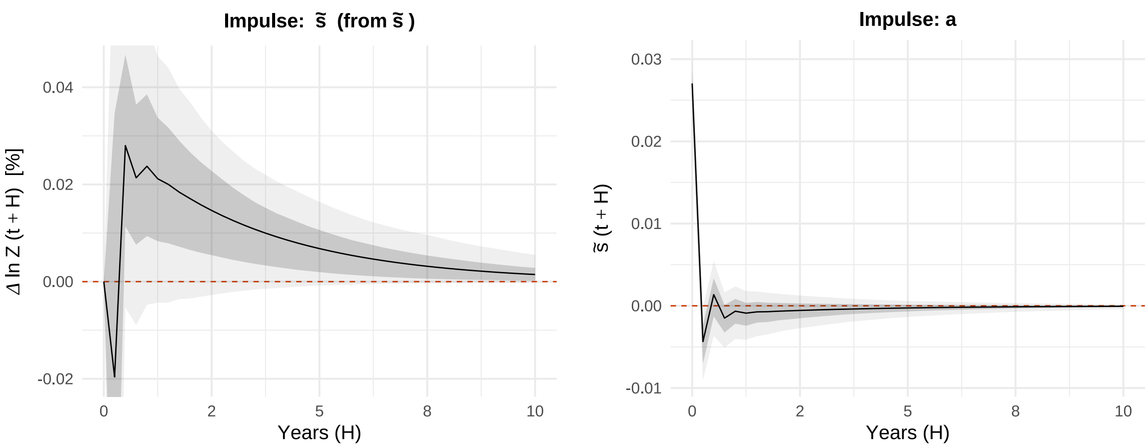
Turning to system dynamics, the Granger causality Wald test (based on a HAC covariance matrix) for effective R&D is always highly significant, except for the specification using $\tilde{s}$, whose p-value (18%) still provides some evidence of predictive content. This weaker result is likely influenced by the shorter sample length and greater measurement error, both of which can substantially limit test power.

IRFs for the two key specifications – the baseline models using $\hat{s}$ and $\tilde{s}$ – are displayed in Figure 3. Structural shocks to effective R&D are always highly persistent: for the $\hat{s}$-based estimates, the 95% confidence interval includes zero only at horizons approaching 10 years. As expected, the $\tilde{s}$-based estimates are noisier, producing wider confidence intervals, but display broadly comparable dynamics, with the 68% confidence interval reaching zero only close to the 10-year horizon. Both specifications support the hypothesis of a null immediate effect of effective R&D on the external factor, assumed in Section 3.1: the response of TFP growth becomes significantly different from zero only after about one year. The systems differ in their response to external productivity shocks: gross effective R&D decreases on impact, while net effective R&D reacts positively. The difference stems from $\hat{s}$ incorporating the external component negatively, whereas $\tilde{s}$ excludes it, thereby confirming the commonly assumed procyclicality of R&D investment.

The cumulative IRFs to the structural shocks identified in the VAR estimated via local projections are shown in Figure 4 (corresponding R^2 values are reported in Appendix C, Figure 9). Since the aim of the local projection exercise is to provide more robust evidence on



(a) Using gross effective R&D



(b) Using net effective R&D

Figure 3: VAR impulse response functions of productivity growth ($\Delta \ln Z$) and effective R&D to structural shocks. Panel (a) shows estimates using the gross effective R&D measure $\hat{s}$, while panel (b) shows estimates using the net effective R&D measure $\tilde{s}$. Shaded areas indicate 95% confidence intervals based on recursive residual bootstrap standard errors. The horizon H is expressed in years.

the dynamic impact of R&D shocks, these projections include five lags of both the external factor and the dependent variable (in levels), chosen to exceed the annual data frequency. With effective R&D shocks from $\hat{s}$, both productivity and consumption cumulative growth show significant positive effects at the 10-year horizon, and, in the case of productivity, an even larger effect at the 20-year horizon. Consumption responds significantly at horizons of 15-20 years only when LN controls are used, which also produce a higher R^2 than the BS factors (Figure 9). Shocks from $\tilde{s}$ yield weaker effects at the 10-year horizon but stronger effects between 15 and 20 years. Overall, shocks to effective R&D orthogonalized to TFP growth shocks appear to have a significant influence on long-run prospects for productivity and consumption.

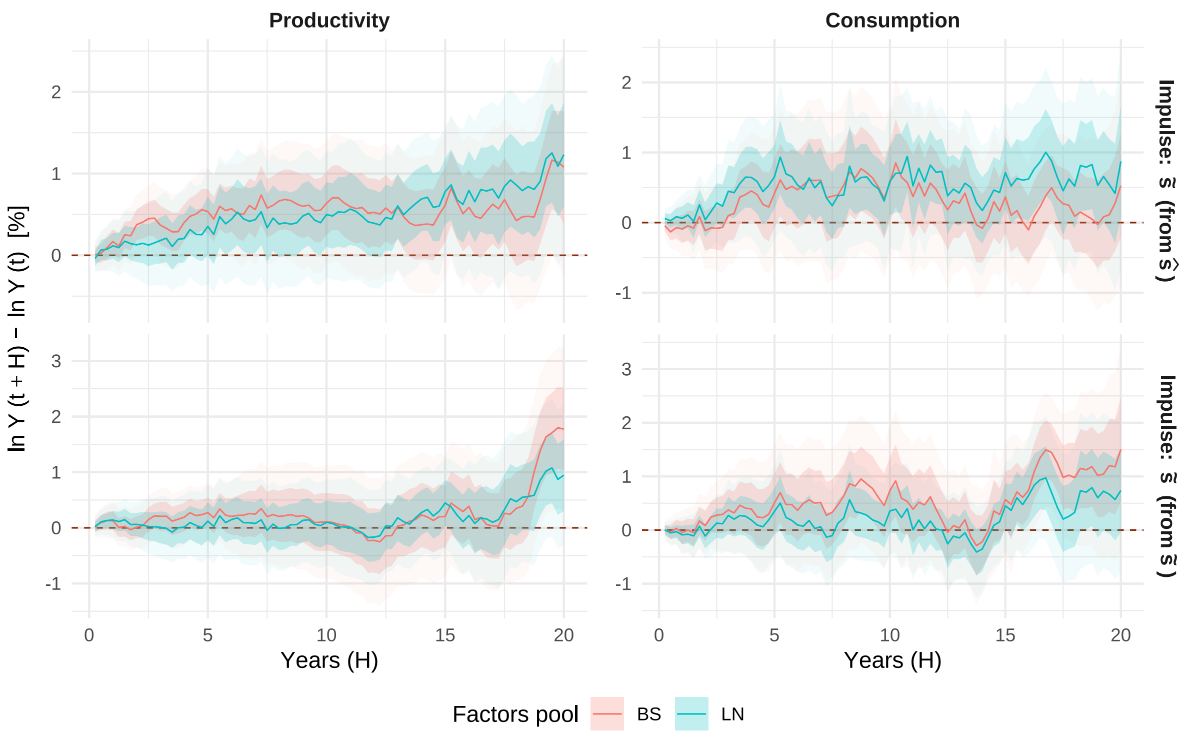


Figure 4: Local projection cumulative impulse response functions of productivity growth ($\Delta \ln Z$) and consumption growth ($\Delta \ln C$) to effective R&D shocks. Top panels show responses to gross effective R&D shocks ($\hat{s}$), while bottom panels show responses to net effective R&D shocks ($\tilde{s}$). Shaded areas indicate 68% and 95% confidence intervals based on Montiel Olea and Plagborg-Møller (2021). BS and LN refer to different factor sets used as controls. Goodness of fit measures (R^2) are shown in Figure 9. The horizon H is expressed in years.

6 The cross-sectional risk premium

6.1 Risk premia estimates

The optimal number of factors in the cross-section of the 183 test assets used for the robust estimation of risk premia is estimated at 6 and 14 under the two criteria of Alessi et al. (2010), while the three criteria of Bai and Ng (2002) suggest 39, 22, and one diverging estimate. Since all values from Bai and Ng (2002) are substantially higher than those from Alessi et al. (2010), which was specifically proposed as an improvement on the former, only the minimum estimate from Bai and Ng (2002) is retained. The first six principal components explain 35.4% of the variance in returns, the first fourteen account for 51.1%, and the first twenty-two for 60.4%. Scree plots of the principal component analysis are shown in Figure 13, Appendix C. A more relevant criterion for identifying the factors closest to the 'true' ones, however, is their ability to price the cross-section of test assets. This depends on their associated market-wide risk premia, which, combined with the test assets' betas, yield predictions for expected returns. From this perspective, the first six factors explain 47.0% of the cross-sectional variance, the first fourteen account for 70.7%, and the first twenty-two reach 83.0% (values for all factors are shown in Figure 14). Notably, factors 7

Table 4: Risk premia estimation following Giglio and Xiu (2021). Each column reports the risk premia associated with the respective specification of effective R&D structural shocks, based on the corresponding estimations in Table 3. t-statistics are reported in square brackets. The test assets are 183 portfolios spanning 1971 Q4 to 2023 Q4. The number of factors (6, 14, and 22) corresponds to optimal selections per Alessi et al. (2010) and Bai and Ng (2002), with 22 being the smallest optimal number from the latter method.

	Baseline	S: **Tot. R&D**	Z: **Raw TFP**	Q: **N.F. Empl.**	$\tilde{s}$
		Horizon: 1 quarter			
6 Factors	0.01	0.02	0.02	0.02	0.02
	[0.93]	[0.90]	[1.22]	[1.03]	[1.28]
14 Factors	0.04	0.03	0.05	0.04	0.04
	[1.32]	[0.74]	[1.35]	[1.12]	[1.08]
22 Factors	−0.01	−0.09	0.01	−0.02	−0.04
	[−0.21]	[−1.30]	[0.09]	[−0.38]	[−0.55]
		Horizon: 2 years			
6 Factors	0.06	0.04	0.08*	0.06	0.10
	[1.63]	[0.91]	[1.87]	[1.63]	[1.44]
14 Factors	0.22**	0.12	0.27***	0.19**	0.29*
	[2.35]	[1.24]	[2.92]	[2.05]	[1.86]
22 Factors	0.15	0.11	0.23*	0.10	0.18
	[1.12]	[0.73]	[1.81]	[0.74]	[0.84]
		Horizon: 4 years			
6 Factors	0.08	0.07	0.09	0.08	0.11
	[1.33]	[1.11]	[1.33]	[1.36]	[0.97]
14 Factors	0.48***	0.34**	0.52***	0.45***	0.69***
	[3.28]	[2.50]	[3.52]	[3.11]	[2.75]
22 Factors	0.54***	0.43**	0.61***	0.48**	0.80**
	[2.80]	[2.23]	[3.17]	[2.52]	[2.28]
Num.Obs.	213	213	213	213	213

* p <0.1, ** p <0.05, *** p <0.01

through 14 account for only 15% of the time-series variation in returns, yet explain 24% of the cross-sectional variation. This suggests that their economic relevance in this application is likely under-estimated by the first Alessi et al. (2010) criterion.

Table 4 reports the estimated risk premia associated with the effective R&D structural shocks, for each optimal number of factors identified by the selection criteria. The first panel, where contemporaneous shocks are used, shows no premia significantly different from zero. By contrast, the second and third panels, where the factor is constructed using moving averages of the shocks at 2-year and 4-year horizons, display sizable and significant premia linked to innovation long-run risk. An exception arises only with the lowest number of test-asset factors: in that case, the premia are not statistically significant, although most t-statistics remain above 1, suggesting some evidence of priced risk. As discussed earlier, this pattern may reflect measurement error that is averages out over time as well as investors' underreaction to R&D news, consistent with Eberhart et al. (2004). The estimated premia are fairly stable across specifications, at about 2% per year. Overall, the results support the prediction that fluctuations in effective R&D are positively priced by investors.

6.2 The cash-flow channel

Table 5 reports the estimated dividend-betas for the additional portfolios in the extended pool relative to the legacy pool. Appendix C.1 reports the sensitivities for the other test assets employed. Regarding effective R&D, the results refer to the baseline structural shock and the baseline levels of (net) effective R&D , $\tilde{s}$.

Consumption sensitivities are predominantly positive, whereas exposures to other risks are often negative, particularly with respect to effective R&D levels. Across horizons, dividend-betas with respect to effective R&D, both structural shocks and levels, are stable. Consumption sensitivities are likewise stable, except for the RD (3-small) portfolio, which exhibits a significant sign reversal. By contrast, dividend-betas with respect to TFP vary sharply, especially in the adjusted specification, suggesting that differences in the moving-average horizon lead the regressor processes to capture different risks.

Regarding the portfolio sorting, several regularities emerge for innovation long-run risk. First, bigger firms consistently show smaller sensitivity in payout growth rates across all sortings, a pattern that extends to other systemic long-run risks as well. For innovation long-run risk specifically, these sensitivities are all negative. Second, dividend-betas are negative across most firm-specific R&D-intensity levels. The exception is small, highly R&D-intensive firms, which exhibit a distinctive response depending on the nature of aggregate R&D changes: their payouts raise when increases are unexpected, but fall when predictable components are included (i.e. with respect to overall effective R&D changes). Third, among small firms, variables related to financing capacity – turnover, profitability, and leverage – correlate positively with sensitivities, whereas those capturing investment opportunities show the opposite pattern, with Tobin's q exhibiting a particularly strong negative relation with payout betas.

