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Abstract

This paper studies how financial conditions affect research and development (R&D) by firms specialized in green innovation. Using U.S. patent data matched with Compustat, we identify "green innovators" as firms with a high cumulative share of green patents. Although they account for a small share of total green patenting, these firms occupy central positions in the green-innovation ecosystem. Estimating firm-level impulse responses to exogenous changes in broad financial conditions, we find that tightening has a disproportionately large and persistent negative effect on the R&D of specialized green innovators. In contrast, R&D by diversified innovators and non-innovators responds only weakly. Green innovators are younger, smaller, and more dependent on external finance, suggesting that financial tightening introduces a systematic bias against upstream green technological development.

1 Introduction

Achieving the low-carbon transition requires more than carbon pricing. A broad consensus has emerged that climate policy must rely on a mix of instruments, including regulation, public investment, and policies aimed at fostering green technological innovation (Newell, 2011). Models of directed technical change show that policies that encourage clean innovation can substantially reduce the long-run welfare costs of climate action and may even offset part of the short-run output losses associated with stricter environmental regulation (Acemoglu et al., 2012).

Both public and private R&D therefore play a central role in the green transition. On the private side, firms' incentives to invest in green R&D depend not only on subsidies and tax credits, but also on financial conditions, which affect their cost of capital, risk-taking capacity, and access to external finance.

This paper studies how changes in financial conditions influence R&D by firms specialized in green innovation. Using U.S. patent data matched with Compustat, we identify a group of "green innovators"—firms whose cumulative share of green patents exceeds a given threshold. Although these firms account for only a small share of total green patenting, we show that they occupy central positions in the green-innovation ecosystem and produce technologies that are widely cited and used across sectors. We compare these firms with other patenting firms, which we call "diversified innovators", and with firms that have no matched patents to date, which we call "non-innovators".

Our main result is that financial tightening has a disproportionately large and persistent negative effect on the R&D expenditure of specialized green innovators. A one-standard-deviation tightening in the Composite Indicator of Systemic Stress (CISS) reduces their R&D intensity by roughly one percentage point at the peak—approximately five times larger than the average response. Diversified innovators and non-innovators respond little. This heterogeneity reflects systematic differences in firm characteristics: green innovators are younger, smaller, and more dependent on external finance.

Methodologically, our approach separates the identification of green innovators from the measurement of innovation outcomes. Rather than using patents as the outcome variable, we use patent data to classify firms by their specialization in green innovation and then examine how their R&D responds to financial conditions. This addresses two limitations of patent-based outcome measures: patent filings are a noisy, lagging indicator of R&D activity, and focusing on patent outcomes obscures differences between firms specialized in green innovation and firms that occasionally produce green patents as part of broader strategies. The trade-off is that R&D is observed at the firm rather than project level, so the estimates capture total R&D by green-specialist firms rather than green-specific R&D directly. Since firms' innovation direction is highly persistent, as discussed in Section 3.1, these responses are likely informative about green R&D by specialized innovators.

Our findings contribute to two strands of literature. First, we relate to work on climate policy and directed technical change (Acemoglu et al., 2012; Aghion et al., 2026). Our analysis complements Aghion et al. (2026), who show that credit tightening disproportionately reduces green patenting because younger firms are both more sensitive to tight financial conditions and more specialized in green innovation. While their analysis focuses on patenting responses to financial constraints, we examine how financial conditions affect the R&D investment of firms specialized in green innovation. Second, we contribute to the literature on monetary policy, financial conditions, and innovation. Our findings help reconcile the results of Känzig et al. (2025), who—using patent data as a proxy—find green innovation to be counter-cyclical. Their analysis gives more weight to high-volume green patenters, whereas our classification is designed to distinguish firms specialized in green innovation, a distinct component of the ecosystem, from firms that produce green patents only occasionally within broader innovation portfolios.

Our results also relate to recent work emphasizing that climate policy may interact with monetary policy through innovation, generating a "green dilemma" for central banks (Fornaro et al., 2025). We provide empirical evidence for one mechanism: fluctuations in financial conditions disproportionately constrain firms operating upstream in the green-technology pipeline.

The remainder of the paper is organized as follows. Section 2 motivates and characterizes our classification of specialized green innovators. Section 3 describes the empirical design. Section 4 presents our main results. Section 5 concludes.

2 Identifying Green Specialists

"Green" is a label that can mean many different things, and different operational definitions identify very different sets of firms. A common approach is to classify firms based on their emissions, treating low-emitting firms as green and high-emitting firms as dirty (e.g., Döttling and Lam, 2024; Bauer et al., 2025). A second approach is to classify firms based on green patenting activity, treating any firm that files green patents as a green innovator.

