Green Business Cycles

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Motivation

Innovation as a driver of the green transition

- **Green innovation** is a key part of the toolkit to addressing climate change
  - Prospect of reducing emissions while maintaining growth
- Increasing investments in R&D and adoption of green technologies
  - 2024: **$269b spending** in the U.S. according to Clean Investment Monitor
  - Public commitments to stimulate green innovation (U.S. IRA, EU Green Deal, ...)
- But: Recent **global headwinds** raise concerns about slowing green transition
  - Covid pandemic, supply chain disruptions, tariffs, ...
  - Tighter financial conditions due to rate increases by central banks

This paper

- How does **green innovation** respond to the **business cycle**?
  - Key question for policymakers to understand in addition to structural drivers
- **Competing theories** on cyclicality of innovation over the business cycle
  - Schumpeterian view: recessions lower opportunity cost of R&D and spur innovation $\rightarrow$ countercyclical
  - Alternative view: recessions depress aggregate demand and tighten financial conditions, constraining innovative efforts $\rightarrow$ procyclical
- Direction and amplitude of cyclicality of innovation is an empirical question
- **Green innovation** may behave differently given its **backloaded payoffs**

This paper

1. Provide new empirical evidence on cyclicality of **green innovation**
   - Based on **universe of patents** filed in the United States and OECD countries
   - Business cycle correlations and impulse responses to well-identified shocks
2. Develop business cycle model with **endogenous green and non-green** innovation
   - Study cyclicality of different types of innovation during **green energy transition**
   - Flesh out mechanisms that can rationalize the empirical findings
3. Evaluate the model predictions **quantitatively**
   - Model calibrated to U.S. data matches empirical responses
   - Additional empirical evidence supporting mechanisms identified in the model

Preview of results

- Overall innovation is **procyclical** but masks important heterogeneity
- **Green innovation** is **countercyclical** while non-green innovation is **procyclical**
  - Not only the share but even **number** of green patents tends to be countercyclical
  - Holds unconditionally over the cycle & conditional on monetary policy **shocks**

    $\Rightarrow$ Informative of underlying channels: cash flows vs. discount rates
  - Holds in United States and internationally & within listed and private firms

Preview of results

- What can account for the **differential cyclicalities** of innovation?

- **Simple channel**: "**Green is in the future**"
  - During green transition, green patents generate profits that are heavily backloaded
  - Business cycle shocks operate at much shorter frequencies

  $\Rightarrow$ Value of green patents and thus patenting less sensitive to business cycle fluctuations

- **General equilibrium effect**: Lower wages in recessions reduce green R&D cost, making green and non-green innovation **effective substitutes** via labor supply

  $\Rightarrow$ Green patenting increases due to reallocation of skilled labor

- Verify empirically using data on **market-implied patent values** and inventors

Related literature

Cyclicality of innovation: Aghion and Saint-Paul 1998; Barlevy 2007; Aghion et al. 2010, 2012; Ouyang 2011; Ma and Zimmermann 2023

⇒ We confirm overall procyclicality but highlight countercyclicality of green innovation

Determinants of green innovation: Popp 2002; Acemoglu et al. 2012; Aghion et al. 2016; Acemoglu et al. 2016; Calel and Dechezleprêtre 2016; Hassler, Krusell, and Olovsson 2021; Känzig 2023; Acemoglu et al. 2023; Aghion et al. 2024; Colmer et al. 2024; Bolton, Kacperczyk, and Wiedemann 2025; Fornaro, Guerrieri, and Reichlin 2025

⇒ Emphasize macro fluctuations as relevant driver, in line with Schumpeterian mechanism

Medium-run fluctuations and endogenous innovation: Comin and Gertler 2006; Anzoategui et al. 2019; Wang and Zhang 2025

⇒ Extend model to distinguish green vs. non-green innovation during green transition

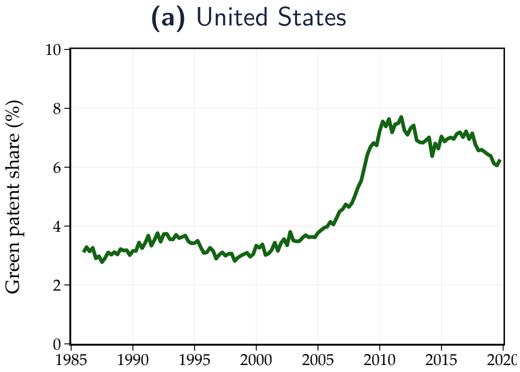
Green innovation over the business cycle

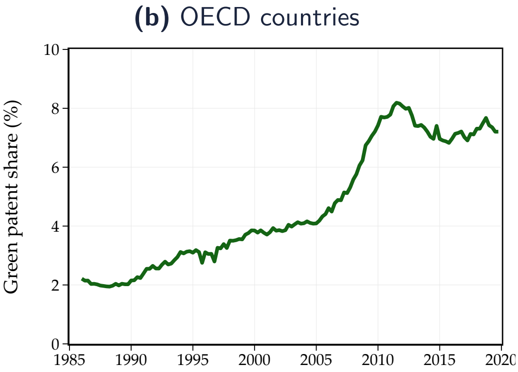
Measuring green innovation

- Measuring innovation is challenging. We focus on **patent data**:
  - Well-established proxy for innovation
  - Consistent record of inventive activity across industries and time
  - Crucially, detailed classification system allows to distinguish nature of innovation
- **Data source and construction**
  - PATSTAT global database: bibliographic info on nearly all patent filings
  - Focus on patent families. Assign filing date and nationality based on first filing
- **Defining green innovation**
  - Identify green patents using IPC/CPC code subclass **Y02**
  - Captures technologies for climate change mitigation or adaptation
  - Patent is green if **any** of its IPC/CPC codes fall under this definition

▸ Y02 categories ▸ Examples

Green patenting in the United States and OECD

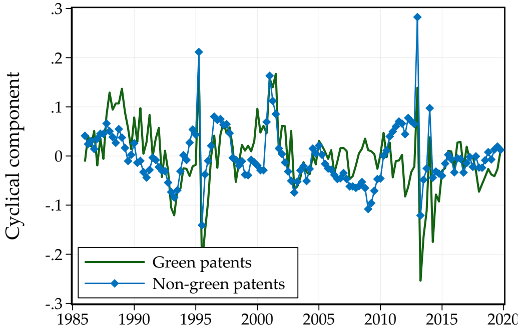




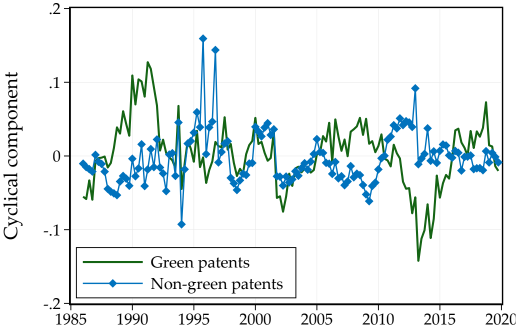
▸ Listed vs. unlisted firms

Cyclical component of green and non-green patenting

(a) United States



(b) OECD countries



Notes: Cyclical components extracted using the Hodrick-Prescott filter with $\lambda = 1,600$

▸ Listed vs. unlisted firms

Patenting and the business cycle

- How does patenting vary with the business cycle?

- Run simple local projections of patenting on business cycle "shocks"

  Special case of Angeletos, Collard and Dellas (2020)

$$y_{t+h} = \alpha^h + \psi^h bc_t + \boldsymbol{\beta}_x^h \mathbf{x}_{t-1} + \varepsilon_{t+h},$$

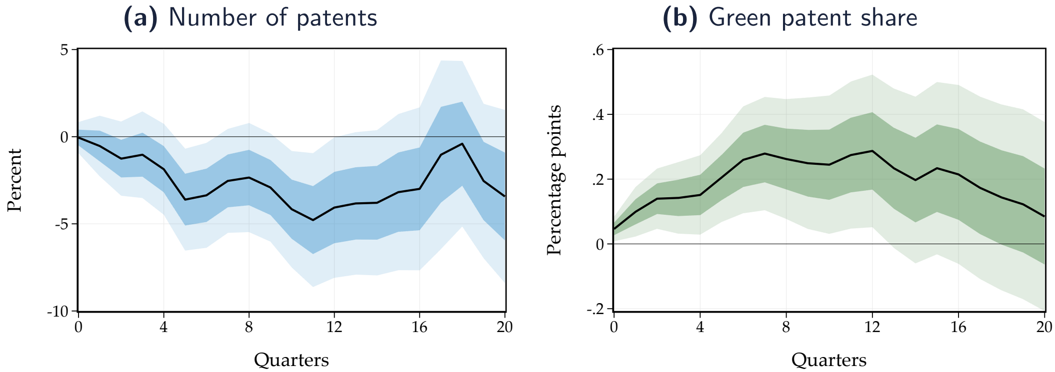
- y_{t+h}: h-quarter ahead aggregate innovation measure

  Number of patents, green patent share, number of green or non-green patents

- bc_t: a business cycle indicator

- These are dynamic correlations, no **causal** interpretation!
  - How does "innovation" in GDP growth affect patenting today and in future

Overall patenting and green patent share

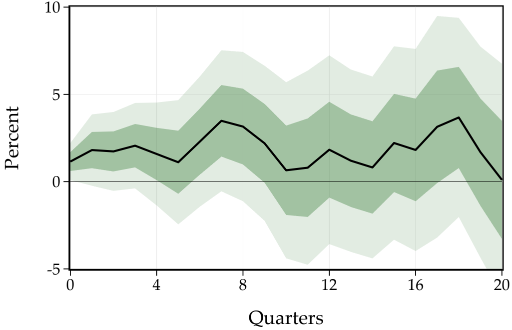


Notes: Shaded areas denote 68% and 95% confidence bands based on lag-augmented SE

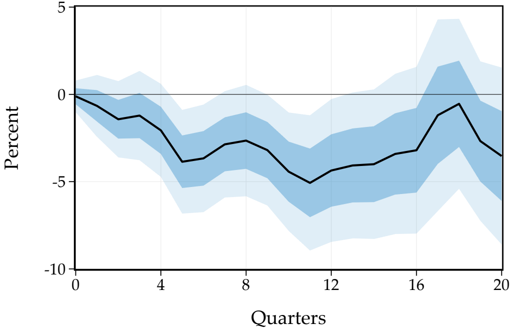
- Overall patenting strongly **procyclical**
  - Total number of patents falls by ∼4% after fall in GDP by 1%
- **But: Green patent share** increases!

