Sustainable Innovation*

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Abstract

We study the macroeconomic effects of innovation on output, CO_2 emissions, and emissions-adjusted total factor productivity, distinguishing between government- and privately funded patents. We document three main results. First, only government-funded innovation generates medium-term gains in emissions-adjusted productivity. However, these gains are followed by a pronounced increase in CO_2 emissions that erodes the long-run productivity expansion once environmental externalities are taken into account. Second, counterfactual simulations attribute this delayed emissions response to a general equilibrium mechanism that crowds in private investment and, in turn, expands production. Third, within both funding categories, green patents are more conducive to sustainable growth, with government-funded innovation associated with far larger average effects. Yet, green private patents in basic research perform comparably to green public patents, pointing to basic research as a main transmission channel. Overall, our findings highlight the central role of the source and direction of innovation in shaping growth and environmental sustainability.

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Keywords: emission-adjusted TFP, public innovation, green patents, rebound.

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1 Introduction

Innovation is widely viewed as the engine of long-run growth and a central instrument of industrial policy. At the same time, decarbonization has become a defining macroeconomic challenge, motivating large public programs that subsidize research, accelerate diffusion of new technologies, and reshape the direction of technical change. These two objectives are often pursued in parallel, and increasingly under the same policy umbrella. Yet the empirical foundations for evaluating innovation policy through a climate lens remain thin.

This paper studies the macroeconomic effects of innovation on output, carbon emissions, and emissions-adjusted total factor productivity. We distinguish innovations by funding source, separating government-funded from privately funded patents, and by technological direction, classifying patents as green versus non-green. This disaggregation is not a matter of detail. The government funds research precisely where private incentives are weak and social spillovers are large, so public and private innovation may differ in their composition, diffusion, and induced responses by firms and households. Recent work emphasizes the macroeconomic impact of government-supported innovation and motivates distinguishing public from private funding when studying aggregate outcomes (Gazzani et al., 2025). Likewise, green innovation is often treated as a direct route to emissions reductions, but the overall environmental effects of innovation depend on how the broader macroeconomy responds, including through investment, production and energy use.

Our contribution is to bring these dimensions together in a unified empirical framework. We build time-series measures of innovation that separate government-funded and privately funded patenting using newly digitized administrative data on government interest in patents, following Gross and Sampat (2025). We measure sustainability using emissions-adjusted total factor productivity, adjusting productivity for the future economic costs of today's carbon emissions (De Ridder and Rachel, 2025). This allows us to evaluate not only whether innovation raises conventional productivity, but also whether it raises productivity once the climate externality is internalized in the productivity metric.

Our baseline empirical approach estimates the dynamic responses of GDP, CO_2 emissions, emissions-adjusted total factor productivity and capital investment to shocks in innovation activity, separately by funding source and by green versus non-green classification. We then strengthen interpretation with counterfactual simulations designed to isolate the role of general equilibrium adjustment, with a particular emphasis on capital investment dynamics. This emphasis is motivated by a simple point. Even when an innovation improves emissions intensity, it may raise aggregate demand and profitability, stimulate capital accumulation, and expand production. These scale and investment responses can generate a delayed increase in emissions that is not visible in partial equilibrium evidence. A growing literature highlights that energy-saving technical change can coexist with economy-wide rebound effects, and that understanding aggregate energy and emissions outcomes requires separating direct technological effects from induced changes in activity and factor accumulation (Känzig and Williamson, 2025). Our analysis shows that these considerations are central for assessing innovation policy, not only for interpreting energy-saving progress.

Three results emerge. First, government-funded innovation is the only category associated with persistent medium-term gains in emissions-adjusted productivity. Second, these gains are followed by a marked increase in carbon emissions at longer horizons, sufficient to offset the longer-run expansion in output once environmental externalities are incorporated. This pattern implies that innovation can improve productivity in the medium run while still generating less favorable environmental outcomes over longer horizons. Third, the direction of innovation matters within each funding regime. Green patents are associated with more sustainable growth than non-green patents in both the public and private sectors. The largest average gains arise from green government-funded innovation, which combines stronger output effects with a more favorable medium-run path for emissions-adjusted productivity. At the same time, the gap between public and private green innovation narrows sharply once one focuses on basic research: green private patents with high scientific reliance perform comparably to green public patents. This suggests that part of the public advantage in sustainable innovation reflects not only who funds innovation, but also the greater concentration of public support in science-based

green research.

A central mechanism links these results. Counterfactual simulations indicate that the delayed emissions response is driven primarily by second-round effects operating through private investment in physical capital. Public innovation crowds in private capital formation, amplifying production scale and raising emissions over time. This channel is quantitatively important because it highlights an overlooked climate implication of innovation policy. Policies designed to raise productivity through public support for innovation can trigger macroeconomic adjustment that increases emissions at horizons that are relevant for climate policy and long-run welfare. At the same time, the evidence on green basic research sharpens the interpretation of this mechanism. It suggests that the strongest sustainable gains arise when innovation policy supports not only cleaner technologies, but also more science-based forms of invention that have broader macroeconomic effects. The same mechanism therefore clarifies why an evaluation of innovation policy that focuses only on near-term emissions intensity, or only on whether patents are labeled green, can substantially mismeasure its long-run environmental consequences.

Related literature. A large literature quantifies the effects of innovation on productivity and output at the firm and aggregate level (Bloom et al., 2019; Akcigit and Van Reenen, 2023; Gazzani et al., 2025). A separate strand of works quantifies the determinants and economic consequences of carbon emissions (Hansen et al., 1981; Hausfather et al., 2020; Dell et al., 2012; Burke et al., 2015; Nath et al., 2024; Bilal and Känzig, 2026). Much less is known about the climate implications of innovation itself, about whether these implications depend on the source of funding, and about how they interact with macroeconomic adjustment.

Our findings speak to several strands of work. First, we connect the literature on public versus private innovation and their macroeconomic effects to the climate macroeconomics literature by providing evidence on how funding source shapes both growth and emissions outcomes. Second, we complement the literature on directed technical change and green innovation by showing that direction matters, but that direction is not sufficient. The general equilibrium investment response can attenuate or even reverse environmen-

tal improvements at longer horizons, consistent with the view that the aggregate effects of energy-saving innovation depend on induced changes in activity and factor accumulation (Känzig and Williamson, 2025). Our analysis also relates to Aghion et al. (2024), who show that financial frictions can slow the transition toward green innovation by disproportionately affecting young, credit-constrained firms, highlighting a complementary channel through which the direction of innovation is shaped. Third, we contribute to the literature on the macroeconomic effects of innovation by emphasizing emissions-adjusted productivity as the relevant outcome in the presence of climate externalities. Building on the view of climate change as a global externality in macroeconomic models (Nordhaus, 1994), and on recent work that incorporates these externalities into measures of productivity (De Ridder and Rachel, 2025), we show that standard productivity gains can differ markedly from welfare-relevant productivity once the environmental externality is taken into account, and that this distinction is central for evaluating innovation policy.

Policy implications. Innovation policy is often justified on both growth and sustainability grounds. Our results suggest that its evaluation should explicitly account for the dynamic, economy-wide response of private physical capital investment and the associated scale effects on production and emissions. More broadly, the climate consequences of innovation depend jointly on who funds innovation, what type of innovation is induced, and how the private sector adjusts its capital accumulation. Designing innovation policy for climate goals may therefore require instruments that shape not only inventive activity but also the investment and production responses that follow.

Outline. The remainder of the paper proceeds as follows. Section 2 describes the data, presents the construction of our patent-based measures of innovation by funding source and technological orientation, and introduces the emissions-adjusted productivity measure. Section 3 sets out the empirical methodology and identification strategy. Section 4 reports the baseline dynamic effects of innovation on output, emissions, and emissions-adjusted productivity, distinguishing between government- and privately funded patents. Section 5 studies heterogeneity by green versus non-green innovation and examines the

role of basic research in shaping the macroeconomic effects of green patents. Section 6 presents the counterfactual analysis and quantifies the contribution of second-round investment responses to the delayed increase in emissions. Section 7 discusses robustness and additional results. Section 8 concludes. The appendices provide details on data construction, patent classification, variable definitions, additional empirical results, robustness exercises, and supplementary figures and tables.

2 Data and Empirical Framework

This section describes the data and econometric framework used in the empirical analysis. We first present the patent data and explain how we classify patents by funding source and technological direction. Next, we document the main descriptive facts on green and non-green innovation and describe the construction of emissions-adjusted total factor productivity. We then outline the local projection framework and the identification strategy used to trace the dynamic effects of innovation on output, emissions, and productivity.

2.1 Patent Data and Green Classification

Our patent data are drawn from the *Government Patent Register* (GPR) compiled by Gross and Sampat (2025), which combines information on government interest and assignees for the universe of U.S. patents. The key advantage of the GPR is that it identifies whether a patent was supported by the federal government using multiple administrative sources, thereby reducing the measurement error that arises from incomplete reporting of government interest in patent records.

For the purposes of this paper, we classify patents along two dimensions: *funding source* and *technological direction*. Along the funding dimension, we define as *government-funded* all patents with recorded federal government interest, regardless of whether the assignee is a private entity or a public agency. This category therefore includes both the *public–private* ("license") and *public–public* ("title") patents in the terminology of Gross and Sampat (2025) and Gazzani et al. (2025). We define as *private* all patents with no recorded government interest. This distinction is the relevant one for our analysis because the pa-

per focuses on whether the macroeconomic and environmental effects of innovation differ depending on the source of funding rather than on the legal ownership of the resulting patent.

Along the technological dimension, we classify patents as *green* or *non-green* using the standard Cooperative Patent Classification (CPC) approach (Migotto and Haščič, 2015). In the baseline definition, a patent is classified as green if it is assigned at least one CPC code in the Y02 family, which covers technologies related to climate change mitigation, or in the closely related Y04S class for smart grids. All remaining patents are classified as non-green.[1] Crossing these two dimensions yields four innovation groups: private non-green, private green, government-funded non-green, and government-funded green patents.

Our baseline sample covers 1950:Q1–2015:Q4. Before 1950, quarterly macroeconomic controls are less consistently available and green patenting is sparse. After 2015, patent registration delays become severe in the GPR, making the most recent counts unreliable.[2] Throughout, we date patents by their *filing date*, following Miranda-Agrippino et al. (2025), since filing dates provide the earliest observable indication of innovative activity and are less affected by changes in examination delays. Patent counts are then aggregated to quarterly frequency.

We complement the GPR with the USPTO CPC Master Classification Files, which are used to assign technology classes and identify green patents. We proxy patents' basicness with the measure on reliance on science by Marx and Fuegi (2020, 2022).

Descriptive statistics. Table 1 summarizes the distribution of patents across funding source and technological direction. Two patterns stand out. First, government-funded patents account for only a small share of total patenting activity. Second, green innovation is disproportionately represented among government-funded patents: while green patents account for only about 5.7% of private patents, their share rises to almost 10% among government-funded patents. This suggests that public support is tilted toward technologies with a stronger climate-mitigation orientation.

Appendix Table D.1 describes the distribution across federal agencies. The Dept. of

[1] We obtain similar results using the narrower green classification based on the clean-technology definitions (Acemoglu et al., 2023).
[2] Although patent data extend beyond 2015, recent counts are affected by grant and reporting lags.

