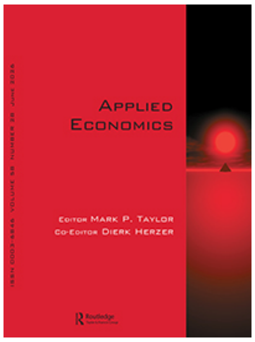

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Business cycles, R&D, and hysteresis: searching for asymmetries

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ABSTRACT

In endogenous growth models where the research and development (R&D) level determines the growth rate of productivity, temporary changes in R&D cause permanent level effects, i.e. hysteresis. When positive and negative shocks move R&D symmetrically, an equally sized positive and negative shock produce R&D booms and busts that generate equal and opposite permanent level effects, so their long-run impacts cancel out. Asymmetries break this offsetting, allowing temporary shocks to influence long-run growth. Because private R&D is well known to be pro-cyclical, understanding whether these asymmetries exist is a necessary first step towards assessing how short-run fluctuations in R&D might translate into long-run growth effects. This paper tests for asymmetries in U.S. aggregate private R&D by applying a McKay-Reis duration and steepness analysis to characterize expansions and contractions in R&D, and endogenous threshold regressions to examine state-dependent pro-cyclicality. The main findings are suggestive duration asymmetries – R&D expansions tend to last longer than contractions – and R&D's pro-cyclicality depends on labour-market and financial conditions: R&D's pro-cyclicality intensifies when unemployment is low or credit is abundant. These patterns highlight the importance of boom periods in shaping R&D dynamics and point to channels through which business cycle shocks could generate growth effects.

KEYWORDS
R&D; hysteresis; asymmetry; state dependence; pro-cyclicality

JEL CLASSIFICATION
O32; O40; E32; C24; E44

I. Introduction

It is well established that aggregate spending on private research and development (R&D) is pro-cyclical in the U.S. and other high-income countries (see Figure 1).[1] In endogenous growth models where productivity growth depends on the level of R&D effort, this pro-cyclicality matters because business cycle shocks that temporarily move R&D generate permanent effects on the level of productivity.[2] In the benchmark case in which shocks are symmetric and private R&D responds symmetrically – so that equally sized booms and busts in R&D translate into equal and opposite level effects – these hysteresis effects offset over time, leaving long-run growth orthogonal to the business cycle. The central question, then, is whether the data support that benchmark symmetry: if expansions and contractions in aggregate private R&D differ systematically, or if R&D's pro-cyclicality changes across economic conditions, temporary shocks need not wash out and can instead cumulate into long-run differences. In that case, the time-average growth rate depends on the frequency and magnitude of shocks.

In the simplest stochastic endogenous growth setting, the symmetry benchmark can fail for three reasons: shocks may be asymmetric, private R&D may respond asymmetrically, or the mapping from R&D to productivity growth may be asymmetric. Any of these breaks the offsetting logic, creating a wedge between the steady-state and time-average growth rates. We focus on the most observable margin, aggregate private R&D, asking (i) whether expansions and contractions differ in duration and steepness and (ii) whether pro-cyclicality is state dependent. We answer these with McKay and Reis (2008) duration-and-steepness analysis and Hansen (2000) endogenous threshold regressions.

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[1] The canonical papers that established this as a stylized fact are Barlevy (2007) and Wälde and Woitek (2004). Nevertheless, simultaneous or earlier work had already observed and discussed aspects of this regularity (examples include Comin and Gertler 2006; Fatás 2000; Griliches 1990; Rafferty 2003; Scherer 1983).

[2] Although endogenous growth theory also emphasizes public R&D (e.g. Huang, Lai, and Peretto 2025), our focus is private R&D because stochastic endogenous-growth models typically emphasize private innovation, and public R&D appears less tightly linked to the business cycle: in post-WWII U.S. data, public R&D growth and GDP growth have a correlation of only 0.09. We use government R&D only as a comparison series; see Pellens et al. (2024) for empirical work on public R&D in innovation leaders.

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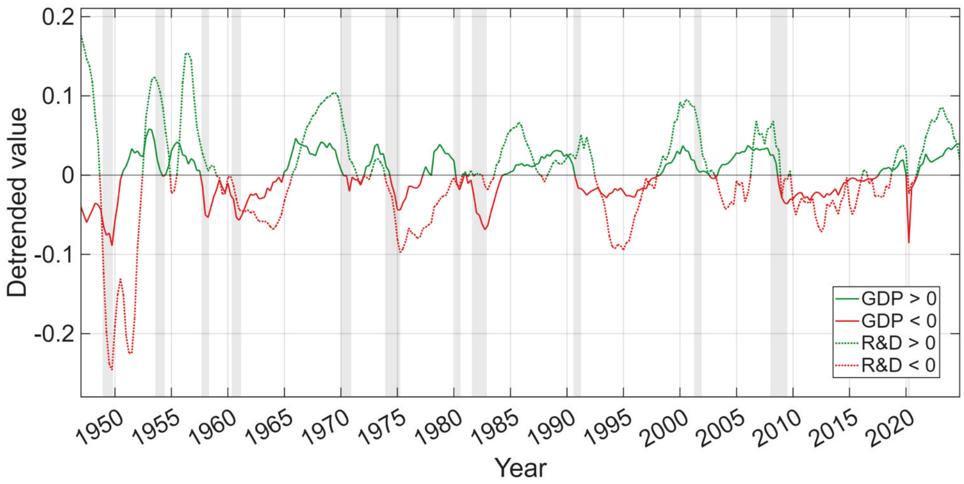

Figure 1. Detrended (Rotemberg HP Filter) GDP and R&D with NBER recessions.

Our empirical strategy is deliberately designed to bring asymmetries to the forefront in a disciplined and model-agnostic way, while remaining anchored in the endogenous-growth framework that motivates the paper. Rather than starting from a specific mechanism that would pin down a particular form of nonlinearity, we use two complementary reduced-form tools that are tailored to detect asymmetries directly in the data. The McKay-Reis duration-and-steepness characterization treats expansions and contractions as distinct phases and asks whether the R&D cycle itself is asymmetric in length or shape, and how its turning points line up with those of output. Endogenous threshold regressions then provide a transparent way to test whether the comovement between R&D and activity differs across economically meaningful states, while estimating the threshold endogenously rather than imposing it. Together, these tools allow us to document asymmetries in aggregate private R&D along two dimensions – phase asymmetries and regime dependence – thereby providing empirical facts that can discipline future theoretical work.

Importantly, our aim is descriptive rather than structural. We do not attempt to identify the shocks that move R&D or to quantify the implied long-run growth effects; instead, we document whether asymmetries and state dependence are present in the aggregate time series, and how they manifest. By doing so, the paper provides a set of empirical targets for models of stochastic endogenous growth that seek to connect cyclical conditions to innovation and long-run outcomes. We then discuss possible theoretical mechanisms that are consistent with the patterns we document and that offer promising avenues for future work.

Previewing the results, we find suggestive evidence of duration asymmetry in private R&D cycles: expansions are consistently longer than contractions across detrending methods. In the more defensible specifications for duration analysis, expansions last roughly 30% to 50% longer than contractions, with the strongest statistical evidence under the Hodrick Prescott (HP) and band-pass filters. The Hamilton (2018) filter yields the same qualitative ordering, although with a smaller and statistically weaker gap. Evidence on steepness is more limited: contractions tend to be steeper in several specifications, but the result is not robust across filters. Together with substantial heterogeneity in the timing of R&D turning points relative to GDP, these findings point to meaningful episode-to-episode variation rather than a single mechanism generating aggregate R&D cycles. This interpretation aligns with a theoretical literature that offers multiple competing channels for pro-cyclical R&D without a clear consensus.[3]

We then test whether this heterogeneity varies systematically with observable macroeconomic conditions using endogenous threshold regressions à la Hansen (2000), allowing the contemporaneous

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[3] Recent reviews include Cerra, Fatás, and Saxena (2023) and Massari and Shadmani (2025).

comovement between private R&D and activity to differ across regimes defined by GDP, unemployment, and financial conditions, including credit, cash flow, spreads, and valuations. The clearest evidence of state dependence emerges for unemployment and credit quantities: R&D's pro-cyclicality is significantly stronger when unemployment is low or credit is abundant. Taken together, the results show that R&D's pro-cyclicality is state dependent, with boom periods playing a central role in aggregate private R&D dynamics and their potential long-run effects.

