The macroeconomic effects of green technology shocks *

Fabrizio Ferriani† Andrea Gazzani‡ Filippo Natoli§

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Abstract

Assessing the economic implications of the transition towards a more environmentally sustainable economy is a daunting task. By employing two granular datasets on US patenting, we exploit variations in the share of granted US patents for pro-climate technologies to identify *news over the path of the green transition*. Anticipated switches to greener technologies act as negative supply shocks in the short run, reducing output and raising consumer prices, thus implying starker trade-offs in the conduct of monetary policy. However, they also induce a persistent reduction in carbon emissions and a recomposition in energy use away from fossil fuels: in the longer run, the adverse economic effects dissipate and the emission intensity of production shrinks persistently, highlighting the benefits of a "green shift". As not being affected by variations in the commitment of climate policy to decarbonize, or in the public concern over future climate risks, green innovation emerges as a powerful, stand-alone driver of the low-carbon transition.

JEL classification: E31, E32, O34, Q5

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†Bank of Italy. Email: fabrizio.ferriani@bancaditalia.it.

‡Bank of Italy. Email: andreagiovanni.gazzani@bancaditalia.it.

§Bank of Italy. Email: filippo.natoli@bancaditalia.it.

1 Introduction

The way to achieve the transition towards a low-carbon economy, as well as its economic implications, are at the forefront of the policy debate. As this process requires a substantial reduction of the environmental impact of production and consumption patterns, it is expected to induce a profound transformation of the economy, which may also substantially affect the aggregate output in the short and medium run. At present, the overall impact of the low-carbon transition is still far from being understood. One reason is that this process entails the interplay of technological progress, policy decisions, and preference changes, which makes its pathway and consequences hard to gauge. Several contributions have focused on a particular dimension of the transition, i.e. regulation on carbon emissions and other policy measures, finding that carbon policies are insufficient in achieving the necessary emission reduction if not accompanied by substantial improvements in green technology (Green, 2021; Metcalf and Stock, 2023; Coenen et al., 2023, among others).

Focusing on green innovation, a nascent literature provides opposite views on how much technological advancements do their job in reducing carbon emissions, and whether they might affect the economy through demand- or supply-side effects. The answer to the latter question has direct policy implications, because the output and inflationary effects of a pro-climate technology push can influence the conduct of monetary and fiscal policy. Understanding the impact of green technology is a daunting task, as it requires isolating its dynamics from that of the whole technological process - which is endogenous to the business cycle and the economic outlook.

To tackle this challenge, we use US patents to measure *the expected strength of the green transition* in the United States. Specifically, we employ two granular datasets to construct a monthly variable proxying for the weight green technology is expected to have in the future technology mix. Such measure is obtained as the share in the number of granted patents that are specifically designed for climate change mitigation over total ones: as patents are taken at their filing date (so before final approval), variations over time in the share reflect *news* of a re-composition towards greener technologies, in the spirit of Miranda-Agrippino et al. (2020). Employing the *ratio* of patents is key as it nets out common trends in US patenting - green and non-green patenting are highly correlated over time being technology partly driven by expected macroeconomic conditions: as a proof of that, our measure passes a broad set of exogeneity tests, and it is orthogonal to the most popular macroeconomic shocks identified in the literature. At the opposite, the naive use of the level of green patenting as a shock for the same purpose would lead to misleading results such as the green transition inducing higher (instead of lower) carbon emissions due to the concurrent effects of other demand-side drivers (see Hasna et al., 2023).[1]

We plug our measure into a Vector Autoregressive (VAR) model of the US economy estimated over 1980-2019 to investigate how anticipated shocks to the green transition might propagate throughout the economy. Our results show that an expected shift towards a greener technology leads to a delayed fall in carbon emissions, a drop in output, and a surge in producer and consumer prices in the short-run. This suggests that a relative green technology push can be interpreted as a *temporary, negative supply-side* shock to the macroeconomic environment. At the root of this downside effect lies the negative impact on aggregate productivity (TFP), possibly due to the fact that being green (emission-constrained) technologies at earlier-stage than brown ones, their higher weight in the tech mix makes production temporarily less efficient. Consumer price indexes increase after the shock, both in the headline and core definitions, also because of higher commodity prices raising input costs for producers. Quantitatively, news on the green transition contributes to non-trivial shares of the variance in the endogenous variables, by accounting

[1] We show this finding in Figures A.1-A.2.

for 4% of industrial production, 15% of the unemployment rate, 10% of commodity prices, and 5% of carbon emissions. This explanatory power suggests that, while shifts to green tech cannot be as powerful as aggregate TFP shocks in driving the US business cycle, they nonetheless explain a significant share of macroeconomic fluctuations.

The key question regarding green innovation is about its effectiveness: as the potential of green technologies unfolds in longer time spans, we also explore the dynamic response of carbon emissions and economic variables over longer horizons by relying on local projections, which are known to be less subject to estimation bias. Our results suggest that the negative implications for economic activity and prices are in fact short-lived. According to the impulse responses, while emissions initially decline more slowly than output, this relationship is reversed after five years, ending up as a persistent reduction in the volume of carbon emissions per unit of produced output: such behavior is consistent with a reversal of the response of industrial production, which turns slightly positive at the same horizon. This dynamics goes hand-in-hand with a recomposition of energy use away from fossil fuels and towards green energy sources, and makes our shock stand apart from a general, negative TFP shock. Hence, the economic costs and the highlighted monetary policy trade-off during the initial phase of the transition dissipate in the long-run.

While technology is the key ingredient in the low carbon transition, such complex process is shaped by various forces, such as climate policy and the general concern over future climate-related financial risks. We repeat our estimates by plugging variables proxying variations in the (national and international) climate policy committment, as well as public attention on climate change, and show that the economic impact of our green technology shock is mostly unaffected by such alternative drivers. This evidence strongly points to green innovation as a stand-alone driver of the low-carbon transition.[2]

[2] The interplay between green technology and climate policy connects this paper to the literature deriving measures of transition risk exposure from media or earnings calls: Engle et al. (2020), Ardia et al. (2023),

This paper contributes to the literature in two important ways. First, it provides a way to evaluate the immediate effects of the low-carbon transition by identifying a news effect, i.e. anticipated technological switches leading to a green steady state. Regarding the US economy, this is the only viable strategy to track the steps towards a low-carbon world far back in time, as such an investigation cannot be carried out comprehensively using carbon regulation only. Second, it highlights the unique propagation of a specific strand of innovation, which includes a specific energy channel – driven by a recomposition of energy sources – and a split between short- and longer-run effects. Under the lens of our findings, the trade-off between going green and fostering economic growth, which confirms earlier model-based results, looks as a temporary effect.[3] Our preferred interpretation of the green technology push refers to the growing strand of literature highlighting the crucial role of changing citizens'/consumers' values, i.e. the engine of a bottom-up, pro-climate demand pressure (Besley and Persson, 2023, Aghion et al., 2023, Accetturo et al., 2022, Phelan and Love, 2023, Hong et al., 2023). In particular, our findings complement, from an empirical side, the modeling approach in Besley and Persson (2023), who argue: "*It is useful and plausible to think about demand patterns as reflecting both prices and values, where some consumers care intrinsically about the environmental effects of their choices. This allows us to characterize a green transition as a process whereby the share of those who hold green values endogenously rises over time, and this raises the profitability of using green technologies. [...] Firms use either green or brown technologies with the technology choice depending on expected future profit. Value and technology transitions are interdependent, as green technologies are more profitable with more green consumers and green values are more attractive with more green producers.*" We document that this trade-off between prices and environment matter for the US business cycle.

Sautner et al. (2023), Gavriilidis et al. (2023), Meinerding et al. (2023).

[3]Among them, evidence based on DSGE models such as Ferrari and Nispi Landi, 2022 and Airaudo et al., 2022, or in larger-scale models such as Bartocci et al., 2022b and Coenen et al., 2023.

The remainder of the paper is organized as follows. Section 2 briefly reviews the relevant literature; Section 3 introduces our measure of green innovation shock and describes the data; Section 4 presents the main empirical findings; Section 5 shows the results coming from robustness exercises; Section 6 concludes.

2 Literature

Our paper connects to several strands of the literature. First, the one related to the low-carbon transition and carbon policy. There exist two different takes on the fundamental drivers of the transition towards a low-emission economy. On one hand, some contributions emphasize the competitive nature of clean and dirty technology (Acemoglu et al., 2016, Ramadorai and Zeni, 2023): according to this view, without supportive climate policy, the less-profitable clean technology sector struggles to thrive and faces the risk of disappearing from the market due to the fierce competition from its dirtier counterparts. This perspective underscores the critical role climate policy plays – a "top-down approach" to achieve a greener economy. Coherently, the empirical research in this field has primarily focused on the impacts of unexpected shocks to the conduct of carbon policy (Nordhaus, 2007, Metcalf and Stock, 2020, Känzig, 2022).[4] On the other hand, recent research points to the pivotal role of consumers and firms' preferences as the engine of the transition. This view revolves around the notion that climate risk concerns, consumer preferences, and competition among firms can by themselves stimulate pro-climate research and development (R&D) efforts (Besley and Persson, 2023, Aghion et al., 2023, Accetturo et al., 2022, Barnett et al., 2022, Phelan and Love, 2023, Hong et al., 2023). This perspective

[4]From the modeling side, contributions in the literature include Golosov et al. (2014), Goulder et al. (2019), Rausch et al. (2011), Ferrari and Nispi Landi (2023); for larger-scale models, see Varga et al. (2022), Bartocci et al. (2022a), Carton et al. (2022), Ernst et al. (2022) and Coenen et al. (2023). Empirically, Lin and Li (2011); Metcalf (2019); Bernard et al. (2018); Ohlendorf et al. (2021).

challenges the idea that climate policy is the sole driver of pro-environment technological advancements.

