Green Business Cycles*

Diego R. Känzig
Northwestern University

Maximilian Konradt
Imperial College Business School

Lixing Wang
University of Bonn

Donghai Zhang
National University of Singapore

March, 2025

Abstract

This paper examines the relationship between green innovation and the business cycle, revealing that while non-green innovation is procyclical, green innovation is countercyclical. This pattern holds unconditionally over the business cycle and conditional on economic shocks. Motivated by these findings, we develop a business cycle model with endogenous green and non-green innovation to explain their cyclical behavior. The key mechanism operates through a "green is in the future" channel: green patents are expected to generate higher profits in the future, making patenting less sensitive to short-term economic downturns. In general equilibrium, this channel is reinforced, making green and non-green innovation effective substitutes. We provide direct evidence supporting the model mechanism using data on market-implied values of green and non-green patents.

JEL classification: E32, O31, Q55, Q58

Keywords: Green innovation, patenting, business cycles, medium-run impacts

*Känzig: Northwestern University, CEPR and NBER (email: dkaenzig@northwestern.edu); Konradt: Imperial College Business School (email: mkonradt@ic.ac.uk); Wang: University of Bonn (email: wang.lixing@uni-bonn.de); Zhang: National University of Singapore (email: donghai.d.zhang@gmail.com). We thank Maarten De Ridder, Yueran Ma, and Toan Phan for helpful comments and suggestions. Konradt acknowledges financial support from the Swiss National Science Foundation (grant 222367). Zhang thanks the Singapore Ministry of Education for financial support under the SSRTG grant SSRC2023-SSRTG-026

1. Introduction

Climate change is the defining challenge of our time, posing severe threats to lives, livelihoods, ecosystems, and the global economy. Fighting climate change through carbon pricing has proven challenging, in large part because of its distributional impacts. These policies often face public opposition, as higher energy costs disproportionately affect lower-income households and carbon-intensive industries. Against this backdrop, green innovation is key for a successful transition, enabling emissions reductions while sustaining economic growth. However, recent global headwinds—such as the Covid pandemic and the following recession—have raised concerns that macroeconomic downturns could slow the green transition. Periods of economic distress may reduce firms' willingness to invest in clean technologies, either due to tighter financial constraints or shifting innovation priorities. Against this backdrop, understanding how green innovation responds to the business cycle is crucial.

This paper provides an anatomy of the cyclicality of innovation. Based on the universe of patents filed in the United States and OECD countries, we document a striking pattern: while overall patenting activity tends to be procyclical, green and non-green innovation follow markedly different cyclical patterns. Specifically, while non-green patenting moves in tandem with the business cycle, decreasing during economic downturns, green patenting is *countercyclical*: it actually increases during economic contractions.

To establish these patterns, we examine the dynamics of patent applications, unconditionally over the business cycle and also conditional on macroeconomic shocks. For the former, we look at the dynamic correlations of the number of patent applications with leading business cycle indicators such as the output gap or cyclical components in industrial production. For the latter, we compute the dynamic causal effects of patenting to macroeconomic shocks using local projections. We focus on monetary policy shocks as a stand-in for well-identified demand shocks but the results also hold true conditional on other shocks such as oil price shocks.

These contrasting cyclical patterns are robust across multiple dimensions. First, we show that the cyclicality is comparable for patenting by listed and private firms. Second, the result holds true not only in the aggregate but also at the firm level. By linking patent data with balance sheet information for U.S. public firms, we find comparable firm-level patenting responses to monetary policy shocks, even when controlling for characteristics such as leverage, size, or firm age. The green patenting response shows little heterogeneity across firms, with the notable exception of book-to-market ratio. Growth firms—those with lower book-to-market values—display a more pronounced green patenting response

during downturns. Third, these cyclical patterns extend beyond national borders. While our primary focus is on the United States, we document similar divergent cyclicality between green and non-green patenting across our sample of OECD countries.

The procyclicality of traditional innovation aligns with the common notion that tighter credit conditions, lower revenues, and reduced profits during economic downturns result in cuts to R&D budgets and a decrease in patenting intensity. What can explain the different cyclicality of green innovation?

To answer this question, we develop a business cycle model with endogenous green and non-green innovation that can account for the different cyclicality of green and non-green patenting. We first study a simple production economy, taking the aggregate level of innovation and labor as given. The production economy consists of a final good producer that assembles the final good using material and energy. The energy input is a composite of fossil fuels and green energy. Intermediate input producers produce non-green materials and green energy varieties.

We show that in this economy, the equilibrium market share of the green energy composite increases over time, and green patents generate higher profits in the future. We label this phenomenon as *Green Is in the Future*. The intuition for this result is as follows. The number of green varieties reflects the productivity of green inputs. Along the green transition, as the green share increases, the productivity of green inputs rises, leading to lower prices and higher demand for green inputs. Consequently, the profits from producing green inputs are higher in the future. This implies that the value of a green patent, which is proportional to the discounted sum of future profits, is more heavily influenced by future profits relative to that of non-green patents.

Taken together with the transitory nature of business cycle shocks, this implies that the value of green patents responds less to macroeconomic shocks than the value of non-green patents. This in turn generates an incentive to change the green patenting intensity by less when faced with macroeconomic shocks.

We close the model by introducing innovators that engage in R&D to create new green and non-green varieties, and a standard household block. The model features a positive externality from the aggregate technological level, assuming that each successful innovation creates new varieties of green energy and materials.

In partial equilibrium, although the relative value of green varieties is countercyclical, the absolute value of green varieties is procyclical. Consequently, green innovations are procyclical in a partial-equilibrium setting, albeit less procyclical than non-green innovations. In general equilibrium, however, there is an additional effect driven by the inelastic supply of skilled labor. When the labor supply curve is positively sloped, a recessionary

shock reduces non-green innovation, which in turn lowers aggregate demand for skilled labor and thus wages. The lower wage then decreases the cost of green R&D, incentivizing firms to undertake more green innovation and offsetting the partial-equilibrium effect.

Thus, the model is able to generate the differential cyclicality of green and non-green innovation observed in the data. Key to this result is the *Green Is in the Future* channel: green patents are expected to generate higher profits in the future, making patenting less sensitive to short-term economic downturns. In general equilibrium, this channel is reinforced through general equilibrium effects via labor supply, making green and non-green innovation effective substitutes.

Crucial to this result is that the value of green patents is less cyclical than the value of non-green patents. We confront this model prediction with the data, leveraging the Kogan et al. (2017) dataset on market-implied values of patents filed in the United States. In line with our model prediction, green patent values move less with the business cycle and macroeconomic shocks such as monetary policy shocks. This holds true at the patent level and for green and non-green value indices at the firm level. Since patent quality is homogeneous in our model, we control for patent quality using a biadic patent dummy and the number of citations. Finally, note that the *Green Is in the Future* is also consistent with our result that growth firms, anticipating a large share of their profits in the distant future, display a stronger green patenting response.

Related literature. This paper contributes to several strands of literature. First, it relates to the extensive body of research on the cyclicality of innovation. A large literature documents that aggregate innovation, as measured by R&D expenditures and patent filings, is procyclical (e.g. Barlevy, 2007; Aghion et al., 2010; Aghion et al., 2012).[1] In the same vein, Ma and Zimmermann (2023) document that contractionary monetary policy shocks decrease innovation. The intuition is that economic contractions reduce firms' cash flows and tighten financial constraints, leading to declines in R&D spending and innovation output. Our findings confirm this broad pattern for overall patenting but highlight an important distinction between green and non-green innovation.

Second, this paper is related to the literature on green innovation and its determinants. Given recent estimates of the social cost of carbon (Burke et al., 2023; Bilal and Känzig, 2024), understanding the drivers of green innovation is of crucial importance. Prior studies have examined how environmental policies, such as carbon pricing and subsidies, influence green technological development (Calel and Dechezleprêtre, 2016;

[1] Wang and Zhang (2024) document the procyclicality of innovation along the extensive margin.

Colmer et al., 2024; Aghion et al., 2016; Känzig, 2023). Acemoglu et al. (2012) emphasize the central role played by market size and price effects on the direction of technical change. Acemoglu et al. (2023) study the effects of the shale gas revolution on green innovation, showing that the natural gas boom discourages green innovation. In a closely related paper, Aghion et al. (2024) study the role of financial barriers to green innovation. They show that young firms that are financially constrained substantially curb their green innovation when faced with a credit shock. While their focus is on young firms in Europe, our analysis centers on more mature listed companies in the United States which are less likely to be financially constrained. Our paper contributes to this literature by documenting the cyclicality of green patenting and providing a theoretical explanation for its countercyclicality. The countercyclicality of green innovation is consistent with the Schumpeterian view (Aghion and Saint-Paul, 1998): economic downturns and the associated fall in wages reduce the opportunity cost of innovative activities and induce higher green innovation, at the expense of non-green innovation.

Our green business cycle model featuring both green and non-green innovations contributes to the existing literature on medium-run fluctuations, which typically emphasize the interplay between technological progress, capital accumulation, and business cycle dynamics (Comin and Gertler, 2006; Anzoategui et al., 2019; Wang and Zhang, 2024). While conventional models usually focus on aggregate economic variables such as output and investment, our framework extends this by incorporating the dynamics of green and non-green innovation and study their dynamics during the green transition. In particular, our model captures how the *Green Is in the Future* mechanism, which emerges during the green transition, in combination with general equilibrium effects via labor supply alter the substitutability between green and non-green innovations across the business cycle.

Outline. The rest of this paper is organized as follows. Section 2 presents our new stylized facts on the cyclicality of green and non-green innovation: in the aggregate and at the firm-level, unconditional and conditional on macroeconomic shocks. Section 3 introduces our business cycle model with green and non-green innovation. In Section 4, we confront key model predictions with the data. Section 5 concludes.

2. Green Innovation Over the Business Cycle

How does innovation activity vary with the business cycle? Does green innovation display a different sensitivity to economic downturns and upswings than other types of innovation? Answering these questions presents two key challenges. First, how to accu-

rately measure different types of innovation. Second, how to best represent the business cycle. For the former, we will rely on patent data—a widely used proxy for innovation (see e.g. Nagaoka, Motohashi, and Goto, 2010). For the latter, we start by documenting the unconditional co-movements of patenting with business cycle indicators before studying the relationship conditional on structural economic shocks.

2.1. Measuring Green Innovation

Measuring innovation presents a fundamental challenge in understanding how technological change responds to economic fluctuations. Patent data offer a well-established proxy for innovation, providing a consistent and detailed record of inventive activity across industries and time. Importantly, patents capture both the scale and nature of innovation: a detailed classification system enables researchers to distinguish between green and non-green technological advances.

The ability to classify patents is a key advantage over R&D expenditure data, another widely used measure of innovation. Unlike patents, R&D expenditure data are typically reported at the aggregate level and lack detailed breakdowns by type of research activity. This poses a challenge because firms engage in many types of research simultaneously that do not necessarily correlate with observable characteristics, making it difficult to disentangle targeted investments in specific technologies from broader innovation efforts. For instance, many firms in carbon-intensive industries display substantial engagement in green R&D. Patents, by contrast, provide a direct and observable measure of directed innovation, which is why we focus on patent data in our study of changes in green innovation.

We rely on the Worldwide Patent Statistical Database (PATSTAT), which encompasses bibliographic information for close to the universe of patents globally. The data allow us to identify patent families—patents representing the same innovation filed at different patent offices. To avoid double counting, we treat all patents in a patent family as a single innovation (see e.g. Hémous et al., 2025). For each patent family, we use the original application date to capture the time of innovation and assign nationality based on the respective filing office.

Our key goal is to measure green innovation. To that end, we use the International Patent Classification (IPC) and Cooperative Patent Classification (CPC) codes associated with patent filings. The OECD has developed specific categories for climate change mitigation technologies (Y02) and smart grids (Y04S), allowing us to systematically identify and track relevant technological advancements (see Migotto and Haščič, 2015). Our def-

inition of green patents is a subset of the patents in Y02, excluding innovations that do not directly compete with fossil-fuel technologies following Acemoglu et al. (2023).[2] Focusing on all Y02E subclasses or including smart grid technologies (Y04S) as in Calel and Dechezleprêtre (2016) produces very similar results (see Appendix B.7).

Since a patent family is typically associated with many IPC/CPC codes, we consider it green when any of the codes meet our criteria. We treat the remaining patents as non-green. Table A.1 in the appendix contains an example of a patent classified as green.

Aggregate trends and fluctuations. Based on our patent database, we compute aggregate patent application counts. Our main focus is on patenting in the United States, but we report similar statistics for the sample of OECD countries as a comparison.[3]

The top left panel of Figure 1 illustrates how the share of green patents relative to total patents filed evolves from the mid-1980s until the end of 2019. We observe a stark increase share of green patents in the U.S. over that period, which accelerated between 2005–2010. Since 2010 the share of green patents has been fairly flat at around 7%. The top right panel shows a similar trend in OECD countries. Overall, these patterns are consistent with the results in Aghion et al. (2024).

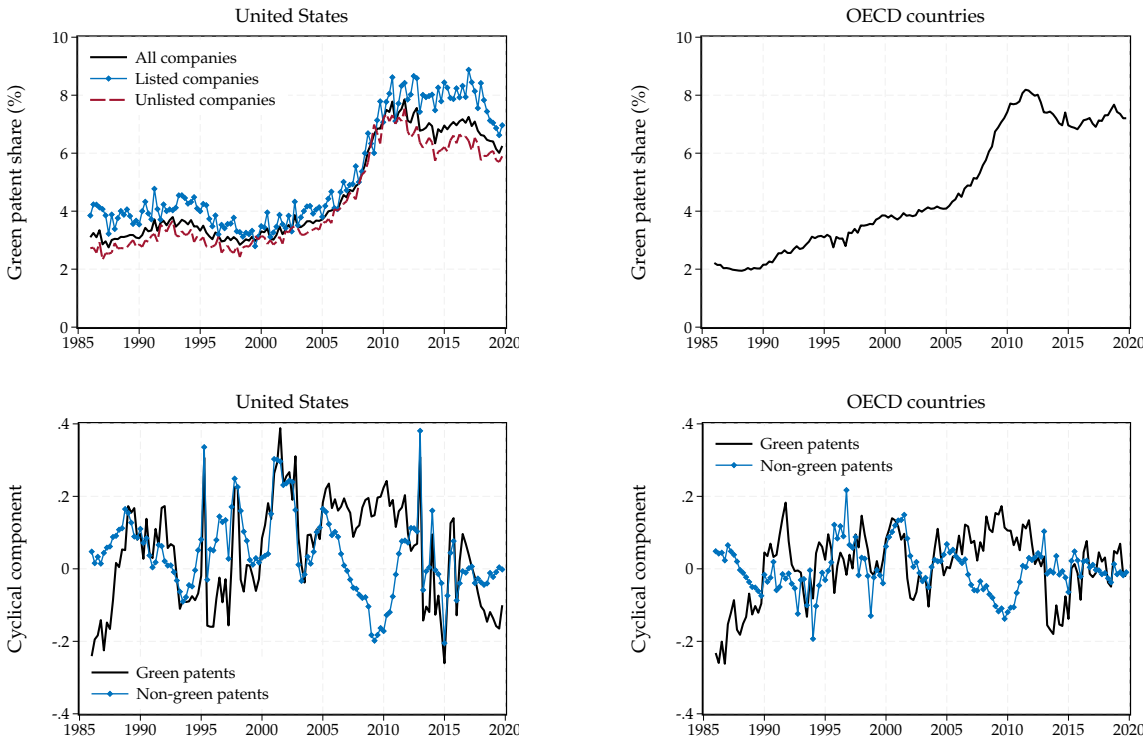
The trend masks the cyclical fluctuations in patenting activity. The bottom two panels of Figure 1 therefore display the cyclical components of the number of green and non-green patents filed in the United States and OECD countries, extracted using the Hamilton (2018) filter. There is substantial variation in patent counts underlying the green patent share. Importantly, there are many periods, including the early 1990s or the late 2000s, where green and non-green patents move in opposite directions.

Firm-level statistics. To get a better understanding of the key green innovators, we merge the PATSTAT dataset with corporate balance sheet data. For the accounting data, we rely on Compustat North America which covers the universe of listed companies in the United States. To match the patent data, we leverage the two leading datasets linking patents to firms. The first is Orbis Intellectual Property, which reports global patent portfolios assigned to Orbis companies (see Hémous et al., 2025) which we link to Compustat using ISIN numbers. The second is the dataset by Arora, Belenzon, and Sheer (2021), which extends the NBER patent database (Hall, Jaffe, and Trajtenberg, 2001), establishing a direct link between USPTO patents and Compustat firms.

[2]Specifically, we exclude patents aimed at reducing pollution from fossil-fuel electricity generation (Y02E20), improving grid efficiency (Y02E40) or storage (Y02E60).

[3]Conducting a separate analysis on OECD countries is insightful, as patents filed with the USPTO account for only 21% of total patents and 22% of green patents filed in these countries, according to our data.

Figure 1: Green innovation in the U.S. and OECD countries, 1986–2019



Notes: The top panels show the share of green patents in the United States and OECD countries. The U.S. green patent share is separately computed for listed and unlisted companies. The bottom panels plot the cyclical components of green and non-green patent counts, extracted using the Hamilton filter. Figure B.3 in the appendix displays cyclical components separately constructed for listed and unlisted companies.

We use the unique patent application number encompassed in both datasets to merge the information in PATSTAT. In total, we are able to match 1.9 million distinct patent families (including more than 99,000 green patents) to close to 2,000 Compustat firms. Reassuringly, the overlap of matched patents across the two datasets is high (for more information, see Appendix A).

Who are the main players in green innovation? We find that a large share of green patents are filed by listed firms (42% of quarterly green patent filings, on average). Among listed firms, Table 1 provides some descriptive statistics on green patenting by firms' size. The bulk of green patenting in the U.S. is concentrated in the largest companies (fourth quartile), which account for more than four of five green patents filed between 1986 to 2019. Although smaller and younger firms patent relatively more in green technology classes, the bottom half of the size distribution accounts for less than 7% of the total green patents in our sample. By contrast, the 20 largest innovators account for close to 50% of

green patent filings (see Table B.1 in the appendix).

Table 1: Green patenting and firm size

	Firm size quartiles			
	First	Second	Third	Fourth
Number of green patents	2,254	4,590	9,285	82,924
Green patent share (%)	21.69	11.67	8.94	10.30
Size	33	207	1,020	13,877
Age	15.02	18.01	22.49	31.01
Book to market ratio	0.25	0.47	0.41	0.38
GHG emission intensity	35.40	34.10	83.71	357.07

Notes: The table reports the total number of green patents and the average share of green patents, calculated for firms across four quartiles of the firm size distribution. Firm size is measured based on average total assets (expressed in million US dollars) reported in Compustat between 1986 to 2019. Average firm age is constructed using the incorporation date, sourced from Worldscope. Average GHG emission intensity based on Scope 1 emissions to revenue reported in Trucost.