Moreover, we discuss mechanisms consistent with the documented asymmetries to help discipline future endogenous-growth modelling, where asymmetries are rarely a central object. The duration pattern – longer R&D expansions than contractions – is consistent with innovation technologies featuring increasing returns (e.g. Massari and Peretto 2026), a useful benchmark for stochastic extensions. The threshold results suggest two channels for state dependence: tight labour markets may shift adjustment towards labour-saving or productivity-raising R&D, and credit booms may amplify aggregate pro-cyclicality if relaxing constraints allows financially constrained firms – whose R&D is more cyclical – to account for a larger share of total R&D.

Literature review

The literature on business cycles and R&D originated in theoretical work, with early contributions dating back at least to Schumpeter (1942). Over time, and motivated by the empirical evidence on the pro-cyclicality of private R&D, economists have proposed a range of mechanisms capable of generating this regularity, as mentioned above. However, much of this work characterizes R&D cyclicality through essentially linear comovement, either because the underlying models imply symmetric responses or because the empirical analysis focuses on average effects. As a result, relatively little is known about whether R&D's pro-cyclicality is state dependent or asymmetric across expansions and contractions in the aggregate data.

One prominent class of models that naturally delivers state dependence is based on financial frictions (e.g. Aghion et al. 2012). In these models, innovative investment is particularly exposed to financing constraints, so that the sensitivity of R&D to cyclical conditions can vary with the tightness of external finance. This implication motivates testing directly, in the aggregate time series, whether the strength of R&D's comovement with activity differs across financial regimes.

A related strand of stochastic endogenous growth macro-finance models embeds innovation into asset-pricing environments, so that innovation effort responds to fluctuations in the discounted value of innovation payoffs (e.g. Croce, Nguyen, and Schmid 2012; Kung and Schmid 2015). In this framework, the incentive to conduct R&D varies over the cycle because both the profitability of successful innovation and the discounting of future payoffs are state dependent, through financial conditions. Related work also emphasizes that labour market dynamics can shape these interactions (Donadelli and Grüning 2016). Taken together, these contributions reinforce the empirical relevance of allowing the R&D and GDP relationship to differ across observable labour-market and financial conditions. On the empirical side, several studies using firm- and industry-level data test the financing-constraints mechanism directly and find that more constrained firms and sectors adjust R&D more strongly in response to shocks.[4] Our contribution is complementary: we ask whether analogous nonlinearities are visible in aggregate private R&D dynamics, using regime-based reduced-form tests.

The closest empirical antecedents are Sedgley, Burger, and Tan (2019) and Massari and Shadmani (2025). Sedgley, Burger, and Tan (2019) test sign asymmetries by allowing R&D growth to respond differently to positive and negative changes in GDP and credit growth, and find none. We instead study phase asymmetries in R&D cycles and regime dependence in pro-cyclicality using endogenous threshold regressions. Massari and Shadmani (2025) show that R&D-driven hysteresis effects are quantitatively important in

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[4] Influential and/or recent studies include Ouyang (2011), Aghion et al. (2012), Kabukcuoglu (2019), Giebel and Kraft (2020), Hardy and Sever (2021), Xue, Yip, and Zheng (2021), Peia and Romelli (2022), Chen and Lee (2023), and Makridis and McGuire (2023).

U.S. aggregate data, motivating our focus on whether the R&D movements behind those effects are symmetric. However, their VAR framework estimates average dynamic responses and does not ask whether R&D booms and busts differ, or whether pro-cyclicality varies across macroeconomic states. Thus, our contribution is to study asymmetries and state dependence in aggregate private R&D, margins that the existing aggregate literature has largely left unexplored.

II. Why do R&D asymmetries matter?

In this section, we present a simple theoretical benchmark that clarifies why asymmetries in R&D responses matter in endogenous-growth settings. We start from the standard knowledge-accumulation equation in which R&D effort governs the growth rate of productivity. We then consider the implications of pro-cyclical R&D under symmetric versus asymmetric responses to temporary shocks. The key point is that asymmetries break the offsetting logic: the time-average of productivity growth need not coincide with the steady-state growth rate. Therefore, long-run growth becomes sensitive to the frequency and magnitude of cyclical disturbances.

The starting point is an R&D technology that sustains endogenous growth. Its simplest form is Romer (1990). Aggregate productivity is strictly increasing in the stock of technological knowledge. The production of new knowledge is governed by

$$A_{t+1} - A_t = f(A_t, L_{A_t}), \qquad (1)$$

where A_t is the stock of technological knowledge, L_{A_t} is R&D labour, and f is strictly increasing in both arguments. In the benchmark case, f is linear in A_t so that $f(A_t, L_{A,t}) = A_t \tilde{f}(L_{A,t})$.[5] Although not necessary (see Massari and Peretto 2026), the linearity simplifies the mathematical structure, such that both sides of the equation can be divided by A_t, yielding:

$$g^A_{t+1} \equiv \frac{A_{t+1} - A_t}{A_t} = \tilde{f}(L_{A,t}), \qquad (2)$$

where g^A_{t+1} is the growth rate of technological knowledge. In steady state, endogenous growth theory implies constant R&D effort, so knowledge, and therefore productivity, grows at a constant rate.

Many stochastic endogenous-growth models imply pro-cyclical private R&D, although the underlying mechanisms differ across contributions. We do not attempt an exhaustive review here and instead refer the reader to Massari and Shadmani (2025) and Cerra, Fatás, and Saxena (2023). For the purposes of the benchmark argument that follows, we take as given a reduced-form relationship in which a business-cycle shock induces a pro-cyclical response of R&D effort, without taking a stand on the specific channel generating that response.

We now illustrate the implications under offsetting shocks. Suppose the economy is hit by a positive and a negative shock of equal size and persistence. If the R&D response is symmetric, the permanent level effects cancel: the R&D boom induced by the positive shock generates the mirror-image of the bust induced by the negative shock, so that business-cycle fluctuations do not alter the long-run level of productivity relative to trend. By contrast, if the two shocks induce asymmetric R&D responses – differing in magnitude or persistence – this offsetting fails and one level effect dominates. In this case, the sequence of cyclical shocks matters: the frequency and size of booms and busts influence the time-average of productivity growth.

Figure 2 illustrates the distinction between symmetric and asymmetric R&D responses to business-cycle shocks. It plots the dynamics of R&D, TFP growth, and the TFP level following a negative shock and a subsequent positive shock of equal magnitude and persistence. The red line depicts the symmetric case, in which R&D responds equally (in absolute value) to positive and negative shocks. The green line depicts an asymmetric case,

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[5] Modern endogenous growth theory often builds on a firm-level innovation technology (see Bond-Smith 2019, for a review). We follow Massari and Shadmani (2025) in using the aggregate representation, which is standard. The strong scale effect of Romer (1990) is common in this literature; however, the key hysteresis logic does not hinge on it and can arise in scale-free models as long as growth can vary along the transition path. For example, this property features in scale-free Schumpeterian models with vertical innovation and endogenous entry such as Peretto and Connolly (2007), where temporary parameter changes produce permanent level effects (see Ferraro, Ghazi, and Peretto 2020, for an application on tax policy). Whether this class of models delivers additional implications for hysteresis beyond quantitative ones remains an open question.