Green versus non-green patenting

(a) Number of green patents



(b) Number of non-green patents



Notes: Shaded areas denote 68% and 95% confidence bands based on lag-augmented SE

- Sizable **decline** in the number of non-green patents mirroring overall fall
- **Green patents** even tend to increase (although less precisely estimated)

▸ Alternative bc measures

Unconditional cyclicality

- Unconditional correlations may confound impacts of **different underlying shocks**
- **Reverse causality** could be of concern, as innovation could drive business cycle
- Study cyclicality of patenting **conditional** on economic shocks
  - Focus on high-frequency **monetary policy shocks** as stand-in for well-identified demand shock ▸ Detail

  ⇒ Informative about the relative strength of *cash flow* and *discount rate* channels
  - Assess robustness using other shocks such as oil price shocks

Cyclicality conditional on monetary policy shocks

- Local projections instrumental variables approach

$$y_{t+h} = \alpha^h + \theta^h r_t + \boldsymbol{\beta}_x^h \mathbf{x}_{t-1} + \varepsilon_{t+h},$$

- y_{t+h}: h-quarter ahead aggregate innovation measure

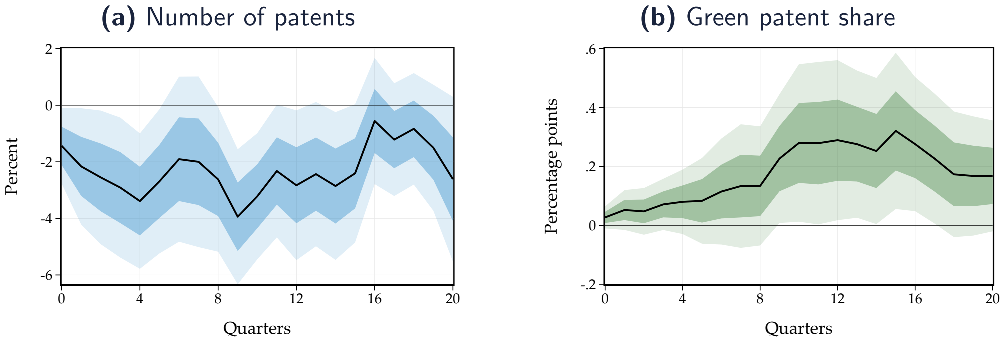
  Green patent share, log number of total, green or non-green patents

- r_t: policy rate
  - Instrumented using monetary surprises from Bauer and Swanson (2023)
  - Average first-stage F-stat. > 10 indicate strong instrument

- $\mathbf{x}_{t-1}$: 4 lags of macro-financial controls

  LHS, policy rate, real GDP, unemployment rate, GDP deflator, excess bond premium, quarterly dummies, linear trend, dummy for zero lower bound period

Conditional response of overall patents and green share

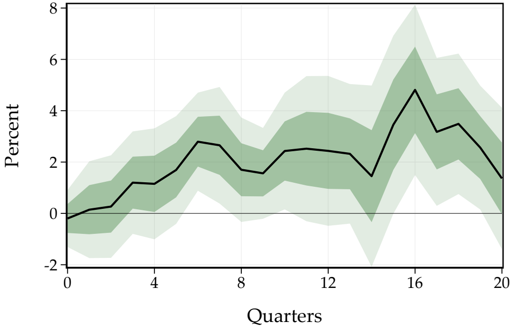


Notes: Shaded areas denote 68% and 95% confidence bands based on lag-augmented SE

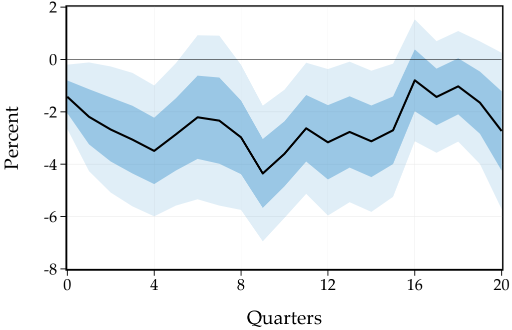
- Overall patenting strongly **procyclical** while green share is **countercyclical**
  - Total number of patents falls by ∼4%, green share rises by 0.3 p.p. after 25 bp monetary tightening ▸ Macro effects
- Comparable effects to simple reduced-form projections

Conditional response of green versus non-green patents

(a) Number of green patents



(b) Number of non-green patents



Notes: Shaded areas denote 68% and 95% confidence bands based on robust SE

- Sizable **decline** in the number of non-green patents
- Non-negligible **increase** in **green patents**

Sensitivity of empirical results

1. Consistent results in United States and OECD countries ▸ More
2. Similar results for patenting by listed and non-listed firms ▸ More
3. Robust to classification of green patents ▸ More
4. Robust to controlling for patent quality ▸ More
5. Robust to using alternative monetary policy shocks ▸ More
6. Consistent results when using commodity price shocks ▸ More

The cyclicality of innovation at the firm level

Green innovation at the firm level

- Firm-level balance sheet data:
  - Compustat North America: universe of U.S. listed firms
- Combine two separate datasets to match patents to firms
  - DISCERN: extends NBER mapping, based on fuzzy matching
  - ORBIS Intellectual Property: global patent portfolios, linked via ISIN
- Matched sample:
  - Match 1.7 million patents (including **93,000 green patents**) to 2,100 firms
  - Exclude firms without a green patent from our sample

$\Rightarrow$ Sharpens identification, allows to test within vs. across-firm margin

Who are the green innovators?

	Firm size quartiles			
	First	Second	Third	Fourth
Number of green patents	2,241	4,560	9,248	82,816
Green patent share (%)	22.04	11.66	8.96	10.46
Size	40	244	1,214	16,750
Age	14.89	17.56	22.78	30.98
Book to market ratio	0.26	0.45	0.42	0.38
GHG emission intensity	38.17	34.62	81.93	316.07

- Small firms innovate relatively more in green
- But bulk of **green innovation** done by very **large firms**
  - Many of these firms have poor carbon footprint
  - Green innovators not necessarily green firms ▸ 20 largest innovators

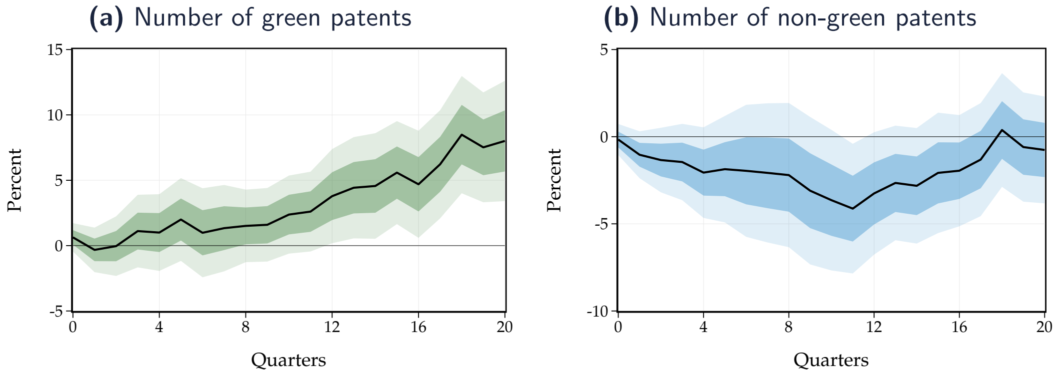
Firm-level local projections

- Panel local projections

$$y_{i,t+h} = \alpha_i^h + \theta^h r_t + \boldsymbol{\beta}_{xi}^h \mathbf{x}_{i,t-1} + \boldsymbol{\beta}_x^h \mathbf{x}_{t-1} + \varepsilon_{i,t+h},$$

- $y_{i,t+h}$: h-quarter ahead innovation measure of firm i
  - Address sparseness in the patent data by applying backward-looking moving average
- α_i^h: firm fixed effects
- $\mathbf{x}_{t-1}$ includes same aggregate controls as before, with 4 lags
- Robust to also controlling for time-varying firm characteristics
  (e.g., size, leverage)

Green versus non-green at the firm level

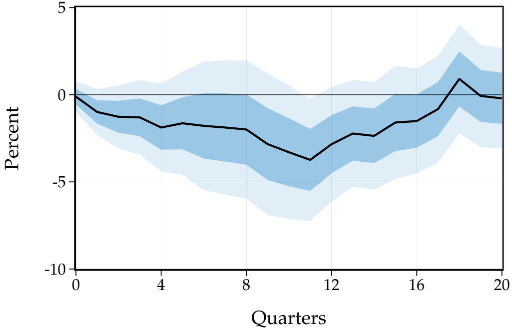


Notes: Shaded areas denote 68% and 95% confidence bands based on Driscoll-Kraay SE

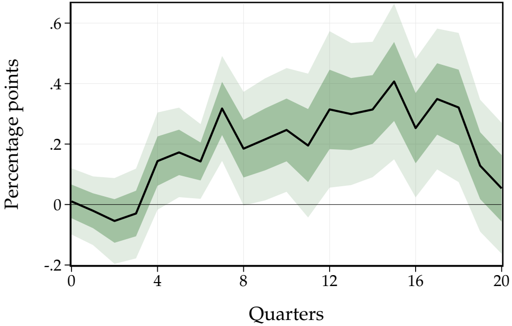
- **Comparable effects** at the firm level
  - Green patenting increases by about 5%, non-green falls by around 5%

Green versus non-green within firm

(a) Number of patents



(b) Green patent share



Notes: Shaded areas denote 68% and 95% confidence bands based on Driscoll-Kraay SE

- Not merely driven by differential patenting responses across firms
  - **Green patent share** even increases **within** firm

Green versus non-green at the firm level using PPML

- Pseudo-Poisson maximum likelihood estimator to handle zeros in patent data

$$\mathrm{E}\Big(\sum_{h=1}^{20} y_{i,t+h}\Big) = \exp(\alpha_i + \theta r_t + \boldsymbol{\beta}_{xi}\mathbf{x}_{i,t-1} + \boldsymbol{\beta}_x \mathbf{x}_{t-1} + \varepsilon_{i,t+h})$$

- Outcome: Cumulative, 20-q ahead number of green/non-green patents of firm i
  - Allows for sufficient lag between R&D decisions and patent filings
- Instrument r_t using monetary surprises
- Parsimonious specification allows for inclusion of **interaction terms**
  - Can sharpen identification controlling for time fixed effects ▸ Details

PPML results: base effects

Dep. var.:	$\sum_{h=1}^{20}$Green patents$_{it+h}$					$\sum_{h=1}^{20}$Non-green patents$_{it+h}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
r_t	1.82***	1.75***		1.57***		-3.43***	-3.41***		-4.70***	
	(0.36)	(0.35)		(0.36)		(0.52)	(0.52)		(0.55)	
$r_t \times btm_{it-1}$		-0.21**	-0.19***				0.26**	0.41***		
		(0.10)	(0.05)				(0.12)	(0.07)		
$r_t \times \overline{gps}_i$				1.34***	1.28***				-0.43	-0.35
				(0.38)	(0.31)				(0.79)	(0.16)
Observations	83,041	82,304	82,304	72,045	72,045	82,966	82,231	82,231	72,841	72,841
Firms	1,552	1,549	1,549	1,397	1,397	1,552	1,549	1,549	1,397	1,397
Time FE	No	No	Yes	No	Yes	No	No	Yes	No	Yes

Notes: Bootstrapped standard errors clustered at the time-level in parentheses

- Semi-elasticities imply **1.8% increase in green**, 3.4% drop in non-green patents
  - Compared to LP estimates: smaller magnitude for green, comparable for non-green

PPML results: conditional on firm-level duration

Dep. var.:	$\sum_{h=1}^{20}$Green patents$_{it+h}$					$\sum_{h=1}^{20}$Non-green patents$_{it+h}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
r_t	1.82***	1.75***		1.57***		-3.43***	-3.41***		-4.70***	
	(0.36)	(0.35)		(0.36)		(0.52)	(0.52)		(0.55)	
$r_t \times \text{btm}_{it-1}$		-0.21**	-0.19***				0.26**	0.41***		
		(0.10)	(0.05)				(0.12)	(0.07)		
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Time FE	No	No	Yes	No	Yes	No	No	Yes	No	Yes

Notes: Bootstrapped standard errors clustered at the time-level in parentheses

- Proxy firms with higher duration by low book-to-market or high green patent share

$\Rightarrow$ Higher duration firms' **green innovation** is more **countercyclical**