A full structural interpretation of the observed patterns in dividend-betas is beyond the scope of this work, but the evidence appears broadly consistent with: (i) firms benefiting from peers' higher R&D investment, unless they simultaneously raise their own R&D investment in response to predictable aggregate R&D increases; (ii) a greater ability to generate internal cash flows – higher turnover and profitability – improving the ability to react to aggregate innovation news, particularly in smaller, typically more constrained firms, although evidence from leverage-sorted portfolios is ambiguous;[24] (iii) aggregate innovation tends to reduce payout growth of 'leading' firms, i.e. the largest and the fastest-growing ones.

[24] In general, higher leverage implies reduced financial slack or even distress. This is difficult to reconcile with the finding that high-leverage portfolios do not exhibit the strongest consumption sensitivities. A more consistent interpretation is that leverage partly proxies for better access to external finance rather than distress, possibly reflecting omitted firm characteristics correlated with leverage—an issue likely exacerbated by the coarse two-by-three sorting used here.

Table 5: Dividend betas for additional test assets from the extended pool at a 1-quarter and 2-year horizons (1975 Q1–2022 Q4). Stocks are double-sorted into 2×3 portfolios by size (NYSE median) and accounting characteristics: *RD* (R&D/market cap), *To* (sales/assets), *Prof* (gross profits/assets), *Lvg* (debt/assets), *AG* (asset growth), and *TQ* (Tobin's Q). Risk factors: Cons. (consumption growth), Raw/Adj. TFP (raw/adjusted total factor productivity), $\tilde{s}$: shock/level (effective R&D shock/level).

Portfolio	**Cons.**		**Raw TFP**		**Adj. TFP**		**$\tilde{s}$: shock**		**$\tilde{s}$: level**	
Horizon	*1*	*8*	*1*	*8*	*1*	*8*	*1*	*8*	*1*	*8*
RD(1-small)	0.09	0.18	0.05	0.39	−0.07	0.03	0.01	0.00	−0.59	−0.58
RD(2-small)	0.06	0.04	0.02	0.46	−0.11	0.19	0.04	−0.02	−1.16	−0.73
RD(3-small)	0.75	−0.68	0.59	1.17	−0.35	0.45	0.54	1.09	−1.55	−3.37
RD(1-big)	0.01	0.03	0.00	0.08	−0.02	−0.01	0.00	−0.03	−0.27	−0.29
RD(2-big)	0.05	0.12	0.01	0.23	−0.03	0.00	0.03	−0.07	−0.36	−0.28
RD(3-big)	0.03	0.09	−0.01	0.24	−0.07	−0.09	−0.02	−0.17	−1.20	−1.20
To(1-small)	0.05	0.13	0.05	0.27	−0.01	0.03	0.02	0.06	−0.25	−0.76
To(2-small)	0.10	0.29	−0.01	0.81	−0.13	0.22	0.01	0.28	0.20	0.99
To(3-small)	0.38	1.06	0.23	1.85	−0.15	0.08	0.12	0.75	2.64	3.53
To(1-big)	0.01	0.06	−0.01	0.08	−0.02	−0.02	−0.01	−0.05	−0.31	−0.40
To(2-big)	0.03	0.09	0.00	0.17	−0.03	−0.03	0.00	−0.07	−0.45	−0.32
To(3-big)	0.04	0.11	0.03	0.29	−0.05	0.02	0.03	0.02	−0.21	−0.24
Prof(1-small)	0.00	−0.01	−0.02	0.20	−0.07	0.11	0.01	−0.18	−1.15	−0.82
Prof(2-small)	0.23	0.58	0.11	0.97	−0.13	−0.12	0.06	0.42	1.00	0.56
Prof(3-small)	0.38	1.34	0.19	2.29	−0.15	0.35	0.09	0.71	3.98	6.16
Prof(1-big)	0.01	0.05	0.00	0.09	−0.02	−0.02	−0.01	−0.02	−0.25	−0.22
Prof(2-big)	0.03	0.08	0.00	0.16	−0.03	−0.09	0.00	−0.12	−0.64	−0.67
Prof(3-big)	0.05	0.13	0.02	0.34	−0.06	0.14	0.03	−0.05	−0.41	−0.07
Lvg(1-small)	0.01	0.15	−0.01	0.20	−0.05	−0.05	0.02	−0.09	−0.73	−0.68
Lvg(2-small)	0.18	0.47	0.08	1.03	−0.19	0.22	0.06	0.17	−0.86	0.00
Lvg(3-small)	0.10	0.30	0.04	0.75	−0.06	0.07	0.01	0.24	1.21	1.54
Lvg(1-big)	0.03	0.09	0.01	0.19	−0.04	−0.01	0.00	−0.07	−0.61	−0.52
Lvg(2-big)	0.02	0.08	0.00	0.14	−0.03	−0.06	0.00	−0.08	−0.36	−0.41
Lvg(3-big)	0.02	0.04	0.00	0.10	−0.02	0.02	0.00	−0.03	−0.19	−0.08
AG(1-small)	0.19	0.82	0.01	1.66	−0.13	0.18	0.04	0.67	2.84	3.12
AG(2-small)	0.18	0.43	0.08	1.02	−0.20	0.16	0.05	−0.07	−1.57	−0.27
AG(3-small)	0.09	0.19	0.05	0.38	−0.05	0.04	0.03	0.09	0.29	0.47
AG(1-big)	0.06	0.14	0.00	0.29	−0.09	−0.05	0.01	−0.14	−1.02	−0.84
AG(2-big)	0.02	0.05	0.01	0.21	−0.01	0.01	0.00	−0.06	−0.30	−0.49
AG(3-big)	0.01	0.07	0.00	0.08	−0.03	−0.02	0.00	−0.04	−0.29	−0.01
TQ(1-small)	0.35	0.87	0.05	2.43	−0.50	0.78	0.18	0.27	−1.51	1.92
TQ(2-small)	0.14	0.65	0.01	1.10	−0.12	−0.15	0.06	0.20	0.36	0.63
TQ(3-small)	0.06	0.14	0.05	0.24	−0.01	0.00	−0.01	−0.06	−0.13	−0.37
TQ(1-big)	0.03	0.15	−0.01	0.25	−0.06	−0.09	−0.02	−0.06	−0.51	−0.47
TQ(2-big)	0.01	0.09	−0.01	0.15	−0.03	−0.07	0.01	−0.05	−0.43	−0.52
TQ(3-big)	0.03	0.03	0.03	0.14	−0.03	0.10	0.01	−0.07	−0.35	0.03

Resulting estimates of risk premia from the cross-sectional step are reported in Table 6. Notably, the premia associated with consumption cash-flow risk differ markedly across horizons: they are highly significant at the 1-quarter horizon but only barely significant in the wide pool at the 2-year horizon. This decline is even more apparent in the cross-sectional R^2, which falls from roughly 20–30% to a range of 2–50% across pools. The magnitude of the premia, at the horizon common to Bansal et al. (2005), exceeds theirs but remains well within the confidence intervals.

Risk premia associated with productivity long-run risk, as measured based on moving averages of raw TFP, are much more consistent: premia are significant for two of the three test-asset pools at both horizons and explanatory power increases at the 2-year horizon. By contrast, estimates based on adjusted TFP are less stable across horizons, exhibiting negative premia at the 1-quarter horizon and positive premia at the 2-year horizon, with R^2 comparable to those for raw TFP, except in the legacy pool, where R^2 drops by over 50%.

Like productivity, the premia associated with innovation long-run risk, based on the structural shocks, are significant for the two widest of the three test-asset pools and remain so across horizons. By contrast, forming the risk factor from effective R&D levels yields premia that are smaller in magnitude and never significant at the 5% level, highlighting the substantial role of the predictable component of effective R&D in pricing. Nonetheless, three of the six premia estimated for effective R&D in levels have t-statistics above 1.2, indicating that some risk is still captured. Overall, these results support the notion that a substantial portion of the premia for holding long-run risk derives from cash-flow risk, consistent with the standard long-run risk framework.

Table 6: Cash-flow risk premia. t-statistics in square brackets. Risk factors: Cons. (consumption growth), Raw/Adj. TFP (raw/adjusted total factor productivity), $\tilde{s}$: shock/level (effective R&D shock/level). The legacy pool comprises 16 test assets (224 observations, 1967 Q1–2022 Q4); the extended pool, 51 test assets (192 observations, 1975 Q1–2022 Q4); and the wide pool, 68 test assets (192 observations, 1975 Q1–2022 Q4).

	Cons.	**Raw TFP**	**Adj. TFP**	**$\tilde{s}$: shock**	**$\tilde{s}$: level**
		Horizon: 1 quarter			
Legacy pool	0.68	0.18	−1.47	1.16	0.02
	[1.60]	[0.84]	[−1.54]	[1.34]	[0.66]
R^2 (%)	30.99	0.87	58.96	38.69	19.84
MAPE (%)	0.19	0.25	0.12	0.18	0.23
Ext. pool	1.72**	1.97***	−2.47**	2.28**	0.06*
	[2.58]	[3.14]	[−2.12]	[2.31]	[1.68]
R^2 (%)	24.85	20.44	17.95	16.77	4.89
MAPE (%)	0.41	0.44	0.43	0.46	0.48
Wide pool	1.45***	1.38**	−1.09***	2.00**	0.03
	[3.11]	[2.39]	[−3.48]	[2.51]	[0.97]
R^2 (%)	18.05	14.16	4.38	14.97	4.06
MAPE (%)	0.45	0.47	0.49	0.47	0.48
		Horizon: 2 years			
Legacy pool	0.26	0.20	0.27	0.35	0.01
	[1.42]	[1.48]	[0.67]	[1.40]	[0.70]
R^2 (%)	54.21	59.62	6.35	55.46	21.37
MAPE (%)	0.15	0.12	0.25	0.15	0.23
Ext. pool	0.32	0.40**	1.17**	0.71**	0.04
	[1.65]	[2.15]	[2.15]	[2.14]	[1.63]
R^2 (%)	3.06	23.66	29.24	20.32	4.58
MAPE (%)	0.48	0.41	0.41	0.44	0.48
Wide pool	0.28*	0.36**	0.42*	0.60*	0.03
	[1.93]	[2.53]	[1.71]	[1.92]	[1.26]
R^2 (%)	2.17	18.61	12.23	17.33	4.96
MAPE (%)	0.49	0.45	0.47	0.46	0.48

* p <0.1, ** p <0.05, *** p <0.01

7 Conclusion

This paper focuses on a theoretical measure of aggregate R&D that captures the mediating effects of idea spillovers and product proliferation on R&D's impact on productivity growth, consistent with both fully- and semi-endogenous growth mechanisms. This measure – termed 'effective R&D' or the 'innovation component' – is designed to reflect the contribution of R&D investments to productivity growth dynamics.

A univariate empirical framework is introduced to recover fluctuations in two versions of this measure: a gross effective R&D series, derived from the cointegration relationship among R&D, TFP, and labor force; and a net measure, constructed recursively relying a one-period TFP growth forecast. Both series are stationary in quarterly U.S. data, though they differ markedly in persistence: the gross measure exhibits half-lives of 3 to 21 years, while the net measure displays a half-life of less than one year.

Embedding either series in a VAR with productivity growth shows that innovation shocks generate persistent movements in productivity growth, propagating over horizons of a decade. Structural identification ensures that shocks to effective R&D are orthogonal to contemporaneous productivity growth, while local projection exercises confirm these dynamics and extend them to consumption growth, which responds to innovation shocks at horizons well beyond the business cycle, possibly up to 15 years.

The paper's primary contribution is demonstrating that shocks to the innovation component constitute a significant cross-sectional risk factor, consistent with long-run risk asset pricing theories, associated to a substantial premium, in the order of 2% annually. This finding is particularly robust given that recent estimation techniques control for omitted risk factors and the structural VAR identification rules out spurious results due to correlations with other productivity-related factors.

The analysis further highlights the importance of the cash-flow channel in innovation long-run risk and reveals heterogeneous exposures across firm characteristics linked to R&D. In particular, payouts of small, R&D-intensive firms increase with aggregate R&D shocks, while those of other R&D-sorted portfolios decline. Measures of internal financing capacity (turnover, profitability) correlate positively with payout sensitivities, whereas proxies for investment opportunities (asset growth, Tobin's q) correlate negatively.

Taken together, these findings establish aggregate innovation as a fundamental macroeconomic risk factor with distinct asset pricing implications. Beyond this contribution, the empirical methodology developed here provides a platform for future work exploring international evidence, firm-level responses, and the differential roles of alternative types of R&D, among others.