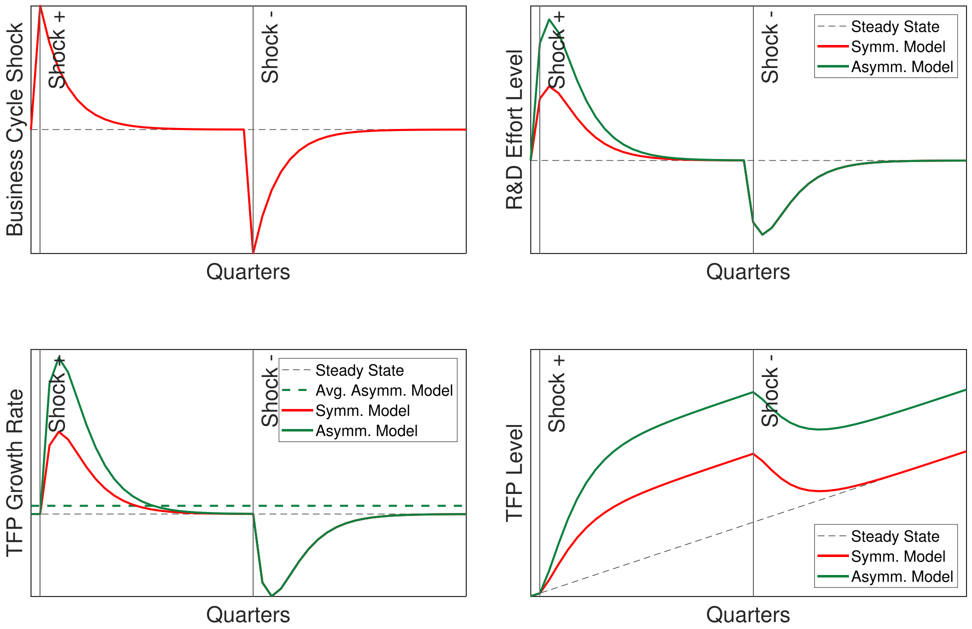

Figure 2. Illustration of hysteresis with asymmetric R&D response.

in which the response to the positive shock is stronger. When only one line is visible, the two cases coincide.

When the negative shock hits, R&D investment falls, which, via (2), temporarily slows productivity growth. This transitory growth slowdown leaves a permanent scar on the level of productivity, shifting the economy onto a lower but parallel path. When the positive shock arrives, R&D rises, productivity growth accelerates temporarily, and the productivity level steps up permanently. Under symmetry, the second level effect offsets the first: the long-run level of productivity returns to the original path. Under asymmetry, the two level effects differ in size, so the offsetting is incomplete and a lasting gap in productivity remains even after the shocks dissipate.

The bottom-left panel highlights the key implication. With asymmetric R&D responses, even symmetric business-cycle shocks can shift the time-average of productivity growth away from the steady-state growth rate, in the direction of the stronger response. In this setting, the magnitude, persistence, and frequency of shocks become determinants of long-run outcomes, something that deterministic models abstract from. Hysteresis by itself generates permanent level effects but leaves the long-run growth rate unchanged; combined with asymmetries, it can also distort the time-average of growth. This provides the central motivation for investigating whether such asymmetries are present in aggregate private R&D.

The simple example in Figure 2 can be read as a stylized two-regime special case of the reduced-form framework we test in the second part of the paper. Our endogenous threshold regressions ask whether the contemporaneous relationship between GDP and private R&D differs across states, with the threshold value estimated from the data and the regime variable allowed to differ from GDP itself. In the figure, by contrast, the regime is defined directly by GDP growth and the threshold is fixed at its steady-state rate. The empirical exercise generalizes this logic by letting the data determine whether such state-dependent slopes exist, and which macroeconomic conditions constitute a distinct regime of R&D pro-cyclicality.

III. Data

We employ several data series for this paper, all at a quarterly frequency for the U.S. in the period between 1947Q1 and 2024Q4, unless specified otherwise. Because the paper centres on understanding the pro-cyclicality of R&D, we use the NIPA series for real GDP and for private R&D

divided by its deflator.[6] This is our preferred measure because the mechanism studied in the paper operates through R&D-based knowledge accumulation rather than broader intangible investment. We also assess robustness to a broader measure of innovation-related intangible investment that adds private fixed investment in software to private R&D. For this exercise, we deflate nominal R&D and nominal software investment separately with their corresponding NIPA intellectual-property-products price indexes and sum the resulting real flows.

Cyclical unemployment is the unemployment rate published by the Bureau of Labour Statistics, minus the noncyclical rate of unemployment produced by the Congressional Budget Office. This is the only time-series that starts in the first quarter of 1949, therefore estimations involving unemployment start in 1949Q1. Finally, we employ a few financial variables. Credit is captured by total credit to the private nonfinancial sector from the Bank for International Settlements, whereas our measure for internal finance is the corporate net cash flow with IVA from the Bureau of Economic Analysis. Additionally, we measure the corporate credit spread with the Moody's Seasoned Aaa and Baa Corporate Bond Yields, and equity financing conditions using a quarterly valuation proxy defined as the log ratio of the market value of nonfinancial corporate equities from the Federal Reserve's Financial Accounts of the United States to nonfinancial corporate after-tax profits from the BEA National Income and Product Accounts.

IV. Question 1: duration, steepness and timing of peaks and troughs

We begin with a univariate analysis of aggregate private R&D cycles, asking whether deviations above and below trend differ in duration or steepness. To do so, we follow the approach of McKay and Reis (2008).

The reason this question is insightful for our purposes is the following: if R&D booms last longer than contractions, the amount of time of faster than steady state growth exceeds the amount of time of slower than steady state growth, thus implying a higher average growth rate than steady state growth. Concerning steepness the implication is the one shown by the asymmetric model in Figure 2. Nevertheless, because the analysis is univariate, it extends beyond business cycle shocks, and it concerns movements in R&D triggered by any cause. Additionally, a relevant and related question concerns the timing of peaks and troughs. Although this does not have direct clear consequences for average productivity growth, it elucidates on the nature of the cyclicality of R&D. First, the answer to this question is directly linked to that of duration of expansions and contractions. Second, it sheds light on the specific mechanisms that drive the pro-cyclicality.

V. Method

Following McKay and Reis (2008), the procedure to perform this analysis is the following:

- separate trend and fluctuations using the modified HP filter proposed in Rotemberg (1999). We also use the standard HP filter, the band-pass filter (Baxter and King 1999), and the Hamilton (2018) filter for robustness;[7]
- rely on the Bry and Boschan (1971) algorithm to identify peaks and troughs;
- compute average duration of expansions and contractions;
- compute steepness of expansions vs contractions as average growth rate during expansions vs contractions;
- produce plots to visualize leads or lags of R&D relative to peaks and troughs of GDP by computing the average deviation from trend of R&D at the GDP peaks, troughs, m quarters before, and n quarters after.

VI. Results

The results for real private R&D, reported in Table 1, and for private R&D deflated with the

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[6] As R&D output prices are difficult to observe directly, the BEA measures much R&D activity from production or input costs. Therefore, we assess the robustness of our results by deflating R&D with the GDP deflator.

[7] We interpret the Hamilton-filtered results with caution in the duration-asymmetry exercise. For persistent series, the Hamilton cycle is closely related to an h-period forecast error, so its persistence and timing are mechanically influenced by the forecast horizon h (Moura 2024). Since duration asymmetry depends on the dating of peaks and troughs, and since the same horizon is applied to both positive and negative phases, the filter may regularize the cycle and attenuate true asymmetries in phase length. We therefore use the Hamilton filter only to assess directional robustness, rather than as a preferred basis for inference.

Table 1. Duration and steepness of real private R&D cycles under alternative filters.

	Expansions	Contractions	Wilcoxon rank-sum *p*-value	Basic *t*-test *p*-value
Panel A. Rotemberg				
Mean duration (quarters)	13.077	10.308	0.128	0.166
Mean steepness	0.011	−0.015	0.079	0.107
Panel B. HP				
Mean duration (quarters)	10.647	7.176	0.031	0.014
Mean steepness	0.009	−0.013	0.007	0.052
Panel C. Band-pass				
Mean duration (quarters)	10.800	8.214	0.098	0.070
Mean steepness	0.008	−0.009	0.128	0.344
Panel D. Hamilton				
Mean duration (quarters)	10.467	9.429	0.413	0.289
Mean steepness	0.020	−0.019	0.285	0.454

Notes: HP uses $\lambda = 1600$. Band-pass uses Baxter and King (1999) with cycle lengths 6–32 quarters. Hamilton uses an 8-quarter lead and 4 lags.

GDP deflator, reported in Table 2, point to duration asymmetries.[8] Across detrending methods, expansions are systematically longer than contractions. The magnitude of the difference is economically meaningful: excluding the Hamilton filter, expansions last roughly 30% to 50% longer than contractions, depending on the measure of R&D and the detrending method. The statistical evidence is strongest under the HP and band-pass filters, and is also suggestive under the Rotemberg trend, especially for R&D deflated with the GDP deflator. The Hamilton filter delivers the same qualitative ordering, with expansions longer than contractions, but the estimated duration gap is smaller and not statistically significant. Given the sensitivity of phase durations to the Hamilton filtering procedure, we interpret this specification mainly as a directional robustness check rather than as decisive evidence against duration asymmetry.