Table 1: Distribution of Green vs. Non-green Patents by Funding

	Private		Government-funded		Total	
Category	Count	%	Count	%	Count	%
Non-green	6,753,826	94.28	204,431	90.59	6,958,257	94.17
Green	409,521	5.72	21,233	9.41	430,754	5.83
Total	7,163,347	100.00	225,664	100.00	7,389,011	100.00

Notes: Panel A reports the distribution of patents by funding source and technological direction. Government-funded patents include all patents with recorded federal government interest, irrespective of assignee type. Green patents are identified using the baseline CPC classification based on Y02 and Y04S codes. Panel B reports the five largest federal agencies by number of government-funded green patents. The across-share is the fraction of all government-funded green patents accounted for by a given agency. The within-share is the fraction of that agency's government-funded patents that are green. Sample: patent filings aggregated over 1950:Q1–2015:Q4.

Energy (DoE) owns the lion's share in green patents, followed by Dept. of Defense (DoD) and National Health Institute (NIH; "Across-share"). However, these patterns reflect a scale effect in the number of patents funded by each agency. Considering the number of green patents out of total patents funded ("Within-share"), DoE is again ranked at the top, followed by the National Science Foundation and NASA, while NIH and DoD are ranked at the bottom.

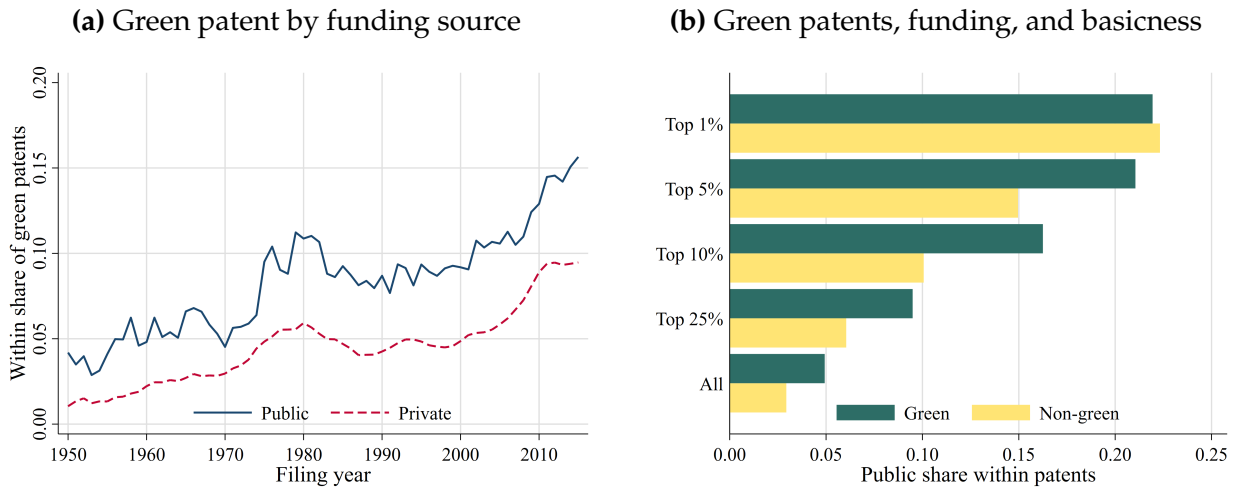
Figure 1 complements these aggregate statistics. Panel (a) shows that the share of green patenting has trended upward over time in both funding categories, consistent with the growing salience of environmental technologies in the U.S. innovation system. Panel (b) shows that more basic (or reliant on science) green patents are typically government-funded.

2.2 Emissions-Adjusted Productivity

A central outcome in the paper is emissions-adjusted total factor productivity (TFPE). Conceptually, TFPE augments standard TFP by incorporating the expected future economic costs implied by current carbon emissions. We build on the framework proposed by De Ridder and Rachel (2025). Their measure captures productivity net of the climate externality and is therefore well suited to evaluating whether innovation raises productivity in an environmentally sustainable manner.

Our implementation follows their approach but extends the TFPE measure back to

Figure 1: Green Patents and Funding Source



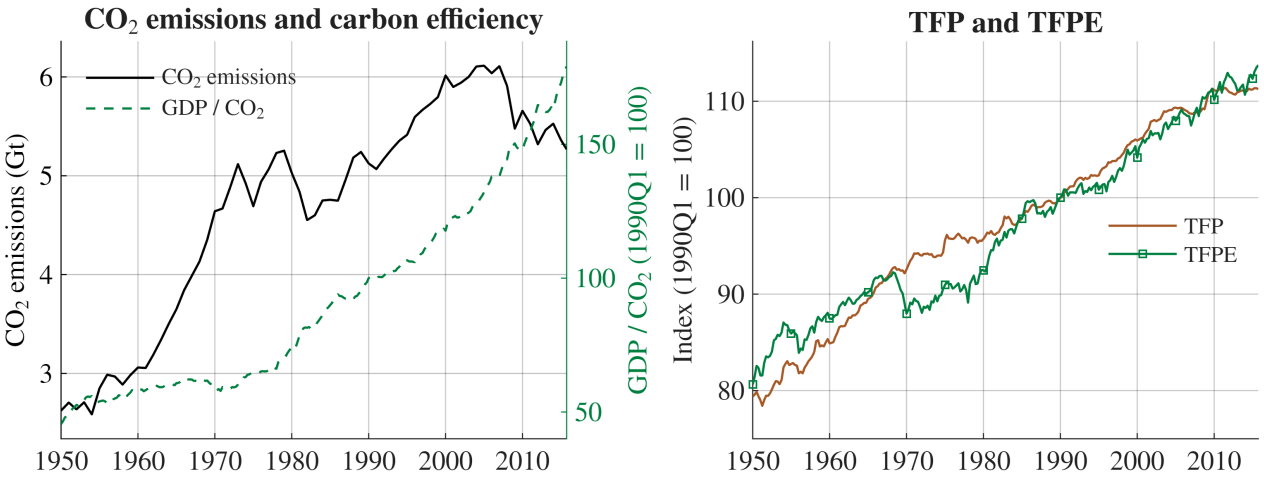
Notes: Panel (a) reports the share of green patents in total patents separately for private and government-funded innovation over time. Panel (b) relates the prevalence of green patents to patent-level measures of importance and scientific reliance, based on forward citations and citations to scientific publications. Green patents are identified using the baseline CPC definition based on Y02 and Y04S codes. Government-funded patents include all patents with recorded federal government interest. Sample: quarterly data, 1950:Q1–2015:Q4.

1950 to match the time span of our patent and macroeconomic data. De Ridder and Rachel (2025) focus on a more recent sample and can thus employ consumption-based emissions, while our longer historical sample requires us to use territorial CO_2 emissions (emissions physically generated within the United States). This choice is dictated by data availability over the full postwar period. It implies that our measure does not capture carbon embodied in net trade as precisely as a consumption-based concept does, but it allows us to build a consistent quarterly series from 1950:Q1–2015:Q4. In the Appendix, we report similar results if we employ their measure for the available sample.

Operationally, TFPE combines information on aggregate productivity and territorial carbon emissions into a single measure of net productivity, where higher emissions reduce effective productivity once environmental damages are internalized. This distinction is central to our analysis. An innovation shock may increase standard TFP while generating a much smaller improvement in TFPE, or even a decline in TFPE at longer horizons, if the associated rise in emissions is sufficiently large. Figure 2 illustrates these points. The left panel reports the evolution of territorial CO_2 emissions and carbon efficiency, measured as GDP per unit of emissions. The right panel compares standard TFP with our territorial-emissions-based TFPE series, illustrating the wedge introduced by the

environmental adjustment.

Figure 2: CO_2 Emissions, TFP, and Emissions-Adjusted TFP



Notes: The left panel reports aggregate U.S. territorial CO_2 emissions (in gigatons) together with an index of carbon efficiency, measured as GDP per unit of CO_2 emissions. The right panel reports standard total factor productivity (TFP), our emissions-adjusted total factor productivity measure based on territorial CO_2 emissions (TFPE), and the corresponding TFPE series based on consumption-based CO_2 emissions following **?**. *All productivity and carbon-efficiency series are normalized to 100 in 1990:Q1. The comparison highlights both the wedge between conventional TFP and emissions-adjusted productivity, and the difference between using territorial versus consumption-based emissions in constructing TFPE. Sample: 1950:Q1–2015:Q4. See the appendix for data sources, historical extension, and construction details.*

2.3 Empirical Framework

Our empirical analysis studies how shocks to innovation affect output, emissions, and productivity over time. The baseline econometric specification builds on Gazzani et al. (2025), adapted to distinguish patents not only by funding source but also by technological direction. Specifically, we estimate local projections on quarterly data and trace the response of macroeconomic outcomes to shocks in each of the four patent series defined above: private non-green, private green, government-funded non-green, and government-funded green patents.

For each horizon h, we estimate regressions of the form

$$y_{t+h} = \alpha_h + \beta_h x_t + \Gamma_h' W_t + u_{t+h},$$

where y_{t+h} denotes the macroeconomic outcome of interest at horizon h, x_t is the innovation measure or innovation shock, and W_t is a vector of controls. The outcomes of interest

include real GDP, CO_2 emissions, TFP, and TFPE.

Our baseline controls include four lags of the dependent variable and of the patent category being shocked, together with standard macroeconomic controls: real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill rate, real per-capita R&D expenditure, as well as the real price of fossil energy. Controlling for the energy price is important in our setting because the composition of innovation between green and non-green technologies may itself respond to exogenous energy-market conditions (Popp, 2002). A rise in fossil energy prices can affect the relative profitability of different technologies, shift research incentives toward energy-saving and cleaner innovation, and alter the macroeconomic propagation of patent shocks. Controlling for fossil-fuel energy prices therefore helps isolate innovation shocks from changes in patent composition induced by energy-market disturbances, in line with the literature on directed technical change and energy-saving innovation (Hassler et al., 2021; Känzig and Williamson, 2025).

All variables except the T-bill are entered in logs. We normalize each innovation shock so that it corresponds to a 1% increase in total patents in order to sterilize size effects across patent groups.

2.4 Identification

Our identification strategy exploits external variation in broad measures of innovation activity for the two funding groups at the core of the analysis. For government-funded patents, we use narrative shocks to federal R&D appropriations following Fieldhouse and Mertens (2023). These shocks isolate unanticipated changes in public research funding orthogonal to the business cycle and thus provide exogenous variation in government-supported inventive activity. For privately funded patents, we use the external instrument developed by Miranda-Agrippino et al. (2025), which identifies shifts in innovation activity that are orthogonal to macroeconomic conditions and expectations.

We estimate impulse responses using local projections with external instruments. For privately funded patents, we implement standard LP-IV following Jordà et al. (2015) and Ramey (2016). For government-funded patents, identification relies on a sequence of lagged instruments that capture the delayed transmission from public R&D to patenting.

We therefore adopt the procedure of Barnichon and Mesters (2020), which uses the full sequence of instruments jointly and imposes an Almon-type restriction to reduce dimensionality. Specifically, the distributed-lag relationship between the instrument and the endogenous variable is approximated by a low-order polynomial, allowing us to summarize a large set of lagged instruments under the assumption that responses evolve smoothly over time. In this setting, we rely on weak-instrument-robust inference, as conventional procedures may be unreliable when instruments are numerous and individually weak.