Put differently, large firms appear to be important drivers behind green innovation in the United States.[4] Interestingly, these firms tend to be not very green based on conventional metrics. For instance, Table 1 suggests that the GHG emissions intensity is substantially higher among larger compared to smaller firms. The patent mix of large firms is also less tilted toward green technology classes relative to smaller firms (see Fornaro, Guerrieri, and Reichlin, 2024). This pattern is consistent with recent evidence in Cohen, Gurun, and Nguyen (2020) showing that utilities and energy companies are key drivers of green innovation.

Firm age, on the other hand, tends to increase with firm size. When examining the book-to-market ratio, growth firms are primarily concentrated in both the lowest and highest quartiles of the size distribution, while value firms are more evenly distributed in the middle.

An important question is how patenting activity in listed companies compares to that in unlisted companies, which are often overlooked due to data limitations. In particular, we construct the green patent share for patents linked to listed firms and separately for

[4]Note that this relationship might differ across countries. For instance, Aghion et al. (2024) document that smaller firms account for the majority of green patenting in German data. However, a direct comparison with their analysis is complicated by the fact that firms in our data tend to be much bigger in size—a firm at the 90th percentile of their fixed asset distribution (97 million EUR) would rank in the bottom quartile of our total asset distribution.

the remaining set of patents, which we attribute to unlisted firms.[5] The top-left panel of Figure 1 shows that the evolution of green patenting in listed firms closely mirrors that of unlisted firms.

2.2. The Cyclicality of Green Innovation at the Macro Level

How does green and non-green innovation fluctuate over the business cycle? Theoretically, the cyclicality of innovation is ambiguous. According to the Schumpeterian view, economic downturns and the associated fall in wages reduce the opportunity cost of innovative activities and induce higher long-term productivity growth (Aghion and Saint-Paul, 1998). However, the effect can also be overturned in the presence of financial constraints (Aghion et al., 2010). Thus, the direction and amplitude of innovation's cyclicality is an empirical question.

Unconditional cyclicality. We begin by reporting simple correlation coefficients between the cyclical components of patent counts with the cyclical component of industrial production and the GDP gap. The results are reported in Table 2.

Table 2: Correlation between patenting and the business cycle, 1986–2019

	United States				OECD		
	Monthly	Quarterly		Annual	Monthly	Quarterly	Annual
	IP	IP	GDP gap	Δ IP	IP	IP	Δ IP
Total	0.38 [0.29, 0.46]	0.40 [0.25, 0.53]	0.28 [0.12, 0.43]	0.36 [0.03, 0.62]	0.37 [0.28, 0.45]	0.39 [0.23, 0.52]	0.32 [-0.02, 0.59]
By patent type:							
Green	-0.19 [-0.29, -0.10]	-0.22 [-0.37, -0.05]	-0.15 [-0.31, 0.02]	-0.18 [-0.49, 0.17]	0.09 [-0.01, 0.18]	0.10 [-0.07, 0.26]	0.06 [-0.29, 0.39]
Non-green	0.40 [0.32, 0.48]	0.43 [0.28, 0.56]	0.30 [0.14, 0.44]	0.38 [0.05, 0.64]	0.38 [0.29, 0.46]	0.39 [0.23, 0.52]	0.32 [-0.02, 0.59]

Notes: The table shows correlation coefficients between the cyclical component of patent counts and business cycle measures. Cyclical components of patent counts and industrial production are extracted using the Hamilton (2018) filter. IP corresponds to U.S. industrial production and global industrial production (Baumeister and Hamilton, 2019), respectively. The GDP gap is based on U.S. CBO projections. Annual correlations use the change in log patents. 95% confidence bands based on Fisher's z-transform in parentheses.

Focusing on total innovation activity, we see that patenting is procyclical. That is,

[5]Compustat accounts for 97-99% of market capitalization of all listed firms in the U.S. between 1975-2015 according to Kahle and Stulz (2017). Because we assign patent nationality based on the original patent office, we expect filings by foreign corporations to be modest.

the number of patents filed moves in tandem with the business cycle: it increases during economic expansions and falls during economic downturns. The procyclicality of innovation is consistent with the idea that tighter credit conditions, lower revenues, and reduced profits during economic downturns result in cuts to R&D budgets and a decrease in patenting intensity (Aghion et al., 2010; Aghion et al., 2012).

Comparing the business cycle correlations of green and non-green patents, a striking pattern emerges. Across different frequencies and measures of the business cycle, non-green patents are significantly positively correlated with the business cycle while the correlation coefficients for green patents are negative. Thus, while non-green patenting turns out to be procyclical in line with conventional wisdom, green patenting appears to be *countercyclical*. This difference is not only economically but also statistically significant at the 95% level, at least at the monthly and quarterly frequency.

We observe a similar pattern in the OECD sample, where the correlation coefficients suggest that non-green patenting is strongly procyclical as in the United States while green patenting turns out to be acyclical. While we focus here on contemporaneous correlations, we obtain consistent results when studying dynamic correlation coefficients using lagged measures of the business cycle (reported in Table B.2 in the appendix).

Cyclicality conditional on economic shocks. While the unconditional time-series evidence is informative, it may confound the impacts of the different underlying shocks driving the business cycle. In addition, reverse causality is a concern, as innovation can drive business cycle fluctuations—for example, through creative destruction. The extent to which creative destruction impacts the business cycle may further differ between green and non-green innovations.

Therefore, it is important to establish the cyclicality of green patenting *conditional* on structural economic shocks. Over our sample period of interest, business cycles are thought to be mainly demand driven. Credibly identifying demand shocks is challenging though. We thus focus on monetary policy shocks, as a well-identified instance of a demand shock. However, our results are robust conditioning on other shocks such as oil price shocks (see Appendix B.6).

To identify monetary policy shocks, we rely on high-frequency identification techniques (Gertler and Karadi, 2015; Nakamura and Steinsson, 2018). Specifically, we employ the monetary surprises constructed by Bauer and Swanson (2023), purged from macroeconomic and financial data. Our results are robust to using the monetary surprises from Miranda-Agrippino and Ricco (2021) or Jarociński and Karadi (2020) (see Appendix B.6).

Equipped with the high-frequency monetary surprises, we estimate the dynamic causal effects of a monetary policy shock on green patenting. Specifically, we estimate a series of local projections (Jordà, 2005) using the monetary surprises as an instrumental variable:

$$y_{t+h} = \alpha^h + \theta^h \text{ffr}_t + \sum_{j=1}^{p} \beta_y^h y_{t-j} + \sum_{j=1}^{p} \boldsymbol{\beta}_z^h \mathbf{z}_{t-j} + \varepsilon_{t+h}, \tag{1}$$

where y_{t+h} corresponds to outcome variable of interest h-quarters ahead, ffr_t refers to the U.S. federal funds rate, which we instrument using monetary surprises, and $\mathbf{z}_t$ is a vector of controls to account for macroeconomic and financial conditions. The controls include lags of the Fed funds rate, log real GDP, the unemployment rate and excess bond premium from Gilchrist and Zakrajšek (2012). Moreover, we include quarterly dummy variables and a linear time trend to account for seasonality and trending behavior, as well as a dummy variable for the period of the zero lower bound, where conventional monetary policy was constrained.[6] As the relevant outcome variables, we consider the green patent share, the number of green and non-green patents (expressed in logs), or the (log) difference between green and non-green patents, respectively. The key object of interest is θ^h, the dynamic causal effect of a monetary policy shock on green innovation. We set $p = 4$ and compute standard errors using the lag-augmentation approach (Montiel Olea and Plagborg-Møller, 2021).

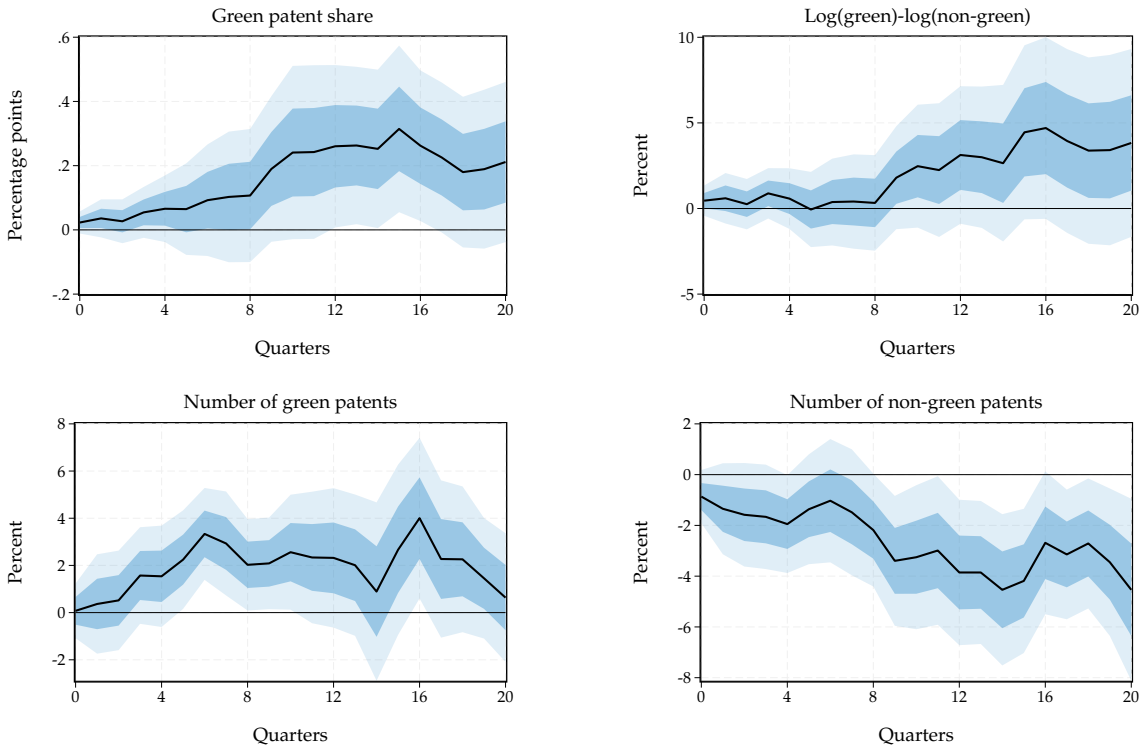
We estimate equation (1) separately for the United States, where we further distinguish between listed and unlisted firm patents, and for the sample of OECD countries. Our estimation sample spans the period from 1986q1, when consistent reporting in the Compustat data begins, and ends in 2019q4 before the Covid pandemic. Due to the substantial reporting lag in the PATSTAT data, extending the sample to more recent periods is challenging.

Reassuringly, the effective F-statistic in the first stage is sufficiently above the rule-of-thumb value of 10. We thus proceed by conducting standard inference. Before looking at the patenting responses, we also confirm that the responses of U.S. macroeconomic variables to our identified monetary policy shocks are consistent with existing empirical evidence, see Appendix B.3. Throughout, we normalize the monetary policy shock to increase the Fed funds rate by 25 basis points.

Turning to the impact on patenting, we first confirm that a contractionary monetary

[6] In the U.S. data there are also apparent spikes in patent filings in 1995q2 and 2015q1, likely induced by changes in U.S. patent law associated with the Uruguay Round Agreements Act and the America Invents Act, respectively. We include two additional dummy variables for these periods.

Figure 2: Green and non-green patenting responses to a monetary policy shock



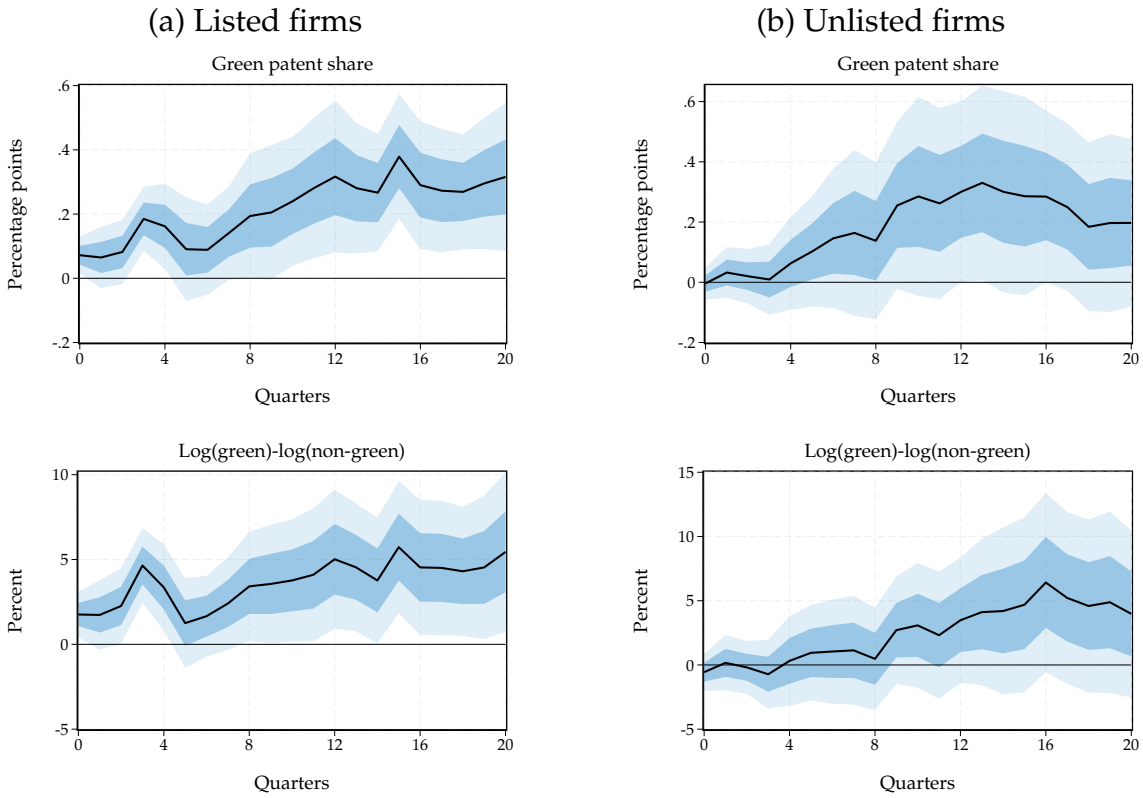
Notes: Impulse responses of green and non-green patenting in the United States to a 25 basis point monetary policy shock, estimated based on Equation (1). The solid line is the point estimate and the dark and light shaded areas are 68 and 95 percent confidence bands based on robust standard errors, respectively.

policy shock leads to a fall in aggregate patenting, consistent with the results in Ma and Zimmermann (2023), see Figure B.2 in the appendix.

Next, we turn to the responses of green and non-green patenting. Figure 2 shows the results. A contractionary monetary policy shock leads to a significant and persistent increase in the green patent share and the log difference between green and non-green patents. The effect is quantitatively large, with a peak increase in the green patent share by 0.3 percentage points after 15 quarters. What is driving the relative increase in green patenting? Comparing the responses of green and non-green patents in the bottom panels reveals that monetary policy shocks cause an increase in green patent applications and a fall in non-green patent applications, both contributing to the rise in the green patent share.

Does the conditional cyclicality of green patenting hold up in both listed and unlisted firms? Figure 3 shows impulse responses estimated separately for the aggregate patent counts associated with listed and unlisted firms, respectively. Interestingly, the increase

Figure 3: Patenting responses in listed and unlisted U.S. firms

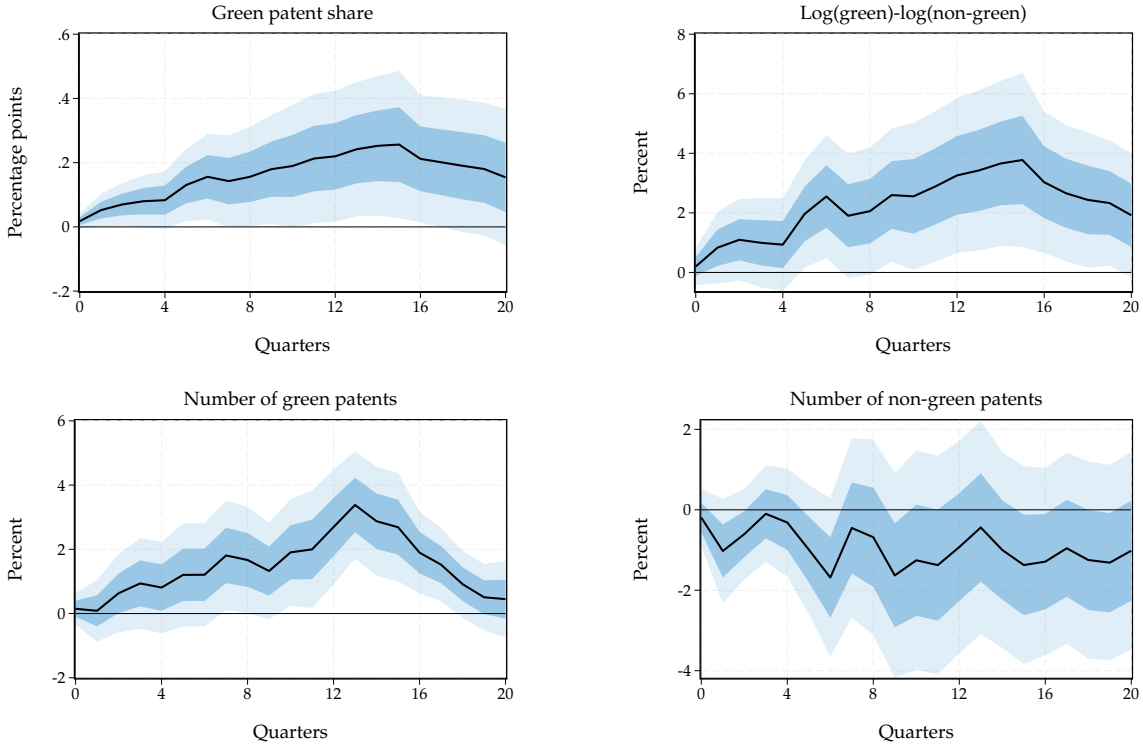


Notes: Impulse responses of green and non-green patenting by listed and unlisted U.S. firms to a 25 basis point monetary policy shock, estimated based on Equation (1). The solid line is the point estimate and the dark and light shaded areas are 68 and 95 percent confidence bands based on robust standard errors, respectively.

in the green patent share, and log difference between green and non-green patents is quantitatively comparable across the two samples, though the shapes differ somewhat.