Both approaches are problematic for the question we ask. Studying how financial conditions affect green R&D requires identifying the firms that actually *do* green R&D as a core business activity—not firms that happen to have low emissions, and not firms that occasionally file a green patent within a much larger and predominantly non-green innovation portfolio.

Two observations make this point concrete. First, the relationship between emissions intensity and green innovation is weak and often goes in unexpected directions. A substantial share of green patenting in our matched sample is undertaken by firms in the upper half of the emissions-intensity distribution—high-emitting firms developing technologies that allow them to comply with environmental regulations. Conversely, many firms with low emissions and high environmental scores do little green innovation, consistent with the disconnect documented by Cohen et al. (2020). Emissions and green innovation capture different dimensions of firm behavior, and using emissions as a proxy for greenness is misleading for our purposes.

Second, most green patents are filed by firms whose innovation portfolio is overwhelmingly non-green. In our sample, the majority of green patents are filed by *diversified* innovators—large diversified firms that file many more non-green patents and produce green patents as a small part of much broader research programs. Studies that treat patent counts as the outcome variable and pool all green patenters together (e.g., Känzig et al., 2025) therefore largely capture the patenting behavior of these firms, for whom green innovation is incidental rather than central. This obscures what happens to the firms whose business model is built around green technology.

To address these problems, we classify firms by the cumulative share of green patents in their total patent portfolio, identifying as "green innovators" those firms whose cumulative green share exceeds 25%. Section 3.1 describes the construction in detail. This procedure selects a small, stable group of roughly fifty firms per quarter that are predominantly active in clean energy, energy storage, smart-grid technologies, and fuel cells—firms whose core business is the development and commercialization of green technology. We analyze this group separately from firms with a lower share of green patenting, which we call "diversified innovators", and from firms with no patents to date, which we call "non-innovators".

Centrality. Although green innovators account for only a small share of green patenting among matched public firms, about 5% of weighted green patent filings, they occupy central positions in the green-innovation ecosystem. Table 1 reports three citation-network measures computed on the green-patent network. *Green forward citations* count the number of subsequent green patents that cite a given patent. *Betweenness centrality* measures how often a patent lies on the shortest citation paths between other green patents, capturing a bridging position in the network. The *top-5% share* is the fraction of a group's green patents that fall in the top 5% of the same-year green-forward-citation distribution.

Table 1: Green patent citation and network metrics by innovator group

Group	Green fwd. citations	Betweenness centrality	Top-5% share
Diversified innovator	7.12	5,644	4.45%
Green innovator	11.17	11,852	8.87%

Green innovators receive more citations from other green patents, occupy more central bridging positions in the green citation network, and produce a disproportionate share of the most influential green patents. This is consistent with anecdotal evidence on the technologies and supply-chain positions of these firms: examples include Enphase Energy (microinverters used in millions of rooftop solar systems), First Solar (thin-film PV deployed in some of the world's largest solar farms), Plug Power (the largest U.S. producer of liquid hydrogen), FuelCell Energy (large fuel-cell parks with integrated CO_2 capture), Tesla (EV-battery manufacturing and the world's largest fast-charging network), and A123 Systems (the first U.S. plant for mass EV-battery production). By providing distinctive technologies, infrastructure, and production capacity, these firms help determine how quickly and at what cost clean-energy systems can be expanded.

Financial characteristics. Green innovators also differ systematically from other firms in ways that matter for the transmission of financial-conditions shocks. Table 2 reports sample averages across the three groups for a set of standard firm-level variables.

Table 2: Full-sample firm characteristics by innovator group

Group	Age	MVE ($bn)	Lev.	β^A	Cash/A (%)	(Capex–OCF)/A (%)	CoC (%)
Non-innovator	15.8	2.54	0.29	1.29	13.74	2.55	8.81
Diversified innovator	23.8	3.70	0.22	3.91	27.39	3.46	9.44
Green innovator	15.6	0.77	0.25	3.93	25.80	7.27	9.58

Notes: Age is measured from the date of incorporation in Worldscope, with the first Compustat appearance used when this is missing (Cloyne et al., 2023). The asset beta β^A is computed by de-levering the equity beta using balance-sheet leverage following Ma and Zimmermann (2023). Leverage is debt in current liabilities plus long-term debt divided by total assets, following Giroud and Mueller (2021). Cash/A is cash and short-term investments divided by total assets. (Capex–OCF)/A is capital expenditures minus operating cash flow, scaled by assets, a proxy for net external-financing needs. CoC is the firm-level perceived cost of capital from Gormsen and Huber (2024).