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A Additional derivations

A.1 A simple full model

Model Closure

To characterize a Balanced Growth Path (BGP) in an economy featuring conditions (6) and (7) from Section 2, first assume the production function

$$Y_t = e^{a_t} I_t^{\xi} L_t \,, \tag{29}$$

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

$$Y_t = C_t + S_t \,, \tag{30}$$

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:

$$S_t = e^{\check{s}_t} Y_t \,. \tag{31}$$

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

The approximately linear law of motion of ideas

From (6) it follows that

$$\ln Z_t = a_t + \xi \ln I_t \,, \tag{32}$$

while from (7) it follows that

$$\Delta \ln I_{t+1} = \ln \left\{ 1 - \phi + \chi \cdot S_t^{\eta} I_t^{-(1-\psi)} Q_t^{-\omega} \right\} \,, \tag{33}$$

which for small values can be well approximated by

$$\Delta \ln I_{t+1} \approxeq -\phi + \chi \cdot S_t^{\eta} I_t^{-(1-\psi)} Q_t^{-\omega} \,. \tag{34}$$

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

$$\exp\left\{ \ln \left[S_t^{\eta} I_t^{-(1-\psi)} Q_t^{-\omega} \right] \right\} = \exp\left\{ \eta \ln S_t - (1-\psi) \ln I_t - \omega \ln Q_t \right\} \tag{35}$$

$$\approxeq 1 + \eta \ln S_t - (1-\psi) \ln I_t - \omega \ln Q_t \,, \tag{36}$$

which leads to

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

This can be more succintly written as

$$\Delta \ln I_{t+1} \approxeq (\chi - \phi) + \chi\eta \left(\ln S_t - \left(\frac{1-\psi}{\eta}\right) \ln I_t - \left(\frac{\omega}{\eta}\right) \ln Q_t\right) . \tag{38}$$

Plugging $\ln I_t$, and the implied $\Delta \ln I_t$, from (32), one gets

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

Rearranging:

$$\Delta \ln Z_{t+1} \approxeq \xi(\chi - \phi) + \xi\chi\eta \left(\ln S_t - \left(\frac{1-\psi}{\eta\xi}\right) (\ln Z_t - a_t) - \left(\frac{\omega}{\eta}\right) \ln Q_t\right) + \Delta a_{t+1} . \tag{40}$$

It is clear that bringing (40) 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 interpretation of empirical results. Therefore, this assumption is maintained in the theoretical analysis of this appendix.

The Balanced Growth Path

Assuming that the consumption share of output is not integrated of order 2 or higher, implies

$$\mathbb{E}\left[\Delta \breve{s}_t\right] = \mu_s . \tag{41}$$

Then,

$$\mathbb{E}\left[\Delta \ln S_t\right] = \mu_s + \mathbb{E}\left[\Delta \ln Y_t\right] \tag{42}$$

$$= \mu_s + \mathbb{E}\left[\Delta a_t + \xi \Delta \ln I_t + \Delta \ln L_t\right] . \tag{43}$$

From stationarity of TFP growth and of the first differences of the external component a_t, $\Delta \ln I_t$ is implied to be stationary too, making its unconditional expectation a finite value. Therefore, differencing both sides of (38), substituting L_t for Q_t, and taking expectations of them returns

$$\mathbb{E}\left[\Delta \ln S_t - \frac{1-\psi}{\eta} \Delta \ln I_t - \frac{\omega}{\eta} \Delta \ln L_t\right] = 0 . \tag{44}$$

Subtracting (44) from (43), one gets an expression for the unconditional expectation of the growth rate of ideas' stock that is only function of structural variables:

$$\mathbb{E}\left[\Delta \ln I_t\right] = \frac{\eta - \omega}{1 - \psi - \xi\eta} \cdot \mathbb{E}\left[\Delta \ln L_t\right] + \frac{\mathbb{E}\left[\Delta a_t\right]}{1 - \psi - \xi\eta} + \frac{\mu_s \eta}{1 - \psi - \xi\eta} . \tag{45}$$

Clearly, the order of integration of a_t does not need to be 0, but cannot be integrated or order 2 or higher either, in this theoretical framework. (45) 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 inputs' 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 effective R&D and rewriting (33) as $\mathbb{E}[\Delta \ln I_t] = \gamma_0' + \gamma_1'(\bar{s} + \tilde{s}_t)$, an expression determining the BGP value of $\bar{s}$ can be derived from

$$\bar{s} = \frac{\mathbb{E}[\Delta \ln I_t] - \gamma_0'}{\gamma_1'} \,. \tag{46}$$

A.2 The derivation of the structural systems

The structural system with gross effective R&D

Considering $\tilde{s}_t = \hat{s}_t + \alpha_Z a_t$, (21) can be rewritten as

$$a_{t+1} = \theta_s(\hat{s}_t + \alpha_Z a_t) + \rho_a a_t + b_{aa}\varepsilon_{a,t+1} \tag{47a}$$
$$\Delta \ln Z_{t+1} = (\gamma_1 + \theta_s)(\hat{s}_t + \alpha_Z a_t) + (\rho_a - 1)a_t + b_{aa}\varepsilon_{a,t+1} \tag{47b}$$
$$\hat{s}_{t+1} + \alpha_Z a_{t+1} = \rho_s(\hat{s}_t + \alpha_Z a_t) + \theta_a a_t + b_{as}\varepsilon_{a,t+1} + b_{ss}\varepsilon_{s,t+1}\,, \tag{47c}$$

from which follows then

$$a_{t+1} = \theta_s \hat{s}_t + (\rho_a + \theta_s\alpha_Z)a_t + b_{aa}\varepsilon_{a,t+1} \tag{48a}$$
$$\Delta \ln Z_{t+1} = (\gamma_1 + \theta_s)\hat{s}_t + (\alpha_Z(\gamma_1 + \theta_s) + \rho_a - 1)a_t + b_{aa}\varepsilon_{a,t+1} \tag{48b}$$
$$\begin{aligned}\hat{s}_{t+1} = {} & (\rho_s - \alpha_Z\theta_s)\hat{s}_t + [\theta_a + \alpha_Z(\rho_s - \rho_a - \alpha_Z\theta_s)]a_t + \\ & (b_{as} - \alpha_Z b_{aa})\varepsilon_{a,t+1} + b_{ss}\varepsilon_{s,t+1}\,.\end{aligned} \tag{48c}$$

Note also that if a_t is I(1), then the system (21) could be rewritten as

$$\Delta a_{t+1} = \theta_s \tilde{s}_t + b_{aa}\varepsilon_{a,t+1} \tag{49a}$$
$$\Delta \ln Z_{t+1} = (\gamma_1 + \theta_s)\tilde{s}_t + b_{aa}\varepsilon_{a,t+1} \tag{49b}$$
$$\tilde{s}_{t+1} = \rho_s \tilde{s}_t + \theta_a a_t + b_{as}\varepsilon_{a,t+1} + b_{ss}\varepsilon_{s,t+1}\,. \tag{49c}$$

and (48) would become

$$a_{t+1} = \theta_s \hat{s}_t + (\theta_s\alpha_Z + 1)a_t + b_{aa}\varepsilon_{a,t+1} \tag{50a}$$
$$\Delta \ln Z_{t+1} = (\gamma_1 + \theta_s)\hat{s}_t + \alpha_Z(\gamma_1 + \theta_s)a_t + b_{aa}\varepsilon_{a,t+1} \tag{50b}$$
$$\begin{aligned}\hat{s}_{t+1} = {} & (\rho_s - \alpha_Z\theta_s)\hat{s}_t + [\theta_a + \alpha_Z(\rho_s - (1 + \theta_s\alpha_Z))]a_t + \\ & (b_{as} - \alpha_Z b_{aa})\varepsilon_{a,t+1} + b_{ss}\varepsilon_{s,t+1}\,.\end{aligned} \tag{50c}$$

As both $\Delta \ln Z_{t+1}$ and $\hat{s}_t$ are strongly supported to be stationary empirically, (50b) implies that a_t must likewise be I(0), except under the strict condition $\theta_s = -\gamma_1$. Note that if $\theta_s = -\gamma_1$, $\hat{s}_t$ would have no impact on productivity growth at all. This restriction is rejected by all the tests in this study; however, this does not constitute conclusive evidence against unit root behavior in a_t, since such behavior would also alter the inferential theory underlying the tests. Anyway, such a possibility would correspond to external factors perfectly offsetting the effect of R&D on TFP growth, thereby canceling any role of R&D, a conclusion at odds with the entire literature on endogenous growth.

2-variable systems

From (21b),

$$a_t = \frac{1}{\rho_a - 1}\left[\Delta \ln Z_{t+1} - (\gamma_1 + \theta_s)\tilde{s}_t - b_{aa}\varepsilon_{a,t+1}\right] , \tag{51}$$

so (21a) can be rewritten as

$$a_{t+1} = \frac{\rho_a}{\rho_a - 1}\Delta \ln Z_{t+1} + \left[\theta_s + \frac{\rho_a(\gamma_1 + \theta_s)}{1-\rho_a}\right]\tilde{s}_t + \frac{b_{aa}}{1-\rho_a}\varepsilon_{a,t+1} . \tag{52}$$

This allows to rewrite the system in (21) as

$$\Delta \ln Z_{t+1} = (\gamma_1 + \theta_s)\tilde{s}_t + \rho_a \Delta \ln Z_t - (\theta_s + \rho_a\gamma_1)\tilde{s}_{t-1} + b_{aa}\varepsilon_{a,t+1} - b_{aa}\varepsilon_{a,t} \tag{53}$$

$$\begin{aligned}\tilde{s}_{t+1} = \rho_s\tilde{s}_t - \frac{\theta_a\rho_a}{1-\rho_a}\Delta \ln Z_t + \left(\theta_a\theta_s + \frac{\theta_a\rho_a(\gamma_1 + \theta_s)}{1-\rho_a}\right)\tilde{s}_{t-1} + \\ b_{as}\varepsilon_{a,t+1} + b_{ss}\varepsilon_{s,t+1} + \frac{\theta_a b_{aa}}{1-\rho_a}\varepsilon_{a,t} ,\end{aligned} \tag{54}$$

Similarly, from system (57),

$$a_t = \frac{1}{\alpha_Z(\gamma_1 + \theta_s) + \rho_a - 1}\left[\Delta \ln Z_{t+1} - (\gamma_1 + \theta_s)\hat{s}_t - b_{aa}\varepsilon_{a,t+1}\right] , \tag{55}$$

so

$$\begin{aligned}a_{t+1} = {} & \frac{\rho_a + \theta_s\alpha_Z}{\alpha_Z(\gamma_1 + \theta_s) + \rho_a - 1}\Delta \ln Z_{t+1} + \\ & \left(\theta_s - (\gamma_1 + \theta_s)\frac{\rho_a + \theta_s\alpha_Z}{\alpha_Z(\gamma_1 + \theta_s) + \rho_a - 1}\right)\hat{s}_t + \\ & b_{aa}\left(\frac{\alpha_Z\gamma_1 - 1}{\alpha_Z(\gamma_1 + \theta_s) + \rho_a - 1}\right)\varepsilon_{a,t+1} ,\end{aligned} \tag{56}$$

resulting in

$$\begin{aligned}\Delta \ln Z_{t+1} = {} & (\gamma_1 + \theta_s)\hat{s}_t + (\rho_a + \theta_s\alpha_Z)\Delta \ln Z_t + \\ & \left[\theta_s(\alpha_Z(\gamma_1 + \theta_s) + \rho_a - 1) - (\gamma_1 + \theta_s)(\rho_a + \theta_s\alpha_Z)\right]\hat{s}_{t-1} +\end{aligned}$$

$$
\begin{aligned}
&b_{aa}\varepsilon_{a,t+1} + (b_{aa}\alpha_Z\gamma_1 - 1)\varepsilon_{a,t} \qquad (57)\\
\hat{s}_{t+1} = (\rho_s - \alpha_Z\theta_s)\hat{s}_t + &\frac{[\theta_a + \alpha_Z(\rho_s - \rho_a - \alpha_Z\theta_s)](\rho_a + \theta_s\alpha_Z)}{\alpha_Z(\gamma_1 + \theta_s) + \rho_a - 1}\Delta \ln Z_t + \\
&[\theta_a + \alpha_Z(\rho_s - \rho_a - \alpha_Z\theta_s)]\left(\theta_s - \frac{(\gamma_1 + \theta_s)(\rho_a + \theta_s\alpha_Z)}{\alpha_Z(\gamma_1 + \theta_s) + \rho_a - 1}\right)\hat{s}_{t-1} + \\
&(b_{as} - \alpha_Z b_{aa})\varepsilon_{a,t+1} + b_{ss}\varepsilon_{s,t+1} + \\
&b_{aa}\left(\frac{[\theta_a + \alpha_Z(\rho_s - \rho_a - \alpha_Z\theta_s)](\alpha_Z\gamma_1 - 1)}{\alpha_Z(\gamma_1 + \theta_s) + \rho_a - 1}\right)\varepsilon_{a,t}\,. \qquad (58)
\end{aligned}
$$

A.3 The recovery of net effective R&D

De-meaned productivity growth (denoted with an overbar) from (8) can be expressed as

$$
\overline{\Delta \ln Z}_{t+1} = \gamma_1 \tilde{s}_t + \tfrac{1}{\alpha_Z}\left(\Delta\tilde{s}_{t+1} - \Delta\hat{s}_{t+1}\right)\,, \qquad (59)
$$

since, from (18), $a_t = \frac{1}{\alpha_Z}\left(\tilde{s}_t - \hat{s}_t\right)$. Rearranging (59) yields

$$
\tilde{s}_{t+1} = \alpha_Z\overline{\Delta \ln Z}_{t+1} + \Delta\hat{s}_{t+1} + (1 - \alpha_Z\gamma_1)\tilde{s}_t\,, \qquad (60)
$$

and recursive substitution of $\tilde{s}_t$ on the right-hand side of (60) gives (19), using κ_s as a shorthand for $1 - \alpha_Z\gamma_1$.