Second, this paper connects to the literature that exploits patents to identify technology shocks.[5] More recently, Miranda-Agrippino et al. (2020) proposed a way to exploit the information embedded in patenting activity to extract news on future TFP growth, and showed that such news causes a business cycle expansion in anticipation of the expected productivity gains. We build on this intuition to construct a news shock regarding the greenness of the future technology mix. Regarding green innovation, a growing literature is investigating the drivers and consequences of green patenting (Popp et al., 2010, Popp, 2019, Cohen et al., 2021, Hege et al., 2023, Moench and Soofi Siavash, 2023, Ciccarelli and Marotta, 2023). The closest paper to ours is Moench and Soofi Siavash (2023), who find that the effects of an increase in the level of green technology are almost identical to those of a general TFP news shock, including *rising* carbon emissions. Such a result is not surprising given the endogeneity of technological progress to current and expected macroeconomic conditions. In contrast, we find that focusing on the *relative* weight of pro-climate patents over total patents is not only a better proxy of a *switch* to greener technology but is also immune from the aforementioned endogeneity issues. Our result, pointing to falling emissions, is also coherent with that in Ciccarelli and Marotta (2023) for a yearly panel of 24 countries, even though, under their international perspective, the reduction in CO2 due to green innovation appears, on average, as more delayed.

[5] Among them, Griliches (1998), Lach (1995), Hall and Trajtenberg (2004), Kogan et al. (2017).

3 Green transition news from patent data

The primary data sources used to construct our green technology news measure for the United States are the *PatEx* and *PatViews* data sets of the U.S. Patent and Trademark Office (USPTO). *PatEx* is a valuable research-oriented, patent-level database (Marco et al., 2017), while *PatViews* provides the *Cooperative Patent Classification* (CPC) for each patent: among them, the category Y02 specifically refers to green patents, i.e. those innovations related to *climate mitigation* efforts. Crucially, the availability of patent data at the monthly rather than annual frequency - as it is for other jurisdictions - allows us to study the business cycle consequences of the transition and, moreover, to tackle the endogeneity in patenting documented in Miranda-Agrippino et al. (2020).

In our analysis, we exclusively consider granted patents due to *PatViews* limitations as we do not have access to the CPC classification for filed but non-granted patents. Nonetheless, granted patents are likely to provide a more robust signal of innovation as they capture the most successful inventions. We follow the narrow definition of green patents in Hege et al. (2023) and, in order to quantify news about the future shifts towards green technology, we calculate the ratio between the number of green patents (pat_G) filed in a given month t to the total number of patents (pat_T) filed in the same month (eq. 1). We consider the filing date (instead of the approval date) as in Miranda-Agrippino et al. (2020) as the literature has documented that the relevant economic news spreads when the application is submitted, way before it is eventually granted. In formulas, we define our green patent proxy as

$$gp_t = \frac{pat_{G,t}}{pat_{T,t}} \tag{1}$$

where $pat_{G,t}$ indicates the number of green patents filed in month t, while $pat_{T,t}$ is the

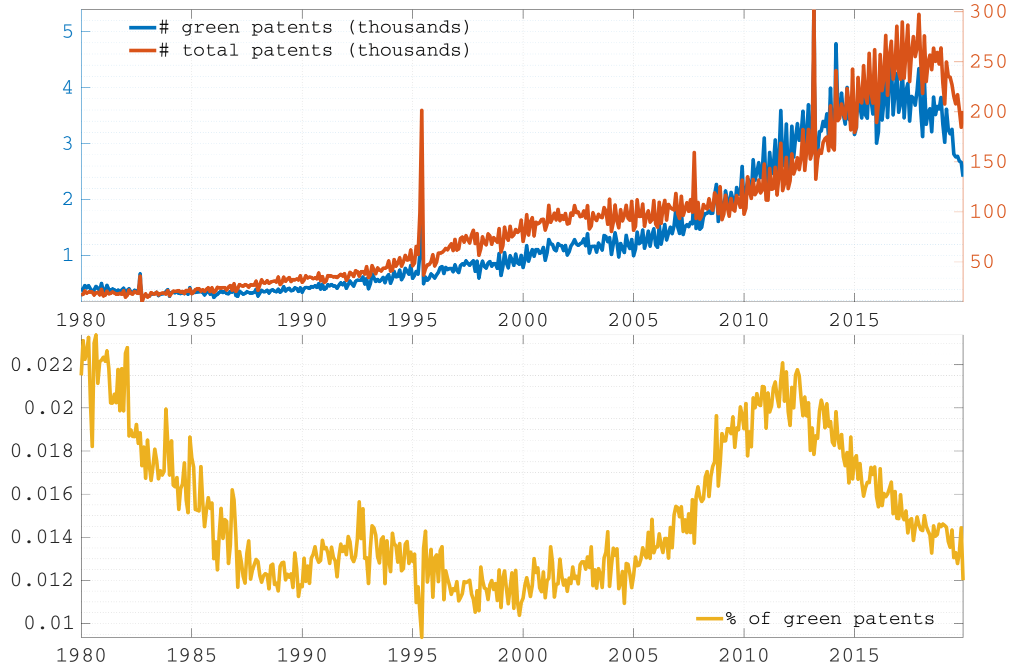

FIGURE 1: *Total vs green patent filing activity (upper panel) and share of green patents over total patents (lower panel); data only refers to granted patents. Source: USPTO PatEx and PatViews.*

total number of patents filed in the same period. Figure 1 displays the dynamics of green vs total patent filing activity (top panel) and of the ratio of the number of green over total patents gp_t (bottom panel) from 1980.

3.1 Exogeneity tests

We run a battery of exogeneity tests for gp_t to multiple factors, such as commodity prices – in particular the price of fossil fuels and metals related to the green transition – and several macroeconomic shocks from the literature as oil supply shocks, monetary and fiscal policy shocks, and carbon pricing shocks. We run the following regression for each potential explanatory factor x_t, which enters the set of regressors both contemporaneously and up to 12-month lags:

$$gp_t = \alpha + \gamma(L)gp_t + \sum_{h=0}^{12} \beta_h x_{t-h} + \varepsilon_t \tag{2}$$

where $\gamma(L)$ is a lagged polynomial for gp_t (which enters in logs) that accounts for its persistence. We specify this regression in levels consistently with our use of gp_t as an endogenous variable in a VAR when we study the macroeconomic implications of the technological green transition.[6] Table 1 reports the Wald statistic and associated p-values from a test on the joint statistical significance of the βs. The test fails to reject the null hypothesis that the aforementioned factors do not affect green patenting and thus it does not diagnostics a spurious contamination of gp_t by confounding factors. The only exceptions are transition metals (panel A - col. 3) and, more modestly, the excess bond premium from Gilchrist and Zakrajšek (2012) (panel B - col. 10). Regarding the former, a positive correlation between gp_t and commodity prices speaks clearly to the fact that news on technological innovations tilted towards the green transition may boost demand of the needed commodities, pushing up their prices. As for the latter, the joint test of statistical significance cannot reject the null at the 10% statistical level Nonetheless, the quantitative evidence of EBP in explaining gp_t is minimal and we run robustness exercises where we use gp_t cleansed from EBP.

[6] In the Appendix we report the same exercise with variables in differences, which yields comparable results.

Table 1: Ortogonality of gp_t

Panel A: Commodity prices and macroeconomic expectations

	(1)	(2)	(3)	(4)
All Commodities	✓			
Fossil Fuels		✓		
Transition Metals			✓	
Consensus Economics				✓
Wald-stat	0.40	0.11	31.78	0.87
p-value	0.52	0.74	0.000***	0.35
N	468	444	468	318

Panel B: Monthly structural shocks

	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Baumeister and Hamilton (2019) oil supply	✓								✓
Känzig (2021) oil supply surprises		✓							✓
Känzig (2021) oil supply shocks			✓						✓
Gertler and Karadi (2015) monetary				✓					✓
Romer and Romer (2004) monetary					✓				✓
Gilchrist and Zakrajšek (2012) EBP						✓			✓
Känzig (2022) carbon policy surprises							✓		✓
Känzig (2022) carbon policy shocks								✓	✓
Wald-stat	0.08	0.66	0.52	0.98	0.08	3.55	0.58	0.055	1.27
p-value	0.77	0.41	0.47	0.32	0.76	0.06*	0.44	0.81	0.26
N	468	468	468	312	180	468	234	234	468

Panel C: Quarterly structural shocks

	(14)	(15)	(16)	(17)	(18)
Romer and Romer (2010) fiscal	✓				
Ramey (2011) fiscal		✓			
Fisher and Peters (2010) fiscal			✓		
Mertens and Ravn (2013) private				✓	
Mertens and Ravn (2013) corporate					✓
Wald-stat	0.42	0.94	0.41	0.01	1.45
p-value	0.51	0.33	0.52	0.91	0.23
N	108	120	112	104	104

Notes. Regression results based on Eq. (2). Dependent variable: $log(gp_t)$. The Wald test statistics correspond to the joint significance test of the controls with associated p-values. Commodity prices are from the World Bank *Pink Sheet* database. Consensus Economics include 1 and 4-year ahead forecasts for US GDP, CPI, and 10-year bond yields. Specification (13) sets missing values of the series to 0 to exploit the full sample.