The scope of the instrumental variable strategy is nevertheless limited by instrument availability. The external instruments are informative for broad government- and privately funded patent series, but cannot be extended in a comparable way to all disaggregated patent categories considered in the paper, particularly along the green/non-green and funding dimensions. Reassuringly, the OLS-based local projection estimates closely track the LP-IV results for the aggregate series. We therefore rely on OLS-based local projections for the disaggregated patent categories.

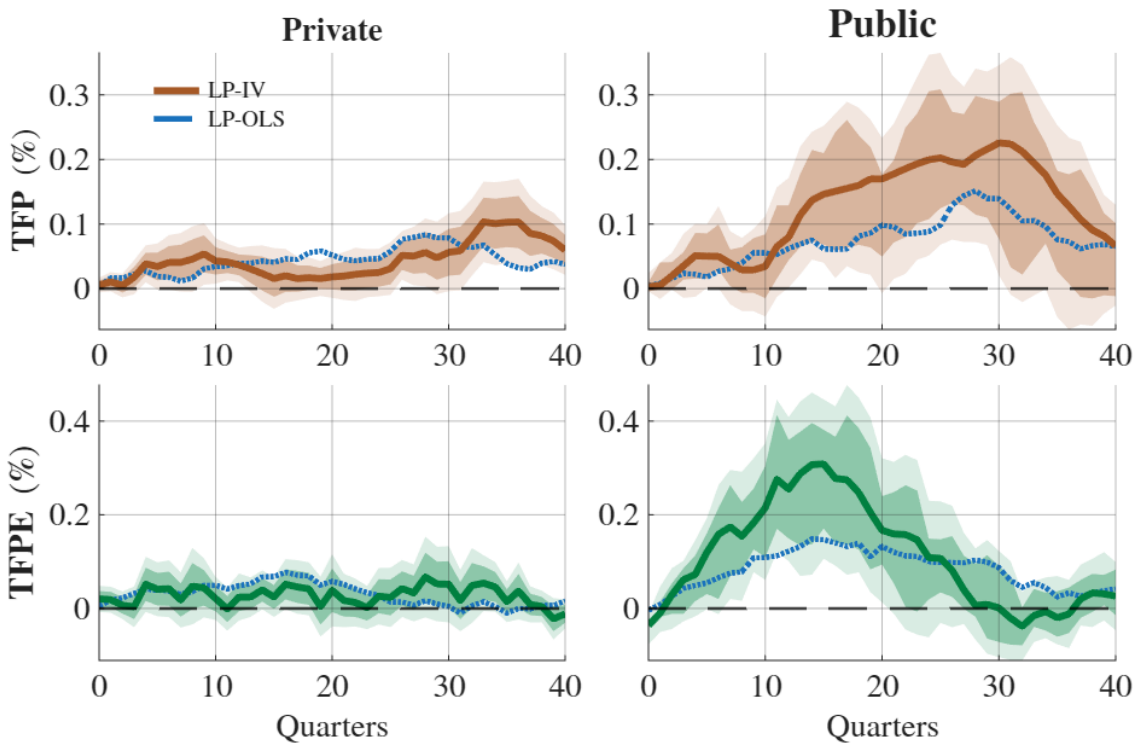
3 Effects on Output, Emissions, and TFP

This section presents the paper's first two main findings. We begin with the instrumental-variable evidence for broad privately funded and government-funded patent aggregates, which provides the sharpest identification of the role of funding source. We then turn to the baseline OLS local projections, which serve as the benchmark specification in the remainder of the paper because they can be implemented uniformly across the broader set of patent definitions.

Instrumental-variable evidence. We start from the LP-IV estimates for broad privately funded and government-funded patent aggregates. These exercises isolate patent fluctuations that are plausibly orthogonal to contemporaneous macroeconomic conditions and therefore provide the cleanest evidence on whether funding source matters for the joint dynamics of productivity, output, and emissions.

Figure 3 establishes the paper's first main result. Both privately funded and

Figure 3: The Impact on Total Factor Productivity

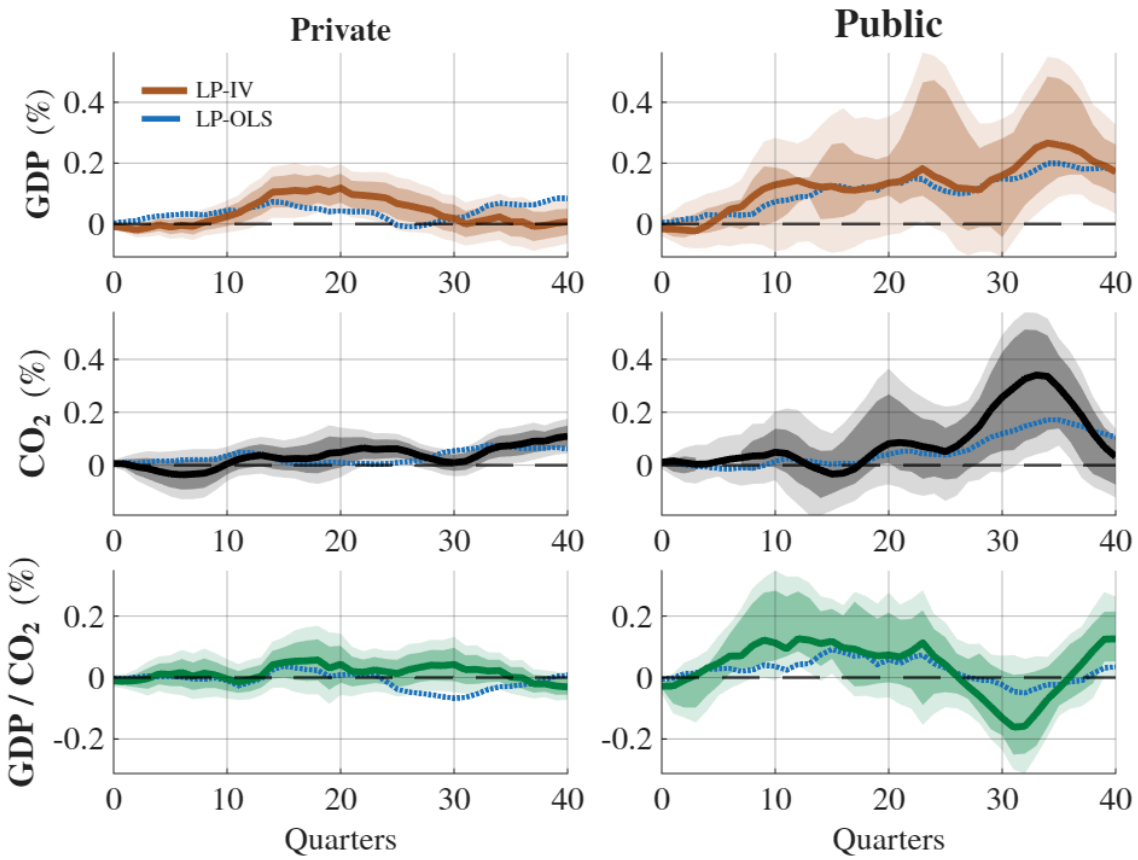


Notes: The figure reports LP-IV responses of standard total factor productivity (TFP) and emissions-adjusted total factor productivity (TFPE) to shocks in broad privately funded and government-funded patent aggregates. The size of the shock is normalized to increase total patents by 1% on impact. IV estimation is conducted in the multiplier framework described in Section 2.4. Shaded areas report 68% and 90% confidence sets. Sample: 1950:Q1–2015:Q4.

government-funded innovation raise conventional TFP, although the peak response to public patents is more than twice as large than to private. Once productivity is adjusted for carbon emissions, however, the contrast between the two funding groups becomes even starker. For privately funded innovation, TFPE's response is small and short-lived. For government-funded innovation, by contrast, TFPE rises strongly and remains positive at medium horizons. The implication is clear: only government-funded innovation is sustainable in the medium-run as it is associated with economically meaningful gains in emissions-adjusted productivity.

Yet, even for public patents, the gains in TFPE dissipate at the end of the impulse horizon. Figure 4 provides insights into this interesting finding. Both funding groups raise GDP, with a visibly stronger response following government-funded innovation. At the same time, the emissions response to government-funded innovation is delayed but sub-

Figure 4: Output and Emissions



Notes: The figure reports IV impulse responses of real GDP, CO_2 emissions, and GDP per unit of emissions to shocks in broad privately funded and government-funded patent aggregates. The size of the shock is normalized to increase total patents by 1% on impact. IV estimation is conducted in the multiplier framework described in Section 2.4. Shaded areas report 68% and 90% confidence sets. Sample: 1950:Q1–2015:Q4.

stantial at the end of the horizon. As CO_2 rises over time, the initial improvement in GDP per unit of emissions gradually dies out. Given that GDP/CO_2 is the correction factor that creates a wedge between TFP and TFPE, the rebound in carbon emissions erodes the medium-run gains in TFPE following government funded innovation at longer horizons.

Simple local projections. We next turn to the baseline OLS local projections. Figures 3–4 display the corresponding point estimates, while Appendix Figure B.1 reports the full estimates with confidence bands.

The OLS results closely mirror the IV evidence. While both private and public innovation raise TFP and GDP, only government-funded patents generate economically meaningful and persistent gains in emissions-adjusted productivity. By contrast, the TFPE re-

sponse to private patents remains small and short-lived. This close alignment motivates using the OLS specification as the benchmark in the remainder of the paper, as it can be implemented uniformly across the broader set of patent classifications.

The OLS estimates also reinforce the source of the longer-run trade-off. Government-funded innovation is followed by a delayed but sizable increase in CO_2 emissions, which gradually compresses output per unit of emissions and erodes the earlier TFPE gains, while private innovation exhibits a more muted pattern throughout.

Taken together, the evidence confirms the central message: government-funded innovation delivers the strongest medium-run improvements in emissions-adjusted productivity, but these gains diminish over time as emissions rise.

4 The Rebound in CO_2 Emissions

Section 3 documented a central tension in government-funded innovation, which delivers the strongest medium-run gains in emissions-adjusted productivity, yet these gains are followed by a pronounced rise in CO_2 emissions at longer horizons. This section investigates the mechanism behind that delayed rebound.

We consider three candidate channels. The first is an energy channel: if innovation lowers the effective cost of fossil fuels, it may incentivize greater energy use that, over time, leads to a rebound effect with more sustained emissions. The second is a general-equilibrium channel operating through private investment in physical capital. Even when innovation initially improves efficiency, it may also stimulate increased production and physical capital accumulation. If so, emissions may rise with a delay as the capital stock adjusts and scale effects materialize. The third is an innovation spillover channel, whereby government-funded innovation crowds in other, potentially more emissions-intensive, private innovation. This is similar to the second channel but relates to innovation and intangible investment rather than physical investment.

We study these mechanisms in two steps. We first examine the responses of the main candidate transmission variables. We then turn to counterfactual exercises that shut down each channel and trace the implications for the path of CO_2 emissions. Across specifica-

tions, the evidence points to the investment channel as the dominant source of the delayed rebound.

4.1 Potential Transmission Channels

Figure 5 reports the dynamic responses of four variables that are informative for the channels underlying the CO_2 rebound: private investment, the real price of fossil energy, energy use, and patenting in other innovation groups.

