Becoming Green: On the Aggregate Effects of Green Technology News Shocks

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Abstract

We empirically explore the macroeconomic implications of anticipations about future technological advancements in the green sector. Utilizing the economic value of green patents granted to publicly listed companies in the U.S., we identify green technology news shocks via a convenient and meaningful decomposition of the innovations from a Bayesian Vector Autorregresion Model (BVAR). These shocks are decomposed into two orthogonal components: *i)* a common technological component shared by both green and non-green innovation, that reproduces response patterns akin to those expected from a technology news shock with long-run impacts on productivity; and *ii)* an idiosyncratic component to green innovation inducing inflationary pressures and stock price reductions. The responses to the orthogonal component suggest the existence of a green transition news content that can be related to expectations of more rigorous carbon policies or stricter environmental standards in the future. Our focus on green innovation deepens our understanding about the effect of technology-specific news shocks and provides information of practical importance for macroeconomic and environmental policies.

Keywords: *Green innovation; Green transition; Technology news; Patents; Impulse-response*

JEL Classification: *E32, O31, O44*

1 Introduction

Green innovation is key in the fight against climate change. By making new low-carbon technologies (LCTs) available, green innovation is a powerful tool in curbing emissions and helping firms and households to adapt to the adverse impact of climate change. The macroeconomic implications of the development of new technologies are an under-explored topic in the empirical literature. From a path-dependency argument (Acemoglu, Akcigit, Hanley, & Kerr, 2016; Aghion, Dechezleprêtre, Hémous, Martin, & Van Reenen, 2016), green innovation disrupts existing carbon-intensive economic systems by rendering current production processes obsolete. It can reduce potential productivity benefits in the short and medium run. Conversely, Ambec and Lanoie (2008) argues that green innovation can boost investment and gradually enhance productivity by improving energy efficiency and reducing energy costs. Green innovation can also generate broader knowledge spillovers than its carbon-intensive counterparts, thus fostering overall innovation (Antoine Dechezlepretre, 2017; Fried, 2018). Yet the empirical evidence on what of these effects dominates is inconclusive.

In this paper, we empirically explore the macroeconomic of anticipations about future technological advancements in the green sector. Following the idea of Cascaldi-García and Vukotic (2022) and Miranda-Agrippino, Hacioglu-Hoke, and Bluwstein (2022), we explode the informational content about future technology contained in the patent data. Utilizing the economic value of green patents granted to publicly listed companies in the U.S. as in Kogan, Papanikolaou, Seru, and Stoffman (2017), we identify green technology news shocks via a convenient and meaningful orthogonalization of the reduced-form innovations from a Bayesian Vector Autorregresion Model (BVAR). These shocks are decomposed into two orthogonal components: *i)* a common technological component shared by both green and non-green innovation, that reproduces response patterns akin to those expected from a technology news shock with long-run impacts on productivity; and *ii)* an idiosyncratic component to green innovation inducing inflationary pressures and stock price reductions.

The responses of key macroeconomic variables to either component reveal interesting insights. A unit increase in the common component of the green technology news generates macroeconomic responses similar to those obtained for news technology innovation described in Cascaldi-García and Vukotic (2022). Concretely, the impact response of utilization-adjusted TFP is zero, while a significant positive effect is first obtained seven to eight quarters after the shock, and remains persistent throughout the examined horizon. In line with Barsky and Sims (2011), the delay between the occurrence of the shock and its actual positive effect on productivity is indicative of the identified component as containing relevant information on future, rather than present, aggregate productivity levels. A positive impact response in output, consumption, investment, and worked hours is obtained with an effect that is short-lasting. Regarding the impulse responses of the macroeconomic variables to a unitary increase in the idiosyncratic content of green technology news, the most salient outcomes are the significant and persistent increase in the consumer price index and the persistent reduction in stock prices. This finding can be rationalized if the idiosyncratic component is interpreted as containing relevant information regarding the green transition in the form of future more stringent climate policy.

This paper is related to two strands of literature. First, the empirical literature on the identification of technology news shocks and their macroeconomic impacts. While existing literature predominantly focuses on aggregate technology news, our focus on green technology-specific news offers a deeper understanding on the impacts depending on the nature of the shocks and provides relevant information for policy decisions. Second, the literature on the economic benefits and costs associated with the green transition. Most of the evidence stems from simulation results derived from large-scale, general equilibrium models. Our contribution enhances the discussion by providing empirical estimates that complement previous works as G. Metcalf (2019), G. E. Metcalf and Stock (2023), or Känzig (2023). A related study by Hasna, Jaumotte, Kim, Pienknagura, and Schwerhoff (2023) at the IMF also examines the macroeconomic and firm-level impacts of green innovation. The key difference is that, unlike their approach, we do not treat patent filings as indicators of actual innovation but rather as signals of future technological developments, in line with Beaudry and Portier (2006). Additionally, our decomposition of shocks into components reflecting technological developments and the green transition represents an innovative contribution to this literature.

The rest of the paper is organized as follows. Section 2 describes the related literature and the contribution of our paper. Section 3 presents the patent data sources and the construction of patent-based innovation indexes, as well as the macroeconomic and firm-level data sources. Section 4 introduces the methodology and the identification and decomposition of structural shocks in the context of a BVAR model. Empirical results, both aggregated and at the firm level, are described in Section 5. Finally, Section 6 concludes.

2 Related Literature

Our paper relates to the empirical literature on identifying technology news shocks and their macroeconomic impacts. Since the seminal work of Beaudry and Portier (2006), a substantial body of research has explored the role of advanced information about technological improvements in driving business cycle fluctuations. A key aspect of this literature is the identification assumptions. Traditional strategies, grounded in economic theory, often combine zero restrictions on the immediate response of TFP with assumptions about the long-run drivers of productivity. For example, Beaudry and Portier (2006) identify technology news shocks as innovations to the stock market index that are orthogonal to current TFP levels. Similarly, Barsky and Sims (2011) assume that technology news shocks are orthogonal to current TFP but maximize the forecast error variance at all horizons from zero to forty quarters. Francis, Owyang, Roush, and DiCecio (2014) propose a related approach, imposing a zero restriction on the immediate response of TFP while assuming that news shocks maximize TFP's forecast error variance at a forty-quarter horizon. Kurmann and Sims (2021) adopt the methodology of Francis et al. (2014) but without the zero-impact restriction. In all cases, the TFP response to news shocks is imposed by the identification strategy rather than emerging as an independent empirical result.

In a pair of recent studies, Cascaldi-García and Vukotic (2022) and Miranda-Agrippino et al. (2022) implement alternative identification strategies that do not impose particular dynamics on the TFP response. Both contributions are based on the premise that patents constitute a relevant source of information on inventive activity and signal potential future technological advancements. Miranda-Agrippino et al. (2022) constructs a proxy for technological news shocks built from the number of quarterly patent applications filed at the USPTO. Cascaldi-García and Vukotic (2022) adds to the literature by exploiting the stock market valuations of patents granted to publicly listed firms, as captured by the innovation index proposed by Kogan et al. (2017). Despite not being explicitly assumed, both papers obtain a shape for the TFP response that aligns with the conceptualization of Beaudry and Portier (2006). Our study extends the methodology of Cascaldi-García and Vukotic (2022) by exploring the identification of technology-specific news shocks. While existing literature predominantly focuses on aggregate technology news, our focus on green technology-specific news offers a deeper understanding on the impacts depending on the nature of the shocks and provides relevant information for policy decisions.

This paper is also linked to the literature on the economic benefits and costs associated with the green transition. In the long-run, the positive benefits of a cleaner economy in terms of mitigating climate change damages are widely recognized, see Acemoglu, Aghion, Bursztyn, and Hemous (2012). Nonetheless, the transition towards a green economy, prompted by carbon taxes and/or subsidies to green investments, involves a complex array of short- to medium-run economic implications of practical importance for macroeconomic and environmental policies. For instance, Goulder and Hafstead (2018) models the economic impact of carbon taxation and estimates that that implementing a carbon tax of 40 dollars per ton starting in 2020 and rising at 5 percent real annually, would result in an output reduction of just over 1 percent by 2035 compared to a scenario without such a tax.