4 The macroeconomic effects

4.1 Econometric framework

Consider the standard VAR model:

$$\mathbf{y}_t = \mathbf{a} + \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{u}_t \tag{3}$$

where p is the lag order, $\mathbf{y}_t$ is a $n \times 1$ vector of endogenous variables, $\mathbf{u}_t$ is a $n \times 1$ vector of reduced-form innovations with covariance matrix $\mathrm{Var}(\mathbf{u}_t) = \mathbf{\Sigma}$, $\mathbf{a}$ is a $n \times 1$ vector of constants, and $\mathbf{A}_1, \ldots, \mathbf{A}_p$ are $n \times n$ matrices. The innovations $\mathbf{u}_t$ can be expressed as a linear combination of the structural shocks ε_t under the assumption of invertibility:

$$\mathbf{u}_t = \mathbf{B}\boldsymbol{\varepsilon}_t$$

$\mathrm{Var}(\varepsilon_t) = \Omega$ is diagonal as the structural shocks are by construction uncorrelated. Conversely, $\Sigma = \mathbf{B}\Omega\mathbf{B}'$ is not diagonal as, generally, the reduced-form residuals are correlated. We are interested in estimating the causal impact of a unique shock in the system, i.e. the technological green transition news shock $\varepsilon_{1,t}$. The task amounts to recovering a single column $\mathbf{b}_1$ of the impact matrix $\mathbf{B}$. To achieve this goal, we are going to employ gp_t as an internal instrument, i.e. an endogenous variable in our VAR that is ordered first in a Cholesky decomposition, under the assumption that our proxy for news on the technological green transition is predetermined with respect to the other variables included in the system. Hence, *gp* can be considered as a proxy for our shock of interest and thus employed as an internal instrument (Plagborg-Møller and Wolf, 2021). We are not interested in the remaining shocks that drive the VAR system.

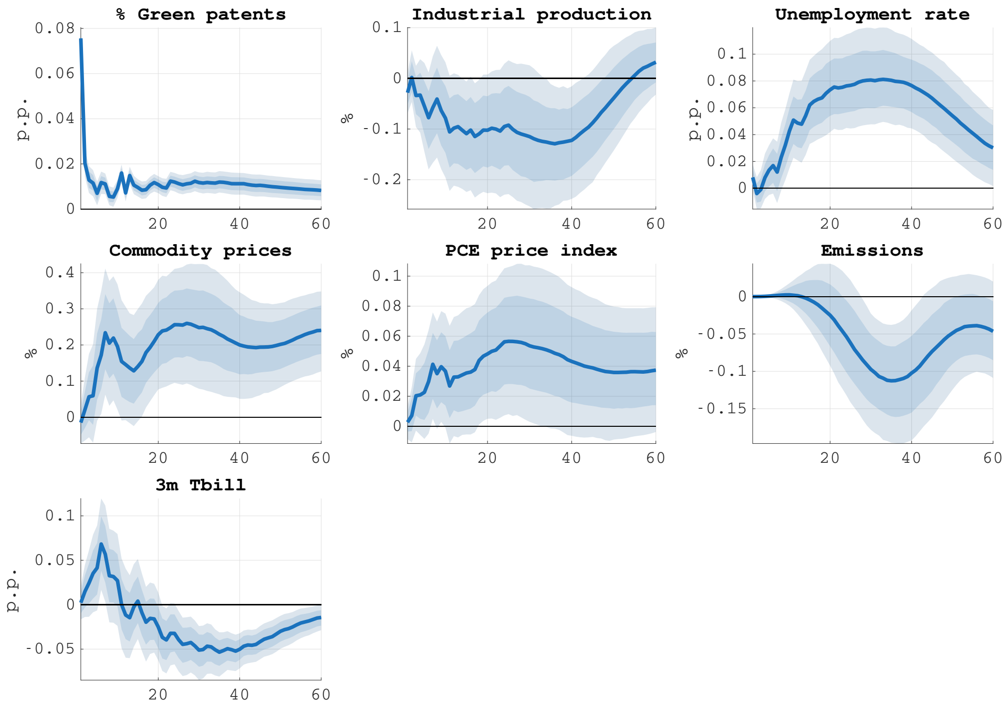

FIGURE 2: *Monthly VAR - Baseline IRFs. Coefficients represent the IRF to a 1 standard deviation increase in gp. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly.*

4.2 Short-run insights from a monthly VAR model

Our monthly VAR model of the US economy includes *gp*, industrial production, the unemployment rate, the commodity producer prices, consumer prices (proxied by the deflator of personal consumer price expenditures or PCE), the levels of CO2 emissions, and the 3-month Tbill rate.[7] The VAR includes 12 lags and the variables enter in log-level following Sims et al. (1990). We estimate the VAR on the sample from January 1980 to December 2019.

Impulse Response Functions. Figure 2 displays the dynamic causal effect, i.e. the impulse responses (IRF), of a news shock of a future recomposition towards green technology on the variables included in the VAR. Consistently with our interpretation of a news shock, all the variables in the system respond with some delay. A one-standard devi-

[7] CO2 emissions are interpolated as in Gavriilidis et al. (2023).

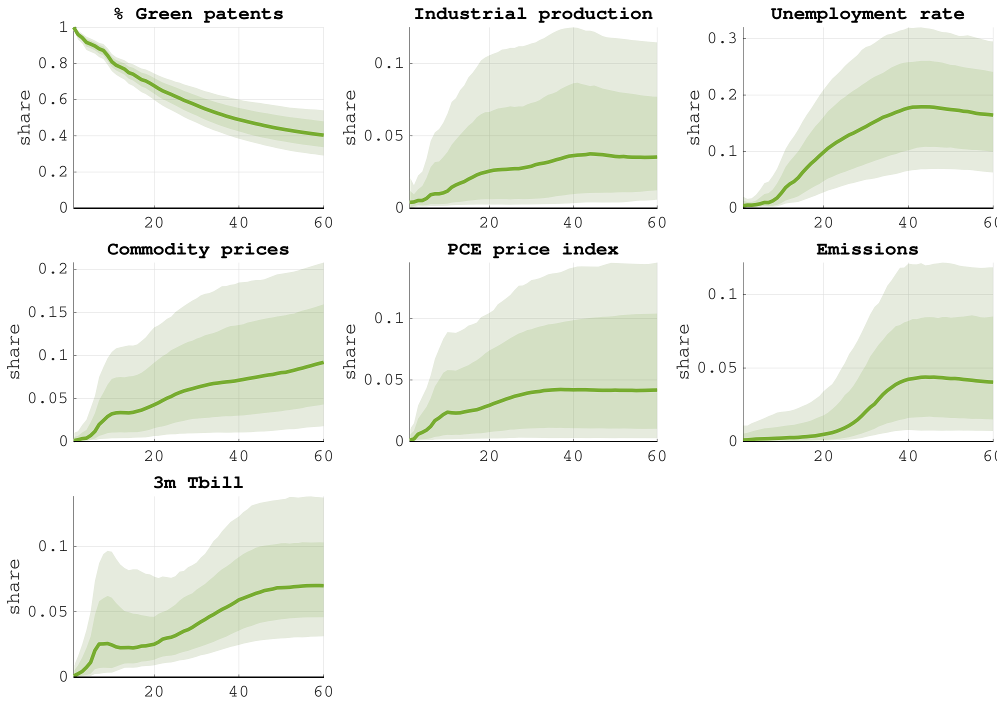

FIGURE 3: *Monthly VAR - Baseline FEVD. The figure displays the FEV contribution of a gp shock based on VAR estimates displayed in Figure 2. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly.*

ation increase in the share of green over total patents induces a reduction in industrial production, which reaches a trough around 10 months after the shock and remains subdued before mean-reverting back to zero. Consistently, the unemployment rate increases, reaching a peak around three years after the shock. Consumer prices as well as commodity prices increase corroborating the interpretation of our news shocks as a negative supply-side disturbance. Green tech innovation is successful in reducing CO2 emissions, albeit the drop occurs with several months of delay. This result is crucial in light of recent findings in the literature pointing to a modest impact of carbon taxes alone in reducing greenhouse emissions.

Forecast Error Variance Decomposition. The forecast error variance decomposition (FEVD) gauges the quantitative relevance of switches towards greener technologies for the US economy (Figure 3). Albeit our shock of interest is not a major driver of the US business cycle, it nonetheless explain a non-negligible share of the forecast error variance of the endogenous variables in the system. This amounts to about 5% for industrial production, PCE prices and emissions, and for a larger share for commodity prices and the unemployment rate. In an alternative exercise that employs weighted measures of gp based on patent citations, we find a much larger quantitative contribution of green tech recomposition. Nonetheless, we maintain the measure of gp in Equation 1 as the baseline because citations employ ex-post information that would not be available in real time to economic agents.

4.3 Short-run insights from a quarterly VAR model

We employ a quarterly VAR model to appraise the implications of green tech recomposition shocks for GDP – a more comprehensive measure of economic activity than industrial production – and for total factor productivity (TFP), a key variable in the business cycle literature. Our results (Figures 4-5) indicate that switches towards greener technologies lead to adecrease in TFP. From a pure economic perspective, a newly developed green technology is arguably less efficient than a brown one in the short run, most likely because the former is less established and at an earlier stage of development, or due to limitations in achieving equivalent output levels once the allowed GHG emissions are constrained. The qualitative and quantitative response of the other variables is consistent with those in the monthly VAR.