Finally, we examine whether the estimated effects extend beyond the sample of U.S. patents. Given the well-documented global spillovers of U.S. monetary policy (Miranda-Agrippino and Rey, 2020), it is interesting to see how green patenting responds across the globe. Figure 4 reports the impulse responses estimated using the OECD data. The results turn out to be similar to the U.S. sample. We find a relative uptick in green patenting as manifested by an increase in the green patent share and the log difference between green and non-green patents. In line with the U.S. evidence, we see an increase the number of green patents and a decline in the number of non-green patents.

Figure 4: Green and non-green patenting responses in OECD countries



Notes: Impulse responses of green and non-green patenting in OECD countries to a 25 basis point U.S. monetary policy shock, estimated based on Equation (1). The solid line is the point estimate and the dark and light shaded areas are 68 and 95 percent confidence bands based on robust standard errors, respectively.

2.3. The Cyclicality of Green Innovation at the Firm Level

The evidence based on aggregate patent counts suggests that green patenting is strongly countercyclical relative to non-green patenting. In this section, we investigate whether the same pattern also holds in a large panel of listed U.S. companies.

Formally, we estimate a panel version of the local projections in equation (1),

$$y_{i,t+h} = \alpha_i^h + \theta^h \text{ffr}_t + \sum_{j=1}^{p} \beta_y^h y_{i,t-j} + \sum_{j=1}^{p} \boldsymbol{\beta}_z^h \mathbf{z}_{t-j} + \varepsilon_{i,t+h}, \tag{2}$$

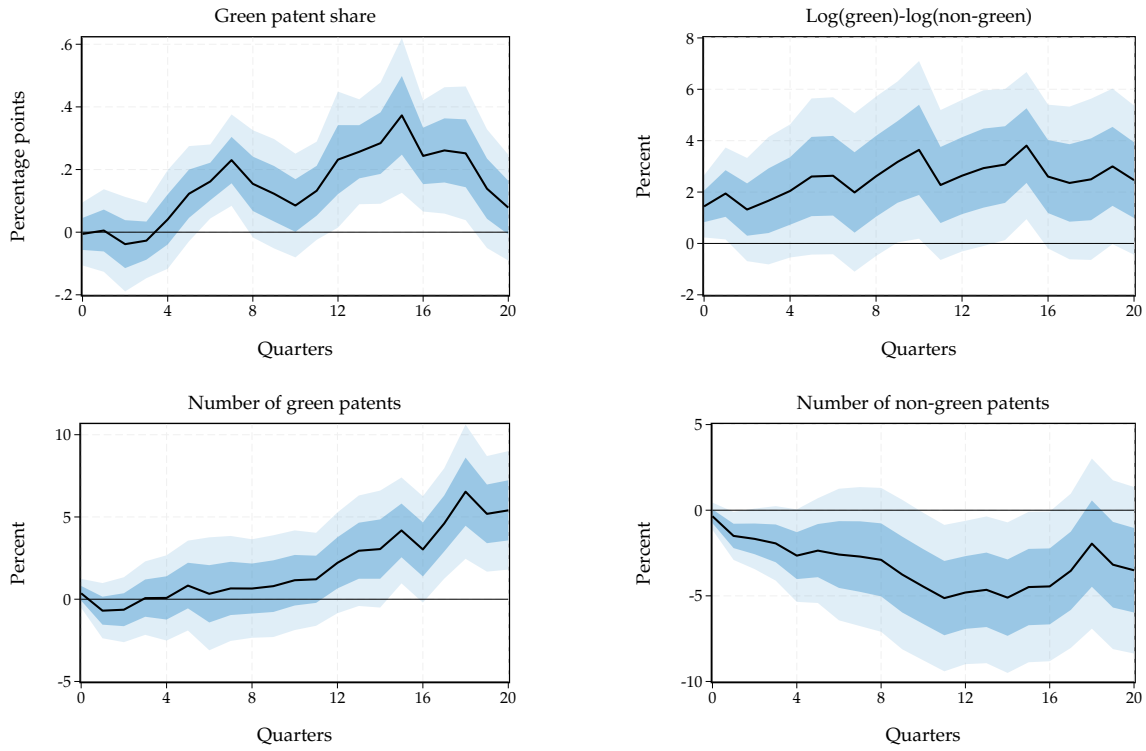
where $y_{i,t+h}$ now corresponds to the outcome variable of firm i, h-quarters ahead. As outcome variables, we consider the green patent share, number of green or non-green patents, or (log) difference between green and non-green patents.[7] In this specification,

[7] We apply a backward-looking 3-quarter moving average to address sparseness in the firm-level patent data.

we also control for firm fixed effects, α_i^h, to absorb any time-invariant firm characteristics. To allow for general forms of cross-sectional and temporal dependence in the panel data, we compute standard errors using the approach in Driscoll and Kraay (1998).

We restrict our sample to companies that are consistently observed for 20 quarters and exclude firms in the finance, insurance, real estate or public administration sectors. We also drop firms without any green patent over our sample period.[8] Our final sample consists of close to 140,000 firm-quarter observations, covering about 2,000 companies and more than 99,000 green patents between 1986q1 and 2019q4.

Figure 5: Green and non-green patenting responses of U.S. firms



Notes: Impulse responses of U.S. firms green and non-green patenting to a 25 basis point monetary policy shock, estimated based on Equation (2). The solid line is the point estimate and the dark and light shaded areas are 68 and 95 percent confidence bands based on Driscoll and Kraay (1998) standard errors, respectively.

Figure 5 displays the dynamic causal effects on green and non-green patenting at the firm-level. The estimated responses align well with the aggregate evidence, both qualitatively and quantitatively. In line with the aggregate estimates, we find a significant increase in the firm-level green patent share, which peaks at above 0.3 percentage points

[8]This assumption follows Hémous et al. (2025), but is not critical for our results.

and persists for close to 20 quarters. This is striking, because it suggests a shift from non-green to green patenting *within* firm. Consistently, we document that this increase is driven by a large and persistent expansion in the number of green patents and a simultaneous contraction in the number of non-green patents, as in the aggregate.

One challenge in the firm-level estimations is the sparseness of the patent data, which we address by applying a moving average in the local projections. However, the presence of zeros, especially in green patent counts, implies missing values when expressing patent counts in logs. To obtain consistent estimates for the number of green (and non-green) patents, we therefore estimate Equation (2) using raw patent counts and normalize impulse responses using the average patent count to obtain percent changes.

As a robust alternative, we also estimate a Pseudo-Poisson Maximum Likelihood (PPML) equation that is more suitable for patent count data (see e.g. Aghion et al., 2024):[9]

$$\mathrm{E}(\sum_{h=1}^{20} y_{i,t+h}) = \exp(\alpha_i + \theta \mathrm{ffr}_t + \sum_{j=1}^{p} \beta_y y_{i,t-j} + \sum_{j=1}^{p} \boldsymbol{\beta}_z \mathbf{z}_{t-j} + \varepsilon_{i,t+h}), \tag{3}$$

where $\sum_{h=1}^{20} y_{i,t+h}$ captures firm i's cumulative number of green and non-green patents, 20 quarters ahead. By focusing on cumulative patents, we allow for a sufficiently long lag between R&D expenditures and patent applications, in line with Hémous et al. (2025). As before, we instrument the Fed funds rate using monetary surprises and include a set of (lagged) controls and firm fixed effects. We conduct inference based on bootstrapped standard errors clustered at the time level.

Table 3 presents the results. The baseline estimates for green and non-green patenting are shown in columns (1) and (6). Consistent with the local projections, we find a significant increase in the number of green patents and a decrease in the number of non-green patents. Quantitatively, a 25 basis point monetary policy shock is associated with a 0.77% rise in the cumulative number of green and a 4.77% decline in the number of non-green patents over the horizon of 20 quarters.[10] Thus, the magnitude of the contraction in non-green patenting is comparable to the local projections estimates.

In columns (2)-(5) and (7)-(10), we study the effects of a monetary contraction conditional on a set of firm characteristics. Specifically, we introduce interaction effects of the federal funds rate with firms' lagged book-to-market and leverage ratio, age and size in equation (3). To facilitate interpretation, we standardize the interaction terms. Introducing the interactions leaves the level effects merely unchanged. For the green patenting

[9] The downside is that we are not able to embed it in a dynamic, local projections framework.

[10] The semi-elasticities are $100 \times (\exp(-0.0489) - 1)\%$ and $100 \times (\exp(0.0077) - 1)\%$, respectively.

Table 3: Effects of interest rate changes on firm-level patent counts, PPML

Dep. var.:	Green patents$_{it+h}$					Non-green patents$_{it+h}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ffr$_t$	0.77**	0.73**	0.85**	-0.18	1.30**	-4.89***	-4.89***	-5.11***	-6.22***	-6.46***
	(0.34)	(0.33)	(0.36)	(0.43)	(0.55)	(0.49)	(0.48)	(0.51)	(0.51)	(0.66)
ffr$_t$ × btm$_{it-1}$		-0.31***					0.06			
		(0.09)					(0.15)			
ffr$_t$ × leverage$_{it-1}$			0.22					-0.21		
			(0.18)					(0.88)		
ffr$_t$ × age$_{it-1}$				-0.26					-0.19**	
				(0.28)					(0.10)	
ffr$_t$ × size$_{it-1}$					0.21					0.17
					(0.24)					(0.27)
Observations	90,805	89,880	86,164	79,121	90,300	90,546	89,672	85,959	78,951	90,041
Firms	1,634	1,631	1,633	1,335	1,634	1,634	1,631	1,633	1,335	1,634

Notes: The table shows PPML coefficients, based on Equation (3). The dependent variables are a firm's cumulative, 20-quarter ahead number of green and non-green patents, respectively. ffr corresponds to the Fed funds rate, instrumented using monetary surprises. We consider a 25 basis point increase. Lagged, standardized firm-level variables interacted with the Fed funds rate include the book-to-market ratio, leverage ratio, age and size (log assets). Bootstrapped standard errors clustered at the time-level in parentheses. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

response, the only significant interaction is book-to-market in column (2). The results suggest that growth firms (i.e. firms with a standard deviation lower book-to-market) display a 0.31% larger increase in the number of green patents, that is economically and statistically significant.

This evidence is consistent with the notion that green profits are primarily realized in the distant future, whereas monetary policy shocks affect profits in the short run, making green innovations less cyclical. In the next section, we develop a business cycle model with endogenous green and non-green innovation that can account for these stylized facts. The key assumption is that green technologies will increase in the future, making the value of green patents and thus the green patenting intensity less sensitive to shorter-term business cycle fluctuations.

3. A Green Business Cycle Model

What is driving the countercyclical nature of green innovation? In this section, we develop a business cycle model with endogenous green and non-green innovation that can

account for the stylized facts on their cyclicality observed in the data.

The model consists of three building blocks: a production block, an innovation block, and a households' block with endogenous labor supply and consumption decisions. Taken together, these components form a general equilibrium (GE) model with endogenous green and non-green innovation.

We begin by describing a simple production economy in Section 3.1, taking overall innovation and labor outcomes as given. This partial equilibrium setting allows us to distill the key mechanisms. In Section 3.4, we embed the production block into a full general equilibrium model and discuss the potential role of GE effects.

3.1. Production Economy

The production economy features a final good that uses both material and energy composites as inputs. The energy input itself is a composite of fossil fuels and green energy.

Final good producer. There is a representative firm that produces final good by employing unskilled labor L_t, a material composite M_t, and an energy composite E_t:

$$Y_t = (Z_t L_t)^{\alpha_L} M_t^{\alpha_M} E_t^{1-\alpha_L-\alpha_M}, \tag{4}$$

where Z_t is an aggregate labor productivity, evolving as

$$\log Z_t = \rho_z \log Z_{t-1} + \sigma_z \varepsilon_t^z. \tag{5}$$

The final good producer combines fossil fuel f_t and a green energy composite G_t into the energy composite E_t via a CES technology:

$$E_t = \left(\theta f_t^{\frac{\rho-1}{\rho}} + (1-\theta) G_t^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}. \tag{6}$$

The parameter ρ governs the elasticity of substitution between fossil fuel and the green energy composite. We assume $\rho > 1$, indicating that f_t and G_t are substitutes.

The green energy composite G_t and the materials composite M_t each aggregate a continuum of differentiated inputs:

$$M_t = \left(\int_0^{A_t^M} m_{ht}^{\frac{1}{\mu_M}} \, dh \right)^{\mu_M}, \qquad G_t = \left(\int_0^{A_t^G} g_{jt}^{\frac{1}{\mu_G}} \, dj \right)^{\mu_G}, \tag{7}$$

where A_t^G and A_t^M denote the number of available green energy and materials varieties, respectively.

The final good producer's optimization problem is:

$$\max_{L_t,\{m_{ht}\},f_t,\{g_{jt}\}} P_t\left[(Z_tL_t)^{\alpha}M_t^{\beta}E_t^{1-\alpha-\beta}\right] - \int_0^{A_t^M} p_{ht}^m\, m_{ht}\, dh - \int_0^{A_t^G} p_{jt}^g\, g_{jt}\, dj - P_t^f\, f_t. \quad (8)$$

Solving this problem yields the following demand equations:

$$m_{ht} = \left(\frac{p_{ht}^m}{P_t^M}\right)^{\frac{\mu_M}{1-\mu_M}} M_t, \qquad g_{jt} = \left(\frac{p_{jt}^g}{P_t^G}\right)^{\frac{\mu_G}{1-\mu_G}} G_t, \quad (9)$$

where $P_t^M = \left(\int_0^{A_t^M} (p_{ht}^m)^{\frac{1}{1-\mu_M}}\, dh\right)^{1-\mu_M}$ and $P_t^G = \left(\int_0^{A_t^G} (p_{jt}^g)^{\frac{1}{1-\mu_G}}\, dj\right)^{1-\mu_G}$ are the corresponding price indices of M_t and G_t.

Intermediate input producers. Intermediate input producers—firms that produce non-green and green varieties, m_{ht} and g_{jt}—maximize profits subject to the demand equations in (9).

Green energy varieties. The green energy varieties are produced by a continuum of firms operating under monopolistic competition. Each green variety g_{jt} is indexed by $j \in [0, A_t^G]$. Consider a generic variety j, its production uses a linear production technology: each unit of green energy variety j requires one unit of final good

$$g_{jt} = Y_t^j \quad (10)$$

where Y_t^j represent the final good used as inputs by variety j.

The profit maximization problem for producing this green energy variety is:

$$\Pi_{jt}^G = \max_{p_{jt}^g} \left(p_{jt}^g\, g_{jt} - g_{jt}\right), \quad (11)$$

subject to the demand equation in (9). Recall that the final good's price is normalized to one.

Let V_{jt}^G denote the value of owning the intellectual property (IP) right to produce the

green variety j. This value is given by:

$$V_{jt}^{G} = \sum_{s=0}^{\tau} \phi^{s} \, \mathbb{E}_{t} \left[\Lambda_{t,t+s} \, \Pi_{j,t+s}^{g} \right], \tag{12}$$

where Π_{jt}^{G} is the period profit, as defined in (11). Future profits, $\Pi_{j,t+s}^{g}$, are discounted by a factor ϕ^{s}, in addition to $\Lambda_{t,t+s}$, the stochastic discount factor. The parameter ϕ reflects the assumption that, in each period, each variety j of green energy input faces a probability $1-\phi$ of becoming obsolete. The IP value equals the discounted sum of profits over a finite period τ, reflecting the fact that innovators hold a patent for a fixed duration.

IP values determine innovators' incentives to innovate. We postpone the discussion of innovators' optimization problems to Section 3.3.

Non-green material varieties. Non-green material varieties are produced and sold similarly to green energy varieties. Each variety m_{ht} is indexed by $h \in [0, A_{t}^{M}]$ and produced via a linear technology:

$$m_{ht} = Y_{t}^{h}, \tag{13}$$

where Y_{t}^{h} represents the final good used as inputs by non-green variety h.

The profit maximization problem for producing the non-green variety h is:

$$\Pi_{ht}^{m} = \max_{p_{ht}^{m}} \left(p_{ht}^{m} m_{ht} - m_{ht} \right), \tag{14}$$

subject to the demand equation in (9). Similar to green varieties, each non-green variety becomes obsolete with probability $1-\phi$.

The value of holding the IP rights to a non-green variety h satisfies:

$$V_{ht}^{M} = \sum_{s=0}^{\tau} \phi^{s} \, \mathbb{E}_{t} \left[\Lambda_{t,t+s} \, \Pi_{h,t+s}^{m} \right]. \tag{15}$$

Fossil fuel. Let R_{t} denote the oil reserves at time t, and f_{t} represent the quantity of oil extracted during period t. The evolution of oil reserves is described by the equation:

$$R_{t+1} = R_{t} - f_{t}, \tag{16}$$

which indicates that oil reserves decrease over time as a result of extraction. The resource

constraint requires the oil reserves in the long run is non-negative:

$$\lim_{t\to\infty} R_t \geq 0 \tag{17}$$

The market of fossil fuel is competitive. The fossil fuel producer hires unskilled labor to produce. The extraction cost in period t is represented by a linear function of oil extracted of the current period:

$$c\left(R_t\right) W_t \cdot f_t, \tag{18}$$

where W_t is the unskilled wage, and $c(R_t)$ denotes the amount of labor required, with $c'(R_t) < 0$. This negative derivative indicates that the marginal cost of extraction increases as the oil reserve depletes.

3.2. Green Is in the Future

Before introducing the endogenous creation of new varieties by innovation, we consider the partial equilibrium of the production economy where both the final good producer and intermediate good producers maximize their profits, taking the evolution of A_t^M and A_t^G as given. We restrict our analysis to the economy with a *Balanced Growth Path* (BGP), which requires A_t^M and A_t^G to share the same growth rate in the long run.[11] This allows us to isolate some of the key mechanisms that can generate the cyclicalities of green and non-green innovation as observed in the data.

A crucial feature of the model is the evolution of the green market share. This leads us to the following proposition:

Proposition 3.1 (Green Is in the Future). *During the green transition:*

(1) The equilibrium market share of green energy, given by $\frac{P_t^G G_t}{P_t Y_t}$*, increases over time.*

(2) The relative profits of green varieties compared to non-green varieties, measured by $\frac{\Pi_t^G}{\Pi_t^M}$*, increase over time.*

Proof. See Appendix. ■

Proposition 3.1 shows that, during the green transition, the equilibrium market share of G_t, denoted by $\frac{P_t^G G_t}{P_t Y_t}$, increases over time, and, green patents generate higher profits in the future. We label this phenomenon as *Green Is in the Future*. The intuition for this result

[11] See Appendix C.1 for a detailed discussion of the existence of BGP.

is as follows. In a Romer (1990)-type growth model, the total number of varieties reflects productivity in the economy. Similarly, in our model, A_t^G measures the productivity of green inputs. During the green transition, A_t^G increases, leading to a decline in the prices of green inputs, which in turn raises demand for these inputs in production. Under monopolistic competition, higher demand results in higher profits. Consequently, the profits from producing green inputs are higher in the future. This implies that the value of a green patent, V_t^G, which is proportional to the discounted sum of future profits, is more heavily influenced by future profits relative to that of non-green patents.