Other group of authors have used New Keynesian frameworks to explore the monetary impacts of transition policies. Ferrari and Nispi Landi (2022), for instance, finds that a current increase in a carbon tax exerts inflationary pressures, whereas anticipated future increases dampen demand. Expectations play a crucial role in determining the prevailing effect. Airaudo, Pappa, and Seoane (2024), in a model for a small open economy, observe that increases in brown energy taxation lead to a rise in firms' marginal costs, with inflationary effects and persistent output losses. Green public investment or subsidies would induce a transition with no inflationary or output costs, albeit without a quick improvement in energy efficiency. Del Negro, di Giovanni, and Dogra (2023) point out that climate policies introduce an inflation-output trade-off, modulated by the relative price stickiness in the dirty and green sectors and whether the policies involve taxes or subsidies. Other relevant references along this line include Bartocci, Notarpietro, and Pisani (2022) and Ferrari and Nispi Landi (2023).

Most of the evidence on the real and monetary consequences of the green transition stems from simulation results derived from large-scale, general equilibrium models. From an empirical perspective, recent contributions examine the macroeconomic effects of carbon taxation, albeit with conflicting findings. G. Metcalf (2019) and Bernard and Kichian (2021), despite adopting different methodological frameworks, conclude that the British Columbia carbon tax does not detrimentally affect output or employment. This view is further supported by G. E. Metcalf and Stock (2023) who find no significant adverse effects on employment or GDP growth of carbon taxation in various European countries. In contrast, Känzig (2023) documents that a carbon policy shock in Europe leads to higher energy prices, lower emissions, and more green innovation, at the cost of a fall in economic activity.

Our analysis contributes to the empirical literature by examining a complementary and under-explored aspect of the green transition: the macroeconomic implications of anticipations about future technological advancements in the green sector. Various mechanisms through which expected and actual green innovation influences economic decisions have been proposed. From a path-dependency argument (Acemoglu et al., 2016; Aghion et al., 2016), green innovation disrupts existing carbon-intensive economic systems by rendering current production processes obsolete. In the short and medium run, potential productivity benefits are reduced. Conversely, Ambec and Lanoie (2008)suggest that green innovation can boost investment and gradually enhance productivity by improving energy efficiency and reducing energy costs. In the same direction, green innovation can generate broader knowledge spillovers than its carbon-intensive counterparts, thus fostering overall innovation (Antoine Dechezlepretre, 2017; Fried, 2018). Our empirical investigation, using U.S. data and a transparent strategy for identifying and decomposing green technology news shocks, addresses this topic.

A related work is the study by Hasna et al. (2023) at the IMF, which examines the macroeconomic and firm-level impacts of green innovation in the short and medium run. Drawing on data on patent fillings in OECD and BRICS countries from 1990 to 2020, these authors find that green patent filings stimulate output through increased investment, yet do not boost aggregate TFP. At the firm level, green patents increase revenue, albeit in a smaller magnitude compared to non-green patents.

Our study deviates from Hasna et al. (2023) in several aspects. First, we do not conceive patent fillings as an indicator of actual innovation but rather as news about future technological developments in the sense of Beaudry and Portier (2006). Second, we employ a transparent identification strategy that does not rely on the use of instrumental variables for addressing potential endogeneity issues.[1] Our strategy uses the market values of the granted patents—instead of patent fillings—to construct the green and non-green innovation indexes in the spirit of Kogan et al. (2017). It provides our innovation indicator with an additional degree of exogeneity coming from the high-frequency variation in asset prices. Technology news shocks are identified within a VAR model assuming convenient

[1]Patent applications may be prompted by current economic booms and/or past news.

meaningful rotations of the reduced-form innovations. Third, we decompose the shocks into information regarding technological developments and information about the green transition. To the best of our knowledge, this is the first paper proposing this type of decomposition.

3 Data

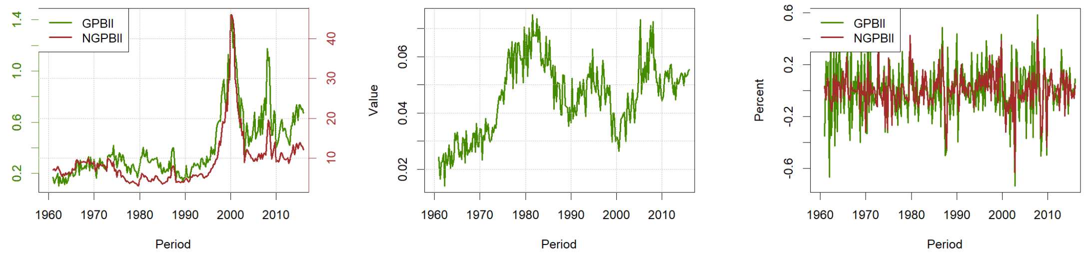
3.1 Patent Data and Green Patent-Based-Innovation-Index (GPBII)

Data on patents is obtained from *Patents View*, a publicly accessible service maintained by the U.S. Patent and Trademark Office (USPTO). For each patent granted between 1960 and 2016, we collect information on the application and grant dates and the technology class indicated by the Cooperative Patent Classification (CPC) code. Based on the CPC code and following the classification system proposed by Haščič and Migotto (2015), we identify the green patents as all patents producing technologies related to climate change mitigation and adaptation, carbon capture and storage, renewable energy generation, pollution abatement, and waste management.

Quarterly data on patents grants is combined with firm-level data from the Centre for Research in Security Prices (CRSP) to construct the Green Patent-Based-Innovation-Index (GPBII) index, following the methodology of Kogan et al. (2017).[2] Shortly, the value of an individual green and non-green patent granted to a publicly listed firm is estimated by filtering the firm's stock price reaction around the patent grant announcement date from other unrelated news. Individual firm-level values are added up each quarter to obtain the indexes presented in Figure 1.

Panel (a) in Figure 1 presents the levels of the GPBII (green) and NGPBII (brown). Both indices seem to evolve following a common trend. From 1990, both indices report a steeper increase that is interrupted at the beginning of the 2000s, with a more marked fall in the NGPBII. The value of the indices seems to follow times of speculation in the market, especially that of the dot-com bubble. In the mid-2000s, the GPBII appears to increase more steadily, but again a strong fall is observed around 2008, during the Great Recession. Even though the variability of both indices is similar—the correlation coefficient of the levels is above 0.83—the levels themselves are not. The ratio presented in Panel (b) shows that the GPBII is around 5% of the NGPBII. However, during the sample period, this ratio has varied significantly, experiencing periods of increase between 1960 and 1982 or 2000 to 2008, where the maximum peaks of the ratio were achieved. Panel (c) plots together the growth rates. The correlation of this measure is around 0.6.

[2] Codes and data files available at the GitHub repository `https://github.com/KPSS2017` were used.



(a) Level (b) Ratio (c) Growth rate

Figure 1: Green and non-green PBIIs.

3.2 Aggregate Macroeconomic Data

For the aggregate analysis, we use data on a range of variables related to technology, real macroeconomics, and forward-looking indicators. The information set in our benchmark model includes the GPBII and NGPBII, utilization-adjusted TFP (Fernald, 2014), output, real consumption, real investment, hours worked, consumer price index, federal funds rates, consumer confidence, and stock prices. These variables are chosen as to encompass the set of variables used in the analysis of CG-V and Miranda-Agrippino et al. (2022), and to cover a wide spectrum of the macroeconomy. All variables are in log levels, following (Sims, Stock, & Watson, 1990), to account for possible cointegration. The data frequency is quarterly and covers the period from 1961:Q1 to 2016:Q4, which is the time window with more reliable data on patents. In the Appendix, we provide more details about the data sources and transformations.