To recover $\tilde{s}_t$ from (19), two estimators are considered. The first, a feasible estimator, $\hat{\tilde{s}}_t$, is constructed using only parameter estimates from previous empirical analysis, while the second, an unfeasible estimator, $\tilde{\tilde{s}}_t$, builds on the feasible one by incorporating the unobservable term:

$$
\hat{\tilde{s}}_t \equiv \hat{\alpha_Z}\left(\sum_{j=0}^{t-1}\hat{\kappa_s}^j(\Delta \ln Z_{t-j} - \hat{\mu})\right) + \sum_{j=0}^{t-1}\hat{\kappa_s}^j\Delta\hat{\hat{s}}_{t-j} \qquad (61)
$$

$$
\tilde{\tilde{s}}_t \equiv \hat{\tilde{s}}_t + \hat{\kappa_s}^t \cdot \tilde{s}_0\,, \qquad (62)
$$

where hats denote empirical estimates.[25] Clearly, the omission of $\tilde{s}_0$ in the feasible recovery estimator $\hat{\tilde{s}}_t$ is likely to introduce bias. Nonetheless, if κ_s^t decays exponentially with t, the continuous mapping theorem implies that $\hat{\tilde{s}}_t$ is consistent, given that the coefficients used are consistent: $\tilde{\tilde{s}}_t \xrightarrow{p} \tilde{s}_t$ as $t \to \infty$. Figure 5 displays estimates of κ_s^t across all specifications and time periods. For specifications based on adjusted TFP, κ_s^t declines rapidly, approaching zero within a few decades from the beginning of the sample, whereas for other specifications the decay is substantially slower, though it eventually becomes negligible. Overall, the available evidence suggests that the feasible estimator provides consistent estimates. Accordingly, these are used in this work, with a burn-in period at the start of the sample long enough to ensure negligible bias, achieved by retaining only observations for which $\hat{\kappa}_s^t < 0.01$.

The precision of $\hat{\kappa}_s$ is evaluated by approximating its sampling variance via the Delta method, based on the standard errors of the underlying parameter estimates. Given the

[25] As argued in Section 3.1, b_s in (20) identifies γ_1 in this analysis.

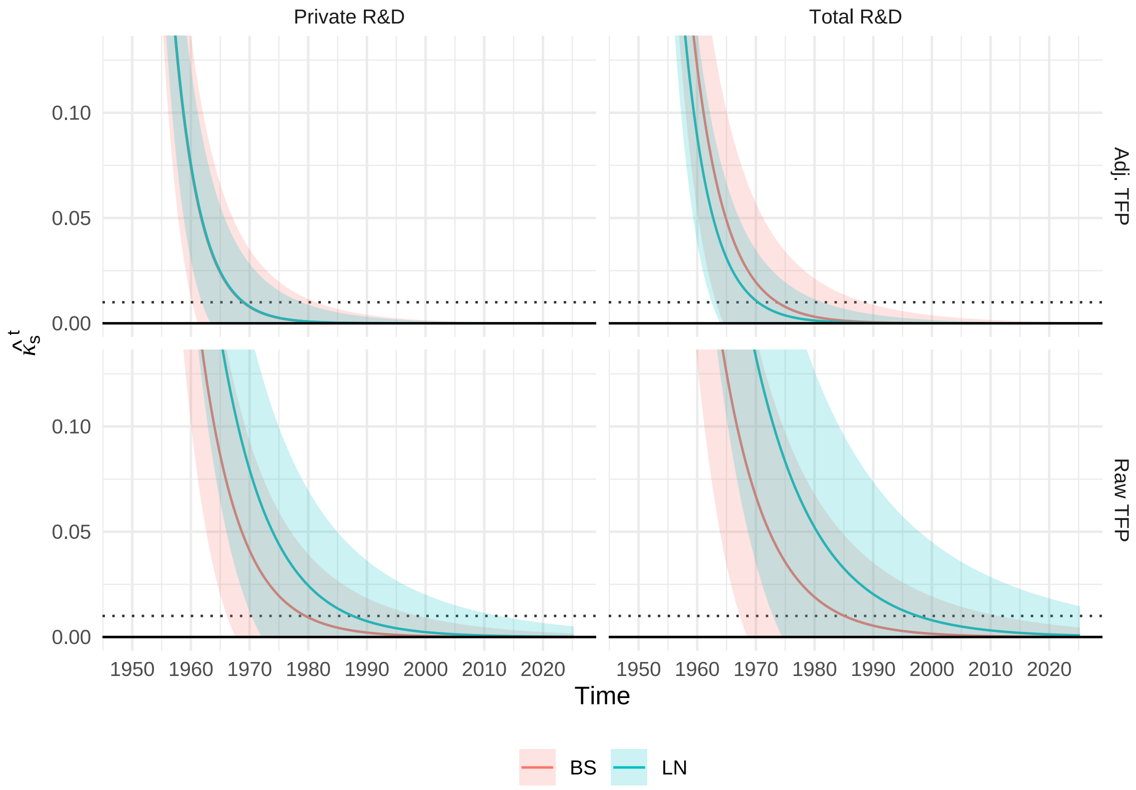

Figure 5: $\hat{\kappa_s}^t$ from all the specifications tested in Table 2. The dotted line marks the 0.01 threshold.

definition of κ_s, this is given by

$$\mathrm{Var}\left[\hat{\kappa}_s|X\right] \approx \hat{b_s}^2 \sigma^2_{\hat{\alpha_Z}} + \hat{\alpha_Z}^2 \sigma^2_{\hat{b_s}} + 2\hat{b_s}\hat{\alpha_Z}\sigma_{\hat{\alpha_Z},\hat{b_s}}, \tag{63}$$

where X denotes all the data in the sample $\{\Delta \ln S_t, \Delta \ln Z_t, \Delta \ln L_t\}_{t=1}^T$. As the estimates of α_Z and b_s are negatively correlated across the 16 specifications in this study (Figure 6), omitting the covariance term yields an heuristic upper bound for the sampling variability of κ_s estimates. This serves as a conservative measure of its standard error for subsequent calculations, $\widehat{\mathrm{Var}(\hat{\kappa}_s|X)}$. Building on this, $\mathrm{Var}\left[\hat{\kappa_s}^t|X\right] \approx t \cdot \hat{\kappa_s}^{t-1}\mathrm{Var}\left[\hat{\kappa_s}|X\right]$, which decreases in t once $t > \frac{\hat{\kappa_s}}{1-\hat{\kappa_s}}$. For instance, using the largest estimate $\kappa_s = 0.972$, $t \cdot \kappa_s^{t-1}$ is strictly decreasing for t exceeding 34 quarters (approximately 9 years).

Precision assessment for the full recovery relies on the infeasible estimator $\tilde{\tilde{s}}_t$, as the feasible estimator, though providing consistent point estimates, does not capture uncertainty from the unobservable initial value $\tilde{s}_0$. Indeed, conditional on the data, the variance of the infeasible estimator $\tilde{\tilde{s}}_t$ can, by the law of total variance, be written as

$$\mathrm{Var}\left[\tilde{\tilde{s}}_t\middle|X\right] = \mathrm{Var}\left(\mathbb{E}\left[\tilde{\tilde{s}}_t\middle|\hat{\boldsymbol{\theta}}, X\right]\middle|X\right) + \mathbb{E}\left[\mathrm{Var}\left(\tilde{\tilde{s}}_t\middle|\hat{\boldsymbol{\theta}}, X\right)\middle|X\right], \tag{64}$$

where $\hat{\boldsymbol{\theta}}$ denotes the estimates of b_s, α_Z, α_L. The first term reflects the sampling variance of

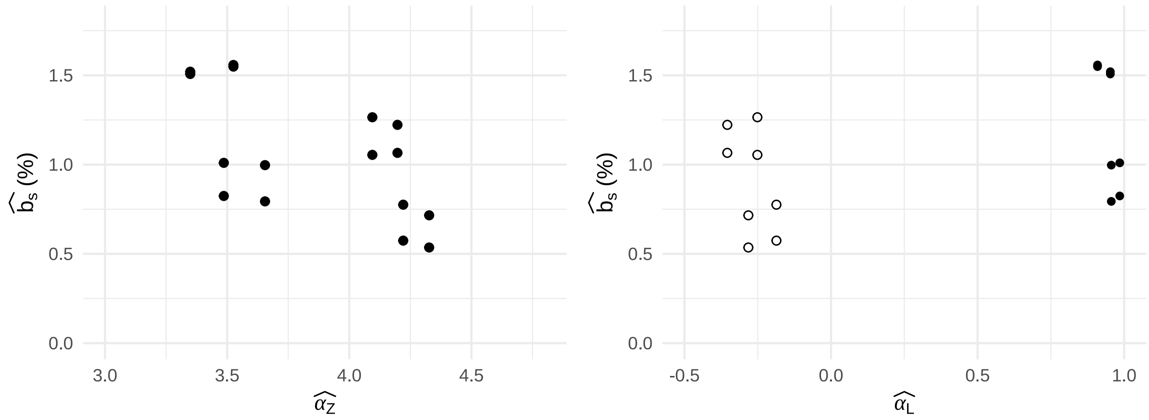

Figure 6: Values of $\hat{b}_s$, $\hat{\alpha_Z}$ (left panel), and $\hat{\alpha_L}$ (right panel) across the 16 specifications considered in this work. Hollow dots indicate specifications where α is not significant at the 10% level. For $\hat{\alpha}_Z$, the linear regression of $\hat{b}_s$ yields a slope of -0.55 with a heteroskedasticity-robust p-value of 1.5%. For $\hat{\alpha}_L$, the slope is not significantly different from zero at the 10% level when all specifications are included ($t = 1.71$), but equals -8.63 with a p-value below 1% when restricted to specifications where $\hat{\alpha}_L$ is significantly different from zero.

the parameter estimates in the observable component, i.e. the feasible recovery estimator $\hat{\tilde{s}}_t$:

$$\mathrm{Var}\left(\mathbb{E}\left[\tilde{\tilde{s}}_t \middle| \hat{\boldsymbol{\theta}}, X\right] \middle| X\right) = \mathrm{Var}\left(\hat{\alpha_Z}\left(\sum_{j=0}^{t-1} \hat{\kappa_s}^j \cdot \overline{\Delta \ln Z}_{t-j}\right) + \sum_{j=0}^{t-1} \hat{\kappa_s}^j \Delta \hat{\tilde{s}}_{t-j} \middle| X\right) \tag{65}$$

$$= \mathrm{Var}\left(\sum_{j=0}^{t-1} \hat{\kappa_s}^j \cdot \overline{\Delta \ln S}_{t-j} - \hat{\alpha_L}\left(\sum_{j=0}^{t-1} \hat{\kappa_s}^j \overline{\Delta \ln L}_{t-j}\right) \middle| X\right), \tag{66}$$

where the first equality follows from $\tilde{s}_0$ being independent of both the parameter estimates and the data sample, with zero mean by definition, while the second equality results from explicitly expressing the first differences of the gross effective R&D. Following the Delta method, this is estimated as

$$\mathrm{Var}\left(\widehat{\mathbb{E}\left[\tilde{\tilde{s}}_t \middle| \hat{\boldsymbol{\theta}}, X\right]} \middle| X\right) = \nabla \tilde{\tilde{s}}_t(\hat{\alpha_Z}, \hat{\alpha_L}, \hat{b}_s)^\top \begin{bmatrix} \widehat{\sigma^2_{\hat{\alpha_Z}}} & \widehat{\sigma_{\hat{\alpha_Z},\hat{\alpha_L}}} & 0 \\ \widehat{\sigma_{\hat{\alpha_Z},\hat{\alpha_L}}} & \widehat{\sigma^2_{\hat{\alpha_L}}} & 0 \\ 0 & 0 & \widehat{\sigma^2_{\hat{b}_s}} \end{bmatrix} \nabla \tilde{\tilde{s}}_t(\hat{\alpha_Z}, \hat{\alpha_L}, \hat{b}_s), \tag{67}$$

where the covariances between $\hat{b}_s$ and $\hat{\alpha}_\bullet$ are conservatively assumed to be zero, following earlier arguments and the evidence in Figure 6,[26] and the gradient evaluated at the point estimates is

$$\nabla \tilde{\tilde{s}}_t(\hat{\alpha_Z}, \hat{\alpha_L}, \hat{b}_s) = \begin{bmatrix} \sum_{j=0}^{t-1} -\hat{b}_s \cdot j \cdot \hat{\kappa_s}^{j-1}\left(\overline{\Delta \ln S}_{t-j} - \hat{\alpha_L}\overline{\Delta \ln L}_{t-j}\right) \\ -\sum_{j=0}^{t-1} \hat{\kappa_s}^j \overline{\Delta \ln L}_{t-j} \\ \sum_{j=0}^{t-1} -\hat{\alpha_Z} \cdot j \cdot \hat{\kappa_s}^{j-1}\left(\overline{\Delta \ln S}_{t-j} - \hat{\alpha_L}\overline{\Delta \ln L}_{t-j}\right) \end{bmatrix}. \tag{68}$$

[26]This assumption is more conservative with respect to α_Z than to α_L, although the evidence does not provide a strong case for a positive covariance in either case.