Green innovators are, on average, substantially smaller than diversified innovators (market value of \$0.77 billion versus \$3.70 billion) and younger (15.6 versus 23.8 years). They have a higher asset beta, indicating greater cyclicality, and are more leveraged than diversified innovators. They face a higher perceived cost of capital and exhibit a higher ratio of capital expenditure net of operating cash flow to assets, consistent with greater reliance on external finance and a focus on early-stage R&D. Their cash-to-asset ratio is lower than that of diversified innovators, indicating lower liquidity.

Taken together, these characteristics describe a category of firms that one would expect, on a priori grounds, to be especially sensitive to financial conditions: young, small, highly cyclical, externally financed, and operating with limited liquidity buffers. This contrasts sharply with the standard view that R&D is relatively insulated from monetary tightening because it is typically financed internally by large incumbents—a view that fits diversified innovators reasonably well but not the firms doing most of the upstream green R&D. The next section turns to the formal estimation of how financial conditions affect their R&D.

3 Empirical Design

3.1 Classification of firms

We extract all USPTO patent applications from 1976 to 2023 with filing date and cooperative patent classification (CPC) code. Patents are classified following Jee and Srivastav (2024), which exploits existing methodologies to identify emission-reducing ("green") and emission-increasing ("dirty") technologies. Patents are then matched to firms using the DISCERN 2.0 patent-to-firm data (Arora et al., 2024a,b). Although the concordance maps granted patents through 2021, we restrict the firm-level sample to end in 2019 to account for patent grant delays and to exclude the COVID period.

For each firm, we compute a time-varying cumulative measure of green-patent intensity:

$$\text{cumulative green}_{i,t} = \frac{\sum_{\tau=t_0}^{t} \text{green patents filed}_{i,\tau}}{\sum_{\tau=t_0}^{t} \text{total patents filed}_{i,\tau}}, \tag{1}$$

where t_0 is the firm's first matched patent filing. We classify firms as:

- **Green innovator** if cumulative $\text{green}_{i,t} \geq 25\%$;
- **Diversified innovator** if $0 \leq$ cumulative $\text{green}_{i,t} < 25\%$;
- **Non-innovator** if the firm has filed no patents to date.

Aghion et al. (2016) document strong path dependence in the direction of technical change: firms with a history of relatively more clean (dirty) innovation are more likely to innovate in clean (dirty) technologies in the future. This persistence implies that firms with a high cumulative share of green patents are likely to continue undertaking green R&D, making our classification a reasonable proxy for current green-innovation activity. As discussed in Section 2, the classification selects a stable population of roughly fifty companies per quarter, with few transitions in and out.

3.2 Financial conditions

We focus on a broad index of financial conditions rather than on the short-term interest rate. Because our sample includes the zero-lower-bound period and episodes of large financial frictions, a broader index better captures the cost and availability of finance faced by firms. As argued by Caballero et al. (2024, 2025) and Lane (2025), the short-term policy rate may be an incomplete measure of the monetary-policy stance, and empirical analyses focused solely on the policy rate risk overlooking the dominant channels through which monetary policy influences real activity. This is particularly relevant in our setting, since we focus on publicly listed companies whose financing is shaped by capital-market conditions beyond the policy rate.

We use the U.S. New Composite Indicator of Systemic Stress (CISS) from the ECB Data Portal, based on the methodology of Hollo et al. (2012), which targets the systemic dimension of financial stress. This series combines fifteen mainly market-based indicators across financial segments and aggregates them using time-varying cross-correlations, in a way analogous to portfolio-risk aggregation. This approach assigns greater weight to periods in which stress is elevated and widespread across markets, explicitly capturing the systemic dimension of financial instability. The New CISS uses a revised equal-weighting scheme for the raw indicators and focuses primarily on market-based measures of risk, with some coverage of credit stress.