The duration asymmetry documented for private R&D is especially notable when compared with other aggregate series. Real GDP, shown in Table 1 displays only mild and statistically weak

Table 2. Duration and steepness of private R&D/GDP deflator cycles under alternative filters.

	Expansions	Contractions	Wilcoxon rank-sum *p*-value	Basic *t*-test *p*-value
Panel A. Rotemberg				
Mean duration (quarters)	12.714	8.429	0.053	0.038
Mean steepness	0.008	−0.012	0.125	0.106
Panel B. HP				
Mean duration (quarters)	10.563	8.125	0.096	0.067
Mean steepness	0.009	−0.011	0.038	0.279
Panel C. Band-pass				
Mean duration (quarters)	11.429	8.571	0.056	0.049
Mean steepness	0.008	−0.009	0.116	0.378
Panel D. Hamilton				
Mean duration (quarters)	9.813	8.800	0.429	0.301
Mean steepness	0.020	−0.019	0.171	0.408

Notes: HP uses $\lambda = 1600$. Band-pass uses Baxter and King (1999) with cycle lengths 6–32 quarters. Hamilton uses an 8-quarter lead and 4 lags.

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[8] Adding software investment does not alter the conclusions.

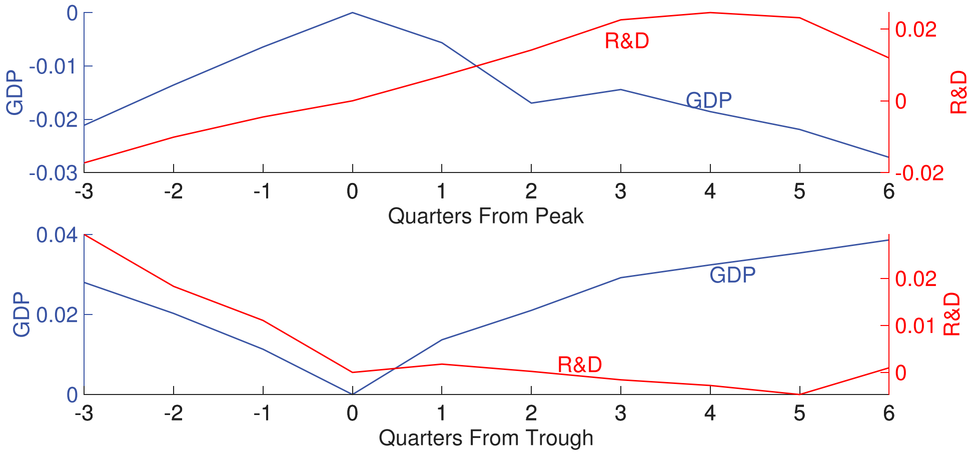

Figure 3. Dynamics of R&D and GDP (Rotemberg HP filter).

duration differences, in line with McKay and Reis (2008), while private investment, in Table 2, shows a clear expansion-contraction gap only under the band-pass filter and even reverses sign under the Hamilton filter. Government R&D, shown in Table A3, displays a different pattern, especially under the Rotemberg filter, with substantially longer phases and no robust asymmetry. Thus, the longer-expansion pattern in private R&D is not simply inherited from aggregate activity or from investment more broadly. Rather, it appears to be a distinctive feature of private R&D cycles.

The evidence on steepness is more limited. Contractions tend to be steeper than expansions in several specifications, and some of the Wilcoxon tests are significant, particularly under the HP filter. However, the result is less robust across filters and across deflation methods than the duration asymmetry. We therefore view the steepness results as suggestive at most, and in the remainder of the paper we focus on the more robust finding that private R&D expansions tend to last longer than contractions.

Figure 3 describes the dynamics of GDP and R&D around GDP peaks and troughs. The curves report the average deviation from trend at the GDP turning point, as well as m quarters before and n quarters after. The figure suggests that R&D peaks tend to lag GDP peaks, while the behaviour around troughs appears closer to coincident, although the recovery of R&D after GDP troughs is more persistent. Figure 4, which reports the same exercise using HP-filtered series, suggests a similar interpretation. R&D peaks generally occur after GDP peaks, with a typical lag of roughly one year. Around troughs, however, a possible reading is that the pattern is more heterogeneous: in some episodes R&D troughs are coincident with GDP

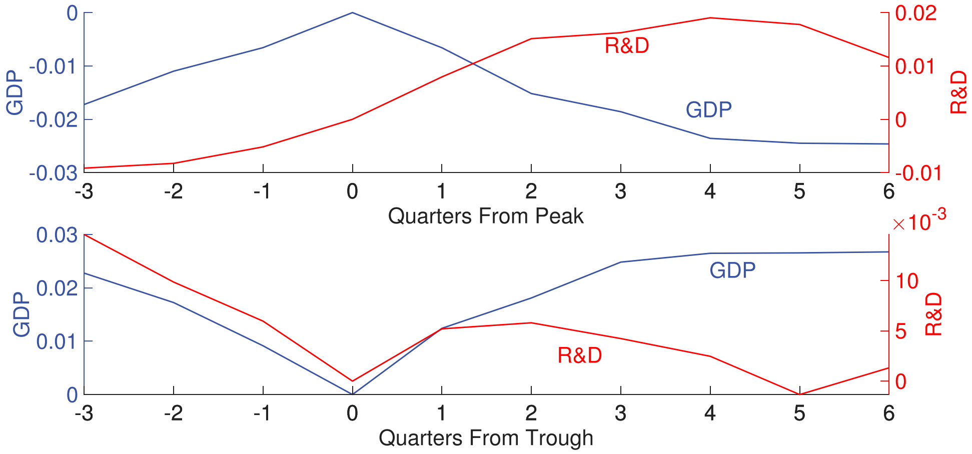

Figure 4. Dynamics of R&D and GDP (HP filter).

Table 3. Timing of R&D turning points relative to GDP turning points.

GDP turning point	R&D turning point	Lag (quarters)
Panel A. Peaks		
1953Q1	1953Q3	2
1955Q3	1956Q3	4
1959Q2	1969Q3	41
1966Q1	1969Q3	14
1968Q2	1969Q3	5
1973Q2	1973Q2	0
1978Q4	1981Q3	11
1989Q1	1991Q2	9
1994Q4	2000Q3	23
2000Q2	2000Q3	1
2006Q1	2008Q2	9
2015Q2	2016Q2	4
2019Q4	2019Q4	0
Panel B. Troughs		
1949Q4	1949Q4	0
1954Q2	1955Q1	3
1958Q2	1964Q1	23
1961Q1	1964Q1	12
1967Q4	1971Q4	16
1970Q4	1971Q4	4
1975Q2	1975Q2	0
1982Q4	1983Q1	1
1993Q3	1995Q1	6
1996Q1	2004Q1	32
2003Q1	2004Q1	4
2011Q3	2012Q3	4
2016Q2	2017Q4	6
2020Q2	2020Q2	0

Notes: The table reports the R&D turning point associated with each GDP turning point and the corresponding lag in quarters.

troughs, while in others they lag GDP troughs by a similar amount of time as peaks.

The visual evidence should be complemented by the turning-point lags reported in Table 3. The average and median lags of R&D troughs relative to GDP troughs are, respectively, 7.93 and 4 quarters, while the corresponding average and median lags for R&D peaks are 9.46 and 5 quarters. The difference between the average paths in Figures 3 and 4 and these summary statistics reflects substantial heterogeneity in the timing of R&D turning points relative to GDP turning points. Although R&D exhibits coincident or only slightly lagged turning points in several episodes, there are also cases in which the lag is very large. In some cases, the associated R&D turning point occurs only after the subsequent GDP turning point, suggesting that the GDP turning point is not always associated with a corresponding R&D turning point. These outliers raise the average lag substantially above the median. Overall, the evidence indicates that R&D peaks tend to lag GDP peaks somewhat more than R&D troughs lag GDP troughs, while troughs display greater episode-to-episode heterogeneity.

Interpretation

Our duration results are consistent with several theoretical mechanisms and related empirical evidence, and they help discipline future modelling.