4 Methodology and Identification

4.1 Aggregate Analysis

We estimate a BVAR model with standard Normal-Inverse-Wishart (NIW) distribution priors. The choice of a BVAR is motivated by its ability to address the curse of dimensionality found in large VAR models, which is particularly relevant in our study. This is because we define a VAR system with more than 10 endogenous variables, an intercept, and four lags, and our data has a quarterly frequency. Initially, we identify the structural shocks of interest following the strategy in CGV. Specifically, we use short-run identification strategy by using the Cholesky decomposition of the variance-covariance matrix of the reduced form residuals, with the GPBII or the NGPBII ordered on top of the information set. The results are presented as median impulse responses to the identified structural shocks, with one-standard-deviation coverage bands provided for inference.

After the initial analysis, we set our benchmark exercise by adopting a procedure that simultaneously utilizes both the GPBII and the NGPBII. This procedure entails decomposing the reduced-form residuals of the GPBII into a common component ($\epsilon^{G}_{C,t}$) and idiosyncratic component ($\epsilon^{G}_{O,t}$), both of them with meaningful interpretation. The impulse responses of the macroeconomic variables to each of these components are obtained using Local Projections Jordà (2005). In the subsequent sections, we elaborate more on these procedures.

5 Empirical Results

5.1 Green technology news shocks independently identified

In an initial empirical exercise, we identify the response of macroeconomic variables to green technology news shocks using the approach of CGV. Specifically, we place the GPBII at the top of the information set and achieve identification through a Cholesky decomposition of the reduced-form residuals in the estimated BVAR model.

This identification strategy assumes that the only structural shock affecting the contemporaneous value of the reduced-form residuals of the GPBII is the green technology news shock, which reflects expectations of future advancements in green technology. To ensure comparability, the shocks are rescaled so that the TFP increases by 1.0% ten quarters after the shock. Green curves in Figure 2 represent the implied dynamic responses of the macroeconomic variables to the identified shock over a twenty-quarter horizon, a duration deemed appropriate for future productivity forecasts. These responses are compared to the brown curves corresponding to the macroeconomic responses to a non-green technology news shock. Brown responses are obtained in a similar process but replacing the GPBII by the NGPBII as the first variable in the system. The latter analysis closely replicates the findings in CGV.[3]

The response patterns of green and non-green technologies exhibit notable similarities. In both cases, there is a significant lag between the initial impact of the technology news shock and its actual effect on TFP. This delay aligns with the expected dynamics of TFP adjustments to technology news shocks. Importantly, economic agents anticipate future productivity gains from technological advancements. This anticipation is reflected in the positive responses of output, investment, and hours worked, consistent with the findings of Beaudry and Portier (2006).

However, is not the similarities but the important differences between each type that motivate our subsequent analyses. Notice that some macroeconomic variables have different responses between the two cases. The response patterns in the price index, federal funds rate, consumer confidence, consumption, and stock prices diverge from those of non-green news technology shocks. In the green case, the price index response is positive and significantly different from zero twenty quarters after the shock. Regarding stock prices, although an initial increase is observed on impact, the response turns permanently negative from the fifth quarter onwards.

This analysis highlights important similarities in the responses of real economic and

[3]CGV use the total PBII, obtained as the sum of the GPBII and the NGPBII. Provided that the NGPBII significantly contributes to the total PBII, a strong similarity in the outcomes of the analysis is expected.

TFP variables to both identified shocks, suggesting that technological progress plays a role in both cases. This observation is further supported by the visual trends in the levels and growth rates of GPBII and NGPBII (Figure 1), as well as the strong correlation of over 0.6 between the two shock series. While this commonality is relevant for policy analysis, our primary focus is on the idiosyncratic component of green technology news shocks, which may explain the distinct reactions of monetary and forward-looking variables. However, this idiosyncratic component cannot be independently identified. Instead, its isolation requires the simultaneous use of GPBII and NGPBII along with a transparent identification strategy, as outlined in the next section.

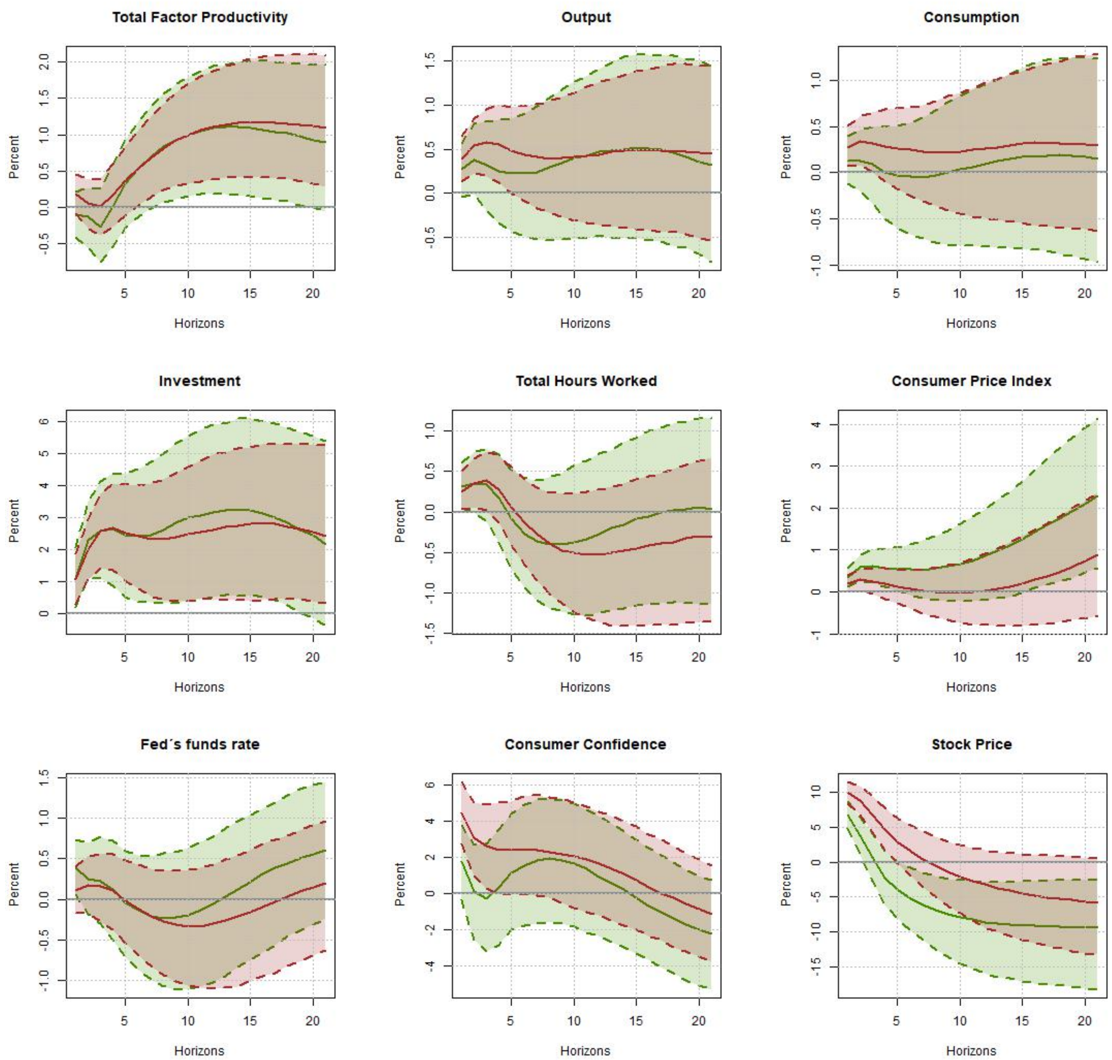


Figure 2: Dynamic responses to green (green curves) and non-green (brown curves) technology news shock identified in independent procedures