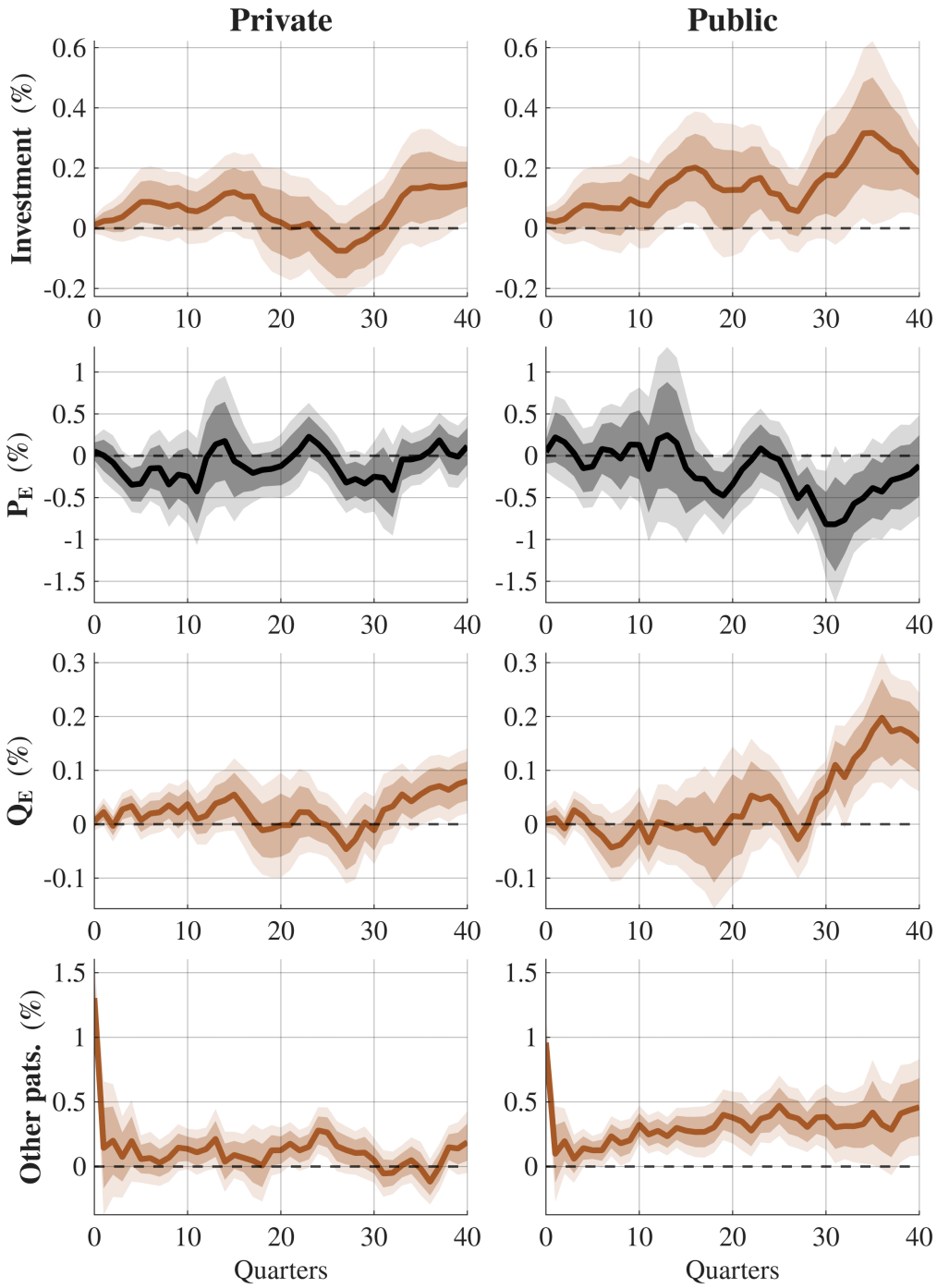
The first row points to a markedly stronger investment response following government-funded innovation. Investment rises under both funding regimes, but the increase is larger and more persistent after public innovation shocks. This pattern is consistent with a general-equilibrium mechanism in which government-funded innovation crowds in private capital formation and thereby sets in motion a delayed expansion in production scale and emissions.

In the second and third rows we document the responses in the real price of fossil energy and the total amount of energy consumed in the US economy. The price of energy falls, reaching a negative peak after about 30 quarters, and after this peak, energy use spikes upward.

Finally, patent spillovers to other innovation groups in the last row are much more persistent after a public innovation shock than after a private one. Public innovation may thus generate spillovers to less sustainable private innovation that can contribute to the rebound in CO_2.

Taken together, these reduced-form patterns already point toward an investment-based general-equilibrium mechanism. They also suggest that any role for the energy channel or for spillovers to other patent groups is likely to be secondary. The next subsection quantifies this ranking more directly by shutting down each channel in turn and tracing the implied counterfactual path of CO_2 emissions.

Figure 5: Transmission Channels



Notes: The figure reports baseline OLS local projections for the responses of private investment, the real price of fossil energy (P_E), energy use (Q_E), and patenting in other innovation groups to shocks in broad privately funded and government-funded patent aggregates. The size of the shock is normalized to increase total patents by 1% on impact. The control set is the same as in Section 2.3. All variables except the T-bill are in logs. Shaded areas report 68% and 90% confidence bands. Sample: 1950:Q1–2015:Q4.

4.2 Counterfactual Analysis

In order to dissect the CO_2 rebound and its main underlying mechanisms we turn to counterfactual analysis (Sims and Zha, 2006; Antolín-Díaz et al., 2021; McKay and Wolf, 2023). The basic idea is to shut down, one at a time, the responses associated with the candidate transmission channels discussed above and compare the implied path of CO_2 emissions with the baseline response to a government-funded innovation shock.

We implement this exercise following Wang (2026) in our local projections framework. Wang (2026) that local projections can implement the same counterfactuals as VAR models, both exploiting a sequence of offsetting shocks (Sims and Zha, 2006; Antolín-Díaz et al., 2021) and with shocks surprising the system only at the impact horizon (McKay and Wolf, 2023). The first approach has the advantage of imposing stronger constraints on the response of an endogenous variable, but suffers from the Lucas critique as agents would be surprised each period. The second approach can only approximately shut down the response of an endogenous variable as it applies a small number of offsetting shocks on impact and traces the resulting counterfactual path, but it is robust to the Lucas critique. We regard the two methods as complementary and present the implications of both.

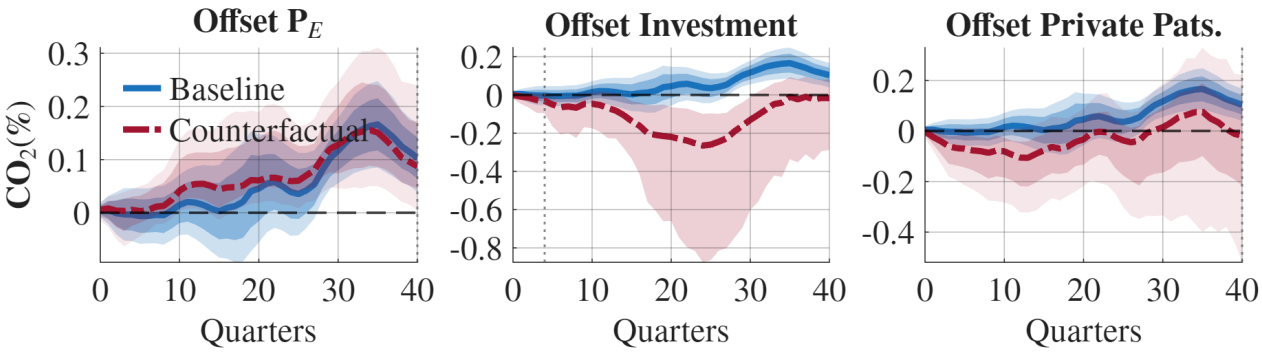
We employ Känzig (2021) oil supply news shocks to offset the response in the price of energy. In the case of surprises only at period zero we also use Baumeister and Hamilton (2019) as multiple shocks give us more power. To offset the response of investment, we exploit investment specific shocks from Ben Zeev and Khan (2015).[3] Finally, to shut down the response of private patents, we use a shocks to private patents that is orthogonal to our main shock to public patents.

Figure 6 summarizes the results of our counterfactual exercises. In both panels, the delayed increase in CO_2 emissions is substantially dampened when we shut down either the response of investment or that of private patents. Neutralizing investment makes the long-horizon emissions path markedly flatter, pointing to second-round effects through capital accumulation and production scale. Likewise, shutting down private patents—which we interpret as a proxy for intangible investment—significantly reduces the re-

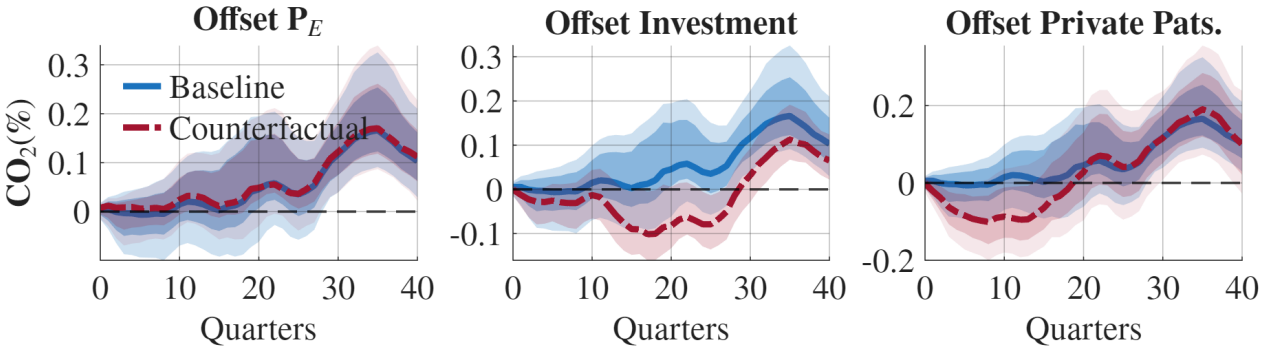
[3]For numerical reasons, in the full offset case we can only shut-down the first four quarters in the response of investment, which nonetheless result in very persistent effects.

Figure 6: Counterfactual for CO_2 Response

(a) Antolín-Díaz et al. (2021) style counterfactual in LP framework



(b) McKay and Wolf (2023) style counterfactual in LP framework



Notes: The figure reports counterfactual paths for the response of CO_2 emissions to a government-funded innovation shock when alternative transmission channels are selectively shut down. Panel (a) uses a sequence of offsetting shocks over the first part of the horizon, in the spirit of a structural scenario exercise. Panel (b) uses a single offsetting shock at impact. In both cases, the strongest attenuation of the delayed emissions response arises when the investment channel is neutralized. Shutting down the energy-price channel has only a limited effect, while closing the response of private patents mainly affects the short-run dynamics. Sample: 1950:Q1–2015:Q4.

bound, highlighting the role of innovation spillovers in propagation. Overall, the evidence indicates that spillovers to investment, both physical and intangible, are the key mechanisms behind the medium-run increase in emissions. By contrast, offsetting the energy-price response has only a modest effect on the emissions path, suggesting that energy prices are not a quantitatively central transmission channel in this context.