The above results, together with the nature of business-cycle-frequency shocks that affect Y_t in the short run, implies that V_t^G is less affected by an exogenous disturbance to Y_t than V_t^M. Proposition 3.2 formalizes this insight: the relative value of producing g_{jt}, defined as $\frac{V_t^G}{V_t^M}$, exhibits countercyclicality. Formally, $\frac{d\log V_t^G}{d\log Y_t} < \frac{d\log V_t^M}{d\log Y_t}$, or equivalently $\frac{d\log\left(V_t^G/V_t^M\right)}{d\log Y_t} < 0$.

Proposition 3.2 (Cyclicality during the Green Transition). *During the Green transition when the share of green energy composite is sufficiently small: The relative value of producing g_{jt}, defined as $\frac{V_t^G}{V_t^M}$, exhibits countercyclicality. Formally, $\frac{d\log V_t^G}{d\log Y_t} < \frac{d\log V_t^M}{d\log Y_t}$, or equivalently $\frac{d\log\left(V_t^G/V_t^M\right)}{d\log Y_t} < 0$.*

Proof. See Appendix. ■

The (cyclical) values of holding green and non-green IPs capture the (cyclical) incentives for innovation. The latter is discussed in the next section.

3.3. Innovators

There is a continuum of innovators indexed by $i \in [0,1]$. Each existing green or non-green variety, as described in the previous section, is created by one of these innovators. Because the innovation decisions for each variety are independent of one another, we need not track which innovator creates/owns which variety.

In each period, each innovator i engages in R&D (innovation) to *create* new varieties. Upon successfully developing a new variety, the innovator sells its IP rights at a price proportional to the value of owning the right to produce for τ years. We now describe this innovation process in more detail.

Let $L_{it,M}^S$ and $L_{it,G}^S$ denote the skilled labor employed in R&D by innovator i for materials and green-energy innovation, respectively. $\vartheta_{it,M}$ and $\vartheta_{it,G}$ represent the probabilities

of successfully creating a new variety of materials and green energy. The innovation technology maps these probabilities to the amount of skilled labor as follows:

$$\vartheta_{it,M} = \zeta_M \left(L^S_{it,M}\right)^\gamma, \tag{19}$$

$$\vartheta_{it,G} = \zeta_G \left(L^S_{it,G}\right)^\gamma, \tag{20}$$

where $0 < \gamma < 1$ and $\zeta_M, \zeta_G > 0$ are time-invariant scaling parameters.

Following Romer (1990), we incorporate a positive externality from the aggregate technological level, by assuming each successful innovation creates A^G_t and A^M_t new varieties of green energy and materials, respectively.

We assume that innovators pay a fixed setup cost, $cV^m_{t,ss}$ or $cV^g_{t,ss}$, for each unit of new innovation. This fixed cost is proportional to the value of innovation in the absence of business cycle shocks. This modeling approach, similar to Barlevy (2007), allows the model to match the cyclicality of innovation observed in the data.

In summary, a innovator i's optimization problem can be expressed as:

$$\max_{L^S_{it,M}} \quad A^M_t \vartheta_{it,M} \left(V^m_t - cV^m_{t,ss}\right) - W^s_t L^S_{it,M}, \tag{21}$$

$$\max_{L^S_{it,G}} \quad A^G_t \vartheta_{it,G} \left(V^g_t - cV^g_{t,ss}\right) - W^s_t L^S_{it,G}, \tag{22}$$

taking wages W^s_t as given.

Aggregation. Let $S^M_t = A^M_t \vartheta_{t,M}$ and $S^G_t = A^G_t \vartheta_{t,G}$ denote the aggregate successful innovation for materials and green energy, respectively. The total amount of varieties then evolves as:

$$A^M_{t+1} = \phi A^M_t + S^M_t, \tag{23}$$

$$A^G_{t+1} = \phi A^G_t + S^G_t. \tag{24}$$

3.4. General Equilibrium

We now embed the production and innovation blocks into a general equilibrium setting. This allows us to incorporate business cycle shocks, as examined in the empirical part of the paper, and to analyze the cyclicality of innovation *outcomes*, rather than just their incentives. More importantly, within this GE setting, a key mechanism emerges that explains the surprising countercyclical pattern of green innovation uncovered in our empirical analysis. To close the economy, we detail the household sector and discuss market

clearing.

Households. All households are identical, which is why we focus on the problem of a representative household. The household derives utility over consumption C_t and labor. They maximize lifetime utility

$$\mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \left(\ln C_t - \frac{1}{1+\eta} L_t^{1+\eta} - \frac{1}{1+\psi} (L_t^s)^{1+\psi} \right) \tag{25}$$

subject to a budget constraint:

$$P_t C_t + Q_t B_{t+1} = B_t + W_t L_t + W_t^s L_t^s + D_t. \tag{26}$$

Here, L_t is the supply of unskilled labor and L_t^s is the supply of skilled labor with corresponding wages W_t and W_t^s, B_t is a risk-free bond and D_t are transfers.

Market clearing. In general equilibrium, all markets have to clear. Labor market clearing of skilled labor requires:

$$\int_0^1 \left(L_{it,G}^S + L_{it,M}^S \right) \, di = L_t^S \tag{27}$$

Final good market market clearing:

$$C_t + \int_0^{A_t^M} m_{ht} \, dh + \int_0^{A_t^G} g_{jt} \, dj = Y_t. \tag{28}$$

The remaining markets clear by Walras' law.

3.5. The Role of General Equilibrium Effects

A key prediction of our partial equilibrium model is that the relative value of green varieties is countercyclical during the green transition, see Proposition 3.2. The countercyclicality of green patent values implies that firms' R&D investment in green, relative to non-green, is also countercyclical. As a result, the green share of new varieties, $\frac{S_t^G}{S_t^G + S_t^M}$, is itself countercyclical. Corollary 3.1 formalizes this result.

Corollary 3.1 (Countercyclical Green Share of New Varieties). *During the green transition—when the share of the green energy composite is sufficiently small—the green share of new varieties, $\frac{S_t^G}{S_t^G + S_t^M}$, is countercyclical.*

Proof. See Appendix. ■

In partial equilibrium, although the relative value of green varieties is countercyclical, the *number* of green varieties is procyclical. Consequently, green innovations are procyclical in a partial-equilibrium setting.

In general equilibrium, however, there is an additional effect driven by the inelastic supply of skilled labor. Here, "inelastic supply" means that the labor supply curve is positively sloped (i.e., not perfectly elastic). In this case, because non-green innovation is more procyclical, a recessionary shock reduces non-green innovation, which in turn lowers aggregate demand for skilled labor and thus wages. The lower wage then decreases the cost of green R&D, incentivizing firms to undertake more green innovation and offsetting the partial-equilibrium effect.

Proposition 3.3 shows that when the supply of skilled labor is sufficiently inelastic—i.e., the labor supply curve is steep—the general-equilibrium effect dominates, making the amount of new green varieties countercyclical.

Proposition 3.3 (General Equilibrium Effects). *During the Green transition—when the share of the green energy composite is sufficiently small—there exists a threshold* $\overline{\psi^z} > 0$*. If the Frisch elasticity of labor supply* ψ^{-1} *is less than* $\overline{\psi^z}^{-1}$*, then in equilibrium:*

$$\frac{\partial \ln S_t^M}{\partial \log Z_t} > 0, \qquad \frac{\partial \ln S_t^G}{\partial \log Z_t} < 0. \tag{29}$$

Proof. See Appendix. ■

Demand shocks. So far, we have focused on a real economy and supply shocks. A result similar to Proposition 3.3 holds conditional on demand shocks. To demonstrate this, we extend the above setup to include nominal rigidities, where retailers face Rotemberg price adjustment costs (see Appendix C.2 for details). We introduce monetary policy through a Taylor rule and incorporate a monetary shock ϱ_t, which follows an AR(1) process:

$$\log \varrho_t = \rho^\varrho \log \varrho_{t-1} + \sigma^\varrho e_t^\varrho. \tag{30}$$

Corollary 3.2 demonstrates that, due to the same general equilibrium effects, green innovations can be countercyclical after demand shocks.

Corollary 3.2. *During the Green transition—when the share of the green energy composite is sufficiently small—there exists a threshold* $\overline{\psi^d} > 0$*. If the Frisch elasticity of labor supply* ψ^{-1} *is*

less than $\overline{\psi^d}^{-1}$*, then in equilibrium:*

$$\frac{\partial \ln S_t^M}{\partial \log \varrho_t} > 0, \qquad \frac{\partial \ln S_t^G}{\partial \log \varrho_t} < 0. \tag{31}$$

Proof. See Appendix. ■

4. Evaluating Model Predictions

The previous section analytically demonstrates that the model can qualitatively rationalize our empirical findings. Section 4.1 shows that, under standard calibrations, the model can quantitatively match the empirical findings. Moreover, Section 4.2 presents direct evidence supporting the model's mechanism, and its magnitude aligns with the estimates implied by the calibrated model.

4.1. A Quantitative Exploration

We now evaluate the quantitative implications of the model. To that end, we carefully calibrate the model to the U.S. economy.

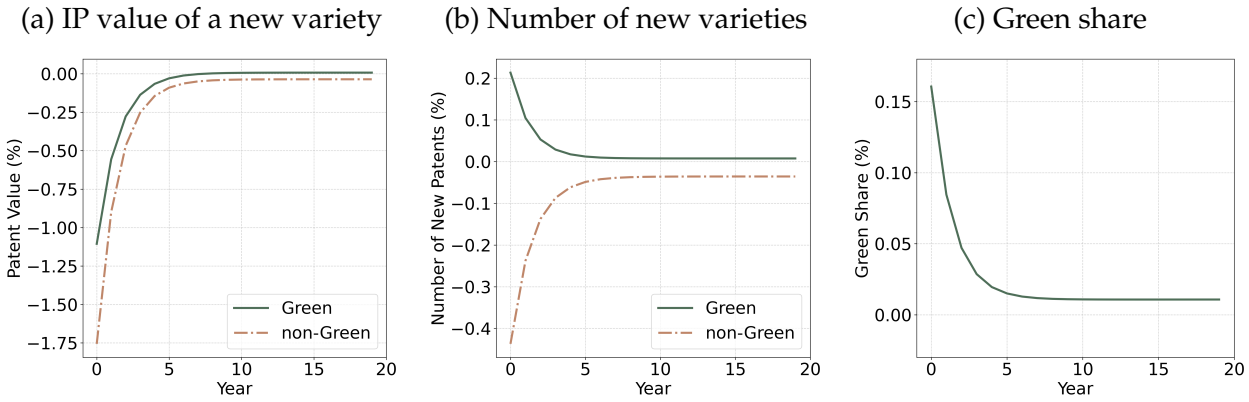
Calibration. We set the discount factor β to match a 2% annual interest rate. The final good technology parameters α_L, α_M are set to 0.5 and 0.4, respectively, which corresponds to a 50% income share of intermediate inputs (Comin and Gertler 2006) and matches a 10% energy share of income. The markup parameters μ_M and μ_G are set to 2 to ensure the existence of a balanced growth path.

Following Acemoglu et al. (2012), we set the elasticity of substitution between green energy and fossil fuels, ρ, to 2. The parameter θ is fixed at 0.5 and the marginal cost of fossil fuel is normalized to 1.

The research elasticity γ is set to 0.5, following Acemoglu et al. (2018). The technology obsolescence rate is set to 0.03, consistent with Comin and Gertler (2006) and recent estimates from Ma (2021). The patent duration parameter τ is set to 15 years, reflecting the maximum patent term of 15-20 years under U.S. patent law.

For labor supply elasticities, we set the Frisch elasticity of labor supply, $1/\eta$, to 2, in line with standard RBC calibrations (Kydland and Prescott 1982; King and Rebelo 1999), to generate meaningful business cycle fluctuations. The inverse Frisch elasticity of skilled labor supply—the key parameter determining the strength of the GE effects—is set to $\psi = 2$, consistent with Chetty et al. (2011)'s estimates and the most recent updates in

Figure 6: Green and non-green patenting responses in the model



Notes: Impulse responses of the value and number of varieties of green and non-green patents to a 25 basis point monetary policy shock, based on the green business cycle model calibrated to the U.S. economy.

Elminejad et al. (2023). This is a conservative choice, as their findings suggest that higher-wage (skilled) workers tend to have lower labor supply elasticity.

Following Ottonello and Winberry (2020), we set $\varphi = 90$ and $\sigma = 10$. The Taylor rule parameters are set to $\phi_\pi = 1.69$ and $\phi_A = 1$, the latter fully offsetting fluctuations in the medium-term component.

We internally calibrate ζ_M, ζ_G to match a 3% GDP growth rate. σ_Z is set to 0.02 to match a 1% standard deviation of output at the business cycle frequency, given a fixed persistence $\rho_z = 0.5$. The fixed setup cost c is set to 0.97 to match a 1.7% standard deviation of the output growth. We calibrate our model to start from an initial state where fossil fuel consumption accounts for 70% of the total energy consumption, which is comparable to the figure reported by the U.S. Energy Information Administration.

Quantitative performance. We now turn to the model's quantitative predictions. Figure 6 shows the impulse responses of green and non-green patenting to a 25 basis point monetary policy shock.

At the core of our model's results is the mechanism highlighted in Proposition 3.2: the IP value of a non-Green new variety is more sensitive to shocks than the IP value of a Green new variety. Panel (a) demonstrates that this difference is quantitatively significant: the value of a non-green new variety declines by approximately three-quarters more than that of a green new variety. In the next section, we provide direct empirical evidence supporting this mechanism.

Panel (b) corresponds to the qualitative results presented in Proposition 3.3 and Corollary 3.2. It is evident that the conditions stated in these analytical results are satisfied un-

der the standard calibration. Specifically, in response to recessionary pressure caused by monetary tightening, the number of new non-Green varieties declines, and due to general equilibrium effects, the number of new Green varieties increases. As a result, the Green share among new varieties rises, as shown in Panel (c). Importantly, the magnitude of the increase in the Green share is comparable to its empirical counterparts in Figures 2 and 4.[12]

Importantly, these results are not explicitly targeted in our calibration. Thus, the model's quantitative performance also serves as an external validation of the model.

4.2. Evidence Supporting the Model Mechanism

In this section, we provide additional empirical evidence supporting the key model mechanisms. At the core of the mechanism is the relative cyclicality of the value of green and non-green innovations. Specifically, to reconcile the cyclicality of green and non-green innovation, green patent values have to be less cyclical than non-green patent values.

To shed light on this mechanism empirically requires additional data on patent values. In a seminal contribution Kogan et al. (2017) construct a dataset of the market-implied value of patents filed with the USPTO. We merge the patent values to our PATSTAT dataset (see Appendix A for more details).

To test the model prediction on the relative cyclicality of patent values, we begin by estimating a set of patent-level regressions:

$$\text{value}_{i,j,t} = \alpha_j + \delta_t + \theta \text{ffr}_t \times \text{green}_{i,j,t} + \varepsilon_{i,j,t}, \tag{32}$$

where $\text{value}_{i,j,t}$ corresponds to the (log) real value of patent i filed by firm j in quarter t. We keep using the federal funds rate, ffr_t instrumented using high-frequency monetary surprises, but also report results using the GDP gap instead, not conditioning on a specific shock. α_j and δ_t denote a set of firm and time fixed effects, respectively. Since our goal is to estimate the relative cyclicality of green and non-green patent values captured by θ, adding time fixed effects allows us to flexibly control for any time-varying common shocks. As quality is homogeneous in the model, we include a dummy for biadic patents, as well as the number of citations.

Table 4 reports the estimated coefficients. Consistent with the model predictions, the values of green patents turn out to be less cyclical than non-green patent values. Starting

[12]Since there is no clear quantitative mapping between new varieties and new patents, we do not comment on the model's quantitative performance in terms of generating changes in the number of new varieties.

Table 4: Relative cyclicality of green and non-green patent values in the data, 1986–2019

	Dependent variable: 100×log(patent value$_{i,j,t}$)			
	(1)	(2)	(3)	(4)
GDP gap$_t$ × green$_{i,j,t}$	-2.34***	-2.26***		
	(0.18)	(0.18)		
ffr$_t$ × green$_{i,j,t}$			2.42***	2.42***
			(0.52)	(0.52)
Observations	1,256,900	1,256,900	1,256,900	1,256,900
Firm fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Quality controls	No	Yes	No	Yes

Notes: The table shows coefficients from a regression of patent valuations on business cycle measures. The real value of patent family i, filed by firm j in quarter t is sourced from Kogan et al. (2017), and expressed in logs. green$_{i,j,t}$ is a dummy variable denoting green patents. The GDP gap$_t$ is based on U.S. CBO projections and ffr$_t$ corresponds to the fed funds rate, in quarter t. Columns (3)-(4) are estimated using 2SLS, with monetary surprises as instrumental variables. We consider a 25 basis point increase in the fed funds rate. Quality controls include a biadic patent dummy and the number of citations. Robust standard errors in parentheses, significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

with the unconditional evidence using GDP gap as a business cycle measure, we estimate a robust, negative coefficient, implying that green patents decrease by less during a recession.

The result also holds true conditioning on monetary policy shocks, identified by instrumenting the Fed funds rate with high-frequency monetary policy surprises. The coefficients are positive and statistically significant, suggesting that green patent values fall by less in response to a contractionary monetary policy shock. Interestingly, the results are also robust when omitting the quality controls.