5.2 Orthogonal decomposition of green technology news shocks

We identify green technology news shocks through a joint procedure that integrates both NGPBII and GPBII into the information set. It is important to emphasize that green technology news shocks share a common component with non-green technology news shocks. To disentangle these components, we estimate a Bayesian Vector Autoregression (BVAR) model and extract the reduced-form residuals. e_t^{NG} and e_t^G, associated with NGPBII and GPBII, respectively. Both residual series are correlated and, presumably, share a common component. Let e_t^{NG} be the reduced-form residual of the NGPBII in the BVAR, e_t^G is the residual of the GPBII and $\epsilon_{C,t}$ is the common component. We assume that the only driver of e_t^{NG} is the common component, while there are two drivers of e_t^G.

$$e_t^{NG} = \epsilon_{C,t}$$
$$e_t^G = \epsilon_{C,t} + \epsilon_{O,t}^G$$

Then, e_t^G can be decomposed into two orthogonal elements. The first element, denoted as $\epsilon_{C,t}$, is obtained as the projection of e_t^G on the e_t^{NG} space and represents the common component of technology news. The second element, $\epsilon_{O,t}^G$, is obtained as the residual of the previous projection and represents the idiosyncratic component of the green technology news. Both components are orthogonal and satisfy $e_t^G = \epsilon_{C,t} + \epsilon_{O,t}^G$.[4] The regression between the two reduced-form residuals yields a coefficient of determination (R^2) of 0.43, indicating that 43% of the variance in green technology news shocks can be attributed to the common component shared with non-green technology news shocks.

The dynamic responses of the macroeconomic variables to a one standard deviation increase in $\epsilon_{C,t}$ and $\epsilon_{O,t}^G$ are obtained using linear Local Projections Jordà (2005). Figures 3 and 4 plot those responses over a horizon of 20 quarters. Both types of shock components induce a significant increase of the GPBII on impact, yet their subsequent response patterns are completely different. Based on the results, we interpret $\epsilon_{C,t}$ as representing a common technological content and $\epsilon_{O,t}^G$ as indicative of the green idiosyncratic component of the green technology news.

5.2.0.1 Responses to the common technological content of green technology news

This section describes the responses of the macroeconomic variables to a unit increase in the common component news technology shock, $\epsilon_{C,t}$. Firstly, we examine the response of the utilization-adjusted TFP, a proxy for the technological advancement of the economy. The conventional identification of news technology shocks relies on zero and sign restrictions to isolate shocks that have no immediate impact on TFP while leading to future increases (Barsky & Sims, 2011; Beaudry & Portier, 2006). In contrast, we remain agnostic as in Cascaldi-García and Vukotic (2022) and Miranda-Agrippino et al. (2022) and our approach does not impose restrictions on the immediate response of TFP nor in the sign response of its future values. Notably, the confidence intervals do not exclude the zero contemporaneous effect. A negative response is observed at horizon $h = 3$ that may be related to Schumpeter's idea of creative destruction. A significant positive effect is first

[4] In Appendix A.1 we consider one alternative to analyze the macroeconomic responses to the idiosyncratic component of the green technology news. The approach uses short-run restrictions of the BVAR with the second variable being the GPBII e_t^G concerning e_t^{NG}. IRFs are obtained directly from the BVAR.

obtained seven to eight quarters after the shock and remains persistent throughout the examined horizon. In line with the conceptualization of news shocks in Barsky and Sims (2011), the delay between the occurrence of the shock and its actual positive effect on productivity is indicative of the identified component as containing relevant information on future, rather than present, aggregate productivity levels.

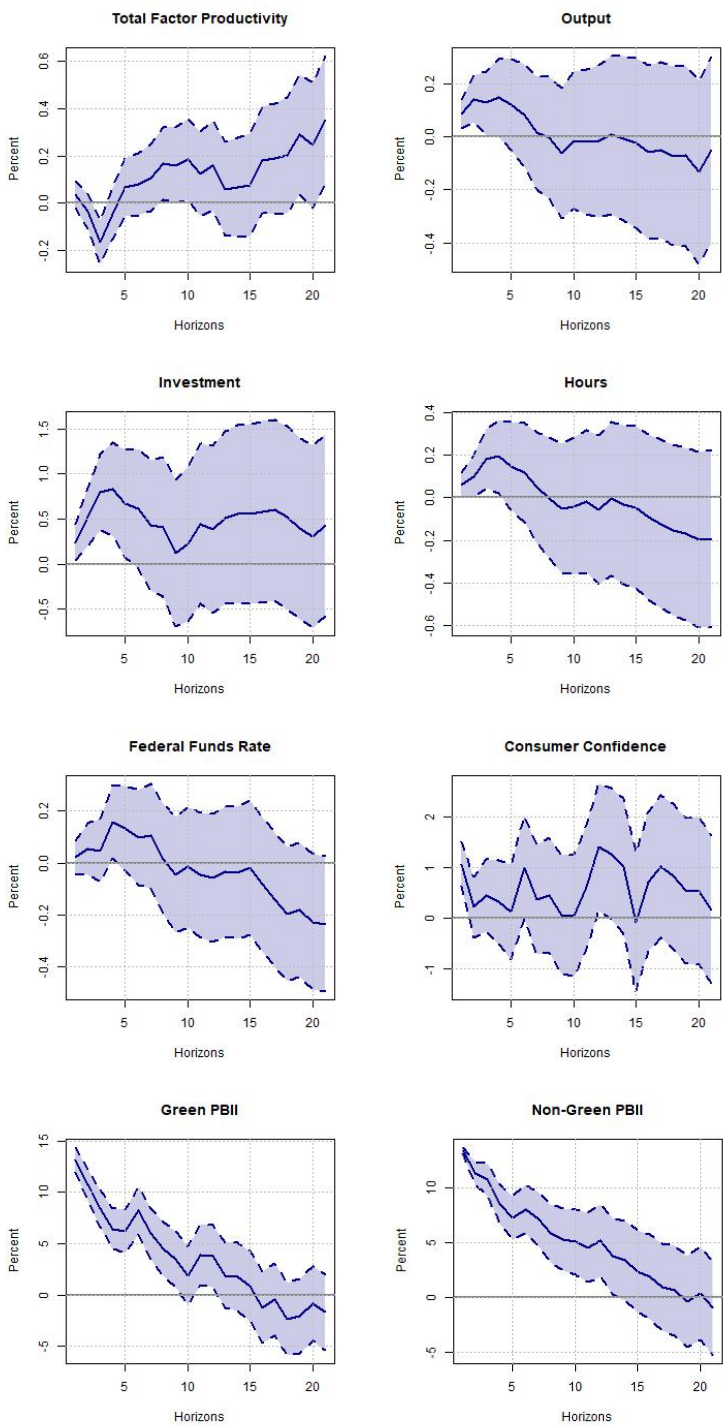


Figure 3: Dynamic responses to the common technological component of the green technology news shock

Regarding real variables, we note a positive impact response in output, consumption, investment, and worked hours, with an effect that is short-lasting. For instance, investment increases on impact and continues to rise for about 4 quarters before converging back to normal. Although the function is positive over the whole horizon, it is non-significant after quarter 6. Forward-looking indicators, as stock prices and consumer confidence, experience a positive strong initial increase that swiftly diminishes and turns non-significant by 4 quarters post-shock onwards. Notice that the positive responses of real variables and forward-looking indicators precede the significant impact on TFP, a finding that reveals the technological information component contained in the green technology shock that prompts economic agents to act upon the realization of the shock. Consumer prices exhibit a weak rise on impact that can be explained by the demand increase induced by the movement in the real variables.

From the described responses, it is possible to relate the common component $\epsilon^G_{C,t}$ to technological content in the form of news about future technological development. The macroeconomic implications are comparable to those described in CGV and the related literature on technological news shocks.

5.2.0.2 Responses to the idiosyncratic transition content of green technology news

Now, we describe the impulse responses of the macroeconomic variables to a unitary increase in $\epsilon^G_{O,t}$ that are plotted in Figure 4. Observe that such movement generates a significant immediate rise in the GPBII, whereas the NGPBII remains unchanged at any horizon. This outcome is a consequence of the orthogonalization process and implies that the responses of other variables in the model are driven by factors not correlated with fluctuations in the non-green innovation. Unlike the response to the technological component discussed in the previous section, the dynamics of the GPBII in the present case show an interesting pattern: after the initial rise, the GPBII eventually stabilizes at a level approximately 5% above the starting point.