  - Robust to controlling for time fixed effects

Other heterogeneity

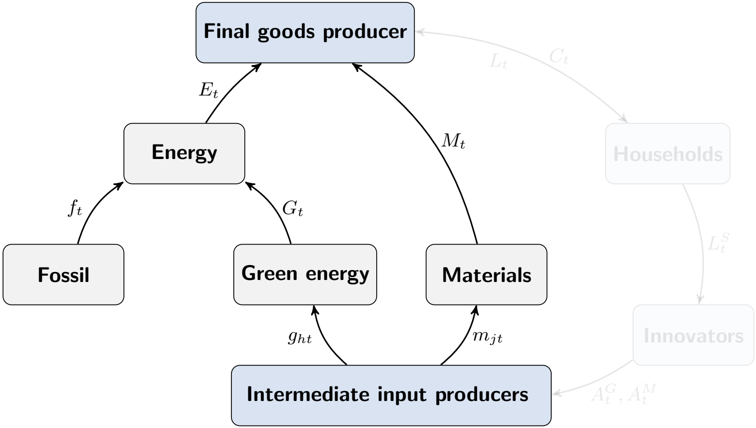
Taking stock

- Empirical findings:
    1. The share of green innovation is countercyclical
    2. Green innovation is countercyclical
- **Next**: Develop business cycle model with endogenous **green** and non-green innovation to study their cyclicality during green transition

⇒ Flesh out channels that can explain the empirical facts

A green business cycle model

The partial equilibrium production economy



- Intermediate inputs are produced under **monopolistic competition**

The model in a nutshell

- Final goods producer combines energy and materials, employing unskilled labor

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

- Energy composite E_t combines fossil fuel f_t and green energy G_t

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

  - Key assumption: $\rho > 1$: Green energy and fossil fuel are substitutes

- Fossil fuel extraction employs linear technology in competitive market

▸ Final goods producer ▸ Energy composite ▸ Fossil fuel ▸ Model w/ brown innovation

The model in a nutshell

- Green energy and non-green material composites aggregate differentiated number of varieties, g_{jt} and m_{ht}:

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

  - A_t^G, A_t^M denote number of available varieties, μ_G, $\mu_M > 1$ capture producer markups

$\Rightarrow$ Productivity growth by increasing number of available varieties (Romer 1990)

- Input demands:

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

Energy composite | Fossil fuel | Final goods producer | Model w/ brown innovation

Value of producing green and material varieties

- Input varieties are produced under monopolistic competition:

$$\Pi^G_{jt} = \max_{p^g_{jt}} \left(p^g_{jt}\, g_{jt} - g_{jt} \right), \quad \Pi^M_{ht} = \max_{p^m_{ht}} \left(p^m_{ht}\, m_{ht} - m_{ht} \right)$$

  subject to input demands

  - Producing a given variety requires one unit of final good

- Each period varieties faces obsolescence with exogenous probability $1 - \phi$
  - Robustness: Endogenize ϕ_t in a Schumpeterian model (Aghion and Howitt 1992)

- Value of green and material input varieties:

$$V^G_{jt} = \sum_{s=0}^{\infty} \phi^s\, \mathbb{E}_t \left[\Lambda_{t,t+s}\, \Pi^g_{j,t+s} \right], \quad V^M_{ht} = \sum_{s=0}^{\infty} \phi^s\, \mathbb{E}_t \left[\Lambda_{t,t+s}\, \Pi^m_{h,t+s} \right]$$

▸ Input demand ▸ Schumpeterian model

Green is in the future

We focus on a **green transition** toward a balanced-growth-path ▸ Lemma

- Green share of energy, $\frac{G_t}{E_t}$ increases iff $\frac{P_t^f}{P_t^G}$ increases, where $P_t^G = \mu_G (A_t^G)^{1-\mu_G}$

For now, taking A_t^M and A_t^G as given, where A_t^G increases during the green transition:

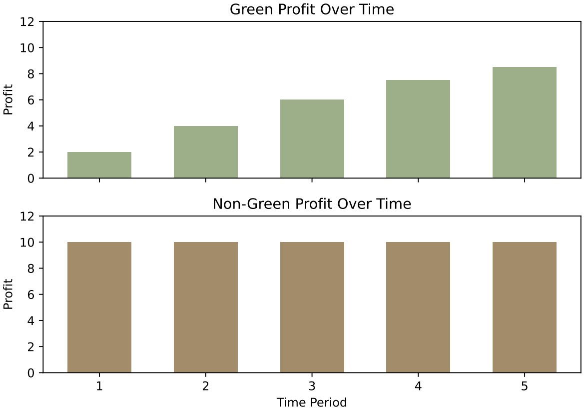
Proposition 1 (Green is in the future)

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

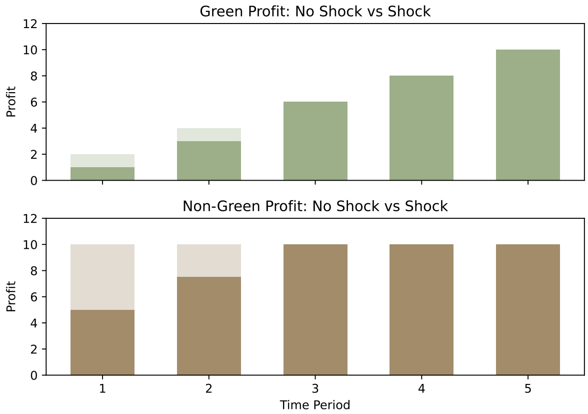
Green is in the future



- During green transition $A_t^G \uparrow \Rightarrow P_t^G \downarrow$ prices of green inputs, relative to P_t^f
- This raises demand for these inputs and leads to higher profits over time

Green is in the future: Cash flow channel

$\Rightarrow$ Value of green input V_t^G less affected by short-run changes in Y_t than V_t^M



Green is in the future: Cash flow channel

Proposition 2 (Cyclicality during the Green Transition)

During the green transition, and holding the discount factor constant, the relative value of producing g_{jt}, defined as $\frac{V_t^G}{V_t^M}$, exhibits countercyclicality:

$$\frac{d \log V_t^G}{d \log Y_t} < \frac{d \log V_t^M}{d \log Y_t} \quad \text{or equivalently} \quad \frac{d \log \left(V_t^G / V_t^M\right)}{d \log Y_t} < 0$$

- Next: How do changes in the **discount factor** impact this result?
    - Green profits are backloaded and hence more sensitive to discount factor

Separating cash flow and discount rate channels

Effect of aggregate shocks on green and material values can be decomposed as:

$$\frac{d \log V_t^K}{d \log Y_t} = \text{Cash flow channel} + \text{Discount rate channel},$$

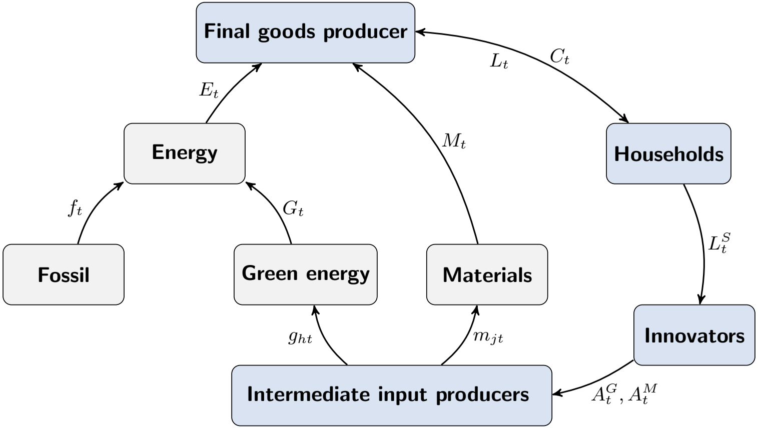
for $K = \{G, M\}$

- Direction of the discount rate channel depends on the **cyclicality of the SDF**:
  - Procyclical SDF dampens the green countercyclicality
  - Countercyclical SDF amplifies the green countercyclicality

$\Rightarrow$ Monetary policy shocks imply procyclical SDF, dampening the cash flow channel

Decomposition

Green and non-green innovation in general equilibrium



- Innovators hire skilled workers from **integrated labor market**

The innovators' R&D problem

- Continuum of $i \in [0, 1]$ innovators develop new green and material varieties
  - Here: Focus on green innovator, but **setup is symmetric**
- Green innovator i chooses skilled labor $L^S_{it,G}$, given wage W^s_t:

$$\max_{L^S_{it,G}} \quad \varphi^G_t L^S_{it,G} \left(V^G_t - cV^G_{t,ss} \right) - W^s_t L^S_{it,G}$$

  - Innovation technology φ^G_t depends on aggregate knowledge accumulation
  - Innovators pay a fixed setup cost $cV^G_{t,ss}$ proportional to variety value
- Aggregate number of new green varieties: $S^G_t = \int_0^1 \varphi^G_t L^S_{it,G} \, di$
- Green technology stock evolves as: $A^G_{t+1} = \phi A^G_t + S^G_t$

▸ Innovation technology

Countercyclical green share of new varieties

- From Proposition 2, **relative value** of green varieties is countercyclical
- This countercyclicality implies that innovators' **R&D investment** in green, relative to non-green marterials, is countercyclical
- As a result, the **green share** of new varieties is also countercyclical:

Proposition 3 (Countercyclical green share of new varieties)

During the green transition, the green share of new varieties, $\frac{S_t^G}{S_t^G+S_t^M}$ is countercyclical

- Holds in general for endogenous SDF (under log utility) ▸ Corollary
  - Under CRRA utility, lower IES can strengthen the discount rate channel

Empirical findings explained by the model

So far:

1. The share of green innovation is countercyclical: ✓
2. Green innovation is countercyclical: x

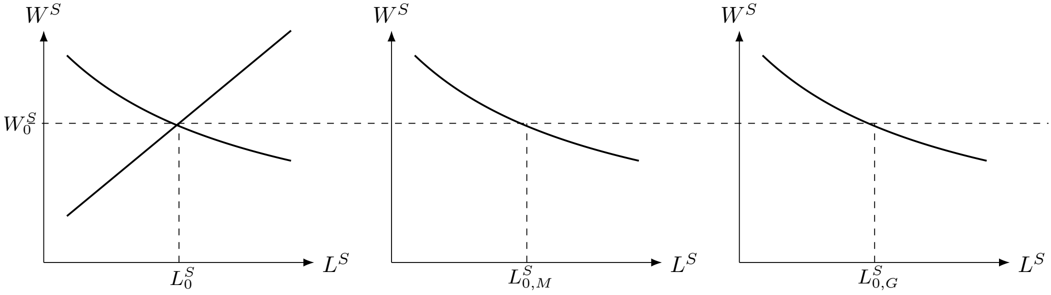
⇒ How can **number of green varieties** be countercyclical in the model?

The role of general equilibrium effects

- **Standard household sector** with endogenous labor supply to close the model
- Recessionary shock
  - Reduces non-green innovation (more than green) $\Rightarrow$ lowers demand for skilled labor and thus wages
  - Households increase labor supply $\Rightarrow$ lowers wages
- **General equilibrium effect** operating through the market for skilled labor
  - Lower wage decreases **cost of green R&D**, incentivizing firms to undertake more green innovation

▸ Household sector ▸ Market clearing

Visualizing the role of general equilibrium effects

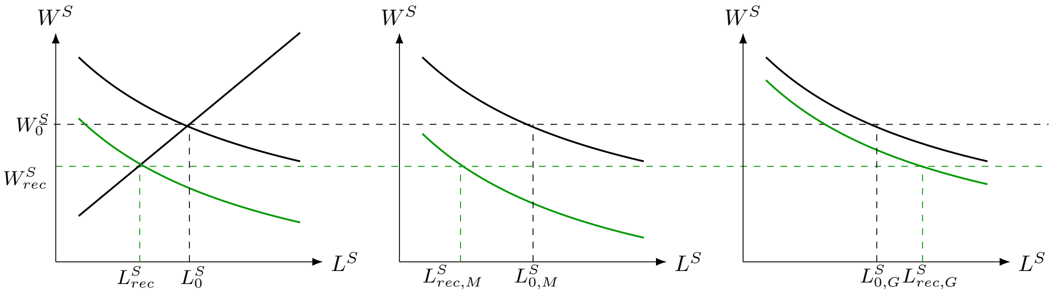


Market of Skilled Labor

Skilled Labor Demand (Non-green)

Skilled Labor Demand (Green)

Visualizing the role of general equilibrium effects



Market of Skilled Labor | Skilled Labor Demand (Non-green) | Skilled Labor Demand (Green)

- A recession lowers demand for skilled labor more in non-green market
- Lower wage reduces cost of green R&D, raising green labor demand

The role of general equilibrium effects

Proposition 4 (General equilibrium effects)

During the Green transition, there exists a threshold $\bar{\epsilon}_x > 0$ such that green innovation is countercyclical, i.e.,

$$\frac{\partial \log S_t^G}{\partial \log Y_t} < 0,$$

if and only if the wage elasticity of skilled labor with respect to output, $\frac{\partial \log W_t^s}{\partial \log Y_t}$, exceeds $\bar{\epsilon}_x$. By contrast, non-green innovation is procyclical, that is, $\frac{\partial \log S_t^M}{\partial \log Y_t} > 0$.