4.4 Evidence on technological recomposition

We study the response of some specific variables to assess whether the incidence of green patents captured by gp produces effects that are coherent with a shift towards green tech.

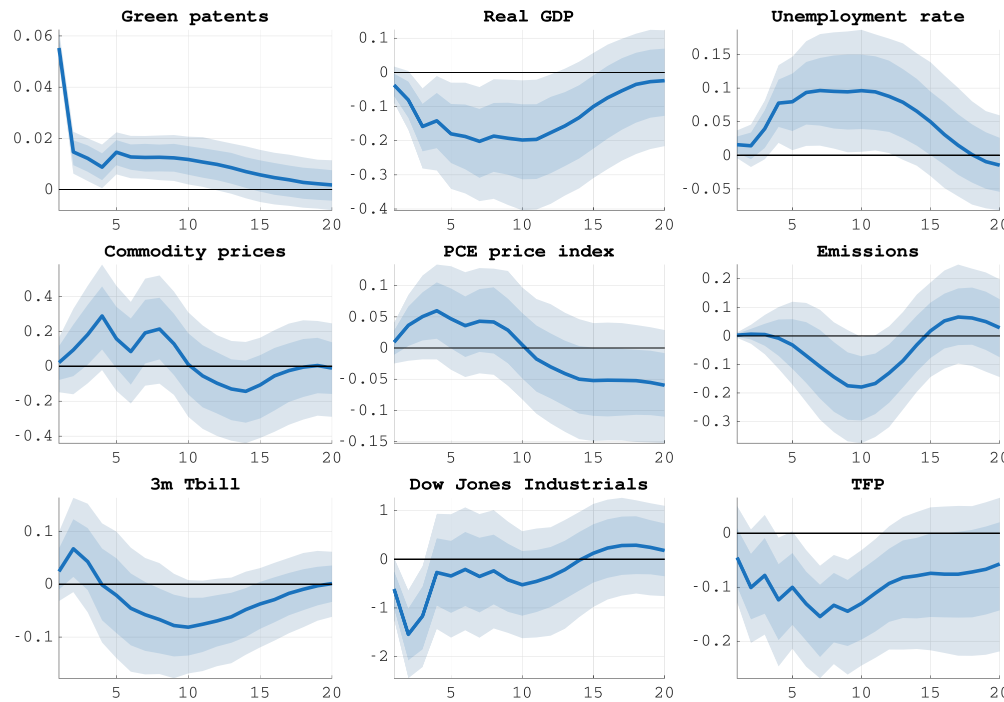

FIGURE 4: *Quarterly VAR: baseline IRFs. Coefficients represent the IRF to a 1 standard deviation increase in gp. Shaded areas denote 68% and 90% confidence bands; the horizon is quarterly.*

Figure 6 provides important insights. First, the emission intensity of industrial production drops significantly, albeit with a strong delay. Second, the share of renewables within the primary energy consumption surges as compared to fossil fuel sources. Third, ESG portfolio funds attract stronger inflows compared to non-ESG funds. Last, core consumer prices respond positively to the shock, thus implying a stringent monetary policy trade-off along the low-carbon transition.

4.5 Long-run effects estimated via local projections

VAR estimates are way more precise than local projections (LP) but the implied IRFs at long horizon are well-known to be potentially biased due to the autoregressive structure projected forward (see Plagborg-Møller and Wolf, 2021). For this reason, we study the long-term implications of shifts to green tech by means of LP estimates in an equivalent

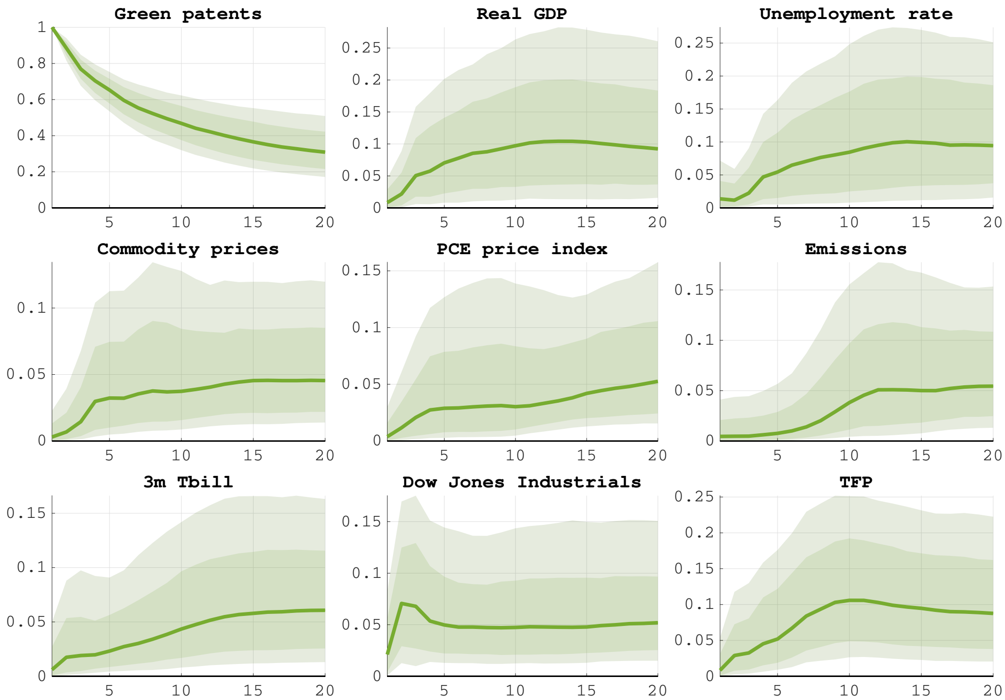

FIGURE 5: *Quarterly VAR: baseline FEVD. The figure displays the FEV contribution of a gp shock based on VAR estimates displayed in Figure 2. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly*

framework to our baseline VAR analysis.

The results reported in Figure 7 suggest that the negative implications of a technological recomposition towards green technology is only temporary: industrial production increases in the long-run and the surge in prices dissipates over long horizons. Conversely, the effect on emissions is very persistent, and even more importantly, the emission intensity of industrial productions falls in the long-run. Its increase in the short-run brings further evidence for the role of the lower productivity of early-green technologies compared to more standard technologies in generating the economic trade-offs in the initial part of the transition path.

This results are also notable from a political economy perspective. If agents can bear its economic costs, the green technology adoption can benefit both consumers and the environment in the long-run.

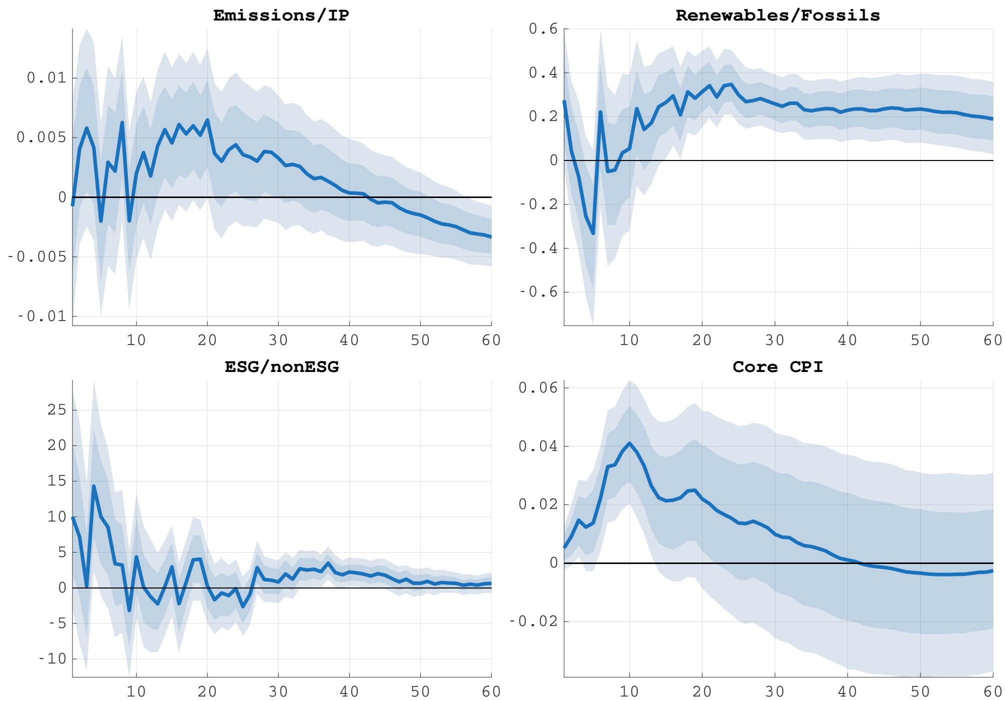

FIGURE 6: *Monthly VAR: green shift interpretation. Coefficients represent the IRF to a 1 standard deviation increase in gp. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly.*

5 Additional results and robustness analysis

In this section we replicate the analysis modifying our empirical strategy along many dimensions, including the definition of the green technology shock, the identification scheme, the specification of the VAR model, and the sample period.