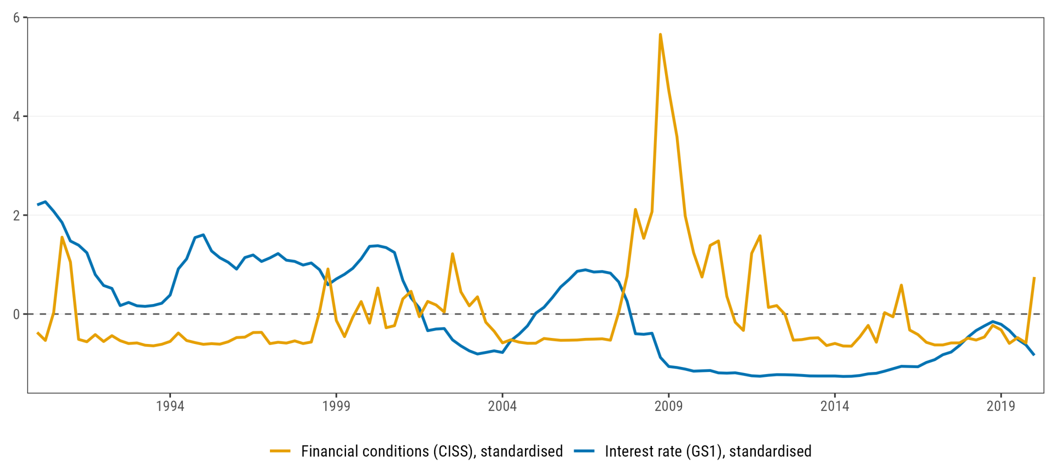

Figure 1: Financial conditions (CISS) and one-year Treasury yield (GS1), standardized.

Figure 1 highlights the absence of a stable relationship between short-term interest rates and broader financial conditions. Periods of tightening or easing in the policy rate do not map consistently into movements in the CISS index. Notably, in the run-up to the Global Financial Crisis, interest rates increased while financial conditions remained relatively loose, whereas during the crisis financial conditions tightened sharply despite a rapid decline in interest rates. Similar episodes of decoupling are also visible in more recent years, as highlighted by Caballero et al. (2025). This pattern suggests that accommodative interest rates do not necessarily coincide with loose broader financial conditions, underscoring the importance of distinguishing between interest-rate policy and broader financial stress when analyzing innovation responses.

3.3 R&D and the estimation sample

We construct a quarterly sample of firm-level observations from 1986Q1 to 2023Q4; due to patent-data availability, our main estimation sample covers 1990Q1–2019Q4. The dependent variable is R&D intensity, defined as R&D expenditure in period t divided by total assets at the beginning of the period:

$$\text{R\&D intensity}_{i,t} = \frac{\text{R\&D expense}_{i,t}}{\text{Total assets}_{i,t}}. \tag{2}$$

3.4 Aggregate VAR

Before turning to firm-level estimates, we summarize the aggregate effects of financial-conditions shocks in a parsimonious benchmark system that also motivates the recursive identification used in the local projections below. Let

$$y_t = (g_t, i_t, r_t, z_t, x_t)', \tag{3}$$

where g_t is real GDP growth, i_t is real investment growth, r_t is real R&D growth, z_t is financial conditions (CISS), and x_t is the one-year Treasury yield. We estimate the reduced-form VAR using Bayesian shrinkage priors, with prior tightness chosen via the hierarchical approach of Giannone et al. (2015). Structural shocks are identified through a Cholesky decomposition of the reduced-form covariance matrix.

This recursive identification imposes the following timing restrictions on contemporaneous responses. GDP, investment, and R&D do not respond within the quarter to shocks in financial conditions or interest rates. Financial conditions may respond contemporaneously to shocks in real activity, but not to interest-rate shocks. The interest rate may respond contemporaneously to all other shocks. Under the same information set, the same financial-conditions shock can be represented equivalently in local-projection form (Plagborg-Møller and Wolf, 2021), which is the approach we adopt for the firm-level analysis.

3.5 Stratified local projection

To allow the response of R&D to financial conditions to vary across firm types, we estimate panel local projections with group-specific coefficients. Let $D^g_{i,t} = \mathbf{1}[\text{Green}_{i,t} = g]$ indicate firm i's group at time t. The baseline specification is:

$$y_{i,t+h} = \mu_{i,h} + \psi_h' Q_t + \sum_{g=1}^{G} \beta_{g,h} D^g_{i,t} FC_t + \sum_{l=0}^{p} \phi_{h,l} y_{i,t-l} + \sum_{g=1}^{G} \gamma_{g,h} D^g_{i,t} r_t + \sum_{l=1}^{p} \sum_{g=1}^{G} \delta'_{g,h,l} D^g_{i,t} w_{t-l} + \xi_{i,t+h}, \tag{4}$$

for $h \in \{0, 1, \ldots, H\}$, where $w_t = (r_t, FC_t, q_t)'$, r_t is real GDP growth (entering contemporaneously), and q_t is the one-year Treasury yield (entering only with lags). Aggregate controls and lags are fully interacted with group dummies to allow flexible heterogeneity. Firm fixed effects $\mu_{i,h}$ absorb permanent differences in R&D levels across firms and industries; quarter-of-year fixed effects $\psi_h' Q_t$ remove seasonal patterns. Time fixed effects are deliberately omitted, so the estimated impulse responses reflect absolute within-firm changes inclusive of general-equilibrium effects.