Moreover, the threshold $\bar{\epsilon}_x$ is decreasing in the degree of countercyclicality in the relative valuation of green versus non-green innovation, $\mathcal{V}_t^G / \mathcal{V}_t^M$.

More on the role of general equilibrium effects

- A **sufficient condition** under which GE channel generates countercyclical number of green varieties:
  - Supply of skilled labor is **inelastic** ▸ Corollary ▸ Visualization
  - Plausible given evidence in Chetty et al. (2011)
- So far focus on real economy. We extend the model to introduce:
  - Nominal rigidities, where retailers face Rotemberg price adjustment costs
  - Monetary policy through a Taylor rule and **incorporate a monetary shock**

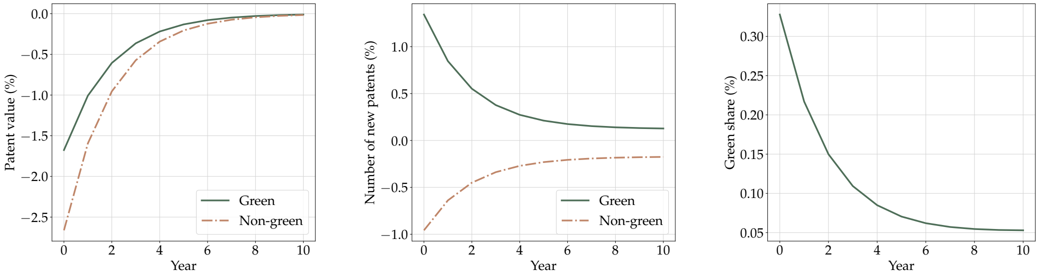
$\Rightarrow$ Derive similar results conditional on monetary shock ▸ Corollary

Evaluating the model predictions

Model responses

- Calibrate model to U.S. economy
  - Key: labor supply less elastic for skilled labor, otherwise standard ▸ Detail

(a) IP value of a new variety **(b)** Number of new varieties **(c)** Green share



Notes: Impulse responses to 25 bp monetary contraction

▸ Importance of discount rate channel

Quantitative robustness checks

1. Varying the intertemporal elasticity of substitution ▸ More
2. Time preference shock ▸ More
3. Green Is in the Future along the transition path ▸ More
4. Accelerating the green transition ▸ More
5. Schumpeterian innovation ▸ More
6. Convex fossil fuel extraction costs ▸ More

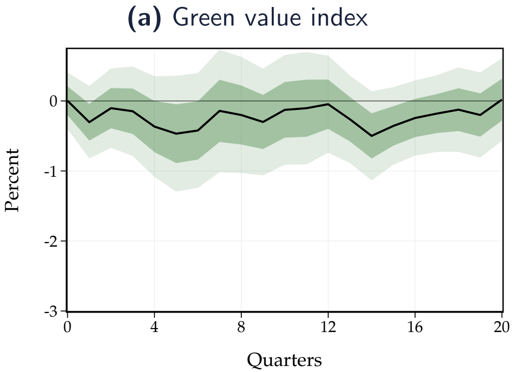
Testing model predictions in the data

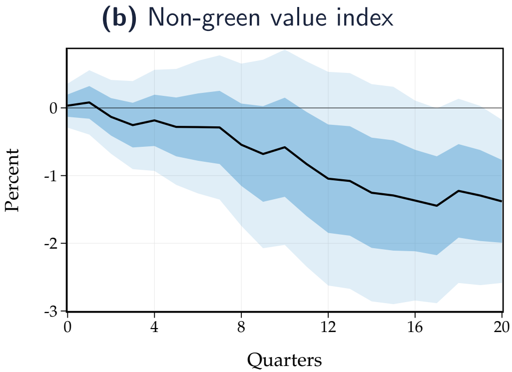
- How does the **value** of patents respond to monetary policy shocks?
- Merge market-implied **patent value data** from Kogan et al. (2017)
  - Construct real aggregate value indices using cumulative values of green and non-green patents at the firm level
  - Focus on **high-quality patents** (cited and filed in multiple countries)
- Estimate firm-level local projections using aggregate value indices

$$value_{i,t+h} = \alpha_i^h + \theta^h r_t + \beta_{xi}^h \mathbf{x}_{i,t-1} + \beta_x^h \mathbf{x}_{t-1} + \varepsilon_{i,t+h}$$

  - Otherwise identical empirical specification as before

Testing model predictions in the data





Notes: Shaded areas denote 68% and 95% confidence bands based on Driscoll-Kraay SE

- In line with the model, valuations are less procyclical for **green patents**
  - Similar results for patent-level regressions

▸ Patent-level regressions

Conclusion

Conclusion

- New stylized fact: **Green innovation** is **countercyclical**
    - Holds both in the aggregate and at the firm level, across countries and shocks
- Can be explained by "green is in the future" along transition
    - Green innovation driven by future profitability, less sensitive to short-run fluctuations
    - In GE, recessions lower wages $\Rightarrow$ reduce green R&D costs $\Rightarrow$ more green innovation
- Important implications for **policy**
    - Short-term business cycle fluctuations can affect green innovation
    - Business cycles complicate interpreting progress of green transition and can confound analyzing impacts of climate policies

Thank you!

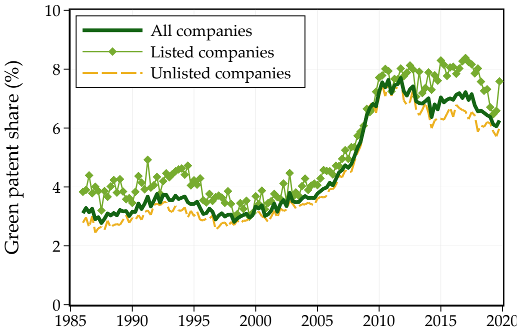
Categories in Y02

CPC code	Description	Number of patents	Share of sample
Y02E	Production, distribution and transport of energy	109682	35.9%
Y02T	Transportation	63053	20.7%
Y02P	Industry and agriculture	61760	20.2%
Y02A	Adaptation to climate change	34258	11.2%
Y02B	Buildings	32598	10.7%
Y02D	ICT aiming at reduction of own energy use	31350	10.3%
Y02W	Wastewater treatment or waste management	14995	4.9%
Y04S	Smart grids	9832	3.2%
Y02C	Capture and storage of greenhouse gases	4416	1.5%

Examples of green patents

Patent number	Patent name	Applicant	Filing date	CPC codes
US5959787	Concentrating coverglass for photovoltaic cells	The Boeing Company	26.11.1996	Y02E
US6461947	Photovoltaic device and making of the same	Hitachi, Ltd.	07.09.2000	Y02E, Y02P
US20070267290	Photovoltaically powered cathodic protection system for automotive vehicle	Ford Global Technologies, LLC	16.05.2006	Y02T
US20180054064	Smart main electrical panel for energy generation systems	Tesla, Inc.	29.09.2016	Y02B, Y02E

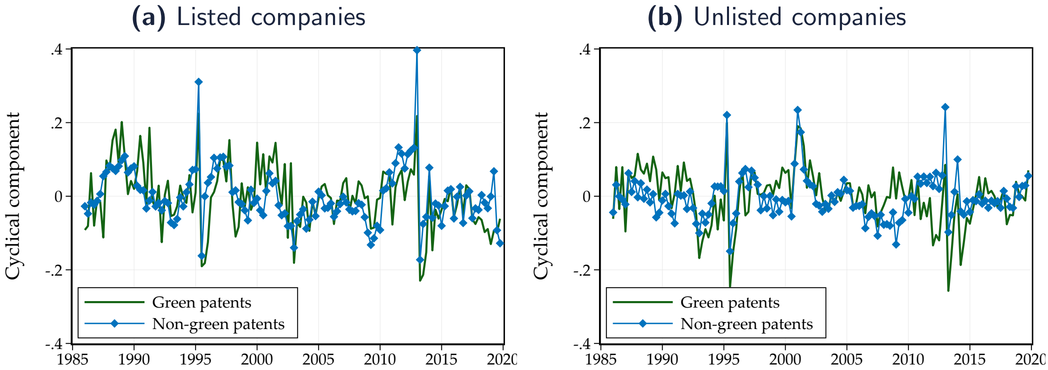
Green patenting by listed and unlisted U.S. firms



- Similar green patenting behavior by listed and unlisted U.S. companies
  - Identified using patents linked to Compustat firms

Back

Cyclicality of green patenting by listed and unlisted U.S. firms



Notes: Cyclical components extracted using the Hodrick-Prescott filter with $\lambda = 1,600$

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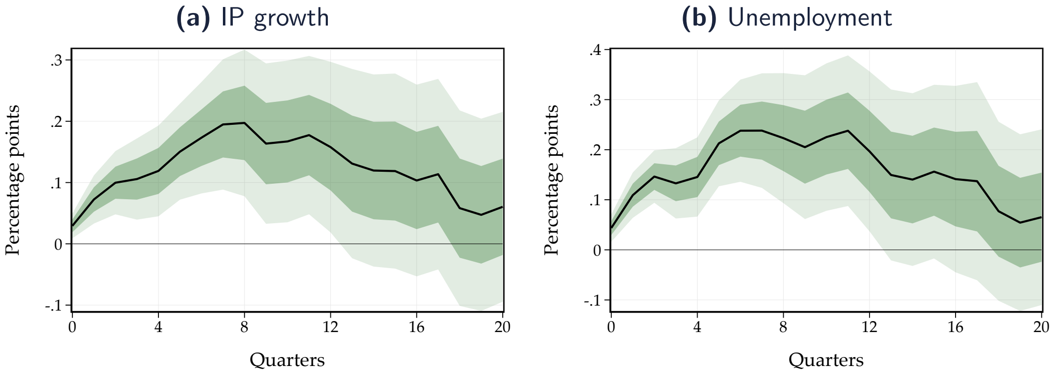
Response of green patent share to other business cycle shocks



Notes: Shaded areas denote 68% and 95% confidence bands based on lag-augmented SE

- Similar response of green patent share to industrial production growth or unemployment shock