First, longer expansions than contractions arise in an endogenous-growth model with non-constant aggregate returns to knowledge accumulation (Massari and Peretto 2026). There, the R&D technology in (1) implies that knowledge growth in (2) depends on the knowledge stock, generating asymmetric convergence: with increasing (decreasing) returns to knowledge, the economy returns to steady-state growth more slowly (quickly) after a temporary positive shock, with the opposite pattern after a negative shock. Massari and Peretto (2026) document evidence consistent with increasing returns in a cross-country panel; our finding that R&D expansions last longer than contractions is consistent with that implication, making a stochastic extension of their framework a promising candidate explanation.

Second, the same phase pattern – longer expansions and a delayed peak – also characterizes employment cycles (Ferraro 2018; McKay and Reis 2008). Models that link labour-market dynamics to R&D pro-cyclicality therefore offer a natural interpretation. In Aysun (2020), New-Keynesian frictions and diminishing returns to production labour induce pro-cyclical R&D labour that adjusts with production labour to equalize marginal products, implying R&D dynamics that mirror employment.

Finally, the pattern may reflect features of R&D adjustment that are often underemphasized: adjustment costs are widely viewed as high (Hall and Lerner 2010). High costs can generate rapid downsizing of R&D in downturns (a coincident trough) but gradual rebuilding in recoveries (a lagged peak). While adjustment costs appear in some models (e.g. Aysun 2020), our evidence suggests they may play a more prominent role by generating asymmetric R&D dynamics.

More broadly, the combination of a large (if only marginally significant) duration difference and substantial heterogeneity in R&D turning points relative to GDP suggests that R&D cyclicality is not governed by a single, stable mechanism. Instead, different episodes likely reflect different underlying disturbances and constraints, which helps rationalize why multiple, potentially complementary theories of pro-cyclical R&D can coexist in the aggregate data.

VII. Question 2: state-dependency of R&D's pro-cyclicality

Is R&D's pro-cyclicality stable over time, or does it vary systematically with the macroeconomic state? This section investigates whether the contemporaneous relationship between aggregate private R&D and output differs across regimes.

The theoretical literature can rationalize pro-cyclical R&D through several mechanisms – ranging from financing constraints and labour-market frictions to broader financial conditions that affect the payoff to innovative investment. While these frameworks share the implication that innovation incentives may be state dependent, they provide limited guidance on which aggregate state variables should matter most, or where thresholds should lie. Empirically, aggregate evidence on asymmetries is relatively scarce and appears sensitive to data frequency and specification: using annual U.S. data and a decomposition approach, Rafferty (2003) reports larger declines in recessions than increases in expansions,[9] whereas Sedgley, Burger, and Tan (2019) find little evidence of sign asymmetry in aggregate data. The micro evidence reviewed above, by contrast, more consistently points to stronger R&D responses among constrained firms or sectors. This motivates a reduced-form approach that tests directly, in aggregate time series, whether R&D's pro-cyclicality depends on different macroeconomic states.

Furthermore, the post-Great Recession hysteresis debate has also shaped a natural prior about innovation over the cycle: if recessions disproportionately disrupt innovative investment – because financing constraints tighten, uncertainty rises, or organizational slack is reallocated —, then R&D's pro-cyclicality should be especially strong in 'bad times', and particularly during severe downturns. The threshold regressions we propose provide a direct reduced-form way to evaluate this hypothesis by allowing the R&D-GDP comovement to differ across labour-market and financial regimes.

Method

We test whether the contemporaneous comovement between aggregate private R&D and output varies across economic regimes by estimating endogenous threshold regressions (Hansen 2000). The slope linking R&D to GDP is allowed to differ across states defined by economic activity, labour-market conditions, and financial conditions, including credit quantities, cash flows, credit spreads, and equity valuations. Because our objective is to document discontinuities in pro-cyclicality, the estimates are reduced-form, state-dependent correlations rather than causal effects of GDP on R&D.

Reverse causality from R&D to GDP is unlikely to drive the contemporaneous relationship: the endogenous-growth channel operates through productivity with lags, and the contemporaneous correlation between aggregate R&D and utilization-adjusted TFP growth is essentially zero, becoming meaningful only beyond three quarters and peaking around four quarters (Massari and Shadmani 2025).

GDP regimes connect our analysis to firm- and industry-level evidence on asymmetric responses to shocks (Aghion et al. 2012; Ouyang 2011) and to aggregate evidence finding no sign asymmetry in U.S. R&D (Sedgley, Burger, and Tan 2019), while our threshold approach estimates the cut-off endogenously rather than imposing it at zero. Unemployment regimes are motivated by theories in which labour-market tightness shapes innovation incentives (Aysun 2020). Financial regimes allow us to distinguish several mechanisms: credit quantities speak to external-finance constraints (Aghion et al. 2012), cash-flow regimes capture

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[9] Rafferty (2003) uses annual firm-financed R&D data and emphasizes data limitations; we view it as suggestive rather than definitive.

internal-finance conditions (Hall and Lerner 2010), and credit spreads and equity valuations proxy for the risk-premium and valuation channels emphasized in macro-finance models Croce, Nguyen, and Schmid (2012); Kung and Schmid (2015). These variables capture distinct mechanisms and should not be interpreted as robustness checks of one another.

An endogenous threshold model answers the following question: is the relationship between the regressor and regressand significantly different above and below an endogenously determined threshold value of the variable X? We estimate this model using the methodology of Hansen (2000), which endogenously determines the threshold value of X that maximizes the fit of the model. Formally, the model is expressed by the equation

$$\begin{aligned} RD_t = \alpha + \beta_1 RD_{t-1} + \beta_2 RD_{t-2} + \beta_3 RD_{t-3} \\ + \beta_4 I_t Y_t + \beta_4^{'}(1 - I_t) Y_t + \varepsilon_t, \end{aligned} \tag{3}$$

where RD_t is growth in real private R&D spending at date t, Y_t is growth in real GDP at date t, I_t is a dummy indicating the state of the economy:

$$I_t = \begin{cases} 0 & \text{for } X_t \leq X^T, \\ 1 & \text{for } X_t > X^T. \end{cases}$$

X^T is the endogenously determined threshold value of X, chosen to minimize the residual sum of squares, i.e. that provides the best fit. We then check whether the F-statistic comparing the model with an endogenous threshold and the same model without the threshold is above the critical value. We estimate separate regressions using unemployment, GDP, total credit to the private nonfinancial sector, corporate net cash flow, the corporate credit spread, and the equity-valuation proxy as alternative threshold variables X. To assess robustness, we vary the transformation of the threshold variable where appropriate. For unemployment, we consider the unemployment gap, defined as the deviation of the actual rate from the natural rate, as well as HP- and Hamilton-filtered unemployment. The HP-filtered specification is our preferred one because the unemployment gap and Hamilton-filtered series tend to place the estimated threshold far in the lower tail, leaving few observations in the low-unemployment regime. For GDP, credit, and cash flow, we use growth rates, HP-filtered deviations, and Hamilton-filtered deviations. For the credit spread and equity-valuation proxy, we report level specifications, since these variables do not yield significant threshold effects and further transformations do not alter that conclusion. Finally, we choose four lags of R&D to control for its autocorrelation as three are suggested by statistical tests and an extra one addresses residual seasonality.[10]

The possible presence of structural breaks in the relationship between GDP and R&D growth could bias the detection of threshold effects. Therefore, in our robustness checks, we first run the Bai and Perron (1998) multiple structural break test, imposing a maximum of two breaks. We then introduce dummies to control for these structural breaks.[11] The Bai-Perron test identifies one break in 1958Q2 according to the Bayesian information criterion, but no break according to the Liu-Wu-Zidek criterion. As a robustness check, we re-estimate the threshold regressions including a post-1958Q2 dummy. The conclusions are unchanged.

Results

Table 4 reports the baseline threshold regressions, where threshold variables are HP-filtered, except for the credit spread, which is left unfiltered. Table 5 reports the corresponding specifications using growth rates for the threshold variables, except for unemployment, which enters as the unemployment gap, and the P/E ratio, which enters in levels. Appendix Tables 4 and 5 repeat the analysis using R&D deflated by the GDP deflator. Appendix Table 7 provides an additional robustness check using Hamilton-filtered threshold variables. Overall, the results provide little support for

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[10] We determine that three is the optimal lag in the following way. First, we inspect the autocorrelation function (ACF) and partial autocorrelation function (PACF) to determine the possible lags. Then, we fit an AR(1), AR(2), and AR(3). The Akaike information criterion (AIC) and Bayesian information criterion (BIC) confirm that the AR(3) provides the best fit. Finally, we run the baseline model without threshold with one, two, and three lags, and once again we confirm that three lags gives us the best model according to the AIC and BIC.