Using the recursive timing structure described above in Section 3.4, the financial-conditions shock in the local projection is the component of FC_t that remains after partialling out contemporaneous GDP growth and the relevant lagged information set:

$$FC_t^{\perp} \equiv FC_t - \mathbb{E}[FC_t \mid r_t, \mathcal{I}_{t-1}], \tag{5}$$

where $\mathcal{I}_{t-1}$ denotes the span of lagged aggregate information included in the projection. This innovation can be interpreted as a tightening in financial conditions unrelated to contemporaneous macroeconomic conditions, reflecting shifts in risk appetite, market liquidity, and intermediation capacity.

We use four lags ($p = 4$) and estimate impulse responses up to a three-year horizon ($H = 12$). To reduce the variance of LP estimators over horizons, we apply the smoothed panel local projections (SPLP) approach of Hartley and Mejia (2025), which penalizes deviations from a low-order polynomial using ridge regression. We smooth toward a quadratic polynomial, and the penalty parameter is chosen via generalized cross-validation. Standard errors are computed using a wild cluster bootstrap (1,000 replications, clustered by date), and IRFs are reported with 95% confidence bands.

4 Empirical Results

4.1 Aggregate effects of financial-conditions shocks

Before turning to the firm-level analysis, we verify that the financial-conditions shock identified in our framework generates aggregate dynamics consistent with a financial-transmission channel. Figure 2 reports impulse responses from the recursively identified Bayesian VAR described in Section 3.4. Solid lines show estimates for the full sample (1990Q1–2019Q4) with 95% credible sets; dashed lines show the corresponding responses estimated on the pre-2008 sample.