The most striking result in Figure 4 is the significant and persistent increase in the consumer price index (CPI). While the immediate effect is modest, the impulse response function exhibits a monotonic upward trend over the entire horizon. This finding can be interpreted by considering that $\epsilon^G_{O,t}$ incorporates relevant information about the green transition. As discussed in Section 5.3, green innovation has the potential to shape future climate policy.

If technological advancements emerge today, regulators may adjust future taxes and environmental standards to facilitate the integration of these innovations into production processes. Consequently, when economic agents receive unexpected news about future green technology developments, they anticipate potential changes in climate policy, which in turn influence present economic outcomes. The sustained rise in inflation, for instance, can be attributed to expected increases in energy prices: as dirty energy becomes relatively more expensive, overall price levels rise.

Moreover, this perspective may also explain the persistent impact of $\epsilon^G_{O,t}$ on green innovation, considering the well-documented role of climate policy in driving technological advancements in the literature.

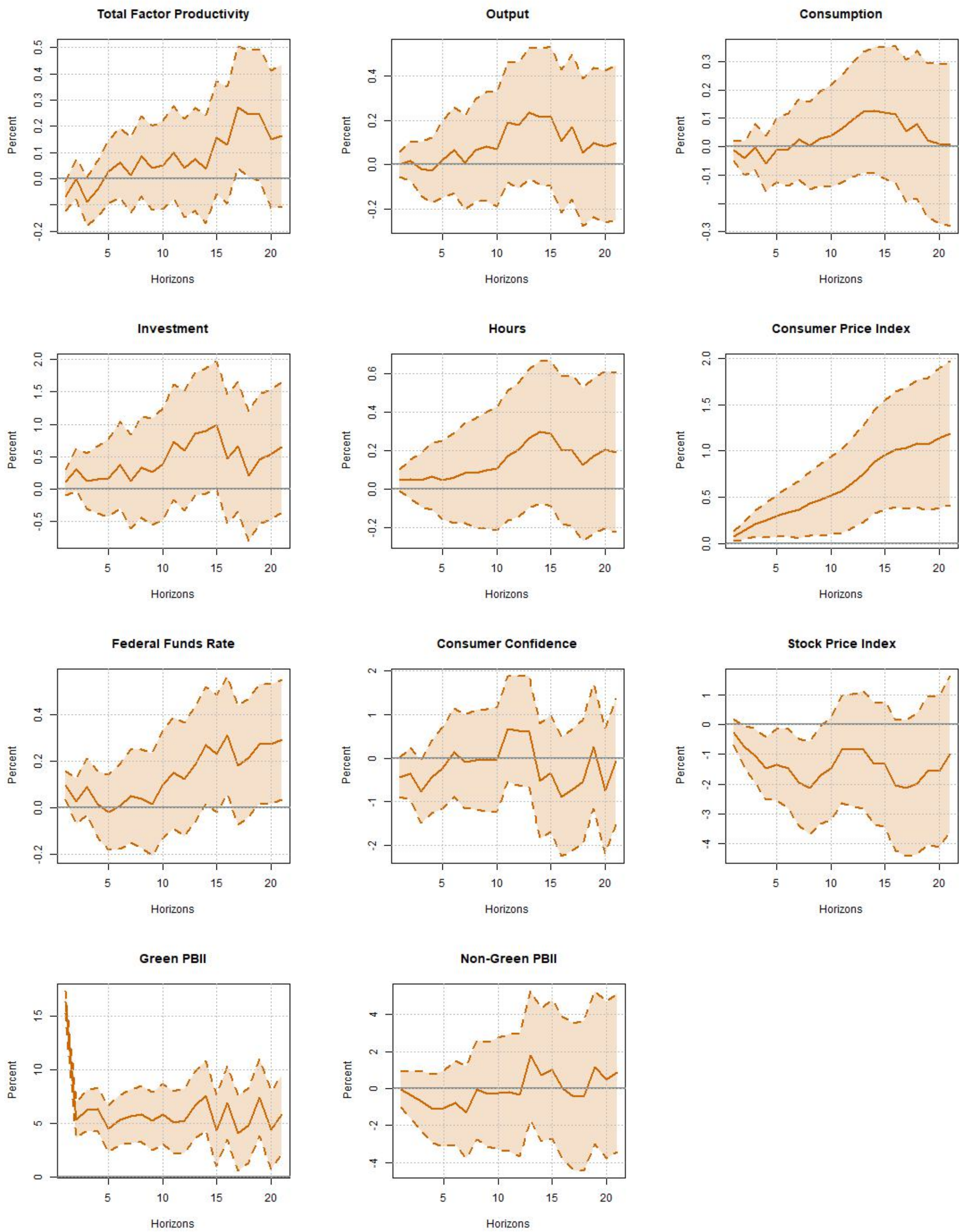


Figure 4: Dynamic responses to the idiosyncratic transition content of green technology news (Baseline)

The monetary policy stance exhibits a mild increase on impact, and its impulse response function shows an increasing behavior over the entire horizon, consistent with the rise in consumer prices. However, the point responses are barely significant, reflecting the policy trade-off introduced by the inflationary pressures. The weakly positive response aligns with the notion that the Central Bank adopts a monetary policy reaction function, placing positive weight on inflation and taking into account the economic consequences of the green transition. Regarding financial markets, it is observed that the stock market experiences a significant downturn following an increase in $\epsilon^{G}_{O,t}$. Stock prices reduce on impact and remain lower throughout the entire horizon, although the impulse response becomes statistically insignificant after 10 quarters post-shock. This pattern again can be explained by changes in expectations regarding a more stringent future climate policy. The responses of the real variables are not significant, although a U-shaped pattern is observable for output, consumption, investment, and hours worked, with the peak response occurring approximately 13 to 14 quarters after the shock. For the TFP, the peak response is observed at the 17th quarter and reaches statistical significance. *Consumer Prices.*—The idiosyncratic component of the green technology news shocks results in a strong and persistent increase in consumer prices. What are the responses of the energy prices and other specific price categories to these components? In Figure 5 we observe that the pattern response of energy prices mirrors that of the overall price index in magnitude and shape. In contrast, core consumer prices do not react in the short run and a significant response is only observed around the 15th quarter following the shock. The responses obtained for the prices of durable goods and services closely resemble those of energy prices, indicating a substantial pass-through from energy inflation. Meanwhile, the price response of non-durable goods parallels that of core prices.