Back

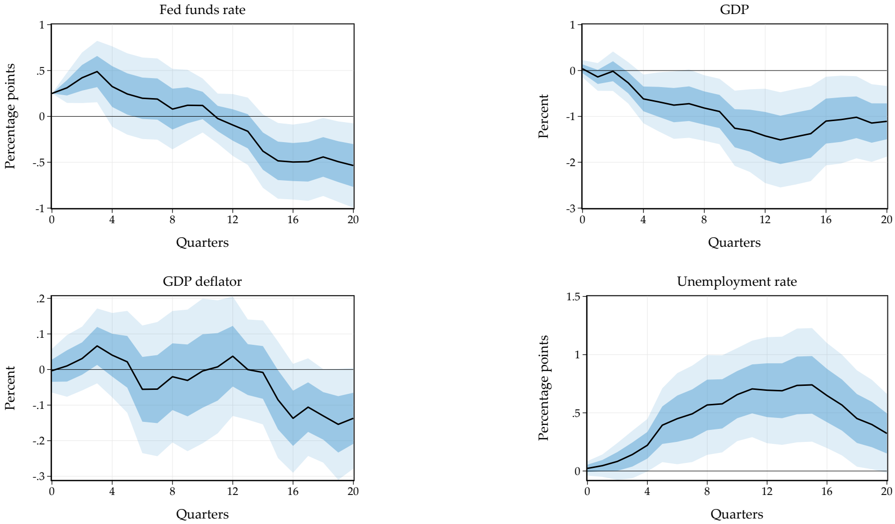
High-frequency monetary policy surprises

- **Identification problem**: monetary policy is endogenous to economic conditions
- **High-frequency identification**: isolate **unexpected component** of monetary policy from financial data around policy announcements
  - E.g. interest rate futures in 30-minutes around FOMC (Gertler and Karadi, 2015; Nakamura and Steinsson, 2018)
  - Confounding factors are priced in ex-ante, unlikely to change in narrow window
- Bauer and Swanson (2023): Regress surprises on lagged macro-financial controls
  - Additional step **purges any remaining predictability**

$\Rightarrow$ We take the surprise series "off-the-shelf", verify robustness to other shocks

◂ Back

Macro impacts of monetary policy shocks



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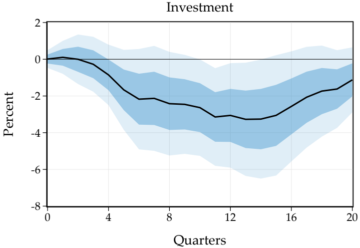
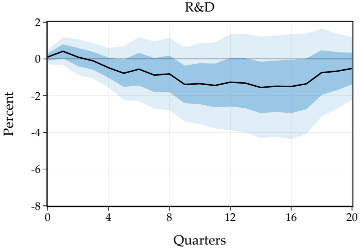
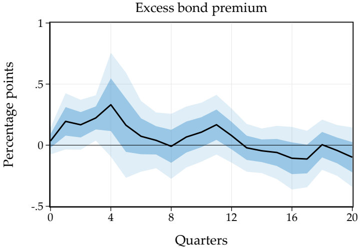
Macro impacts of monetary policy shocks







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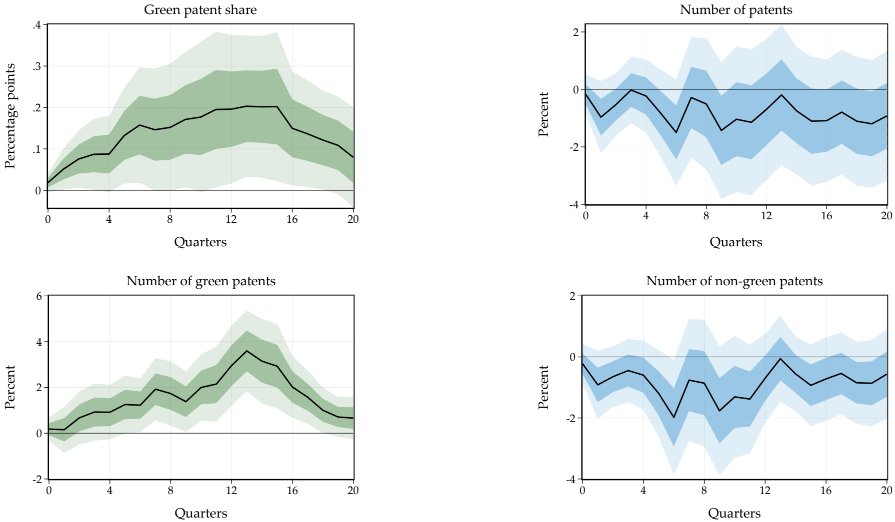
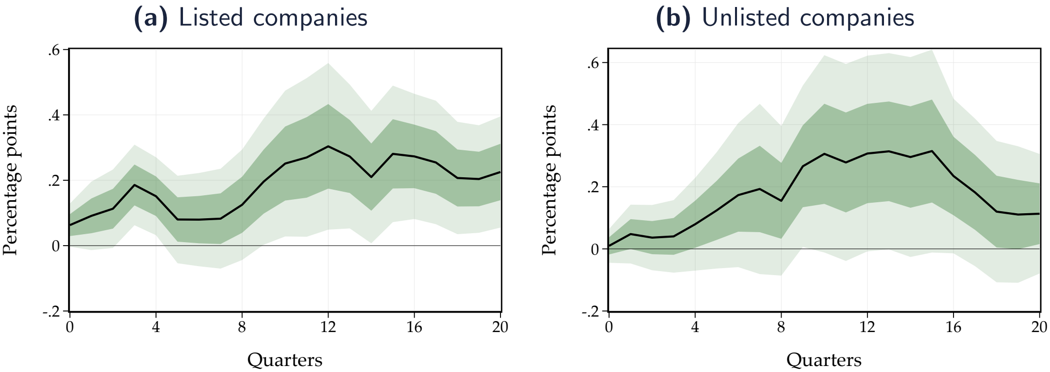
Patenting response in OECD countries



◂ Back

Green patent share response of listed and unlisted U.S. firms

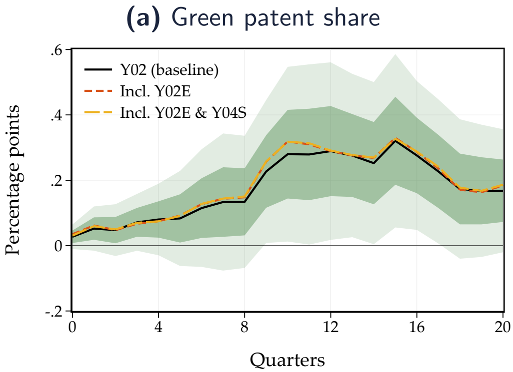


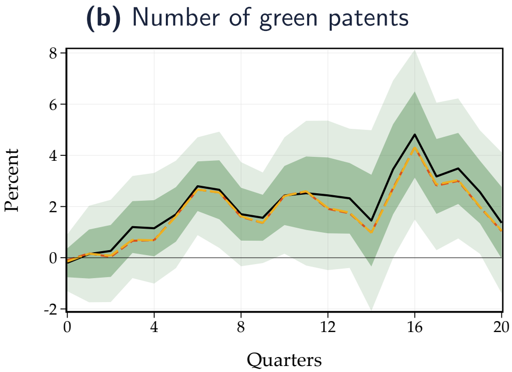
Notes: Shaded areas denote 68% and 95% confidence bands based on robust SE

- Similar results for listed (based on Compustat) and unlisted firms

Back

Sensitivity with respect to green patent classification





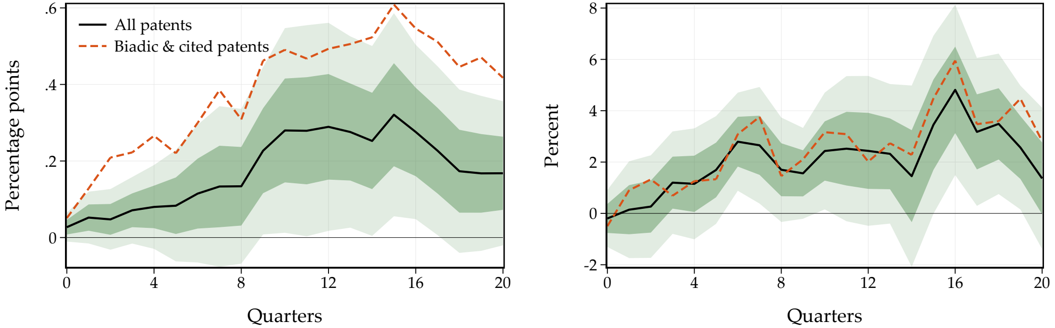
Notes: Shaded areas denote 68% and 95% confidence bands based on robust SE

- Robust to including patents aimed at decarbonizing fossil fuel electricity generation (Y02E20-Y02E60) and smart grid technologies (Y04S)

Back

Sensitivity with respect to patent quality

(a) Green patent share **(b)** Number of green patents



Notes: Shaded areas denote 68% and 95% confidence bands based on robust SE

- Comparable results conditional on cited patents filed in multiple countries

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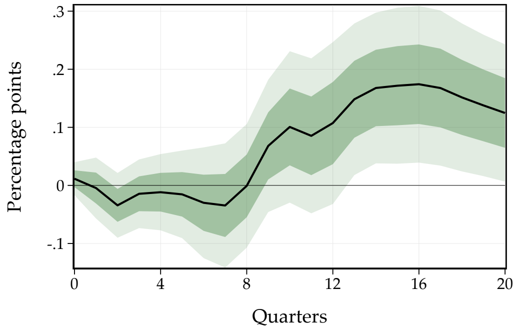
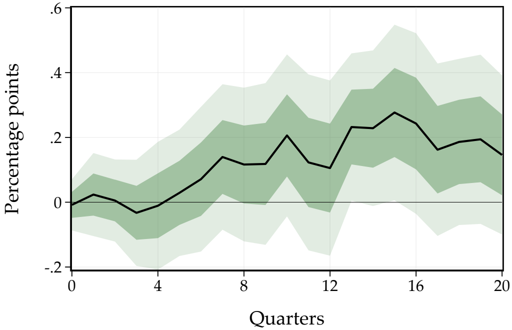
Green patent share response using alternative monetary shocks



Notes: Shaded areas denote 68% and 95% confidence bands based on robust SE

- Comparable results with monetary surprises by Jarociński and Karadi (2020) in first stage

Green patent share response conditional on oil shocks



Notes: Shaded areas denote 68% and 95% confidence bands based on robust SE

- Recessionary oil supply shock (raising energy prices) increases green patent share
  - Instrument WTI using Känzig (2021) oil supply news shocks
  - Map dynamic responses to 10 USD increase in real WTI price

◂ Back

Green Innovation by the 20 Largest U.S. 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

◂ Back

Mapping out heterogeneity in patenting responses

- Add interaction term to PPML estimator

$$\mathrm{E}(\sum_{h=1}^{20} y_{i,t+h}) = \exp(\alpha_i + \delta_t + \gamma r_t d_{i,t-1} + \boldsymbol{\beta}_{xi}\mathbf{x}_{i,t-1} + \varepsilon_{i,t+h})$$

- $d_{i,t-1}$: lagged, standardized firm-level characteristic
- δ_t: Time fixed effects
- Bootstrap standard errors clustered at the time level

◂ Back

Other dimensions of heterogeneity

Dep. var.:	Green patents$_{it+h}$					Non-green patents$_{it+h}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
r_t	1.57***	0.81*	2.09***	1.83***	1.76***	-4.09***	-4.60***	-5.11***	-3.51***	-3.45***
	(0.38)	(0.46)	(0.59)	(0.36)	(0.37)	(0.52)	(0.55)	(0.64)	(0.53)	(0.53)
$r_t \times$ leverage$_{it-1}$	0.31					-0.47				
	(1.30)					(3.90)				
$r_t \times$ age$_{it-1}$		-0.25					-0.11			
		(0.29)					(0.09)			
$r_t \times$ size$_{it-1}$			0.06					0.10		
			(0.26)					(0.21)		
$r_t \times$ st debt$_{it-1}$				0.06					0.05	
				(0.04)					(0.05)	
$r_t \times$ tobinsq$_{it-1}$					0.06					0.02
					(0.05)					(0.04)
Observations	78,899	74,555	82,643	80,298	81,402	78,915	74,372	82,590	80,354	81,400
Firms	1,552	1,291	1,552	1,510	1,544	1,552	1,291	1,552	1,510	1,544

Notes: Bootstrapped standard errors clustered at the time-level in parentheses

Back

- Little heterogeneity with other observable firm-level characteristics

The energy composite

- Energy composite E_t generated from fossil fuel f_t and green energy G_t
  - CES technology:

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

  - ρ governs the elasticity of substitution between f_t and G_t
  - Assumption: $\rho > 1$. Green energy and fossil fuel are substitutes

Back

The final goods producer

- Production function:

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

  - where L_t: unskilled labor, M_t: material composite, E_t: energy composite

- Aggregate labor productivity: $\ln Z_t = \rho_z \ln Z_{t-1} + \sigma_z \varepsilon_t^z$

Back

The fossil fuel market

- We follow Acemoglu, Akcigit, and Kerr (2016) to model the fossil fuel market
- **Competitive markets:** Extraction follows a linear technology:

$$f_t = \xi_f \cdot y_t^f,$$

where $\xi_f > 0$ governs extraction productivity.