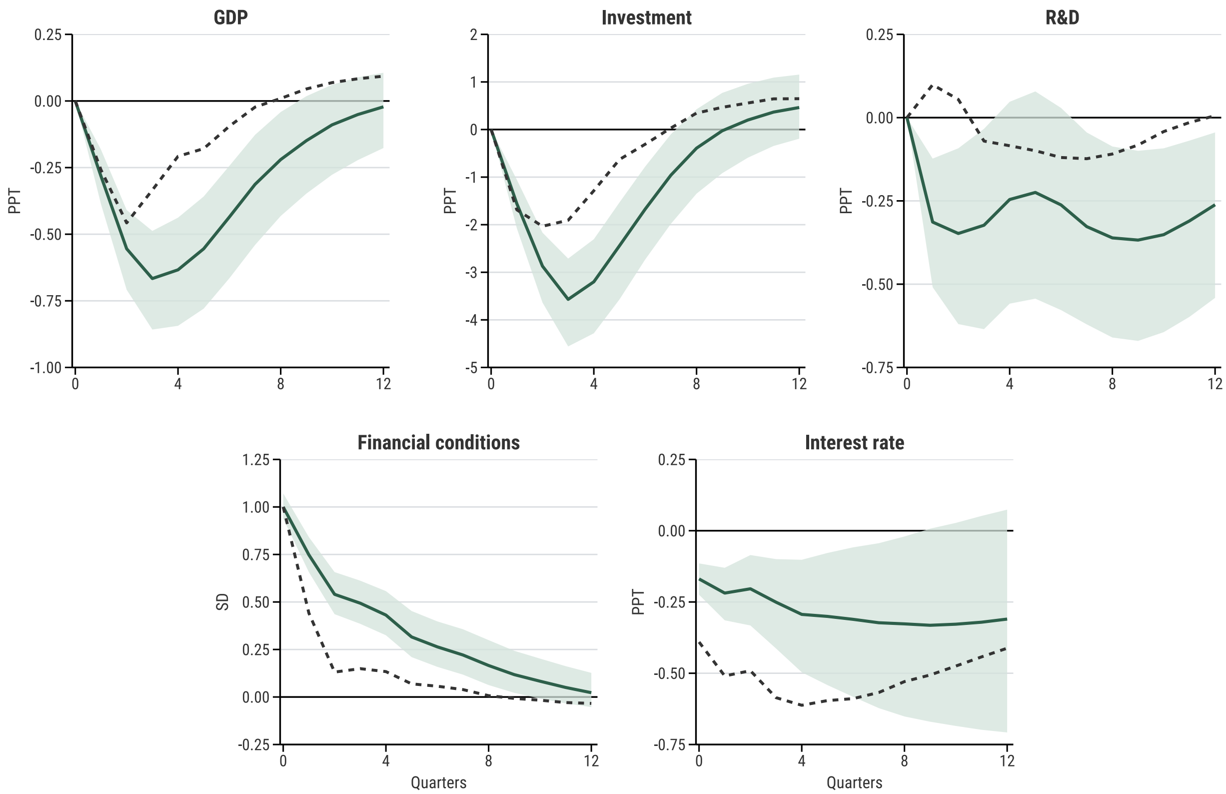

Figure 2: Impulse responses to a financial-conditions shock from a recursively identified Bayesian VAR. Solid lines: full sample, 1990Q1–2019Q4, with shaded 95% credible sets. Dashed lines: pre-2008 sample, 1990Q1–2007Q4.

A tightening in financial conditions leads to a sharp contraction in aggregate activity. GDP growth and investment fall on impact and gradually recover over subsequent quarters, with effects that are statistically well-identified. The response of aggregate R&D is negative but smaller and less precisely estimated, consistent with the view that R&D is generally less responsive to monetary tightening than tangible investment (Döttling and Ratnovski, 2023; Hall and Lerner, 2010). Estimating the VAR on the pre-2008 sample yields qualitatively similar dynamics, though effects are somewhat weaker when the post-financial-crisis period is excluded. These aggregate results confirm that the financial-conditions shock operates through a recognizable macroeconomic transmission channel.

The modest aggregate response of R&D, however, conceals substantial heterogeneity across firms. The next subsection shows that this aggregate response is the average of two very different patterns: a small response for the majority of innovators, and a large, persistent contraction concentrated among the specialized green innovators identified in Section 2.

4.2 Main result: heterogeneous response of R&D

Figure 3 reports the impulse response function of R&D intensity to a one-standard-deviation tightening in the CISS, separately by innovator group. Solid lines show estimates from the baseline specification (equation 4); dashed lines show the corresponding responses from an otherwise identical bivariate specification in which the lagged interest-rate controls are omitted. Shaded areas indicate 95% confidence bands.

Baseline IRF – Effect of Financial Conditions Shocks on R&D Intensity

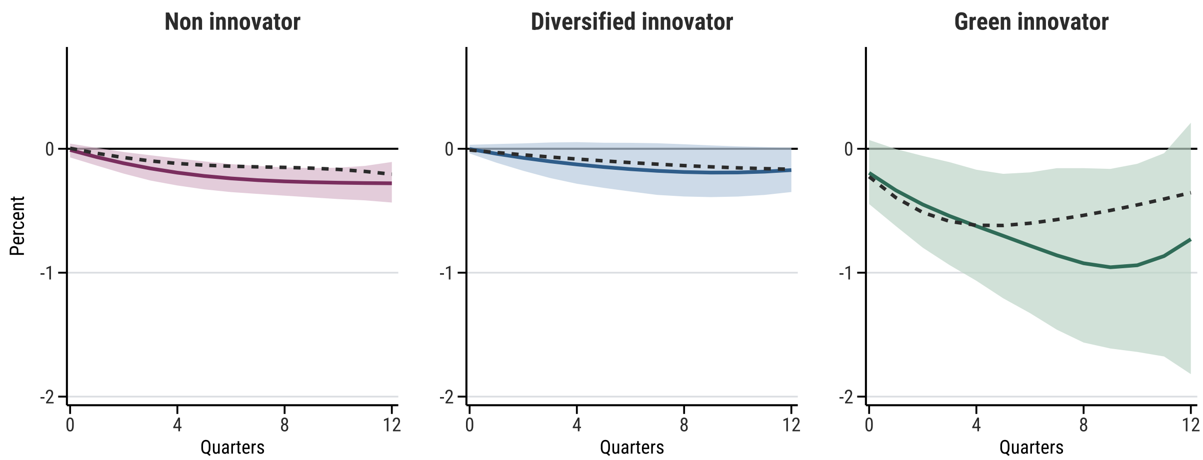

Figure 3: Impulse responses of R&D intensity to a financial-conditions shock from the stratified local projections. Solid lines show estimates from the baseline specification, while dashed lines show the corresponding responses from a bivariate specification that omits the interest-rate control. Shaded areas indicate 95% confidence bands.