Overall, the counterfactual evidence points to a clear interpretation of the medium-run CO_2 rebound. The main propagation mechanism does not appear to operate through the price of energy, whose shutdown leaves the emissions response largely unchanged. Instead, the rebound is mostly accounted for by spillovers to investment, broadly defined to include both tangible capital accumulation and intangible accumulation through private innovation. In this sense, government-funded innovation seems to raise emissions not

because it directly relaxes energy scarcity or alters energy prices, but because it stimulates subsequent private economic activity and innovation, thereby expanding production scale over time. More broadly, these findings suggest that the environmental effects of public innovation shocks cannot be understood without accounting for the endogenous investment and innovation responses they set in motion.

5 Green Innovation

A natural next question is whether what matters for sustainable macroeconomic performance is only *who* funds innovation or also *what kind* of technologies that innovation produces. The previous sections showed that government-funded and privately funded innovation have different implications for productivity, output, and emissions. We now refine that comparison by distinguishing between green and non-green patents within each funding regime. This distinction is important because innovation policy is often expected to support decarbonization by redirecting technical change toward cleaner technologies, yet the aggregate consequences of that redirection may still depend on the broader macroeconomic adjustment that follows.

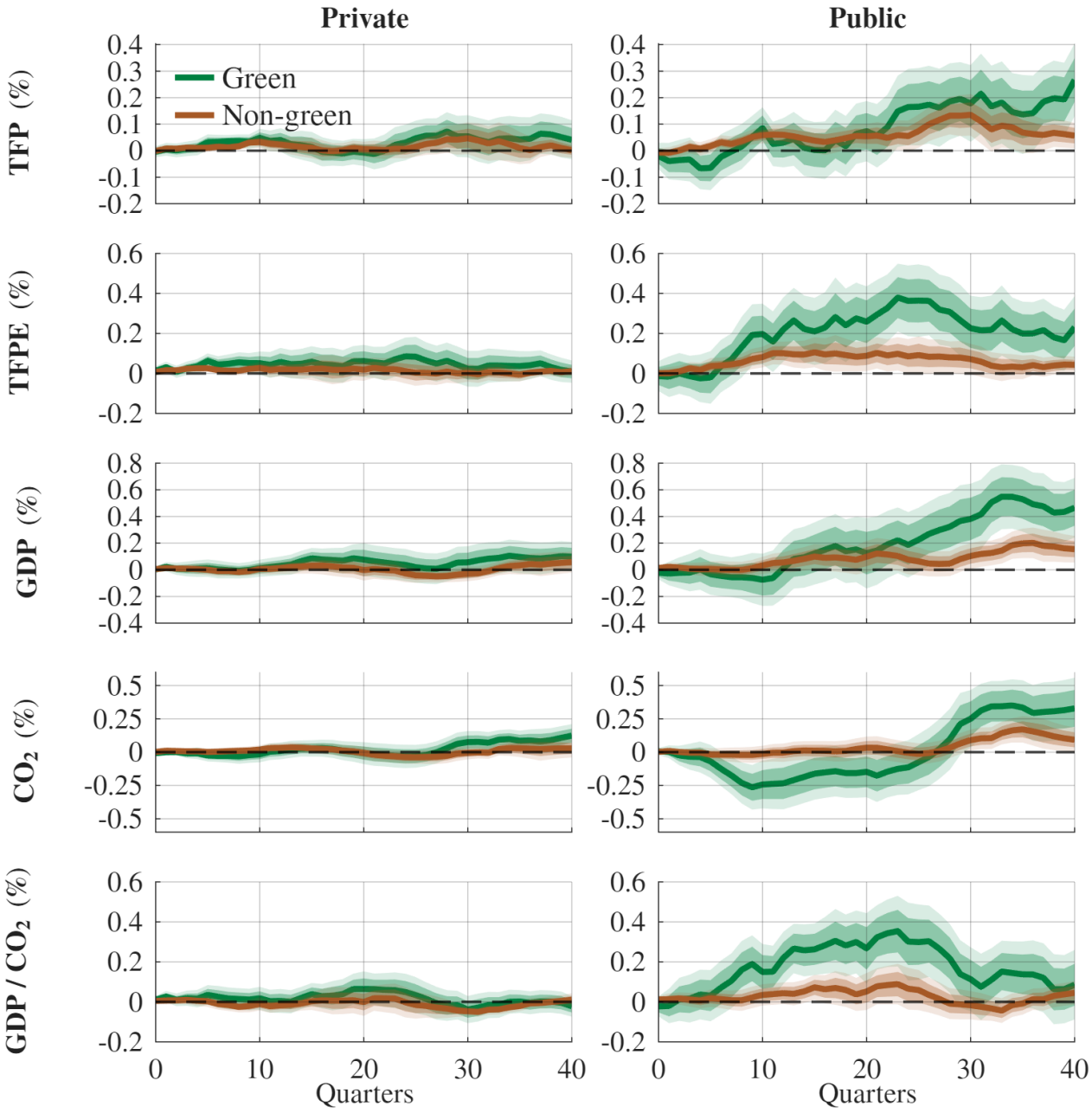
5.1 Funding and Technology

Figure 7 reports the responses to green and non-green patent shocks separately for privately funded and government-funded innovation. Three results stand out.

First, within both funding groups, green innovation is associated with a more favorable growth–emissions trade-off than non-green innovation. Relative to non-green patent shocks, green patent shocks tend to produce larger improvements in emissions-adjusted productivity and a stronger increase in GDP per unit of emissions. This pattern suggests that the direction of technical change matters for sustainability.

Second, this green advantage is far more pronounced in the government-funded segment than in the privately funded one. Green government-funded patent shocks generate the strongest responses of TFPE and GDP per unit of emissions in the paper, together with a sizable increase in output and an initially negative response of CO_2 emissions. Although

Figure 7: Green versus Non-green Innovation by Funding Source



Notes: The figure compares the responses of TFP, TFPE, GDP, CO_2 emissions, and GDP per unit of emissions to green and non-green patent shocks within each funding group. Responses are estimated using the baseline OLS local-projection specification described in Section 2.3. Each shock is normalized to increase total patents by 1% on impact. The control set includes four lags of the patent category being shocked and the dependent variable, real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill rate, real per-capita R&D expenditure, the number of patents in the other innovation groups, and the real price of fossil energy. All variables except the T-bill are in logs. Shaded areas report 68% and 90% confidence bands. Sample: 1950:Q1–2015:Q4.

emissions eventually rebound, the medium-run profile remains substantially more favorable than for non-green public innovation. Put differently, once both funding source and

technological direction are taken into account, the combination delivering the strongest improvement in sustainable macroeconomic performance is green government-funded innovation.

Third, the distinction between green and non-green innovation is quantitatively much smaller within privately funded innovation. Green private patents perform somewhat better than non-green private shocks, but the differences are modest across the main macroeconomic outcomes. Output and conventional TFP increase only mildly, the response of TFPE remains limited, and the improvement in GDP per unit of emissions is small compared with the public green case. This suggests that technological direction also matters in the private sector, but that private green innovation alone does not reproduce the stronger sustainability gains associated with public green innovation.

These results qualify the evidence from the previous sections in an important way. The earlier analysis showed that government-funded innovation delivers larger gains in emissions-adjusted productivity than privately funded innovation, but that these gains are partly offset by a delayed rebound in emissions. Figure 7 shows that this public advantage is not uniform across technologies. Rather, it is concentrated to a large extent in the green component of government-funded innovation. At the same time, even green public innovation is not immune from the general-equilibrium mechanism identified above: emissions fall on impact and in the short run, but they do not remain permanently below baseline. These results suggest that other type of policies can play a key role to complement the spillovers generate even by green innovation policy.

5.2 The Role of Green Basic Research

The results above suggest that the superior sustainability performance of government-funded innovation may reflect not only the source of funding, but also the type of knowledge being produced. A natural hypothesis is that public innovation is more than private innovation, and that this difference in technological content helps account for its stronger macroeconomic effects. To explore this mechanism, we turn to a measure of patents' reliance on science based on Marx and Fuegi (2020, 2022). In particular, we split private patent into those in the top 10% of the science-reliance distribution and those in the bot-

tom 90%, and we do so separately for green and non-green technologies.

We focus on private patents because the corresponding decomposition for government-funded patents is too sparse once we intersect funding source, technology type, and basicness. The exercise should therefore be read as suggestive evidence on mechanism: it asks whether private innovation becomes more similar to public innovation when it is more science-reliant.

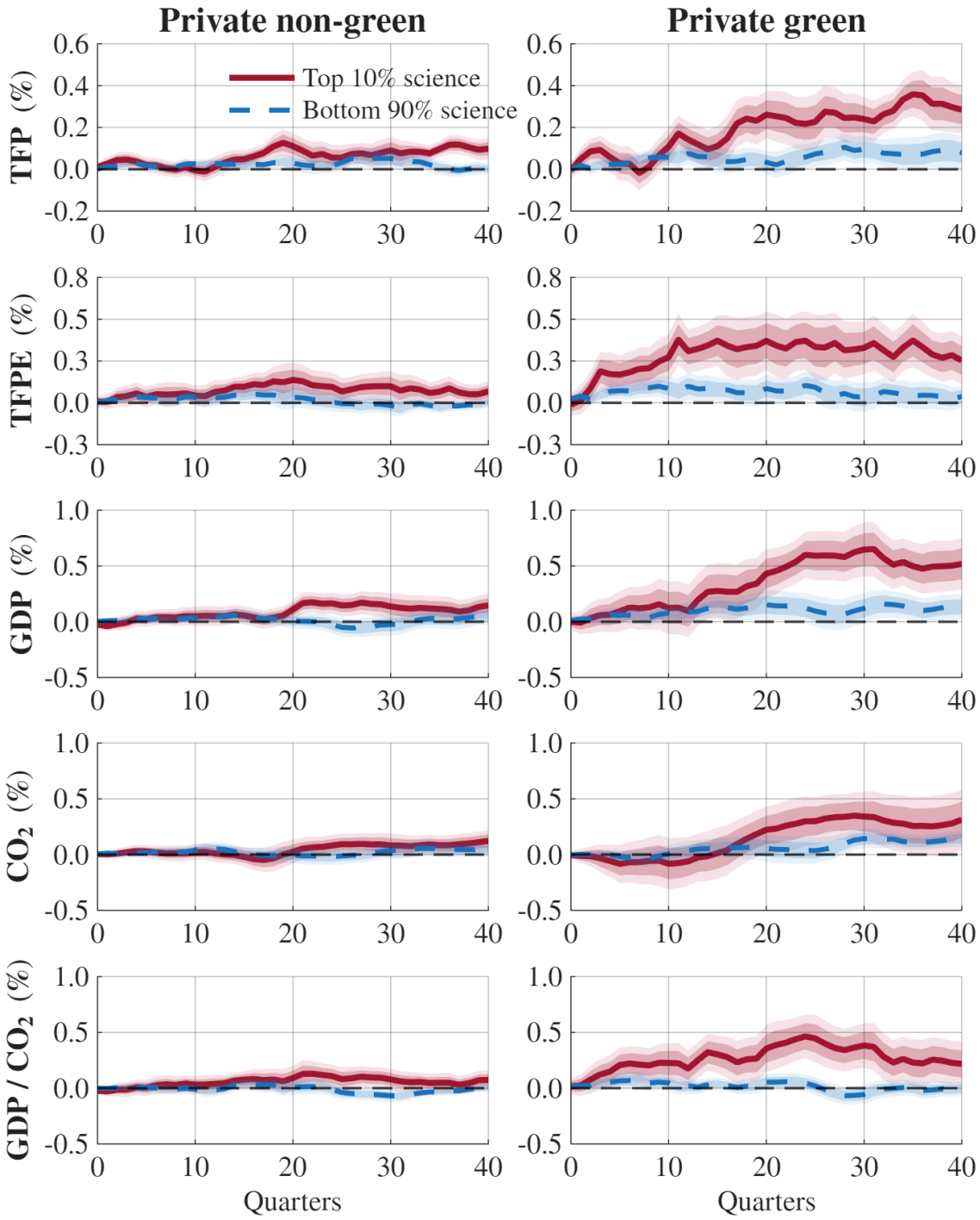
Figure 8 reports the results where three findings stand out. First, within private innovation, science-reliant patents generate substantially stronger macroeconomic effects than the rest of the distribution. This is true for both green and non-green technologies, but it is especially pronounced for green private innovation. In the top science-reliance decile, green private patent shocks lead to markedly larger gains in TFP, TFPE, GDP, and GDP per unit of emissions than green private patents in the bottom 90% of the distribution. By contrast, the bottom 90% display only muted responses across all outcomes.