  - Robustness: Convex extraction cost function (Bornstein, Krusell and Rebelo 2023)

- Evolution of oil reserves R_t is described by

$$R_{t+1} = R_t - f_t.$$

- Resource constraint:

$$\lim_{t\to\infty} R_t \geq 0.$$

◂ Back

Demand for green and material varieties

Final good producer's optimization problem

$$\max_{L_t,\{m_{ht}\},f_t,\{g_{jt}\}} P_t\left[(Z_t L_t)^{\alpha_L} M_t^{\alpha_M} E_t^{1-\alpha_L-\alpha_M}\right] - \int_0^{A_t^M} p_{ht}^m\, m_{ht}\, dh - \int_0^{A_t^G} p_{jt}^g\, g_{jt}\, dj - P_t^f f_t$$

Input demand

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

Price indices

$$P_t^M = \left(\int_0^{A_t^M} (p_{ht}^m)^{\frac{1}{1-\mu_M}}\, dh\right)^{1-\mu_M}, \quad P_t^G = \left(\int_0^{A_t^G} (p_{jt}^g)^{\frac{1}{1-\mu_G}}\, dj\right)^{1-\mu_G}$$

Back

Condition for the Green transition

Lemma (Condition for the Green Transition)

Define the Green Transition as the process in which the green share of energy, $\frac{G_t}{E_t}$*, increases during the transition period. The economy undergoes the Green Transition if and only if* $\frac{P_t^f}{P_t^G}$ **increases over time**, *where* $P_t^G = \mu_G (A_t^G)^{1-\mu_G}$.

Back

Disentangling cash flow and discount rate channels

Effect of aggregate shocks on green and material values can be decomposed as:

$$\frac{d\log V_t^K}{d\log Y_t} = \underbrace{\sum_{s=0}^{\infty} \phi^s \frac{\Lambda_{t,t+s,ss}\Pi^K_{t+s,ss}}{V^K_{t,ss}} \frac{d\log \Pi^K_{t+s}}{d\log Y_t}}_{\text{Cash flow channel}} + \underbrace{\sum_{s=0}^{\infty} \phi^s \frac{\Lambda_{t,t+s,ss}\Pi^K_{t+s,ss}}{V^K_{t,ss}} \frac{d\log \Lambda_{t,t+s}}{d\log Y_t}}_{\text{Discount rate channel}:=\Xi^K},$$

for $K = \{M, G\}$

Corollary 3 (Discount Factor Channel)

During the Green transition, a procyclical SDF $\left(\frac{\partial \log \Lambda_{t+s,t+s+1}}{\partial \log Y_t} > 0 \text{ for } s \in \mathbb{N}\right)$ implies that $\frac{d\ \Xi^G}{d\log Y_t} > \frac{d\ \Xi^M}{d\log Y_t}$, whereas a countercyclical SDF implies that $\frac{d\ \Xi^G}{d\log Y_t} < \frac{d\ \Xi^M}{d\log Y_t}$.

$\Rightarrow$ Countercyclical (procyclical) SDF amplifies (dampens) green countercyclicality

Back

Balanced growth path and green transition

- We assume the economy is on a **green transition** along a **BGP**
- **Green transition** requires pace of green innovation exceeds obsolescence rate ϕ
  - Confirm this holds for empirically plausible calibrations
- **Balanced growth path** is a sequence of allocations and prices, such that:
  - The equilibrium conditions of the model are satisfied at each t
  - Aggregate variables Y_t, C_t, M_t, E_t grow at a constant rate as $t \to \infty$
  - Input shares $\frac{1}{Y_t}\int_0^{A_t^M} m_{ht}dh$ and $\frac{1}{Y_t}\int_0^{A_t^G} m_{jt}dj$ converge to constants as $t \to \infty$
- **Existence of BGP** requires that in the long run, as $f_t \to 0$:
  - Technology levels grow at the same rate over time, satisfying $A_t^M = \iota A_t^G$
  - Y_t grows at constant exponential rate determined by technology levels

Back

Innovation technology

- Innovators hire skilled labor for R&D: $L^S_{it,M}$, $L^S_{it,G}$
- **Linear** technology of innovation with productivity (Romer 1990):

$$\varphi_t^M = \zeta_M A_t^M \left(L^S_{t,M}\right)^{-(1-\nu)}, \qquad \varphi_t^G = \zeta_G A_t^G \left(L^S_{t,G}\right)^{-(1-\nu)}$$

  - $\zeta_M, \zeta_G > 0$ are scaling parameters
  - Congestion externality $0 < \nu < 1$: as more innovators engage in R&D, each innovation becomes less effective due to competition $\rightarrow$ prevents corner solutions

Back

Cyclicality during the Green Transition in GE

- Cash flow channel dominates under log utility assumption

Corollary 4 (Cyclicality during the Green Transition in GE)

During the green transition in the general equilibrium with an endogenous SDF, conditional on both preference and TFP shocks, the relative value of innovation, defined as $\frac{\mathcal{V}_t^G}{\mathcal{V}_t^M}$, exhibits countercyclicality.

Formally, $\frac{d\log \mathcal{V}_t^G}{d\log Y_t} < \frac{d\log \mathcal{V}_t^M}{d\log Y_t}$, or equivalently $\frac{d\log\left(\mathcal{V}_t^G/\mathcal{V}_t^M\right)}{d\log Y_t} < 0$.

Back

The household sector

- Focus on representative household, as all households are identical

- Maximize expected present value of utility over consumption and labor:

$$\mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \left(\varrho_t^D \log C_t - \frac{\bar{\omega}}{1+\eta} L_t^{1+\eta} - \frac{\bar{\omega}^s}{1+\psi} \left(L_t^s\right)^{1+\psi} \right)$$

  - Time preference shock: $\ln \varrho_t^D = \rho_D \ln \varrho_{t-1}^D + \sigma_D \varepsilon_t^D$

- The consumer's budget constraint:

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

◂ Back

Market clearing

- Labor market clearing of skilled and unskilled labor:

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

- Intermediate inputs market clearing:

$$M_t = \int_0^{A_t^M} m_{ht} dh, \quad G_t = \int_0^{A_t^G} g_{jt} dj$$

- Final good market clearing:

$$C_t + M_t + G_t + \xi_f^{-1} f_t = Y_t$$

- The remaining markets clear by Walras' law

◂ Back

GE effects depending on elasticity of labor supply

- The strength of GE channel depends on elasticity of skilled labor supply:

Corollary 1

During the Green transition, 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:

$$\frac{\partial \log S_t^M}{\partial \log Y_t} > 0, \qquad \frac{\partial \log S_t^G}{\partial \log Y_t} < 0.$$

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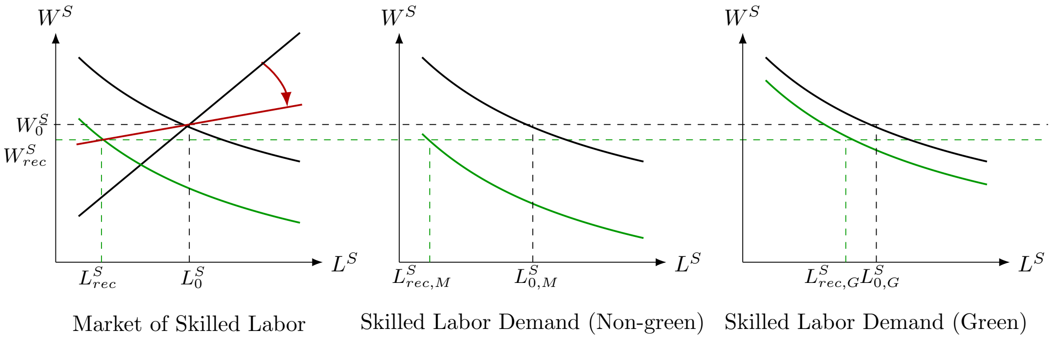
GE effects depending on elasticity of labor supply



- More elastic supply of labor dampens strength general equilibrium channel

GE channel conditional on monetary policy shocks

We extend the model to include

- Nominal rigidities, where retailers face Rotemberg price adjustment costs
- Monetary policy through a Taylor rule and incorporate a monetary shock ϱ_t

Corollary 2

During the green transition, there exists a threshold $\bar{\epsilon}_m > 0$. If the wage elasticity to output of skilled labor, $\frac{\partial \log W_t^s}{\partial \log \varrho_t^m}$, is greater than $\bar{\epsilon}_m$, then in equilibrium:

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

Next slide: more on the model extension

Back

More on model extension incorporating monetary shock: I/III

- **Households** purchase basket of differentiated retail goods indexed by i:

$$\tilde{Y}_t = \left(\int_0^1 \tilde{y}_{it}^{\frac{\sigma-1}{\sigma}} \, di \right)^{\frac{\sigma}{\sigma-1}}$$

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

- Demand function for variety i: $\tilde{y}_{it} = \left(\frac{\tilde{p}_{it}}{\tilde{P}_t} \right)^{-\sigma} \tilde{Y}_t$
  - Aggregate demand: $\tilde{Y}_t$
  - Price of variety i: $\tilde{p}_{it}$

- Corresponding price index $\tilde{P}_t = \left(\int_0^1 \tilde{p}_{it}^{1-\sigma} dk \right)^{\frac{1}{1-\sigma}}$

Back

More on model extension incorporating monetary shock: II/III

- Fixed mass of **retailers** $i \in [0, 1]$ produce retail goods from final good producer
  - Production technology is one-to-one: $\tilde{y}_{it} = y_{it}$
  - y_{it}: amount of final good purchased by retailer i

- Retailers set prices with Rotemberg price adjustment costs: $\frac{\varphi}{2}\left(\frac{\tilde{p}_t}{\tilde{p}_{t-1}} - 1\right)^2 \tilde{Y}_t$

- Each retailer maximizes its expected discounted profit subject to demand:

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

◂ Back

More on model extension incorporating monetary shock: III/III

- Retailers' optimal price-setting condition:

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

- The **central bank** follows a Taylor Rule:

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

- ϱ_t is a monetary shock:

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

◂ Back

Robustness: Brown Innovation

- Identical setup for brown energy composite F_t, aggregating brown varieties f_{st}:

$$F_t = \left(\int_0^{A_t^F} f_{st}^{\frac{1}{\mu_F}} \, ds \right)^{\mu_F}$$

- Energy composite then aggregates green and brown components via CES technology:

$$E_t = \left(G_t^{\frac{\rho-1}{\rho}} + F_t^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}$$