The second term, on the other hand, captures the uncertainty arising from the unobservability of the initial effective R&D, $\tilde{s}_0$, which, conditional on the parameter estimates, is the only remaining random quantity:

$$\mathbb{E}\left[\mathrm{Var}\left(\tilde{\tilde{s}}_t\middle|\hat{\boldsymbol{\theta}}, X\right)\middle|X\right] = \mathbb{E}\left[\hat{\kappa_s}^{2t}\cdot\mathrm{Var}\left(\tilde{s}_0\middle|\hat{\boldsymbol{\theta}}, X\right)\middle|X\right] \tag{69}$$

$$= \mathbb{E}\left[\hat{\kappa_s}^{2t}\middle|X\right]\mathrm{Var}(\tilde{s}_0|X) + \mathrm{Cov}\left[\hat{\kappa_s}^{2t}, \mathrm{Var}\left(\tilde{s}_0\middle|\hat{\boldsymbol{\theta}}, X\right)\middle|X\right]. \tag{70}$$

Under stationarity of $\tilde{s}_t$ and a consistent recovery provided by $\hat{\tilde{s}}_t$, both $\mathrm{Var}(\tilde{s}_0 \mid X)$ and $\mathrm{Var}(\tilde{s}_0 \mid \hat{\boldsymbol{\theta}}, X)$ can be consistently estimated by

$$\widehat{\sigma^2_{\tilde{\tilde{s}}}} = \frac{1}{T}\sum_{t=1}^{T}(\hat{\tilde{s}}_t)^2 \tag{71}$$

$$= \frac{1}{T}\sum_{t=1}^{T}\left\{(\overline{\Delta \ln S}_t - \hat{\alpha_L}\overline{\Delta \ln L}_t)^2\left[\sum_{l=0}^{T-t}\hat{\kappa_s}^{2l}\right]\right\}. \tag{72}$$

Then, approximating $\hat{\kappa_s}^{2t}$ using a second-order expansion and applying the Delta method to approximate the covariance term,

$$\mathbb{E}\left[\widehat{\mathrm{Var}\left(\tilde{\tilde{s}}_t\middle|\hat{\boldsymbol{\theta}}, X\right)}\middle|X\right] = \left(\hat{\kappa_s}^{2t} + t(2t-1)\hat{\kappa_s}^{2(t-1)}\cdot\mathrm{Var}\widehat{(\hat{\kappa}_s|X)}\right)\widehat{\sigma^2_{\tilde{\tilde{s}}}} + \nabla\kappa^{2t}(\hat{\kappa_s})\mathrm{Var}\widehat{(\hat{\kappa}_s|}X)\nabla\widehat{\sigma^2_{\tilde{\tilde{s}}}}(\hat{\kappa_s}), \tag{73}$$

where

$$\nabla\kappa^{2t}(\hat{\kappa_s}) = 2t\cdot\hat{\kappa_s}^{2t-1} \tag{74}$$

$$\nabla\widehat{\sigma^2_{\tilde{\tilde{s}}}}(\hat{\kappa_s}) = \frac{1}{T}\sum_{t=1}^{T}\left\{(\overline{\Delta \ln S}_t - \hat{\alpha_L}\overline{\Delta \ln L}_t)^2\left[\sum_{l=0}^{T-t} l\cdot\hat{\kappa_s}^{2l-1}\right]\right\}. \tag{75}$$

The total variance of the effective R&D recovery is thus quantified by

$$\widehat{\mathrm{Var}\left[\tilde{\tilde{s}}_t\middle|X\right]} = \mathrm{Var}\left(\mathbb{E}\left[\widehat{\tilde{\tilde{s}}_t\middle|\hat{\boldsymbol{\theta}}}, X\right]\middle|X\right) + \mathbb{E}\left[\mathrm{Var}\left(\widehat{\tilde{\tilde{s}}_t\middle|\hat{\boldsymbol{\theta}}}, X\right)\middle|X\right]. \tag{76}$$

A.4 The cash-flow-based asset pricing framework

According to the argument presented in the main text, Bansal et al. (2005) adopt the simpler cross-sectional pricing condition

$$\mathbb{E}_t\left[R^i_{t+1}\right] - R^f_t = \lambda_x\beta^i_x \tag{77}$$

as a reasonable approximation of the theoretical long-run risk pricing equation. The pricing equation in (27) then follows from applying the Campbell (1996) decomposition, which expresses unexpected returns as the sum of news about future cash-flow growth and discount rates:

$$\ln R^i_{t+1} - \mathbb{E}_t\left[\ln R^i_{t+1}\right] \approx \delta^i_{D,t+1} - \delta^i_{R,t+1} \tag{78}$$

where

$$\delta^i_{D,t} = \{\mathbb{E}_t - \mathbb{E}_{t-1}\}\left[\sum_{j=0}^{\infty}\bar{\kappa}^j \Delta \ln D^i_{t+j}\right], \quad \delta^i_{R,t} = \{\mathbb{E}_t - \mathbb{E}_{t-1}\}\left[\sum_{j=1}^{\infty}\bar{\kappa}^j \ln R^i_{t+j}\right]. \tag{79}$$

This decomposition implies that any return beta can be approximated as the difference between a dividend beta, $\beta^i_{x,D}$, and a discount-rate beta, $\beta^i_{x,R}$:[27]

$$\beta^i_x = \frac{\text{Cov}\left[R^i_t\,,\,\varepsilon_{x,t}\right]}{\text{Var}\left[\varepsilon_{x,t}\right]} \approx \frac{\text{Cov}\left[\delta^i_{D,t}\,,\,\varepsilon_{x,t}\right]}{\text{Var}\left[\varepsilon_{x,t}\right]} - \frac{\text{Cov}\left[\delta^i_{R,t}\,,\,\varepsilon_{x,t}\right]}{\text{Var}\left[\varepsilon_{x,t}\right]} = \beta^i_{x,D} - \beta^i_{x,R}\,, \tag{80}$$

and focusing on the dividend beta alone isolates the component of risk stemming from assets' fundamentals, abstracting from that arising through the discount-rate channel.

The beta estimates from (28) are asymptotically equivalent to those from

$$\frac{1}{H}\sum_{l=1}^{H}\Delta \ln D^i_{t+l} = \breve{\beta}^i_{0,D} + \hat{\beta}^i_{x,D}\varepsilon_{s,t} + \breve{u}^i_{t+1}\,. \tag{81}$$

The latter formulation makes the interpretation of the sensitivity as the 'long-lasting impact on cash-flow growth' more explicit, thereby better clarifying the mapping between the sensitivity estimates and the theoretical parameter $\beta^i_{x,D}$ from (80). However, as illustrated by Hodrick (1992), the former offers inferential advantages in small samples. The premium λ_x is then estimated by regressing the dividend-betas on the assets' returns.

B Details on the data

B.1 Macroeconomic data

This section presents the macroeconomic data, showing the series and descriptive statistics.

[27]The approximation follows from both (78) and $R^i_t \approx 1 + \ln R^i_t$. See Campbell and Vuolteenaho (2004) for a systematic application.

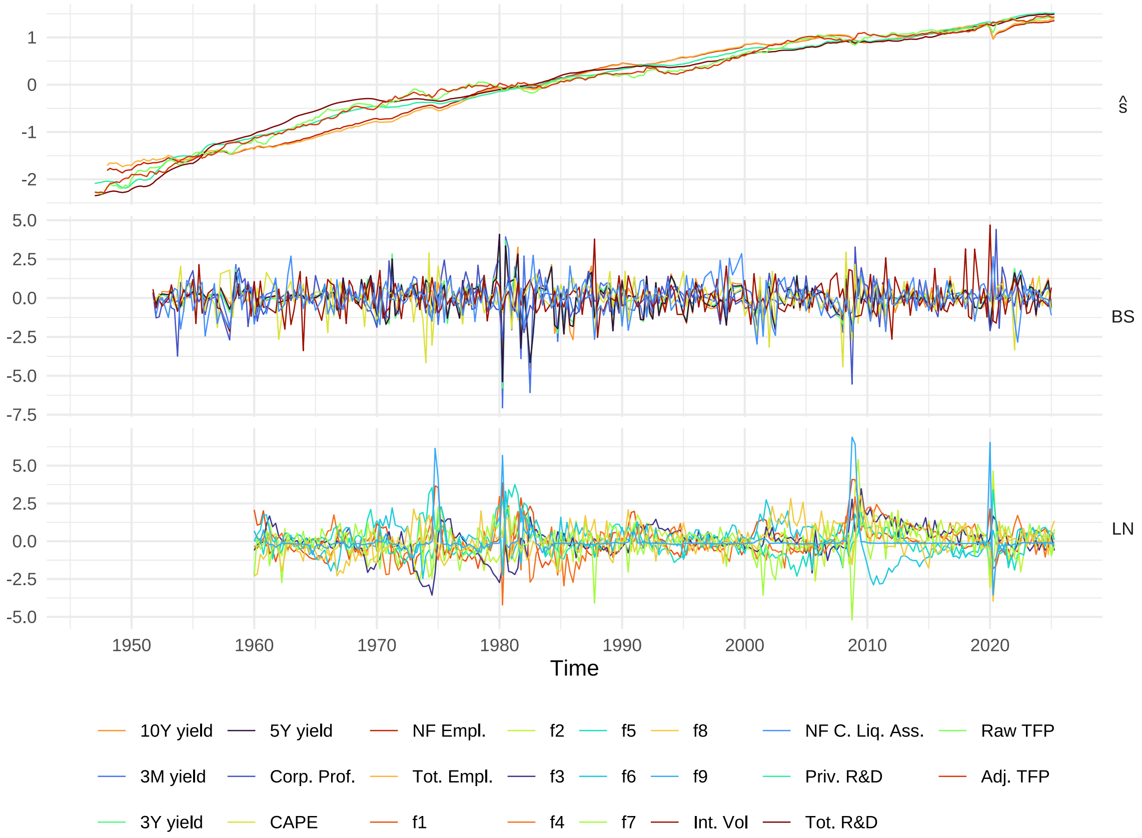

Figure 7: Raw macroeconomic data. $\hat{s}$ denotes the panel showing data used to estimate effective R&D, while BS and LN indicate the respective factor sets.

Table 7: Descriptive statistics: effective R&D data. *N. Obs.* is the number of observations. tt and tt^2 are the time trend and squared time trend coefficients (with HAC standard errors); *ADF* and *KPSS* are stationarity tests in levels; *AR(1)* is the coefficient from an AR(1) fit.

	Priv. R&D	**Tot. R&D**	**Raw TFP**	**Adj. TFP**	**Tot. Empl.**	**N.F. Empl.**
tt	0.017***	0.019**	0.018***	0.018***	0.018***	0.017***
tt^2	0.000	0.000	0.000***	0.000	0.000***	0.000***
AR(1)	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
ADF	−1.482	−2.027**	−2.346**	−2.891***	−1.353	−0.948
KPSS	2.004***	1.924***	1.976***	1.978***	2.001***	2.011***
N. Obs.	314	314	314	314	310	310

* p <0.1, ** p <0.05, *** p <0.01

Table 8: Descriptive statistics: BS factors. *N. Obs.* is the number of observations. tt and tt^2 are the time trend and squared time trend coefficients (with HAC standard errors); *ADF* and *KPSS* are stationarity tests in levels; *AR(1)* is the coefficient from an AR(1) fit.