Second, the difference between high-science and low-science patents is much larger for green technologies than for non-green ones. Among private non-green patents, the top 10% of science-reliant innovations perform somewhat better than the rest, but the quantitative differences remain limited. Among private green patents, instead, the top 10% produce a response profile that is much closer to what we previously documented for government-funded green innovation: stronger productivity gains, larger output effects, and a substantially more favorable path for emissions-adjusted performance.

Third, this pattern helps rationalize the earlier public-private differences. The results suggest that part of the public advantage may stem from the fact that government-funded innovation is disproportionately concentrated in basic research. This interpretation is particularly compelling for green technologies, where basicness appears to amplify both the productivity gains and the improvement in sustainability outcomes.

Taken together, these findings point to a mechanism linking funding source, technological direction, and basicness. Public innovation appears to outperform private innovation in part because it is more likely to support science-based technological advances, especially in green domains. While we cannot test this directly within the public sample because of limited patent counts in the relevant intersections, the private-sector evidence

Figure 8: Heterogeneity by technology and basic research



Notes> The figure compares the responses of TFP, TFPE, GDP, CO_2 emissions, and GDP per unit of emissions to green and non-green patent shocks within each funding group. Responses are estimated using the baseline OLS local-projection specification described in Section 2.3. Each shock is normalized to increase total patents by 1% on impact. The control set includes four lags of the patent category being shocked and the dependent variable, real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill rate, real per-capita R&D expenditure, the number of patents in the other innovation groups, and the real price of fossil energy. All variables except the T-bill are in logs. Shaded areas report 68% and 90% confidence bands. Sample: 1950:Q1–2015:Q4.

strongly suggests that reliance on science is an important component of the broader public advantage documented in the paper.

6 Conclusion

This paper investigates how innovation shapes macroeconomic performance and the carbon footprint of economic activity when innovations are separated by funding source and by environmental orientation. The empirical evidence points to a systematic difference between public and private inventive activity. Innovations associated with government support are the ones that translate into sustained improvements in productivity once emissions are incorporated into the productivity metric, whereas privately financed innovation exhibits weaker gains along this dimension. At the same time, the longer-run emissions response complicates the growth dividend of public support: the expansionary effects that follow government-funded innovation are accompanied, with a delay, by higher carbon emissions, so that the long-horizon assessment is materially less favorable when environmental damages are considered.

A second contribution is to clarify why emissions rise when innovation appears to improve efficiency. The counterfactual evidence is most consistent with a general equilibrium adjustment in which public innovation stimulates private capital formation. As capital deepening and scale increase, emissions rise even in the absence of large changes in energy prices or energy composition, highlighting the importance of investment-driven second-round effects for understanding the climate footprint of innovation policy.

Finally, the direction of technical change matters in economically meaningful ways. Green innovation improves the growth-emissions trade-off within both public and private funding regimes, and the strongest combination of economic expansion and environmental performance is associated with green innovation supported by the government. At the same time, the comparison between public and private green innovation becomes more nuanced once attention shifts to basic research. Green private patents with a stronger basic-research component perform comparably to green public patents, suggesting that science-based innovation is a central channel through which green technologies generate

aggregate effects. This finding suggests that part of the advantage of public green innovation reflects its stronger orientation toward basic research rather than public funding per se. Taken together, these results imply that evaluating innovation policy requires tracing not only the immediate productivity gains from new technologies, but also the form of innovation being encouraged and the induced macroeconomic adjustments that shape emissions over time.

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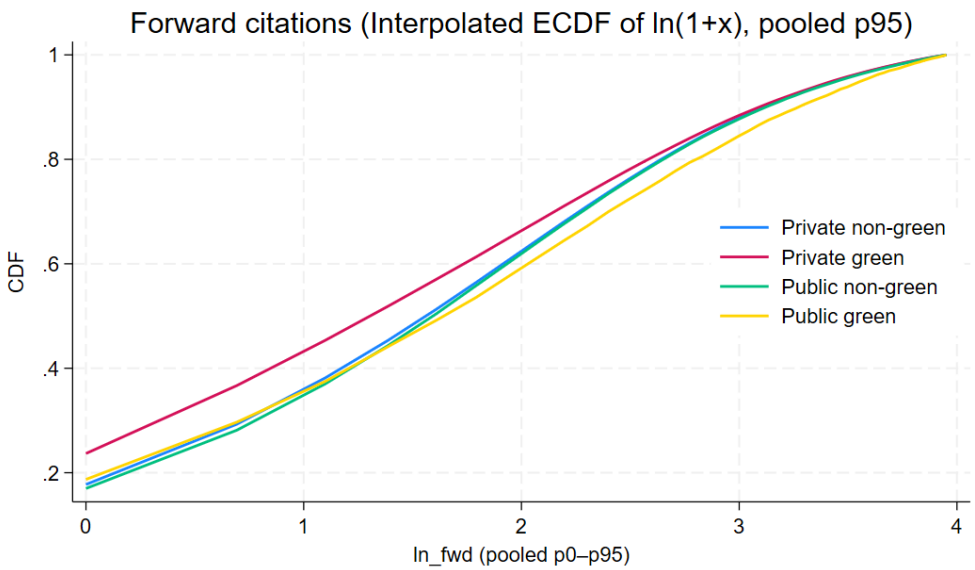
A Data Sources and Details

Table A.1: Importance/Basicness

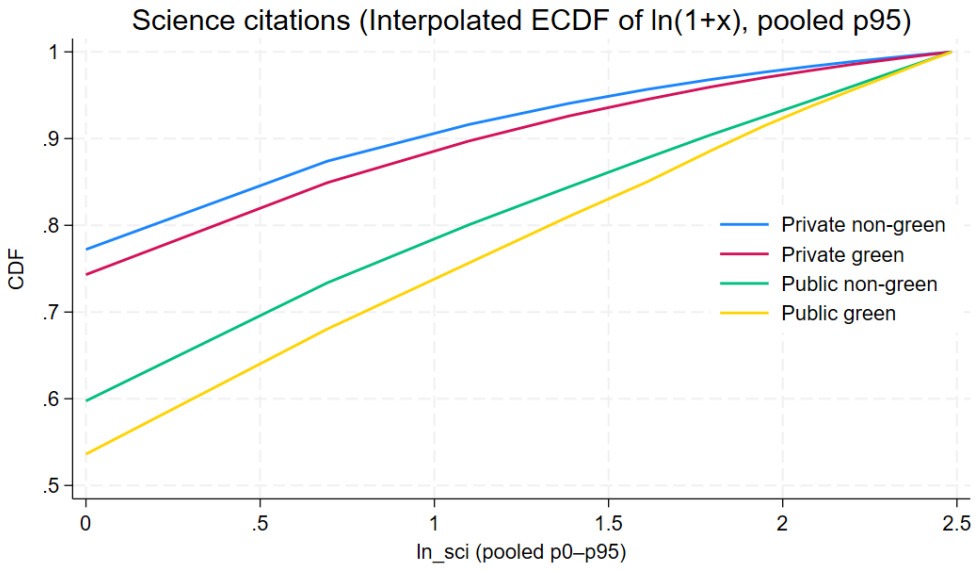
Statistic	Private non-green	Private green	Public non-green	Public green
	Panel B: Forward citations			
N	6753826	409521	204431	21233
Mean	14.03	11.65	13.88	14.28
Std	42.41	32.83	36.39	27.73
p10	0.00	0.00	0.00	0.00
p25	1.00	1.00	1.00	1.00
Median	5.00	4.00	5.00	5.00
p75	13.00	12.00	13.00	16.00
p90	30.00	28.00	31.00	36.00
p95	51.00	46.00	53.00	57.00
p99	153.00	114.00	149.00	135.00
Skew	16.53	20.40	14.45	6.26
Kurt	498.02	1071.60	509.24	72.08
	Panel C: Citations of scientific papers			
N	6753826	409521	204431	21233
Mean	2.67	4.28	16.81	19.31
Std	15.78	23.13	42.88	47.14
p10	0.00	0.00	0.00	0.00
p25	0.00	0.00	0.00	0.00
Median	0.00	0.00	1.00	2.00
p75	1.00	1.00	13.00	16.00
p90	4.00	6.00	53.00	59.00
p95	10.00	17.00	88.00	99.00
p99	58.00	91.00	188.00	214.00
Skew	22.49	18.65	6.58	6.48
Kurt	1095.01	723.55	77.51	81.30