- With brown innovation, green transition requires P_t^F / P_t^G is increasing

- Conditional on green transition, green profits are more backloaded (Proposition 1: ✓)

⇒ The main results of the model remain valid:

  - Relative value and share of green varieties is countercyclical (Propositions 2&3: ✓)
  - Number of green varieties is countercyclical due to GE effect (Proposition 4: ✓)

Back

Robustness: Aghion-Howitt Model

- Green energy input aggregation (symmetric for materials): $G_t = \left(\int_0^1 A_{jt}^g g_{jt}^{\frac{1}{\mu_G}} \, dj\right)^{\mu_G}$
- Quality ladder: $A_{jt}^g = \lambda^{n_{jt}} A_{j0}^g$
    - Productivity multiplier $\lambda^{n_{jt}}$ tracks technological progress (quality improvements)
- Value of a product line subject to endogenous probability of creative destruction, ϕ_{jt}^g:

$$V_{jt}^g(\lambda A_{jt}^g) = \Pi_{jt}^g(\lambda A_{jt}^g) + (1 - \phi_{jt}^g) E_t \Lambda_{t,t+1} V_{jt+1}^g(\lambda A_{jt}^g)$$

- There is no analytical solution to innovation rate, but we can still show:
    - Conditional on green transition, green profits are more backloaded (Prop. 1: ✓)
    - For a linear innovation technology in partial equilibrium setup, relative value and share of green varieties is countercyclical (Propositions 2&3: ✓)

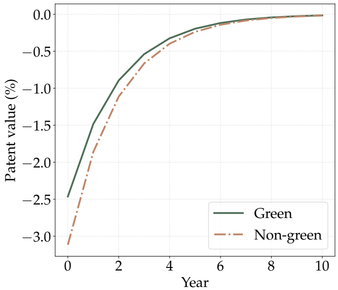
◂ Back

Robustness: Aghion-Howitt Model

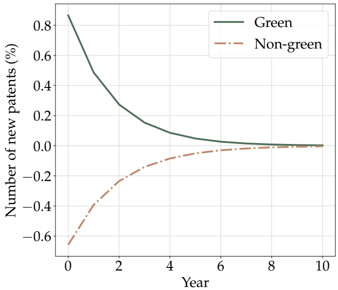
Back

- Similar responses as in baseline model, although dampened response of green share

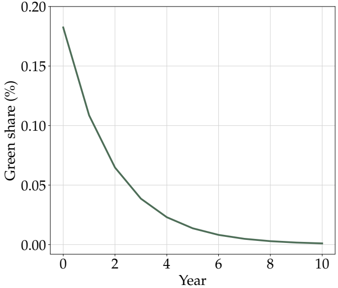
(a) IP value of a new variety



(b) Number of new varieties



(c) Green share



Notes: Impulse responses to 25 bp monetary contraction

Calibration: innovation parameters ζ_M, ζ_L, and λ to match a long-run creative destruction rate of 8% and output growth rate of 3%

Calibration

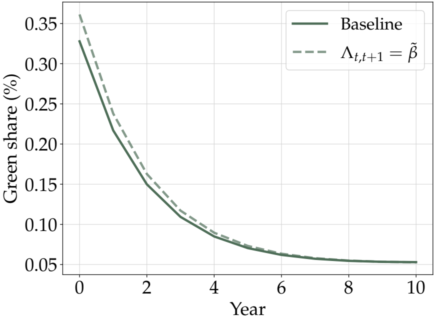
Parameter	Description	Value	Target / Source / Comments
β	Discount factor	0.98	Match 2% annual rate
α_L	Final good labor share	0.5	Comin and Gertler (2006)
α_M	Final good material share	0.4	Matches 10% energy income share
μ_M, μ_G	Markups	2	Ensures balanced growth path
ρ	Substitution between green and fossil energy	2	Acemoglu et al. (2012)
f_0	Initial share of fossil in energy mix	80%	U.S. EIA
γ	Research elasticity	0.5	Acemoglu et al. (2018)
$1-\phi$	Obsolescence rate	0.03	Comin and Gertler (2006), Ma (2021)
τ	Patent duration	15	U.S. patent law
$1/\eta$	Frisch elasticity of labor supply	2	Kydland and Prescott (1982); King and Rebelo (1999)
$1/\psi$	Frisch elasticity of skilled labor	0.5	Chetty et al. (2011); Elminejad et al. (2023)
ζ_M, ζ_G	Innovation scaling parameters	–	Match 3% GDP growth
c	Fixed setup cost	0.97	Matches 1.7% output growth std. dev.
φ	Price adjustment cost parameter	90	Ottonello and Winberry (2020)
σ	Elasticity of substitution between final good varieties	10	Ottonello and Winberry (2020)
φ_π	Taylor rule inflation coefficient	1.69	Calibrated
φ_A	Taylor rule medium-term component response	1	Full offset of medium-term shocks
σ_Z	Std. dev. of technology shock	0.02	Matches 1% output std. dev.
ρ_z	Persistence of technology shock	0.5	Assumed

Back

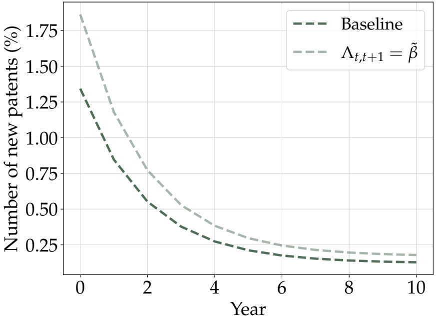
Decomposition: Holding the discount factor fixed

Back

(a) Green share of new patents



(b) Number of new green varieties



Notes: Impulse responses to 25 bp monetary contraction

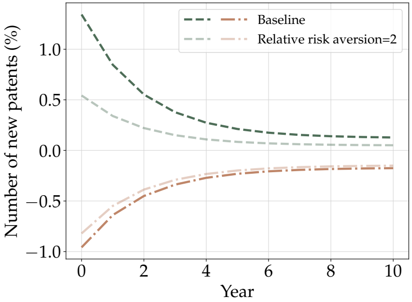
- Discount rate channel goes against cash flow channel, as SDF is procyclical
    - But: small quantitative difference shows that **cash flow channel dominates**

Robustness: Varying the intertemporal elasticity of substitution

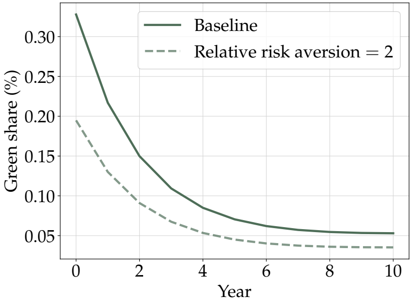
Back

- CRRA utility: $U_t = \frac{C_t^{1-\sigma}}{1-\sigma} - \frac{\bar{\omega}}{1+\eta} L_t^{1+\eta} - \frac{\bar{\omega}^s}{1+\psi} \left(L_t^s\right)^{1+\psi}$
- Increasing $\sigma = 2$: Lower IES, strengthening the discount rate channel
  - $\Rightarrow$ Agents shift less consumption into the future, which hurts green more

(a) New Patents



(b) Green share of new patents



Notes: Impulse responses to 25 bp monetary contraction

Robustness: Time preference shock

- Recall from household problem:

$$\mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \left(\varrho_t^D \log C_t - \frac{\bar{\omega}}{1+\eta} L_t^{1+\eta} - \frac{\bar{\omega}^s}{1+\psi} \left(L_t^s \right)^{1+\psi} \right)$$

- Time preference shock ϱ_t^D alters margin utility of consumption, as well as IES

$\Rightarrow$ Can generate a countercyclical SDF:

$$\Lambda_{t,t+1} = \beta \frac{\varrho_{t+1}^D C_t}{\varrho_t^D C_{t+1}}$$

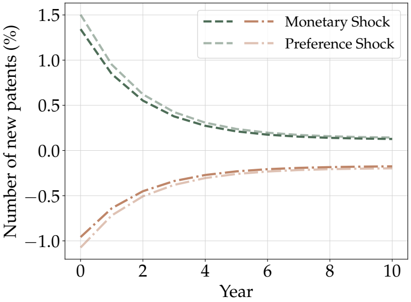
  - $\varrho_t^D \downarrow$ lowers output but increases SDF

Robustness: Time preference shock

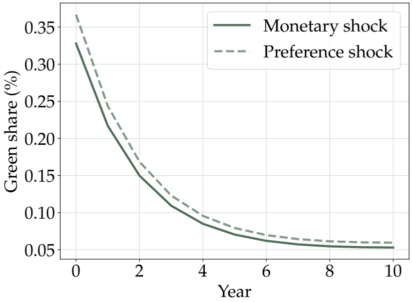
◂ Back

- Stronger green patenting responses to contractionary time preference shock
  - Why? Discount rate channel reinforces cash flow channel
  - But: small quant. difference confirms **cash flow channel is main driver**

(a) New Patents



(b) Green share of new patents



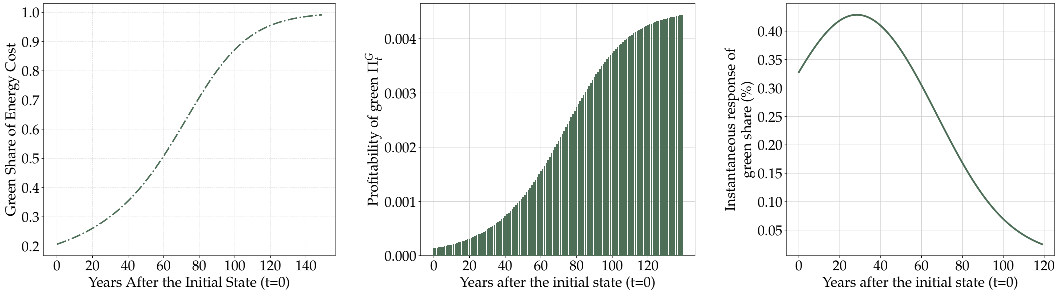
Notes: Impulse responses to a time preference/monetary shock that reduces output by 1% at $t = 0$

Robustness: Green Is in the Future along the transition path

Back

- **(a)**: Green energy share rises gradually along transition path (50% after 60 years)
- **(b)**: Green profits $\Pi_t^G = (\mu_G - 1)\bar{g}_t$ follow similar trajectory

(a) Green Share of Energy **(b)** Profit of Green Production **(c)** Green Share of New Patents

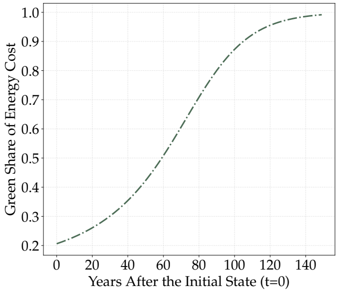


Robustness: Green Is in the Future along the transition path

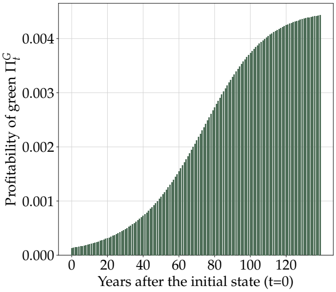
Back

- **(c)**: Instantaneous response of the green share to monetary shock at different t
  - Green is in the future strengthens in short-term with slope of green profits, vanishes in long-term as green profits stabilize