Alternative definitions of gp. Employing a citation-weighted measure of patents to build gp yields qualitatively similar results. For this purpose, we retrieve from *PatentsView* the information on the total number of citations associated with each patent. More precisely, we rely on the number of citations made to U.S. patent applications by other U.S. patents. Using this information significantly boosts the explanatory power of green tech recomposition shocks (see Figure A.3).[8] We do not employ this weighted measure as a baseline

[8] The number of citations per patent comes from PatViews; we associate patents to firm using the matching provided by Arora et al. (2021a) and Arora et al. (2021b)

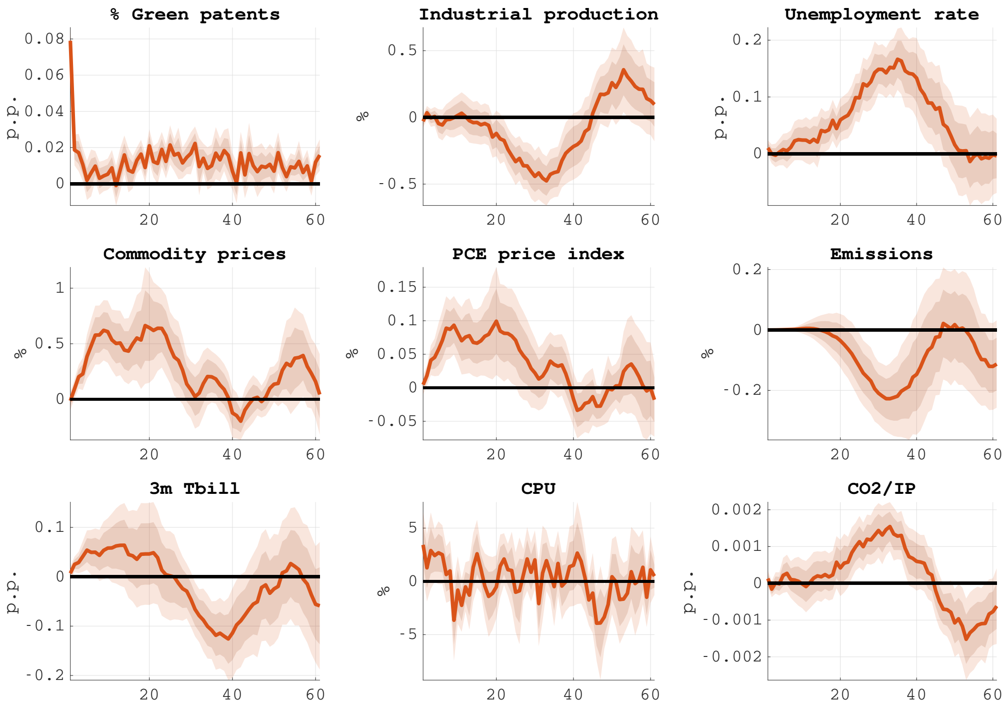

FIGURE 7: *Monthly Local Projection (LP) estimates. Coefficients represent the IRF to a 1 standard deviation increase in gp. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly. CPU stands for the climate policy uncertainty index of Gavriilidis et al. (2023).*

because it uses information that is not available in real-time to economic agents. Results consistent with our baseline hold also if we exclude from our analysis green patents filed by the US oil and gas industry. This evidence confirms that our results are pervasive across industrial sectors and not limited to energy-producing firms, which recent literature has found to lead green innovation (Cohen et al., 2021).

Subsets of gp. The CPC classification also provides sub-categories of green patents: energy, goods, transport, building, and digital. We repeat our analysis for these categories and find results that are comparable to the aggregate measure overall (Figures A.5-A.9). Among them, a green push seems to produce larger effects when it comes from the building industry and from the goods and energy ones.

Alternative identification strategy. Our baseline analysis employs gp as an internal instrument within a VAR model. Comparable results hold if we include both the number of non-green and green patents (in logs) in the VAR and identify our shock of interest as the unpredictable change in the number of green patents (not their share) *that is orthogonal* to surprise changes in non-green patents (Figure A.4). This amounts to ordering the number of non-green patents first and the number of green patents second in a recursively identified SVAR where we are interested only in the second structural shock. As we have already mentioned, this orthogonality condition is necessary to identify a technological configuration that leads to a fall in carbon emissions and is thus consistent with the green transition.

Alternative VAR specifications. The conclusions from our analysis hold in a large set of alternative specifications of the baseline VAR. In terms of variables, we made the following modifications: i) we include stock prices; ii) we include indexes of climate change news, climate concern and climate policy uncertainty from Engle et al. (2020), Ardia et al. (2023) and Gavriilidis et al. (2023); iii) we include commodity prices; iv) we employ measures of gp that are cleaned ex-ante from a wide set of commodity prices and expected economic conditions (see Table 1); vi) we purge gp_t from measures of financial stress and correlation with the global financial cycle such as the VIX and the EBP (see Figure A.10-A.11); vii) we include the total number of patents in the VAR and impose that this variable is not affected by our green transition news shock at any horizon (Figure A.12). This exercise measures the impact of green innovation controlling for porential endogenous variation in the number of patents due to the business cycle; viii) we use carbon emissions based on production data from the U.S. Energy Information Administration (EIA) data rather than the consumption-based measure (available on at annual frequency and interpolated as described in Section 3).

6 Conclusions

Our study sheds light on the macroeconomic and environmental implications of technological advancements toward a low-carbon economy. We identify a news shock that proxies anticipated future shifts towards green technology, which we find behaving as a negative supply-side shock. In the short term, this shock depresses output, increases unemployment and consumer prices, and abates carbon emissions. However, the negative implications for economic activity and prices are relatively short-lived and in the long-run the economy recovers and emissions fall, benefiting from a greener technological mix. Our research provides empirical evidence for a market-driven transition in which innovation plays a crucial role. The progress towards a more sustainable future is costly, however our study suggests that while short-term economic adjustments may pose challenges, the adoption of greener technologies emerges as an important complement of policy measures such as carbon taxes and may enhance long-term synergies to achieve emission reduction objectives.

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Appendix

	(1)	(2)	(3)	(4)
All Commodities	✓			
Fossil Fuels		✓		
Transition Metals			✓	
Consensus Forecast				✓
Wald-stat	5.40	1.98	1.74	4.40
p-value	0.02**	0.15	0.18	0.03**
N	467	443	467	317

(a) *Commodity prices and macroeconomic expectations*

	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Baumeister and Hamilton (2019) oil supply	✓								✓
Känzig (2021) oil supply surprises		✓							✓
Känzig (2021) oil supply shocks			✓						✓
Gertler and Karadi (2015) monetary				✓					✓
Romer and Romer (2004) monetary					✓				✓
Gilchrist and Zakrajšek (2012) EBP						✓			✓
Känzig (2022) carbon policy surprises							✓		✓
Känzig (2022) carbon policy shocks								✓	✓
Wald-stat	0.32	0.57	0.25	1.39	0.08	2.64	1.49	0.00	1.45
p-value	0.57	0.44	0.61	0.23	0.76	0.10	0.22	0.97	0.22
N	456	456	456	312	180	456	234	234	456

(b) *Monthly structural shocks*

	(14)	(15)	(16)	(17)	(18)
Romer and Romer (2010) fiscal	✓				
Ramey (2011) fiscal		✓			
Fisher and Peters (2010) fiscal			✓		
Mertens and Ravn (2013) private				✓	
Mertens and Ravn (2013) corporate					✓
Wald-stat	1.40	0.32	0.26	0.24	0.27
p-value	0.23	0.56	0.60	0.62	0.38
N	108	120	112	104	104

(c) *Quarterly structural shocks*

Table A.1: **Ortogonality of** gp_t. Notes: Regression results based on Eq. (\ref{eq:gp_reg}). Dependent variable: $dgp_t = 100 * (log(gp_t) - log(gp_t - 1))$. The Wald test statistics correspond to the joint significance test of the controls with associated p-values.

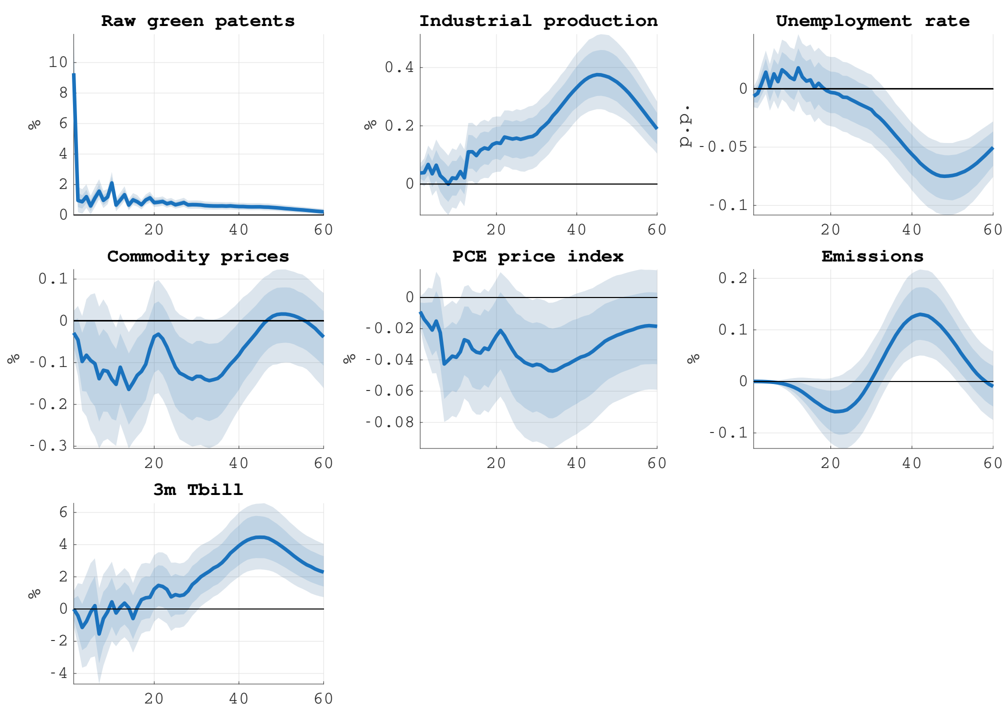

FIGURE A.1: *Monthly VAR: shocks to green patents. Coefficients represent the IRF to a 1 standard deviation increase in the raw number of green patents. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly.*