	CAPE	**10Y yield**	**3M yield**	**3Y yield**	**5Y yield**	**Int. Vol**	**Corp. Profits**	**N.F. Liq. Assets**
tt	−0.001	−0.004*	−0.003	−0.004*	−0.004*	0.002	0.002	0.005*
tt^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(1)	−0.334***	−0.053	−0.187***	−0.117*	−0.102*	−0.297***	0.031	0.068
ADF	−13.638***	−11.188***	−13.206***	−11.844***	−11.734***	−15.514***	−10.569***	−10.688***
KPSS	0.078*	0.184*	0.099*	0.144*	0.170*	0.259*	0.052*	0.097*
N. Obs.	270	270	270	270	270	270	270	269

* p <0.1, ** p <0.05, *** p <0.01

Table 9: Descriptive statistics: LN factors. *N. Obs.* is the number of observations. tt and tt^2 are the time trend and squared time trend coefficients (with HAC standard errors); *ADF* and *KPSS* are stationarity tests in levels; *AR(1)* is the coefficient from an AR(1) fit.

	f1	**f2**	**f3**	**f4**	**f5**	**f6**	**f7**	**f8**	**f9**
tt	0.005	0.005	0.002	−0.004	−0.001	0.006	−0.001	0.017***	0.003
tt^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000***	0.000
AR(1)	0.725***	0.360***	0.749***	0.426***	0.703***	0.620***	0.138**	0.513***	0.329***
ADF	−6.467***	−7.252***	−4.577***	−6.929***	−4.911***	−5.758***	−10.204***	−7.415***	−9.526***
KPSS	0.324*	0.514**	0.525**	0.373*	0.224*	0.278*	0.190*	0.603**	0.062*
N. Obs.	262	262	262	262	262	262	262	262	262

* p <0.1, ** p <0.05, *** p <0.01

B.2 Financial data

Cash-flow growth rates

First, a measure $h_{i,t}$ of capital gain is computed for each stock by adjusting CRSP ex-dividend returns RETX for share repurchases as

$$h_{i,t} = \left(\frac{P_{i,t+1}}{P_{i,t}}\right) \cdot \min\left(\frac{n_{i,t+1}}{n_{i,t}}, 1\right) . \tag{82}$$

For each portfolio, these stock-level measures are aggregated using market-capitalization weights to obtain a portfolio capital gain series $h_{p,t}$. From each portfolio series, the value of one dollar invested at the beginning of the sample is computed recursively as $V_{p,t+1} = h_{p,t+1}V_{p,t}$ with $V_{p,0} = 1$. Payouts are then given by $D_{p,t+1} = y_{p,t+1}V_{p,t}$, where $y_{p,t+1}$ is the portfolio dividend yield, obtained from $R_{p,t} = h_{p,t} + y_{p,t}$. Capital gains are less than proportional to price appreciation when equivalent shares outstanding decline, typically due to share repurchases, which are a form of payout not recorded in dividend data. Quarterly dividend series are obtained by summing monthly values and deflating them with the implicit price deflator for nondurable and services consumption, constructed as in Bureau of Economic Analysis (2024). The series are log-transformed and, following Bansal et al. (2005), de-seasoned with a 4-quarter rolling mean to remove residual seasonality. Finally, cash-flow growth rates are computed as first differences of the log-transformed, de-seasoned real quarterly payouts.

Portfolio Formation

To mitigate liquidity concerns, the sample is restricted to common stocks with market capitalization above the 1st percentile of the monthly NYSE distribution and share prices above \$2, removing less than 0.4% of total market capitalization. Firms must also have at least twelve consecutive monthly observations to enter the final sample. Portfolio construction follows standard methodology: portfolios are formed at the end of June, value-weighted, and held until the following June. Sorting variables are Market capitalization (Size), Book-to-Market (BM), Momentum (Mom), firm-specific R&D intensity (RD), Turnover (To), Profitability (Prof), Leverage (Lvg), Asset growth (AG), Tobin's Q (TQ), and Industry (Ind). Most variables are sorted using a 2×3 framework, where stocks are first split by whether market capitalization is above or below the NYSE median and then divided into terciles within each size group. Exceptions are Size, BM, and Mom, which follow univariate sorts as in Bansal et al. (2005), and Industry, which is directly classified. All portfolios exhibit patterns consistent with established literature.

Size portfolios All firms are assigned to quintiles based on market capitalization relative to NYSE breakpoints. Both returns and cash-flow growth decrease with size.

BM portfolios All non-financial firms (SIC outside 6000–6999) are assigned to quintiles based on book equity in fiscal year $t-1$ to market capitalization at end of calendar year $t-1$, relative to NYSE breakpoints. Both returns and cash-flow growth increase with the B/M ratio.

Mom portfolios All firms are assigned to quintiles based on cumulative returns from month $t-12$ to month $t-1$. Both returns and cash-flows increase with momentum.

RD portfolios See Chan et al. (2001) and Lin (2011). All non-financial and non-utility firms (SIC outside 4000–4999, 6000–6999) are ranked by R&D expenditures from the previous fiscal year to market capitalization at end of calendar year $t-1$. Returns and cash-flow growth increase with with R&D intensity in both small and big portfolio.

To portfolios See Haugen and Baker (1996). All firms are assigned to quintiles based on the sales-to-assets ratio from the previous fiscal year. Returns and cash-flow growth increase with turnover for both small and big portfolios.

Prof portfolios See Fama and French (2015), Hou et al. (2015), and Novy-Marx (2013). All non-financial and non-utility firms are sorted on gross profits over assets. Returns and cash-flow growth increase with profitability for both small and big portfolios, with stronger effects among small portfolios.

Lvg portfolios See Bhandari (1988). All non-financial firms are sorted on debt-to-assets ratio, used instead of debt-to-market capitalization for consistency with corporate finance literature (e.g. Rajan and Zingales 1995) and with other sorts related to financing capabilities in this study. Returns and cash-flow growth increase with leverage among small portfolios, while cash-flow growth decreases among big portfolios, with returns showing no clear pattern.

AG portfolios See Cooper et al. (2008) and Hou et al. (2015). All non-financial and non-utility firms are sorted on asset growth (first difference of assets over lagged value). Both cash-flow growth and returns decrease with asset growth for small and big portfolios.

TQ portfolios See Hou et al. (2015). All firms are sorted on Tobin's Q, defined as (assets - book equity + market capitalization) / assets as in Chung and Pruitt (1994). Cash-flow growth and returns clearly decrease with Tobin's Q for small portfolios, with no evident pattern for big portfolios.

C Additional tables and figures

C.1 Tables

This subsection presents supplementary tables on correlations, R&D measures, and test asset portfolio statistics.

Table 10: Correlation among error correction terms from the specifications in Table 1.

	Baseline	S: Tot. R&D	Z: Raw TFP	Q: N.F. Empl.
S: Tot. R&D	0.880	.	.	.
Z: Raw TFP	0.855	0.721	.	.
Q: N.F. Empl.	0.997	0.858	0.859	.
Est. Meth.: IM	0.511	0.504	0.377	0.503

Table 11: Correlation among estimates of $\tilde{s}_t$ from the specifications in Table 2.

Specification	Baseline		S: Tot. R&D		Z: Raw TFP		Q: N.F. Empl.	
	BS	LN	BS	LN	BS	LN	BS	LN
Baseline-LN	1.000	.	.	.	.	.	.	.
S: Tot. R&D-BS	0.777	0.777	.	.	.	.	.	.
S: Tot. R&D-LN	0.806	0.806	0.996	.	.	.	.	.
Z: Raw TFP-BS	0.858	0.859	0.640	0.641	.	.	.	.
Z: Raw TFP-LN	0.853	0.853	0.644	0.636	0.994	.	.	.
Q: N.F. Empl.-BS	0.998	0.998	0.752	0.781	0.868	0.862	.	.
Q: N.F. Empl.-LN	0.998	0.998	0.752	0.781	0.868	0.861	1.000	.

Table 12: Correlation among estimates of structural shocks from the VAR specifications in Table 3.

	Baseline	S: Tot. R&D	Z: Raw TFP	Q: N.F. Empl.
S: Tot. R&D	0.690	.	.	.
Z: Raw TFP	0.915	0.630	.	.
Q: N.F. Empl.	0.991	0.699	0.901	.
$\tilde{s}$	0.926	0.646	0.837	0.929

* p <0.1, ** p <0.05, *** p <0.01

Table 13: Summary statistics of the (updated) Kung and Schmid (2015) R&D intensity measure. Column 1 reports yearly R&D expenditure (S, NSF) and R&D stock (I, BLS) for 1963-2020 (yearly observations from 1986 onward); columns 2-3 show data from the baseline specifications in the main analysis. ξ corresponds to commonly used labor-share values, following the original paper. T denotes the number of observations; σ, the standard deviation; tt and tt^2, linear and quadratic time trends; *ADF* and *KPSS*, respective stationarity tests; *AR(1)*, the first-order autoregressive coefficient; and *HL*, the implied half-life based on AR(1).

$\tilde{s}_t$:	$(\ln S_t - \ln I_t)$	$(\ln S_t - \frac{1}{\xi}\ln Z_t)$	
$1-\xi$:	–	0.35	0.3
T	62	314	314
σ	0.321	0.864	0.835
tt	-0.043	0.01	0.01
tt^2	0.000	-0.00	-0.00
ADF	-2.82^{*}	3.80	3.72
KPSS	1.29^{***}	0.82^{***}	0.79^{***}
AR(1)	0.995^{***}	1.000^{***}	1.000^{***}
	(0.063)	(0.000)	(0.000)
HL low	40.2	∞	∞
HL high	∞	∞	∞

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

Table 14: Granger causality F-test p-values from a VAR of effective R&D (s) and the aggregated innovation measure of Kogan et al. (2017) (KPSS), both included as structural shocks orthogonal to productivity growth, estimated from a first-step bivariate VAR with productivity growth (as in Table 3). VAR lags are selected by Hannan–Quinn information criterion (max 10); k denotes second-step VAR lags. Results are shown using standard, HC, and HAC covariance estimators.

	Baseline	S**: Tot. R&D**	Z**: Raw TFP**	Q**: N.F. Empl.**	$\tilde{s}$
k	1	1	2	1	1
N. Obs.	298	298	298	298	216
GC(s) p.v.	0.072	0.926	0.095	0.074	0.073
GC(KPSS) p.v.	0.786	0.395	0.667	0.662	0.154
GC(s) HC p.v.	0.069	0.934	0.131	0.072	0.066
GC(KPSS) HC p.v.	0.838	0.436	0.699	0.745	0.345
GC(s) HAC p.v.	0.011	0.921	0.013	0.008	0.031
GC(KPSS) HAC p.v.	0.824	0.497	0.636	0.719	0.288

* p <0.1, ** p <0.05, *** p <0.01

Table 15: Descriptive statistics of the legacy pool test assets used in Section 3.3. Quarterly returns and cash-flow growth rates are reported from 1967 Q1 to 2022 Q1; summary statistics include mean and standard deviation.

Portfolio	**CF Growth Mean**	**CF Growth SD**	**Returns Mean**	**Returns SD**
Size(1)	134.68	604.09	2.47	13.20
Size(2)	68.34	373.78	2.31	11.83
Size(3)	36.33	193.21	2.18	10.77
Size(4)	29.38	161.65	2.14	10.06
Size(5)	6.38	36.26	1.59	8.34
BM(1)	3.09	16.54	1.72	9.76
BM(2)	2.31	21.74	1.78	8.86
BM(3)	1.49	17.17	1.67	8.22
BM(4)	3.47	36.58	1.96	8.65
BM(5)	8.70	69.61	2.41	9.37
Mom(1)	1.11	20.96	1.47	12.61
Mom(2)	7.44	74.50	1.75	9.31
Mom(3)	8.34	58.26	1.78	8.47
Mom(4)	17.24	107.76	1.85	8.77
Mom(5)	34.09	280.68	1.98	11.66

Table 16: Descriptive statistics of the additional test assets in the extended pool used in Section 3.3. Quarterly returns and cash-flow growth rates are reported from 1975 Q1 to 2022 Q1; summary statistics include mean and standard deviation.

Portfolio	CF Growth Mean	CF Growth SD	Returns Mean	Returns SD
RD(1-small)	5.23	44.17	2.58	12.32
RD(2-small)	4.53	67.45	2.84	13.13
RD(3-small)	20.34	314.97	4.04	15.79
RD(1-big)	0.97	9.79	1.72	8.42
RD(2-big)	5.90	35.87	2.39	9.02
RD(3-big)	4.04	34.68	2.60	9.69
To(1-small)	3.69	27.70	2.29	10.46
To(2-small)	13.36	73.27	3.01	12.29
To(3-small)	32.86	157.91	3.41	11.99
To(1-big)	0.72	9.65	1.78	8.75
To(2-big)	3.08	18.27	2.08	8.64
To(3-big)	4.88	23.34	2.40	8.62
Prof(1-small)	1.90	42.75	2.29	13.44
Prof(2-small)	15.08	82.61	3.06	12.50
Prof(3-small)	39.22	189.22	3.57	12.47
Prof(1-big)	0.98	10.70	1.75	9.26
Prof(2-big)	3.10	18.54	2.29	8.78
Prof(3-big)	6.87	36.63	2.31	8.70
Lvg(1-small)	4.16	46.37	2.63	12.97
Lvg(2-small)	11.64	87.41	2.97	11.91
Lvg(3-small)	14.02	66.32	3.02	11.99
Lvg(1-big)	2.46	16.73	2.10	9.63
Lvg(2-big)	2.79	17.32	2.15	8.17
Lvg(3-big)	1.70	11.32	2.09	7.92
AG(1-small)	25.67	144.45	3.43	13.38
AG(2-small)	12.67	99.21	2.97	12.37
AG(3-small)	6.93	40.81	2.73	12.37
AG(1-big)	4.67	31.69	2.41	9.08
AG(2-big)	3.33	18.94	2.22	8.18
AG(3-big)	1.47	14.16	1.87	9.25
TQ(1-small)	29.50	248.34	3.45	13.17
TQ(2-small)	16.36	91.69	3.12	12.02
TQ(3-small)	3.18	29.12	2.56	13.60
TQ(1-big)	3.18	26.42	2.18	8.53
TQ(2-big)	2.42	15.68	2.29	8.31
TQ(3-big)	3.05	17.48	1.99	9.94

Table 17: Descriptive statistics of the additional test assets in the wide pool used in Section 3.3. Quarterly returns and cash-flow growth rates are reported from 1967 Q1 to 2022 Q1; summary statistics include mean and standard deviation.