Focusing first on the baseline specification (solid lines), the response of R&D intensity to a financial-conditions tightening differs sharply across groups. Non-innovators and diversified innovators respond little; their R&D intensity falls modestly, with effects that are economically small and statistically weak throughout the three-year horizon. In contrast, the response of green innovators is large, persistent, and statistically significant. At its peak (around 8–10 quarters after the shock), a one-standard-deviation increase in financial tightness reduces green-innovator R&D intensity by roughly one percentage point. The estimated effect on R&D by green innovators is approximately five times larger than the average response across innovators, supporting our central conjecture: financial conditions disproportionately constrain firms specialized in green innovation.

4.3 Reconciling with the literature on aggregate R&D

How do these results compare with the literature on aggregate R&D? The evidence on aggregate R&D is less conclusive than that on aggregate investment, both conceptually and empirically. R&D expenditure involves intangible, non-collateralizable assets, long development horizons, and substantial adjustment frictions, all of which dampen its responsiveness to monetary-policy-induced changes in financing conditions (Hall and Lerner, 2010). Consistent with this view, Döttling and Ratnovski (2023) show that contractionary monetary policy depresses tangible investment sharply, whereas intangible investment—such as R&D, software, and organizational capital—responds significantly less. Similarly, Ma and Zimmermann (2023) find that monetary tightening leads to sizable declines in R&D spending, venture-capital activity, and future innovation output, with highly heterogeneous effects across firms, consistent with the idea that R&D and innovation depend more on firms' liquidity, risk tolerance, and specialized financing than on the policy rate per se.

Although the standard view in the innovation literature is that R&D is relatively insulated from monetary tightening—because it is typically financed internally by large, incumbent firms—this logic does not extend neatly to green innovation. As identified by our classification, green innovators are young companies more dependent on external finance than other innovators. These firms operate with high leverage, greater external-financing needs, lower liquidity buffers, and significant technological and policy uncertainty. This explains why their R&D expenditure is more sensitive to changes in financial conditions than the R&D of established firms in traditional sectors.

4.4 The role of the interest rate

The role of the interest-rate control is informative. Comparing the solid and dashed lines in Figure 3, omitting the lagged q_t controls from the local projections attenuates the estimated response of R&D expenditure for green innovators, but leaves the responses of non-innovators and diversified innovators essentially unchanged.

The interpretation is as follows. When lags of q_t are omitted, the innovation to financial conditions reflects a broader combination of underlying forces, including both exogenous financial stress and the endogenous monetary-policy response to that stress. As a result, the bivariate impulse response captures the broader effect of financial conditions, which may be attenuated if policy accommodation partially offsets the direct impact of financial tightening. Consistent with this interpretation, the attenuation of the green-innovator response when the interest rate is omitted suggests that their R&D responds both to the non-rate component of financial conditions *and* to the component linked to (or best isolated by conditioning on) the interest rate. Conditioning on lags of q_t helps to isolate the component of financial-conditions movements that is not explained by the prior monetary-policy path, yielding a larger and more persistent estimated effect.

For non-innovators and diversified innovators, in contrast, the financial-conditions index appears close to a sufficient statistic: conditioning on the interest rate adds little incremental identifying information beyond what is already contained in the financial-conditions measure.

4.5 Robustness

We have verified that our results are robust along several dimensions. First, the impulse responses are quantitatively and qualitatively similar under an alternative recursive ordering in which financial conditions are placed last, allowing them to respond contemporaneously to both real activity and interest rates. Second, varying the green-patent threshold to 20% or 30% yields the expected pattern: lowering the threshold attenuates the estimated response, while raising it amplifies it, indicating that the most pronounced heterogeneity is concentrated among firms with the highest cumulative share of green patents. Third, estimating the aggregate VAR under the alternative ordering and on the pre-2008 sample yields qualitatively similar dynamics to those reported in Figure 2, confirming that our aggregate results are not driven by the baseline placement of financial conditions before the interest rate.

5 Conclusion

This paper studies how financial conditions affect R&D by firms specialized in green innovation. Using patent data to identify a stable group of green innovators among U.S. publicly listed firms, and estimating firm-level impulse responses to shocks in broad financial conditions, we show that financial tightening has a disproportionately large and persistent negative effect on the R&D expenditure of these firms. In contrast, R&D by diversified innovators and non-innovators responds only weakly.

Our evidence suggests that this heterogeneity reflects differences in financial structure. Specialized green innovators—a category with a central role in the green-technology ecosystem—are smaller, more cyclical, and more reliant on external finance. As a result, fluctuations in financial conditions, capturing shifts in risk appetite, liquidity, and credit supply, translate into stronger contractions in upstream green technological development.