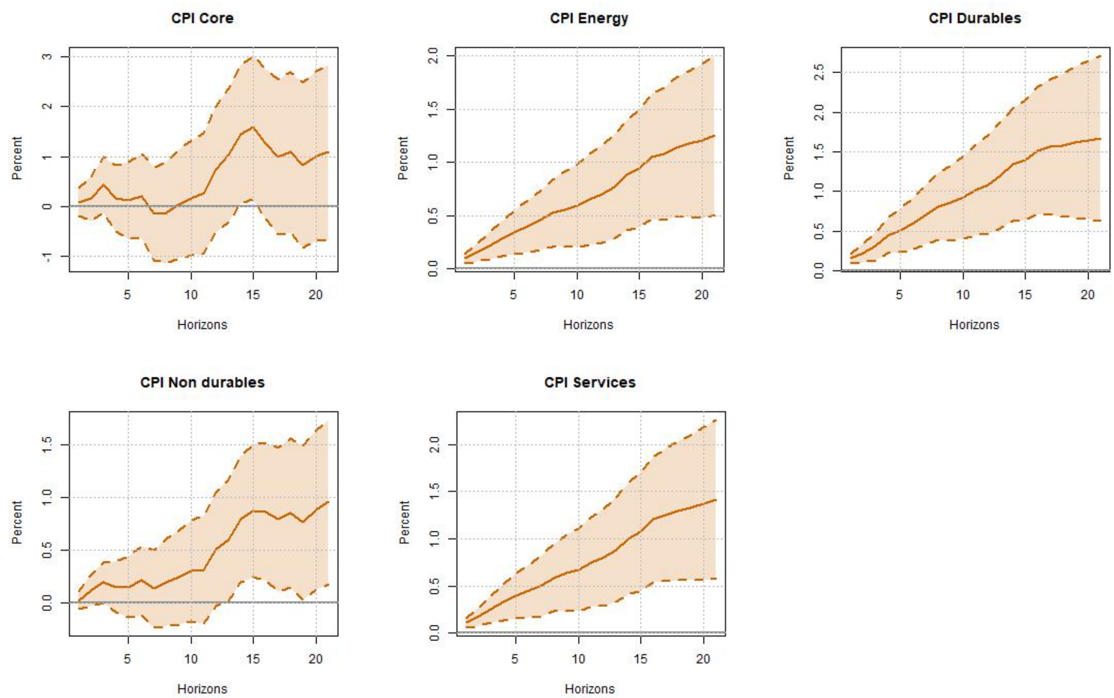


Figure 5: Dynamic responses to the idiosyncratic transition content of green technology news (CPI components)

Stock Prices.—To better understand the decline in aggregate stock prices, Figure 6 examines the stock price responses of selected industries potentially impacted by changes in environmental regulations. Except for the mining sector, all analyzed industries experienced a reduction in their stock prices. For the oil and gas and automobile sectors, the reduction is transitory, with the response becoming non-significant from the 10th horizon onwards, mirroring the dynamics of the aggregated stock price index. In contrast, the electricity and retail sectors exhibit a more persistent fall in their stock prices. Observed responses align with the green technology news as containing a transition content, which carries implications of future changes in environmental regulations and the necessary investments required to adapt to upcoming technological scenarios.

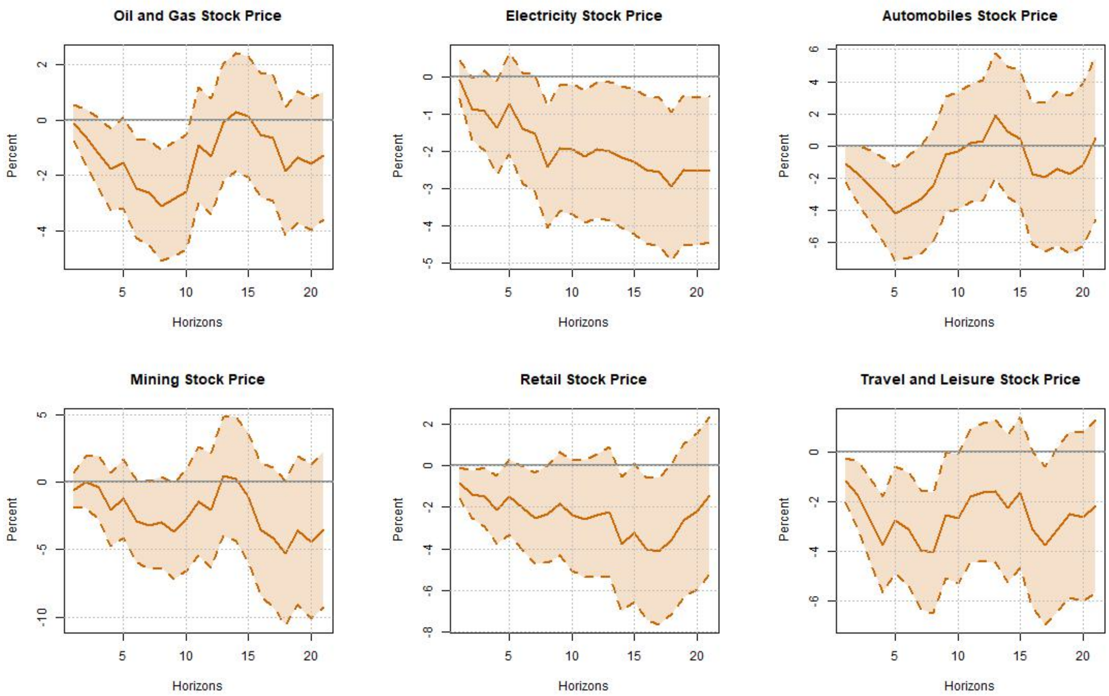


Figure 6: Dynamic responses to the idiosyncratic transition content of green technology news (Stock prices by industry)

5.3 The Role of Climate Policy

The differing responses to both components of green news technology shocks suggest that the mechanisms through which the common and idiosyncratic components impact stock prices and consumer prices are distinct. In this section, we show that these mechanisms may be driven by two key factors:

1. Unlike the common component, the idiosyncratic component leads to a reduction in fossil energy consumption as a share of GDP. This reduction is not driven by changes in the price of the energy (which is proxied by the WTI price index) and hence is driven by a demand side of fossil consumption. This may be linked to a shift toward different energy sources, consistent with the mechanism proposed by Airaudo et al.

(2024) to explain greenflation.

2. The idiosyncratic component also results in an increase in both the Environmental Policy Stringency (EPS) index, as developed by Botta and Koźluk (2014), and the Climate Policy Uncertainty (CPU) index, introduced by Gavriilidis (2021). This suggests that the idiosyncratic component heightens expectations of stricter future carbon regulations and more rigorous environmental standards.

Figures 7 and 8 illustrate the responses of several climate policy-related variables to the common and idiosyncratic components, respectively. These responses are estimated using the local projection methodology outlined in Section 5.1.2. The most notable differences between the two types of shocks are observed in the responses of the energy efficiency indicator (measured as the ratio of total fossil fuel consumption to GDP) and the EPS indexes.

On the one hand, while the common component of green technology shocks has no impact on energy efficiency, the idiosyncratic component significantly reduces the ratio of fossil energy consumption to GDP. This decline helps explain the observed rise in the CPI in the macroeconomic analysis as it may imply a change to a more expensive energy source used in the economy. This mechanism is similar to the one proposed by Airaudo et al. (2024) to explain greenflation. Notably, this reduction in energy efficiency is not driven by higher energy prices, which could otherwise account for both the CPI increase and the drop in fossil fuel consumption. This is evidenced by the lack of response of the WTI index (oil price) to the idiosyncratic component shock. Moreover, when energy efficiency is included in the system of equations within the BVAR model used to identify these shocks, the idiosyncratic component no longer triggers an increase in the CPI. Detailed responses of macroeconomic variables to these shocks are presented in Figure A2 of the Appendix.

On the other hand, the climate policy uncertainty index and the environmental policy stringency indexes (including total, market-based, and technological support policies) significantly increased following the shock. This rise is particularly immediate for market-based policies, which encompass measures such as carbon taxes, nitrogen taxes, diesel taxes, and CO_2 trading schemes. Such an increase likely reflects heightened expectations of stricter carbon regulations and more rigorous environmental standards in the future. As a result, firms may anticipate weaker future performance, prompting financial markets to respond with lower stock valuations and less favorable firm-level variables such as sales and profits.

Interestingly, these policy stringency indexes exhibit a negative response to the common component of green technology shocks. This response may help explain the positive responses observed in firm-level variables such as sales, profits, and investment.