[11] Similarly, the presence of regimes could lead to detecting structural breaks that do not exist. For this reason, we introduce the structural break test only for robustness.

Table 4. Threshold regression results, HP-filtered threshold variables.

	Linear	Threshold Regression				
		GDP	Unemp	Credit	Cash Flow	Baa-Aaa
Break value		1.006	−0.524	0.423	1.866	0.663
constant	0.341^{**}	0.367^{**}	0.397^{**}	0.472^{***}	0.329^{**}	0.344^{**}
	(0.128)	(0.128)	(0.126)	(0.131)	(0.128)	(0.129)
RD_{t-1}	0.556^{***}	0.541^{***}	0.546^{***}	0.549^{***}	0.558^{***}	0.551^{***}
	(0.054)	(0.054)	(0.053)	(0.053)	(0.054)	(0.055)
RD_{t-2}	0.229^{***}	0.240^{***}	0.228^{***}	0.226^{***}	0.228^{***}	0.228^{***}
	(0.061)	(0.060)	(0.059)	(0.060)	(0.061)	(0.061)
RD_{t-3}	-0.309^{***}	-0.318^{***}	-0.325^{***}	-0.311^{***}	-0.308^{***}	-0.309^{***}
	(0.061)	(0.061)	(0.060)	(0.060)	(0.061)	(0.061)
RD_{t-4}	0.031	0.001	0.010	0.033	0.021	0.032
	(0.054)	(0.055)	(0.054)	(0.053)	(0.055)	(0.055)
Y_t	0.476^{***}					
	(0.075)					
ABOVE		0.784^{***}	0.410^{***}	0.657^{***}	0.601^{***}	0.458^{***}
		(0.149)	(0.078)	(0.090)	(0.104)	(0.083)
BELOW		0.408^{***}	0.865^{***}	0.210^{**}	0.385^{***}	0.531^{***}
		(0.080)	(0.158)	(0.106)	(0.092)	(0.129)
R^2	0.478	0.486	0.493	0.497	0.481	0.477
RSS	638.221	626.253	596.798	613.133	631.968	637.635
AIC	236.674	232.862	219.064	226.362	235.651	238.392
BIC	259.035	258.950	245.083	252.450	261.739	264.480
# obs. above		76	219	107	181	66
# obs. below		231	85	200	126	241
F-stat		5.733	7.670	12.276	2.969	0.276
Critical Value		3.732	4.674	5.562	4.036	7.010

Notes: Coefficients with significance stars as superscripts; standard errors in parentheses on the following row. The threshold variable is the cyclical component after removing the HP-filtered trend, with the exception of the the credit spread.

the view that downturns are especially important for R&D pro-cyclicality. When significant asymmetries emerge, they instead point to stronger pro-cyclicality in good economic states.

The unemployment specifications provide evidence that R&D pro-cyclicality strengthens when labour markets are especially tight, with the estimated response to GDP growth roughly twice as large in low-unemployment regimes as in high-unemployment regimes. However, the strength of the statistical evidence depends on the detrending method and on the R&D deflator. When private R&D is deflated by the GDP deflator, the threshold effect is statistically significant both when unemployment enters as the unemployment gap and when it enters as its HP-filtered cyclical component. When private R&D is deflated by its own deflator, the threshold effect remains significant for HP-filtered unemployment, but not for the unemployment gap. This weaker inference appears to reflect the location of the estimated threshold rather than a change in the relationship: the endogenous thresholds often correspond to particularly low unemployment states, which occur relatively infrequently in the post-war U.S. data and leave few observations in the low-unemployment regime. Consistent with this interpretation, the slope coefficients are fairly stable across specifications, while statistical significance weakens when the low-unemployment regime is sparsely populated. Sensitivity exercises that move the threshold exogenously slightly away from the extreme tail (Table 6) yield statistically significant slope differences, and the Hamilton-filtered specification displays a similar pattern of consistent point estimates but lower precision.

The credit-regime results are stronger and more robust. Across specifications, R&D remains pro-cyclical in both credit regimes, but its responsiveness to GDP growth is substantially larger when credit conditions are favourable. In most specifications, the slope coefficient in the high-credit regime is roughly three times as large as the corresponding coefficient in the low-credit regime. Thus, the

Table 5. Threshold regression results, threshold in growth or cyclical unemployment and P/E ratio.

	Linear	Threshold Regression				
		GDP	Unemp	Credit	Cash Flow	P/E
Break value		1.336	−1.186	0.787	4.988	13.250
constant	0.341^{**}	0.340^{**}	0.413^{***}	0.360^{***}	0.347^{**}	0.322^{**}
	(0.128)	(0.129)	(0.128)	(0.127)	(0.128)	(0.130)
RD_{t-1}	0.556^{***}	0.556^{***}	0.537^{***}	0.527^{***}	0.562^{***}	0.496^{***}
	(0.054)	(0.054)	(0.054)	(0.055)	(0.055)	(0.056)
RD_{t-2}	0.229^{***}	0.229^{***}	0.231^{***}	0.247^{***}	0.229^{***}	0.297^{***}
	(0.061)	(0.061)	(0.060)	(0.060)	(0.061)	(0.061)
RD_{t-3}	-0.309^{***}	-0.308^{***}	-0.323^{***}	-0.309^{***}	-0.307^{***}	-0.271^{***}
	(0.061)	(0.061)	(0.060)	(0.060)	(0.061)	(0.060)
RD_{t-4}	0.031	0.031	0.013	0.018	0.028	0.027
	(0.054)	(0.055)	(0.055)	(0.054)	(0.054)	(0.055)
Y_t	0.476^{***}					
	(0.075)					
ABOVE		0.466^{***}	0.435^{***}	0.615^{***}	0.571^{***}	0.393^{***}
		(0.090)	(0.077)	(0.089)	(0.113)	(0.084)
BELOW		0.493^{**}	0.847^{***}	0.239^{**}	0.422^{***}	0.552^{***}
		(0.107)	(0.192)	(0.111)	(0.090)	(0.118)
R^2	0.478	0.476	0.488	0.490	0.478	0.446
RSS	638.221	638.123	603.356	621.004	635.578	533.928
AIC	236.674	238.627	222.386	230.278	237.400	189.826
BIC	259.035	264.715	248.405	256.366	263.488	215.587
# obs. above		66	257	195	44	203
# obs. below		241	47	112	263	90
F-stat		0.046	4.358	8.318	1.248	1.447
Critical Value		3.086	7.395	4.019	3.126	8.645

Notes: Coefficients with significance stars as superscripts; standard errors in parentheses on the following row. The threshold variable for GDP, credit and cash flow is in growth rate. Unemployment is the unemployment rate minus its natural rate, and the P/E enters as a ratio.

evidence suggests that credit expansions amplify the cyclical sensitivity of aggregate private R&D.

The evidence is weaker for internal finance and GDP regimes. For internal finance, measured by cash flows, we find no statistically significant threshold effects across specifications. The GDP-regime results are also fragile. The threshold effect is statistically significant only when GDP enters as an HP-filtered cyclical component. We find no statistically significant asymmetries when GDP is detrended with the Hamilton filter or when cyclical GDP is measured as the deviation from CBO potential output. We therefore interpret the GDP-regime results cautiously and do not view them as robust evidence of state-dependent R&D pro-cyclicality.

Taken together, the specifications using the P/E ratio and credit spread do not support the macro-finance interpretation of state-dependent R&D incentives emphasized by Croce, Nguyen, and Schmid (2012) and Kung and Schmid (2015). Variables more directly related to valuations and risk premia do not reproduce the state dependence found for credit quantities. This evidence should be interpreted cautiously, however, since the macro-finance mechanisms motivating these variables typically imply smooth variation in innovation incentives, rather than a discrete change at an estimated threshold.

Interpretation

Our results admit multiple interpretations, and existing frameworks provide only partial guidance because asymmetries are rarely treated as a central object. We therefore offer two complementary avenues – one new hypothesis and one modification of a standard mechanism – and invite future research to formalize, test, and distinguish among them.