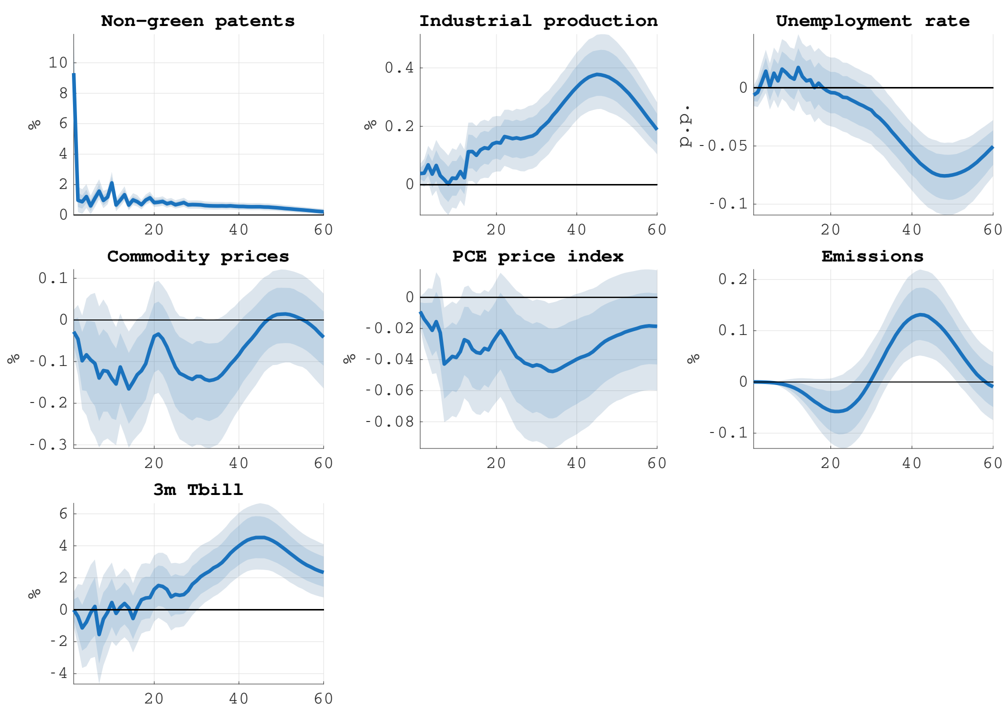

FIGURE A.2: *Monthly VAR: shocks to non green patents. Coefficients represent the IRF to a 1 standard deviation increase in the raw number of non green patents. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly.*

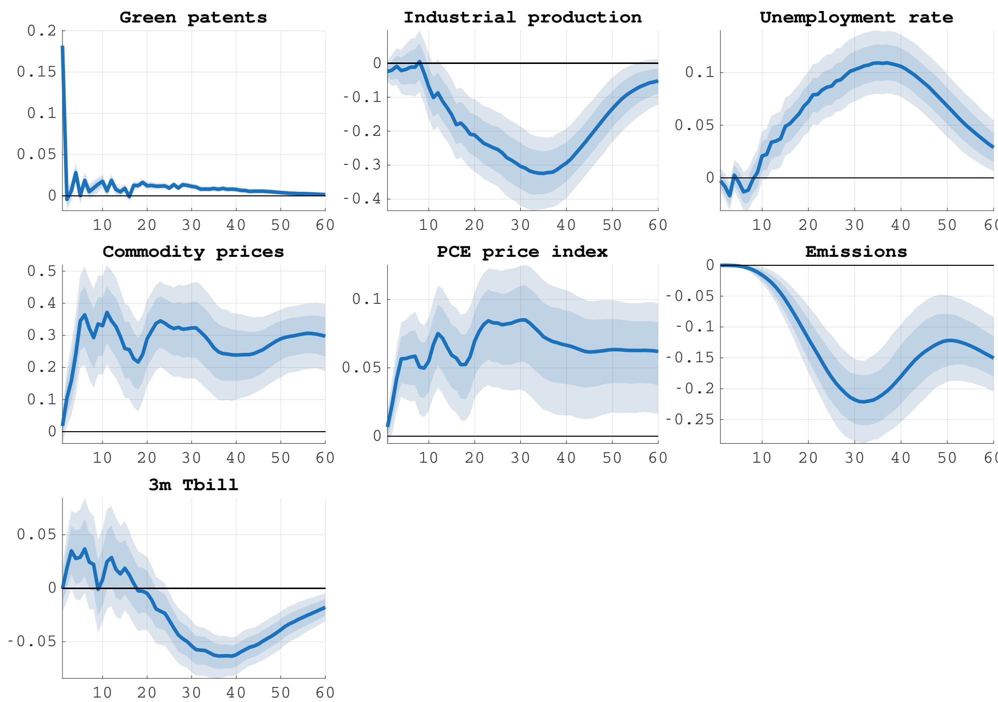

FIGURE A.3: *Monthly VAR: citations. Coefficients represent the IRF to a 1 standard deviation increase in a citation weighted measure of gp. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly.*

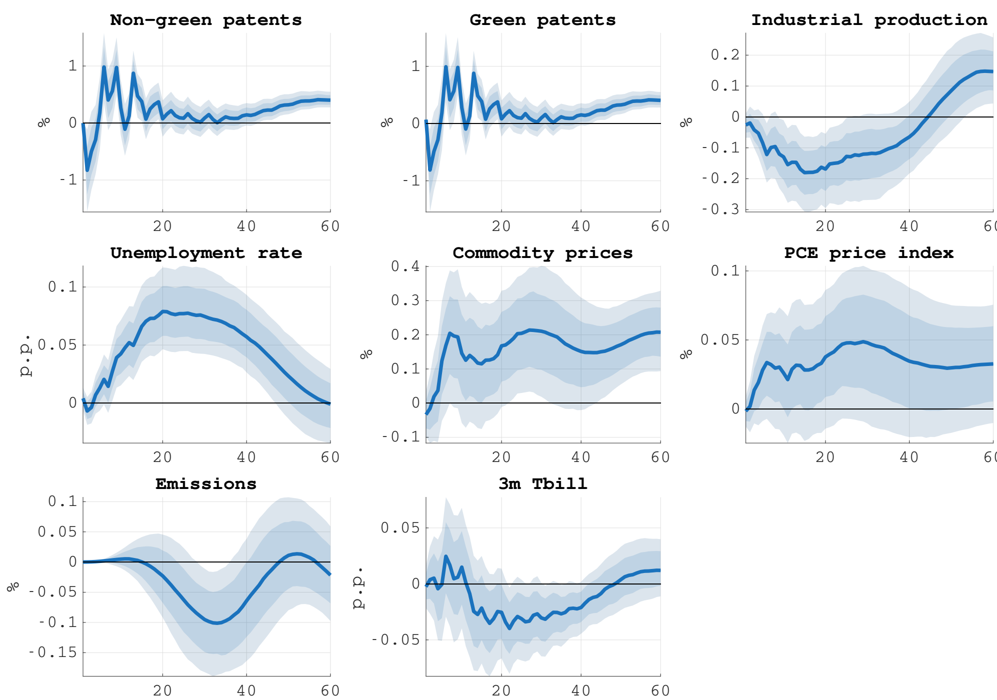

FIGURE A.4: *Monthly VAR: alternative identification strategy ordering the number of green patents second after the number of non green patents. Coefficients represent the IRF to a 1 standard deviation increase in the number of green patents. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly.*