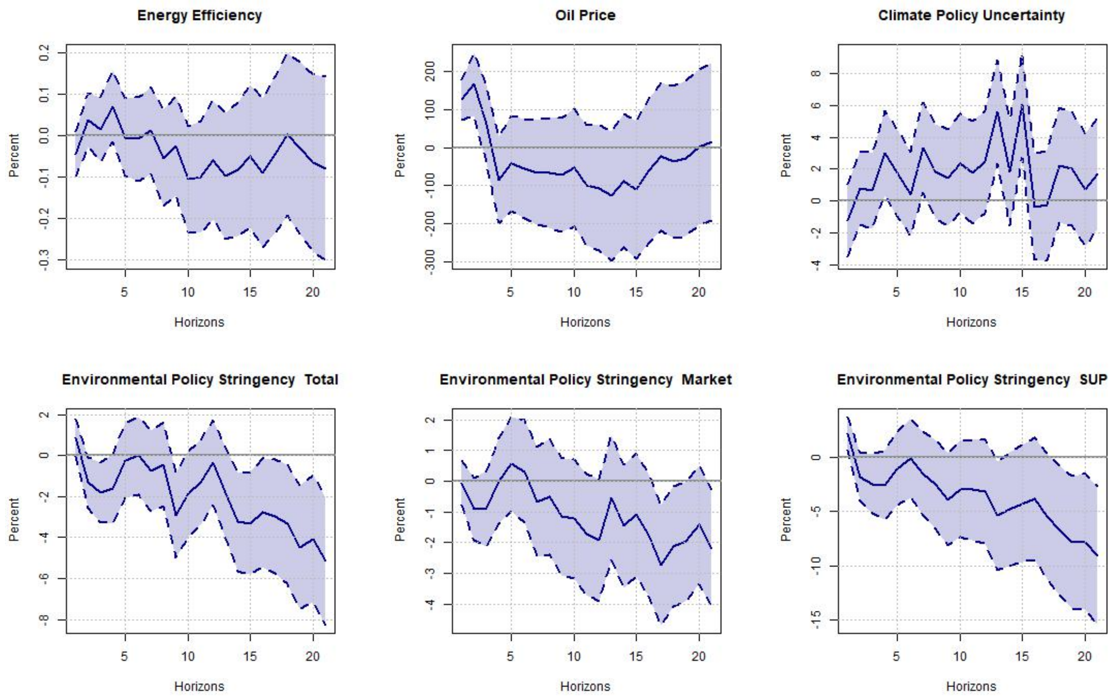


Figure 7: Dynamic responses of climate policy variables to the common component of green technology news shocks

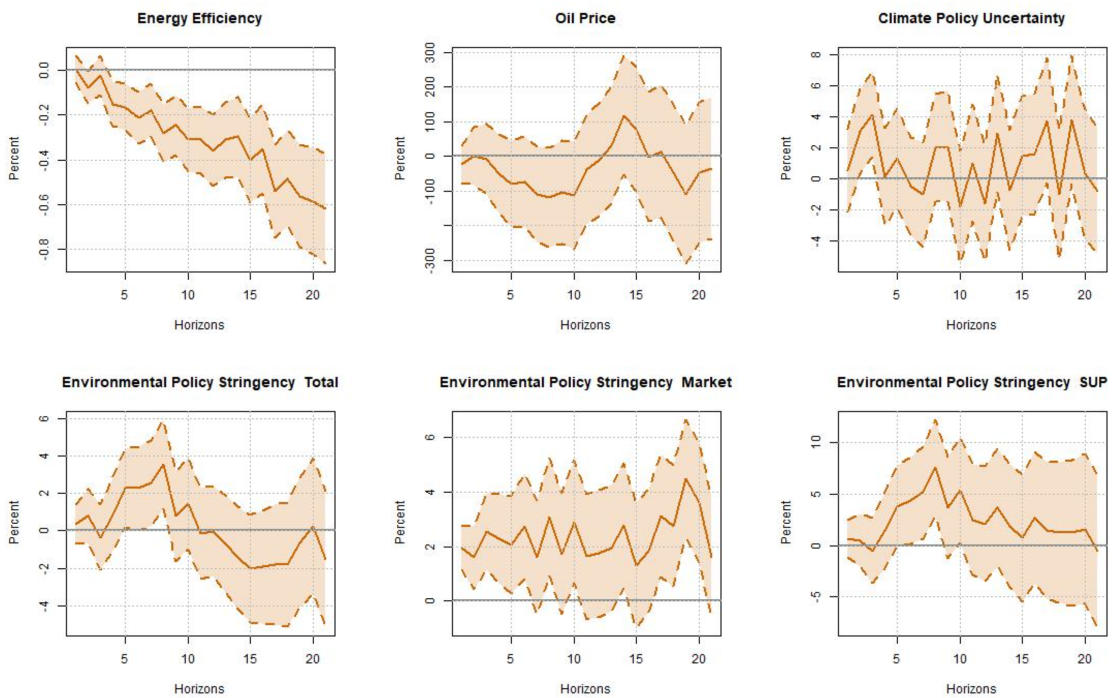


Figure 8: Dynamic responses of climate policy variables to the idiosyncratic component of green technology news shocks

6 Conclusion

This paper examines how green technology news shocks propagate through the economy, offering both aggregate and firm-level evidence. These shocks are decomposed into two orthogonal components. The first component reflects the technological content, capturing news about future developments in the green sector. The second component, interpreted as the transition component, generates macroeconomic responses consistent with anticipated changes in future climate policy, potentially influencing inflation dynamics and stock prices. This research provides quantitative estimates of the economic impact of the green transition through a mechanism that has been underexplored in the literature: the effects of green innovation. By focusing on green innovation, we enhance our understanding of technology-specific news shocks and offer insights of practical relevance for macroeconomic and environmental policy.

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A Appendix

A.1 Aggregate and Firm-level Data Sources

This Appendix gives more details on the sources of the data used in the aggregate and firm level analyses.

Table A1: Data description and sources

Variable	Description	Source
Aggregate Analysis:		
GPBII and NGPBII	Green and Non-Green Patent Based Innovation index	Patents view + Kogan et al. (2017)
TFP	Total Factor Productivity	Fernald (2014)
Output	U.S. Real Gross Domestic Product	FRED
Consumption	U.S. Real Consumption	FRED
Investment	U.S. Real Investment	FRED
Hours	Non-farm Business Sector: Hours Worked for All Workers	FRED
Consumer Price Index	Consumer Price Index for All Urban Consumers: All Items	FRED
Federal Funds Rate	Effective federal funds rate	FRED
Consumer Confidence	Consumer Confidence Index	Michigan Survey of Consumers
Stock Price Index	Standard and Poor's 500 Composite Stock Price Index	Robert Shiller's website
CPI Core	U.S. CPI for all urban consumers: all items less food and energy	FRED
CPI Energy	U.S. CPI for all urban consumers: energy	FRED
CPI Durables	U.S. CPI for all urban consumers: durables	FRED
CPI Non-durables	U.S. CPI for all urban consumers: non-durables	FRED
CPI Services	U.S. CPI for all urban consumers: services	FRED
Oil and Gas stock price	Average oil and gas sectoral stock price index	Datastream
Electricity Stock Price	Average electricity sectoral stock price index	Datastream
Automobiles Stock Price	Average automobiles sectoral stock price index	Datastream
Mining Stock Price	Average mining sectoral stock price index	Datastream
Retail Stock Price	Average retail sectoral stock price index	Datastream
Travel and Leisure Stock Price	Average travel and leisure sectoral stock price index	Datastream
Firm-level Analysis:		
Capital Stock	Property plan and equipment	Compustat
Sales	Sales divided by turnover	Compustat
Profit	Sales minus cost of goods sold	Compustat
Liquidity	Cash and short term investments to total assets ratio	Compustat
Leverage	Total debt to total assets ratio	Compustat

A.2 Identification Using a Choleski Rotation

The QR approach to decomposing the reduced-form residuals e_t^G is equivalent to a Choleski rotation in a system where NGPBII is ordered first and GPBII is ordered second within the information set. Identification is achieved by assuming that green technology news shocks, which induce movement in the GPBII, do not affect the NGPBII on impact. This assumption suggests a higher degree of exogeneity for the non-green innovation, which is plausible if we conceive green technology innovation as nested within non-green innovation. The impulse responses to a structural green technology news shock, identified under this ordering assumption, are identical to those in Figure 4 computed using local projections. For comparison, Figure A1 presents the impulse responses from the estimated VAR model that produce similar interpretations. The decision to maintain the QR results as baseline is motivated by the possibility to obtain responses to the common projected component.