Portfolio	**CF Growth Mean**	**CF Growth SD**	**Returns Mean**	**Returns SD**
Ind(Cars)	3.71	106.84	2.11	13.17
Ind(Chems)	22.46	433.41	1.87	10.62
Ind(Clths)	6.30	58.46	2.32	13.02
Ind(Cnstr)	26.06	209.55	2.28	11.84
Ind(Cnsum)	28.52	248.93	2.23	8.49
Ind(Durbl)	2.83	62.31	1.17	11.33
Ind(FabPr)	9.56	144.51	1.95	10.75
Ind(Finan)	6.38	49.55	2.03	10.68
Ind(Food)	13.22	113.91	2.18	8.32
Ind(Machn)	49.53	450.87	2.14	12.97
Ind(Mines)	1.46	32.69	1.46	13.13
Ind(Oil)	22.92	186.66	2.09	11.28
Ind(Other)	9.51	50.02	1.78	9.35
Ind(Rtail)	27.08	275.63	2.24	10.67
Ind(Steel)	2.21	48.84	1.50	14.83
Ind(Trans)	3.91	77.20	1.80	10.51
Ind(Utils)	1.51	13.95	1.50	7.51

Table 18: Dividend betas for the test assets in the legacy pool at a 1-quarter and 2-year horizons (1967 Q1–2022 Q4). Stocks are double-sorted into 2 $\times$ 3 portfolios by size (NYSE median) and accounting characteristics: *RD* (R&D/market cap), *To* (sales/assets), *Prof* (gross profits/assets), *Lvg* (debt/assets), *AG* (asset growth), and *TQ* (Tobin's *Q*). Risk factors: Cons. (consumption growth), Raw/Adj. TFP (raw/adjusted total factor productivity), $\tilde{s}$: shock/level (effective R&D shock/level).

Portfolio	**Cons.**		**Raw TFP**		**Adj. TFP**		**$\tilde{s}$: shock**		**$\tilde{s}$: level**	
Horizon	*1*	*8*	*1*	*8*	*1*	*8*	*1*	*8*	*1*	*8*
Size(1)	0.23	3.27	−0.24	3.75	−0.49	0.55	0.58	1.85	14.20	24.02
Size(2)	1.00	1.64	0.54	3.20	−0.42	−0.07	0.21	1.63	0.61	−0.69
Size(3)	0.37	1.08	0.09	1.98	−0.39	−0.14	0.12	0.66	−1.97	−1.16
Size(4)	0.18	0.98	−0.10	1.40	−0.32	−0.22	0.06	0.48	−1.75	−0.39
Size(5)	0.06	0.21	0.01	0.36	−0.06	−0.06	0.00	−0.12	−0.98	−1.02
BM(1)	0.03	0.04	0.02	0.09	−0.02	0.04	0.02	−0.02	−0.23	−0.13
BM(2)	0.01	0.07	−0.01	0.14	−0.04	−0.04	0.00	−0.07	−0.57	−0.45
BM(3)	0.02	0.08	−0.01	0.12	−0.03	−0.08	−0.01	−0.02	−0.36	−0.55
BM(4)	0.03	0.13	0.00	0.23	−0.07	−0.10	0.01	−0.08	−0.73	−0.62
BM(5)	0.11	0.30	0.01	0.53	−0.09	0.07	−0.02	0.27	0.19	0.71
Mom(1)	0.03	0.02	0.02	0.14	−0.02	0.07	−0.02	−0.02	−0.14	−0.08
Mom(2)	0.07	0.41	−0.05	0.44	−0.15	−0.35	0.00	−0.22	−2.62	−3.76
Mom(3)	0.08	0.31	0.01	0.41	−0.09	−0.03	0.03	0.10	−0.92	−1.27
Mom(4)	0.10	0.35	0.06	0.52	−0.11	−0.36	−0.02	−0.18	−1.29	−1.64
Mom(5)	0.26	0.67	0.01	1.14	−0.11	−0.77	0.27	−0.31	−2.10	−3.27

Table 19: Dividend betas for the additional test assets of the wide pool at a 1-quarter and 2-year horizons (1967 Q1–2022 Q4). Stocks are double-sorted into 2×3 portfolios by size (NYSE median) and accounting characteristics: *RD* (R&D/market cap), *To* (sales/assets), *Prof* (gross profits/assets), *Lvg* (debt/assets), *AG* (asset growth), and *TQ* (Tobin's Q). Risk factors: Cons. (consumption growth), Raw/Adj. TFP (raw/adjusted total factor productivity), $\tilde{s}$: shock/level (effective R&D shock/level).

Portfolio	**Cons.**		**Raw TFP**		**Adj. TFP**		**$\tilde{s}$: shock**		**$\tilde{s}$: level**	
Horizon	*1*	*8*	*1*	*8*	*1*	*8*	*1*	*8*	*1*	*8*
Ind(Cars)	0.16	0.40	0.05	0.60	−0.12	−0.21	0.02	0.35	−0.80	−1.03
Ind(Chems)	0.40	0.93	−0.47	1.38	−0.86	−1.15	−0.02	0.48	−7.24	−3.46
Ind(Clths)	−0.01	0.26	−0.09	0.25	−0.12	−0.19	0.04	0.13	−0.78	−0.41
Ind(Cnstr)	0.37	0.37	0.21	1.34	−0.28	0.67	0.14	0.33	−0.79	2.65
Ind(Cnsum)	−0.12	0.19	−0.28	0.09	−0.25	−0.38	−0.03	−1.10	−3.76	−2.34
Ind(Durbl)	0.04	0.14	0.04	0.30	−0.06	−0.04	0.02	−0.07	−0.94	−0.86
Ind(FabPr)	0.03	0.26	0.01	0.79	−0.03	0.01	−0.05	−0.01	0.35	−0.32
Ind(Finan)	0.05	0.33	0.00	0.41	−0.04	−0.04	−0.01	0.01	−0.51	−0.99
Ind(Food)	0.11	0.09	0.13	0.59	0.01	0.42	−0.11	−0.15	−0.80	−1.20
Ind(Machn)	0.54	1.95	0.09	2.66	−0.74	−1.57	0.16	−0.53	−12.11	−10.32
Ind(Mines)	0.01	0.08	0.01	0.11	−0.02	−0.03	−0.02	−0.15	−0.40	0.19
Ind(Oil)	0.09	1.60	−0.16	1.76	−0.19	−0.65	0.03	0.38	1.29	0.86
Ind(Other)	0.07	0.11	0.05	0.38	−0.03	0.07	0.03	−0.17	−0.90	−1.11
Ind(Rtail)	0.48	0.44	0.20	1.52	−0.50	0.12	0.42	0.13	−5.32	−4.26
Ind(Steel)	0.03	0.16	0.03	0.19	−0.04	−0.18	0.00	0.11	0.00	−0.16
Ind(Trans)	0.03	0.24	−0.02	0.24	−0.09	−0.18	−0.04	−0.17	−1.17	−0.54
Ind(Utils)	0.01	0.03	0.01	0.07	−0.01	−0.01	0.00	0.00	−0.07	−0.21

C.2 Figures

These figures complement the main text by showing key diagnostics, estimated quantities, and the variance explained by principal components of test assets.

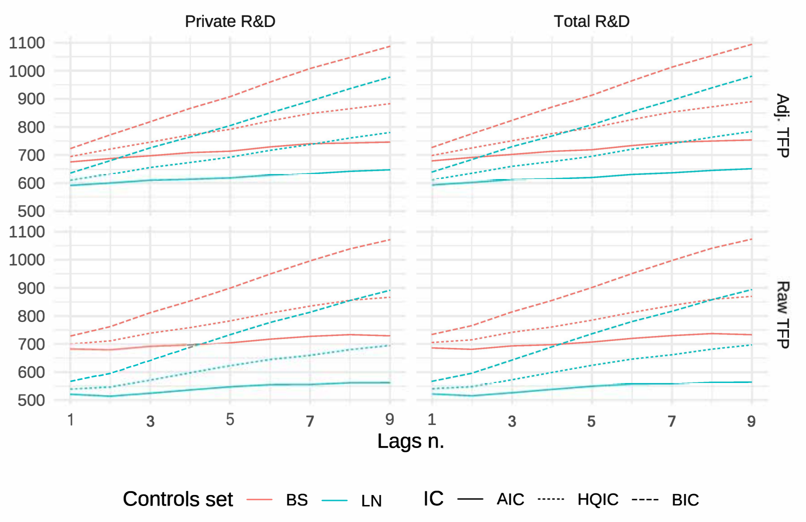

Figure 8: Information criteria from regressions on the largest sample common to all specifications, using baseline employment, were used to select the regressions reported in Table 2. Results using nonfarm employment are visually indistinguishable.

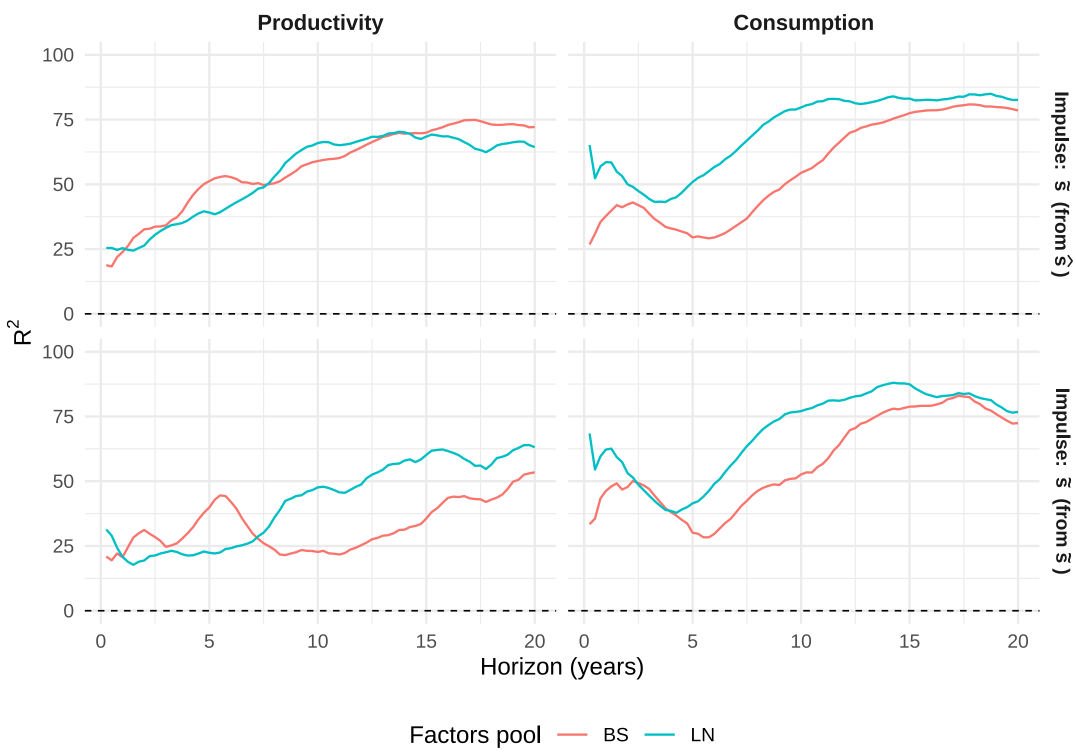

Figure 9: R^2 of local projection regressions over forecast horizons for productivity and consumption, corresponding to the cumulative impulse responses shown in Figure 4.