Alternatively, we create firm-level patent valuations, tracking the market-implied value of the stock of green and non-green patents over time. Based on these valuations, we estimate firm-level green and non-green patent value responses to monetary policy shocks. Our estimation equation reads as follows:

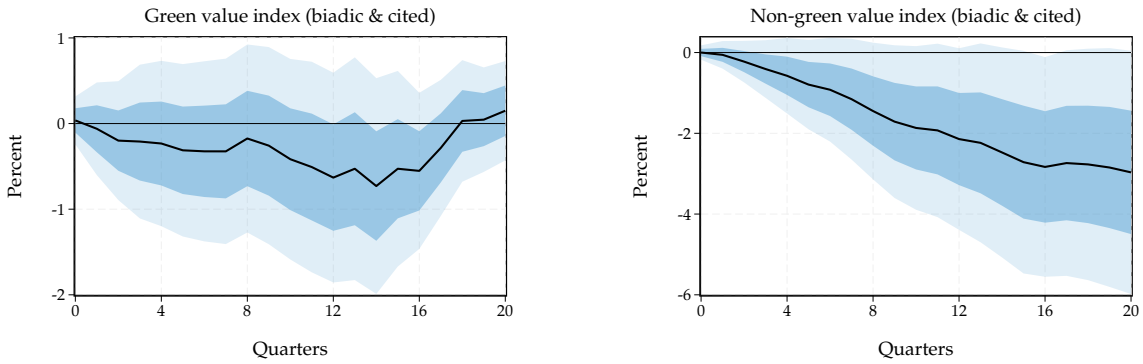
$$\text{value}_{i,t+h} = \alpha_i^h + \theta^h \text{ffr}_t + \sum_{j=1}^{p} \beta_v^h \text{value}_{i,t-j} + \sum_{j=1}^{p} \boldsymbol{\beta}_z^h \mathbf{z}_{t-j} + \varepsilon_{i,t+h}, \tag{33}$$

where value$_{i,t+h}$ corresponds to the real value of green (non-green) innovations by firm i,

h periods ahead. ffr_t is the Fed funds rate, instrumented with high-frequency monetary policy surprises. To control for quality, we focus only on biadic patents that received at least one citation in the construction of the firm-level value indices.

Figure 7 shows the corresponding impulse responses. Consistent with the model predictions, we estimate a significant and persistent decline of non-green patents following a 25 basis point monetary policy shock. By contrast, the response of green patents is much less pronounced. Notably, the magnitudes are comparable to those obtained in our calibrated model, as shown in Panel (a) of Figure 6.

Figure 7: Impulse resopnses of U.S. firms' green and non-green patent values



Notes: Impulse responses of U.S. firms' green and non-green patent values to a 25 basis point monetary policy shock, estimated based on Equation (33). The dependent variable is the cumulative real value of firm-level patents, sourced from Kogan et al. (2017), separately computed for green and non-green patents and expressed in logs. The solid line is the point estimate and the dark and light shaded areas are 68 and 95 percent confidence bands based on Driscoll and Kraay (1998) standard errors, respectively.

Overall, we find strong evidence that the value of green patents relative to the value non-green patents is countercyclical, in line with the key predictions of our model. Thus, under empirically relevant calibrations, our model is able to reproduce the stylized facts on the cyclicality of green and non-green innovation.

5. Conclusion

Our findings fundamentally reshape how we understand the relationship between economic cycles and the green transition. The countercyclicality of green innovation suggests that economic downturns might not necessarily hinder, but could even stimulate investment in clean technologies, with our data showing significant increases in green patenting during periods when non-green innovation contracts. This pattern holds true across both

aggregate and firm-level analyses, challenging conventional wisdom about the uniform effects of economic cycles on innovation. To explain this phenomenon, we develop a business cycle model with green and non-green innovation in which the expected future increase in green market share makes green innovation less sensitive to short-term economic fluctuations. In general equilibrium, this channel is reinforced via effects on labor costs, lowering the cost of green R&D and incentivizing firms to undertake more green innovation during downturns.

These empirical patterns suggest a nuanced approach to climate innovation policy across different phases of the business cycle. To support the green transition, targeted support for green R&D—such as tax credits or direct research subsidies—is particularly important during economic booms. This is especially relevant as economic expansions usually last much longer than recessions. Economic downturns, on the other hand, have a natural cleansing effect, redirecting innovation efforts from non-green to green technologies of the future. Additionally, policies that enhance the future value of green patents—such as credible long-term carbon pricing mechanisms or green technology adoption commitments—would further strengthen the *Green Is in the Future* effect, making green innovation even more resilient to economic fluctuations. While our analysis focuses primarily on patent data and may not capture all forms of green innovation, the consistent patterns across multiple countries and firm types suggest robust underlying mechanisms. Successfully aligning innovation policy with these natural cyclical patterns could significantly accelerate the pace of the green transition without sacrificing economic growth.

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Online Appendix

Green Business Cycles

Diego R. Känzig
Maximilian Konradt
Lixing Wang
Donghai Zhang

Contents

A. Data **38**
A.1. Patent Data . . . 38
A.2. Firm Data . . . 40
A.3. Matching Patents to Firms . . . 40
A.4. Aggregate Patent Counts . . . 41
A.5. Macroeconomic Data . . . 42

B. Additional Charts and Tables **43**
B.1. Green Innovation by the 20 Largest U.S. Innovators . . . 43
B.2. Cyclicality of Patenting with Lagged Activity Measures . . . 44
B.3. Responses of Macroeconomic Variables to Monetary Policy Shock . . . 45
B.4. Responses of Total Patents . . . 46
B.5. Additional Results for Listed and Unlisted U.S. Firms . . . 46
B.6. Alternative Shock Measures . . . 47
B.7. Alternative Green Patent Classifications . . . 49
B.8. Distinguishing between Patent Quality . . . 50
B.9. Responses using USPTO Data . . . 51
B.10. Robustness to Firm-level Patent Counts . . . 52

C. Model Appendix **53**
C.1. Balanced Growth Path . . . 53
C.2. General Equilibrium with Demand Shocks . . . 54

D. Equilibrium Conditions **55**

E. Proof **58**

References Appendix **64**

A. Data

In this appendix, we provide additional information on the sources and the construction of our dataset. We discuss the sources for the patent and firm-level data as well as how we match patents to firms. Finally, we provide additional detail on how we aggregate the patent counts and on the sources of the additional macro time series used in our analysis.

A.1. Patent Data

Our main source of patent data is the World Patent Statistical Database (PATSTAT), which encompasses bibliographic information for close to the universe of patents globally. We use the autumn 2023 edition (version 5.22).

We follow the previous literature (e.g. Dechezleprêtre et al., 2023) to focus on patent families, i.e. patents representing the same innovation filed at different patent offices. For each patent family we use the original application date to capture the time of the innovation and assign nationality based on the respective filing office.

To measure green innovation, we use International Patent Classification (IPC) and Cooperative Patent Classification (CPC) codes. Specifically, we apply the OECD definition (Migotto and Haščič, 2015) to classify patent families in subclass Y02 of the C/IPC, which includes technologies that reduce greenhouse gases.[1] We classify patent families with multiple C/IPC codes as green if any of the respective codes meet our criteria. We treat the remaining patent (families) as non-green.

Table A.1 provides an example of a patent family related to a power transmission apparatus for hybrid vehicles by Hitachi Ltd. filed at five different patent offices. The patent family is classified as green because it includes multiple CPC codes in subclass Y02T. Because the first patent was filed with the USPTO, we treat it as a U.S. patent and use September 2000 as the relevant date.

PATSTAT also reports information on patent citations. We compute citation counts at the family level, excluding any self citations within the same family. To measure quality, we additionally define biadic patents, filed with at least two of the three major patent offices (USPTO, EPO and JPO).

[1] Following Acemoglu et al. (2023) we exclude technologies that do not directly compete with fossil-fuel technologies, including those aimed at reducing pollution from fossil-fuel electricity generation (Y02E20), improving grid efficiency (Y02E40) or storage (Y02E60).

Table A.1: Example of a green patent family by Hitachi Ltd.

Patent number	Patent name	Filing date	CPC codes
US7185722	Power transmission apparatus of motor vehicles	01.09.2000	B60W 20/00, B60K 6/442, B60K 6/48, B60K 6/547, B60W 10/02, B60W 10/06, B60W 10/08, B60W 10/10, F16D 25/0638, F16H 3/089, F16H 61/0437, Y02T 10/6221, Y02T 10/6234, Y02T 10/6286, Y10S 903/914, Y10S 903/917, Y10S 903/919, Y10S 903/945, Y10S 903/946, Y10T 74/19014, Y10T 74/19242, Y10T 74/19284, Y10T 477/23
EP1122111	A power transmission apparatus for hybrid vehicles	04.09.2000	B60K 6/442, B60K 6/48, B60K 6/547, B60W 10/02, B60W 10/06, B60W 10/08, B60W 10/10, B60W 20/00, F16H 3/089, F16H 61/0437, Y10S 903/945, Y10S 903/946, Y10S 903/914, Y10S 903/917, Y10S 903/919, Y10T 74/19014, Y10T 74/19284, Y10T 74/19242, Y02T 10/62, B60K 2006/268, B60K 17/02, F16D 25/0638
DE000060021163	Antriebsübertragungsvorrichtung für Hybridfahrzeuge	04.09.2000	B60K 6/442, B60K 6/48, B60K 6/547, B60W 10/02, B60W 10/06, B60W 10/08, B60W 10/10, B60W 20/00, F16H 3/089, F16H 61/0437, Y10S 903/945, Y10S 903/946, Y10S 903/914, Y10S 903/917, Y10S 903/919, Y10T 74/19014, Y10T 74/19284, Y10T 74/19242, Y02T 10/62, B60K 2006/268, B60K 17/02, F16D 25/0638
KR1020010077862	Power transmission apparatus of motor vehicles	04.09.2000	B60W 20/00, B60K 6/442, B60K 6/48, B60K 6/547, B60W 10/02, B60W 10/06, B60W 10/08, B60W 10/10, F16D 25/0638, F16H 3/089, F16H 61/0437, Y02T 10/6221, Y02T 10/6234, Y02T 10/6286, Y10S 903/914, Y10S 903/917, Y10S 903/919, Y10S 903/945, Y10S 903/946, Y10T 74/19014, Y10T 74/19242, Y10T 74/19284, Y10T 477/23
EP1122110	A power transmission apparatus of motor vehicles	02.02.2001	B60K 6/442, B60K 6/48, B60K 6/547, B60W 10/02, B60W 10/06, B60W 10/08, B60W 10/10, B60W 20/00, F16H 3/089, F16H 61/0437, Y10S 903/945, Y10S 903/946, Y10S 903/914, Y10S 903/917, Y10S 903/919, Y10T 74/19014, Y10T 74/19284, Y10T 74/19242, Y02T 10/62, B60K 2006/268, B60K 17/02, F16D 25/0638
US20010042647	Power transmission apparatus of motor vehicles	02.02.2001	B60W 20/00, B60K 6/442, B60K 6/48, B60K 6/547, B60W 10/02, B60W 10/06, B60W 10/08, B60W 10/10, F16D 25/0638, F16H 3/089, F16H 61/0437, Y02T 10/6221, Y02T 10/6234, Y02T 10/6286, Y10S 903/914, Y10S 903/917, Y10S 903/919, Y10S 903/945, Y10S 903/946, Y10T 74/19014, Y10T 74/19242, Y10T 74/19284, Y10T 477/23
KR1020010078264	Power transmission apparatus of motor vehicles	02.02.2001	B60W 20/00, B60K 6/442, B60K 6/48, B60K 6/547, B60W 10/02, B60W 10/06, B60W 10/08, B60W 10/10, F16D 25/0638, F16H 3/089, F16H 61/0437, Y02T 10/6221, Y02T 10/6234, Y02T 10/6286, Y10S 903/914, Y10S 903/917, Y10S 903/919, Y10S 903/945, Y10S 903/946, Y10T 74/19014, Y10T 74/19242, Y10T 74/19284, Y10T 477/23
JP2001287555	Power transmission of automobile	02.02.2001	Y02T 10/62, Y02T 10/7072

Notes: For more information, see https://patentscope.wipo.int/search/en/detail.jsf?docId=US41976272.

A.2. Firm Data

We rely on Compustat North America for accounting data on listed U.S. companies. Following Cloyne et al. (2023) we exclude Compustat companies in the finance, insurance, real estate or public administration sectors and drop firms which report data for fewer than 20 quarters, or have missing investment or sales figures for more than 20 quarters. We measure firm age using the date of incorporation, which we supplement from Thomson Reuter's WorldScope.

In contrast to Cloyne et al. (2023), we only exclude firms with negative or missing age when we explicitly study firm heterogeneity, including the effects on younger and older firms. Otherwise, we include firms even if the age variable is negative.[2] We limit our attention to years with consistent reporting, starting in 1986q1.

Table A.2 lists a set of firm-level variables constructed from the Compustat data. To limit the impact of outliers, we winsorize the book-to-market ratio at the 1^{st} and 99^{th} percentile in each year. We also merge data on firm-level emissions from Trucost using company ISIN codes. We focus on the Scope 1 GHG emission intensity (scaled by revenue), which is available for roughly half of the companies in our dataset.

Table A.2: Firm-level data description

Variable	Compustat definition
Size	log(atq)
Investment	log(capxq)
Leverage ratio	(dlcq+dlttq)/atq
Book-to-market	ceqq/(prccq*cshoq)
R&D intensity	xrdq/atq

A.3. Matching Patents to Firms

Measuring U.S. firms' innovation activity requires matching patents to firm-level data. To maximize the number of successful matches, we rely on two different datasets. The first is Orbis Intellectual Property, which links global patent portfolios to Orbis companies (see Dechezleprêtre et al., 2023). We map Orbis to Compustat companies using the ISIN identifier, which implies we are measuring innovation at the U.S. group level.

Second, we also employ the mapping by Arora, Belenzon, and Sheer (2021), which

[2] Age data is noisy, e.g. because of firm mergers/IPOs, etc. Firm-level estimates are consistent when we apply more restrictive criteria.

establishes a link between USPTO patents and Compustat firms based on a fuzzy matching approach and extends the NBER patent database (Hall, Jaffe, and Trajtenberg, 2001).[3] Combining the matches in both datasets we are able to link 1.9 million distinct patent families to Compustat firms, including more than 99,000 green patents.[4]

We use the unique patent application number encompassed in both datasets to merge the relevant information from PATSTAT. In particular, we construct firm-level patent counts for green and non-green patents at quarterly frequency. To that end, we retain patents filed with the USPTO and international filings.

In addition to patent counts, we are also interested in quantifying patent values. We therefore match our firm-level data with market-implied patent value data constructed by Kogan et al. (2017), extended to 2020. Consistent with our earlier definition, we focus on the first patent in a patent family to infer its value, but verify that taking an average value does not impact our results. Lastly, to dynamically study the value of firms' innovation, we construct cumulative value indices for green and non-green patents at the firm-level.

A.4. Aggregate Patent Counts

In order to assess the correlation of innovation activity with the business cycle, we compute aggregate patent counts. First, we construct separate series for U.S. green and non-green patents based on USPTO filings. Second, we compute similar patent counts for OECD countries, including filings with the respective national offices and the EPO. For the OECD, we also include international applications filed under the Patent Cooperation Treaty, but verify that excluding them does not impact our estimates.

Third, since Compustat covers close to the universe of listed companies in the U.S., we can also aggregate our matched firm-level patents to compute separate counts for listed and unlisted U.S. firms.[5] To control for potential seasonality, we apply an X-11 filter to our constructed aggregate patent counts.

[3] For more details on the approach, see Arora et al. (2024).

[4] Reassuringly, the two mappings overlap significantly: Orbis identifies 1.2 million total (67,000 green) patents, while applying Arora, Belenzon, and Sheer (2021) results in 0.9 million total (48,000 green) matched patents.

[5] Compustat accounts for 97-99% of market capitalization of all listed firms in the U.S. between 1975-2015 according to Kahle and Stulz (2017). Because we assign patent nationality based on the original patent office, we expect that filings by foreign corporations are modest.

A.5. Macroeconomic Data

We complement the innovation and firm-level data with a set of aggregate macroeconomic and financial variables, listed in Table A.3.

Table A.3: Macro data description and sources

Variable	Description	Source
U.S. data		
Monetary surprise	Purified high-frequency monetary surprises from Bauer and Swanson (2023)	Michael Bauer's website
Excess bond premium	Gilchrist and Zakrajšek (2012)	FRB website
Federal funds rate	FEDFUNDS	FRED
Real GDP	GDPC1	FRED
Unemployment rate	UNRATE	FRED
Industrial production	INDPRO	FRED
GDP gap	Gap between actual GDP (GDPC1) and CBO projections (GDPPOT)	FRED
1-year rate	GS1	FRED
OECD data		
Industrial production	Global IP index by Baumeister and Hamilton (2019)	Christiane Baumeister's website
Real GDP	Based on 19 OECD countries	OECD
Unemployment rate	Based on 9 OECD countries with consistent data	OECD

Notes: Due to data limitations, we construct the unemployment series based on data from 9 major OECD countries that consistently report since 1986. These countries include the United States, Germany, Japan, Australia, the United Kingdom, New Zealand, Chile and Canada.

B. Additional Charts and Tables

In this appendix, we report a number of additional results, as well as robustness checks.

B.1. Green Innovation by the 20 Largest U.S. Innovators

Table B.1: Green patenting by 20 largest innovators

	Patenting measure		
Company	Total patents	Green patents	Green patent share
INTL BUSINESS MACHINES CORP	129,491	3,797	2.93
INTEL CORP	60,633	4,116	6.79
MICROSOFT CORP	55,079	1,192	2.16
HP INC	52,319	1,872	3.58
QUALCOMM INC	39,359	3,235	8.21
RTX CORP	35,953	6,222	17.31
GENERAL MOTORS CO	29,405	5,148	17.51
MOTOROLA SOLUTIONS INC	27,752	1,255	4.52
APPLE INC	26,243	1,711	6.52
TEXAS INSTRUMENTS INC	25,257	1,176	4.66
FORD MOTOR CO	24,280	5,839	24.05
XEROX HOLDINGS CORP	23,753	456	1.92
JOHNSON & JOHNSON	23,448	435	1.85
EASTMAN KODAK CO	21,301	258	1.21
BOEING CO	20,763	2,824	13.60
DU PONT (E I) DE NEMOURS	19,913	1,581	7.94
DELL TECHNOLOGIES INC	19,756	791	4.00
ORACLE CORP	19,089	329	1.72
AT&T INC	18,986	388	2.04
PROCTER & GAMBLE CO	18,461	413	2.24

Notes: The table reports patent measures for the 20 largest innovators in the U.S. between 1986–2019, based on total patent counts.

B.2. Cyclicality of Patenting with Lagged Activity Measures

Table B.2 reports simple correlation coefficients between the cyclical components of patent counts with the lagged cyclical component of industrial production and the GDP gap. The first three columns are based on monthly data, and consider 3-month, 6-month and 12-month lags of industrial production. The last three columns use quarterly data with 1, 2, and 4-quarter lags of the GDP gap, respectively.