The labour market regime we identify leads us to propose a new hypothesis regarding the cyclicality of R&D: R&D becomes more strongly pro-cyclical when firms facing a positive demand shock are unable to hire additional workers. When such a shock occurs, firms seek to increase production, which typically requires more labour. If the labour market is slack, hiring is relatively easy. However, in a tight labour market, hiring becomes difficult and costly. In this context, firms may invest in labour-saving technologies to reduce reliance on additional workers or in technologies that raise labour productivity, thereby expanding output without increasing employment. This specific channel of R&D pro-cyclicality has not been explored in the literature. We conjecture that incorporating a search-and-matching model of the labour market into existing frameworks of pro-cyclical R&D could generate a dependence of optimal R&D investment on labour market tightness consistent with our findings. Additionally, studying the cyclicality of developing or adopting labour-saving technologies may offer a promising direction for future research.

Regarding credit regimes, our results do not align with the simplest version of the financial-frictions hypothesis, in which R&D pro-cyclicality should be strongest when credit is scarce. Instead, we find stronger pro-cyclicality when credit is abundant. We therefore propose a modified interpretation that can reconcile our aggregate evidence with firm-level studies showing that financially constrained firms exhibit stronger R&D cyclicality.

The financial frictions hypothesis is strongly supported by firm-level studies reviewed above, which generally find that financially constrained firms exhibit greater R&D pro-cyclicality, while this pattern is weaker or absent among unconstrained firms. A key contribution that helps reconcile our aggregate-level findings with this literature comes from Brown, Fazzari, and Petersen (2009), who analyse firm-level and aggregate R&D during the 1990s – a period of both financial expansion and rising R&D spending. They show that mature firms' R&D is largely unaffected by changes in external or internal financing, whereas young firms' R&D is highly responsive to financial conditions. Notably, they find that young firms account for approximately 75% of the aggregate R&D boom in that decade. This evidence suggests that the composition of aggregate R&D varies systematically with the state of financial markets: during financial booms, financially constrained young firms contribute meaningfully to total R&D's dynamics. Instead, in periods of scarce financing opportunities, aggregate R&D mostly reflects the R&D of older and larger firms.

Building on their findings, we hypothesize that this composition effect could generate the kind of asymmetry we observe at the macro level. During financial booms, when constrained firms become more active, their pro-cyclical R&D behaviour may drive aggregate patterns. Outside such periods, these firms contribute little to total R&D, leaving aggregate dynamics to be shaped mainly by unconstrained firms, whose investment is less sensitive to financial conditions. Under this view, the pro-cyclicality emphasized in the firm-level literature becomes macroeconomically relevant only when financing is abundant.

This modified hypothesis opens new avenues for both empirical and theoretical research. On the empirical side, while much of the existing literature focuses on financial crises, our findings suggest that greater attention should be directed towards understanding financial booms. On the theoretical side, models should move beyond representative-firm frameworks and incorporate forms of firm heterogeneity that can generate or account for variation in financial constraints across firms.

VIII. Conclusion

This paper studies whether aggregate private R&D exhibits asymmetric pro-cyclicality, and why such asymmetries matter for linking business-cycle shocks to long-run growth in endogenous growth settings. Across a range of tests, the central finding is that R&D's pro-cyclicality is strongest in 'good times' – a perspective that complements a literature that often emphasizes recessions and weak recoveries. The results therefore shift attention towards understanding R&D booms and the conditions under which temporary shocks may translate into persistent productivity differences.

Using post-WWII U.S. data, we document several reduced-form patterns. R&D expansions last longer than contractions; peaks tend to lag GDP peaks, while troughs are closer to coincident with GDP troughs. At the same time, turning points in GDP and R&D do not align reliably, indicating substantial heterogeneity across episodes and cautioning against treating GDP dynamics as a sufficient proxy for R&D dynamics. Consistent with that heterogeneity, endogenous threshold regressions (Hansen 2000) reveal clear regime dependence: the contemporaneous comovement between R&D and activity is significantly stronger when unemployment is low and when credit conditions are lax.

Specifically, our results provide reduced-form moments that can discipline future quantitative theory. Models designed to explain the asymmetries documented here should be able to generate R&D expansions that last roughly 30% to 50% longer than contractions, as well as substantially stronger R&D responsiveness to GDP in favourable economic states. Across our preferred specifications, the estimated response is approximately twice as large in low-unemployment regimes than in high-unemployment regimes, and about three times as large during periods of credit abundance than during periods of credit scarcity. These findings motivate several directions for future work, including (i) assessing the pro-cyclicality of investment in labour-saving technologies, and (ii) modelling financing constraints with firm heterogeneity to capture composition effects over the financial cycle.

Finally, our evidence is deliberately reduced-form: we document state-dependent comovement without identifying structural shocks or tracing full dynamic propagation. Future work that combines shock identification with impulse-response evidence for R&D and productivity is essential for magnitudes and for monetary and fiscal stabilization analysis. While our results are consistent with the possibility that policy-relevant 'good states' (e.g. tight labour markets or abundant credit) amplify R&D pro-cyclicality – echoing the 'high-pressure economy' intuition (Cerra, Fatás, and Saxena 2023) – credible policy prescriptions require a structural framework that jointly accounts for innovation incentives, financing conditions, labour-market dynamics, and the lag from R&D to productivity.

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Author contributions

CRediT: **Filippo Massari:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing; **Hedieh Shadmani:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing.

Disclosure statement

The authors report there are no competing interests to declare.

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Data availability statement

The data that support the findings of this study are publicly available from the Federal Reserve Economic Data (FRED) database maintained by the Federal Reserve Bank of St. Louis at https://fred.stlouisfed.org.

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Appendix A additional results and robustness

Table A1. Duration and steepness of real GDP cycles under alternative filters.

	Expansions	Contractions	Wilcoxon rank-sum *p*-value	Basic *t*-test *p*-value
Panel A. Rotemberg				
Mean duration (quarters)	11.500	9.455	0.402	0.227
Mean steepness	0.007	−0.007	0.444	0.497
Panel B. HP				
Mean duration (quarters)	8.846	7.428	0.211	0.191
Mean steepness	0.007	−0.007	0.461	0.498
Panel C. Band-pass				
Mean duration (quarters)	9.500	7.455	0.138	0.114
Mean steepness	0.005	−0.006	0.134	0.246
Panel D. Hamilton				
Mean duration (quarters)	9.600	9.909	0.416	0.441
Mean steepness	0.008	−0.010	0.336	0.213

Notes: HP uses $\lambda = 1600$. Band-pass uses Baxter and King (1999) with cycle lengths 6–32 quarters. Hamilton uses an 8-quarter lead and 4 lags.

Table A2. Duration and steepness of real private investment cycles under alternative filters.

	Expansions	Contractions	Wilcoxon rank-sum *p*-value	Basic *t*-test *p*-value
Panel A. Rotemberg				
Mean duration (quarters)	10.438	8.800	0.275	0.184
Mean steepness	0.028	−0.035	0.238	0.228
Panel B. HP				
Mean duration (quarters)	8.941	8.882	0.255	0.486
Mean steepness	0.027	−0.029	0.333	0.391
Panel C. Band-pass				
Mean duration (quarters)	10.125	6.941	0.022	0.018
Mean steepness	0.019	−0.023	0.110	0.210
Panel D. Hamilton				
Mean duration (quarters)	8.563	10.133	0.249	0.165
Mean steepness	0.038	−0.033	0.251	0.228

Notes: HP uses $\lambda = 1600$. Band-pass uses Baxter and King (1999) with cycle lengths 6–32 quarters. Hamilton uses an 8-quarter lead and 4 lags.

Table A3. Duration and steepness of real government R&D cycles under alternative filters.

	Expansions	Contractions	Wilcoxon rank-sum *p*-value	Basic *t*-test *p*-value
Panel A. Rotemberg				
Mean duration (quarters)	16.500	24.289	0.215	0.134
Mean steepness	0.011	−0.009	0.443	0.344
Panel B. HP				
Mean duration (quarters)	9.000	11.286	0.057	0.118
Mean steepness	0.007	−0.005	0.331	0.166
Panel C. Band-pass				
Mean duration (quarters)	8.000	9.467	0.152	0.218
Mean steepness	0.006	−0.006	0.491	0.382
Panel D. Hamilton				
Mean duration (quarters)	8.444	7.333	0.164	0.239
Mean steepness	0.018	−0.018	0.400	0.449

Notes: HP uses $\lambda = 1600$. Band-pass uses Baxter and King (1999) with cycle lengths 6–32 quarters. Hamilton uses an 8-quarter lead and 4 lags.