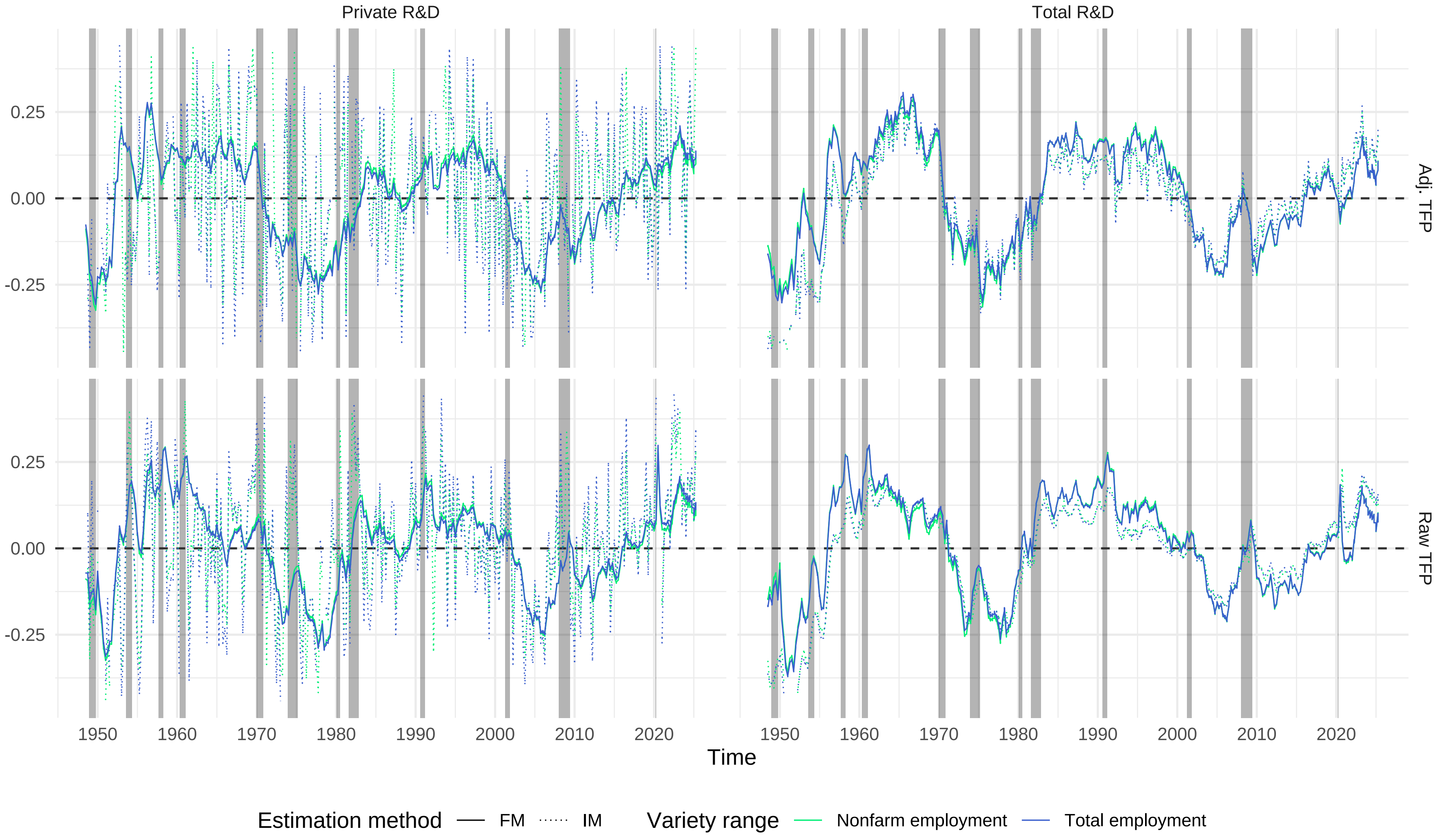

Figure 10: Error correction terms from all estimated cointegration relationships; selected estimates are in Table 1. Shaded areas indicate NBER recessions.

Figure 11: $\tilde{s}_t$ from all specifications tested. Bands show 95% confidence intervals assuming normality, with variance computed as in (64). Shaded areas indicate NBER recessions.

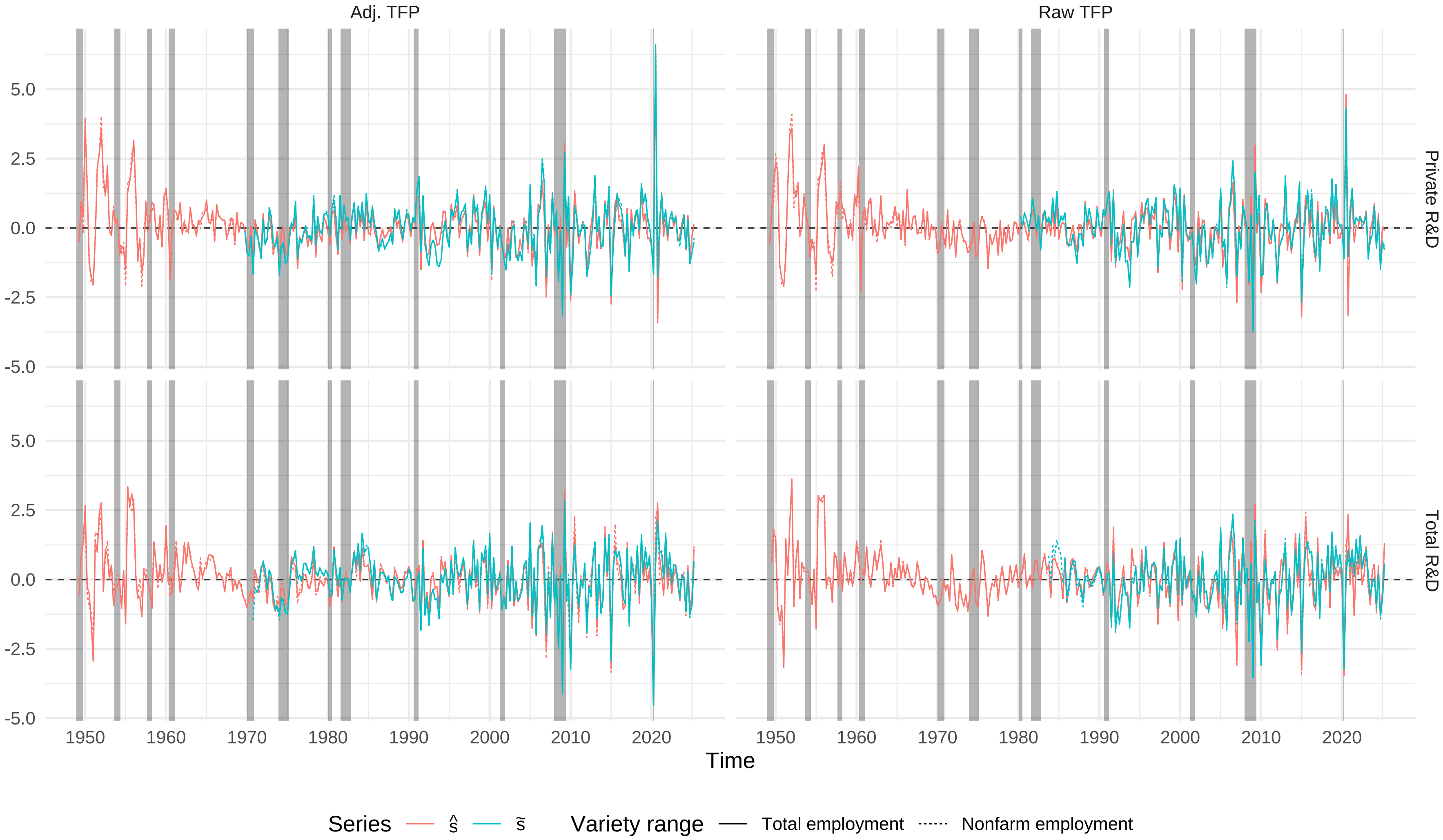

Figure 12: Structural shocks from VAR estimations; selected results are reported in Table 3. Shaded areas indicate NBER recessions.

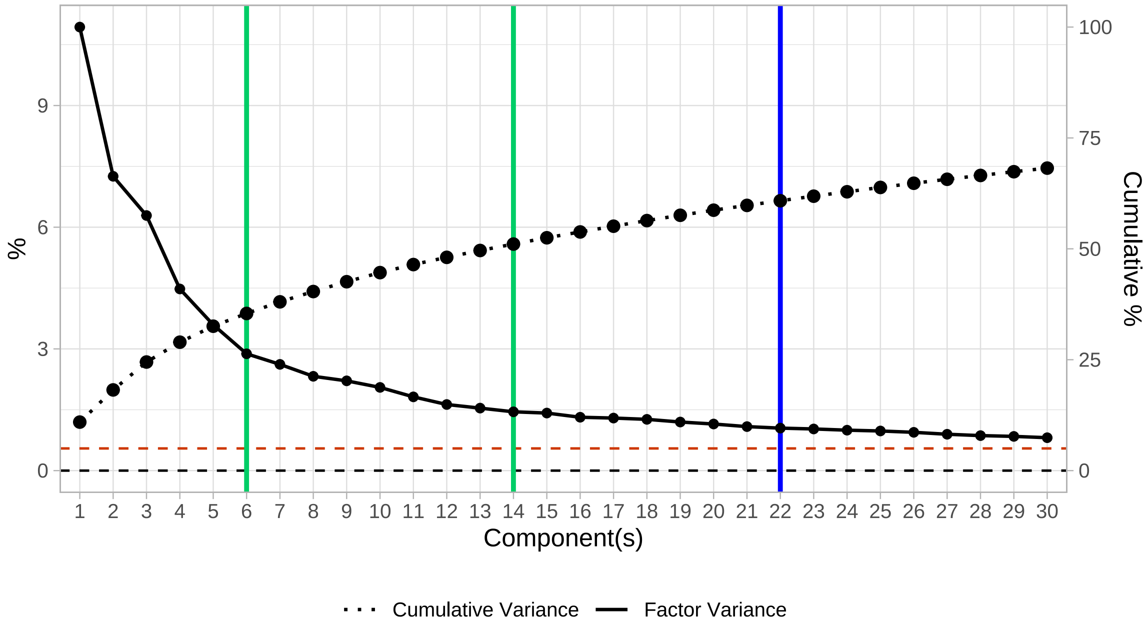

Figure 13: Principal component scree plots of the test assets in Section 3.3. The left y-axis shows the variance explained by each factor (solid line), and the right y-axis shows the cumulative variance explained (dotted line). Vertical green lines indicate the optimal number of factors according to Alessi et al. (2010), while the vertical blue line marks the minimum optimal number of factors as in Bai and Ng (2002). The horizontal red line corresponds to the reciprocal of the number of test assets.

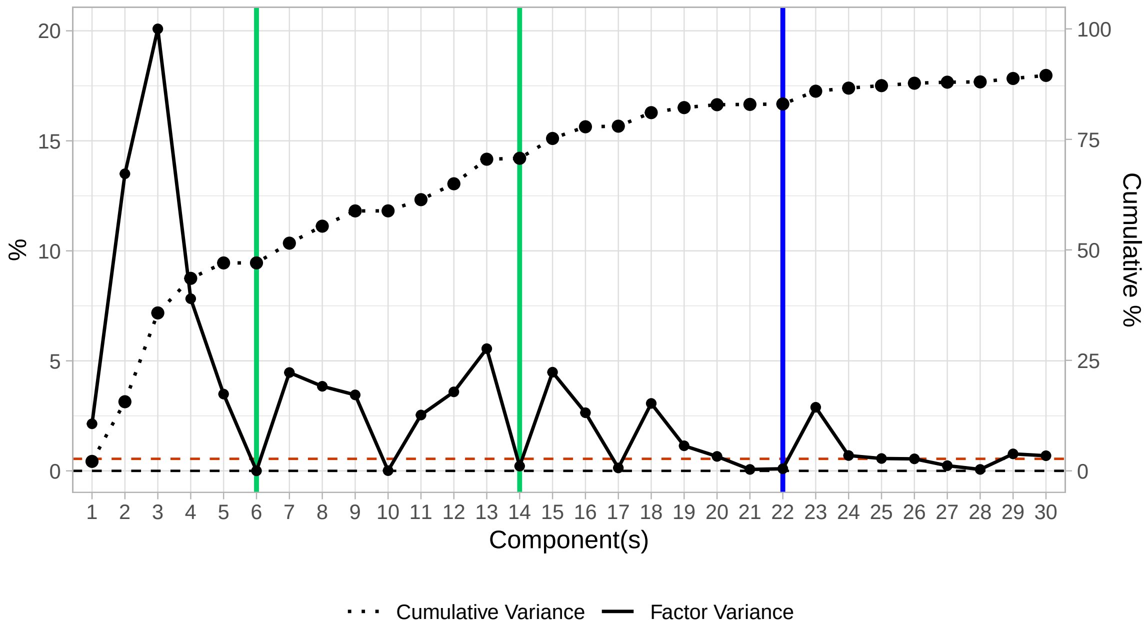

Figure 14: Cross-sectional average returns: variance explained by the principal components used as risk factors in Section 3.3. The left y-axis shows the variance explained by each factor (solid line), and the right y-axis shows the cumulative variance explained (dotted line). Vertical green lines indicate the optimal number of factors according to Alessi et al. (2010), while the vertical blue line marks the minimum optimal number of factors as in Bai and Ng (2002). The horizontal red line corresponds to the reciprocal of the number of test assets.