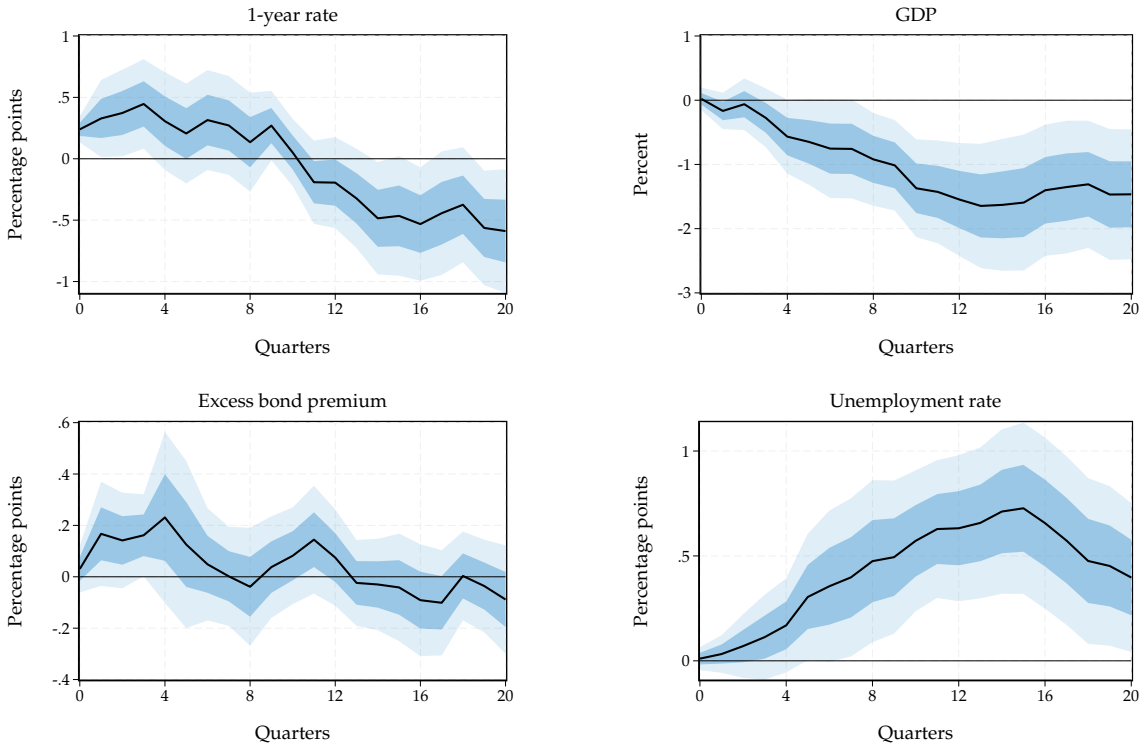
Table B.2: Correlation between patenting and lagged business cycle measures

	Industrial production			GDP gap		
	3 months	6 months	12 months	1 quarter	2 quarters	4 quarters
Total	0.37 [0.28, 0.45]	0.36 [0.27, 0.44]	0.31 [0.22, 0.40]	0.30 [0.14, 0.45]	0.31 [0.14, 0.45]	0.28 [0.11, 0.43]
By patent type:						
Green	-0.18 [-0.27, -0.08]	-0.16 [-0.25, -0.06]	-0.08 [-0.17, 0.02]	-0.07 [-0.23, 0.10]	-0.01 [-0.18, 0.16]	0.11 [-0.07, 0.27]
Non-green	0.40 [0.31, 0.48]	0.38 [0.30, 0.46]	0.33 [0.24, 0.41]	0.32 [0.16, 0.46]	0.32 [0.15, 0.46]	0.28 [0.11, 0.43]

Notes: The table shows correlation coefficients between the cyclical component of patent counts and lagged business cycle measures in the United States. Cyclical components of patent counts and industrial production are extracted using the Hamilton (2018) filter. IP corresponds to industrial production and the GDP gap is based on CBO projections. 95% confidence bands based on Fisher's z-transform in parentheses.

B.3. Responses of Macroeconomic Variables to Monetary Policy Shock

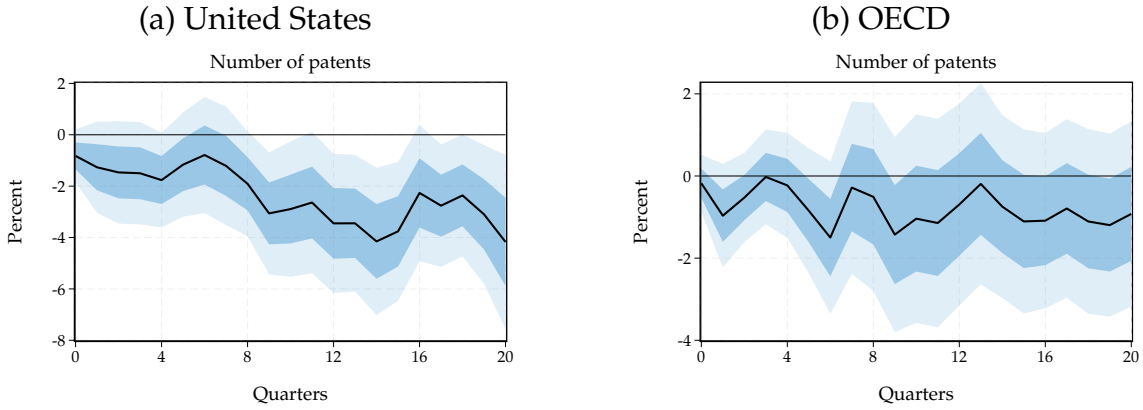
Figure B.1: Macroeconomic effects of a U.S. monetary policy shock



Notes: Impulse responses to a 25 basis point monetary policy shock, estimated based on Equation (1). The solid line is the point estimate and the dark and light shaded areas are 68 and 95 percent confidence bands based on robust standard errors, respectively.

B.4. Responses of Total Patents

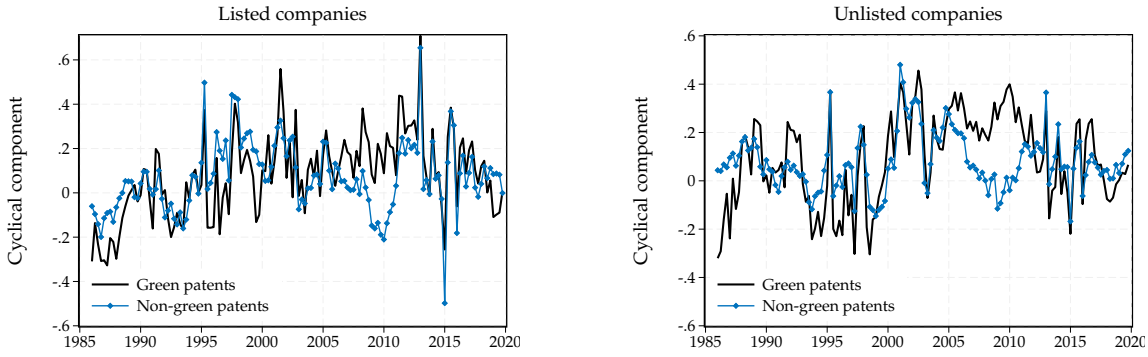
Figure B.2: The effects of an interest rate increase on total patents



Notes: Impulse responses to a 25 basis point increase in the Fed funds rate, based on Equation (1). The solid line is the point estimate and the dark and light shaded areas are 68 and 95 percent confidence bands based on robust standard errors, respectively.

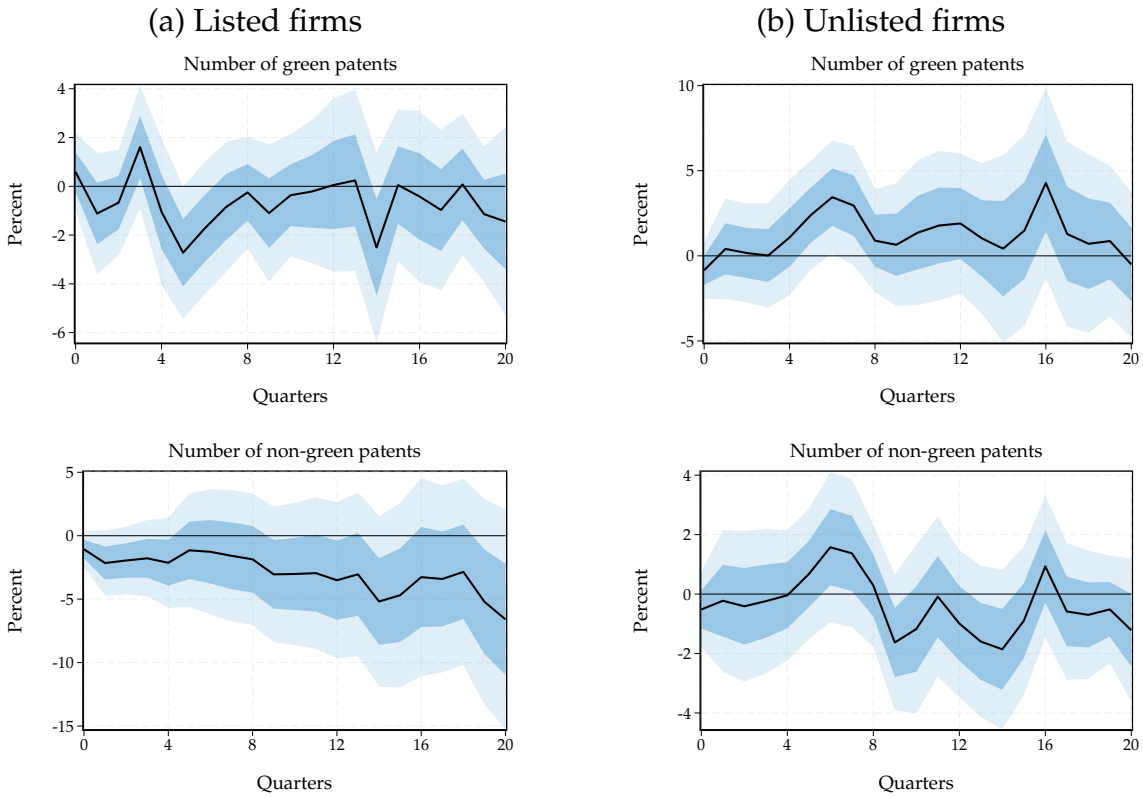
B.5. Additional Results for Listed and Unlisted U.S. Firms

Figure B.3: Cyclical component of green and non-green patents by U.S. companies



Notes: The figure shows the cyclical components of green and non-green patent counts, extracted using the Hamilton filter, for listed (left panel) and unlisted (right panel) U.S. companies.

Figure B.4: Green and non-green patenting responses by listed and unlisted U.S. firms



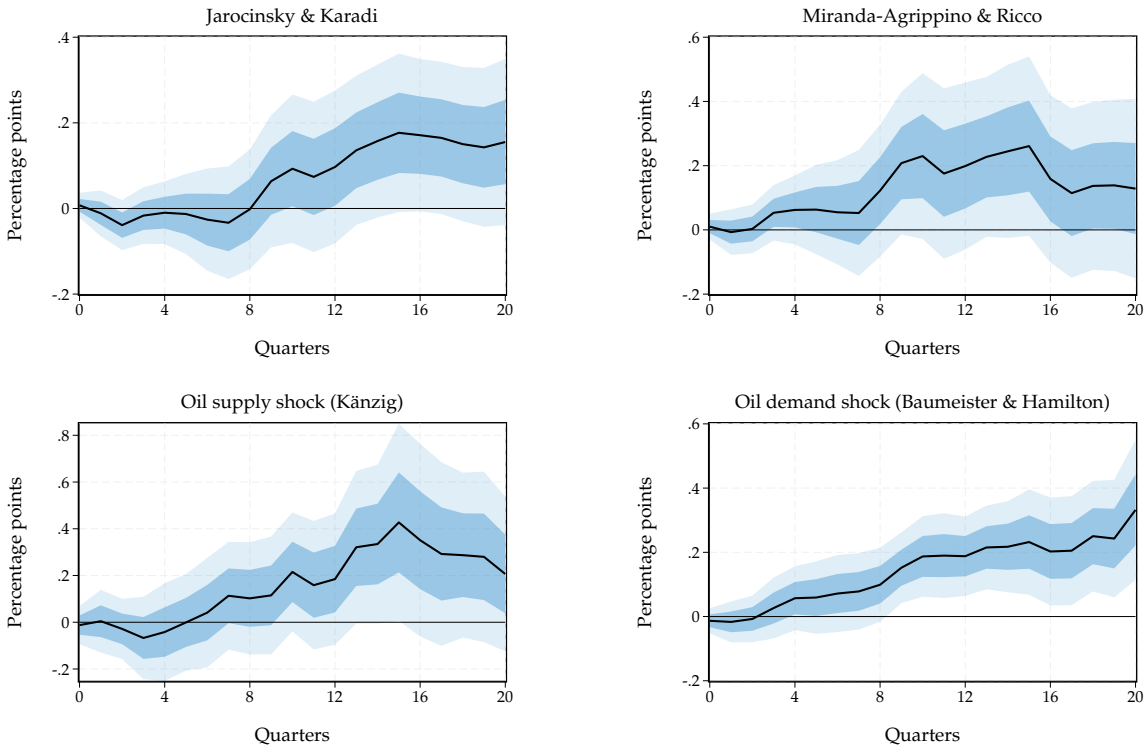
Notes: Impulse responses of green and non-green patents by listed and unlisted U.S. firms to a 25 basis point monetary policy shock, estimated based on Equation (1). The solid line is the point estimate and the dark and light shaded areas are 68 and 95 percent confidence bands based on robust standard errors, respectively.

B.6. Alternative Shock Measures

Our baseline analysis relies on a local projections approach using the monetary surprises by Bauer and Swanson (2023) as an instrument. The top two panels of Figure B.5 show similar dynamic responses of the U.S. green patent share, estimated using the monetary surprises by Jarociński and Karadi (2020) and Miranda-Agrippino and Ricco (2018) as instruments, respectively. Reassuringly, the responses align with our baseline estimates.

As alternative shock measures, the bottom two panels of Figure B.5 consider the impacts of oil shocks on the green patent share. Specifically, we use the oil supply shock identified in Känzig (2021) and the oil demand shock by Baumeister and Hamilton (2019) as an instrument for the real oil price in an otherwise identical empirical setup. The responses, normalized to increase the real oil price by 10 USD, display a similarly persistent increase as in our main analysis.

Figure B.5: Patenting responses to alternative macroeconomic shocks

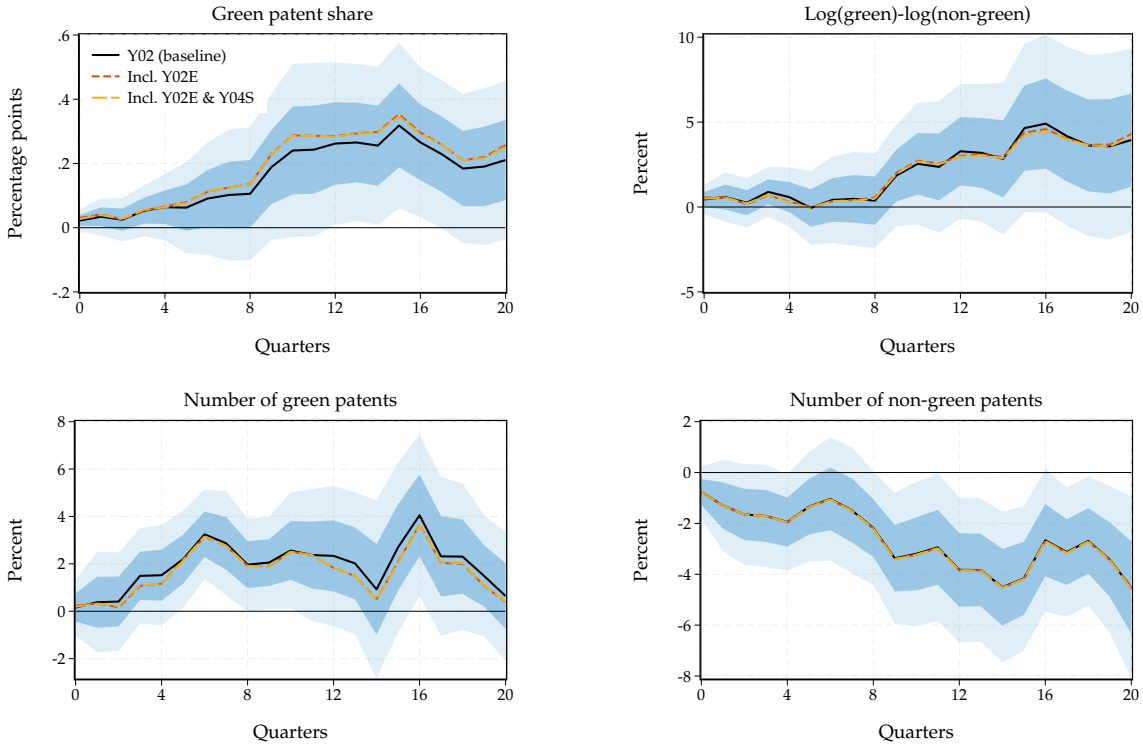


Notes: Green patenting responses to alternative monetary policy as well as other macroeconomic shocks. The top two panels display impulse responses to a 25 basis point monetary policy shock, identified using the Jarociński and Karadi (2020) or the Miranda-Agrippino and Ricco (2018) monetary surprises, respectively. The bottom two panels show the patenting responses for a 10 USD increase in the real oil price (WTI), using the oil shocks by Känzig (2021) and Baumeister and Hamilton (2019) as instruments. The solid lines are the point estimate and the dark and light shaded areas are 68 and 95 percent confidence bands based on robust standard errors, respectively.

B.7. Alternative Green Patent Classifications

Our baseline classification of green patents follows Acemoglu et al. (2023) to include Y02, but exclude Y02E20, Y02E40 and Y02E60. Figure B.6 verifies that the responses in the U.S. are robust to alternative classifications. First, we include all Y02E subclasses of the CPC, which leads to comparable responses. Second, following Calel and Dechezleprêtre (2016), we check that including smart grid technologies (CPC class Y04S) does not meaningfully impact our estimates.