Figure A.1: Stochastic Dominance

(a) Forward citations



(b) Science citations



B Additional Results

Figure B.2: Transmission Channels with LP-IV

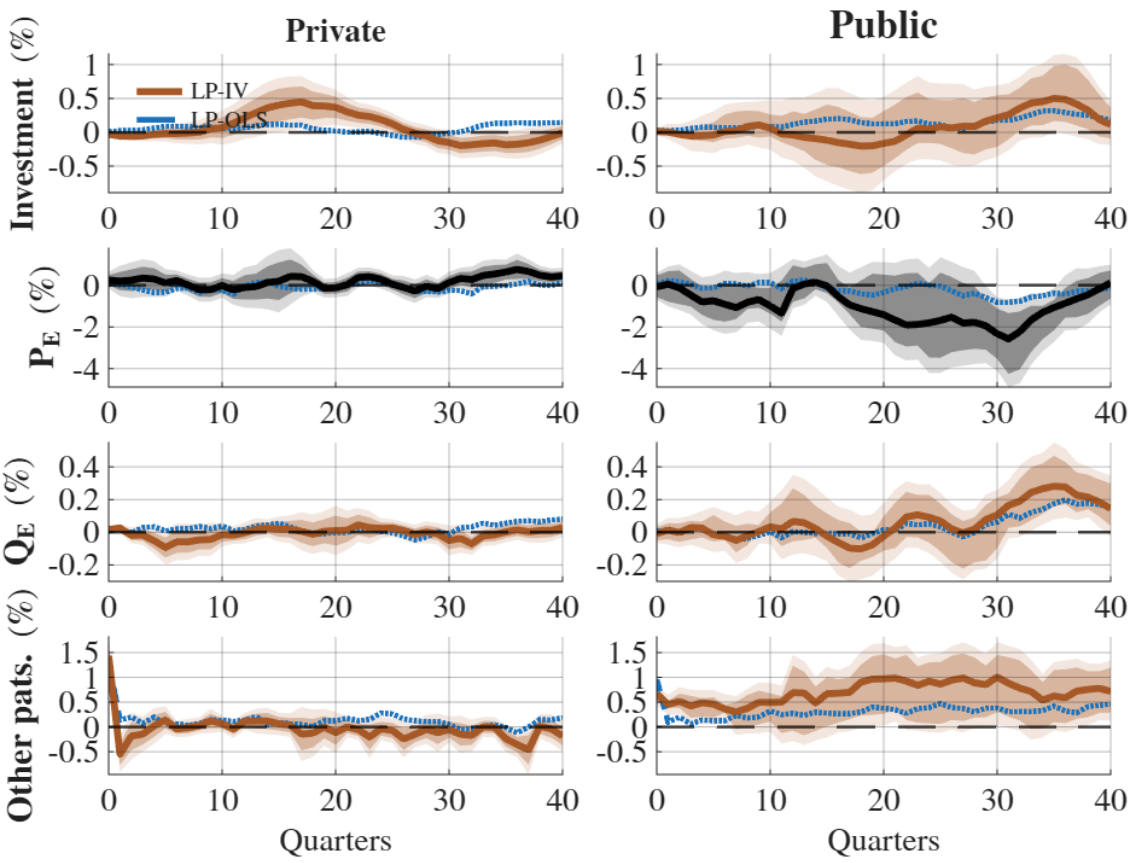
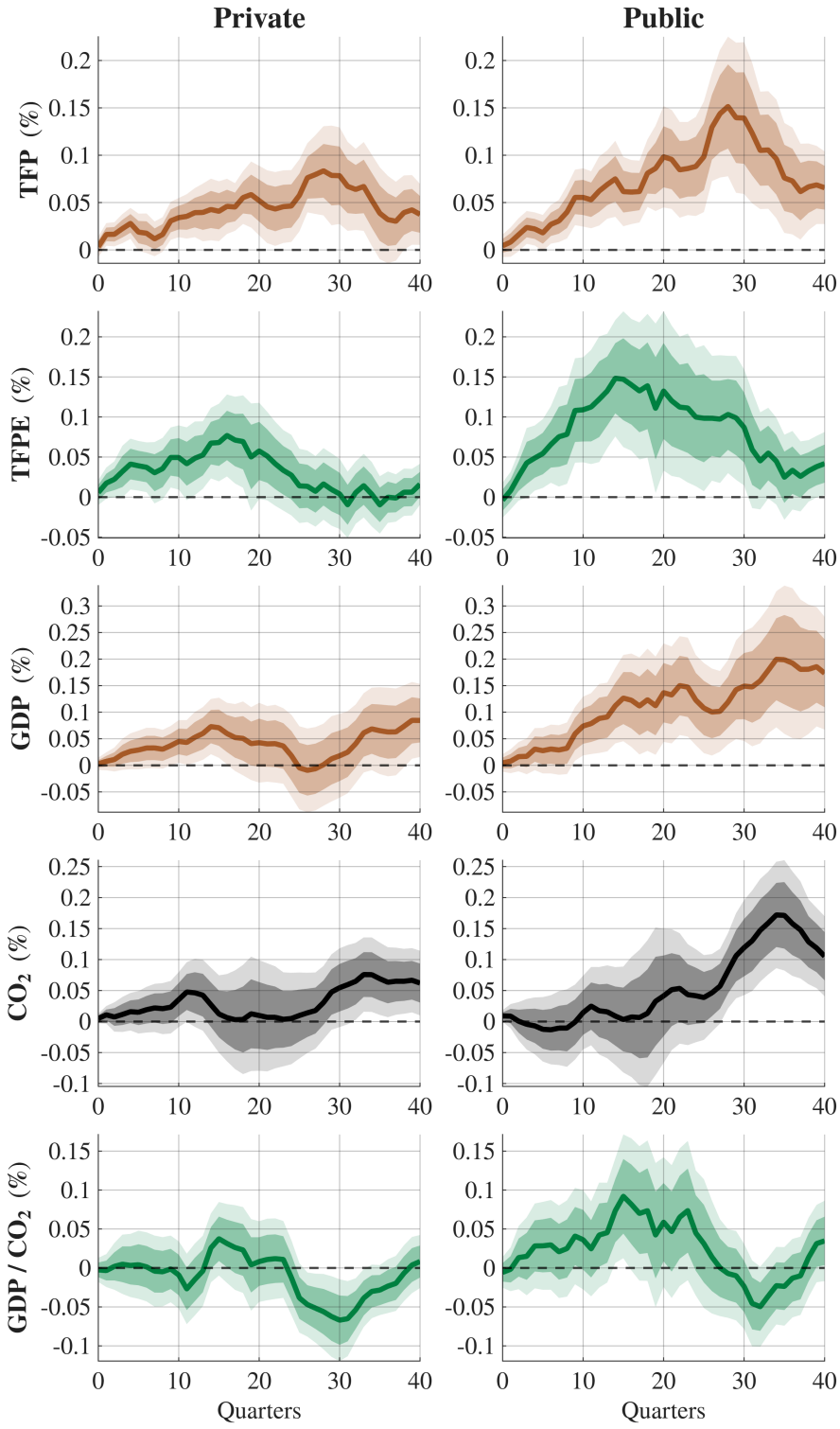


Figure B.1: OLS LP Main Results



Notes: The figure reports baseline OLS local projections for the responses of TFP, TFPE, GDP, CO_2 emissions, and GDP per unit of emissions to shocks in broad privately funded and government-funded patent aggregates. The size of the shock is normalized to increase total patents by 1% on impact. The control set includes four lags of the patent category being shocked and the dependent variable, real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill rate, real per-capita R&D expenditure, the number of patents in the other innovation groups, and the real price of fossil energy. All variables except the T-bill are in logs. Shaded areas report 68% and 90% confidence bands. Sample: 1950:Q1–2015:Q4.

Figure B.3: Government-private patents - LP OLS

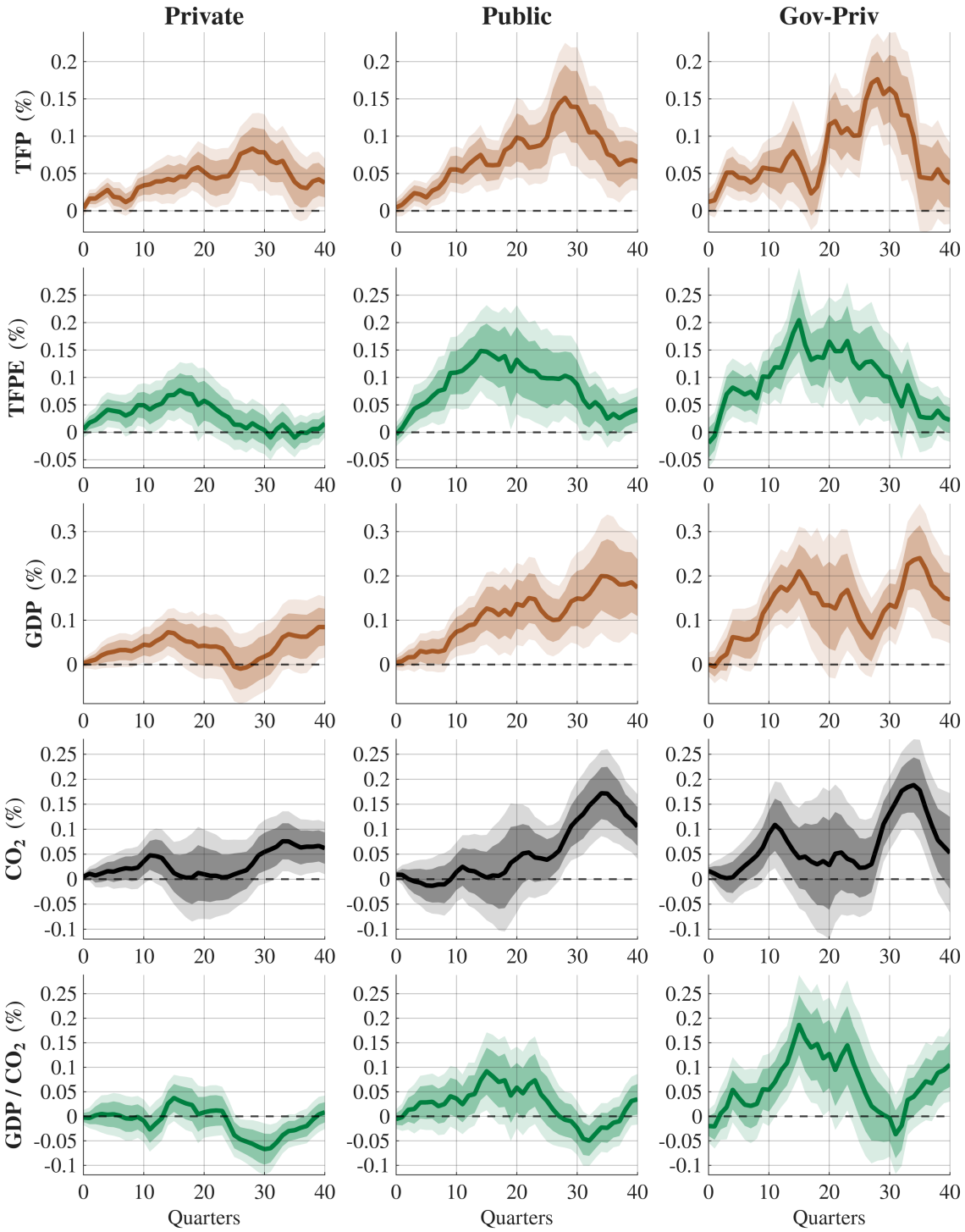
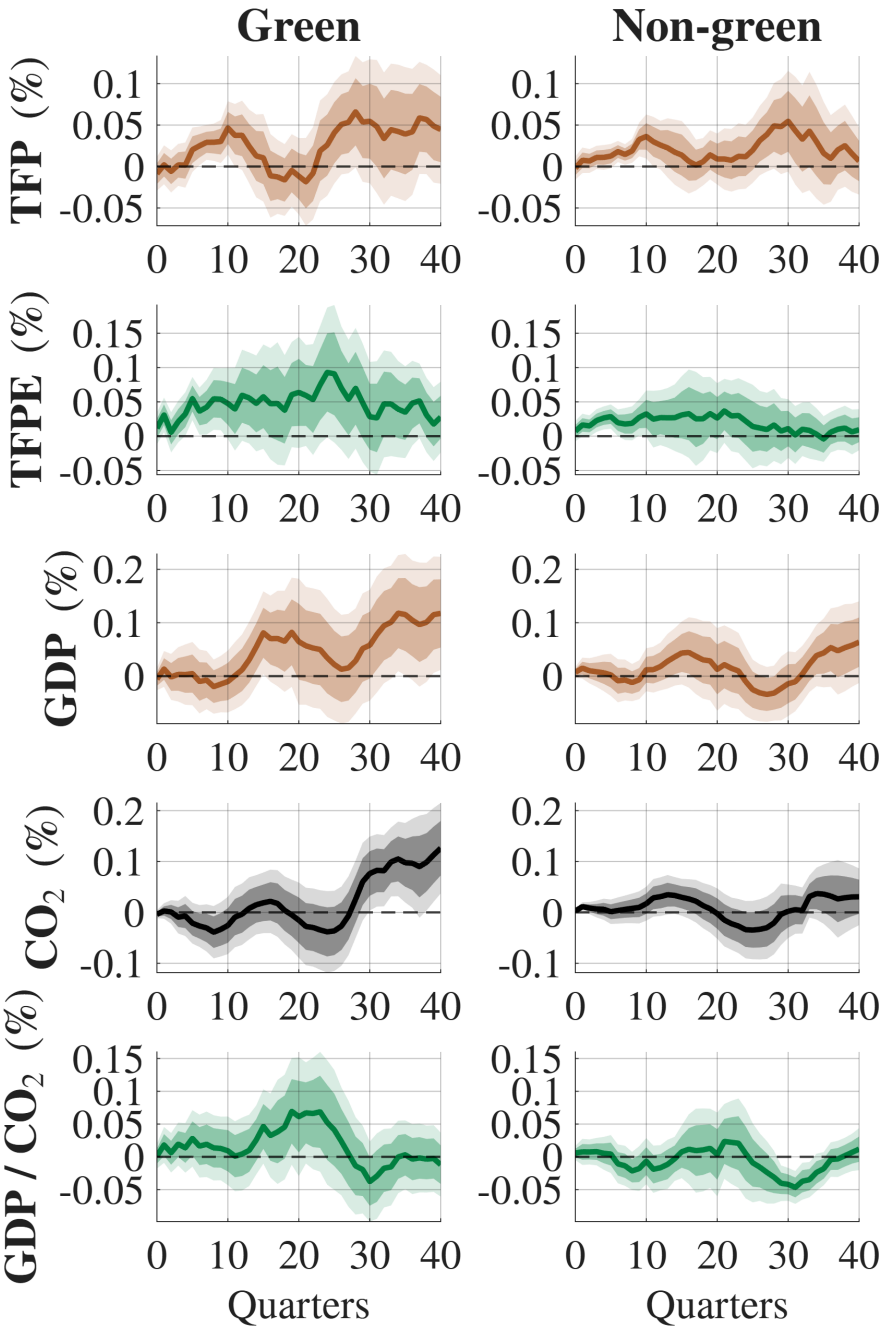