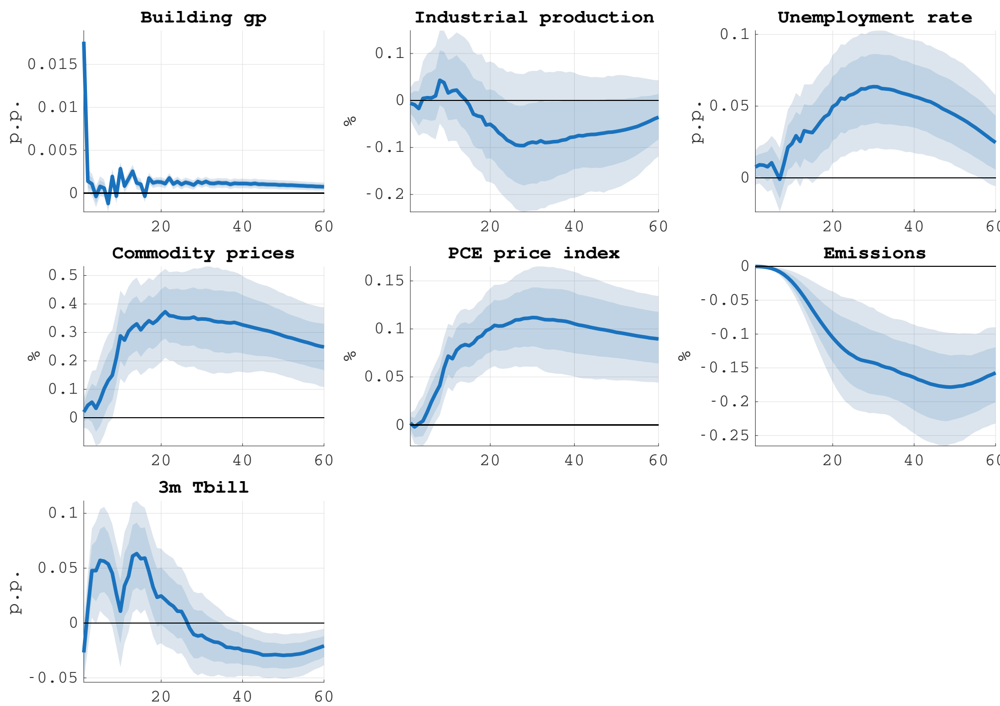

FIGURE A.5: *Monthly VAR: buildings. Coefficients represent the IRF to a 1 standard deviation increase in gp, limiting the analysis to green patents in the building sector. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly.*

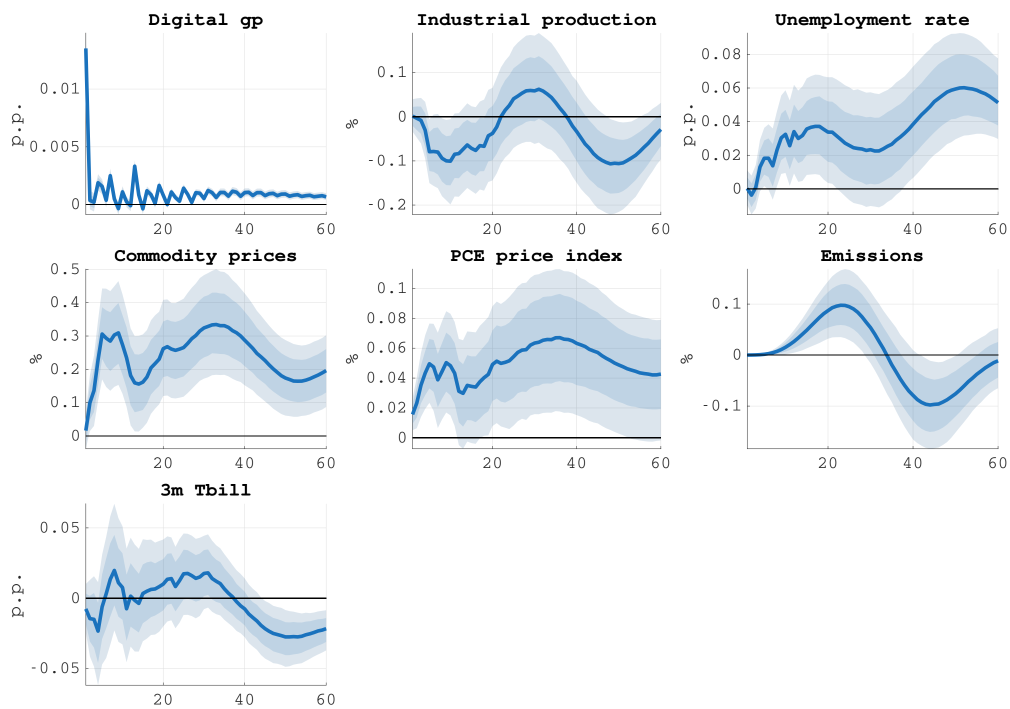

FIGURE A.6: *Monthly VAR: digital. Coefficients represent the IRF to a 1 standard deviation increase in gp, limiting the analysis to green patents in the digital sector. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly.*

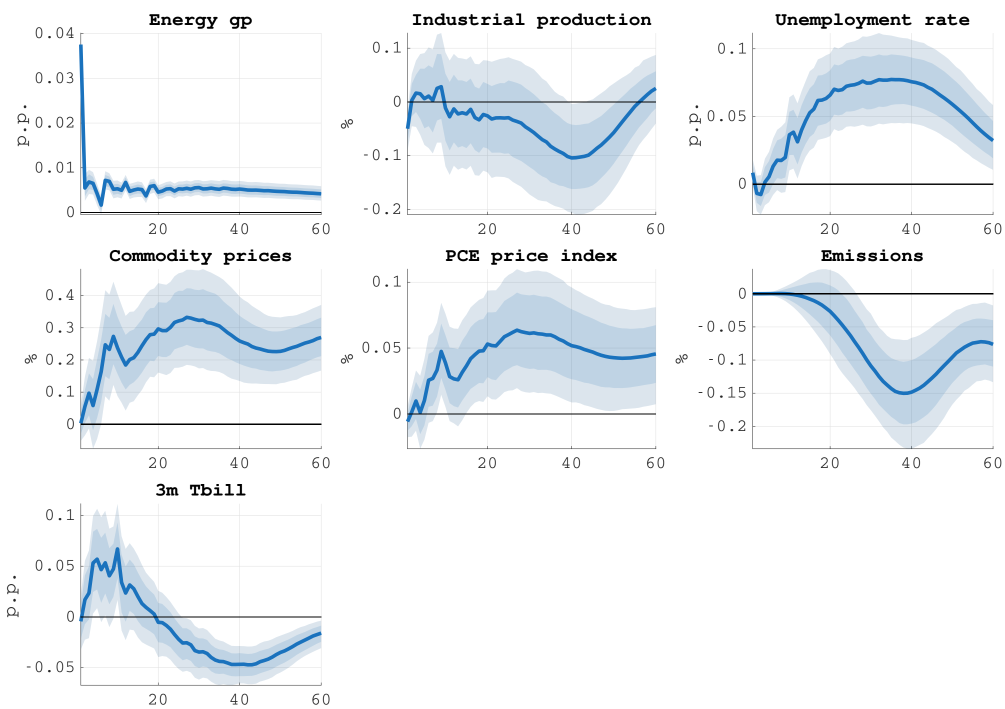

FIGURE A.7: *Monthly VAR: energy. Coefficients represent the IRF to a 1 standard deviation increase in gp, , limiting the analysis to green patents in the energy sector. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly.*

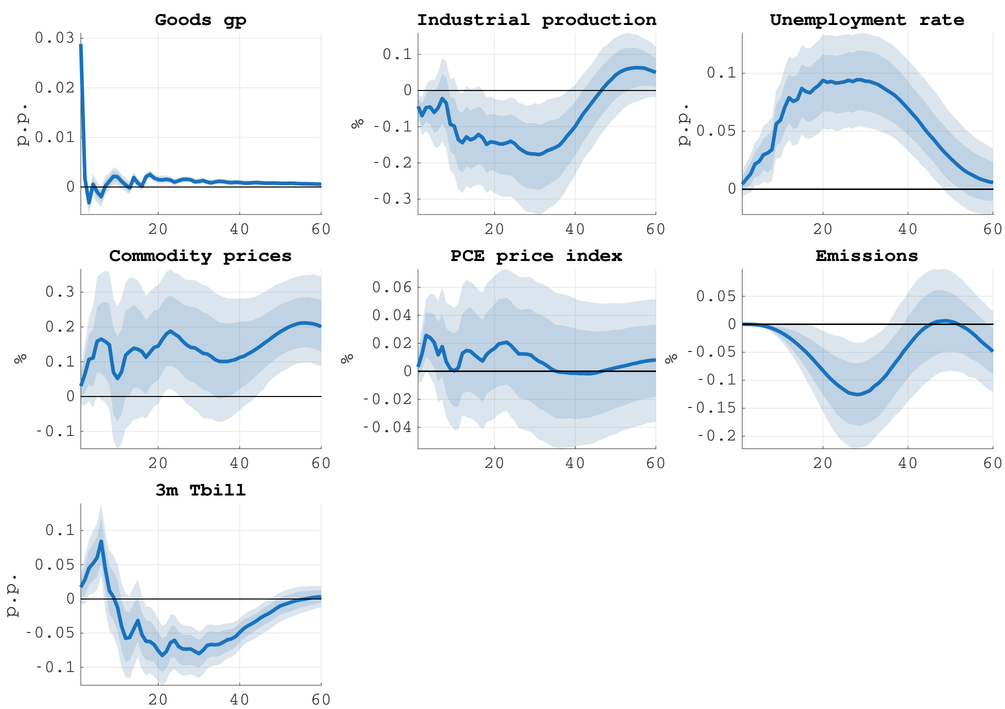

FIGURE A.8: *Monthly VAR: goods. Coefficients represent the IRF to a 1 standard deviation increase in gp, , limiting the analysis to green patents in the good sector. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly.*