Figure B.6: Patenting responses using alternative green patent classifications

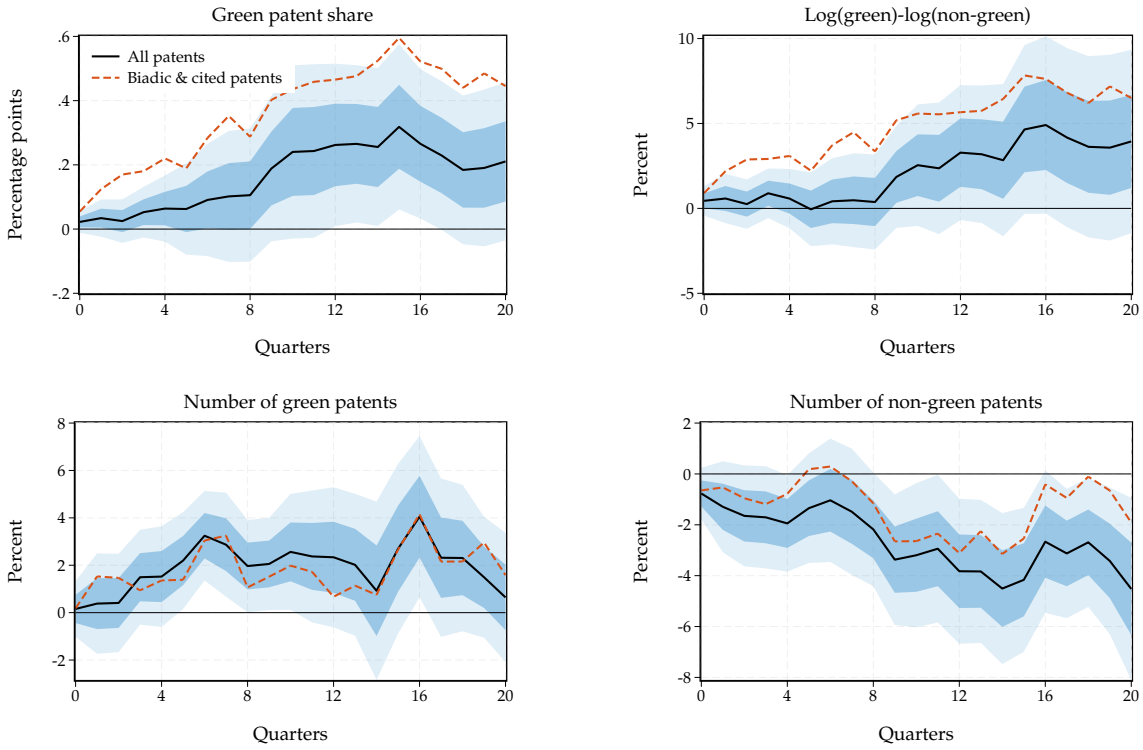


Notes: Impulse responses to a 25 basis point monetary policy shock, estimatedbased on Equation (1). The solid line is the point estimate for the baseline green patent classification and the dark and light shaded areas are 68 and 95 percent confidence bands based on robust standard errors, respectively. The orange dotted and yellow dashed lines are estimated classifying CPC codes Y02E and Y04S as green.

B.8. Distinguishing between Patent Quality

In the baseline estimation we include all patent families, regardless of quality. To control for patent quality, we closely follow Hémous et al. (2025) to focus on biadic patents (filed in at least two of the three major patent offices) with at least on citation. Figure B.7 shows that the estimated responses for the U.S. sample are consistent.

Figure B.7: Robustness with respect to patent quality

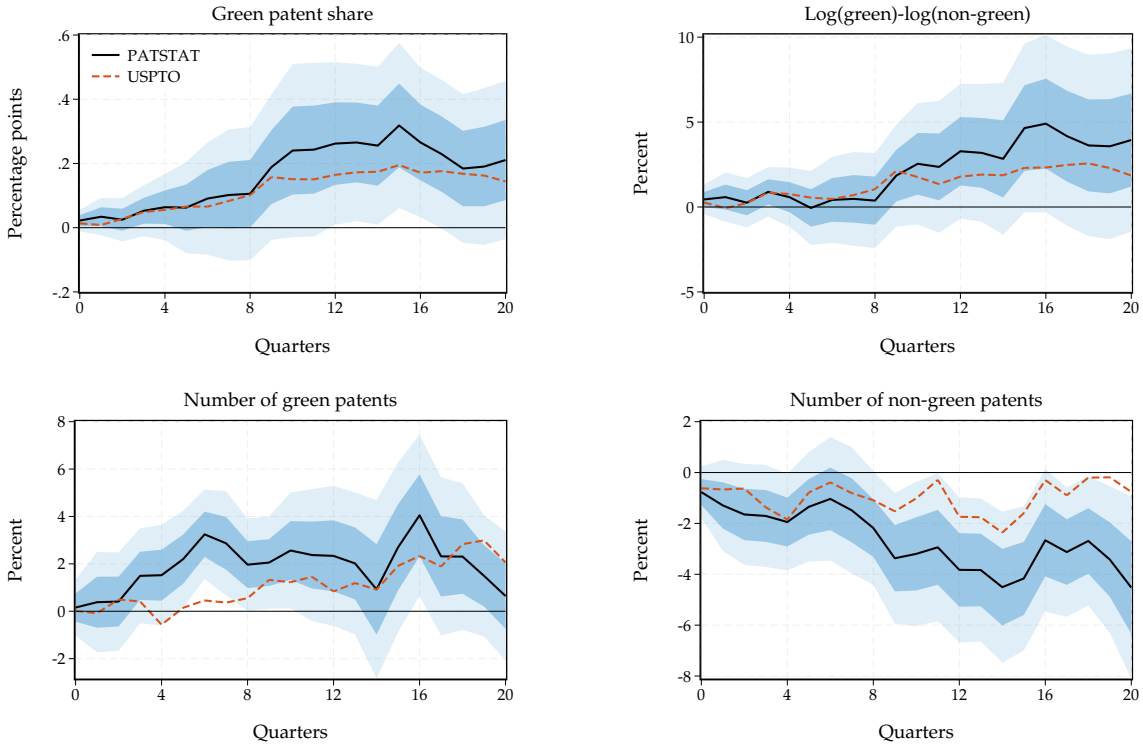


Notes: Impulse responses to a 25 basis point monetary policy shock, estimated based on Equation (1). The solid line is the point estimate and the dark and light shaded areas are 68 and 95 percent confidence bands based on robust standard errors, respectively. The orange dotted line is estimated using only biadic patent families with at least one citation.

B.9. Responses using USPTO Data

We rely on PATSTAT data for our main analysis, but verify that the estimates are comparable when using USPTO data. Patent counts can differ across the two sources, because of the way patent applications are registered and the treatment of PCT patent applications. We keep focusing on patent families, but include all families filed with the USPTO (even when the first filing in the family was with a foreign office). Figure B.8 illustrates that the estimated responses in the U.S. are comparable for PATSTAT and USPTO data.

Figure B.8: Patent responses based on USPTO data

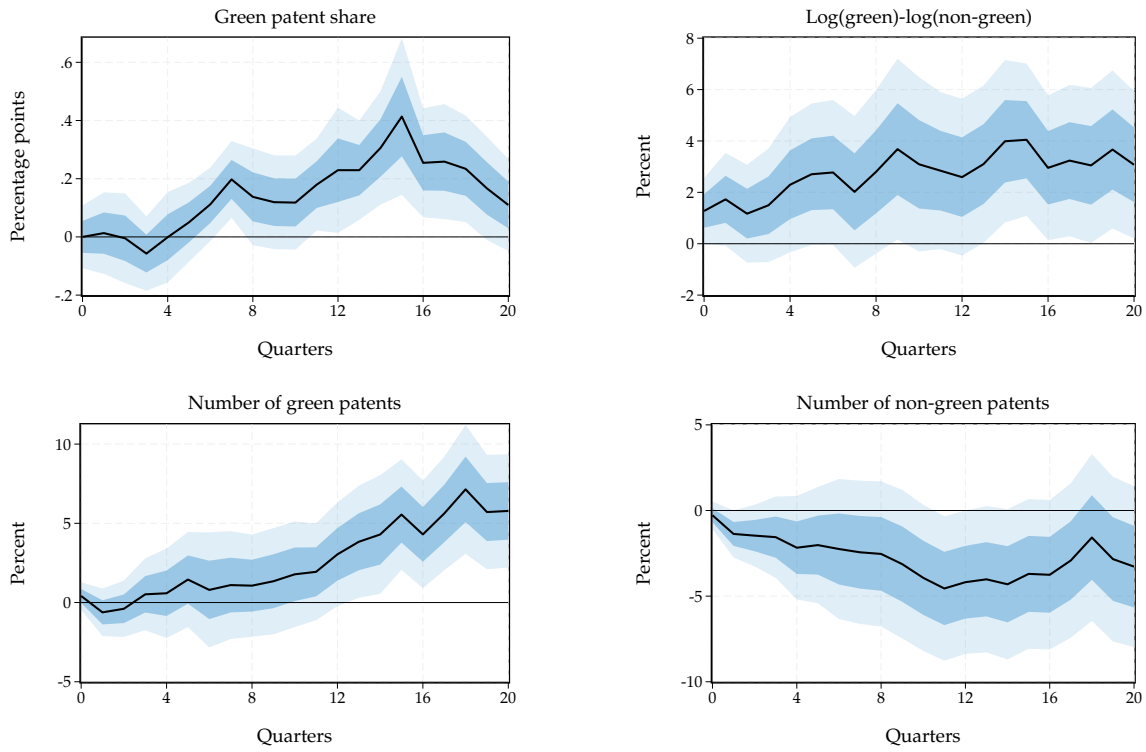


Notes: Impulse responses to a 25 basis point monetary policy shock, estimated based on Equation (1). The solid line is the point estimate and the dark and light shaded areas are 68 and 95 percent confidence bands based on robust standard errors, respectively. The orange dotted line is estimated using USPTO data.

B.10. Robustness to Firm-level Patent Counts

In our main analysis, we only retain matched patents of U.S. companies if they were originally filed with the USPTO or represent an international application filed under the Patent Cooperation Treaty. Here we adopt a less restrictive approach to include all patents filed with the USPTO at any point. As Figure B.9 illustrates, the corresponding firm-level responses are comparable to our baseline estimates.

Figure B.9: Robustness to firm-level patent counts



Notes: Impulse responses to a 25 basis point monetary policy shock, estimated based on Equation (2). The solid line is the point estimate and the dark and light shaded areas are 68 and 95 percent confidence bands based on Driscoll and Kraay (1998) standard errors, respectively.

C. Model Appendix

C.1. Balanced Growth Path

Consider the limit where the green transition is completed, and the production technology simplifies to:

$$Y_t = (1-\theta)^{\frac{\rho-1}{\rho}} L_t^{\alpha_L} M_t^{\alpha_M} G_t^{1-\alpha_L-\alpha_M}. \tag{1}$$

The first-order conditions are given by:

$$\alpha_L \frac{P_t Y_t}{L_t} = W_t, \tag{2}$$

$$\alpha_M \frac{P_t Y_t}{M_t} = P_t^M, \tag{3}$$

$$(1-\alpha_L-\alpha_M)\frac{P_t Y_t}{G_t} = P_t^G. \tag{4}$$

Given the price equations:

$$P_t^M = \left(A_t^M\right)^{1-\mu_M} \mu_M P_t, \tag{5}$$

$$P_t^G = \left(A_t^G\right)^{1-\mu_G} \mu_G P_t, \tag{6}$$

substituting into equations (3) and (4), we obtain:

$$M_t = \frac{\alpha_M}{\mu_M}\left(A_t^M\right)^{\mu_M-1} Y_t, \tag{7}$$

$$G_t = \frac{1-\alpha_L-\alpha_M}{\mu_G}\left(A_t^G\right)^{\mu_G-1} Y_t. \tag{8}$$

Substituting (7) and (8) into (1):

$$Y_t = (1-\theta)^{\frac{\rho-1}{\rho}} L_t^{\alpha_L}\left(\frac{\alpha_M}{\mu_M}\left(A_t^M\right)^{\mu_M-1} Y_t\right)^{\alpha_M}\left(\frac{1-\alpha_L-\alpha_M}{\mu_G}\left(A_t^G\right)^{\mu_G-1} Y_t\right)^{1-\alpha_L-\alpha_M}. \tag{9}$$

Rearranging, we obtain:

$$Y_t = \bar{Z} L_t \left(A_t^M\right)^{\frac{\alpha_M(\mu_M-1)}{\alpha_L}}\left(A_t^G\right)^{\frac{(1-\alpha_L-\alpha_M)(\mu_G-1)}{\alpha_L}}, \tag{10}$$

where $\bar{Z} = (1-\theta)^{\frac{\rho-1}{\rho}} \left(\frac{\alpha_M}{\mu_M}\right)^{\frac{\alpha_M}{\alpha_L}} \left(\frac{1-\alpha_L-\alpha_M}{\mu_G}\right)^{\frac{1-\alpha_L-\alpha_M}{\alpha_L}}$.

On the balanced growth path, the ratios $\frac{\int_0^{A_t^M} m_{ht}\,dh}{Y_t}$ and $\frac{\int_0^{A_t^G} g_{jt}\,dj}{Y_t}$ must remain constant over time. Moreover, A_t^G, A_t^G have to be growing such that $f_t \to 0$ in the long run.

Assumption C.1. *To ensure the existence of a Balanced Growth Path, the following conditions hold:*

1. *In the long run, A_t^M and A_t^G have to be growing over time.*
2. *In the long run, the technology levels satisfy $A_t^M = \iota A_t^G$.*
3. *The exponents satisfy the constraint:*

$$\frac{\alpha_M}{\alpha_L}(\mu_M - 1) + \frac{1-\alpha_L-\alpha_M}{\alpha_L}(\mu_G - 1) = 1. \tag{11}$$

C.2. General Equilibrium with Demand Shocks

Now consider instead of demanding final goods, households purchase a basket of differentiated retail goods indexed by i:

$$\tilde{Y}_t = \left(\int_0^1 \tilde{y}_{kt}^{\frac{\sigma-1}{\sigma}}\,dk\right)^{\frac{\sigma}{\sigma-1}}, \tag{12}$$

where $\sigma > 1$ is the elasticity of substitution between varieties.

Given the aggregate demand $\tilde{Y}_t$, the demand function for each variety k follows $\tilde{y}_{kt} = \left(\frac{\tilde{p}_{kt}}{\tilde{P}_t}\right)^{-\sigma} \tilde{Y}_t$, where $\tilde{p}_{kt}$ is the price of variety k and $\tilde{P}_t$ is the corresponding price index $\tilde{P}_t = \left(\int_0^1 \tilde{p}_{kt}^{1-\sigma} dk\right)^{\frac{1}{1-\sigma}}$. The household's budget constraint now takes the form:

$$\tilde{P}_t C_t + Q_t B_{t+1} = B_t + W_t L_t + W_t^s L_t^s + D_t. \tag{13}$$

Retailer A fixed mass of retailers $k \in [0,1]$ produces differentiated retail goods from the final good producer. The production technology is one-to-one, $\tilde{y}_{kt} = y_{kt}$, where y_{kt} is the amount of final good that the retailer k purchased. Retailers set prices with Rotemberg price adjustment costs:

$$\frac{\varphi}{2}\left(\frac{\tilde{p}_t}{\tilde{p}_{t-1}} - 1\right)^2 \tilde{Y}_t. \tag{14}$$

Each retailer maximizes its expected discounted profit:

$$\mathbb{E}_t \sum_{s=0}^{\infty} \beta^s \Lambda_{t+s} \left[\left(\tilde{p}_{k,t+s} - P_{t+s} \right) \tilde{y}_{k,t+s} - \frac{\varphi}{2} \left(\frac{\tilde{p}_{k,t+s}}{\tilde{p}_{k,t+s-1}} - 1 \right)^2 \tilde{Y}_{t+s} \right], \tag{15}$$

subject to its demand. The optimal price-setting condition:

$$(1-\sigma) + \sigma \frac{P_t}{\tilde{P}_t} - \varphi \Pi_t \tilde{P}_t^{-1} + \mathbb{E}_t \Lambda_{t,t+1} \varphi \Pi_{t+1} (1 + \Pi_{t+1}) \tilde{P}_{t+1}^{-1} = 0 \tag{16}$$

Monetary Policy The central bank follows a Taylor Rule:

$$R_t = \beta^{-1} \left(\frac{A_{t+1}}{A_t} \right)^{\phi_A} \Pi_t^{\phi_\pi} \varrho_t. \tag{17}$$

where ϱ_t is a monetary shock:

$$\log \varrho_t = \rho^\varrho \log \varrho_t + \sigma^\varrho e_t^\varrho \tag{18}$$

D. Equilibrium Conditions

Households The consumption Euler equation:

$$1 = \beta \mathbb{E}_t \left(\frac{C_t}{C_{t+1}} \Pi_{t+1}^{-1} R_t \right). \tag{19}$$

Unskilled Labor Supply:

$$W_t = \bar{\omega} C_t \tilde{P}_t. \tag{20}$$

Skilled Labor Supply:

$$W_t^s = \bar{\omega}^s C_t \tilde{P}_t (L_t^s)^\psi. \tag{21}$$

Final Good Producer The optimization of the final good producer yields the following FOCs:

$$\alpha_L \frac{P_t Y_t}{L_t} = W_t \tag{22}$$

$$\alpha_M \frac{P_t Y_t}{M_t} = P_t^M \tag{23}$$

$$(1-\alpha_L-\alpha_M)\frac{P_t Y_t}{E_t}\theta E_t^{\frac{1}{\rho}} f_t^{-\frac{1}{\rho}} = P_t^f \tag{24}$$

$$(1-\alpha_L-\alpha_M)\frac{P_t Y_t}{E_t}(1-\theta) E_t^{\frac{1}{\rho}} G_t^{-\frac{1}{\rho}} = P_t^G \tag{25}$$

The final good producer's demand of intermediate good and clean energy input:

$$m_{ht} = \left(\frac{p_{ht}^m}{P_t^M}\right)^{\frac{\mu_M}{1-\mu_M}} M_t, \tag{26}$$

$$g_{jt} = \left(\frac{p_{jt}^g}{P_t^G}\right)^{\frac{\mu_G}{1-\mu_G}} G_t. \tag{27}$$

Because the market of final good is perfectly competitive:

$$P_t = \left(\frac{W_t}{\alpha_L}\right)^{\alpha_L} \left(\frac{P_t^M}{\alpha_M}\right)^{\alpha_M} \left(\frac{P_t^E}{1-\alpha_L-\alpha_m}\right)^{1-\alpha_L-\alpha_m} Z_t^{-\alpha}. \tag{28}$$

where by Shephard's Lemma,

$$P_t^E = \left(\theta (P_t^f)^{1-\rho} + (1-\theta)(P_t^G)^{1-\rho}\right)^{\frac{1}{1-\rho}}. \tag{29}$$

Intermediate Good Producer

$$p_{ht}^m = \mu_M P_t, \tag{30}$$

$$p_{jt}^g = \mu_G P_t. \tag{31}$$

Fossil Fuel The price-setting condition of fossil fuel producer:

$$P_t^f = c(R_t) W_t. \tag{32}$$

Innovation

$$\gamma A_t^M \zeta_M \left(L_{it,M}^S\right)^{\gamma-1} V_t^m = W_t^s. \tag{33}$$

$$\gamma A_t^G \zeta_G \left(L_{it,G}^S\right)^{\gamma-1} V_t^g = W_t^s. \tag{34}$$