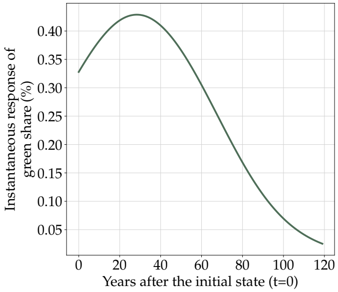
(a) Green Share of Energy



(b) Profit of Green Production



(c) Green Share of New Patents

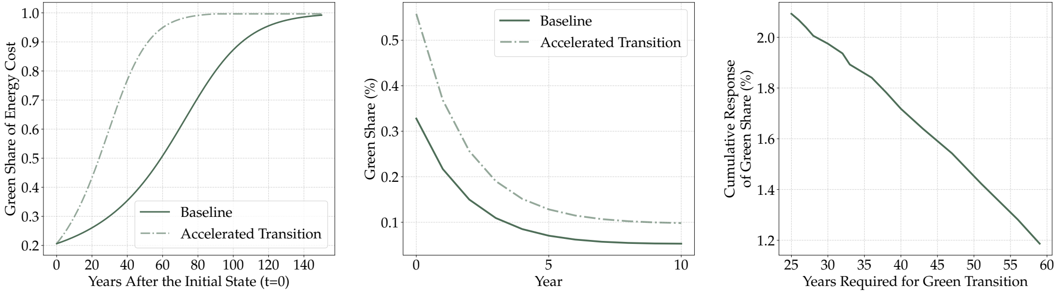


Robustness: Accelerated green transition

◂ Back

- **(a)**: Increasing scale parameters of innovation ζ_G and ζ_M by 20%
  - New green and non-green varieties arrive at faster pace relative to survival probability

(a) Green Share of Energy   **(b)** IRF of Green Share $t = 0$ **(c)** Green Share of New Patents

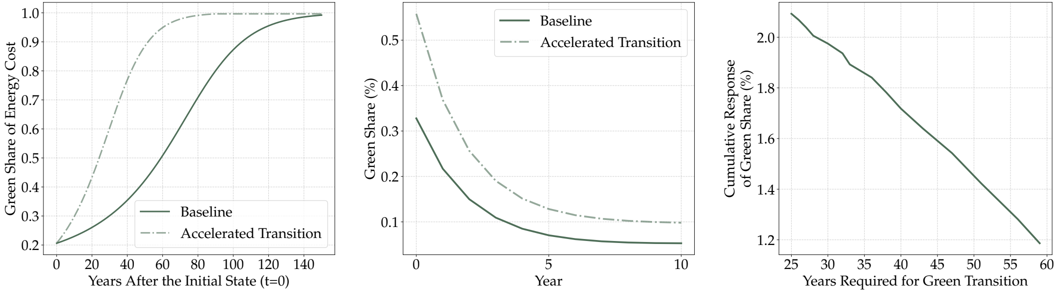


Robustness: Accelerated green transition

Back

- **(b)**: Green share becomes more countercyclical in response to monetary shock
  - In the short-term, slope of green profits becomes "steeper"

(a) Green Share of Energy **(b)** IRF of Green Share $t = 0$ **(c)** Green Share of New Patents

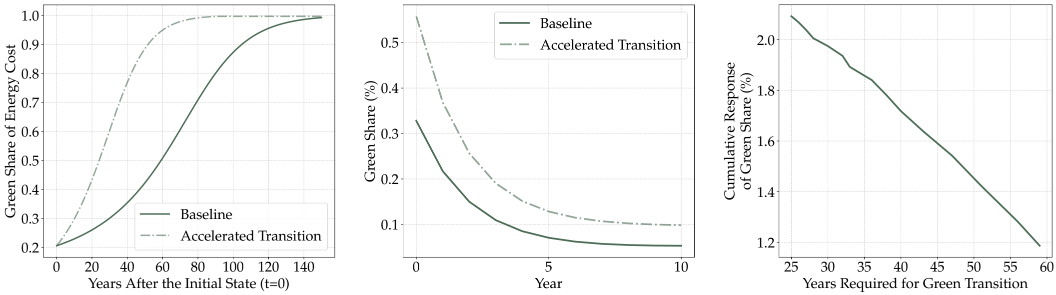


Robustness: Accelerated green transition

Back

- **(c)**: Green share response depending on years required to reach 50% green energy
  - Faster transition implies stronger green countercyclicality in short-term

(a) Green Share of Energy **(b)** IRF of Green Share $t = 0$ **(c)** Green Share of New Patents



Robustness: Convex fossil fuel extraction cost function

- Extraction cost depends nonlinearly on the extraction rate (Bornstein et al. 2023)
  - Generates increasing marginal costs as observed in the data

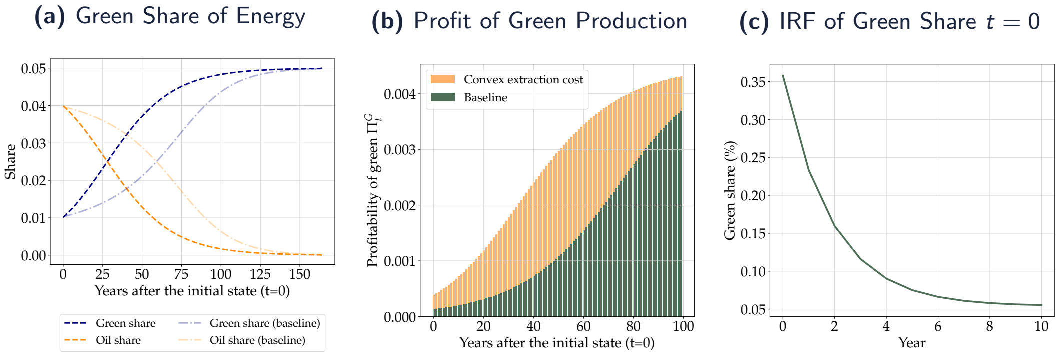
$$c^F(\theta_t) = \psi^F(\theta_t)^{\eta^F} R_t$$

  - $\theta_t \equiv \frac{f_t}{R_t}$ denotes the extraction rate
  - Set $\eta^F = 2$ (Bornstein et al. 2023), normalize scale parameter $\psi^F = 1$
- Procyclical movements in fossil price accelerates the green transition
  - Green profits become more frontloaded $\rightarrow$ amplifies procyclicality
- But: fossil fuel becomes relatively cheaper in recessions, dampening substitution

Robustness: Convex fossil fuel extraction cost function

Back

⇒ Countercyclicality of green share still holds



Notes: Impulse responses to 25 bp monetary contraction under the alternative fossil extraction technology

Patent-level regressions

- Alternatively, run regressions at the patent level

$$value_{j,i,t} = \alpha_i + \delta_t + \theta r_t \times green_{j,i,t} + \varepsilon_{j,i,t}$$

- $value_{j,i,t}$: (log) real value of patent j filed by firm i in quarter t
  - $green_{j,i,t}$: green patent dummy
- Control for firm i and time t fixed effects
- Control for patent quality: biadic patent dummy and number of citations

Patent-level regressions

	Dependent variable: $100\times\log(\text{patent value}_{j,i,t})$			
	(1)	(2)	(3)	(4)
$\Delta\text{GDP}_t \times \text{green}_{j,i,t}$	-2.12***	-2.05***		
	(0.48)	(0.61)		
$\text{r}_t \times \text{green}_{j,i,t}$			2.48***	2.47***
			(0.52)	(0.52)
Observations	1,256,917	1,256,917	1,256,917	1,256,917
Firm fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Quality controls	No	Yes	No	Yes

Notes: 1 pp increase in ΔGDP_t and 25 bp increase in r_t. Robust SE in parentheses

- Green patent values are less cyclical than non-green patent values
    - Holds unconditionally and conditional on monetary policy shocks

Back

Evidence from USPTO patent renewals

- Test model prediction that green patents exhibit more backloaded profits
- U.S. patents must be renewed at 3.5, 7.5, and 11.5 years to stay active
  - We can track these using data on USPTO maintenance fee payments
- Estimate logistic regression of renewal probability of patent j:

$$P(renewal)_{j,t} = \alpha + \delta_t + \theta \, green_{j,t} + \varepsilon_{j,t},$$

  - Control for patent quality, time fixed effects
- Robustness: Duration measure and maintenance score (Porter et al. 2024)

Evidence from USPTO Patent Renewals

	Logit	OLS	
Dependent variable:	$P(\text{renewal})_{j,t}$	$\text{Duration}_{j,t}$	$\text{Maintenance score}_{j,t}$
	(1)	(2)	(3)
$\text{green}_{j,t}$	0.36***	0.36***	0.09***
	(0.01)	(0.01)	(0.00)
Observations	3,652,350	3,652,350	3,652,350
Pseudo R^2	0.07	0.06	0.06
Quality controls	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes

- Green patents are likelier to be renewed, consistent with more backloaded profits
    - Unconditional renewal probability is 77%

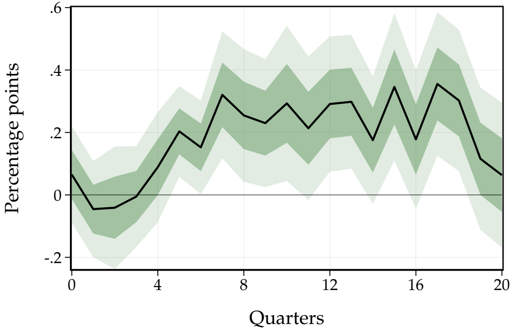
Back

Evidence on green inventors

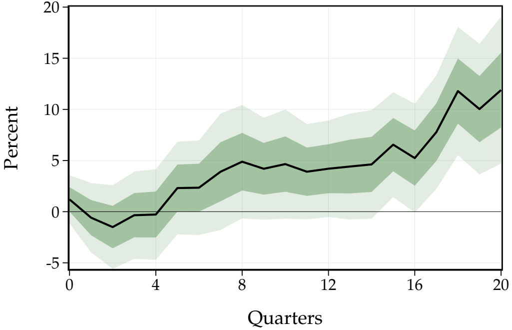
- **Model prediction:** Recessions reduce skilled wages, reducing cost of green R&D
  - Green and non-green innovation become substitutes via labor supply
- Test using bibliographic patent data on inventors
  - Classify green or non-green inventors based on patenting activity
- Construct **firm-level measures** of **green inventors**:
  - Number and share of inventors working on green patents
  - Number inventors working on *first* green patent
  - Share of inventors first working on green patents relative to total non-green inventors

Suggestive evidence on the labor market channel

(a) Share of green inventors



(b) Number of green inventors



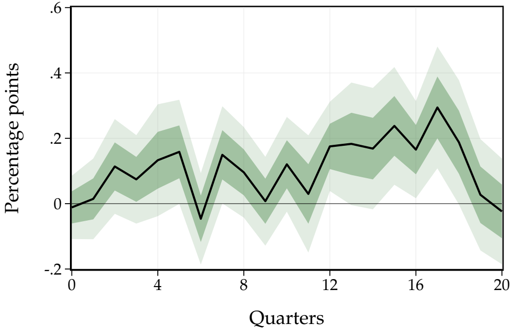
Notes: Shaded areas denote 68% and 95% confidence bands based on Driscoll-Kraay SE

- Number and share of green inventors increases at the firm-level

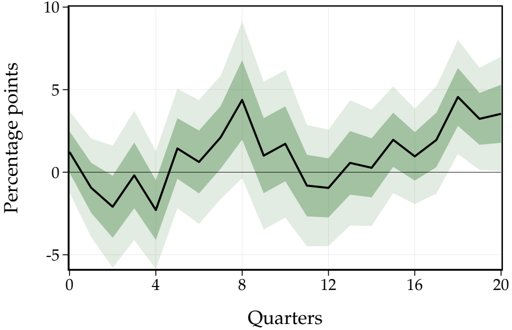
◂ Back

Evidence on new green inventors

(a) Share of new green inventors



(b) Number of new green inventors



Notes: Shaded areas denote 68% and 95% confidence bands based on Driscoll-Kraay SE

- Number and share of **new green inventors** increases at the firm-level
  - Overall increase partially explained by inventors that have not previously patented at the firm

◂ Back