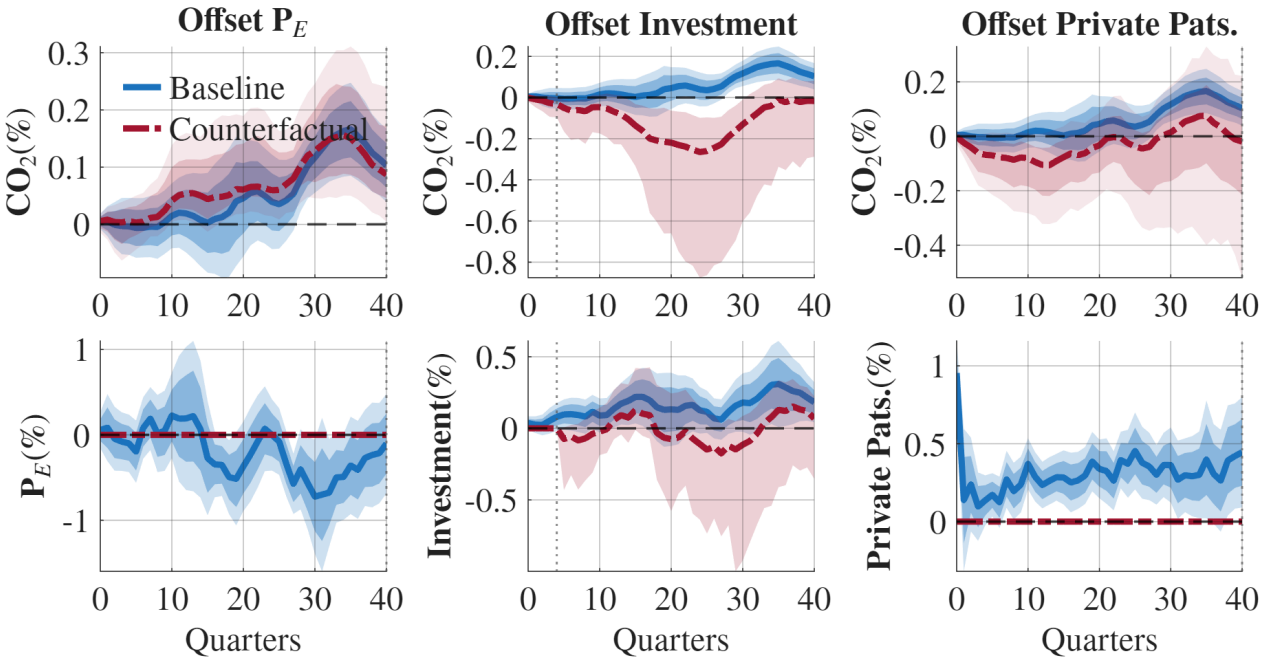
Figure B.4: Green vs Non-green patents



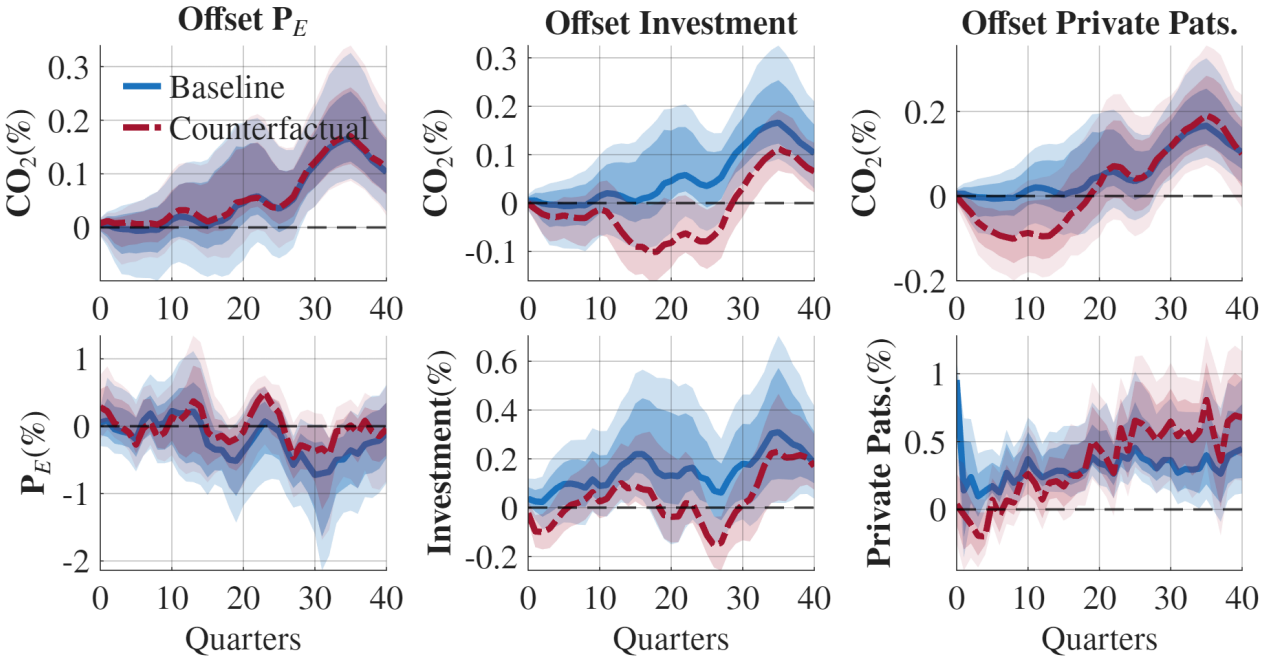
C Counterfactual

Figure C.1: Counterfactual for CO_2 Response

(a) Counterfactual - Sequence of Offsetting Shocks



(b) Counterfactual - One Offsetting Shock



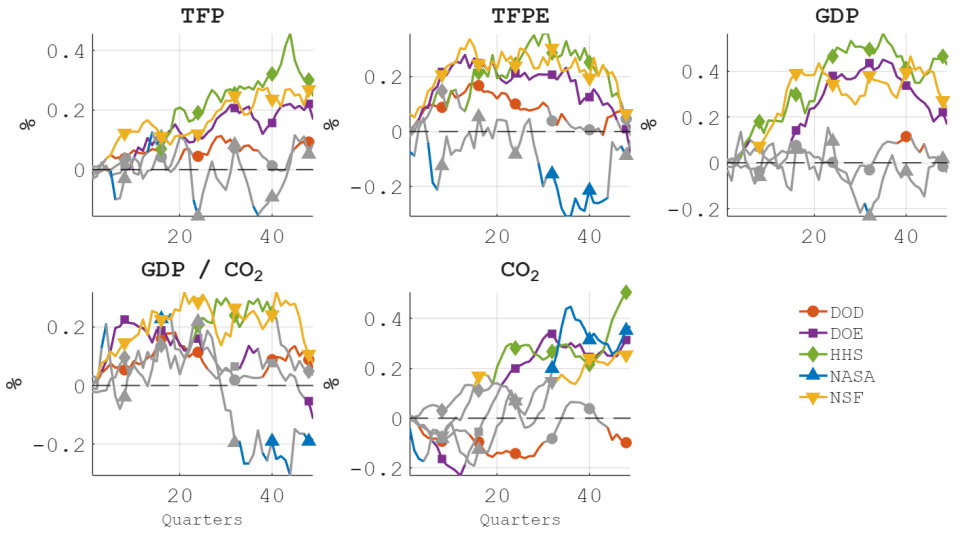
Notes: The figure reports counterfactual paths for the response of CO_2 emissions to a government-funded innovation shock when alternative transmission channels are selectively shut down. Panel (a) uses a sequence of offsetting shocks over the first part of the horizon, in the spirit of a structural scenario exercise. Panel (b) uses a single offsetting shock at impact. In both cases, the strongest attenuation of the delayed emissions response arises when the investment channel is neutralized. Shutting down the energy-price channel has only a limited effect, while closing the response of private patents mainly affects the short-run dynamics. Sample: 1950:Q1–2015:Q4.

D The Role of Federal Agencies

Table D.1: Top Federal Agencies Funding Green Patents

Agency	Count	Across-share (%)	Within-share (%)
Department of Energy (DoE)	9,256	42	26
Department of Defense (DoD)	5,672	26	5
National Institutes of Health (NIH)	2,813	13	6
National Science Foundation (NSF)	1,505	7	10
NASA	1,292	6	10

Figure D.1: All public patents



Notes: The figure displays the dynamic effects of innovation shocks by agency breakdown. Panel (a) reports the results for all public patents. Panel (b) for gov-priv patents. IRFs are estimated by local projections with 4 lags. The size of the shock is normalized such as to increase total patents by a peak of 1%. The set of controls includes four lags of the patent group shocked and the dependent variable, real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill, real per-capita R&D expenditure, and the number of patents in other groups. All variables except the T-bill are in logs. The solid line represents the point estimate, while the shaded areas report 68% and 90% confidence intervals computed from Newey and West (1987) standard errors. Sample: 1950:Q1-2015:Q4.