Retailer

$$(1-\sigma) + \sigma \frac{P_t}{\tilde{P}_t} - \varphi \Pi_t \tilde{P}_t^{-1} + \mathbb{E}_t \Lambda_{t,t+1} \varphi \Pi_{t+1} (1+\Pi_{t+1}) \tilde{P}_{t+1}^{-1} = 0 \tag{35}$$

Monetary Policy The central bank follows a Taylor Rule:

$$R_t = \beta^{-1} \left(\frac{A_{t+1}}{A_t}\right)^{\phi_A} \Pi_t^{\phi_\pi} \varrho_t. \tag{36}$$

TFP Growth Rate Given equilibrium condition (23) and the auxiliary optimality condition for optimization E_t:

$$(1-\alpha_L-\alpha_M)\frac{P_t Y_t}{E_t} = P_t^E, \tag{37}$$

we can substituting them into the production technology of the final good:

$$Y_t = \left(\frac{\alpha_M}{\mu_M}\right)^{\frac{\alpha_M}{\alpha_L}} (1-\alpha_L-\alpha_M)^{\frac{1-\alpha_L-\alpha_M}{\alpha_L}} L_t (A_t^M)^{\frac{\alpha_M}{\alpha_L}(\mu_M-1)} (P_t/P_t^E)^{\frac{1-\alpha_L-\alpha_M}{\alpha_L}} \tag{38}$$

By the definition of TFP,

$$A_t = (A_t^M)^{\frac{\alpha_M}{\alpha_L}(\mu_M-1)} (P_t/P_t^E)^{\frac{1-\alpha_L-\alpha_M}{\alpha_L}} \tag{39}$$

E. Proof

From equation (25):

$$\begin{aligned}\frac{P_t^G G_t}{P_t Y_t} &= (1-\alpha_L-\alpha_m)(1-\theta)E_t^{\frac{1}{\rho}-1}G_t^{1-\frac{1}{\rho}} \\ &= (1-\alpha_L-\alpha_m)(1-\theta)\left(\theta\left(\frac{f_t}{G_t}\right)^{\frac{\rho-1}{\rho}}+(1-\theta)\right)^{-1}. \end{aligned} \tag{40}$$

Combining equations (24) and (25), we obtain:

$$\frac{f_t}{G_t} = \left(\frac{\theta}{1-\theta}\frac{P_t^G}{P_t^f}\right)^{\rho}. \tag{41}$$

From the clean energy producer's optimization and the fossil fuel price-setting equation:

$$\frac{f_t}{G_t} = \left(\frac{\theta}{1-\theta}\frac{\left(A_t^G\right)^{1-\mu_G}\mu_G P_t}{c(R_t)W_t}\right)^{\rho} = \left(\frac{\theta}{1-\theta}\frac{\left(A_t^G\right)^{-\mu_G}\mu_G}{c(R_t)w_t}\right)^{\rho}, \tag{42}$$

which is declining over time. Therefore, when $\rho > 1$, it follows that $\frac{P_t^G G_t}{P_t Y_t}$ is increasing over time.

Since the production of varieties of intermediate inputs and clean energy inputs is homogeneous:

$$M_t = \left(A_t^M\right)^{\mu_M}\bar{m}_t, \tag{43}$$

$$G_t = \left(A_t^G\right)^{\mu_G}\bar{g}_t, \tag{44}$$

equations (23) and (40) imply:

$$\frac{P_t^G G_t}{P_t^M M_t} = \frac{A_t^G \mu_G \bar{g}_t}{A_t^M \mu_M \bar{m}_t} = \frac{\alpha_M(1-\theta)}{(1-\alpha_L-\alpha_m)}\left(\theta\left(\frac{f_t}{G_t}\right)^{\frac{\rho-1}{\rho}}+(1-\theta)\right)^{-1}. \tag{45}$$

Since A_t^G / A_t^M remains constant:

$$\frac{\bar{g}_t}{\bar{m}_t} = \frac{A_t^M}{A_t^G} \frac{\mu_M \alpha_M (1-\theta)}{\mu_G (1-\alpha_L-\alpha_M)} \left(\theta \left(\frac{f_t}{G_t} \right)^{\frac{\rho-1}{\rho}} + (1-\theta) \right)^{-1} \tag{46}$$

is increasing over time. Moreover, when $t \to \infty$:

$$\bar{g}_t = \kappa \frac{\mu_M \alpha_M}{\mu_G (1-\alpha_L-\alpha_M)} \bar{m}_t \tag{47}$$

where $\lim_{t\to\infty} \frac{A_t^G}{A_t^M} = \kappa > 0$.

Consider a one-shot shock to Z_t.

$$V_t^M = (p_t^M - P(Z_t))\bar{m}(Z_t) + V_{t,ss}^M = (\mu_M - 1)P(Z_t)\bar{m}(Z_t) + V_{t,ss}^M, \tag{48}$$

$$V_t^G = (p_t^G - P(Z_t))\bar{g}(Z_t) + V_{t,ss}^G = (\mu_G - 1)P(Z_t)\bar{g}(Z_t) + V_{t,ss}^G. \tag{49}$$

Thus, we obtain the following result:

$$\frac{\partial \log V_t^M}{\partial \log Y_t} = \frac{(\mu_M - 1)P(Z_t)\bar{m}(Z_t)}{V_{t,ss}^M} \left(\frac{\partial \log \bar{m}(Z_t)}{\partial \log Z_t} + \frac{\partial \log P(Z_t)}{\partial \log Z_t} \right) \frac{\partial \log Z_t}{\partial \log Y_t}, \tag{50}$$

$$\frac{\partial \log V_t^G}{\partial \log Y_t} = \frac{(\mu_G - 1)P(Z_t)\bar{g}(Z_t)}{V_{t,ss}^G} \left(\frac{\partial \log \bar{g}(Z_t)}{\partial \log Z_t} + \frac{\partial \log P(Z_t)}{\partial \log Z_t} \right) \frac{\partial \log Z_t}{\partial \log Y_t}. \tag{51}$$

From equation (23), we have:

$$P_t^M M_t = A_t^M \mu_M P_t \bar{m}_t = \alpha_M P_t Y_t, \tag{52}$$

which implies that:

$$\bar{m}(Z_t) = \frac{\beta}{\mu_G} y(Z_t). \tag{53}$$

Similarly, by equation (46) and (42):

$$\bar{g}(Z_t) = \frac{A_t^M}{A_t^G} \frac{\mu_M \alpha_M (1-\theta)}{\mu_G (1-\alpha_L-\alpha_M)} \left(\theta \left(\frac{\theta}{1-\theta} \frac{\left(A_t^G\right)^{-\mu_G} \mu_G}{c(R_t) w(Z_t)} \right)^{\rho-1} + (1-\theta) \right)^{-1} \bar{m}(Z_t) \tag{54}$$

Therefore,

$$\frac{\partial \log \bar{m}(Z_t)}{\partial \log Y_t} = \frac{\partial \log y(Z_t)}{\partial \log \left(A_t y(Z_t)\right)} = 1, \tag{55}$$

$$\begin{aligned}\frac{\partial \log \bar{g}(Z_t)}{\partial \log Y_t} &= \frac{(\rho-1)\theta c(R_t)\left(c(R_t)w(Z_t)\right)^{-\rho}}{\theta\left(c(R_t)w(Z_t)\right)^{1-\rho} + (1-\theta)(A_t^{1-\mu_G}\mu_G)^{1-\rho}} \frac{\partial w(Z_t)}{\partial \log Y_t} + \frac{\partial \log y(Z_t)}{\partial \log Y_t} \\ &= \frac{(\rho-1)\theta c(R_t)\left(c(R_t)w(Z_t)\right)^{-\rho}}{\theta\left(c(R_t)w(Z_t)\right)^{1-\rho} + (1-\theta)(A_t^{1-\mu_G}\mu_G)^{1-\rho}} \frac{\partial w(Z_t)}{\partial \log y(Z_t)} + 1 \end{aligned} \tag{56}$$

It follows that:

$$\frac{\partial \log \bar{g}(Z_t)}{\partial \log Y_t} \Big/ \frac{\partial \log \bar{m}(Z_t)}{\partial \log Y_t} = \frac{(\rho-1)\theta c(R_t)\left(c(R_t)w(Z_t)\right)^{-\rho} w(Z_t)}{\theta\left(c(R_t)w(Z_t)\right)^{1-\rho} + (1-\theta)(A_t^{1-\mu_G}\mu_G)^{1-\rho}} \frac{\partial \log w(Z_t)}{\partial \log y(Z_t)} + 1 \tag{57}$$

It follows that:

$$\frac{\partial \log V_t^G}{\partial \log Y_t} \Big/ \frac{\partial \log V_t^M}{\partial \log Y_t} = \frac{(\mu_G-1)\bar{g}_t}{(\mu_M-1)\bar{m}_t} \frac{V_{t,ss}^M}{V_{t,ss}^G} \frac{\left(\frac{\partial \log \bar{g}(Z_t)}{\partial \log Z_t} + \frac{\partial \log P(Z_t)}{\partial \log Z_t}\right)}{\left(\frac{\partial \log \bar{m}(Z_t)}{\partial \log Z_t} + \frac{\partial \log P(Z_t)}{\partial \log Z_t}\right)} \tag{58}$$

Recall:

$$\begin{aligned}\frac{\bar{g}_t}{\bar{m}_t} = \frac{A_t^M}{A_t^G} \frac{\mu_M \alpha_M (1-\theta)}{\mu_G(1-\alpha_L-\alpha_M)} &\left(\frac{1-\theta}{\theta} \frac{c(R_t)w(Z_t)}{\left(A_t^G\right)^{-\mu_G}\mu_G}\right)^{\rho-1} \\ &\times \left(\theta + (1-\theta)\left(\frac{1-\theta}{\theta} \frac{c(R_t)w(Z_t)}{\left(A_t^G\right)^{-\mu_G}\mu_G}\right)^{\rho-1}\right)^{-1}. \end{aligned} \tag{59}$$

By equation (57), $\frac{\partial \log \bar{g}(Z_t)}{\partial \log Y_t} / \frac{\partial \log \bar{m}(Z_t)}{\partial \log Y_t}$ is bounded above by $1 + \partial \log w(Z_t)/\partial \log y(Z_t)$ and $\frac{\bar{g}_t}{\bar{m}_t}$ goes to zero for A_t^G sufficiently small, which implies:

$$\frac{\partial \log V_t^G}{\partial \log Y_t} \Big/ \frac{\partial \log V_t^M}{\partial \log Y_t} = 0. \tag{60}$$

Moreover, when it reaches the balanced growth path,

$$\frac{(\mu_M-1)P_t\bar{m}_t}{V_{t,ss}^M} = \frac{(\mu_G-1)P_t\bar{g}_t}{V_{t,ss}^G} = \frac{1}{1-\beta\frac{A_t}{A_{t+1}}\phi} \tag{61}$$

where $\frac{A_t}{A_{t+1}}$ denotes the steady state growth rate. And

$$\frac{\partial \log \bar{g}(Z_t)}{\partial \log Y_t} = \frac{(\rho-1)\theta c(R_t)\left(c(R_t)w(Z_t)\right)^{-\rho}}{\theta\left(c(R_t)w(Z_t)\right)^{1-\rho} + (1-\theta)(A_t^{1-\mu_G}\mu_G)^{1-\rho}} \frac{\partial w(Z_t)}{\partial \log y(Z_t)} + 1 \to 1 \tag{62}$$

which implies:

$$\frac{\partial \log V_t^G}{\partial \log Y_t} / \frac{\partial \log V_t^M}{\partial \log Y_t} \to 1 \tag{63}$$

as t goes to infinity.

Therefore, by the Intermediate Value Theorem, if the market share of the clean composite is sufficiently small (such that A_t^G sufficiently small):

$$\frac{\partial \log V_t^G}{\partial \log Y_t} / \frac{\partial \log V_t^M}{\partial \log Y_t} < 1 \tag{64}$$

holds.

Proof of Corollary. From equation (33) and (34):

$$L_{it,M}^S = \left(\frac{W_t^s}{\gamma N_t \zeta_M V_t^m}\right)^{\frac{1}{\gamma-1}}, \tag{65}$$

$$L_{it,G}^S = \left(\frac{W_t^s}{\gamma A_t \zeta_G V_t^g}\right)^{\frac{1}{\gamma-1}}. \tag{66}$$

Therefore, in equilibrium, the new varieties can be solved as:

$$S_t^M = N_t \zeta_M \left(L_{t,M}^S\right)^{\gamma} = N_t \zeta_M \left(\frac{W_t^s}{\gamma N_t \zeta_M V_t^m}\right)^{\frac{\gamma}{\gamma-1}}, \tag{67}$$

$$S_t^G = A_t \zeta_M \left(L_{t,G}^S\right)^{\gamma} = A_t \zeta_G \left(\frac{W_t^s}{\gamma A_t \zeta_G V_t^g}\right)^{\frac{\gamma}{\gamma-1}} \tag{68}$$

Because $\rho > 1$, by Theorem 3.1, we have

$$\frac{\partial \log V_t^G}{\partial \log Z_t} / \frac{\partial \log V_t^M}{\partial \log Z_t} = \frac{\partial \log V_t^G}{\partial \log Y_t} / \frac{\partial \log V_t^M}{\partial \log Y_t} < 1, \tag{69}$$

which suggests that

$$\frac{\partial \log S_t^G}{\partial \log Z_t} / \frac{\partial \log S_t^M}{\partial \log Z_t} < 1. \tag{70}$$

Let us denote

$$s_t^G = \frac{S_t^G}{S_t^G + S_t^M}, \tag{71}$$

Taking logs and differentiating with respect to Z_t:

$$\frac{\partial \log s_t^G}{\partial \log Z_t} = \frac{\partial \log S_t^G}{\partial \log Z_t} - \frac{\partial \log (S_t^G + S_t^M)}{\partial \log Z_t}. \tag{72}$$

Using the log-total derivative rule:

$$\frac{\partial \log (S_t^G + S_t^M)}{\partial \log Z_t} = \frac{S_t^G}{S_t^G + S_t^M} \frac{\partial \log S_t^G}{\partial \log Z_t} + \frac{S_t^M}{S_t^G + S_t^M} \frac{\partial \log S_t^M}{\partial \log Z_t}. \tag{73}$$

Substituting:

$$\frac{\partial \log s_t^G}{\partial \log Z_t} = \left(1 - \frac{S_t^G}{S_t^G + S_t^M}\right) \frac{\partial \log S_t^G}{\partial \log Z_t} - \frac{S_t^M}{S_t^G + S_t^M} \frac{\partial \log S_t^M}{\partial \log Z_t}. \tag{74}$$

Rewriting:

$$\frac{\partial \log s_t^G}{\partial \log Z_t} = \frac{S_t^M}{S_t^G + S_t^M} \left(\frac{\partial \log S_t^G}{\partial \log Z_t} - \frac{\partial \log S_t^M}{\partial \log Z_t} \right) \tag{75}$$

$$= \frac{S_t^M}{S_t^G + S_t^M} \left(\frac{\partial \log S_t^G}{\partial \log Z_t} / \frac{\partial \log S_t^M}{\partial \log Z_t} - 1 \right) \frac{\partial \log S_t^M}{\partial \log Z_t}. \tag{76}$$

Because

$$\left(\frac{\partial \log S_t^G}{\partial \log Z_t} / \frac{\partial \log S_t^M}{\partial \log Z_t} - 1 \right) < 0, \tag{77}$$

and $\log S_t^M$ is procyclical, it suggests that the green share of new varieties s_t is countercyclical. ■

Proof of Corollary. We start by combining the skilled labor demand conditions (34) and

(33) with the skilled labor market clearing condition:

$$L^S_{it,M} = \left(\frac{e^{\varrho_t} C_t \bar{\omega}^s (L^S_{t,M} + L^S_{t,G})^{\psi}}{\gamma N_t \zeta_M V_t^m} \right)^{\frac{1}{\gamma-1}}, \tag{78}$$

$$L^S_{it,G} = \left(\frac{e^{\varrho_t} C_t \bar{\omega}^s (L^S_{t,M} + L^S_{t,G})^{\psi}}{\gamma A_t \zeta_G V_t^g} \right)^{\frac{1}{\gamma-1}}. \tag{79}$$

By combining equations (78) and (79) with the skilled labor market clearing condition, we obtain:

$$L^S_t = (e^{\varrho_t} C_t \bar{\omega}^s)^{\frac{1}{\gamma-1-\psi}} \left[(\gamma N_t \zeta_M V_t^m)^{-\frac{1}{\gamma-1}} + (\gamma A_t \zeta_G V_t^g)^{-\frac{1}{\gamma-1}} \right]^{\frac{\gamma-1}{\gamma-1-\psi}} \tag{80}$$

$$= (e^{\varrho_t} C_t \bar{\omega}^s)^{\frac{1}{\gamma-1-\psi}} (\gamma N_t \zeta_M V_t^m)^{\frac{1}{\psi+1-\gamma}} \left[1 + \left(\frac{\gamma N_t \zeta_M V_t^m}{\gamma A_t \zeta_G V_t^g} \right)^{\frac{1}{\gamma-1}} \right]^{\frac{1-\gamma}{\psi+1-\gamma}}. \tag{81}$$

Substituting, we obtain:

$$L^S_{it,M} = (e^{\varrho_t} C_t \bar{\omega}^s)^{\frac{1}{\gamma-1-\psi}} (\gamma N_t \zeta_M V_t^m)^{\frac{1}{\psi+1-\gamma}} \left[1 + \left(\frac{\gamma N_t \zeta_M V_t^m}{\gamma A_t \zeta_G V_t^g} \right)^{\frac{1}{\gamma-1}} \right]^{\frac{\psi}{\gamma-1-\psi}}, \tag{82}$$

$$L^S_{it,G} = (e^{\varrho_t} C_t \bar{\omega}^s)^{\frac{1}{\gamma-1-\psi}} \left[1 + \left(\frac{\gamma N_t \zeta_M V_t^m}{\gamma A_t \zeta_G V_t^g} \right)^{\frac{1}{\gamma-1}} \right]^{\frac{\psi}{\gamma-1-\psi}} (\gamma N_t \zeta_M V_t^m)^{\frac{1}{\psi+1-\gamma}} \left(\frac{A_t \zeta_G V_t^g}{N_t \zeta_M V_t^m} \right)^{\frac{1}{1-\gamma}}. \tag{83}$$

The first three terms are common across both expressions. Regarding the last term, in equation (83), it is counter-cyclical. The procyclicality of equation (83) decreases as ψ increases, with the limiting behavior that when $\psi = 0$, it is procyclical, while as $\psi \to \infty$, it becomes countercyclical. By the intermediate value theorem, the corollary follows.

■

References Appendix

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