These findings carry two main implications. First, broad financial conditions matter for innovation beyond movements in the short-term interest rate, highlighting the importance of the financial channel in the transmission of macroeconomic shocks to innovation. Second, financial tightening may introduce a systematic bias against the green transition by disproportionately constraining the firms that play a central role in the clean-technology ecosystem. Understanding and potentially mitigating this channel is key for aligning macro-financial stabilization with long-run climate objectives.

References

Acemoglu, D., P. Aghion, L. Bursztyn, and D. Hemous (2012). "The Environment and Directed Technical Change." *American Economic Review* 102(1), 131–66.

Aghion, P., A. Bergeaud, M. De Ridder, and J. Van Reenen (2026). "Lost in Transition: Financial Barriers to New Technologies." Working Paper, March 2026.

Aghion, P., A. Dechezleprêtre, D. Hemous, R. Martin, and J. Van Reenen (2016). "Carbon Taxes, Path Dependency, and Directed Technical Change." *Journal of Political Economy* 124(1), 1–51.

Arora, A., S. Belenzon, L. Cioaca, L. Sheer, H. M. Shin, and D. Shvadron (2024a). "DISCERN 2.0:

Duke Innovation & SCientific Enterprises Research Network." Dataset, Zenodo. doi: 10.5281/zenodo.3594642.

Arora, A., S. Belenzon, L. Cioaca, L. Sheer, and D. Shvadron (2024b). "Back to the Future: Are Big Firms Regaining their Scientific and Technological Dominance? Evidence from DISCERN 2.0." Manuscript.

Bauer, M. D., E. A. Offner, and G. D. Rudebusch (2025). "Green Stocks and Monetary Policy Shocks: Evidence from Europe." *European Economic Review.*

Caballero, R. J., T. E. Caravello, and A. Simsek (2024). "Financial Conditions Targeting." NBER Working Paper.

Caballero, R. J., T. E. Caravello, and A. Simsek (2025). "FCI-star." Working Paper.

Cloyne, J., C. Ferreira, M. Froemel, and P. Surico (2023). "Monetary Policy, Corporate Finance, and Investment." *Journal of the European Economic Association.*

Cohen, L., U. G. Gurun, and Q. H. Nguyen (2020). "The ESG-Innovation Disconnect: Evidence from Green Patenting." NBER Working Paper.

Döttling, R., and A. Lam (2024). "Monetary Policy, Carbon Transition Risk, and Firm Valuation."

Döttling, R., and L. Ratnovski (2023). "Monetary Policy and Intangible Investment." *Journal of Monetary Economics* 134, 53–72.

Fornaro, L., V. Guerrieri, and L. Reichlin (2025). "Monetary Policy for the Green Transition."

Giannone, D., M. Lenza, and G. E. Primiceri (2015). "Prior Selection for Vector Autoregressions." *Review of Economics and Statistics* 97(2), 436–451.

Giroud, X., and H. M. Mueller (2021). "Firm Leverage and Employment Dynamics." *Journal of Financial Economics* 142(3), 1381–1394.

Gormsen, N. J., and K. Huber (2024). "Firms' Perceived Cost of Capital." NBER Working Paper.

Hall, B. H., and J. Lerner (2010). "The Financing of R&D and Innovation." In *Handbook of the Economics of Innovation*, vol. 1, 609–639.

Hartley, J., and J. Mejia (2025). "Smooth Panel Local Projections." SSRN.

Hollo, D., M. Kremer, and M. Lo Duca (2012). "CISS: A Composite Indicator of Systemic Stress in the Financial System." ECB Working Paper.

Jee, S. J., and S. Srivastav (2024). "Knowledge spillovers between clean and dirty technologies: evidence from the patent citation network." *Ecological Economics* 224, 108310.

Känzig, D. R., M. Konradt, L. Wang, and D. Zhang (2025). "Green Business Cycles." NBER Working Paper.

Lane, P. R. (2025). "The Transmission of Monetary Policy: Financial Conditions and Credit Dynamics." Speech, 5th WE_ARE_IN Conference, Frankfurt.

Ma, Y., and K. Zimmermann (2023). "Monetary Policy and Innovation." NBER Working Paper.

Newell, R. G. (2011). "The Energy Innovation System: A Historical Perspective." In *Accelerating Energy Innovation*. University of Chicago Press.

Plagborg-Møller, M., and C. K. Wolf (2021). "Local Projections and VARs Estimate the Same Impulse Responses." *Econometrica* 89(2), 955–980.