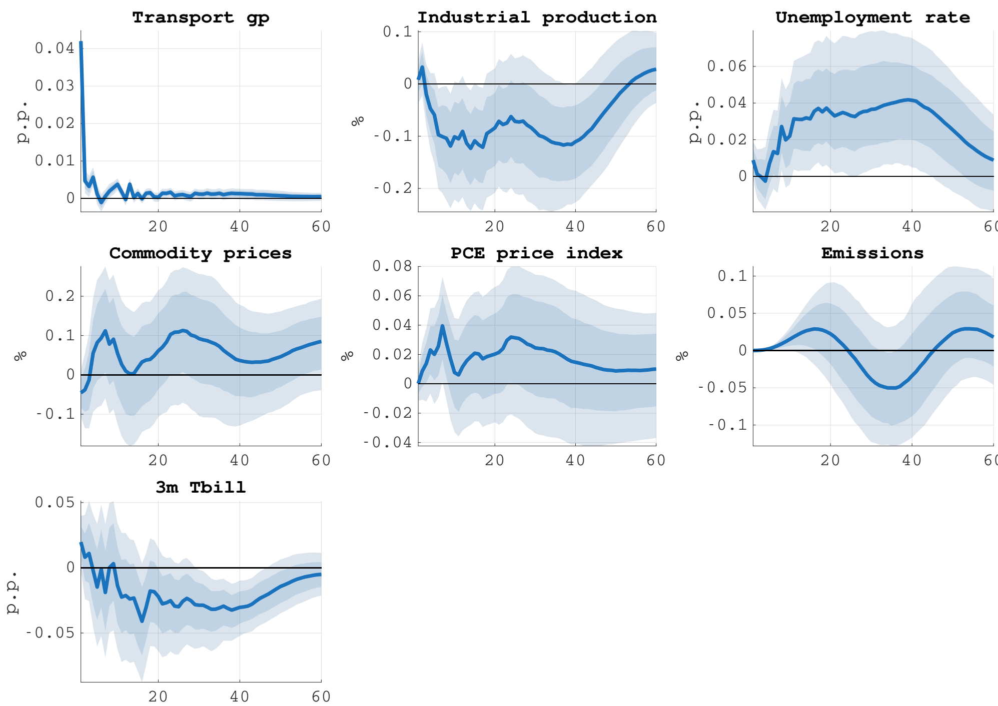

FIGURE A.9: *Monthly VAR: transport. Coefficients represent the IRF to a 1 standard deviation increase in gp, limiting the analysis to green patents in the transport sector. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly.*

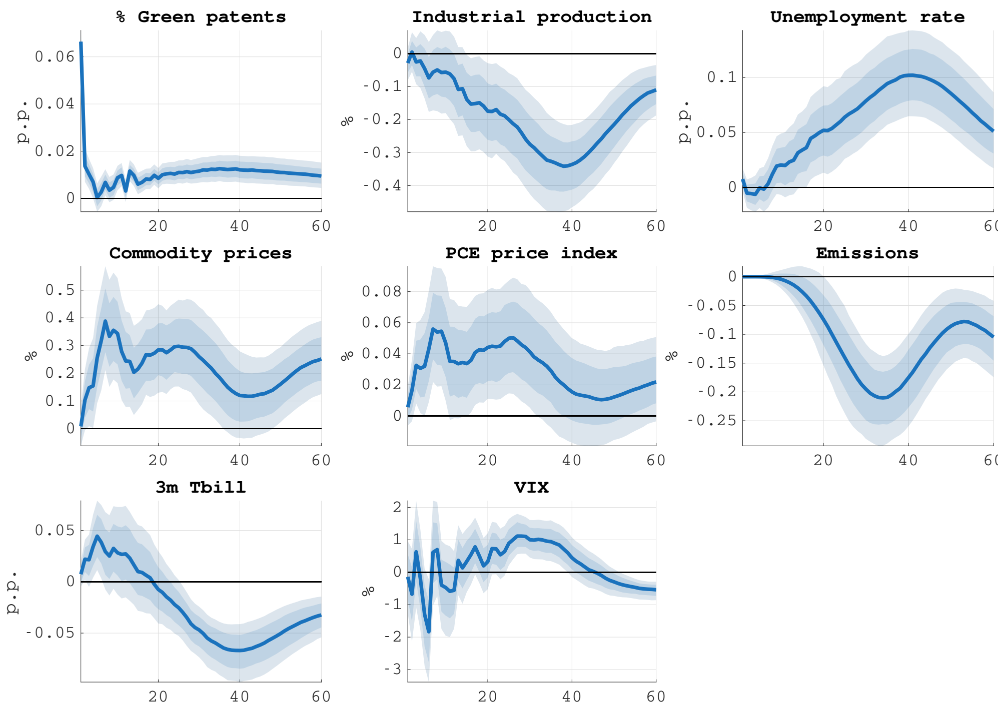

FIGURE A.10: *Monthly VAR: controlling for VIX. Coefficients represent the IRF to a 1 standard deviation increase in gp. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly.*

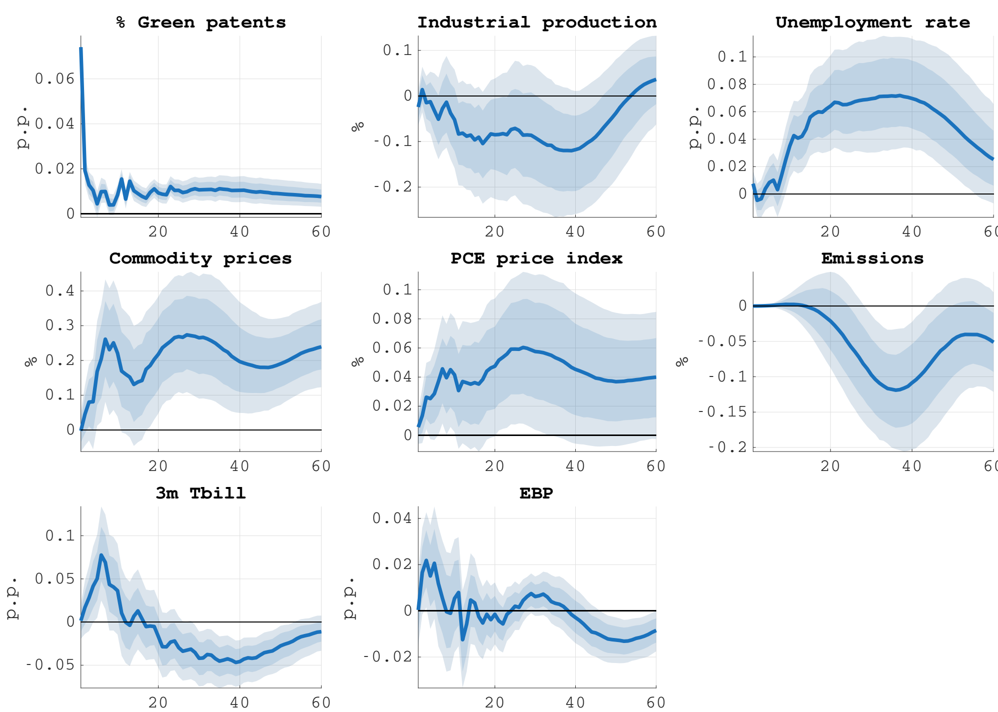

FIGURE A.11: *Monthly VAR: controlling for EBP. Coefficients represent the IRF to a 1 standard deviation increase in gp. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly.*

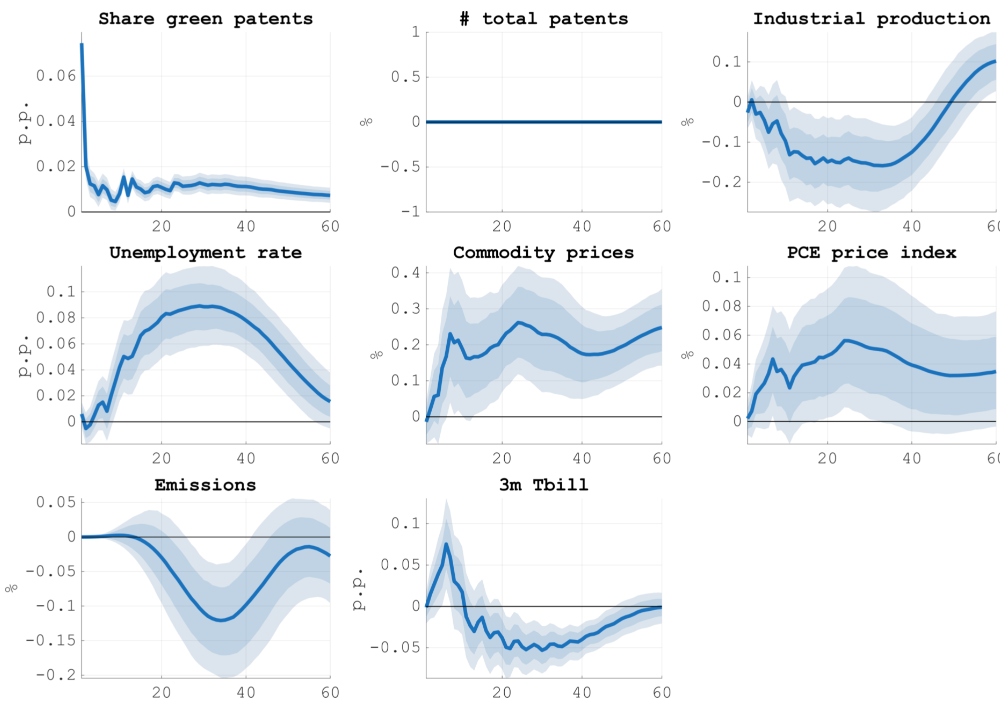

FIGURE A.12: *Monthly VAR: imposing no variations in the total number of parents. Coefficients represent the IRF to a 1 standard deviation increase in gp. Shaded areas denote 68% and 90% confidence bands; the horizon is monthly.*