Table A4. Threshold regression results, HP-filtered threshold variables, R&D deflated with GDP deflator.

	Linear	Threshold Regression			
		GDP	Unemp	Credit	Cash Flow
Break value		1.006	−0.478	0.389	4.803
constant	0.349**	0.376**	0.409**	0.447***	0.348**
	(0.125)	(0.123)	(0.122)	(0.129)	(0.125)
RD_{t-1}	0.564***	0.544***	0.544***	0.560***	0.565***
	(0.055)	(0.055)	(0.054)	(0.055)	(0.055)
RD_{t-2}	0.228***	0.250***	0.240***	0.220***	0.229***
	(0.062)	(0.062)	(0.059862)	(0.061012)	(0.0612)
RD_{t-3}	−0.275***	−0.288***	−0.285***	−0.274***	−0.274***
	(0.062)	(0.061)	(0.061)	(0.062)	(0.062)
RD_{t-4}	−0.016	−0.057	−0.053	−0.012	−0.17
	(0.055)	(0.056)	(0.054)	(0.054)	(0.055)
Y_t	0.427***				
	(0.075)				
ABOVE		0.817***	0.349***	0.566***	0.461***
		(0.147)	(0.078)	(0.091)	(0.125)
BELOW		0.338***	0.854***	0.225**	0.414***
		(0.080)	(0.155)	(0.106)	(0.085)
R^2	0.488	0.502	0.504	0.498	0.486
RSS	631.576	612.257	588.293	617.033	631.330
AIC	233.461	225.924	214.700	228.309	235.341
BIC	255.822	252.012	240.719	254.397	261.429
# obs. above		76	215	109	55
# obs. below		231	89	198	252
F-stat		9.466	9.687	7.071	0.117
Critical Value		3.955	4.217	6.434	3.023

Notes: Coefficients with significance stars as superscripts; standard errors in parentheses on the following row. The threshold variable is the cyclical component after removing the HP-filtered trend.

Table A5. Threshold regression results, threshold in growth or cyclical unemployment, R&D deflated with GDP deflator.

	Linear	Threshold Regression			
(lr)2–2(lr)3–6		GDP	Unemp	Credit	Cash Flow
Break value		1.336	−1.186	0.787	2.600
constant	0.342^{**}	0.351^{***}	0.429^{***}	0.361^{**}	0.343^{**}
	(0.130)	(0.125)	(0.123)	(0.123)	(0.125)
RD_{t-1}	0.573^{***}	0.564^{***}	0.534^{***}	0.537^{***}	0.566^{***}
	(0.062)	(0.055)	(0.055)	(0.055)	(0.055)
RD_{t-2}	0.322^{***}	0.228^{***}	0.243^{***}	0.251^{***}	0.230^{***}
	(0.067)	(0.062)	(0.061)	(0.062)	(0.062)
RD_{t-3}	-0.356^{***}	-0.275^{***}	-0.280^{***}	-0.283^{***}	-0.275^{***}
	(0.061)	(0.061)	(0.060)	(0.060)	(0.061)
RD_{t-4}	0.031	0.031	0.013	0.018	0.028
	(0.054)	(0.055)	(0.055)	(0.054)	(0.054)
Y_t	0.388^{***}				
	(0.102)				
ABOVE		0.442^{***}	0.373^{***}	0.581^{***}	0.483^{***}
		(0.090)	(0.076)	(0.088)	(0.098)
BELOW		0.404^{**}	0.892^{***}	0.163	0.374^{***}
		(0.107)	(0.187)	(0.110)	(0.096)
R^2	0.488	0.488	0.500	0.503	0.488
RSS	631.576	631.389	593.081	610.228	629.927
AIC	233.461	235.370	217.164	224.905	234.658
BIC	255.822	261.458	243.184	250.993	260.746
# obs. above		66	257	195	44
# obs. below		241	47	112	263
F-stat		0.089	7.211	10.495	0.785
Critical Value		4.130	5.646	6.767	6.321

Notes: Coefficients with significance stars as superscripts; standard errors in parentheses on the following row. The threshold variable for GDP, credit and cash flow is in growth rate. Unemployment is the unemployment rate minus its natural rate.

Table A6. Threshold regression results with exogenous threshold for the natural rate of unemployment.

	Linear	Threshold Regression			
		Unemp	Unemp	Unemp	Unemp
Break value		−1.1	−1.0	−0.9	−0.8
constant	0.342^{**}	0.394^{**}	0.397^{**}	0.400^{**}	0.390^{**}
	(0.130)	(0.129)	(0.129)	(0.128)	(0.128)
RD_{t-1}	0.573^{***}	0.545^{***}	0.543^{***}	0.541^{***}	0.544^{***}
	(0.062)	(0.055)	(0.055)	(0.054)	(0.054)
RD_{t-2}	0.322^{***}	0.225^{***}	0.226^{***}	0.227^{***}	0.225^{***}
	(0.067)	(0.060)	(0.060)	(0.060)	(0.060)
RD_{t-3}	-0.356^{***}	-0.320^{***}	-0.319^{***}	-0.323^{***}	-0.321^{***}
	(0.064)	(0.061)	(0.060)	(0.060)	(0.060)
RD_{t-4}	0.031	0.025	0.024	0.019	0.024
	(0.054)	(0.055)	(0.054)	(0.054)	(0.054)
Y_t	0.388^{***}				
	(0.102)				
ABOVE		0.450^{***}	0.447^{***}	0.435^{***}	0.444^{***}
		(0.078)	(0.078)	(0.078)	(0.078)
BELOW		0.679^{***}	0.694^{***}	0.756^{***}	0.693^{***}
		(0.179)	(0.176)	(0.168)	(0.165)
R^2	0.478	0.483	0.483	0.486	0.484
RSS	631.576	609.102	608.475	605.334	607.888
AIC	233.461	225.267	224.954	223.381	224.661
BIC	255.822	251.286	250.973	249.400	250.680
# obs. above		254	244	239	233
# obs. below		50	60	65	71
F-stat		1.515	1.822	3.372	2.111
Critical Value		1.986	1.986	1.986	1.986

Notes: Coefficients with significance stars as superscripts; standard errors in parentheses on the following row. The threshold variable for GDP, credit and cash flow is in growth rate. Unemployment is the unemployment rate minus its natural rate.

Table A7. Threshold regression results, Hamilton-filtered threshold variables.

	Linear	Threshold Regression			
		GDP	Unemp	Credit	Cash Flow
Break value		3.23	−1.266	−3.981	−4.383
constant	0.341**	0.400**	0.345***	0.450**	0.389***
	(0.128)	(0.133)	(0.133)	(0.132)	(0.133)
RD_{t-1}	0.520***	0.400***	0.493***	0.516***	0.528***
	(0.054)	(0.055)	(0.056)	(0.054)	(0.055)
RD_{t-2}	0.229***	0.247***	0.293***	0.231***	0.241***
	(0.061)	(0.060)	(0.061)	(0.060)	(0.060)
RD_{t-3}	−0.309***	−0.303***	−0.278***	−0.311***	−0.303***
	(0.061)	(0.060)	(0.061)	(0.060)	(0.060)
RD_{t-4}	0.031	0.026	0.021	0.028	0.033
	(0.054)	(0.055)	(0.056)	(0.053)	(0.054)
Y_t	0.476***				
	(0.075)				
ABOVE		0.561***	0.421***	0.524***	0.485***
		(0.164)	(0.076)	(0.076)	(0.084)
BELOW		0.446***	0.682***	−0.070	0.406***
		(0.078)	(0.214)	(0.190)	(0.121)
R^2	0.478	0.452	0.446	0.467	0.451
RSS	638.221	585.687	533.967	568.818	585.923
AIC	236.674	214.700	189.847	205.933	214.822
BIC	259.035	240.627	215.608	231.860	240.748
# obs. above		44	246	284	204
# obs. below		258	47	52	96
F-stat		0.460	1.424	9.163	0.342
Critical Value		3.792	8.075	2.894	4.134

Notes: Coefficients with significance stars as superscripts; standard errors in parentheses on the following row. The threshold variable is the cyclical component after removing the trend obtained with the Hamilton filter with an 8-quarter lead and 4 lags.