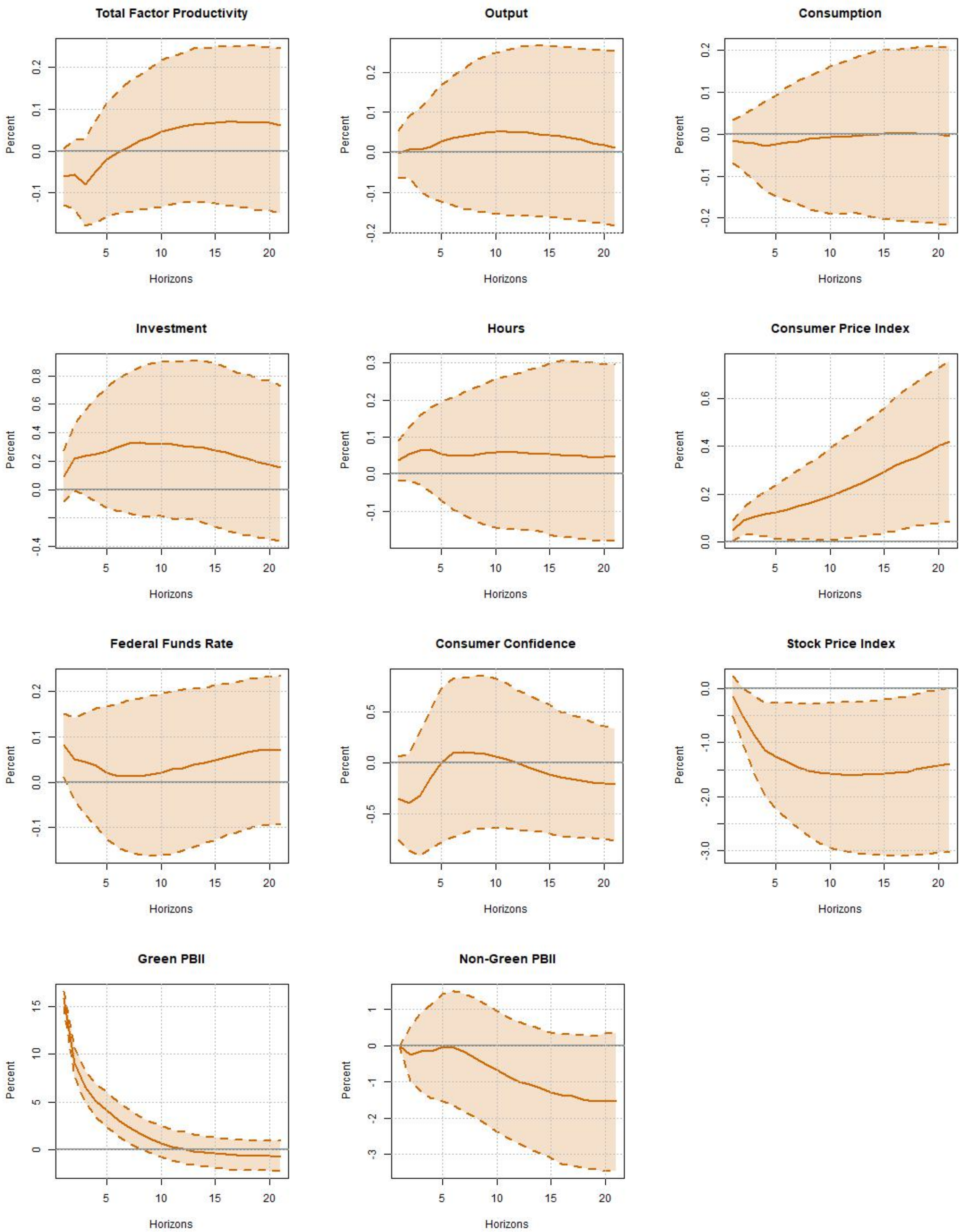

Figure A1: Dynamic responses to green technology news shocks identified using Choleski

A.3 Including Energy Efficiency in the BVAR

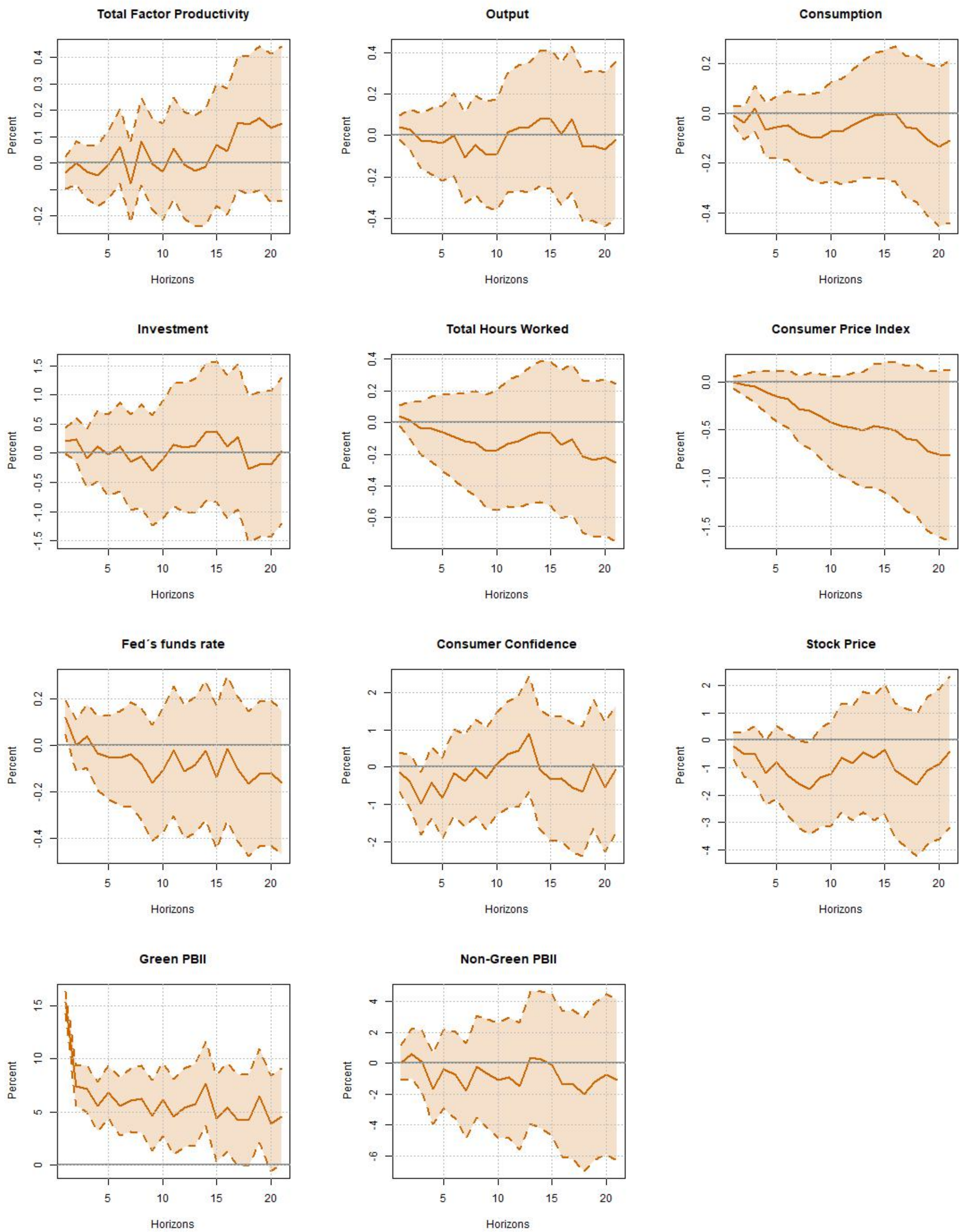

Figure A2: Dynamic responses to the idiosyncratic transition content of green technology news including the energy efficiency in the BVAR system.